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

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Outline

Motivation

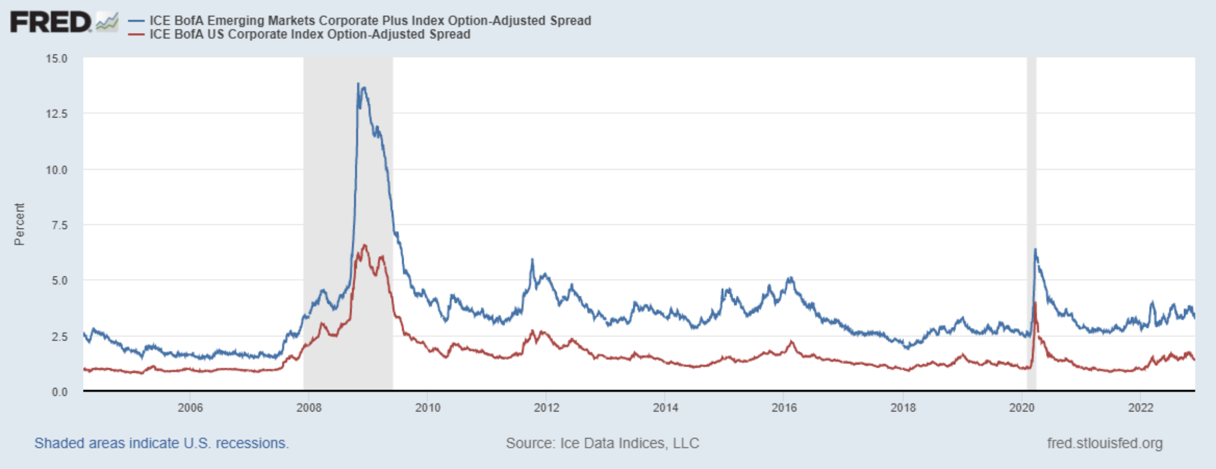

Figure: Spreads are much higher for emerging countries in periods of high financial uncertainty. This will have implications for the dynamics of private investment, the most volatile component of GDP by spending; see Castillo et al. (2007).

Introduction-Motivation

- Historically, emerging economies have been particularly affected by the constant changes in international conditions;
- Recent literature has emphasized financial market frictions as a significant source of macroeconomic fluctuations;
- 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, implications of external decisions, and other factors;
- Research on these effects in Latin America is limited;

Introduction-Motivation

- The study of Peru's case is significant, as the country has undergone substantial changes...
  - Peru grappled with high levels of debt, a significant reliance on the US dollar in deposits and loans, and considerable uncertainty regarding domestic prices;
  - Adoption of an inflation targeting (IT) regime in 2002, fiscal rules,...
  - Uncertainty regarding the Peruvian economy has diminished, thanks to increased confidence in institutions such as the Central Reserve Bank of Peru (BCRP);

Objectives

- This article seeks to contribute to our understanding of how financial uncertainty shocks affect Peru, a small, open, commodity-exporting economy;
- We investigate how these shocks influence private investment, diverging from prior studies that focus on their impact on GDP;
- We incorporate the period encompassing the COVID-19 pandemic, employing nonlinear models to capture the evolving nature of uncertainty during this time;
- We use a family of TVP-VAR-SV models;

Literature Review

Effects on...

- Private Investment; see Bernanke (1983), and Bloom (2009).
- Employment; see Leduc and Liu (2013), and Caggiano et al. (2014).
- Risk Premium; see Baum et al. (2009), Arellano et. al (2010), Gourio et al. (2013), Gilchrist et al. (2014), and Caldara et al. (2016).

Similar to a shock of...

- Supply, in EMEs; see Farfán (2018), Bhattarai et al. (2019), Krumar et al. (2021), Giraldo et al. (2023), and Miescu (2023).
- Demand, in AEs; see Bloom (2009), Petrakis et al. (2014), Krumar et al. (2021), and Miescu (2023).
- Both, according to the scenario; see Alessandri and Mumtaz (2019), and Nalban and Smădu (2021).

Asymmetries

- In Effects; see Caggiano et al. (2014), Alessandri and Mumtaz (2019), and Nalban and Smădu (2021).
- Between Countries; see Carriére-Shallow and Céspedes (2013), Redl (2020), and Miescu (2023).

Peru

- Uncertainty; see Farfán (2018), Vega and Pinelo (2022), and Giraldo et al. (2023).
- Confidence indexes; see Arenas and Morales (2013), BCRP (2016), and Sánchez and Vasallo (2023).

Methodology: The TVP-VAR-SV Model

Based on Chan and Eisenstat (2018):

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

where:

$$\begin{aligned}
\mathbf{y}_t &= \widetilde{\mathbf{X}}_t\beta_t + \mathbf{W}_t\gamma_t + \epsilon_t, & \widetilde{\mathbf{X}}_t &= I_n \otimes (1, \mathbf{y}'_{t-1}, \ldots, \mathbf{y}'_{t-p}),\\
\mathbf{y}_t &= \mathbf{X}_t\boldsymbol{\theta}_t + \epsilon_t, & \mathbf{X}_t &= (\widetilde{\mathbf{X}}_t, \mathbf{W}_t),\\
\beta_t &= vec((\boldsymbol{\mu}_t, \mathbf{B}_{1,t}, \ldots, \mathbf{B}_{p,t})'), & &\\
\boldsymbol{\theta}_t &= (\beta'_t, \gamma'_t)', & &\\
\boldsymbol{\theta}_t &= \boldsymbol{\theta}_{t-1} + \boldsymbol{\eta}_t, & \boldsymbol{\eta}_t &\sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_\theta),\\
\boldsymbol{\Sigma}_t &= \mathrm{diag}(\exp(h_{1,t}), \ldots, \exp(h_{n,t})), & &\\
\mathbf{h}_t &= \mathbf{h}_{t-1} + \zeta_t, & \zeta_t &\sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_h).
\end{aligned}$$

The Seven Models

Table: Models

Models	Description
TVP-VAR-SV	VAR with time-varying coefficients and SV
TVP-VAR	TVP-VAR with $\mathbf{h}_t = \mathbf{h}_0$
TVP-VAR-R1-SV	TVP-VAR-SV with $\boldsymbol{\beta}_t = \boldsymbol{\beta}_0$
TVP-VAR-R2-SV	TVP-VAR-SV with $\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_0$
TVP-VAR-R3-SV	TVP-VAR-SV, where only intercepts are time-varying
CVAR-SV	VAR simple with SV
CVAR	VAR simple

Detailed information of these models can be found in Section 4 and Appendix A of Chan and Eisenstat (2018).

Estimation Algorithm (Gibbs Sampling)

Each block of parameters is estimated separately conditioned to the update of the other blocks. Based on precision sampling of Chan and Jeliazkov (2009):

1. Draws from $(\boldsymbol{\theta}|\mathbf{y}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}(\hat{\boldsymbol{\theta}}, \mathbf{K}_\theta^{-1})$;
2. Draws from $(\mathbf{h}|\mathbf{y}, \boldsymbol{\theta}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}(\hat{\mathbf{h}}, \mathbf{K}_h^{-1})$;
3. Using conditional distributions of the diagonal elements in $\boldsymbol{\Sigma}_\theta$, draws are obtained from $(\sigma^2_{\theta_i}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{\theta_i} + \frac{T}{2}, S_{\theta_i} + \frac{1}{2}\Sigma_{t=1}^{T}(\theta_{i,t} - \theta_{i,t-1})^2)$ for $i = 1, ..., k_\theta$;
4. Draws of the diagonal elements of $\boldsymbol{\Sigma}_h$: $(\sigma^2_{h_j}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{h_j} + \frac{T}{2}, S_{h_j} + \frac{1}{2}\Sigma_{t=1}^{T}(h_{j,t} - h_{j,t-1})^2)$ for $j = 1, ..., k_h$;
5. Draws for the initial condition $\boldsymbol{\theta}_0$: $(\boldsymbol{\theta}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\hat{\boldsymbol{\theta}}_0, \mathbf{K}_{\theta_0}^{-1})$;
6. Draws for the initial condition $\mathbf{h}_0$: $(\mathbf{h}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\hat{\mathbf{h}}_0, \mathbf{K}_{h_0}^{-1})$;
7. Previous (1) to (6) steps are repeated N times.

Hyperparameters $\nu_{\theta_i}, S_{\theta_i}, \nu_{h_j}, S_{h_j}$ and other are given in Section of Priors and Hyperparameters.
Further details are found in Appendix A of Chand and Eisenstat (2018).

Computing Marginal Log-Likelihood

- The marginal likelihood is: $p(\mathbf{y}|M_m) = \int p(\mathbf{y}|\boldsymbol{\theta}_m, M_m)p(\boldsymbol{\theta}_m|M_m)d\boldsymbol{\theta}_m$.
- Chan and Eisenstat (2015) propose a precise and eficient estimate of the marginal likelihood based on importance sampling:

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

- The estimator $\hat{p}_{IS}(\mathbf{y})$ meets the characteristics of being consistent and unbiased, regardless of the value that $g(\boldsymbol{\theta}_n)$ acquires.
- The Cross Entropy method is used to optimally choose $g(\boldsymbol{\theta}_n)$ so that the $\hat{p}_{IS}(\mathbf{y})$, the estimator of the marginal likelihood, has minimum variance.
- Further details are found in Appendix B of Chan and Eisenstat (2018).
- Calculate the Bayes Factor: $BF_{i,j} = \frac{p(\mathbf{y}|M_i)}{p(\mathbf{y}|M_j)}$. We prefer M_i, BF times than the M_j.

Computing DIC

- Deviation measure:
$$D(\boldsymbol{\theta}) = -2\log f(\mathbf{y}|\boldsymbol{\theta}) + 2\log h(\mathbf{y}).$$
- Effective number of parameters:
$$p_D = \overline{D(\boldsymbol{\theta})} - D(\widetilde{\boldsymbol{\theta}}),$$
where $\overline{D(\boldsymbol{\theta})} = -2E_{\boldsymbol{\theta}}\left[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}\right] + 2\log h(\mathbf{y})$ is the posterior mean deviation and $\widetilde{\boldsymbol{\theta}}$ is an estimator of $\boldsymbol{\theta}$.
- The deviance information criterion (DIC) is defined as:
$$DIC = \overline{D(\boldsymbol{\theta})} + p_D.$$
- Therefore, we have (assuming $h(\mathbf{y}) = 1$):
$$DIC = -4E_{\boldsymbol{\theta}}\left[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}\right] + 2\log f(\mathbf{y}|\widetilde{\boldsymbol{\theta}}).$$

Data and Identification

The identification is done recursively à la Sims (1980), where the order of the contemporaneous relationships is as follows:

$$p_t^* \rightarrow u_{f_t}^* \rightarrow e_t \rightarrow pi_t \rightarrow \pi_t,$$

where:

- p_t^*: Export Price Index (EPI), in annual growth;
- $u_{f_t}^*$: External Financial Uncertainty, VIX index;
- e_t: Nominal Exchange Rate, in annual growth;
- pi_t: Real Private Investment, in annual growth;
- π_t: Inflation Rate, in levels.

Data in Figures

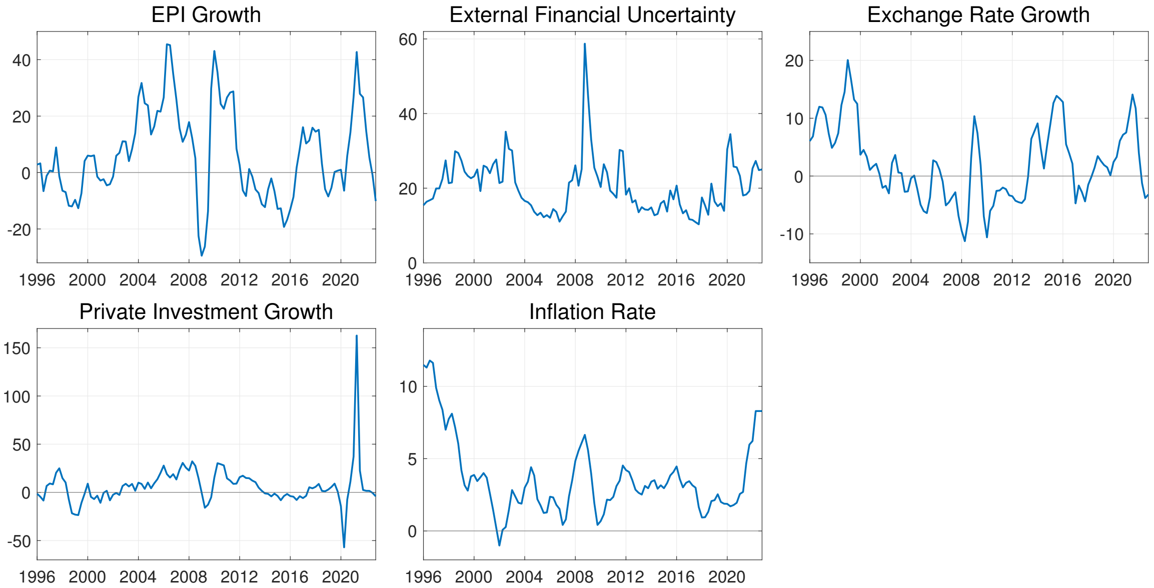

Figure: Time Series. Sample 1996Q1-2022Q4

Priors

Priors for the hyperparameters are non-informative in all models:

- $\boldsymbol{\theta}_0 \sim \mathcal{N}(\mathbf{a}_\theta, \mathbf{V}_\theta)$, $\mathbf{h}_0 \sim \mathcal{N}(\mathbf{a}_h, \mathbf{V}_h)$;
- $\mathbf{a}_\theta = 0, \mathbf{V}_\theta = 10 \times \mathbf{I}_{k_\theta}$;
- $\mathbf{a}_h = 0, \mathbf{V}_h = 10 \times \mathbf{I}_n$;
- $\upsilon_{\theta_i} = 5, \upsilon_{h_j} = 5$;
- $S_{\theta_i} = 0.01^2$(for lagged variables); $S_{\theta_i} = 0.1^2$(for intercepts);
- $S_{h_j} = 0.1^2$.

Time Varying Evidence

Table: Tests for Time Variation in Coefficients and Volatility

	Coefficients	Subsample 1	Subsample 2	Subsample 3	Full Sample
Kolmogorov-Smirnov	$\gamma_{i,t}$	10/10	10/10	10/10	8/10
	$\beta_{i,t}$	26/30	26/30	25/30	28/30
	$\mathbf{h}_{i,t}$	5/5	5/5	5/5	5/5
$t-$test	$\gamma_{i,t}$	8/10	10/10	9/10	9/10
	$\beta_{i,t}$	24/30	24/30	22/30	26/30
	$\mathbf{h}_{i,t}$	5/5	5/5	4/5	5/5

Number of time-varying parameters to Kolmogorov-Smirnov test and $t-$test are reported. $\gamma_{i,t}$ represents the coeffcients of contemporaneous relationships, $\beta_{i,t}$ are the coefficients associate to intercepts and lagged variables and $\mathbf{h}_{i,t}$ 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).

Selection of Models

- Lag length$=1$.
- 11,000 simulations; burning first 1,000, 10 parallel chains. Therefore: 100,000 simulations remained; thining is 1 in 10. Result: 10,000 simulations used to calculate the DIC and the log-ML$_{CE}$.
- Both criteria: the worst models are the CVAR and the TVP-VAR: both without SV component.
- The improved fitting is not due mainly to the time-varying VAR coefficients, but rather to the inclusion of the SV in the models.

Selection of Models

Table: Model Selection

Modelo	$LogML_{CE}$	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

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.

Stochastic Volatility

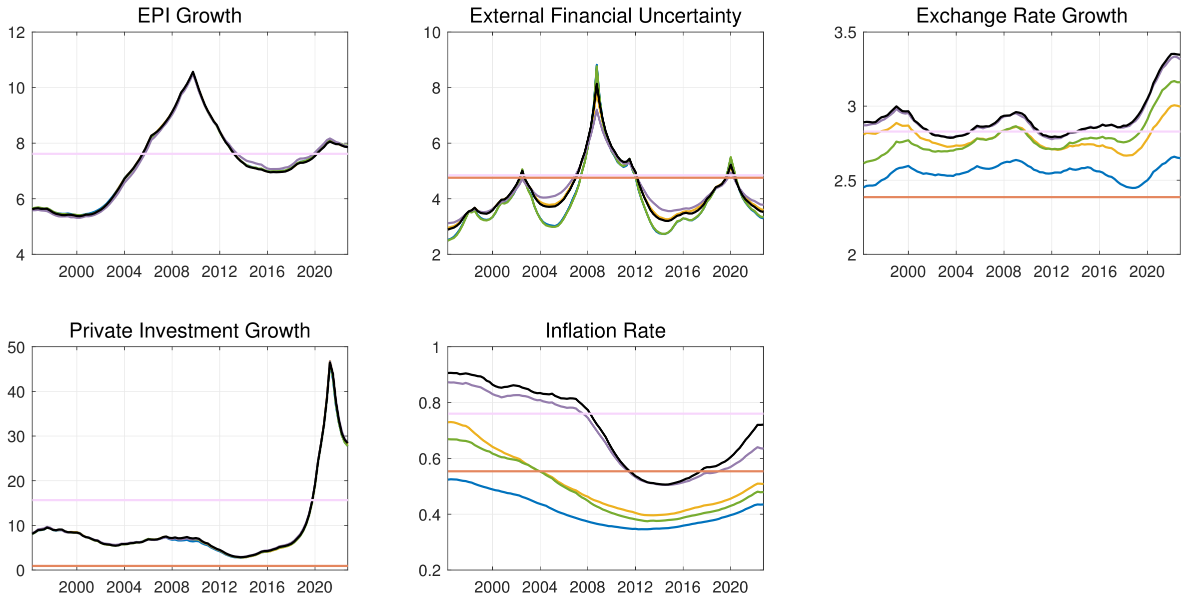

Figure: Median Values of the Standard Deviation of the Innovations of the Equations. The blue line represents the TVP-VAR-SV; red line: TVP-VAR; yellow line: TVP-VAR-R1-SV; green line: TVP-VAR-R2-SV; purple line: TVP-VAR-R3-SV; black line: CVAR-SV; pink line: CVAR.

Impulse Response Functions (1)

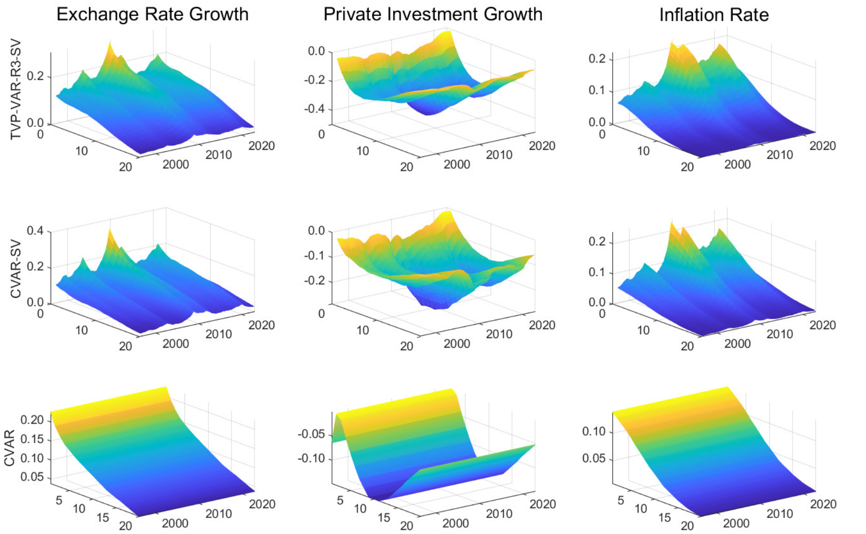

Figure: Median Time-Varying IRFs for the TVP-VAR-R3-SV, CVAR-SV and CVAR Models. The shock is normalized to an increase of Uncertainty by 1% at each point in the sample period.

Impulse Response Functions (2)

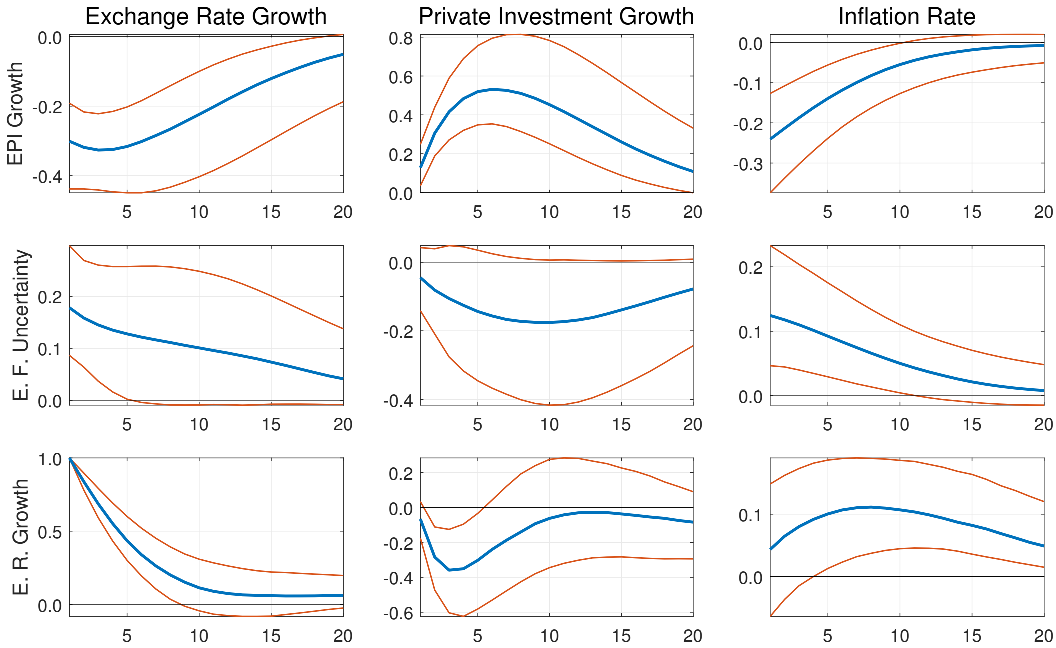

Figure: Median IRFs for the CVAR-SV Model. The blue lines are the medians. The red lines its 68% error band.

Impulse Response Functions (2)

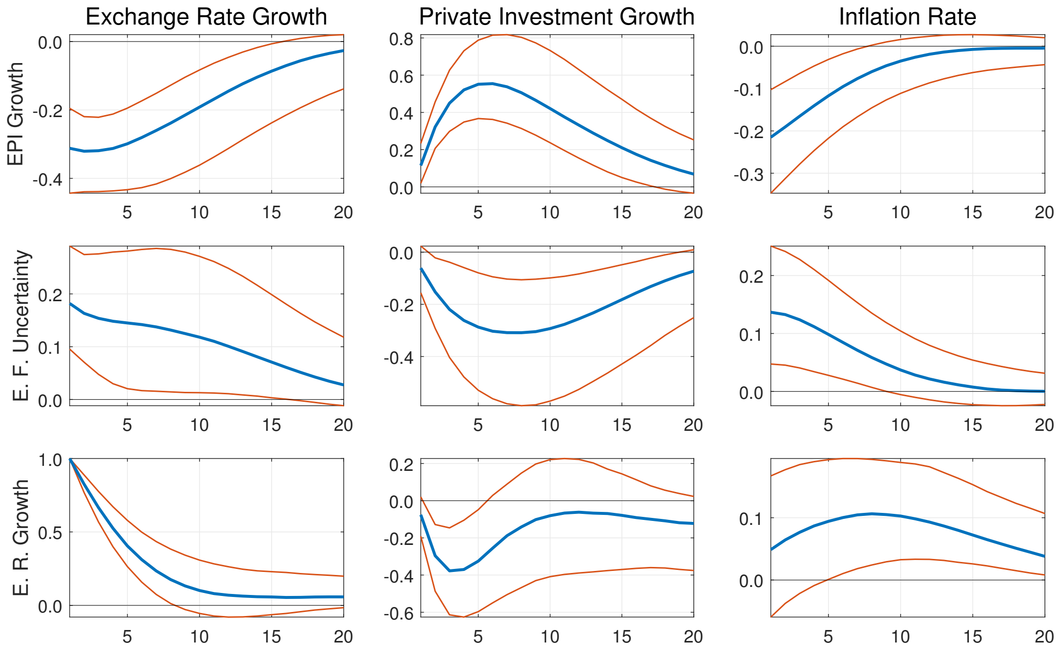

Figure: Median IRFs for the TVP-VAR-R3-SV Model. The blue lines are the medians. The red lines its 68% error band.

Impulse Response Functions (3)

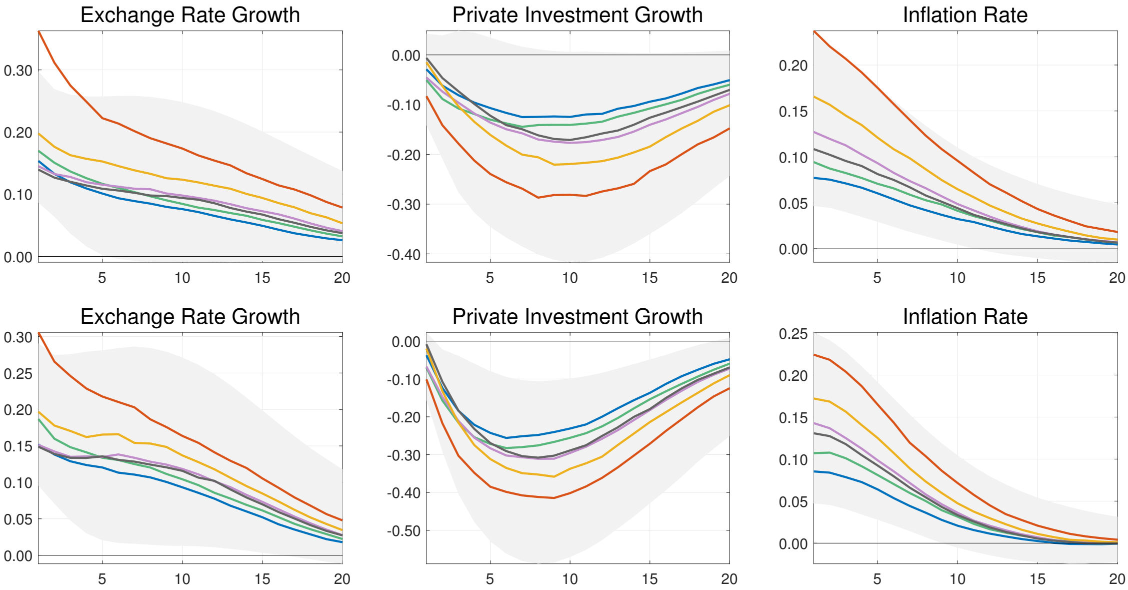

Figure: Evolution of IRFs at specific periods over time for the CVAR-SV and TVP-VAR-R3-SV Models. The grey shadows are the 68% error bands. The blue line represents the IRFs for the 1998Q1, green line: 2003Q3 period; red line: 2008Q4; purple line: 2017Q1; yellow line: 2020Q2; and grey line: 2021Q2.

Forecast Error Variance Decomposition

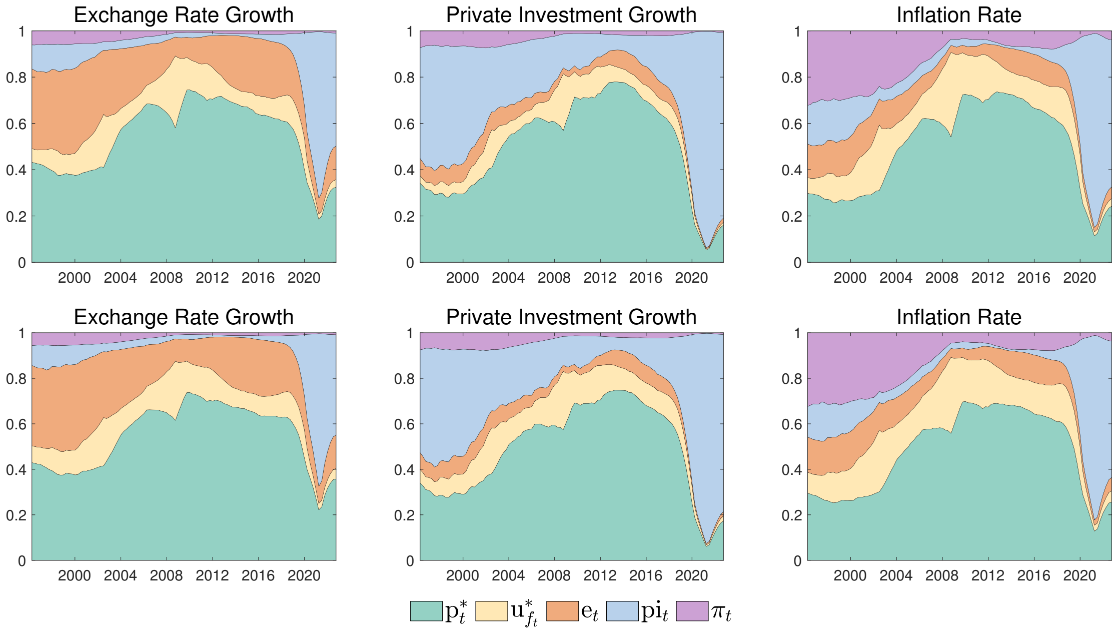

Figure: Time Evolution of FEVDs for the CVAR-SV and TVP-VAR-R3-SV Models; $h = 20$ quarters

Historical Decompositions

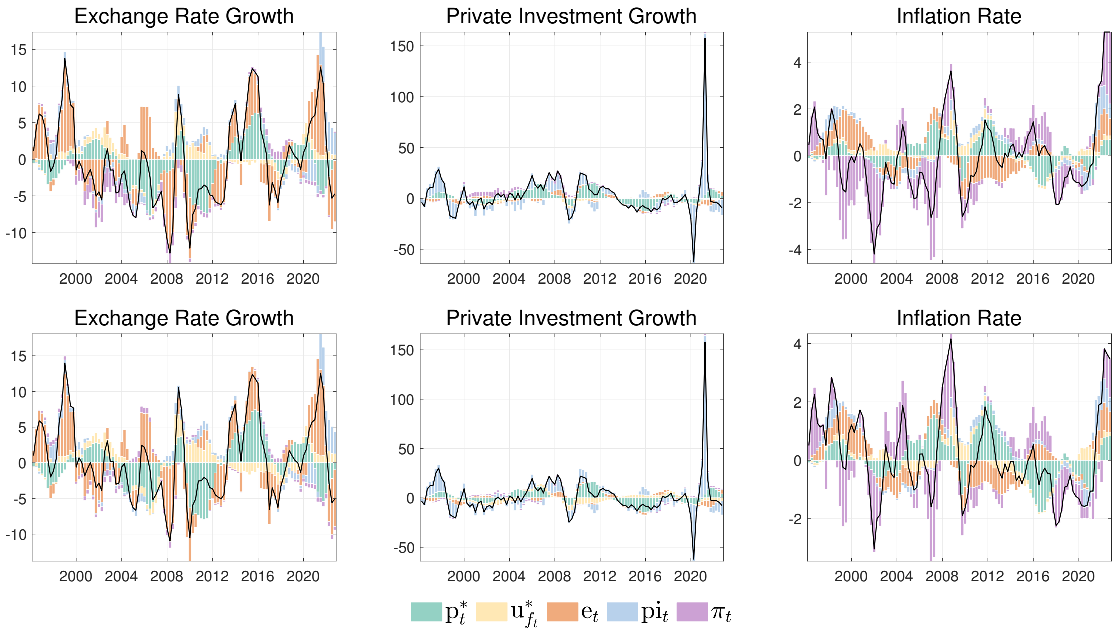

Figure: HDs for CVAR-SV and TVP-VAR-R3-SV Models

Alternative Models

We perfome two alternative models that incorporate two uncertainty measures, respectively, in our set of five variables:

1. Domestic Financial Uncertainty (u_{f_t}), measured as the conditional volatility of the IGBVL returns through a GARCH(1,1)-t model.
2. Risk Premium (ρ), measured as the spread between Peru's interbank rate and the Federal Funds effective rate.

The following is concluded:

1. u_{f_t} shock has a negative impact in the short-term on the private investment growth.
2. $u^*_{f_t}$ shock has a positive effect on u_{f_t}, that is evidence of a potential spillover effect.
3. ρ shock has a negative impact between the medium- to long-term on the private investment growth.
4. ρ continue as supply shocks, but u_{f_t} does not have significant effects on inflation rate.

Robustness Exercises

Three Exercises of them are based on the baseline:

1. Adding GDP Growth (y_t).
2. Adding Interest Rate (i_t).
3. Adding External Survey-based Uncertainty ($u^*_{sb_t}$), measured by the monthly average deviations of each quarter from the mean of the entire sample of the US Business Confidence Index.

The following is concluded:

1. The CVAR-SV model is selected by the DIC in 2 exercises.
2. $u^*_{f_t}$ continues as a supply shock.
3. The effects of the $u^*_{f_t}$ shocks on the private investment growth are three times higher than those on the GDP growth.
4. $u^*_{f_t}$ shock positively and significantly impacts the interest rate in the medium- to long-term within the CVAR-SV model.
5. $u^*_{sb_t}$ is a demand shock; i.e., decrease private investment growth and inflation rate, possibly because of it relies on a survey of investors' economic outlook.

Conclusions

- A simple VAR with stochastic volatility has been chosen as the best-fitting model, and it allows to have similar conclusions in the IRFs, FEVDs and HDs compared to the TVP-VAR-R3-SV model, the second selected model.
- $u^*_{f_t}$ shock has negative and significant effects on private investment growth in the medium- to long-term, as in the case of the ρ. The effects of u_{f_t} are shown in the short-term and it is possible that part of its impact is explained by a spillover effect of the $u^*_{f_t}$.
- The effects of $u^*_{f_t}$ shocks on the private investment growth are three times greater than those on the GDP growth, as GDP depends on various factors beyond those related to confidence or access to capital.
- $u^*_{f_t}$ shock behaves like an AS shock because it reduces the level of economic activity, while increasing the inflation rate.
- Impacts of the $u^*_{f_t}$ shocks are asymmetric. In an unfavorable financial condition, both reduces private investment growth in much more than a double against than periods of calm.