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Time-Varying Effects of Financial Uncertainty Shocks on Macroeconomic Fluctuations in Peru

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To my parents, Sumner and Zara, for their unconditional support and for instilling in me valuable values.

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Abstract

This article employs a family of VAR models with time-varying parameters and stochastic volatility (TVP-VAR-SV) to estimate the impact of external financial uncertainty shocks on a set of macroeconomic variables in Peru for the period from 1996Q1 to 2022Q4. The main findings can be summarized as follows: (i) a simple VAR model with stochastic volatility is sufficient to capture uncertainty dynamics compared to TVP-VAR alternatives; (ii) uncertainty shocks have a negative and significant impact on private investment growth in the medium and long term; (iii) the impact on private investment growth is three times greater than that on GDP growth; (iv) uncertainty shocks behave like aggregate supply shocks, leading to an increase in the inflation rate; and (v) uncertainty shocks have stronger effects in scenarios characterized by unfavorable financial conditions.

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

Contents

1 Introduction

Recent literature has emphasized financial market frictions as a significant source of macroeconomic fluctuations. This idea (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014; Caldara et al., 2016; Alessandri et al., 2023) suggests that emerging market economies (EMEs) experience more protracted and pronounced economic downturns compared to advanced economies (AEs). This difference is often linked to political challenges, underdeveloped financial markets, the substantial implications of external decisions, and other factors (Redl, 2020; Miescu, 2022; Giraldo et al., 2023). However, the research on these effects in Latin America is limited.

Against this backdrop, this article seeks to contribute to our understanding of how financial uncertainty shocks affect Peru, a small, open, commodity-exporting economy. Specifically, we investigate how these shocks influence private investment, diverging from prior studies that focus on their impact on GDP (Farfán, 2018; Llosa et al., 2022). Additionally, we incorporate the period encompassing the COVID-19 pandemic, employing nonlinear models to capture the evolving nature of uncertainty during this time. Our objective is to validate the findings highlighted in the literature review within the context of Peru. Previous research suggests that as business confidence wanes and uncertainty mounts, external capital inflows decrease, and private investment contracts because business owners tend to adopt a “wait and see” approach (Bernanke, 1983; Bloom et al., 2007; Baum et al., 2009; Bloom, 2009; Arellano et al., 2012; Carrière-Swallow and Céspedes, 2013; Gourio et al., 2013). Furthermore, uncertainty functions as a negative supply shock, resulting in higher inflation in EMEs (Bhattarai et al., 2019; Kumar et al., 2021; Miescu, 2022; Giraldo et al., 2023). Lastly, we find that the effects of uncertainty vary across different financial scenarios (Alessandri and Mumtaz, 2019; Nalban and Smădu, 2021) and between AEs and EMEs (Carrière-Swallow and Céspedes, 2013; Redl, 2020; Miescu, 2022).

The study of Peru’s case is significant, as the country has undergone substantial changes since the adoption of an inflation targeting (IT) regime in 2002. Prior to this policy shift, Peru grappled with high levels of debt, a significant reliance on the U.S. dollar in deposits and loans, and considerable uncertainty regarding domestic prices (Armas and Grippa, 2006). Empirical evidence currently suggests that private investment has experienced more stable growth rates, and uncertainty regarding the Peruvian economy has diminished, thanks to increased confidence in institutions such as the Central Reserve Bank of Peru (BCRP).

To explore these issues, we employ a family of VAR models with time-varying parameters and stochastic volatility (TVP-VAR-SV), building on the methodology developed by Chan and Eisenstat (2018). We evaluate and select the most suitable model using two criteria: (i) the logarithmic marginal likelihood calculated through the cross-entropy method ($LogML_{CE}$), identifying the model most likely to generate the data; and (ii) the deviance information criterion (DIC), striking a balance between model performance and complexity.

Our key findings are as follows: First, the stochastic volatility (SV) component proves to be a robust measure for assessing the impact of financial uncertainty shocks, but the inclusion of time-varying intercepts also yields valuable insights. Second, we observe that external financial uncertainty shocks exert a significant and negative effect on private investment growth over the medium to long term. Third, the influence on private investment growth significantly surpasses that on GDP growth, with a threefold difference. Fourth, external financial uncertainty behaves as an adverse supply shock, decelerating economic activity while stoking inflation. Finally, our analysis underscores the asymmetrical nature of these effects, with more pronounced impacts in unfavorable financial scenarios compared to normal conditions.

The article's structure is as follows: In Section 2, we provide a comprehensive literature review, discussing the complex relationship between uncertainty shocks, their transmission mechanisms, inflation dynamics, and the asymmetric effects observed under various economic scenarios. Section 3 describes our methodology, detailing how we estimate and compare a family of TVP-VAR-SV models. In Section 4, we present the dataset and conduct a thorough analysis using Impulse Response Functions (IRFs), Forecast Error Variance Decomposition (FEVD), and Historical Decomposition (HD). Section 5 is dedicated to robustness checks, ensuring the reliability of our baseline scenario results. Finally, Section 6 summarizes our main conclusions and policy implications.

2 Literature Review

The study of uncertainty shocks and their impact on macroeconomic fluctuations can be categorized into three main areas: (i) understanding their transmission channels, (ii) determining whether they behave like demand or supply shocks, and (iii) exploring their asymmetric effects.

Firstly, uncertainty shocks have gained significance in both academic research and policymaking due to their substantial influence on economic cycles, particularly through real and financial markets. In the real sector, researchers examine how heightened uncertainty affects private investment, often leading to project delays as businesses adopt a cautious "wait-and-see" approach (Bernanke, 1983; Bloom, 2009). The concept of "irreversibility" is crucial here, as reversing investment decisions incurs substantial costs. Uncertainty can also reduce hiring, contributing to higher unemployment rates, especially during economic downturns (Caggiano et al., 2014; Leduc and Liu, 2016).

On the financial side, uncertainty influences the risk premium and credit conditions. When financial conditions deteriorate, credit spreads and the cost of capital rise due to higher default risk. This, in turn, has real implications, as firms may have difficulty meeting financial obligations, thereby facing costly defaults (Arellano et al., 2012; Gilchrist et al., 2014; Caldara et al., 2016). In response, firms often reduce their leverage in the short term (Baum et al., 2009). In EMEs with less-developed financial markets, uncertainty can also impact businesses by limiting access to credit and causing capital outflows (Carrière-Swallow and Céspedes, 2013; Gourio et al., 2013).

Secondly, there is a body of literature aiming to determine whether uncertainty shocks act more like negative aggregate demand (AD) shocks, decelerating economic activity and lowering inflation, or resemble aggregate supply (AS) shocks, which tend to increase inflation. There is evidence that uncertainty shocks behave as AS shocks in EMEs but as AD shocks in AEs. In their study for India, Kumar et al. (2021) share this view, given the country's high dependence on imported oil (in contrast with the U.S., where inflation is primarily a demand issue). This perspective finds support in research on various countries, including Peru (Farfán, 2018), Latin America (Bhattarai et al., 2019; Giraldo et al., 2023), a group of 15 EMEs (Miescu, 2022), and AEs like the U.S. (Bloom, 2009) and the Eurozone (Petrakis et al., 2014). Miescu (2022) argues that uncertainty shocks behave as AS shocks in EMEs due to their experience with stagflation or because their central banks struggle to mitigate price effects, as domestic uncertainty shocks are not purely exogenous and often originate in spillover effects from AEs. To address this, Miescu (2022) develops uncertainty indexes for each EME following the methodology of Jurado et al. (2015) and Ludvigson et al. (2021), based on the Chicago Board Options Exchange (CBOE) Volatility Index, a global measure of uncertainty.

For their part, Alessandri and Mumtaz (2019) argue that the nature of an uncertainty shock is closely linked to financial conditions. In the case of the U.S., they contend that, in normal times, uncertainty shocks behave as AS shocks in the short term, leading to reduced output and increased inflation. However, during financial distress, they transform into AD shocks. This perspective aligns with evidence from the Eurozone (Nalban and Smădu, 2021) and with research focusing on U.S. recessions (Caggiano et al., 2014; Leduc and Liu, 2016).

The importance of characterizing uncertainty shocks lies in their policy implications. For instance, in Peru, the BCRP implements conventional countercyclical policies to encourage economic growth in response to AD shocks, but also relies on unconventional instruments, such as reserve requirements and net international reserves, in the case of AS shocks (Castillo, 2019).

Thirdly, uncertainty shocks have also been studied based on their asymmetric effects on economic activity under different financial scenarios and across countries. Alessandri and Mumtaz (2019) employ a threshold Bayesian VAR model to show that uncertainty shocks have a higher cumulative asymmetric impact during financial distress in the U.S. than during normal times. They also conclude that negative shocks have a more substantial effect in unfavorable scenarios than positive ones, aligning with the idea that bad news can influence decision-making more profoundly than good news. Nalban and Smădu (2021) also find asymmetries in output growth for the Eurozone using the same methodology. Consistently, Caggiano et al. (2014) demonstrate that U.S. uncertainty shocks have a more significant impact on unemployment during recessions.

Moreover, there is evidence of asymmetric effects between groups of countries. Carrière-Swallow and Céspedes (2013) suggest that the effects in EMEs are more profound than in AEs. EMEs experience much more severe declines in private investment and consumption in response to uncertainty shocks, and take significantly longer to recover because these shocks are more persistent in those countries. Miescu (2022) confirms this by comparing the results for EMEs with those for AEs obtained by Redl (2020). The effect on GDP growth in AEs is, on average, 2.5 times smaller than in EMEs.

In the case of Peru, studies on the impact of uncertainty shocks are limited and are often conducted using panel data models (Bhattarai et al., 2019; Miescu, 2022), or encompass multiple countries (Carrière-Swallow and Céspedes, 2013; Llosa et al., 2022; Giraldo et al., 2023). For comparison, Farfán (2018), employing a Bayesian VAR model, concludes that a domestic financial uncertainty shock has a real impact and behaves like a negative AS shock, as it increases inflation while decelerating economic activity, as measured by a proxy of GDP growth. Additionally, uncertainty shocks depreciate the domestic currency, leading to two consequences: boosting exports by making Peruvian goods cheaper, but increasing the probability of defaulting on payments, thereby discouraging private investment. Farfán (2018) introduces a domestic uncertainty index, measured by the monthly variance of the daily returns of the Lima

Stock Exchange's General Stock Index (IGBVL) instead of the CBOE Volatility Index (VIX), which measures global uncertainty. Similarly, Vega and Pinelo (2022) provide an approximation to a domestic index through a Natural Language Processing (NLP) algorithm that analyzes the occurrence of words related to uncertainty in the BCRP Annual Report. The index is on an annual frequency and accurately captures years of high domestic uncertainty.

Additionally, the study of uncertainty in Peru has approached the issue from a different perspective, focusing on the notion of "certainty." This approach involves incorporating a Business Confidence Index (BCI) into private investment models. According to Bachmann et al. (2013), these types of indicators are likely to capture the sentiment of decision-makers. Similar to the impact of uncertainty, a decrease in confidence regarding future prospects often leads to a reduction or cancellation of planned business expenditures (Kuzmanović and Sanfey, 2013). In Peru, the two main BCIs are produced by the BCRP and Apoyo Consultoría, a consulting firm. These indices are generated through surveys conducted among key figures such as chairpersons, stakeholders, managers, and CEOs, who provide insights into their future investment plans and economic outlook. A comparative analysis (Arenas and Morales, 2013) reveals that particularly the BCRP BCI exhibits a high level of predictive and anticipatory power concerning the future dynamics of private investment. This finding aligns with those for other EMEs and developing countries like Chile (Albagli et al., 2019), Uruguay (Lanzilotta, 2014), and the Caribbean (Janada and Ruxandra Teodoru, 2020), as well for AEs such as the U.S. (Khan and Upadhayaya, 2020) and the Eurozone (De Bondt and Schiaffi, 2015).

However, while the conclusion regarding the significance of the BCI is supported by existing literature, it is worth noting that it might be somewhat biased due to the omission of external variables such as the export price index or terms of trade, which have been extensively documented as relevant factors in the Peruvian economy (Castillo et al., 2007; Mendoza Bellido and Collantes Goicochea, 2018; Rodríguez et al., 2018; Gondo and Vega, 2019; Portilla et al., 2022; Chávez and Rodríguez, 2023; Meléndez Holguín and Rodríguez, 2023; Rodríguez et al., 2023a; Rodríguez et al. (2023b). Two articles provide more reliable insights in this regard. Firstly, BCRP (2016) uses a Structural VAR model to indicate that the BCI and the terms of trade explain 18% and 34% of the FEVD of private investment growth, respectively. Secondly, Sánchez and Vasallo (2023a), employing a family of TVP-VAR-SV models, demonstrate that expectations shocks exert a persistent, positive, and significant influence on private investment growth up to eight quarters ahead. Additionally, the study reveals that the importance of expectations has grown over time, with their impact being nearly 40% greater in 2019 compared to 17 years earlier.

This article aims to investigate how financial uncertainty shocks impact the Peruvian economy, following the three previously mentioned lines of study: (i) examine their effects on exchange rate growth, private investment growth, and inflation in the baseline model, and on GDP growth and interest rates through robustness exercises; (ii) assess whether these shocks resemble AS shocks by analyzing their impact on inflation; and (iii) test their asymmetric effects over time and under various scenarios.

3 Methodology

3.1 The TVP-VAR-SV Model

The benchmark model we employ is a TVP-VAR-SV model based on the work by Chan and Eisenstat (2018). In this model, we define a vector $\mathbf{y}_t = (y_{1,t}, ..., y_{n,t})'$ of n endogenous variables, formulated as follows in its structural form:

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

where $\mathbf{B}_{0,t}$ is an $n \times n$ lower triangular matrix of contemporary effects with ones on the diagonal, $\boldsymbol{\mu}_t$ is an $n\times1$ vector of time-varying intercepts, $\mathbf{B}_{1,t}, \mathbf{B}_{2,t}...\mathbf{B}_{p,t}$ are the $n\times n$ matrices of coefficients of the lagged endogenous variables, and $\boldsymbol{\Sigma}_t = diag(\exp(h_{1,t}), ..., \exp(h_{n,t}))$ are the log volatilities of the structural errors $\mathbf{h}_t = (h_{1,t}, ..., h_{n,t})'$ specified as an independent random walk process:

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

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

For model estimation, we transform (1) into a reduced form. It is worth noting that the system can be estimated recursively since the variance matrix $\boldsymbol{\Sigma}_t$ is diagonal; i.e., structural errors are orthogonal.

We consider groups of time-varying parameters. The first group is a $k_{\boldsymbol{\beta}} \times 1$ vector of time-varying intercepts and the coefficients of the lagged endogenous variables, denoted as $\boldsymbol{\beta}_t = vec((\boldsymbol{\mu}_t, \mathbf{B}_{1,t}, ..., \mathbf{B}_{p,t})')$. The second group is a $k_{\boldsymbol{\gamma}} \times 1$ vector of time-varying coefficients characterizing the contemporaneous relationships between the variables $\boldsymbol{\gamma}_t$. It is important to highlight that $k_{\boldsymbol{\beta}} = n(np+1)$ and $k_{\boldsymbol{\gamma}} = n(n-1)/2$. Therefore, we can express (1) as:

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

where $\tilde{\mathbf{X}}_t = \mathbf{I}_n \otimes (1, \mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-p})$ and $\mathbf{W}_t$ is an $n \times k_{\boldsymbol{\gamma}}$ matrix that contains the appropriate elements of $-\boldsymbol{y}_t$[1]. Defining $\mathbf{X}_t = (\tilde{\mathbf{X}}_t, \mathbf{W}_t)$, the model can be written as a generic state-space model:

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

where $\boldsymbol{\theta}_t = (\boldsymbol{\beta}'_t, \boldsymbol{\gamma}'_t)'$ has a $k_{\boldsymbol{\theta}} = k_{\boldsymbol{\beta}} + k_{\boldsymbol{\gamma}}$ dimension. All parameters follow a random walk process:

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

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

We consider 7 models for estimation. The first is a TVP-VAR-SV specification where all parameters $\boldsymbol{\theta}_t = (\boldsymbol{\beta}'_t, \boldsymbol{\gamma}'_t)'$ are time-varying with SV. Additionally, to analyze the individual contribution of the three groups of parameters, we have three variations of the

[1] 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 $i = 1, 2$.

TVP-VAR-SV model: (i) a TVP-VAR-R1-SV model, where the intercepts and the parameters associated with the lagged endogenous variables are constant (i.e., $\boldsymbol{\beta}_t = \boldsymbol{\beta}_0$); (ii) a TVP-VAR-R2-SV model, where the coefficients associated with contemporaneous relationships between the variables are constant (i.e., $\gamma_t = \gamma_0$); and (iii) a TVP-VAR-R3-SV model, where only the intercepts $\boldsymbol{\mu}_t$ are time-varying parameters. Additionally, we have a TVP-VAR model, where all parameters are time-varying but without SV. Finally, we estimate a CVAR-SV model with non-time-varying parameters but with SV; and a simple VAR (CVAR) model with non-time-varying parameters and homoscedastic variance.

3.2 Estimation Algorithm

We employ the Gibbs sampling method to estimate the posterior parameters. The draws are based on the precision sampling technique proposed by Chan and Jeliazkov (2009), which was further developed in Chan and Eisenstat (2018). This approach involves dividing the parameters into blocks and estimating each one separately. These estimates are then used to generate conditional updates for the other parameter blocks.[2] For the TVP-VAR-SV models, the algorithm operates as follows: (i) the draws are obtained by sampling from $(\boldsymbol{\theta}|\mathbf{y}, \mathbf{h}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}}, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}, \mathbf{K}_\theta^{-1})$, where $\mathbf{K}_\theta = \mathbf{H}_\theta' \mathbf{S}_\theta^{-1} \mathbf{H}_\theta + \mathbf{X}' \boldsymbol{\Sigma}^{-1} \mathbf{X}$ and the mean $\widehat{\boldsymbol{\theta}} = \mathbf{K}_{\boldsymbol{\theta}}^{-1}(\mathbf{H}_{\boldsymbol{\theta}}' \mathbf{S}_{\boldsymbol{\theta}}^{-1} \mathbf{H}_{\boldsymbol{\theta}} \alpha_{\boldsymbol{\theta}} + \mathbf{X}' \boldsymbol{\Sigma}^{-1} \mathbf{y})$, with $\alpha_{\boldsymbol{\theta}} = \mathbf{H}_{\boldsymbol{\theta}}^{-1} \widetilde{\alpha}_{\boldsymbol{\theta}}$. The matrices $\mathbf{H}_\theta$, $\mathbf{S}_\theta$, $\boldsymbol{\Sigma}$, and $\widetilde{\alpha}_{\boldsymbol{\theta}}$ are described in Appendix A of Chan and Eisenstat (2018); (ii) we obtain the draws for $(\mathbf{h}|\mathbf{y}, \boldsymbol{\theta}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}}, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}(\widehat{\mathbf{h}}, \mathbf{K}_h^{-1})$; (iii) the draws for the diagonal elements in $\boldsymbol{\Sigma}_{\boldsymbol{\theta}}$ and $\boldsymbol{\Sigma}_h$ are obtained from the conditional distributions $(\sigma^2_{\boldsymbol{\theta}_i}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{\boldsymbol{\theta}_i} + \frac{T}{2}, S_{\boldsymbol{\theta}_i} + \frac{1}{2}\sum_{t=1}^T (\theta_{it} - \theta_{i,t-1})^2)$ for $i = 1, \ldots, k_\theta$, and $(\sigma^2_{h_j}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{h_j} + \frac{T}{2}, S_{h_j} + \frac{1}{2}\sum_{t=1}^T (h_{jt} - h_{j,t-1})^2)$ for $j = 1, \ldots, k_h$, respectively; (iv) we obtain the draws for the initial conditions $\boldsymbol{\theta}_0$ from $(\boldsymbol{\theta}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}}, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}_0, \mathbf{K}_{\boldsymbol{\theta}_0}^{-1})$, where $\mathbf{K}_{\boldsymbol{\theta}_0} = \mathbf{V}_{\boldsymbol{\theta}}^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{\theta}}^{-1}$ and $\widehat{\boldsymbol{\theta}}_0 = \mathbf{K}_{\boldsymbol{\theta}_0}^{-1}(\mathbf{V}_{\boldsymbol{\theta}}^{-1} \mathbf{a}_{\boldsymbol{\theta}} + \boldsymbol{\Sigma}_{\boldsymbol{\theta}}^{-1} \boldsymbol{\theta}_1)$, and we obtain the draws for the initial conditions $\mathbf{h}_0$ from $(\mathbf{h}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}}, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widehat{\mathbf{h}}_0, \mathbf{K}_{h_0}^{-1})$, 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 (v) we repeat steps (i)-(iv) N times. The hyperparameters $\nu_{\boldsymbol{\theta}_i}$, $S_{\boldsymbol{\theta}_i}$, ν_{h_j}, S_{h_j}, $\mathbf{a}_{\boldsymbol{\theta}}$, $\mathbf{V}_{\boldsymbol{\theta}}$, $\mathbf{a}_h$ and $\mathbf{V}_h$ are defined in Section 4.2.

3.3 Model Comparison

To compare the models discussed above and select the most suitable one, we employ two criteria: the log-marginal likelihood calculated using the cross-entropy method ($LogML_{CE}$) and the DIC.

3.3.1 Log-Marginal Likelihood ($LogML_{CE}$)

Our first criterion, the $LogML_{CE}$, is based on the approach introduced by Chan and Eisenstat (2015), which offers a more accurate and less time-consuming calculation method. The $LogML_{CE}$ is essentially the density forecast from the model, evaluated at the observed data $\boldsymbol{y}$.

[2] A comprehensive explanation of the estimation method for the TVP-VAR-SV model and other restricted models can be found in Section 4 and in Appendix A of Chan and Eisenstat (2018).

Given the priors, we estimate $\widehat{p}(\mathbf{y})$ using the importance sampling density $g(\boldsymbol{\theta}_n)$:

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

The importance sampling density is obtained through the cross-entropy method, which measures the distance between the prior and posterior densities. Then, $g(\boldsymbol{\theta}_n)$ acquires independent draws $\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, ...\boldsymbol{\theta}_N$. However, it is worth noting that the estimator $\widehat{p}(\mathbf{y})$ is sensitive to the variance of $g(\boldsymbol{\theta}_n)$. Hence, it is crucial that the chosen solution for $g(\boldsymbol{\theta}_n)$ minimizes the variance of the estimator.[3]

Additionally, the $LogML_{CE}$ enables us to compare different sets of models using the Bayes Factor (BF) to determine which model is most likely to generate the data. The Bayes factor is defined as follows: $BF_{ij} = \frac{p(y|M_i)}{p(y|M_j)}$, and if BF_{ij} equals k, then model M_i is k times preferred over model M_j.

3.3.2 Deviance Information Criterion (DIC)

Our second criterion is the DIC. While initially introduced in Spiegelhalter et al. (2002), this article employs the version proposed by Chan and Grant (2016).[4] In order to compute DIC, we define a function $f(\mathbf{y}|\boldsymbol{\theta})$ representing the likelihood of the model and another function $h(\mathbf{y})$ related to the data. The goodness of fit is then denoted as $D(\boldsymbol{\theta}) = -2\log f(\mathbf{y}|\boldsymbol{\theta}) + 2\log h(\mathbf{y})$. DIC also requires a measure of the complexity of the model, denoted as $p_D = \overline{D(\boldsymbol{\theta})} - D(\widetilde{\boldsymbol{\theta}})$, which quantifies the effective number of parameters. Notably, $\overline{D(\boldsymbol{\theta})}$ represents the mean posterior deviation, defined as $\overline{D(\boldsymbol{\theta})} = -2E_{\boldsymbol{\theta}}[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2\log h(\mathbf{y})$, and $\widetilde{\boldsymbol{\theta}}$ is a estimator of $\boldsymbol{\theta}$. Consequently, DIC is defined as the sum of the posterior mean deviation and the actual number of parameters $DIC = \overline{D(\boldsymbol{\theta})} + p_D$. By substituting the previously mentioned definitions and assuming $h(\mathbf{y}) = 1$, we obtain:

$$DIC = -4E_{\boldsymbol{\theta}}[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2\log f(\mathbf{y}|\widehat{\boldsymbol{\theta}}). \tag{6}$$

4 Empirical Results

4.1 Data

The proposed models are estimated using a set of five variables, two external and three domestic, at a quarterly frequency over the period from 1996Q1 to 2022Q4. The external variables encompass the export price index (EPI) growth (p_t^*) and the external financial uncertainty index (u_{ft}^*). The domestic variables comprise nominal exchange rate growth (e_t), real private investment growth (pi_t), and the inflation rate (π_t). Nearly all of the data is sourced from the BCRP, except for u_{ft}^*, which is obtained from the Federal Reserve Economic Data (FRED) repository.

The EPI, exchange rate, and private investment figures are expressed as annual variations, while the inflation rate corresponds to the annual growth of the Consumer

[3]Detailed information on the integrated likelihood estimation can be found in Section 4 and Appendix B of Chan and Eisenstat (2018).

[4]We opt for this version, based on integrated likelihood, over alternatives (e.g., conditional DIC), which tend to favor overfitted models (Chan and Eisenstat, 2018).

Price Index (CPI). The external financial uncertainty index is derived from the VIX index, calculated based on mid-quote prices of the S&P 500 index call and put options. It gauges the 30-day expected volatility of the U.S. stock exchange market. Appendix 5 shows that external financial uncertainty within the sample peaked during the Global Financial Crisis (GFC) in 2008-2009. During these years, private investment growth decelerated, whereas exchange rate growth and the inflation rate surged to their highest levels since the beginning of the observation period.

The identification process uses recursive restrictions, following Sims (1980). This technique orders contemporaneous relationships from the most exogenous to the most endogenous. The initial assumption is that EPI growth is the most exogenous, primarily influenced by variables associated with external demand, which are not incorporated into the model. Consequently, fluctuations in EPI generate financial market uncertainty, encouraging capital outflows and leading to increased exchange rate growth. Finally, this has a detrimental impact on private investment growth while simultaneously driving up the inflation rate.

4.2 Priors

The priors for the hyperparameters are non-informative in all the models. We assume that the initial conditions are Gaussian: $\boldsymbol{\theta}_0 \sim \mathcal{N}(\mathbf{a}_{\boldsymbol{\theta}}, \mathbf{V}_{\boldsymbol{\theta}})$ and $\mathbf{h}_0 \sim \mathcal{N}(\mathbf{a}_h, \mathbf{V}_h)$. The error covariance matrices for the state equations are diagonal: $\boldsymbol{\Sigma}_{\boldsymbol{\theta}} = diag(\sigma^2_{\boldsymbol{\theta}_1}, \ldots, \sigma^2_{\boldsymbol{\theta}_n})$ and $\boldsymbol{\Sigma}_h = diag(\sigma^2_{h_1}, \ldots, \sigma^2_{h_n})$. The elements of these matrices follow an Inverse Gamma distribution and are independently distributed as $\sigma^2_{\boldsymbol{\theta}_i} \sim \mathcal{IG}(\nu_{\boldsymbol{\theta}_i}, S_{\boldsymbol{\theta}_i})$ for $i = 1, \ldots, k_{\boldsymbol{\theta}}$ and $\sigma^2_{\boldsymbol{\theta}_i} \sim \mathcal{IG}(\nu_{\boldsymbol{\theta}_i}, S_{\boldsymbol{\theta}_i})$ for $i = 1, \ldots, k_{\boldsymbol{\theta}}$. Following Chan and Eisenstat (2018), we set the hyperparameters as $\mathbf{a}_{\boldsymbol{\theta}} = 0$, $\mathbf{V}_{\boldsymbol{\theta}} = 10 \times \mathbf{I}_{k_{\boldsymbol{\theta}}}$, $\mathbf{a}_h = 0$, $\mathbf{V}_h = 10 \times \mathbf{I}_n$ and $\nu_{\boldsymbol{\theta}_i} = \nu_{h_j} = 5$. Finally, we assume $S_{\boldsymbol{\theta}_i} = 0.1^2$ for the intercepts, $S_{\boldsymbol{\theta}_i} = 0.01^2$ for the coefficient of the lagged variables, and $S_{h_j} = 0.1^2$.

4.3 Evidence of Time Variation in Parameters and Volatility

As preliminary evidence to test the presence of coefficient variability over the period, Appendix 1 presents two statistics: the Kolmogorov-Smirnov (K-S) and the $t-$test. To conduct this analysis, it is necessary to first estimate the TVP-VAR-SV model. We consider three subsamples and the full sample. The first subsample covers the period from 1996Q2 to 2009Q3, the second from 2009Q4 to 2022Q4, and the third from 2003Q3 (when the BCRP adopted the interest rate as a monetary policy instrument) to 2022Q4.

Regarding the variance matrix, both tests suggest full variability, supporting the use of a model that incorporates SV. For the intercepts and the coefficients associated with the lags of the variables, there is evidence that 86% and 80% of them are time-varying according to the K-S test and the $t-$test, respectively, for the subsamples. In the case of the full sample, these percentages increase for both tests. Furthermore, the K-S test indicates full variability in the coefficients associated with the contemporary relationships, while the $t-$test shows almost full variability.

4.4 Results

This section compares the seven different models mentioned at the end of Section 3.1. To determine the best-fitting model, we use the $LogML_{CE}$ and DIC criteria. We consider one lag ($p = 1$) by comparing the $LogML_{CE}$ of TVP-VAR-SV model versions between zero and four lags. Additionally, we find that the Bayesian Information Criterion (BIC) of a CVAR model version also selects one lag.

4.4.1 Model Selection

Appendix 2 presents the two selection criteria introduced in the previous section along with their respective standard deviations from 10 parallel chains.

According to the $LogML_{CE}$, the best-fitting model is the TVP-VAR-R1-SV, where only the coefficients associated with the contemporary relationships are time-varying. Using the BF, this model is 3.9×10^1 times more preferred than the second-best model, the TVP-VAR-SV, and 9.8×10^1 times more preferred than the third-best model, the CVAR-SV. On the other hand, models without the SV component appear to be the least preferred, as the TVP-VAR-R1-SV model is 1.7×10^{53} more preferred than the penultimate one, the CVAR model, and 4.9×10^{60} more preferred than the last one, the TVP-VAR model.

In terms of the DIC, the CVAR-SV is selected as the best-fitting model. It then selects the TVP-VAR-R3-SV and TVP-VAR-R1-SV as the second and third best models. Given the discrepancy in the best-fitting model between both criteria, we decided to be guided by the DIC, as it penalizes model complexity.[5] Consequently, the analysis focuses on the CVAR-SV and TVP-VAR-R3-SV models, as they provide relevant insights. Furthermore, we believe that the selection of both models via the DIC is consistent with the nature of uncertainty, which often behaves in a non-systematic manner. Thus, it should not necessarily affect the relationship between lagged variables but mainly its SV component.

The SV feature is common in the best-fitting models according to both the $LogML_{CE}$ and the DIC, whereas it is lacking in the two least suitable models. Appendix 6 shows the median of the standard deviations of the errors for each equation. For EPI growth and uncertainty, errors exhibit the highest volatility during the GFC. Other variables exhibit subdued error volatility, reflecting a moderation in the growth dynamics of the Peruvian variables. However, during the COVID-19 pandemic, we observe increased volatility in the errors of domestic variables, particularly in the case of private investment growth, which experienced a significant initial decline followed by a notable rebound. It is worth noting that these conclusions cannot be obtained using the CVAR and TVP-VAR models, as they do not incorporate the SV feature, resulting in constant standard deviations of the innovations over the entire period.

4.4.2 Impulse Response Functions (IRFs)

Appendix 7 shows the 3D IRFs of exchange rate growth, private investment growth, and the inflation rate to a 1% increase in external financial uncertainty. These IRFs are normalized, meaning they should be interpreted as elasticities. In the case of the CVAR model, the analysis provides the same responses for the entire period, as the model's coefficients and SV are constant throughout. For the TVP-VAR model, private investment growth exhibits particularly atypical responses.

Regarding exchange rate growth, both the CVAR-SV and TVP-VAR-R3-SV models show their highest positive responses during 2008-2009. Specifically, a 1% increase

[5] The $LogML_{CE}$ only allows us to assess how the observed data is likely to be generated by each of the models.

in external financial uncertainty in 2008Q4 led to a 0.36% increase in exchange rate growth for the CVAR-SV model and a 0.30% increase for the TVP-VAR-R3-SV model in the following quarter. Such high magnitudes in responses are not observed in other periods.

For private investment growth, both models also indicate their most significant negative responses during 2008-2009. In this case, a 1% increase in external financial uncertainty in 2008Q4 resulted in a 0.28% decrease in private investment growth nine quarters ahead for the CVAR-SV model and a 0.40% decrease seven quarters ahead for the TVP-VAR-R3-SV model. Other notable negative responses occur in 2011Q4 and 2020Q1, at 0.26% and 0.23%, respectively, both ten quarters ahead for the CVAR-SV model. These responses are associated with specific events, such as the beginning of the economic slowdown, the election of President Ollanta Humala, the European sovereign debt crisis (2011Q4), and the onset of the COVID-19 pandemic (2020Q1).

In terms of the inflation rate, both models again show their highest positive responses in 2008Q4. A 1% increase in external financial uncertainty in this period led to a 0.24% increase in the inflation rate for both the CVAR-SV and TVP-VAR-R3-SV models in the following quarter. Other periods with similarly high positive responses include 2011Q3 and 2020Q1, with 0.21% and 0.18% increases in the first quarter ahead, respectively, for both models. These results suggest that financial uncertainty in Peru behaves like an AS shock, leading to increased inflation while dampening demand, consistent with findings in other studies (Farfán, 2018; Llosa et al., 2022; Miescu, 2022; Giraldo et al., 2023).

Appendix 8 presents the average medians of the IRFs for the three domestic variables in response to an external financial uncertainty shock. In the case of exchange rate growth, all models yield very similar initial responses, with differences becoming more noticeable after several periods. For private investment growth, the TVP-VAR-R3-SV model shows the most significant negative impact. Generally, all models display similar negative responses, except the TVP-VAR model. Regarding the inflation rate, responses are consistent across all models, except the TVP-VAR-R1-SV model, which exhibits a higher magnitude of impact.

Appendix 9 displays the median IRFs for the two selected models, CVAR-SV and TVP-VAR-R3-SV, for shocks in EPI growth, external financial uncertainty, and exchange rate growth. The results are robust across models. A 1% increase in external financial uncertainty leads to a significant 0.18% currency depreciation for the CVAR-SV model, persisting for four quarters, and a 0.13% increase in the inflation rate for ten quarters. Additionally, uncertainty negatively affects private investment growth, with responses not reaching statistical significance. The TVP-VAR-R3-SV model yields more extended periods of significant responses for exchange rate growth and the inflation rate. For private investment growth, negative responses are significant from the third to the eighth quarter ahead, peaking at a 0.3% decrease in the eighth quarter.

For a meaningful comparison with other economic factors, and in line with Peru's stylized facts, we identified several significant observations. Firstly, an increase in EPI growth attracts capital inflows, especially when metal prices are high, leading to the appreciation of the domestic currency. This, in turn, stimulates private investment growth, aligning with findings from various research papers[6] (Castillo et al., 2007; Men-

[6]Likewise, existing literature supports the positive impact of EPI growth shocks on GDP growth, likely due to their influence on private investment (Chávez and Rodríguez, 2023; Meléndez Holguín and Rodríguez, 2023; Rodríguez et al., 2023a; Rodríguez et al., 2023b).

doza Bellido and Collantes Goicochea, 2018; Rodríguez et al., 2018; and Gondo and Vega, 2019). Additionally, EPI growth contributes to a reduction in the inflation rate through the exchange rate pass-through effect. Furthermore, a shock in exchange rate growth is found to diminish private investment growth over the course of five subsequent quarters. This relationship can be explained by Peru's historical experience with high dollarization. Currency depreciation raises the costs associated with importing capital goods, acquiring new products, and foreign currency-based indebtedness due to balance-sheet effects (Armas and Grippa, 2006; Arenas and Morales, 2013).

Appendix 10 displays various IRFs over different periods in the dataset. The 1998Q1 period starts the sample; 2003Q3 sees the introduction of the reference interest rate as a monetary policy tool; 2008Q4 coincides with the GFC outbreak; 2017Q1 aligns with the El Niño Southern Oscillation (ENSO); and 2020Q1 marks the onset of the COVID-19 pandemic, with 2021Q2 indicating the beginning of the post-pandemic rebound. These observations confirm the presence of asymmetric responses in macroeconomic variables to increased uncertainty, consistent with arguments made in studies on AEs (Alessandri and Mumtaz, 2019; Nalban and Smădu, 2021). Notably, since the GFC, the effects are much more pronounced than in calmer periods. Interestingly, responses during the COVID-19 pandemic exhibit a similar magnitude to those during calm periods, possibly because a pandemic resembles a macroeconomic uncertainty shock rather than a financial uncertainty shock.[7] Comparing magnitudes, the responses of exchange rate growth, private investment growth, and the inflation rate are nearly twice as large during the GFC, a crisis scenario, compared to 2003Q3, a calmer period.

4.4.3 Forecast Error Variance Decomposition (FEVD)

Appendix 11 shows the FEVDs of exchange rate growth, private investment growth, and the inflation rate. In general, the results from the CVAR-SV and TVP-VAR-R3-SV models are similar, delivering a significant message about the increasing importance of external financial uncertainty shocks in explaining the overall forecast error variance during financial crises.

At the beginning of the sample, spanning from 1996 to 1999, the external financial uncertainty shock accounts for 7.9%, 4.2%, and 9.4% of the variance in exchange rate growth, private investment growth, and the inflation rate, respectively, according to the CVAR-SV model. These contributions grow during the years 2000-2007, reaching 12.2%, 8.3%, and 15.7%, respectively. Notably, the highest contributions occurred in 2002, likely attributed to Argentina's sovereign debt default, which raised concerns about economic stability in Latin America. Refer to Chen et al. (2013) for Brazil and Venezuela. Subsequently, during the 2008-2009 GFC, the impact from the external financial uncertainty shock escalated to 21.9%, 16.8%, and 27%, respectively. This demonstrates an asymmetry in FEVD contributions, where uncertainty shocks exert a greater influence on domestic macroeconomic variables during crisis periods. This result aligns with findings from intertemporal IRFs.

In tandem with the growing importance of uncertainty shocks, there is also an increasing contribution from the EPI growth shock throughout the sample. This aligns

[7] Macroeconomic uncertainty shocks have significant long-term recessionary impacts as they directly influence demand and output variables. For their part, financial uncertainty shocks impact the financial market by eroding confidence and reducing access to financing sources, among other reasons, which could eventually affect real variables as well (Jurado et al., 2015; Basile and Girardi, 2018). The GFC serves as a prominent example of financial uncertainty evolving into macroeconomic uncertainty.

in magnitude with findings from Chávez and Rodríguez (2023), and Rodríguez et al. (2023a, 2023b), who employed a similar methodology. The EPI growth shock gained significance in the early 2000s, as Peru expanded its trade activities, particularly with China, which became a crucial trading partner (Mendoza Bellido, 2013).

Lastly, there is a moderation in the contributions of uncertainty shocks towards the end of the sample period, associated with a calmer financial market environment. Even during the COVID-19 pandemic, uncertainty shocks had minimal impact for the three domestic variables. As the pandemic can be viewed as an AD shock and, primarily, an AS shock (Sánchez and Vassallo, 2023b), private investment shocks became more relevant during those years.

4.4.4 Historical Decomposition (HD)

Appendix 12 shows the HDs[8] for exchange rate growth, private investment growth, and the inflation rate. These HDs are defined based on the contributions of each variable's shock to its overall deviation from the deterministic path.

In the case of exchange rate growth, both the CVAR-SV and TVP-VAR-R3-SV models reveal a negative relationship with EPI growth during 2004-2012. This aligns with the downward pressure exerted by EPI growth shocks, driven by increased capital inflows during that period. Notably, the external financial uncertainty shock only becomes relevant during the GFC. Specifically, in 2009, this shock contributed 2.2 percentage points to the total increase of 1.6% in exchange rate growth for the CVAR-SV model and 2.5 percentage points to the total increase of 3.4% for the TVP-VAR-R3-SV model.

For private investment growth in both models, its own shocks play a substantial role in explaining deviations across the entire sample. Additionally, EPI growth shocks show a positive relationship with total deviations and were significant in explaining increases during the 2004-2012 period. While external financial uncertainty shocks make a modest contribution throughout most of the sample, their impact grows during the GFC. In 2009, uncertainty shocks contributed -2.5 and -5.3 percentage points to the total deviations of -13.9% and 17.1% in private investment growth for the CVAR-SV and TVP-VAR-R3-SV models, respectively.

For the inflation rate, the contributions of its own shocks and EPI growth are substantial, while the impact of external financial uncertainty shocks remains relatively lower throughout the sample, even during the GFC.

4.5 Alternative Models

In this subsection, we explore two alternative models that incorporate uncertainty measures, with a focus on their impact on private investment growth and inflation rate.

4.5.1 Spillover Effects

The literature on uncertainty in EMEs suggests that shocks in these countries are not purely exogenous and may experience spillover effects from AEs[9] (Kamber et al., 2016; Gamba-Santamaria et al., 2017; Miescu, 2022). To account for this, we introduce a proxy for domestic financial uncertainty (u_{f_t}) as the third variable in our model. We

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

[9]While there is also literature on these effects in AEs, the common finding shared with EMEs is that the U.S. is a net exporter of spillover effects (Colombo, 2013; Klößner and Sekkel, 2014).

measure this uncertainty using the conditional volatility of IGBVL returns, estimated through a $GARCH(1,1)-t$ model. Additionally, we explore alternative uncertainty indexes using $GJR-GARCH(1,1)-t$, SV, $SV-t$, and $SV-t$ with leverage models. These models yield very similar indexes.

Appendix 3 displays the model selection for the alternative model (a). Similar to the baseline model, TVP-VAR-R1-SV ranks as the best-fitting model based on $LogML_{CE}$, while the CVAR-SV model performs best according to the DIC. The TVP-VAR-R3-SV model is the third-best model according to the DIC, with the TVP-VAR-R1-SV model in the second position.

Appendix 13 presents the median IRFs for the CVAR-SV and TVP-VAR-R3-SV models, considering both external and domestic financial uncertainty shocks. Introducing a second uncertainty measure reduces the number of significant quarters ahead for the responses of private investment growth and the inflation rate to an external financial uncertainty shock. For private investment growth, the negative hump-shaped response in the baseline model becomes a more pronounced short-term impact, although significant for only three quarters ahead.

Regarding domestic financial uncertainty shocks, they also appear to have a negative short-term effect on private investment growth, with a nearly 2% impact for a 1% increase in this uncertainty. Importantly, this impact on private investment growth may be indirectly influenced by external financial uncertainty through a potential spillover effect. According to the CVAR-SV model, a 1% increase in external financial uncertainty raises domestic financial uncertainty by 1.1% in the first quarter ahead, while the TVP-VAR-R3-SV model shows a 0.6% increase in the first quarter ahead, with significance extending to five quarters ahead. However, domestic financial uncertainty does not seem to significantly impact the inflation rate.

Appendix 14 illustrates the FEVDs for private investment growth and the inflation rate. In both variables, the contribution of external financial uncertainty shocks is more substantial compared to the baseline model, while the contribution of domestic financial uncertainty shocks remains close to zero. This finding suggests that domestic financial uncertainty shocks do not significantly affect total variances, possibly due to the limited size and development of the Lima Stock Exchange, which may not significantly influence investors' decision-making. However, it is worth noting that this result may underestimate the impact, as external financial uncertainty shocks might partially assume some of the contribution, given the strong correlation between both series.

Appendix 15 shows the HDs for private investment growth and the inflation rate. For private investment growth, the contributions of uncertainty shocks are lower throughout the sample. Particularly, in the TVP-VAR-R3-SV model, the external financial uncertainty shock explains 3.0 percentage points of the total decrease in private investment growth of 9.8% in 2002, roughly 30% of the total decline. Domestic financial uncertainty shocks do not contribute during that year. However, in 2009, the contribution of the domestic financial uncertainty shock accounts for approximately 10.9% of the total decrease in private investment growth, which is close to the 12.0% contribution of the external financial uncertainty shock. During this crisis period, the impact of domestic financial uncertainty shocks increases substantially, possibly due to a rise in the spillover effect. Gamba-Santamaria et al. (2017) have found that this effect is asymmetric and increased during the GFC for Colombia and Chile. In the case of the inflation rate, the results of the TVP-VAR-R3-SV model align with those of the baseline model. For the CVAR-SV model, domestic financial uncertainty shocks positively contribute to the inflation rate from 2009 to 2016.

4.5.2 Risk Premium Effects

The literature on uncertainty emphasizes the role of credit spreads and risk premiums as sources of uncertainty in financial markets, as they serve as indicators of the effective “risk-taking capacity” of financial intermediaries (Arellano et al., 2012; Gilchrist and Zakrajšek, 2012; Caldara et al., 2016). Therefore, we incorporated a proxy for the risk premium (ρ) into the third position of our model. This proxy is derived from the spread between Peru’s interbank interest rate and the Federal Funds effective rate, representing a measure of uncertainty related to investing in Peru.

Appendix 3 presents the model selection outcomes for the alternative model (b). Similar to the baseline model and the alternative model (a), TVP-VAR-R1-SV is the best-fitting model based on the $LogML_{CE}$ criterion. However, according to the DIC, the TVP-VAR-R3-SV model emerges as the best fit, with the CVAR-SV model ranking fifth.

Appendix 16 illustrates the median IRFs for the two selected models, CVAR-SV and TVP-VAR-R3-SV, in response to external financial uncertainty and risk premium shocks. On one hand, the CVAR-SV model exhibits statistically significant responses in private investment growth beginning in the fourth quarter and with a higher magnitude in response to external financial uncertainty shocks. For the TVP-VAR-R3-SV model, the responses in private investment growth show higher magnitudes compared to the baseline model but are significant for almost the same duration. Similarly, the inflation rate responses are similar between the two models but exhibit significance for approximately half the duration. On the other hand, risk premium shocks lead to a reduction in private investment growth for nearly twenty quarters, according to the CVAR-SV model, and eleven quarters according to the TVP-VAR-R3-SV model. However, the CVAR-SV model appears to overestimate the impact, with almost double the magnitude. No clear relationship is observed in the inflation rate responses, as they are not statistically significant.

Appendix 17 illustrates the FEVDs for private investment growth and the inflation rate. Contributions from external financial uncertainty shocks on private investment growth are similar to those in the alternative model (a) and the baseline model, respectively. In contrast, risk premium shocks contribute significantly to both domestic macroeconomic variables during the period 1996-2001, when the risk premium consistently exceeded 500 basis points. The risk premium shock accounts for 67.9% and 45.4% of the FEVD in private investment growth for the CVAR-SV and TVP-VAR-R3-SV models, respectively. Over the same period, it contributes 50.4% and 38.6% to the total variance of the inflation rate for both models, respectively.

Appendix 18 displays the HDs of private investment growth and the inflation rate. While contributions from external financial uncertainty shocks exhibit lower magnitudes in private investment growth during the GFC, they are approximately similar for the inflation rate when compared to the baseline model. In contrast, negative contributions from risk premium shocks are particularly prominent during the years 1997-2001 according to the TVP-VAR-R3-SV model. Notably, in 1999, the risk premium shock explains 13.0 percentage points of the total decrease of 12.7% in private investment growth and 0.4 percentage points of the total decrease of 0.1% in the inflation rate.

5 Robustness Exercises

To validate the results of Section 4, we conducted three robustness exercises and estimated their respective IRFs, FEVDs, and HDs.[10] The exercises are as follows: (i) adding GDP growth (y_t) in the fifth position of the model; (ii) including the interbank interest rate (i_t) in the sixth position; and (iii) introducing external survey-based uncertainty ($u^*_{sb_t}$) in the third position. The emphasis is on private investment growth, the inflation rate, and the new aggregate variable.

5.1 Adding GDP Growth

Appendix 4 shows the model selection for exercise (i). The results remain consistent with the baseline, as the TVP-VAR-R1-SV model is selected based on $LogML_{CE}$, while the CVAR-SV and TVP-VAR-R3-SV models are chosen according to the DIC.

In the median IRFs, the responses of private investment growth and the inflation rate mirror those of the baseline. Additionally, GDP growth decreases in response to an external financial uncertainty shock, as previously demonstrated in Farfán (2018) and Llosa et al. (2022). The responses of GDP growth are nearly as persistent as those of private investment growth, but the magnitude of the impact on GDP growth is approximately one-fourth of that on private investment growth. This observation aligns with findings in Chile[11](Cerda et al., 2018). As GDP depends on many factors other than those related to confidence or access to capital, the increase in external financial uncertainty reduces GDP growth much less than private investment growth.

In FEVDs, the contributions of external financial uncertainty shocks to the total variance of private investment growth are smaller in magnitude than in the baseline, likely because part of the uncertainty contribution is diverted toward explaining GDP growth.

In HDs, the contributions of external financial uncertainty remain robust relative to the baseline model. The contributions of uncertainty to GDP growth are similar to those for private investment growth.

5.2 Adding Interest Rate

Appendix 4 presents the model selection results for exercise (ii), which are identical to those of alternative model (b) in terms of $LogML_{CE}$ and DIC.

In the median IRFs, private investment growth responses are not statistically significant, while inflation rate responses resemble those of the baseline model. Interest rate responses are positive but only become statistically significant in the tenth and fifteenth quarters ahead for the CVAR-SV model. However, they remain statistically insignificant for all quarters ahead in the TVP-VAR-R3-SV model. This suggests that monetary policy does not react (or reacts several quarters ahead) to an increase in external financial uncertainty, even though it does have significant effects on the inflation rate.

Regarding FEVDs, the relevance of external financial uncertainty is similar in terms of dynamics and magnitude to the baseline for private investment growth and the inflation rate. Concerning the interest rate, uncertainty contributes 9.7% and 9.4%

[10] All the figures are in an Appendix available upon request.

[11] Additionally, Albagli et al. (2019) discovered a similar relationship in response magnitudes between private investment growth and private consumption growth.

during the years 2000-2007 for the CVAR-SV and TVP-VAR-R3-SV models, respectively. However, during the GFC (2008-2009), these contributions increase to 24.8% and 22.9% for both models, before decreasing toward the end of the sample.

In the case of HDs, the contributions of external financial uncertainty remain consistent with the baseline model but with a smaller magnitude in the case of private investment growth. The contributions of uncertainty shocks to the interest rate deviations are relatively small in magnitude, except during 2009-2010. In 2009, it explains 0.6 percentage points of the total 0.6% decrease and 0.9 percentage points of the total 0.9% decrease, according to the CVAR-SV and TVP-VAR-R3-SV models, respectively; i.e., uncertainty shocks account for nearly all of the decrease during that year. In 2010, the contribution diminishes to 13.4% and 32.3% of the total decrease, respectively.

5.3 Adding External Survey-Based Uncertainty

External survey-based uncertainty is a global measure derived from the U.S. Business Confidence Index. We transform it using the monthly average deviations of each quarter from the mean of the entire sample. This index is obtained from the Organization for Economic Co-operation and Development (OECD) repository.

Appendix 4 shows the model selection results for exercise (iii). There is a consensus in favor of the CVAR-SV model based on both criteria.

In the median IRFs, the responses of private investment growth resemble those of the alternative model (a), where the conclusions regarding external survey-based uncertainty align closely with those of domestic financial uncertainty. The key difference emerges in the responses of the inflation rate for both uncertainty sources. While external financial uncertainty is an AS shock, external survey-based uncertainty behaves like an AD shock. This can be attributed to the measure's construction, which relies on a survey of investors' economic outlook. This survey-based approach makes it partially analogous to an external private investment growth shock and, consequently, an AD shock.

In the FEVDs, the contributions of both uncertainties are consistent with those of the alternative model (a). In the HDs, the contributions of external financial uncertainty remain robust compared to the baseline model.

5.4 Other Robustness Exercises

We conducted three additional robustness exercises: (i) changing the order of private investment growth and the inflation rate; (ii) adding one lag based on $LogML_{CE}$ and the Hannan-Quinn Information Criterion (HQIC); and (iii) incorporating an external macro-uncertainty measure, the index of Jurado et al. (2015). However, we decided to present only the previous exercises, as they yield the most relevant conclusions.

Additional exercise (i) is fully consistent with the baseline model. Exercise (ii) selects CVAR-SV as the best-fitting model according to both criteria, but private investment growth responses are not statistically significant for all quarters ahead. Exercise (iii) also designates CVAR-SV as the best-fitting model based on both criteria. However, the responses of all variables to EPI growth, external financial uncertainty, and external macro uncertainty are not statistically significant. Additionally, the FEVDs overestimate the contributions of external financial uncertainty shocks.

6 Conclusions

In this article, we have estimated a group of TVP-VAR-SV models to determine the impact of external financial uncertainty shocks on exchange rate growth, private investment growth, and the inflation rate in Peru for the period 1996Q1-2022Q4. We employed the methodology of Chan and Eisenstat (2018), which allows us to estimate the effects of uncertainty across three main areas of study in the literature: (i) transmission channels of uncertainty, (ii) similarity between an AD or AS shock, and (iii) asymmetric effects over time and under different scenarios. Additionally, we investigated (i) a possible spillover effect on a domestic financial uncertainty index, (ii) the effects of the risk premium, and (iii) through robustness exercises, the effects of uncertainty on GDP growth and the interest rate.

The first conclusion is that a simple VAR with stochastic volatility is selected as the best-fitting model, based on the DIC, a criterion that penalizes the complexity of models. In general, the common feature among the best models is SV, which appears sufficient for studying the impact of uncertainty shocks on the Peruvian economy. In this regard, the CVAR-SV model allowed us to draw similar conclusions compared to TVP-VAR-R3-SV, the second selected model.

The second conclusion is that external financial uncertainty shocks have negative and significant effects on private investment growth, with a substantial impact in the medium to long term. When domestic financial uncertainty is included, both exhibit a significant impact in the short term. There is evidence that external financial uncertainty also has an indirect short-term effect via domestic financial uncertainty, suggesting a possible spillover effect. The inclusion of the risk premium shows significant impacts in the medium to long term.

The third conclusion is that the effects of external financial uncertainty on private investment growth are three times greater than those on GDP growth, as GDP depends on various factors beyond those related to confidence or access to capital.

The fourth conclusion is that external financial uncertainty behaves like an AS shock, as it reduces economic activity while increasing inflation. It significantly affects the inflation rate for up to ten quarters ahead.

The fifth conclusion is that the impacts of external financial uncertainty on economic activity are asymmetric. In unfavorable financial conditions, uncertainty reduces private investment growth and increases exchange rate growth and the inflation rate to a greater extent compared to periods of calm.

The policy implication of our results is that in the face of an increase in external financial uncertainty, the authorities should intervene as if it were an AS shock. The central bank should implement both conventional and unconventional policies to mitigate the adverse effects on private investment growth and inflation.

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Appendix

Appendix 1: Tests for Time Variation in Coefficients and Volatility

	Coefficients	Subsample 1	Subsample 2	Subsample 3	Full Sample
	γ_{it}	10/10	10/10	10/10	8/10
Kolmogorov-Smirnov	$\boldsymbol{\beta}_{it}$	26/30	26/30	25/30	28/30
	$\boldsymbol{h}_{it}$	5/5	5/5	5/5	5/5
	γ_{it}	8/10	10/10	9/10	9/10
$t-$test	$\boldsymbol{\beta}_{it}$	24/30	24/30	22/30	26/30
	$\boldsymbol{h}_{it}$	5/5	5/5	4/5	5/5

Source: Own elaboration. Note: Number of time-varying parameters to Kolmogorov-Smirnov test and $t-$test are reported. γ_{it} represents the coeffcients of contemporaneous relationships, $\boldsymbol{\beta}_{it}$ are the coefficients associate to intercepts and lagged variables and $\boldsymbol{h}_{it}$ are the variances of innovations. These two tests are performed for the full sample, subsample 1 (1996Q2-2009Q3), subsample 2 (2009Q4-2022Q4) and subsample 3 (2003Q3-2022Q4).

Appendix 2: Models Selection

Model	$LogML_{CE}$	SD	Rank	DIC	SD	Rank
TVP-VAR-SV	-1622.099	0.073	2	3011.921	0.812	5
TVP-VAR	-1758.187	1.066	7	3088.444	1.581	6
TVP-VAR-R1-SV	**-1618.437**	**0.131**	**1**	2980.626	0.640	3
TVP-VAR-R2-SV	-1623.402	0.154	4	2999.845	1.155	4
TVP-VAR-R3-SV	-1625.369	0.240	5	2976.713	0.441	2
CVAR-SV	-1623.020	0.032	3	**2965.526**	**0.463**	**1**
CVAR	-1741.004	0.009	6	3121.052	0.216	7

Source: Own elaboration. Note: 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. $LogML_{CE}$ 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.

Appendix 3: Alternative Check: Models Selection

Model	$LogML_{CE}$	SD	Rank	DIC	SD	Rank
(a) Domestic Financial Uncertainty						
TVP-VAR-SV	-1723.936	0.326	4	3134.613	1.235	5
TVP-VAR	-1924.395	2.963	7	3255.723	2.243	7
TVP-VAR-R1-SV	**-1705.426**	**0.232**	**1**	3059.719	0.746	2
TVP-VAR-R2-SV	-1730.467	0.256	5	3132.376	1.224	4
TVP-VAR-R3-SV	-1715.773	0.221	2	3059.838	0.607	3
CVAR-SV	-1716.248	0.047	3	**3046.976**	**0.204**	**1**
CVAR	-1853.140	0.009	6	3232.056	0.142	6
(b) Risk Premium						
TVP-VAR-SV	-1821.812	0.214	3	3311.120	2.048	4
TVP-VAR	-2050.832	2.426	7	3526.526	5.065	6
TVP-VAR-R1-SV	**-1818.634**	**0.179**	**1**	3258.643	0.583	2
TVP-VAR-R2-SV	-1820.618	0.177	2	3285.350	0.696	3
TVP-VAR-R3-SV	-1825.977	0.309	4	**3243.112**	**0.750**	**1**
CVAR-SV	-1827.319	0.087	5	3352.166	5.296	5
CVAR	-2029.619	0.009	6	3595.409	0.215	7

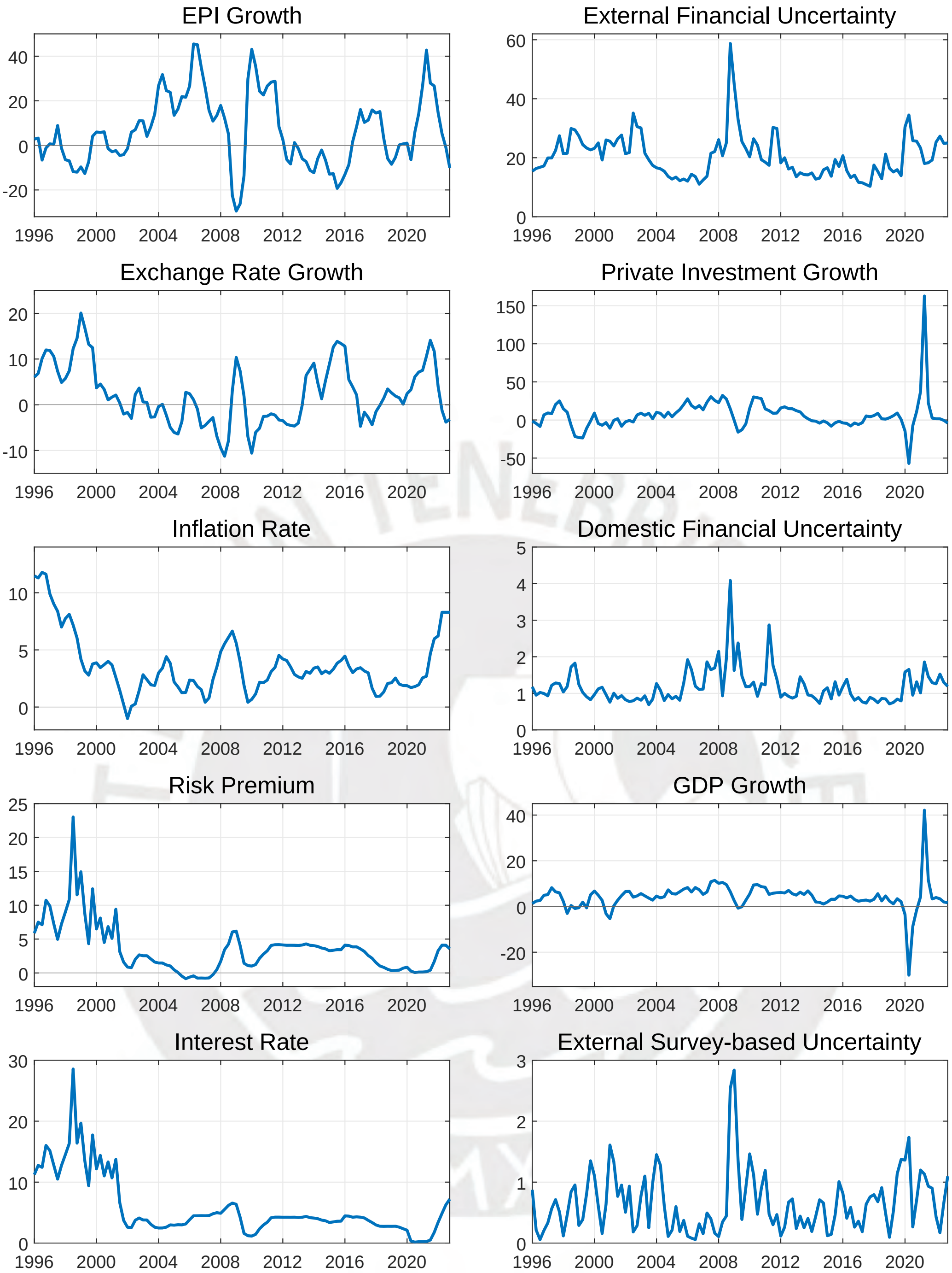
Source: Own elaboration. Note: For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. $LogML_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where 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.

Appendix 4: Robustness Check: Models Selection

Model	$LogML_{CE}$	SD	Rank	DIC	SD	Rank
(i) GDP Growth						
TVP-VAR-SV	-1915.007	0.136	2	3508.389	1.448	5
TVP-VAR	-2062.997	1.280	7	3597.399	2.072	6
TVP-VAR-R1-SV	**-1910.159**	**0.188**	**1**	3462.530	0.451	3
TVP-VAR-R2-SV	-1918.750	0.209	4	3493.849	1.220	4
TVP-VAR-R3-SV	-1919.694	0.374	5	3452.107	0.779	2
CVAR-SV	-1916.421	0.047	3	**3437.775**	**0.538**	**1**
CVAR	-2050.941	0.012	6	3626.401	0.166	7
(ii) Interest Rate						
TVP-VAR-SV	-1829.978	0.157	5	3314.715	1.604	4
TVP-VAR	-2055.249	2.743	7	3520.273	6.556	6
TVP-VAR-R1-SV	**-1818.278**	**0.165**	**1**	3247.974	0.618	2
TVP-VAR-R2-SV	-1825.140	0.246	4	3277.222	1.357	3
TVP-VAR-R3-SV	-1824.965	0.390	3	**3220.055**	**0.542**	**1**
CVAR-SV	-1820.570	0.062	2	3431.740	22.807	5
CVAR	-2041.940	0.008	6	3610.875	0.132	7
(iii) External Survey–based Uncertainty						
TVP-VAR-SV	-1742.962	0.187	5	3175.542	1.513	5
TVP-VAR	-1907.002	1.193	7	3277.595	2.755	7
TVP-VAR-R1-SV	-1730.329	0.294	2	3113.326	0.408	3
TVP-VAR-R2-SV	-1742.642	0.325	4	3153.683	1.314	4
TVP-VAR-R3-SV	-1734.945	0.370	3	3097.894	0.681	2
CVAR-SV	**-1729.975**	**0.034**	**1**	**3077.906**	**0.327**	**1**
CVAR	-1858.209	0.010	6	3245.084	0.229	6

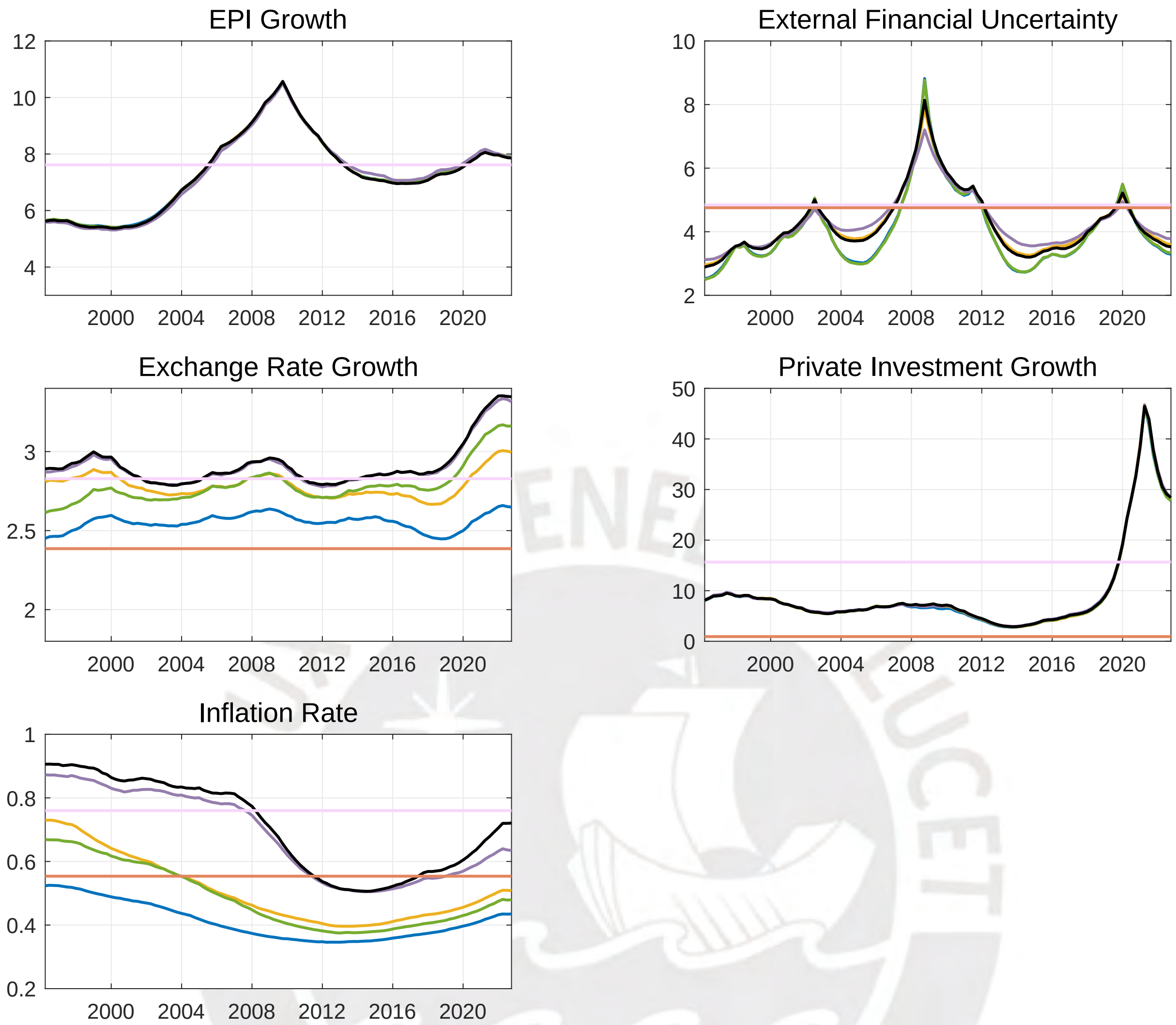
Source: Own elaboration. Note: For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. $LogML_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where 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.

Appendix 5: Time Series



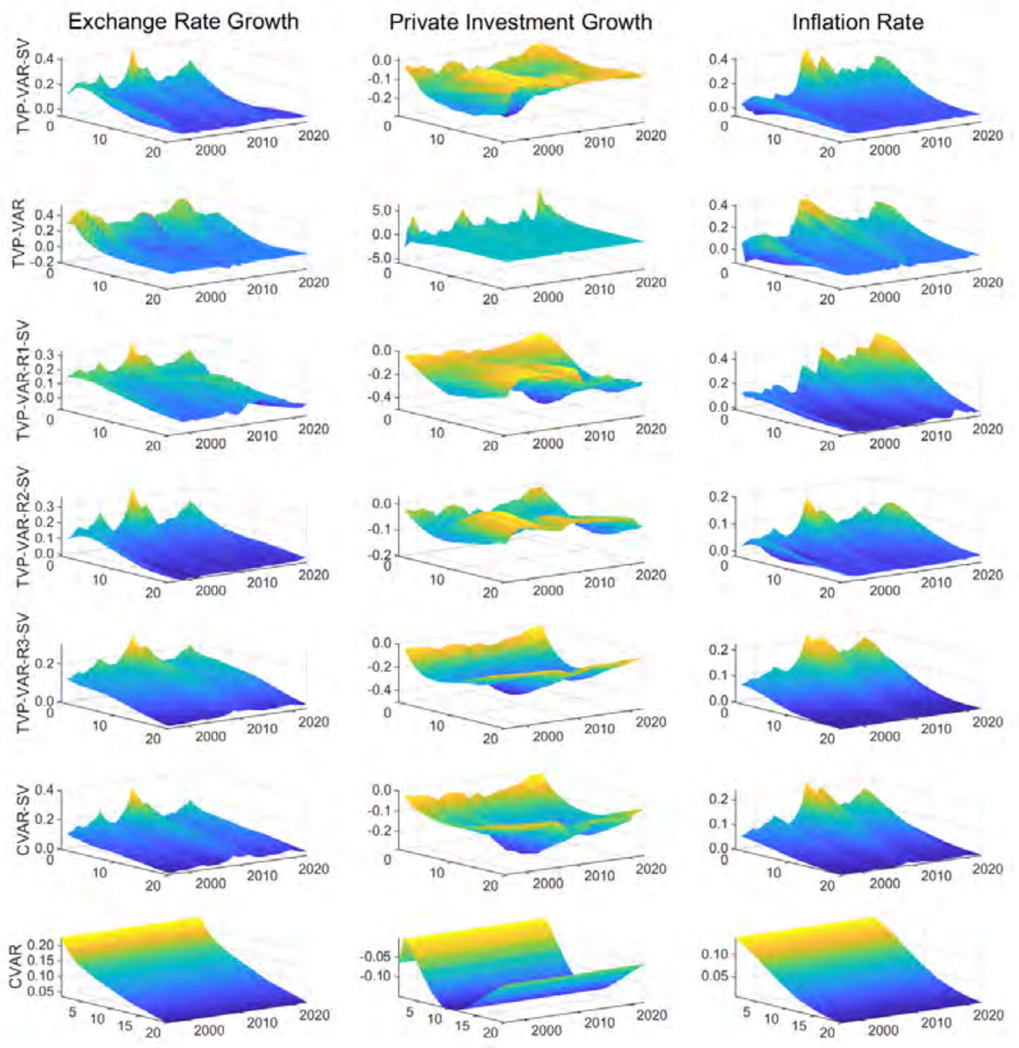
Source: Banco Central de Reserva del Perú (BCRP) and Federal Reserve Economic Data (FRED). Own elaboration. Note: Sample: 1996Q1-2022Q4.

Appendix 6: Mean Values of the Standard Deviation of the Innovations of the Equations



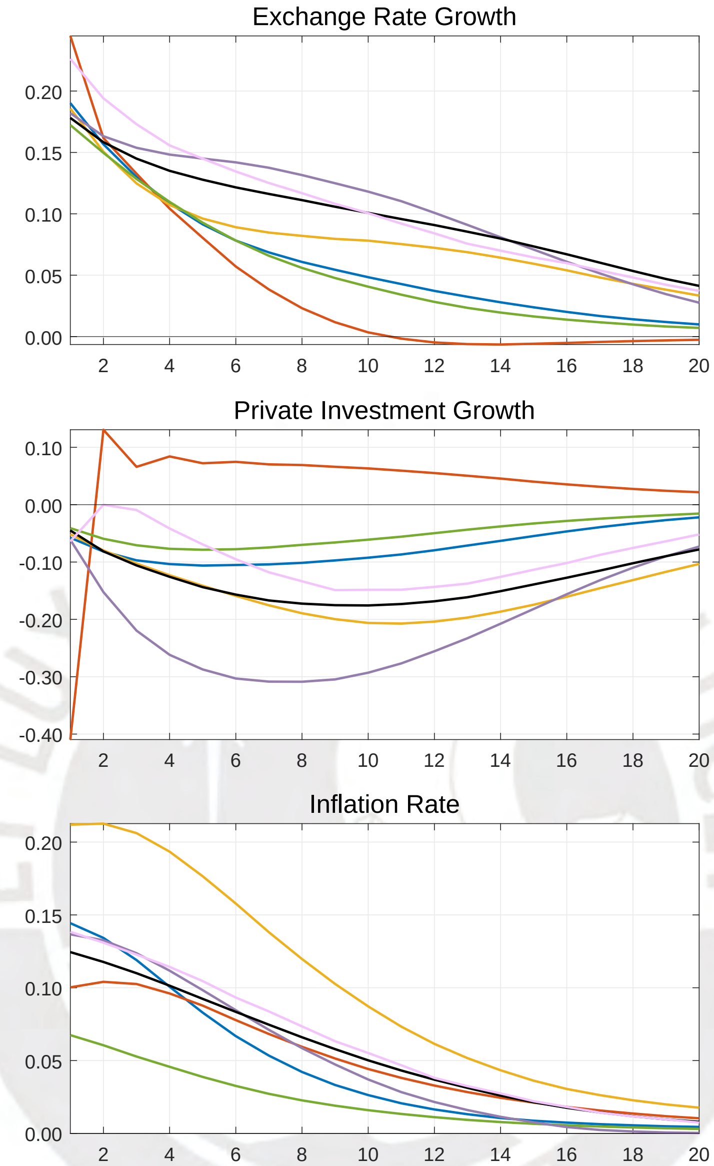
Source: Own elaboration. Note: The blue line represents the TVP-VAR-SV; red line: TVP-VAR; yellow line: TVP-VAR-R1-SV; green line: TVP-VAR-R2-SV; purple line: TVP-VAR-R3-SV; black line: CVAR-SV; pink line: CVAR.

Appendix 7: Median Time-Varying IRFs to an External Financial Uncertainty Shock



Source: Own elaboration. Note: The shock is normalized to an increase of Uncertainty by 1% at each point in the sample period.

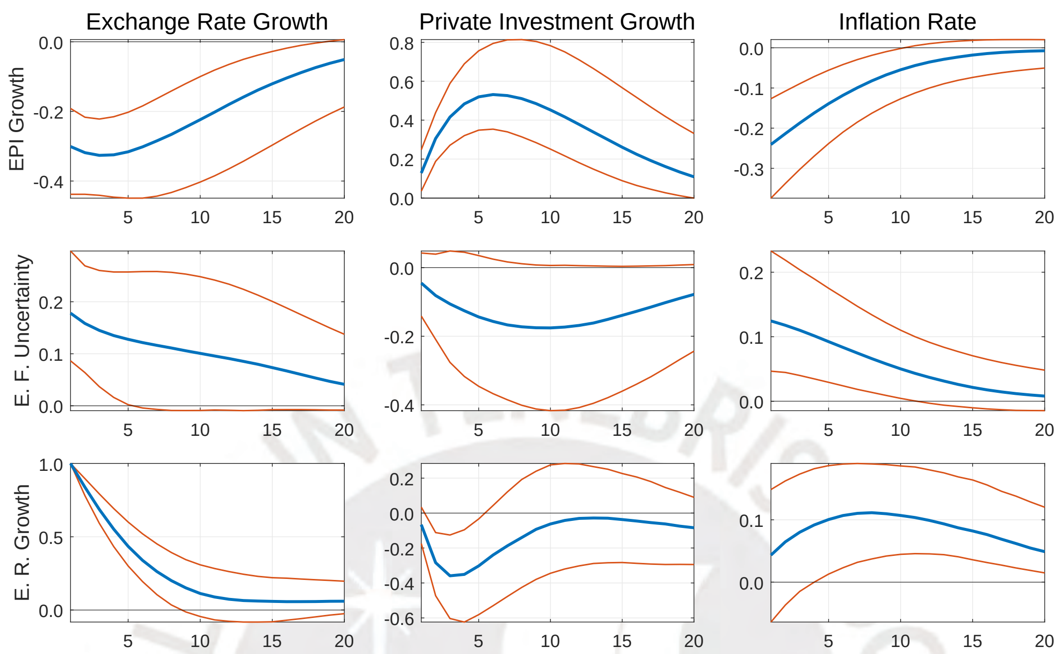
Appendix 8: Median IRFs of Domestic variables from an External Financial Uncertainty Shock for all the Models



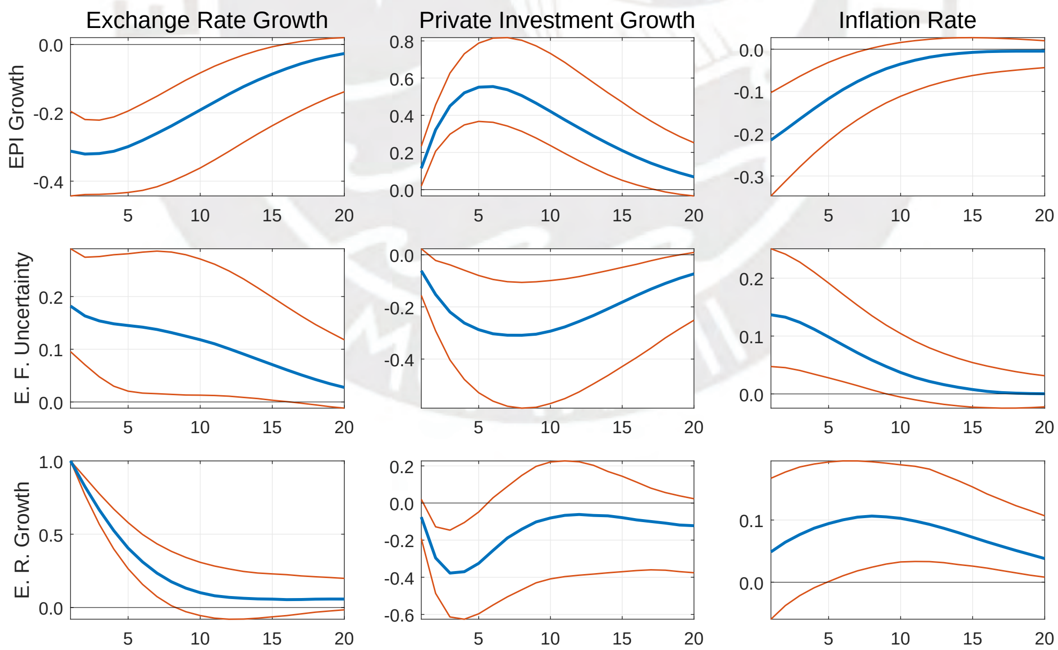
Source: Own elaboration. Note: The blue line represents the TVP-VAR-SV; red line: TVP-VAR; yellow line: TVP-VAR-R1-SV; green line: TVP-VAR-R2-SV; purple line: TVP-VAR-R3-SV; black line: CVAR-SV; pink line: CVAR.

Appendix 9: Median IRFs of Domestic variables to an EPI Growth, External Financial Uncertainty and Exchange Rate Growth Shocks for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



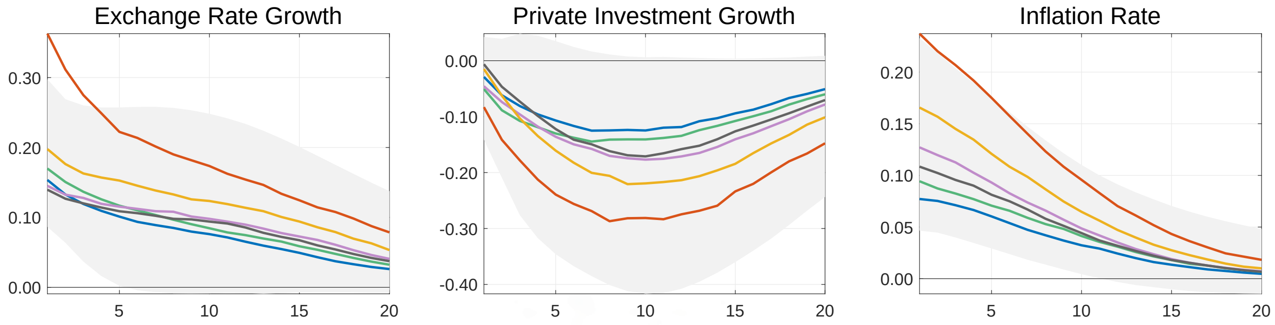
(b) TVP-VAR-R3-SV



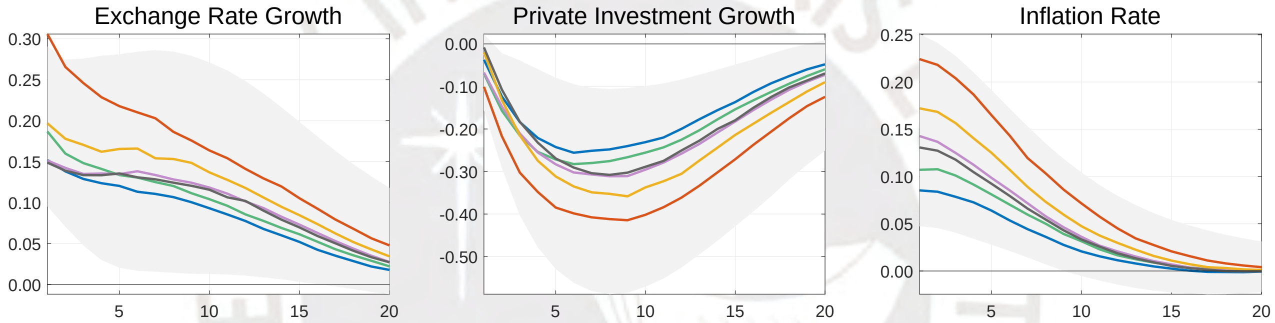
Source: Own elaboration. Note: The blue lines are the medians. The red lines its 68% error band.

Appendix 10: Evolution of IRFs of Domestic variables from an External Uncertainty Shocks at specific periods over time for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



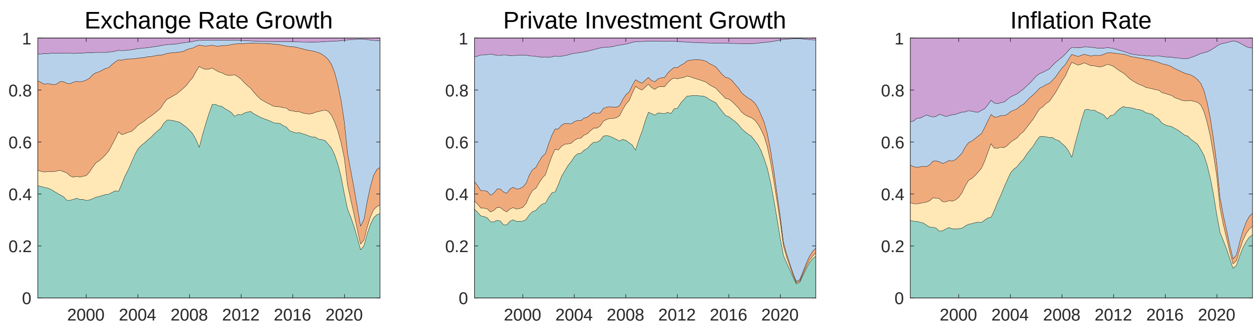
(b) TVP-VAR-R3-SV



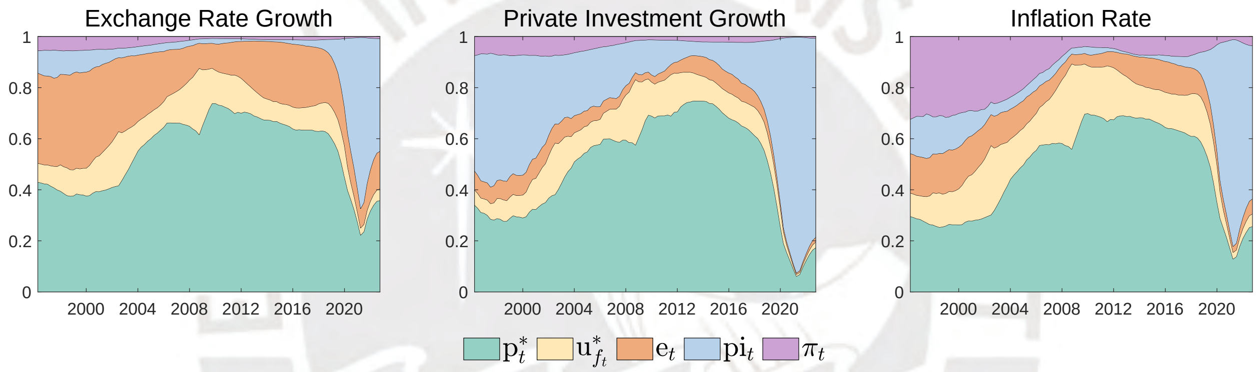
Source: Own elaboration. Note: The grey shadows are the 68% error bands. The blue line represents the IRFs for the 1998Q1, green line: 2003Q3 period; red line: 2008Q4; purple line: 2017Q1; yellow line: 2020Q2; and grey line: 2021Q2.

Appendix 11: Time Evolution of the FEVDs of Exchange Rate Growth, Private Investment Growth and Inflation Rate for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



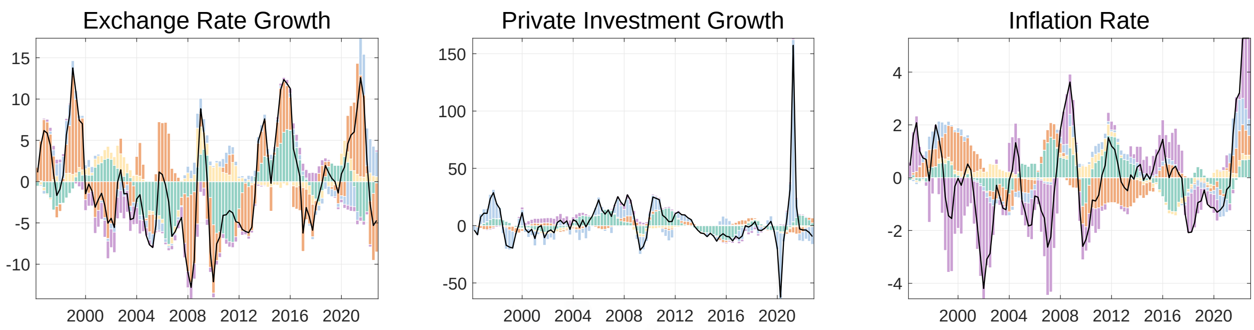
(b) TVP-VAR-R3-SV



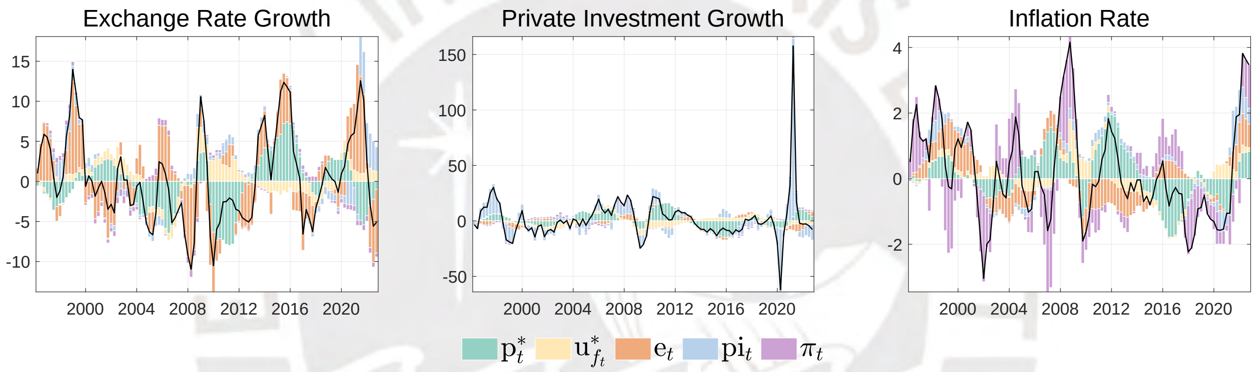
Source: Own elaboration. Note: The forecast horizon is $h = 20$ quarters.

Appendix 12: HDs of Exchange Rate Growth, Private Investment Growth and Inflation Rate for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



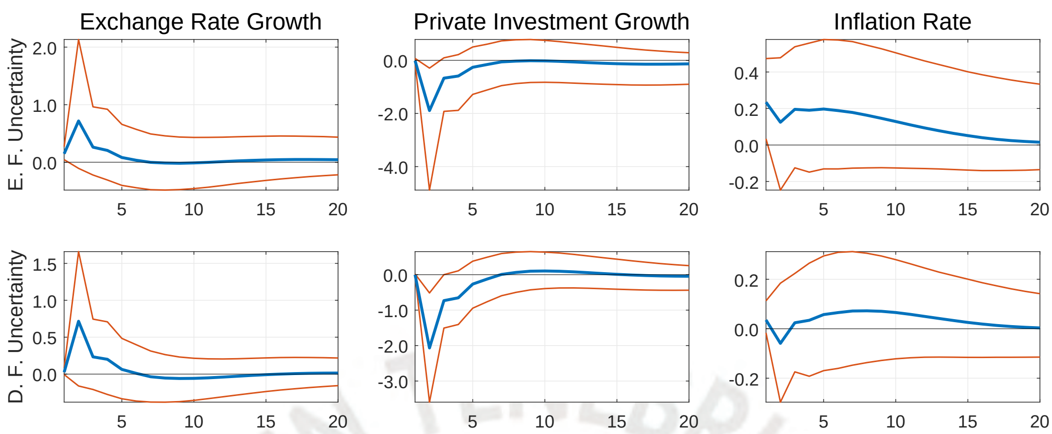
(b) TVP-VAR-R3-SV



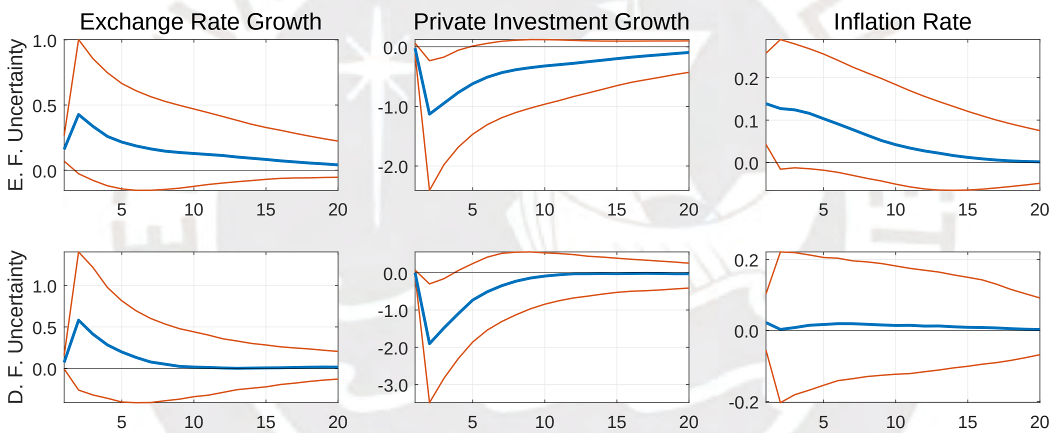
Source: Own elaboration.

Appendix 13: Alternative Model (a). Median IRFs of Exchange Rate Growth, Private Investment Growth and Inflation Rate to an External and Domestic Financial Uncertainty Shocks for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



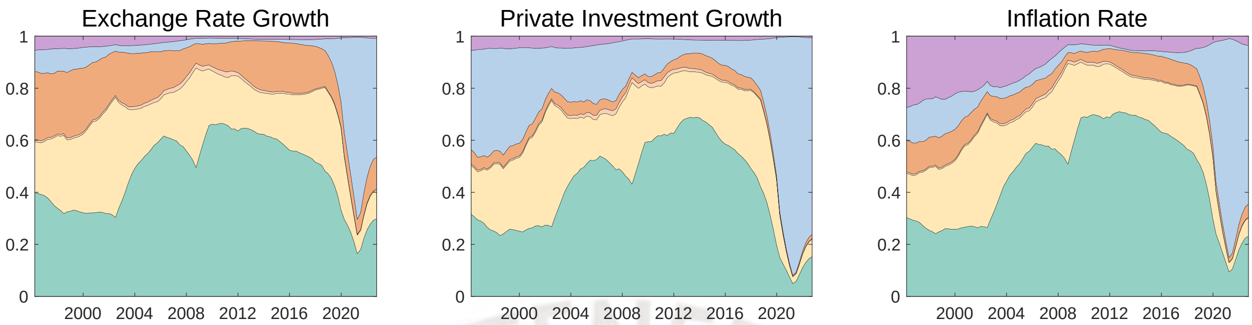
(b) TVP-VAR-R3-SV



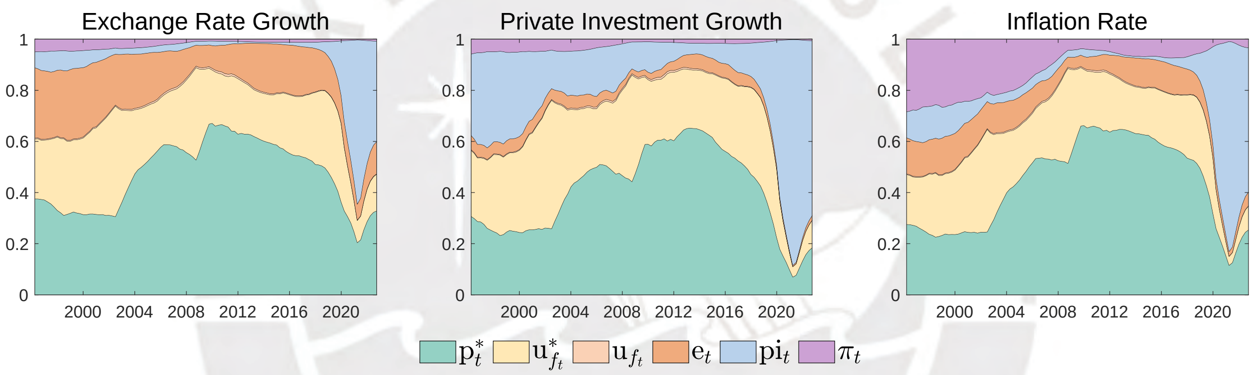
Source: Own elaboration. Note: The blue lines are the medians. The red lines its 68% error band.

Appendix 14: Alternative Model (a). Time Evolution of the FEVDs of Exchange Rate Growth, Investment Growth and Inflation Rate for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



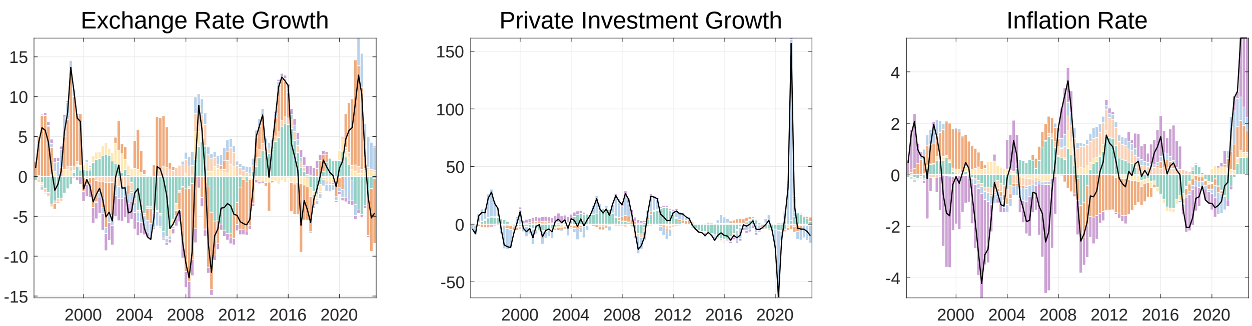
(b) TVP-VAR-R3-SV



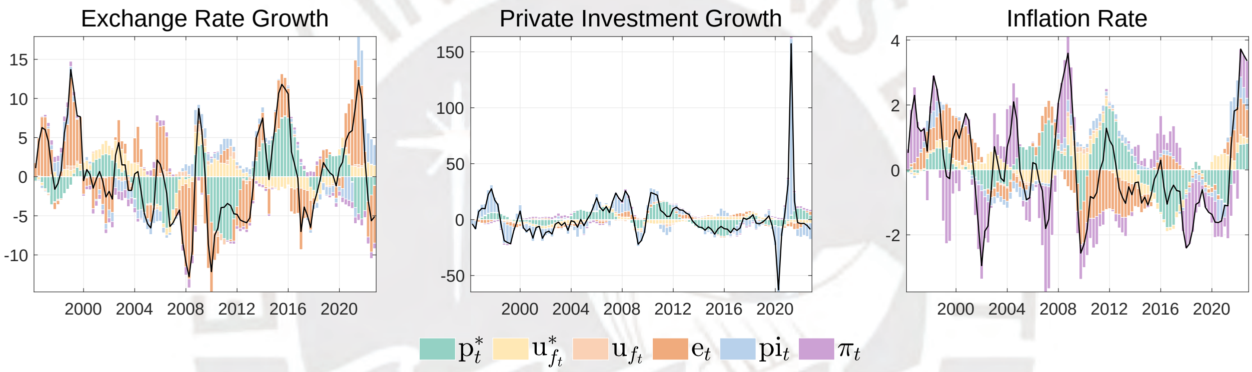
Source: Own elaboration. Note: The forecast horizon is $h = 20$ quarters.

Appendix 15: Alternative Model (a). HDs of Exchange Rate Growth, Private Investment Growth and Inflation Rate for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



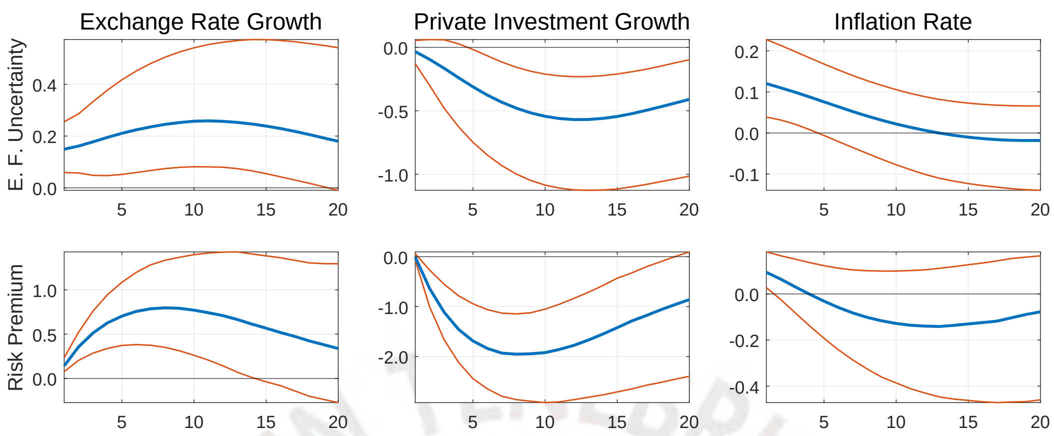
(b) TVP-VAR-R3-SV



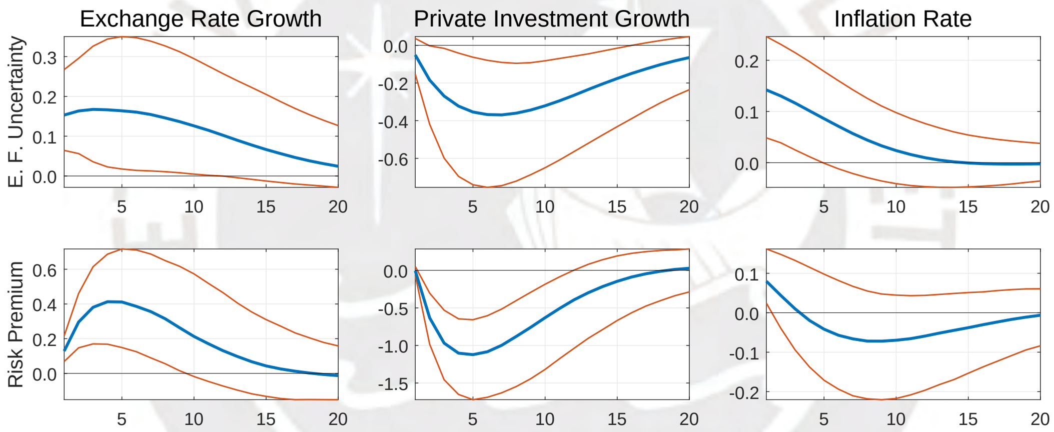
Source: Own elaboration.

Appendix 16: Alternative Model (b). Median IRFs of Exchange Rate Growth, Private Investment Growth and Inflation Rate to an External Financial Uncertainty and Risk Premium Shocks for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



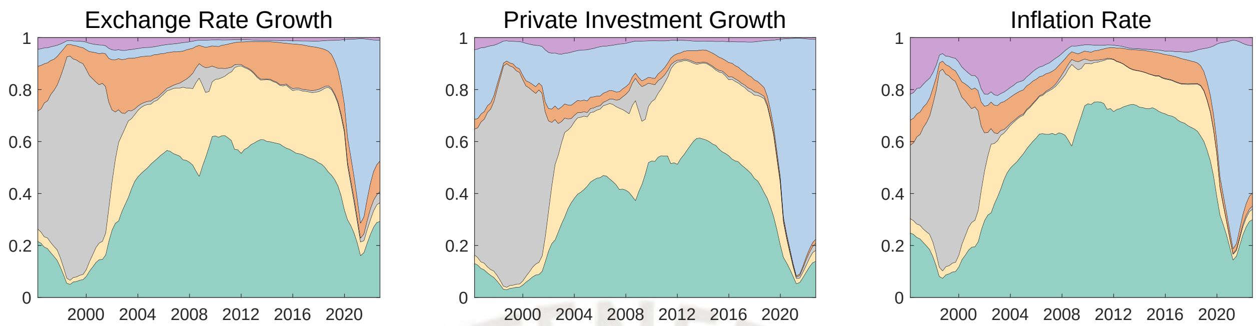
(b) TVP-VAR-R3-SV



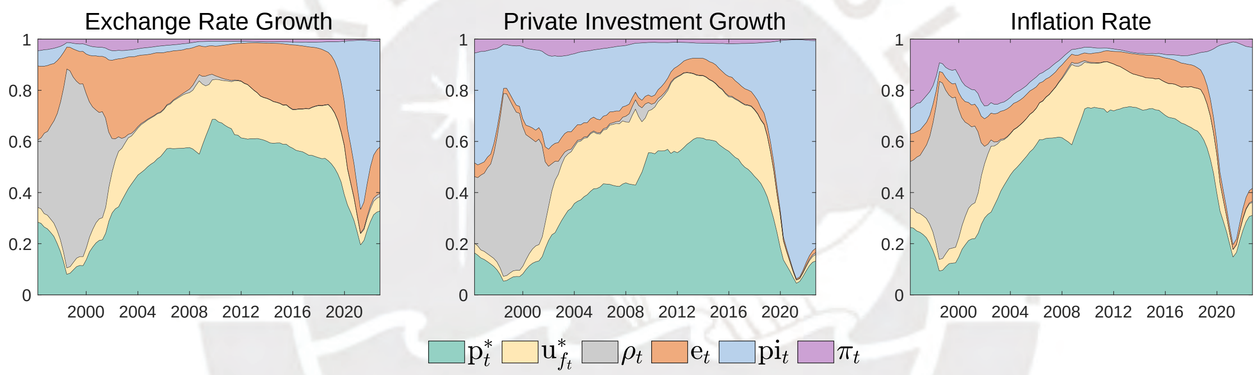
Source: Own elaboration. Note: The blue lines are the medians. The red lines its 68% error band.

Appendix 17: Alternative Model (b). Time Evolution of the FEVDs of Exchange Rate Growth, Investment Growth and Inflation Rate for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



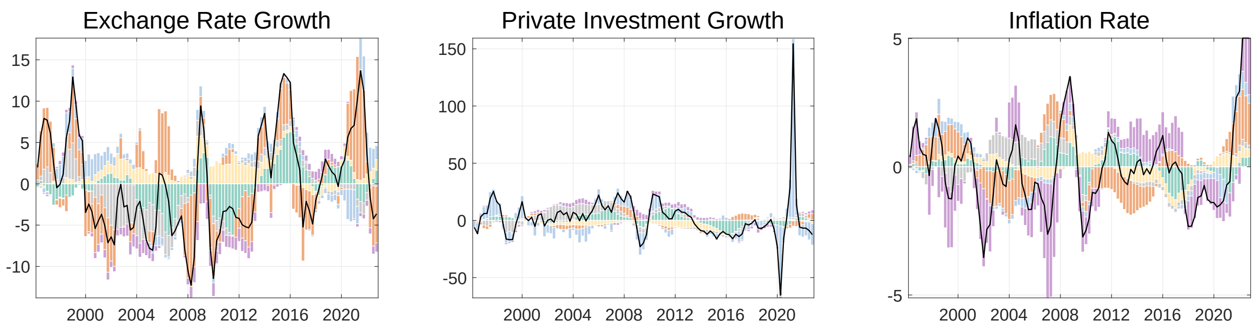
(b) TVP-VAR-R3-SV



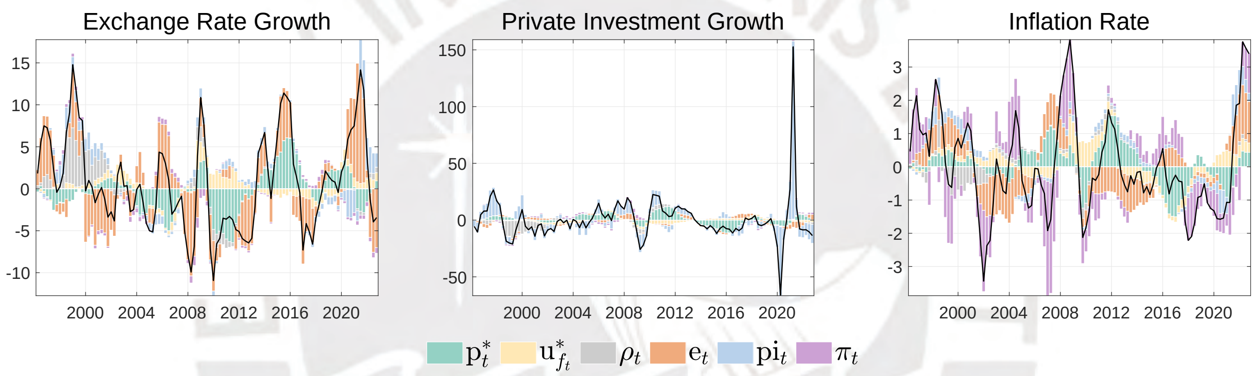
Source: Own elaboration. Note: The forecast horizon is $h = 20$ quarters.

Appendix 18: Alternative Model (b). HDs of Exchange Rate Growth, Private Investment Growth and Inflation Rate for the CVAR-SV and TVP-VAR-R3-SV Models

(a) CVAR-SV



(b) TVP-VAR-R3-SV



Source: Own elaboration.