Global Uncertainty Shocks and Their Effects on LATAM Financial Markets and the Aggregate Economy*

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Abstract

The increase in uncertainty has harmful effects on both financial markets and the aggregated economy. At a global level, we have observed events that are known to have increased uncertainty and volatility in different indicators, especially the recent announcements associated with changes in trade policies (2025). These shocks generally involve an increase in indicators such as the VIX (volatility), the EPU (economic policy uncertainty), as well as collateral effects in both advanced and emerging financial markets. These effects are generally observed as a supply shock, generating higher inflation and lower economic activity. In this context, we seek to measure the impact of this type of combined shock on Latin American financial markets (measured through the EMBI, the exchange rate, and stock market indexes), as well as on activity and inflation. The countries analyzed are Brazil, Chile, Colombia, Mexico, and Peru, and the sample includes monthly data from January 2004 to September 2025. To quantify these effects, we estimated a Bayesian Hierarchical Panel VAR model, which has an external block that represents global markets and is not affected by shocks in the LATAM block. The global uncertainty shock are identified through zero and sign restrictions. Results indicate that, these shocks produce a favorable effect on the financial markets of the economies under analysis, in terms of a strengthened currency, lower country risk, and a temporary expansion in the stock market.

JEL Classification: C23, E44

Key words: Panel Bayesian Vector Autorregressions, Uncertainty

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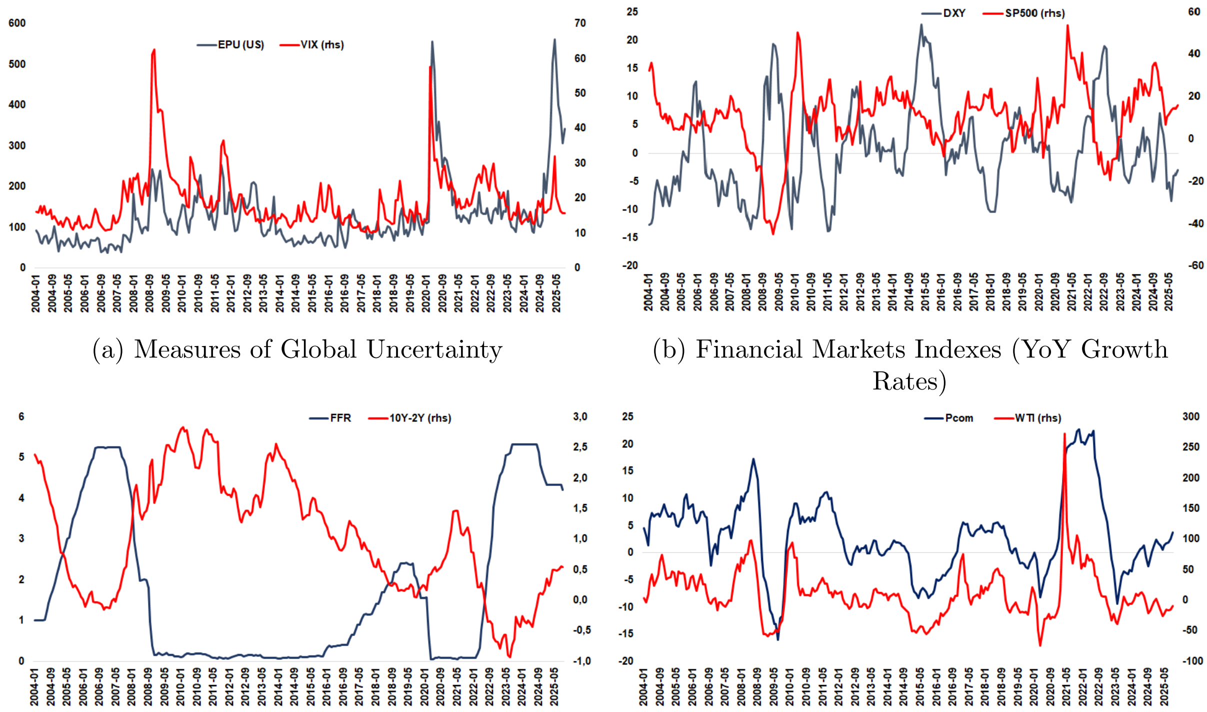
1 Introduction

Uncertainty is today a main driving force for determining macroeconomic fluctuations. The latter is manifested in the postponement of investment decisions and the signing of contracts. This has an impact that is first recorded in the financial markets. In fact, there are different sources of uncertainty, which can be both supply and demand-related (see e.g. Fasani and Rossi (2018), Alessandri and Mumtaz (2019), Pagliacci (2021), Guerrieri *et al.* (2022), among others).

Rising uncertainty has detrimental effects on both financial markets and the broader economy. Globally, events have been known to increase uncertainty and volatility in various indicators, such as the international financial crisis (2008-09), the Taper Tantrum (2013), COVID-19 (2020-21), and also recent announcements associated with changes in trade policies (2025). These shocks generally involve an increase in indicators such as the VIX (volatility), the EPU (economic policy uncertainty), and morecently the TPU (trade policy uncertainty), as well as a contraction of the stock market (S&P500), a steepening of the yield curve of safe assets (US Treasuries) and, as we have seen recently, a weakening of the dollar globally (DXY).

These effects generally manifest as a supply shock, although there is no consensus in the academic literature, generating higher inflation and lower economic activity (see e.g. empirical results from Alessandri and Mumtaz (2019) and more recently Llosa *et al.* (2025) for Latin American Economies). All of these sources have a detrimental impact on financial markets, generating greater amplification and higher volatility. Ultimately, this can be translated into negative and persistent macroeconomic fluctuations that could trigger an economic policy response (e.g. monetary policy through the central bank interest rate, macroprudential policies, etc.). Today, tariff shocks are a new source of uncertainty affecting the global economy, and it is therefore appropriate to examine the dynamic impact of these types of shocks on financial markets and the aggregate economy, beyond the effects seen in an international economics textbook. It is also important to note that many of these events are exogenous from the perspective of emerging markets, including Latin American economies. It is therefore important to quantify the effects of these events (see Figure 1) on these emerging economies in order to anticipate the potential collateral damage that may result from them, i.e. in terms of the exchange rate, stock markets, EMBI spreads and, ultimately, in the macroeconomic variables such as output and inflation.



(a) Measures of Global Uncertainty

(b) Financial Markets Indexes (YoY Growth Rates)

(c) Level and Slope of US Treasuries' Yield Curve

(d) Commodity Prices Indexes (YoY Growth Rate)

Figure 1: Global Financial Markets Data

Literature Review

Regarding the connection between Uncertainty and Business Cycles, we can find the work of Bloom (2009), Leduc and Liu (2016), Bloom *et al.* (2018), Caldara *et al.* (2019), Caggiano *et al.* (2020), Baker *et al.* (2020), among others. In addition, we can emphasize the connection with the financial markets, mentioning the work of Christiano *et al.* (2014), Gilchrist and Zakrajšek (2012), Caldara *et al.* (2016), Fasani and Rossi (2018), Arellano *et al.* (2019), Alessandri and Mumtaz (2019), Pagliacci (2021), Guerrieri *et al.* (2022), among others.

The Emerging Markets Economies have several financial restrictions, and in this strand of the literature we can mention the work of Calvo *et al.* (2006), Uribe and Yue (2006), García-Cicco *et al.* (2010), Mendoza and Yue (2012), Aoki *et al.* (2018) and Akinci and Queraltó (2018).

Finally, talking explicitly about Uncertainty in Emerging Markets (including LATAM economies), we can find the work of Carrière-Swallow and Céspedes (2013), Miescu (2018), Bhattarai *et al.* (2020), and more recently Llosa *et al.* (2025).

This paper quantifies the dynamic effects of a rise in global uncertainty on domestic financial and macroeconomic variables for a group of countries in Latin America (Brazil, Chile, Colombia, Mexico and Peru). Regarding the empirical strategy, it estimates a Bayesian Hierarchical Panel VAR for LATAM countries with an exogenous block that considers the US and Global variables. The model includes both macroeconomic and financial variables and is estimated with Bayesian Markov Chain Monte Carlo (MCMC) methods for the sample 2004-2025. Moreover, Global Uncertainty shocks are identified through a mixture of zero and sign restrictions. Monthly data is used in order to capture the high frequency events and their correlation with macroeconomic variables, choosing a midpoint between quarterly and daily data. Moreover, a hierarchical panel vector autoregressive model is used to jointly model Latin American countries, taking advantage of shared characteristics, and the fact that they are affected by the same common global shocks.

The main results indicate in first place that **an increase in Uncertainty that resembles a negative supply shock leads to:**

- A rise in uncertainty indicators (VIX, EPU, TPU) and Inflation, and fall in US Dollar (DXY), Stock Markets (S&P500) and Economic Activity.
- Results also suggest a rise in Commodity and Oil Prices, as well as in the slope of the US Treasuries' yield curve and a slightly dovish response of the Fed.
- In terms of the average effects on the LATAM block, in the short run there is an appreciation of the domestic currency, as well as a fall in the EMBI spread and a rise in the stock markets.
- Nevertheless, in the medium run there is a fall in inflation and an uncertain effect in economic activity. Given the fact that the five economies under study apply the Inflation Targeting Regime (IT), the average response of the central bank is to cut the interest rate after one year, given the persistent effect on inflation.

Given these sources of uncertainty, and the heterogeneity in their effects across countries, there is still an open question as to what kind of shock we are seeing today hitting the global economy. In light of this, our agenda considers the calculation of alternative uncertainty measures using stochastic volatility methodologies, following Jurado *et al.* (2015), Alessandri and Mumtaz (2019) and also Llosa *et al.* (2025).

The document is organized as follows: section 2 describes the empirical model used for the analysis, section 3 describes the data employed in the empirical exercise and explains the bayesian estimation procedure, section 4 describes the identification procedure for structural shocks, section 5 takes stock of the obtained results and postulates general conclusions, and section 6 makes the final remarks and sketches a future agenda.

2 A Bayesian Hierarchical Panel VAR model

2.1 Main setup

We assume in this section that each economy can be modeled as an individual Vector Autorregressive (VAR) model with an exogenous block[1]. Then we combine efficiently the information of the N economies under study in order to perform the estimation. A crucial point in this setup is the fact that the exogenous block is common to all the four economies, so that the dynamic effects derived from these external shocks will be easily comparable.

In this context, consider the set of countries $n = 1, \ldots, N$, where each country n is represented by a VAR model with exogenous variables:

$$y_{n,t} = \sum_{l=1}^{p} B'_{n,l} y_{n,t-l} + \sum_{l=0}^{p} B^{*\prime}_{n,l} y^*_{t-l} + \Delta_n z_t + u_{n,t} \tag{1}$$

where $y_{n,t}$ is a $M_1 \times 1$ vector of endogenous domestic variables, y^*_t is a $M_2 \times 1$ vector of endogenous foreign variables for the foreign block, z_t is a $W \times 1$ vector of exogenous variables such as trends, $u_{n,t}$ is a $M_1 \times 1$ vector of reduced form shocks such that $u_{n,t} \sim N(\mathbf{0}, \Sigma_n)$, $E\left(u_{n,t} u'_{m,t}\right) = \mathbf{0}, n \neq m \in \{1, \ldots, N\}$, p is the lag length and T_n is the sample size for each country $n \in \{1, \ldots, N\}$.

At the same time, there exists an exogenous block that evolves independently, such that

$$y^*_t = \sum_{l=1}^{p} \Phi^{*\prime}_l y^*_{t-l} + \Delta^* z_t + u^*_t \tag{2}$$

with $u^*_t \sim N(\mathbf{0}, \Sigma^*)$ and $E\left(u^*_t u'_{n,t}\right) = \mathbf{0}$.

The latter model can be expressed in a more compact form for each country $n \in \{1, \ldots, N\}$, so

[1]This setp has been previously used in Gondo and Pérez Forero (2018) and Gondo and Pérez Forero (2019).

that:

$$\begin{bmatrix} \mathbf{I}_{M_1} & -B^{*\prime}_{n,0} \\ \mathbf{0} & \mathbf{I}_{M2} \end{bmatrix} \begin{bmatrix} y_{n,t} \\ y^*_t \end{bmatrix} = \sum_{l=1}^{p} \begin{bmatrix} B'_{n,l} & B^{*\prime}_{n,l} \\ \mathbf{0} & \Phi^{*\prime}_l \end{bmatrix} \begin{bmatrix} y_{n,t} \\ y^*_t \end{bmatrix} + \begin{bmatrix} \Delta_n \\ \Delta^* \end{bmatrix} z_t + \begin{bmatrix} \Sigma_n & \mathbf{0} \\ \mathbf{0} & \Sigma^* \end{bmatrix} \begin{bmatrix} u_{n,t} \\ u^*_t \end{bmatrix} \tag{3}$$

System (1) represents the small open economy in which its dynamics are influenced by the big economy block (2) through the parameters $B^{*\prime}_{n,l}$ and $\Phi^{*\prime}_l$. On the other hand, the big economy evolves independently, i.e. the small open economy cannot influence the dynamics of the big economy. Even though block (2) has effects over block (1), we assume that the block (2) is independent of block (1), and thus it will keep the same coefficients for each country model. This type of *Block Exogeneity* has been applied in the context of SVARs by Cushman and Zha (1997), Zha (1999) and Canova (2005), among others. Moreover, it turns out that this is a plausible strategy for representing small open economies such as the Latin American ones, since they are influenced by external shocks i.e. commodity prices fluctuations.

3 Data Description and Bayesian Estimation

We include the following variables for the exogenous block (2004M1:2025M9): i) US CPI YoY Inflation, ii) US Industrial Production (YoY Growth), iii) Effective Federal Funds Interest Rate (in % - annual terms), iv) Slope of the US Treasuries Yield Curve (10Y-2Y) (in % - annual terms), v) DXY Dollar Index (YoY Growth), vi) S&P500 Stock Market Index (YoY Growth), vii) Commodity Prices Index (YoY Growth), viii) WTI Oil Prices (YoY Growth), ix) Economic Policy Uncertainty Index of US (EPU), x) Trade Policy Uncertainty Index (TPU)[2], xi) VIX Index of Uncertainty.

We also include the following variables for the domestic block (2004M1:2025M9)[3]: i) CPI YoY Inflation, ii) Monthly Indicator of Economic Activity (YoY Growth), iii) Domestic Central Bank Interest Rate (in % - annual terms), iv) Monetary Base (YoY Growth), v) Exchange rate (YoY domestic currency depreciation w.r.t. to USD), vi) EMBI Spread, vii) Stock Market Index (YoY Growth)

Regarding this list of variables, the data sources are the FRED Database of the Federal Reserve Bank of St. Louis, Trading Economics, International Financial Statistics (IFS) of the International Monetary Fund (IMF), and Central Bank Websites, including the BCRPData of the Central Reserve Bank of Peru (BCRP). Given the specified priors ($A.14$) and the joint likelihood function ($A.1$), we combine efficiently these two pieces of information in order to get the estimated parameters included in Θ. Using Bayes' theorem we have that:

$$p(\Theta \mid Y) \propto p(Y \mid \Theta)\, p(\Theta) \tag{4}$$

Our target is to maximize the right-hand side of equation (4) [4] in order to get Θ. The common practice in Bayesian Econometrics (see e.g. Koop (2003) and Canova (2007) among others) is to simulate the posterior distribution ($A.15$) in order to conduct statistical inference. This is since any object of interest that is also a function of Θ can be easily computed given the simulated

[2]See Caldara *et al.* (2020). The TPU index has been downloaded from Matteo Iacoviello's website.
[3]See Figures in Appendix C.
[4]See details in Appendix A, especially the equation ($A.15$)

posterior. In this section we describe a Markov Chain Monte Carlo (MCMC) routine that helps us to accomplish this task.

3.1 A Gibbs sampling routine

In general, if the likelihood function has a very complex functional form, it is difficult to sample from the posterior distribution $p(\Theta \mid Y)$. However, in this case there exists an analytical expression for the posterior distribution, which can be solved using a Gibbs Sampling routine, which is much simpler than the Metropolis-Hastings routine for the general case. In this process, it is useful to divide the parameter set into different blocks and factorize ($A.15$) appropriately.

Recall that $\Theta = \left\{ \{\beta_n, \Sigma_n\}_{n=1}^{N}, \beta^*, \Sigma^*, \tau, \overline{\beta}, \tau_X \right\}$. Then, use the notation Θ/χ whenever we denote the parameter vector Θ without the parameter . Details about the form of each block can be found in Appendix B.

The routine starts here. Set $k = 1$ and denote K as the total number of draws. Then follow the steps below:

1. Draw $p(\beta^* \mid \Theta/\beta^*, \mathbf{y}^*, \mathbf{y}_n)$. If the candidate draw is stable keep it, otherwise discard it.
2. For $n = 1, \ldots, N$ draw $p(\beta_n \mid \Theta/\beta_n, \mathbf{y}^*, \mathbf{y}_n)$. If the candidate draw is stable keep it, otherwise discard it.
3. Draw $p(\Sigma^* \mid \Theta/\Sigma^*, \mathbf{y}^*, \mathbf{y}_n)$.
4. For $n = 1, \ldots, N$ draw $p(\Sigma_n \mid \Theta/\Sigma_n, \mathbf{y}^*, \mathbf{y}_n)$.
5. Draw $p(\tau_X \mid \Theta/\tau_X, Y)$.
6. Draw $p\left(\overline{\beta} \mid \Theta/\overline{\beta}, Y\right)$. If the candidate draw is stable keep it, otherwise discard it.
7. Draw $p(\tau \mid \Theta/\tau, Y)$.
8. If $k < K$ set $k = k + 1$ and return to Step 1. Otherwise stop.

A complete cycle of all these steps gives us a draw for the parameter set Θ.

3.2 Estimation setup

We run the Gibbs sampler for $K = 150,000$ and discard the first $100,000$ draws in order to minimize the effect of initial values. Moreover, in order to reduce the serial correlation across draws, we set a thinning factor of 50, i.e. given the remaining $50,000$ draws, we take 1 every 50 and discard the remaining ones. As a result, we have $1,000$ draws for conducting inference. Specific details about how we conduct inference and assess convergence can be found in Appendix B.

Following the recommendation of Gelman (2006) and Jarociński (2010), we assume a uniform prior for the standard deviation, which translates into a prior for the variance as

$$p(\tau) \propto \tau^{-1/2} \tag{5}$$

by setting $v = -1$ and $s = 0$ in ($A.8$).

Regarding the Minnesota-style prior, we do not have any information about the value of the hyper-parameters. Thus, we set conservative values of $\phi_1 = 0.5$, $\phi_2 = 1$ and $\phi_3 = 2$ in equation ($A.6$). More specifically, ϕ_1 is related to the *a priori* difference between own lags and lags of other variables; ϕ_2 is related to the *a priori* heteroskedasticity coming from exogenous variables[5]; and $\phi_3 = 2$ means that the shrinking pattern of coefficients is quadratic. It is worth mentioning that, in order to have symmetry, we set the same hyper-parameter values for the exogenous block, i.e. $\phi_1^* = 0.5$, $\phi_2^* = 1$ and $\phi_3^* = 2$ in equation ($A.11$). Finally, the exogenous block has a standard Minnesota Prior, and we set an autorregressive parameter of 0 for the prior mean of the first lag of the own variable in each VAR equation.

[5]Since this is a VARX, i.e. a model that includes the lags of exogenous variables, we cannot set a very large value of this hyper parameter as in standard Minnesota prior applications.

4 Global Uncertainty Shocks Identification

In order to quantify the effects of increased uncertainty at a global level, this section discusses the restrictions that need to be imposed, that is, a set of macroeconomic and financial assumptions associated with the most recent events related with higher uncertainty, so that these effects are completely isolated and identified. We impose the following type of restrictions: i) The first group is related with zero restrictions in the contemporaneous coefficients matrix, as in the old literature of Structural VARs, i.e. Sims (1980) and Sims (1986). ii) The second group are the sign restrictions as in Canova and De Nicoló (2002) and Uhlig (2005), where we set a horizon of three months.

The exogenous block has $M2$ variables, suggesting that it potentially has $M2$ structural shocks. Nevertheless, in this context of partial identification we can only identify a subset of them[6]. In our case, we are only interested in one type of shocks (sources of uncertainty), i.e. the one associated with aggregated supply. Here we explain the assumptions associated with each shock presented in Table 1.

Var / Shock	Name	Global Uncertainty shock
Domestic Block	$\mathbf{y}$	?
Consumer Price Index	CPI_{US}	$\geqslant 0$
Industrial Production	Y_{US}	$\leqslant 0$
VIX	VIX	$\geqslant 0$
TPU	TPU	$\geqslant 0$
EPU$_{(US)}$	EPU_{US}	$\geqslant 0$
DXY	DXY	$\leqslant 0$
S&P500	$SP500$	$\leqslant 0$

Table 1: Identifying Restrictions

[6] As a result, the remaining shocks are unidentified. However, it turns out that this is not an econometric problem, since the literature of SVARs with sign restrictions explains that in order to conduct proper inference the model needs to be only partially identified (Rubio-Ramírez *et al.*, 2010).

Global Uncertainty shock: It raises all indicators of uncertainty (VIX, TPU and EPU), weakening the dollar (DXY) and the stock markets (S&P500), but also weakens the economy and produces a higher inflation. The latter is usually associated with an aggregated negative supply shock, and in this case, the weakening of the US Dollar is a scenario that has been observed since the beginning of 2025 and the announcement of tariff policies. It should be clear that, while other potential sources of uncertainty exist, this document focuses entirely on supply-side sources. Demand shocks (or any other potential sources of uncertainty) will be explored in a follow-up to this document and are not included in this version. In any case, a demand shock would be related to an acceleration of economic activity, along with other potential side effects, and this would imply the use of another set of additional sign restrictions. The latter is beyond the scope of this paper. Thus, using the estimated posterior distribution for the reduced form, we employ the algorithm described in appendix F applying the restrictions presented in Table 1. It is also important to mention that the use of zero and sign restrictions allows the identification of a set of models, which may have different frictions and microfoundations, and this also opens an additional window for future research.

5 Results

In this section we present the main results for the impulse responses obtained for the identified structural shocks. In each case we compute the posterior distribution for the entire horizon of $h = 36$ months and then we plot the median value and the 68% confidence interval. We present for each shock the effect on the exogenous block, for the average impulse response derived from $\overline{\beta}$, and the median values for each country in order to capture a sense of heterogeneity across the countries under study. Results for individual countries including the error bands can be found in Appendix D.

5.1 Global Uncertainty Shock

An increase in Uncertainty that resembles a negative supply shock leads to a rise in uncertainty indicators (VIX, TPU and EPU) and Inflation, and fall in US Dollar (DXY), Stock Markets (S&P500) and Economic Activity (Y_{US}). The results are depicted in Figure 2, where a moderately persistent (hump-shaped) effect on inflation and economic activity can be observed during the first year. A faster effect can also be seen on financial variables (DXY and SP 500), and also an immediate effect on uncertainty indicators. Results also suggest a rise in Commodity and Oil Prices, as well as in the slope of the US Treasuries' yield curve, although these latter effects are not statistically significant. No significant reaction from the Fed's monetary policy interest rate is observed after this shock. Sign restrictions are applied for a 3-month horizon, as indicated in the green areas.

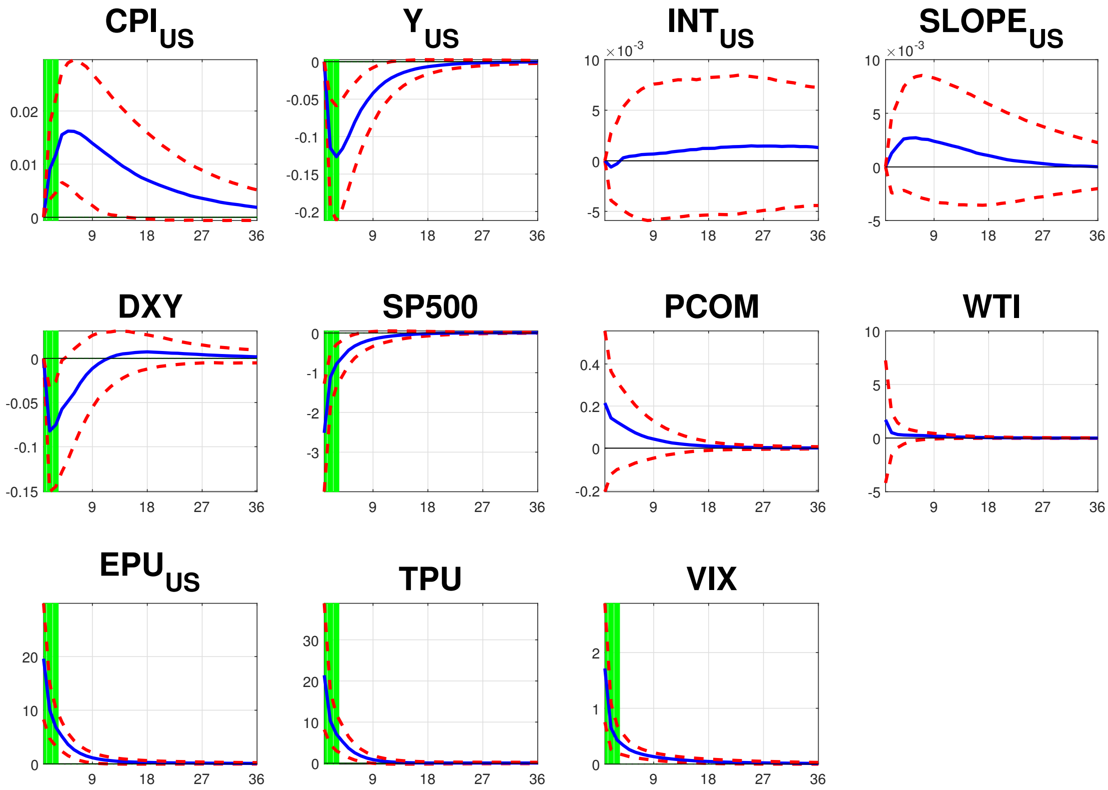


Figure 2: Global Uncertainty Shock: Exogenous Block - Median Value and 68% Confidence Interval

In terms of the average effects on the LATAM block, as it is depicted in Figure 3, in the short run there is an appreciation of the domestic currency, as well as a fall in the EMBI spread and a rise in the stock markets. Nevertheless, in the medium run there is a fall in inflation and an uncertain effect in economic activity. Given the fact that the five economies under study apply the Inflation Targeting Regime (IT), the average response of the central bank is to cut the interest rate after one year, given the persistent effect on inflation. Part of this effect may be associated with the pass-through of the exchange rate to prices, although this has been decreasing in recent years.

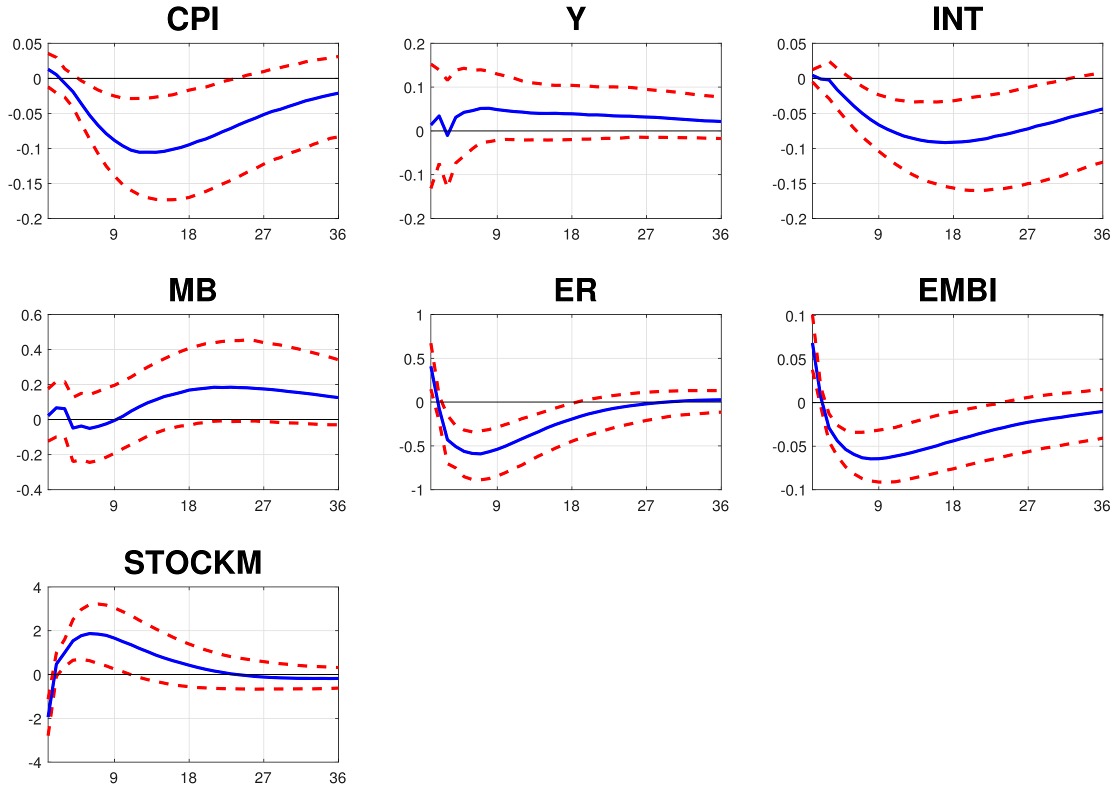


Figure 3: Global Uncertainty Shock: Average Effect in LATAM - Median Value and 68% Confidence Interval

As a complement of the previous result, Figure 4 shows the median values for the responses of each countries. We can see in particular that there are difference in the response of the central banks through the interest rate, with a relative more dovish response in the case of Mexico and Brazil with respect to Peru and Chile.

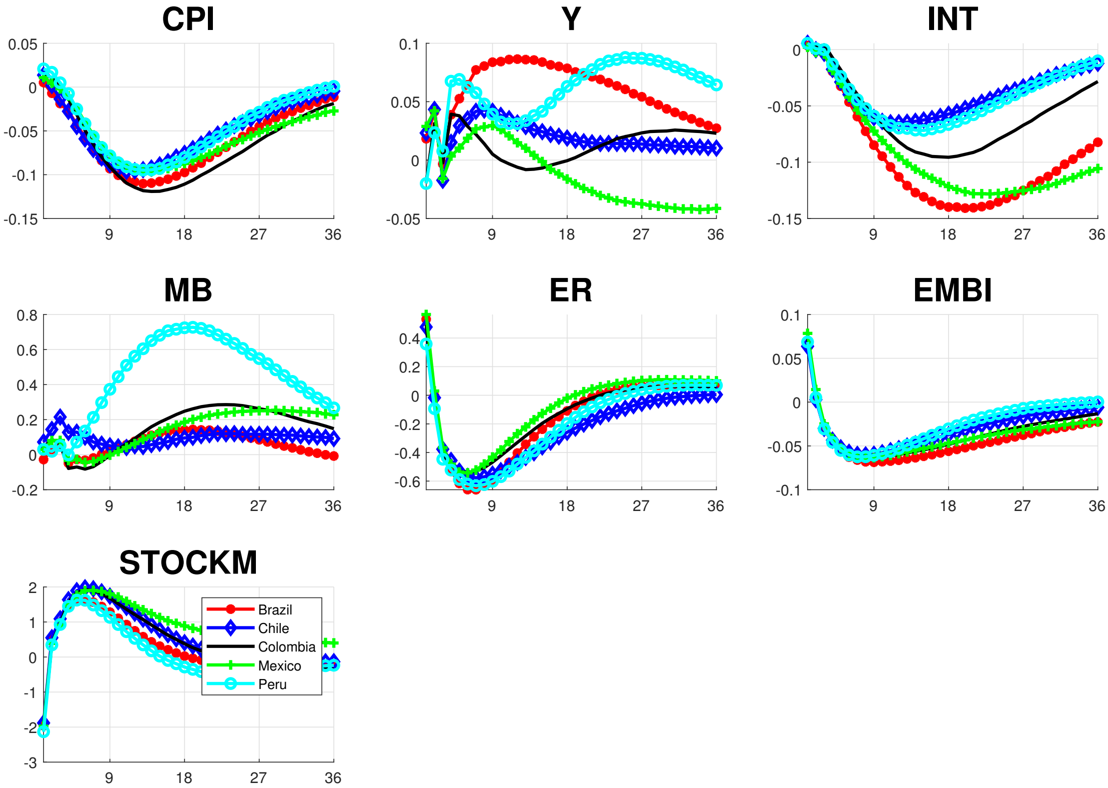


Figure 4: Global Uncertainty shock comparison - Median Values

6 Concluding Remarks

This work quantifies the dynamic effects of changes in global uncertainty on domestic financial and macroeconomic variables for a group of countries in Latin America (Brazil, Chile, Colombia, Mexico and Peru). It estimates a Bayesian Hierarchical Panel VAR for LATAM countries with an exogenous block that considers the US and Global variables. The model includes both macroeconomic and financial variables and is estimated with MCMC methods for the sample 2004-2025. Global Uncertainty shocks are identified through a mixture of zero and sign restrictions.

An increase in Uncertainty that resembles a negative supply shock leads to: i) A rise in uncertainty indicators (VIX, TPU EPU) and Inflation, and fall in US Dollar (DXY), Stock Markets (S&P500) and Economic Activity, ii) Results also suggest a rise in Commodity and Oil Prices, as well as in the slope of the US Treasuries' yield curve and a slightly dovish response of the Fed, iii) In terms of the average effects on the LATAM block, in the short run there is an appreciation of the domestic currency, as well as a fall in the EMBI spread and a rise in the stock markets, iv) Nevertheless, in the medium run there is a fall in inflation and an uncertain effect in economic activity. Given the fact that the five economies under study apply the Inflation Targeting Regime (IT), the average response of the central bank is to cut the interest rate after one year, given the persistent effect on inflation.

Future Research agenda will consider the inclusion of Stochastic Volatility components in each unit of the Panel VAR, so that we can obtain new measures of uncertainty from the data, following Jurado *et al.* (2015), Alessandri and Mumtaz (2019) and also Llosa *et al.* (2025). Another alternative specification is the possibility of including other uncertainty indicators in order to improve the robustness of the analysis. Demand shocks (or any other potential sources of uncertainty) will be explored in a follow-up to this document. In any case, a demand shock would be related to an acceleration of economic activity, along with other potential side effects, and this would imply the use of another set of additional sign restrictions. Finally, it is also important to mention that the use of zero and sign restrictions allows the identification of a set of models, which may have different frictions and microfoundations, and this also opens an additional window for future research.

A Additional Technical Details for the Statistical Model

A.1 The Linear Regression form and the Log-Likelihood Function

Reduced form estimation is performed independently by blocks as in Zha (1999). Assuming that we have a sample $t = 1, \ldots, T_n$ for each country $n \in \{1, \ldots, N\}$, the regression model for the domestic block can be re-expressed as

$$Y_n = X_n B_n + U_n \tag{A.1}$$

where we have the data matrices $Y_n \, (T_n \times M_1)$, $X_n \, (T_n \times K)$, $U_n \, (T_n \times M_1)$, with $K = M_1 p + W$ and the corresponding parameter matrix $B_n \, (K \times M_1)$. In particular

$$B_n = \begin{bmatrix} B'_{n,1} & B'_{n,2} & \cdots & B'_{n,p} & B^{*\prime}_{n,1} & B^{*\prime}_{n,2} & \cdots & B^{*\prime}_{n,p} & \Delta'_n \end{bmatrix}'$$

The model in equation (A.1) can be re-written such that

$$\mathbf{y}_n = (I_{M_1} \otimes X_n)\, \beta_n + \mathbf{u}_n$$

where $\mathbf{y}_n = vec\,(Y_n)$, $\beta_n = vec\,(B_n)$ and $\mathbf{u}_n = vec\,(U_n)$ with

$$\mathbf{u}_n \sim N\,(0, \Sigma_n \otimes I_{T_n - p})$$

Under the assumption of normality of the error terms, the likelihood function for each country is given by:

$$p\,(\mathbf{y}_n \mid \beta_n, \Sigma_n) = N\,((I_{M_1} \otimes X_n)\, \beta_n, \Sigma_n \otimes I_{T_n - p})$$

$$\begin{aligned} p\,(\mathbf{y}_n \mid \beta_n, \Sigma_n) = (2\pi)^{-M_1(T_n - p)/2} \left| \Sigma_n \otimes I_{T_n - p} \right|^{-1/2} \times \\ \exp\left(-\frac{1}{2} \left(\mathbf{y}_n - (I_{M_1} \otimes X_n)\, \beta_n\right)' \left(\Sigma_n \otimes I_{T_n - p}\right)^{-1} \left(\mathbf{y}_n - (I_{M_1} \otimes X_n)\, \beta_n\right) \right) \end{aligned} \tag{A.2}$$

where $n = 1, \ldots, N$.

On the other hand, the exogenous block estimation is as follows. First, rewrite equation (2) as a regression model

$$Y^* = X^* \Phi^* + U^*$$

Where we have the data matrices $Y^* \left(T^* \times M_2\right)$, $X^* \left(T^* \times K^*\right)$, $U^* \left(T^* \times M_2\right)$, with $K^* = M_2 p + W$ and the corresponding parameter matrix $\Phi^* \left(K^* \times M_2\right)$, and in particular:

$$\Phi^* = \begin{bmatrix} \Phi_1^{*\prime} & \Phi_2^{*\prime} & \cdots & \Phi_p^{*\prime} & \Delta^{*\prime} \end{bmatrix}'$$

The regression model can then be re-written such that

$$\mathbf{y}^* = \left(I_{M_2} \otimes X^*\right) \beta^* + \mathbf{u}^*$$

where $\mathbf{y}^* = vec\left(Y^*\right)$, $\beta^* = vec\left(\Phi^*\right)$ and $\mathbf{u}^* = vec\left(U^*\right)$ with

$$\mathbf{u}^* \sim N\left(0, \Sigma^* \otimes I_{T^*-p}\right)$$

Under the assumption of normality of the error terms, we have the likelihood function for the exogenous block:

$$p\left(\mathbf{y}^* \mid \beta^*, \Sigma^*\right) = N\left(\left(I_{M_2} \otimes X^*\right) \beta^*, \Sigma^* \otimes I_{T^*-p}\right)$$

$$\begin{aligned} p\left(\mathbf{y}^* \mid \beta^*, \Sigma^*\right) &= (2\pi)^{-M_2(T^*-p)/2} \left|\Sigma^* \otimes I_{T^*-p}\right|^{-1/2} \times \\ \exp &\begin{pmatrix} -\frac{1}{2}\left(\mathbf{y}^* - \left(I_{M_2} \otimes X^*\right) \beta^*\right)' \left(\Sigma^* \otimes I_{T^*-p}\right)^{-1} \times \\ \left(\mathbf{y}_n - \left(I_{M_2} \otimes X^*\right) \beta^*\right) \end{pmatrix} \end{aligned} \tag{A.3}$$

As a consequence of the previous analysis, the statistical model described above has a joint likelihood function. Denote $\Theta = \left\{\left\{\beta_n, \Sigma_n\right\}_{n=1}^{N}, \beta^*, \Sigma^*\right\}$ as the set of parameters, then the likelihood function is

$$p(\mathbf{y},\mathbf{y}^* \mid \Theta) \propto |\Sigma^*|^{-T^*/2} \prod_{n=1}^{N} |\Sigma_n|^{-T_n/2} \times \exp \left(\begin{array}{c} -\frac{1}{2}\sum_{n=1}^{N} (\mathbf{y}_n - (I_{M_1} \otimes X_n)\beta_n)' (\Sigma_n \otimes I_{T_n - p})^{-1} \times \\ (\mathbf{y}_n - (I_{M_1} \otimes X_n)\beta_n) \\ -\frac{1}{2} (\mathbf{y}^* - (I_{M_2} \otimes X^*)\beta^*)' (\Sigma^* \otimes I_{T^*-p})^{-1} \times \\ (\mathbf{y}_n - (I_{M_2} \otimes X^*)\beta^*) \end{array} \right) \tag{A.4}$$

A.2 Priors

Given the normality assumption of the error terms, it follows that each country coefficients vector is normally distributed. As a result, we assume a normal prior for them in order get a posterior distribution that is also normal, i.e. a conjugated prior:

$$p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) = N\left(\overline{\beta}, \tau O_n\right) \tag{A.5}$$

with $\overline{\beta}$ as the common mean and τ as the overall tightness parameter. The covariance matrix O_n takes the form of the typical Minnesota prior (Litterman, 1986), i.e. $O_n = diag\left(o_{ij,l}\right)$ such that

$$o_{ij,l} = \begin{cases} \frac{1}{l^{\phi_3}} & , i = j \\ \frac{\phi_1}{l^{\phi_3}} \left(\frac{\widehat{\sigma}_j^2}{\widehat{\sigma}_i^2} \right) & , i \neq j \\ \phi_2 & , exogenous \end{cases} \tag{A.6}$$

where

$$i, j \in \{1, \ldots, M_1\} \text{ and } l = 1, \ldots, p$$

and $\widehat{\sigma}_j^2$ is the variance of the residuals from an estimated $AR(p)$ model for each variable $j \in \{1, \ldots, M_1\}$. In addition, we assume the non-informative priors:

$$p\left(\Sigma_n\right) \propto |\Sigma_n|^{-\frac{1}{2}(M_1+1)} \tag{A.7}$$

In a standard Bayesian context, $\overline{\beta}$ and τ would be hyper-parameters that are supposed to be calibrated. In contrast, in a hierarchical context (see e.g. Gelman *et al.* (2003)), it is possible to derive a posterior distribution for both and therefore estimate them. That is, we estimate it from the data without imposing any particular tightness for the prior distribution of the coefficients. Following Gelman (2006) and Jarociński (2010)[7] we assume an inverse-gamma prior distribution for τ, so that

$$p(\tau) = IG\left(\frac{\upsilon}{2}, \frac{s}{2}\right) \propto \tau^{-\frac{\upsilon+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\tau}\right) \tag{A.8}$$

Finally, we assume the non-informative prior:

$$p\left(\overline{\beta}\right) \propto 1 \tag{A.9}$$

In addition, coefficients of the exogenous block have a traditional Litterman prior with

$$p(\beta^*) = N\left(\overline{\beta^*}, \tau_X O_X\right) \tag{A.10}$$

where $\overline{\beta^*}$ assumes an AR(1) process for each variable and $O_X = diag\left(o^*_{ij,l}\right)$ such that

$$o^*_{ij,l} = \begin{cases} \frac{1}{l^{\phi_3^*}} & , i = j \\ \frac{\phi_1^*}{l^{\phi_3^*}}\left(\frac{\widehat{\sigma}_j^2}{\widehat{\sigma}_i^2}\right) & , i \neq j \\ \phi_2^* & , exogenous \end{cases} \tag{A.11}$$

where

$$i, j \in \{1, \ldots, M_2\} \text{ and } l = 1, \ldots, p$$

and similarly $\widehat{\sigma}_j^2$ is the variance of the residuals from an estimated $AR(p)$ model for each variable $j \in \{1, \ldots, M_2\}$. As in the domestic block, we assume the non-informative priors for

[7] See Pérez Forero (2015) for a similar application for Latin America.

the covariance matrix of error terms, so that:

$$p\left(\Sigma^{*}\right) \propto \left|\Sigma^{*}\right|^{-\frac{1}{2}\left(M_{2}+1\right)} \tag{A.12}$$

Moreover, since this is a hierarchical model, we also estimate the overall tightness parameter for the prior variance as in the domestic block, so that we again assume the inverse-gamma distribution:

$$p\left(\tau_{X}\right) = IG\left(\frac{\upsilon_{X}}{2}, \frac{s_{X}}{2}\right) \propto \tau_{X}^{-\frac{\upsilon_{X}+2}{2}} \exp\left(-\frac{1}{2}\frac{s_{X}}{\tau_{X}}\right) \tag{A.13}$$

As a result of the hierarchical structure, our statistical model presented has several parameter blocks. Denote the parameter set as Θ, such that:

$$\Theta = \left\{\left\{\beta_{n}, \Sigma_{n}\right\}_{n=1}^{N}, \beta^{*}, \Sigma^{*}, \tau, \overline{\beta}, \tau_{X}\right\}$$

so that the joint prior is given by ($A.5$), ($A.7$), ($A.8$), ($A.9$), ($A.10$), ($A.12$) and ($A.13$):

$$\begin{aligned} p(\Theta) \propto & \prod_{n=1}^{N} p\left(\Sigma_{n}\right) p\left(\beta_{n} \mid \overline{\beta}, O_{n}, \tau\right) p(\tau) \\ = & \prod_{n=1}^{N} \left|\Sigma_{n}\right|^{-\frac{1}{2}\left(M_{1}+1\right)} \times \\ & \tau^{-\frac{N M_{1} K}{2}} \exp\left(-\frac{1}{2} \sum_{n=1}^{N}\left(\beta_{n}-\overline{\beta}\right)^{\prime}\left(\tau^{-1} O_{n}\right)^{-1}\left(\beta_{n}-\overline{\beta}\right)\right) \times \\ & \tau^{-\frac{\upsilon+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\tau}\right) \times \\ & \left|\Sigma^{*}\right|^{-\frac{1}{2}\left(M_{2}+1\right)} \times \\ & \tau_{X}^{-\frac{M_{2} K^{*}}{2}} \exp\left(-\frac{1}{2}\left(\beta^{*}-\overline{\beta^{*}}\right)^{\prime}\left(\tau_{X}^{-1} O_{X}\right)^{-1}\left(\beta^{*}-\overline{\beta^{*}}\right)\right) \times \\ & \tau_{X}^{-\frac{\upsilon_{X}+2}{2}} \exp\left(-\frac{1}{2}\frac{s_{X}}{\tau_{X}}\right) \end{aligned} \tag{A.14}$$

A.3 The Posterior Distribution

Given ($A.1$) and ($A.14$), the posterior distribution (4) takes the form:

$$
p(\Theta \mid \mathbf{y}, \mathbf{y}^*) \propto |\Sigma^*|^{-\frac{T^*+M_2+1}{2}}
$$

$$
\prod_{n=1}^{N} |\Sigma_n|^{-\frac{T_n+M_1+1}{2}} \times \exp\begin{pmatrix} -\frac{1}{2}\sum_{n=1}^{N}(\mathbf{y}_n-(I_{M_1}\otimes X_n)\beta_n)'(\Sigma_n\otimes I_{T_n-p})^{-1} \\ (\mathbf{y}_n-(I_{M_1}\otimes X_n)\beta_n) \\ -\frac{1}{2}(\mathbf{y}^*-(I_{M_2}\otimes X^*)\beta^*)'(\Sigma^*\otimes I_{T^*-p})^{-1} \\ (\mathbf{y}_n-(I_{M_2}\otimes X^*)\beta^*) \end{pmatrix} \times
$$

$$
\tau^{-\frac{(NM_1K+v)}{2}} \exp\left(-\frac{1}{2}\left[\sum_{n=1}^{N}\left(\beta_n-\overline{\beta}\right)' O_n^{-1}\left(\beta_n-\overline{\beta}\right)+s\right]\frac{1}{\tau}\right) \times
$$

$$
\tau_X^{-\frac{(M_2K^*+v_X)}{2}} \exp\left(-\frac{1}{2}\left[\left(\beta^*-\overline{\beta^*}\right)' O_X^{-1}\left(\beta^*-\overline{\beta^*}\right)+s_X\right]\frac{1}{\tau_X}\right) \tag{A.15}
$$

B Gibbs sampling details

The algorithm described in subsection 3.1 uses a set of conditional distributions for each parameter block. Here we provide specific details about the form that these distributions take and how they are constructed.

1. Block 1: $p(\beta^* \mid \Theta/\beta^*, \mathbf{y}^*)$: Given the likelihood ($A.1$) and the prior

$$
p\left(\beta^* \mid \overline{\beta^*}, \tau\right) = N\left(\overline{\beta^*}, \tau_X O_X\right)
$$

then the posterior is Normal

$$
p(\beta^* \mid \Theta/\beta^*, \mathbf{y}^*) = N\left(\widetilde{\beta}^*, \widetilde{\Delta}^*\right) \tag{B.1}
$$

with

$$
\widetilde{\Delta}^* = \left(\Sigma^{*-1}\otimes X^{*\prime}X^* + \tau_X^{-1}O_X^{-1}\right)^{-1}
$$

$$
\widetilde{\beta}^* = \widetilde{\Delta}^*\left(\left(\Sigma^{*-1}\otimes X^{*\prime}\right)(\mathbf{y}^*) + \tau_X^{-1}O_X^{-1}\overline{\beta^*}\right)
$$

2. Block 2: $p(\beta_n \mid \Theta/\beta_n, \mathbf{y}_n)$: Given the likelihood ($A.1$) and the prior

$$p\left(\beta_n \mid \overline{\beta}, \tau\right) = N\left(\overline{\beta}, \tau O_n\right)$$

then the posterior is Normal

$$p(\beta_n \mid \Theta/\beta_n, \mathbf{y}_n) = N\left(\widetilde{\beta}_n, \widetilde{\Delta}_n\right) \tag{B.2}$$

with

$$\widetilde{\Delta}_n = \left(\Sigma_n^{-1} \otimes X_n' X_n + \tau^{-1} O_n^{-1}\right)^{-1}$$

$$\widetilde{\beta}_n = \widetilde{\Delta}_n \left(\left(\Sigma_n^{-1} \otimes X_n'\right)(\mathbf{y}_n) + \tau^{-1} O_n^{-1} \overline{\beta}\right)$$

3. Block 3: $p(\Sigma^* \mid \Theta/\Sigma^*, \mathbf{y}^*)$: Given the likelihood ($A.1$) and the prior

$$p(\Sigma^*) \propto |\Sigma^*|^{-\frac{1}{2}(M_2+1)}$$

Denote the residuals

$$U^* = Y^* - X^* B^*$$

as in equation ($A.1$). Then the posterior variance term is Inverted-Wishart centered at the sum of squared residuals:

$$p(\Sigma^* \mid \Theta/\Sigma^*, \mathbf{y}^*) = IW\left(U^{*\prime} U^*, T^*\right) \tag{B.3}$$

4. Block 4: $p(\Sigma_n \mid \Theta/\Sigma_n, \mathbf{y}_n)$: Given the likelihood ($A.1$) and the prior

$$p(\Sigma_n) \propto |\Sigma_n|^{-\frac{1}{2}(M_1+1)}$$

Denote the residuals

$$U_n = Y_n - X_n B_n$$

as in equation ($A.1$). Then the posterior variance term is Inverted-Wishart centered at the sum of squared residuals:

$$p\left(\Sigma_n \mid \Theta/\Sigma_n, \mathbf{y}_n\right) = IW\left(U_n' U_n, T_n\right) \tag{B.4}$$

5. Block 5: $p\left(\tau_X \mid \Theta/\tau_X, Y\right)$: Given the priors

$$p\left(\tau_X\right) = IG\left(s, \upsilon\right) \propto \tau_X^{-\frac{\upsilon_X+2}{2}} \exp\left(-\frac{1}{2}\frac{s_X}{\tau_X}\right)$$

$$p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) = N\left(\overline{\beta}, \tau O_n\right)$$

then the posterior is

$$p\left(\tau_X \mid \Theta/\tau_X, Y\right) = IG\left(\frac{M_2 K + \upsilon_X}{2}, \frac{\sum_{n=1}^{N}\left(\beta_n - \overline{\beta}\right)' O_n^{-1}\left(\beta_n - \overline{\beta}\right) + s_X}{2}\right) \tag{B.5}$$

6. Block 6: $p\left(\overline{\beta} \mid \Theta/\overline{\beta}, Y\right)$: Given the prior

$$p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) = N\left(\overline{\beta}, \tau O_n\right)$$

by symmetry

$$p\left(\overline{\beta} \mid \beta_n, O_n, \tau\right) = N\left(\overline{\beta}, \tau O_n\right)$$

Then taking a weighted average across $n = 1, \ldots, N$:

$$p\left(\overline{\beta} \mid \left\{\beta_n\right\}_{n=1}^{N}, \tau\right) = N\left(\overline{\overline{\beta}}, \overline{\Delta}\right) \tag{B.6}$$

with

$$\overline{\Delta} = \left(\sum_{n=1}^{N} \tau^{-1} O_n^{-1}\right)^{-1}$$

$$\overline{\overline{\beta}} = \overline{\Delta} \left[\sum_{n=1}^{N} \tau^{-1} O_n^{-1} \beta_n \right]$$

7. Block 7: $p(\tau \mid \Theta/\tau, Y)$: Given the priors

$$p(\tau) = IG(s, \upsilon) \propto \tau^{-\frac{\upsilon+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\tau}\right)$$

$$p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) = N\left(\overline{\beta}, \tau O_n\right)$$

then the posterior is

$$p(\tau \mid \Theta/\tau, Y) = IG\left(\frac{NM_1K + \upsilon}{2}, \frac{\sum_{n=1}^{N}\left(\beta_n - \overline{\beta}\right)' O_n^{-1}\left(\beta_n - \overline{\beta}\right) + s}{2}\right) \tag{B.7}$$

A complete cycle around these seven blocks produces a draw of Θ from $p(\Theta \mid Y)$.

C Data Description

In this section we present the plots from the data described in section 3, the one that covers the period 2004:M1-2025:M9. The variables in figures are already transformed, i.e. we show how they enter to the empirical model.

C.1 Domestic variables

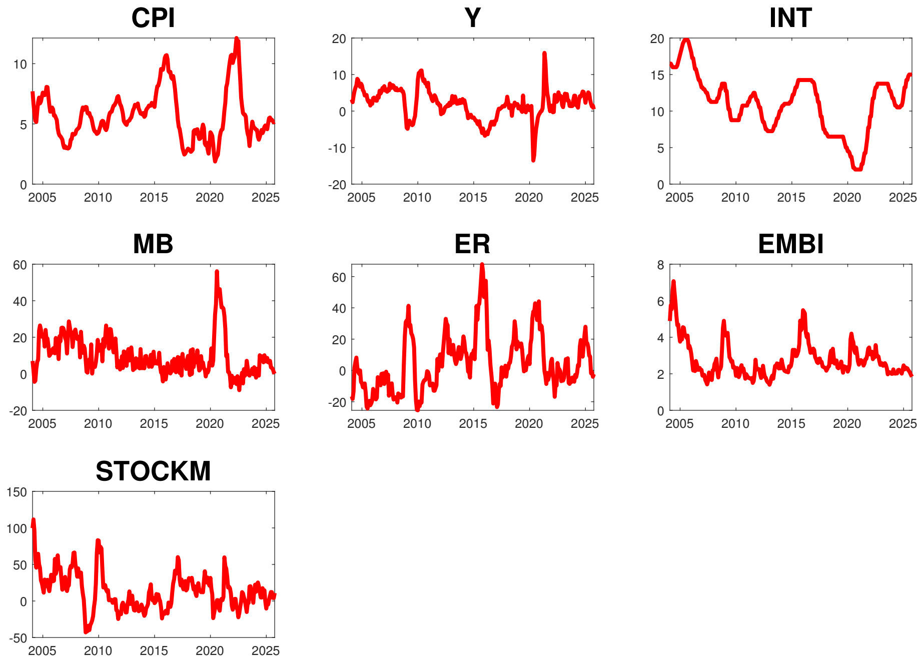


Figure C.1: Brazilian Data

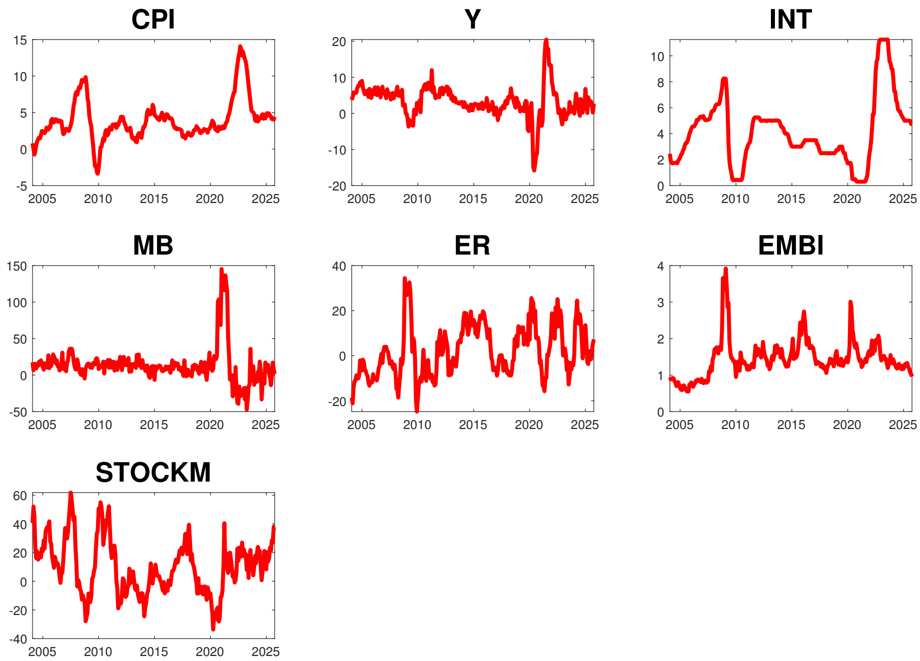


Figure C.2: Chilean Data

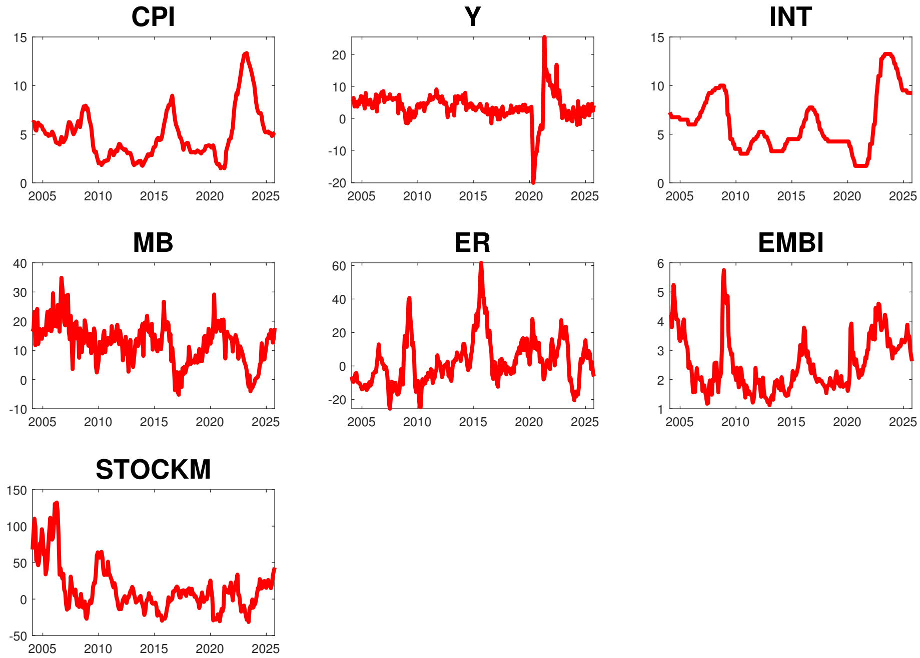


Figure C.3: Colombian Data

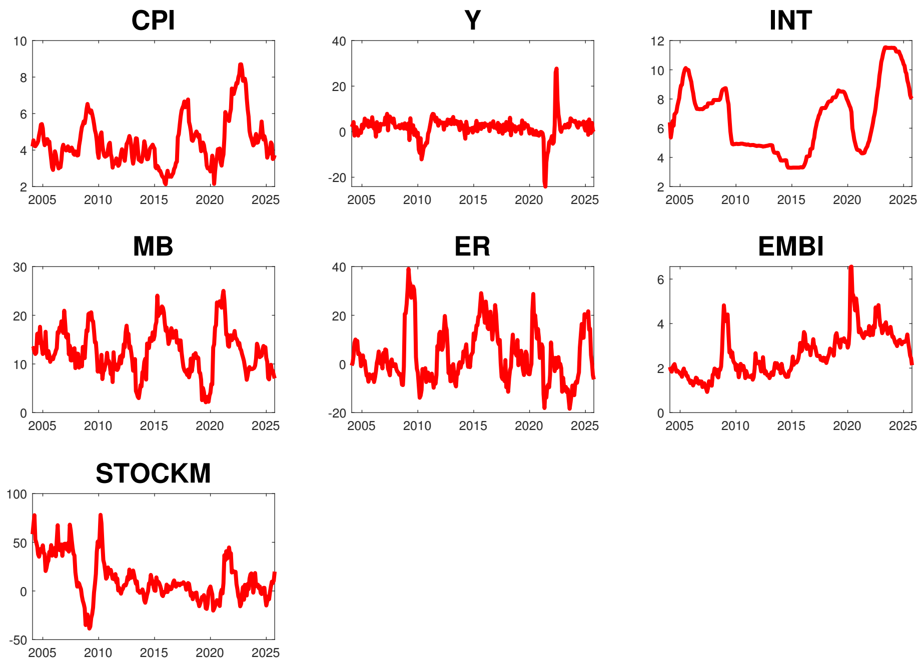


Figure C.4: Mexican Data

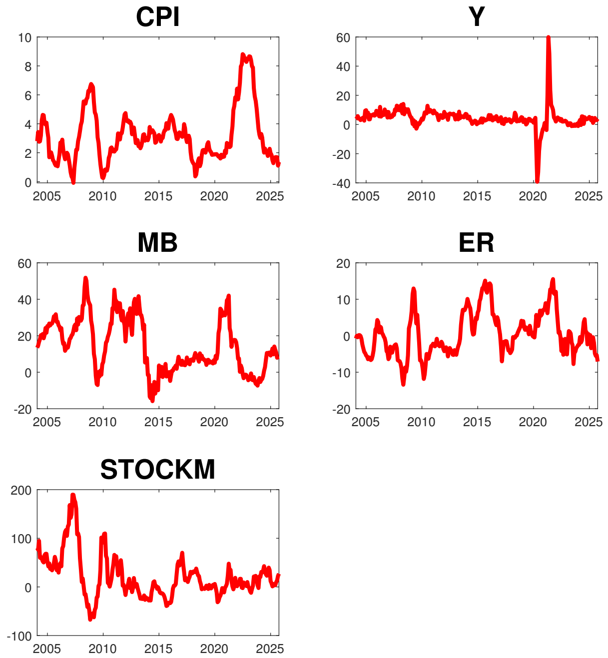


Figure C.5: Peruvian Data

C.2 Exogenous variables

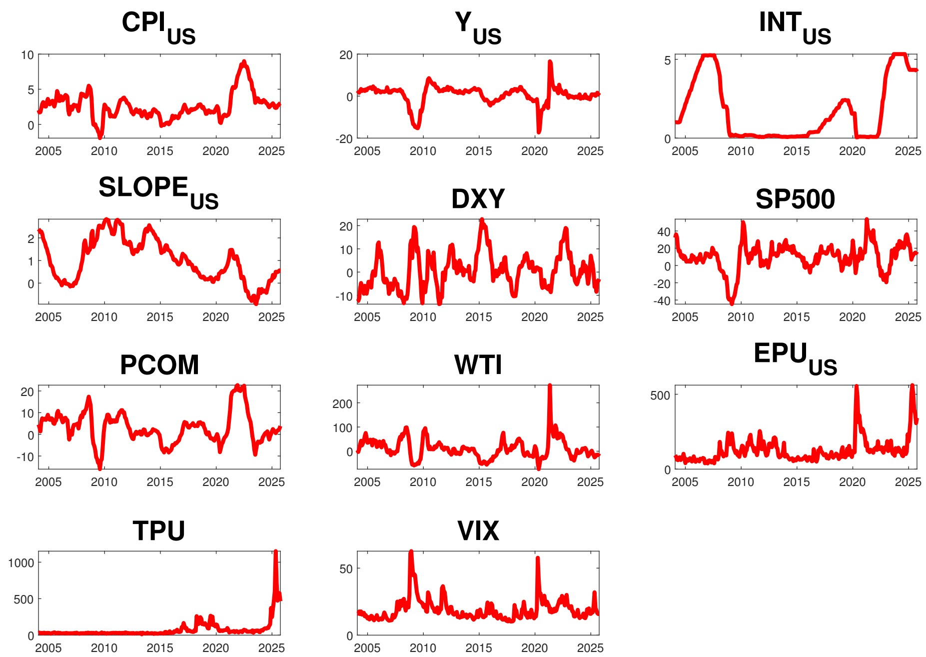


Figure C.6: Exogenous Data

D Impulse responses details

For each draw of Θ from the posterior distribution, we compute the companion form of the compact model as in equation ($A.1$). Then we compute the median value and the 68% credible interval for each impulse response. Results are shown below.

D.1 Global Uncertainty Shock

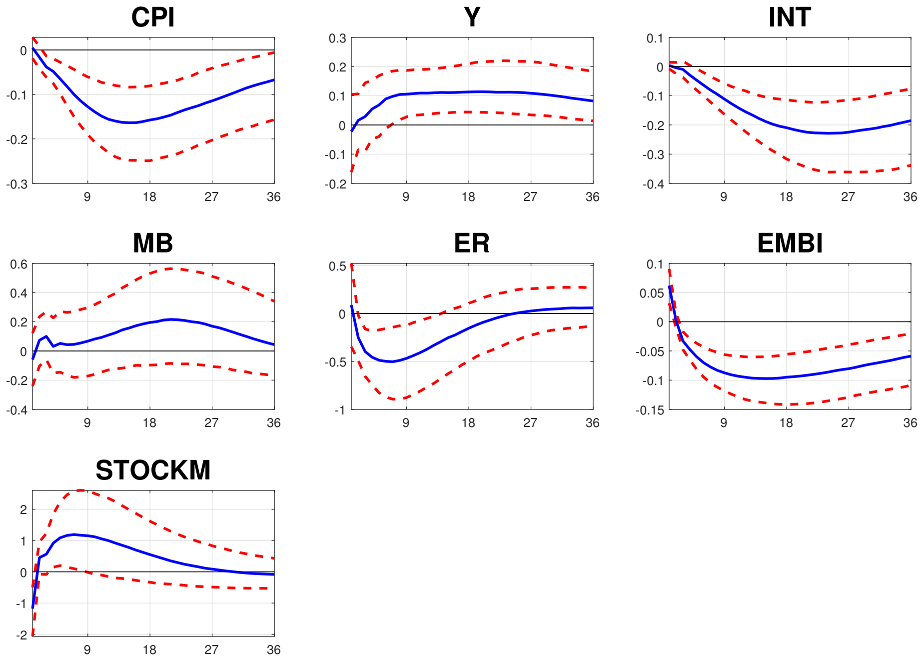


Figure D.1: Global Uncertainty Shock effects in Brazil, median value and 68% confidence interval

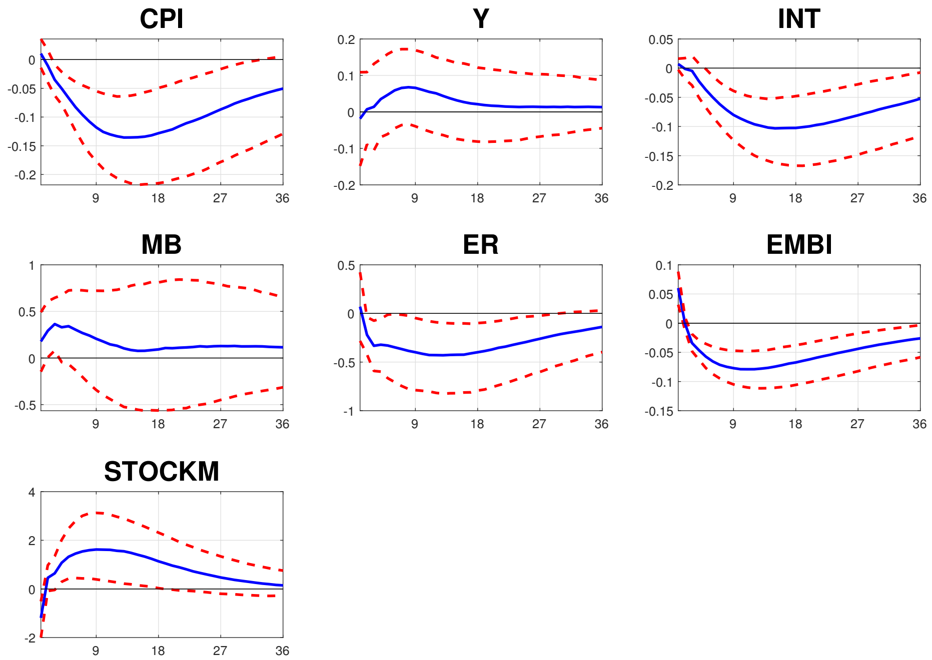


Figure D.2: Global Uncertainty Shock effects in Chile, median value and 68% confidence interval

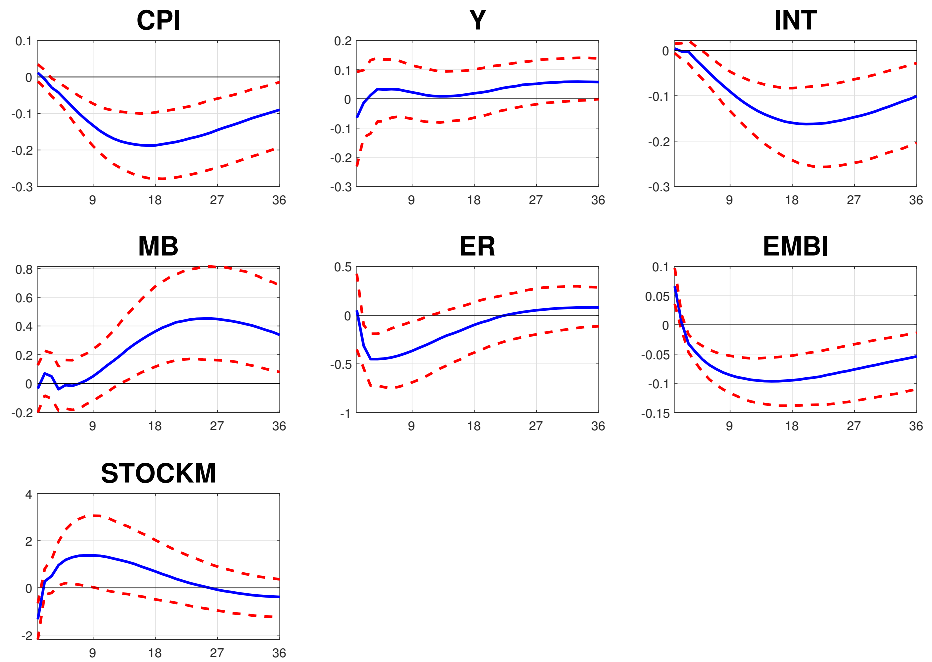


Figure D.3: Global Uncertainty Shock effects in Colombia, median value and 68% confidence interval

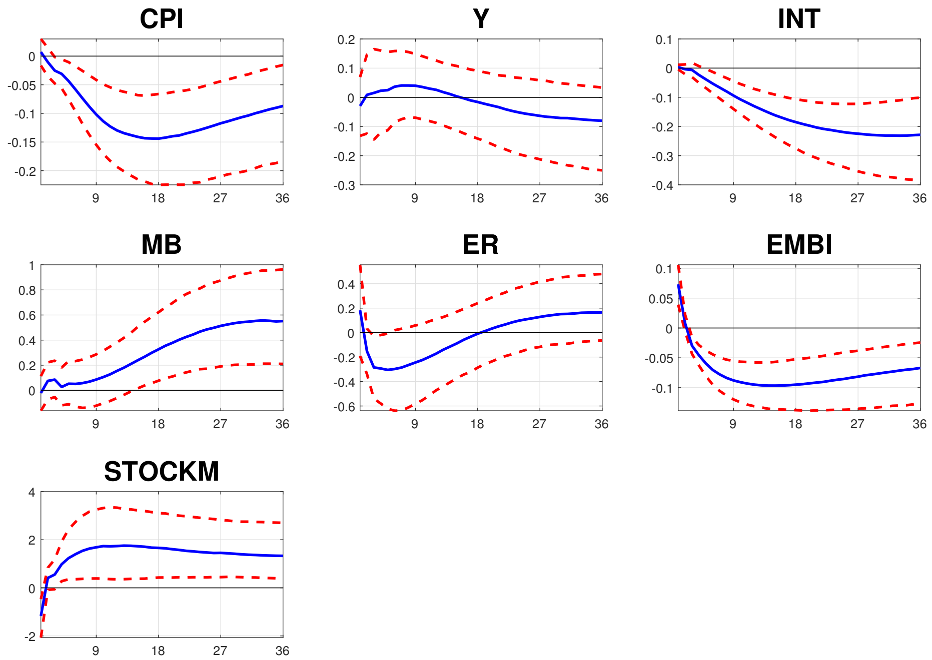


Figure D.4: Global Uncertainty Shock effects in Mexico, median value and 68% confidence interval

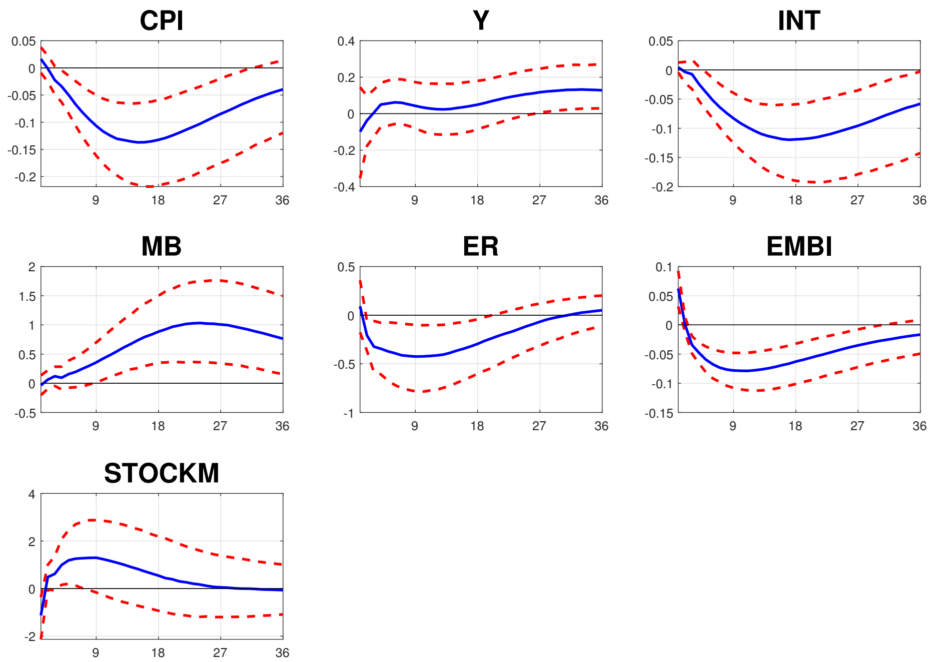


Figure D.5: Global Uncertainty Shock effects in Peru, median value and 68% confidence interval

E Posterior distribution of hyperparameters

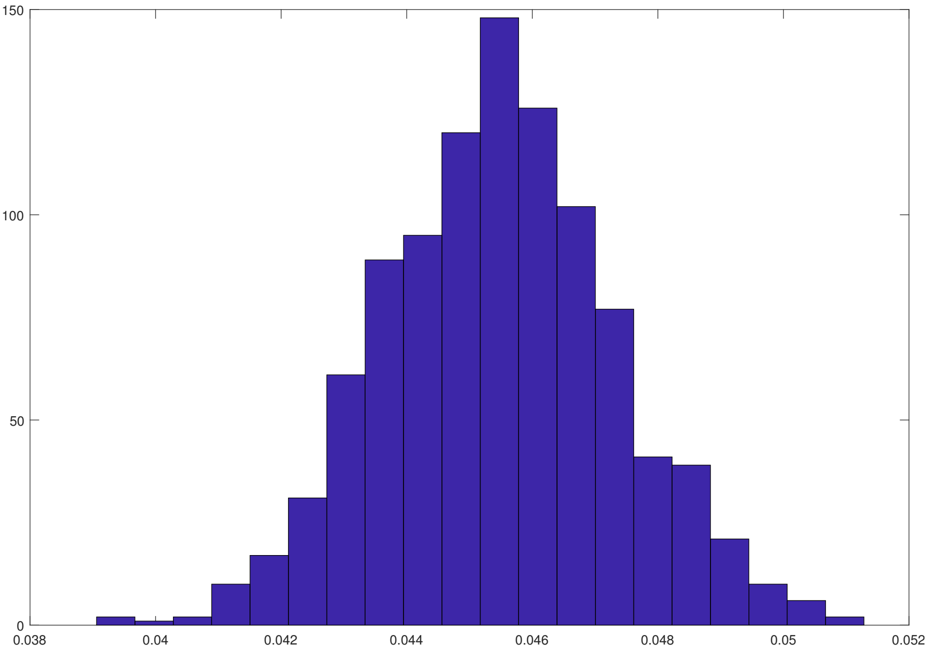


Figure E.1: Posterior distribution of $\sqrt{\tau_X}$

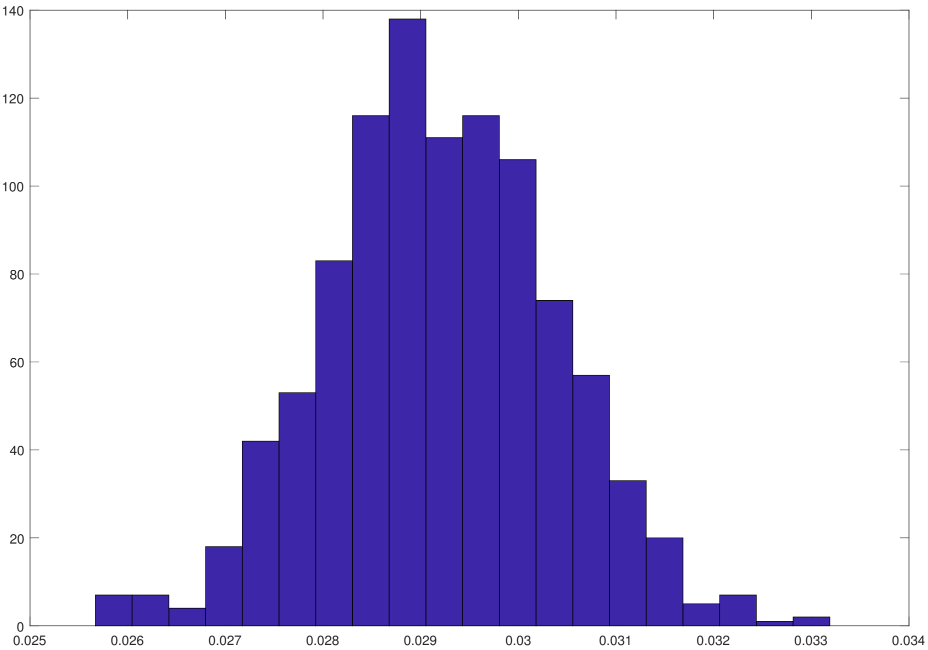


Figure E.2: Posterior distribution of $\sqrt{\tau}$

F The algorithm for Zero and Sign Restrictions

In this stage we use as an input the results from the estimation of subsection 3.1, i.e. the posterior distribution of the reduced-form of the model. Then we take draws from this distribution as it is described in the following estimation algorithm[8]:

1. Set first $K = 1,000$ number of draws.

2. Draw (β_k^*, Σ_k^*) from the posterior distribution (foreign block) and get $(\mathbf{A}_0^*)_k = (P^*)^{-1}$ from the *Cholesky* decomposition of $\Sigma_k^* = P^*(P^*)'$.

3. Draw $\mathbf{X}^* \sim N(0, I_{n^*})$ and get $\mathbf{Q}^*$ such that $\mathbf{Q}^*\mathbf{R}^* = \mathbf{X}^*$, i.e. an orthogonal matrix $\mathbf{Q}^*$ that satisfies the QR decomposition of $\mathbf{X}^*$. The random matrix $\mathbf{Q}^*$ has the uniform distribution with respect to the Haar measure on $O(n)$(Arias *et al.*, 2018).

4. Construct the matrix:

$$\overline{\mathbf{Q}^*} = \begin{bmatrix} \mathbf{I}_{k^*} & \mathbf{0}_{(k^* \times M_2 - k^*)} \\ \mathbf{0}_{(M_2 - k^* \times k^*)} & \mathbf{Q}^* \end{bmatrix}$$

   That is, a subset of $k^* < n^*$ variables in $(\mathbf{y}^*)$ are going to be *slow* and therefore they do not rotate. This is how we impose zero restrictions in this case.

5. Draw $(\beta_{n,k}, \Sigma_{n,k})$ from the posterior distribution (domestic block) and get $(A_{n,0})_k = (P_n)^{-1}$ from the *Cholesky* decomposition of $\Sigma_{n,k} = P_n(P_n)'$.

6. Draw $\mathbf{X} \sim N(0, I_{M_1})$ and get $\mathbf{Q}$ such that $\mathbf{QR} = \mathbf{X}$, i.e. an orthogonal matrix $\mathbf{Q}$ that satisfies the QR decomposition of $\mathbf{X}$. The random matrix $\mathbf{Q}$ has the uniform distribution with respect to the Haar measure on $O(n)$(Arias *et al.*, 2018).

7. Construct the matrix:

$$\overline{\mathbf{Q}} = \begin{bmatrix} \mathbf{I}_{k} & \mathbf{0}_{(k \times M_1 - k)} \\ \mathbf{0}_{(M_1 - k \times k)} & \mathbf{Q} \end{bmatrix}$$

   That is, a subset of $k < n$ variables in $(\mathbf{y})$ are going to be *slow* and therefore they do not

[8] See Uhlig (2005), among others.

rotate. This is how we impose zero restrictions in this case.

8. Compute the matrices $\overline{\mathbf{A}}_{n,0} = (\mathbf{A}_{n,0})_k \overline{\mathbf{Q}}$ and $\overline{\mathbf{A}^*}_0 = (\mathbf{A}_0^*)_k \overline{\mathbf{Q}^*}$, then recover the system (3) and compute the impulse responses.

9. If sign restrictions are satisfied, keep the draw and set $k = k + 1$. If not, discard the draw and go to Step 10.

10. If $k < K$, return to Step 2, otherwise stop.

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