BANCO CENTRAL DE RESERVA DEL PERÚ

Cross-Border flows and the effect of Global Financial shocks in Latin America

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Abstract

This work quantifies the effect of changes in global financial conditions on cross-border flows and domestic financial and macroeconomic variables for a group of countries in Latin America. Using the BIS database of international banking statistics, we consider heterogeneous effects of different types of international financing (credit from global banks to domestic banks and non-financial firms and bond issuance by non-financial firms), on the behavior of the domestic banking system and the transmission to the real economy through the link between bank credit, investment and output. Consistent with the implications from a DSGE model such as Aoki *et al.* (2018), our results show that an increase in foreign interest rates translate into lower external funding for banks and thus into lower credit growth and higher domestic interest rates. This effect is amplified through an exchange rate depreciation due to capital outflows. We find evidence of larger drop in flows from global banks to domestic banks relative to those from global banks to non-financial firms. In terms of the real economy, we observe a reduction in GDP growth, although not significant, and an increase in inflation due to the pass through effect from the exchange rate to prices.

JEL Classification: C23, E44, F21, F32

Keywords: Panel Vector Autoregressions, Exogenous Block, Bayesian Estimation, Cross-Border flows

1 Introduction

After the Global Financial Crisis, financial markets experienced a significant increase in cross-border flows from advanced economies (AE) to emerging market economies (EME). Low interest rates in AE and better relative macroeconomic fundamentals in EME contributed to an increase in capital flows to EME and to a doubling of the stock of dollar debt in EME (see Figure 1). In particular, Latin America increased its access to foreign funding, both in terms of bank credit and bond issuance in international capital markets. However, since 2013 both cross-border credit and domestic credit in the region have slowed down (see Figure 2).
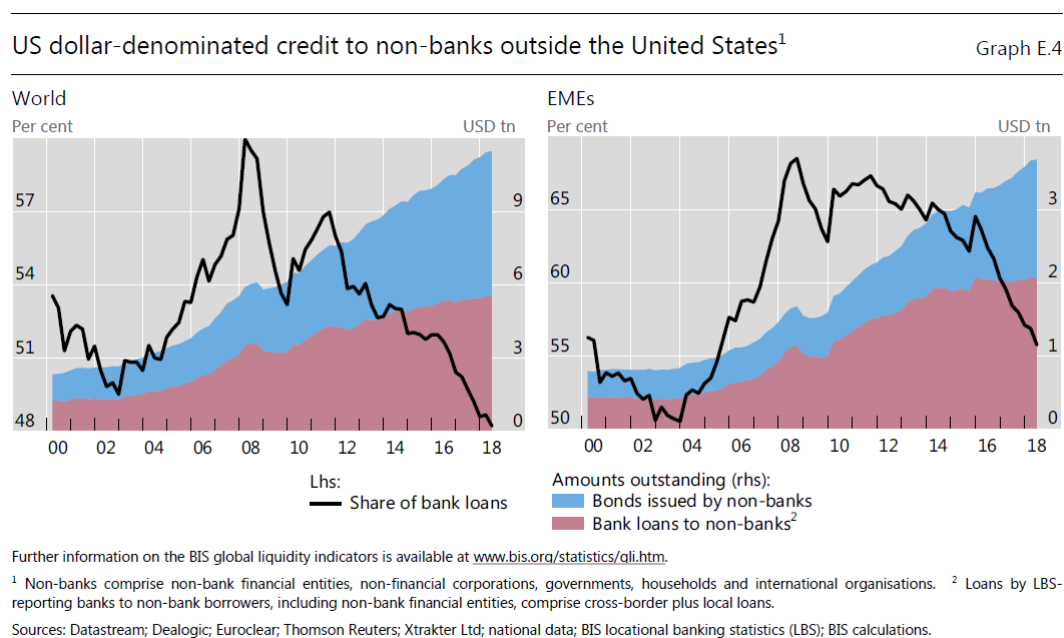
Figure 1: Cross-Border Flows (Bank for International Settlements (2018), Chart E4)

Cycles in cross-border flows and in the cost of external borrowing may affect the cost of financing investment for non-financial firms. For instance, easier and cheaper access to international financing translates into lower costs for corporates that take loans or issue debt abroad. For the domestic financial system, local banks find cheaper external funding, which reduce intermediation margins and thus translates also into cheaper domestic borrowing for non-financial firms that borrow domestically. This second channel can be observed through an increase in

the loan-to-deposit ratios in Latin America. This pattern could pose financial vulnerabilities, especially if there is a sharp reversal in non-core funding conditions. Hence, several countries in the region have coped with the surge in capital inflows by using macroprudential policies more actively.
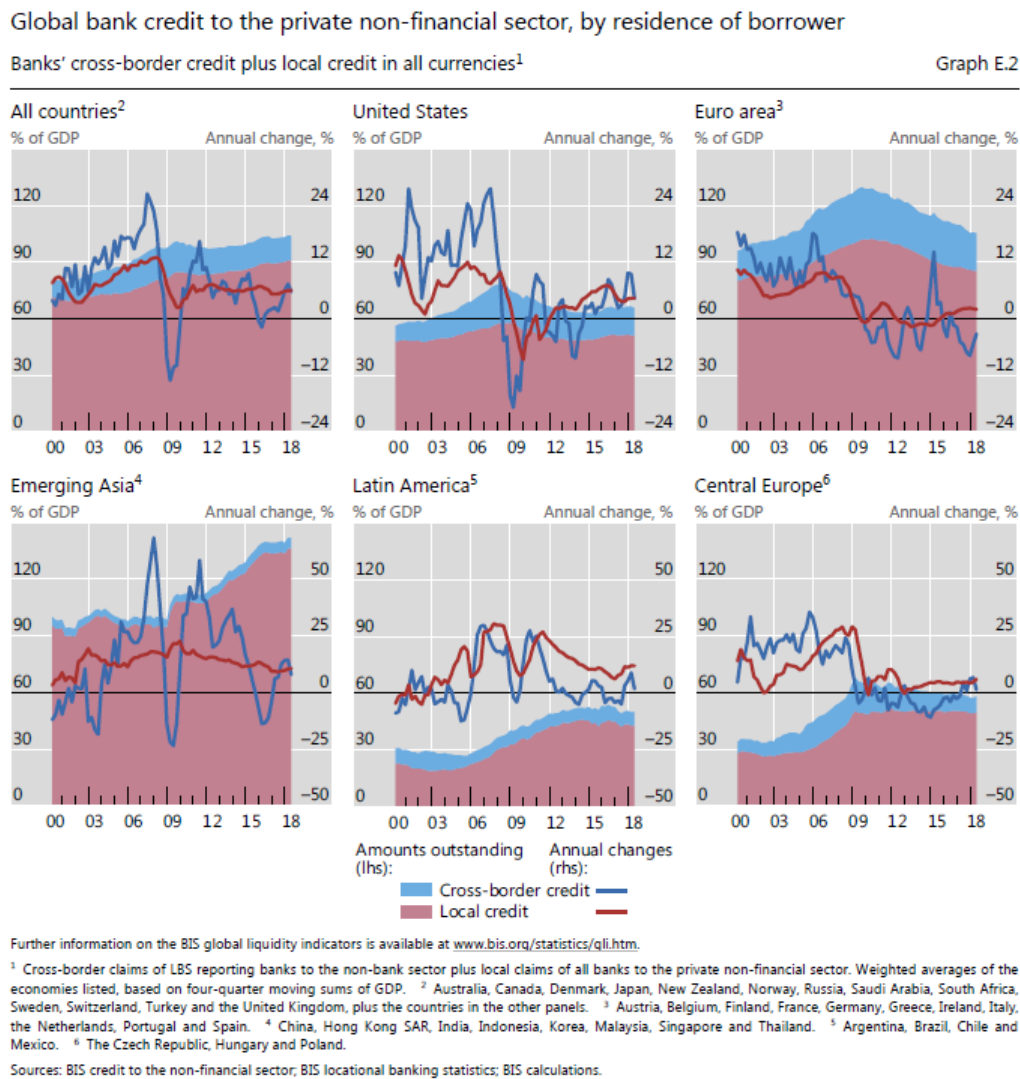

Figure 2: Cross-Border Flows (Bank for International Settlements (2018), Chart E2)

In this work we empirically quantify the transmission mechanism of global financial shocks on domestic macroeconomic and financial variables. We calculate the effect on access to different types of cross-border financing to each Latin American country in the sample (Brazil, Chile,

Colombia, Mexico and Peru), their effect on the behavior of the domestic banking system and the transmission to the real economy (investment and output). We a use the relatively novel database of cross-border flows from the Bank for International Settlements (BIS) statistics to differentiate the impact through cross-border flows i) from global banks to domestic banks, ii) from global banks to non-financial firms, and iii) through international bond issuance by non-financial corporates.

Our empirical exercise is motivated by the theoretical transmission mechanisms in the DSGE model developed in Aoki *et al.* (2018). In their model, a global financial shock increases the foreign interest rate and depreciates the exchange rate, which reduces the net worth and intermediation by banks with a currency mismatch between foreign currency liabilities and domestic currency assets. The pass-through from exchange rate depreciation to prices leads to a monetary policy tightening, which further affects banks and reduces credit growth. We validate this transmission mechanism and evaluate if the main channel operates through the domestic banking sector or through direct foreign borrowing of the corporate sector.

The empirical approach considers a hierarchical Bayesian Panel VAR (Ciccarelli and Rebucci, 2006; Jarociński, 2010; Canova and Pappa, 2011) with an exogenous block (Gondo and Pérez Forero, 2018) to calculate the response of domestic financial and macroeconomic variables to exogenous shocks to VIX and long-term foreign interest rates. We consider the possibility of heterogeneous responses between bank and non-bank cross border flows, and from flows coming from the US and from the rest of AEs.

We also evaluate the presence of commonalities in the pattern of cross border flows across countries. For this, we estimate a Time-Varying Panel VAR with an exogenous component for the sample 2001-2017. Using Cross-border flows data we identify a common component, country and variable specific components for Latin America, where the model takes into account dynamic inter-dependencies and time-varying parameters (Canova and Ciccarelli, 2009)[1], since we want to exploit the interaction among Latin American countries and also take into account the institutional changes present in the sample of analysis. We observe a significant heterogeneity in

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[1]See also Canova and Ciccarelli (2013).

cross-border flows determinants for the region. This means that, besides a common component that represents the synchronization of all countries, there exist country-specific and variable specific indicators, together with an exogenous component, that are able to explain part of the observed cross-border flows.

Our results are qualitatively consistent with the transmission mechanism depicted by Aoki *et al.* (2018). An increase in foreign interest rates reduces external funding for banks and affects domestic financial conditions by increasing domestic loan rates and reducing external funding for banks. The reduction in cross-border flows is larger for flows from global banks to domestic banks relative to those towards non-financial firms or debt issuance by non-financial corporates. The increase in the cost of foreign funding propagates to domestic banks as reflected by lower loan supply and exposure to non-core funding. In terms of the real economy, we observe some reduction in GDP growth and increase in inflation. Thus, monetary policy reacts by increasing domestic interest rates to contain inflationary pressures, further increasing the cost of domestic funding.

Related Literature. Our work relates to the strand of literature that analyzes the effect of the global financial cycle (Borio, 2014), and in particular on small open economies (Rey, 2016). We complement this by including the heterogeneous behavior of cross-border flows to bank and non-bank corporations, both in terms of loans from global banks and through bond issuance.

It also relates to that on the determinants of capital flows, where global factors such as US monetary policy and VIX as indicators of global liquidity seem to be highly relevant (Cerutti *et al.*, 2017; Fratzscher, 2012; Avdjiev *et al.*, 2017) although domestic factors such as country risk and macroeconomic fundamentals determine the magnitude of these flows (Fratzscher, 2012; Ghosh *et al.*, 2014). Global banks seem to have a key role in the transmission of external shocks (Cetorelli and Goldberg, 2012; Bruno and Shin, 2014). Extreme portfolio flow surges and retrenchments are mainly driven by global risk (Forbes and Warnock, 2012), although portfolio flows to EME have been mainly driven by interest rate differentials (Ahmed and Zlate, 2014). We build on this static framework and include dynamic response of domestic financial and real

variables to changes in capital flow patterns.

In addition, our work relates to the literature on bilateral cross border bank flows and the impact of monetary policy (Correa *et al.*, 2018) and uncertainty (Choi and Furceri, 2019), where an increase in the US policy rate and in uncertainty reallocates flows towards safer counter parties.We extend this to include cross-border flows to non-banks.

We take theoretical models as a starting point to motivate our empirical exercise. Aoki *et al.* (2018) presents the propagation of global financial shocks through the cost of external funding for domestic banks and its impact on loan provision, amplified due to a currency mismatch between external funding in dollars and loans in domestic currency. Other models with price rigidities and financial frictions in small open economies show that monetary and macroprudential policies can reduce exposure to financial stability risks related to excessive capital inflows and its easing effect on financing conditions (Medina and Roldos, 2014; Unsal, 2013).

The document is organized as follows: section 2 shows the data description, section 3 describes the hierarchical Panel VAR model used for the structural analysis together with the results, section 4 describes the Time-Varying Panel VAR model used for finding the main determinants of the Cross-Border Flows together with the results and section 5 discusses the main conclusions.

2   The BIS Data about Cross-Border Flows

Our main data source for data on cross border flows comes from the BIS International Banking Statistics. We use the locational banking statistics based on residence of the banking office, as we want to capture the ability of banking offices operating in Latin America to obtain funding from abroad. As mentioned by BIS, these data includes outstanding claims (financial assets) and liabilities of internationally active banks located in reporting countries on counter-parties residing in more than 200 countries. In order to build the stock of cross border lending, we add the outstanding claims of internationally active banks in reporting countries on counterparties re-

siding in a representative sample of Latin American countries. We separate these claims by type of recipient agent: (i) banks and (ii) non-bank financial and non-financial corporations.

Data on debt issuance by non-financial corporates in world capital markets comes from the BIS International Debt Securities Statistics. We use the definition for international debt securities, which are issued outside the country where the borrower resides. As mentioned by BIS, they compile information from a security-by-security database using information from commercial data providers.

Our sample includes quarterly data from 2001 to 2017, a sample period consistent with the adoption of inflation targeting in most countries. For each country included in our study (Brazil, Chile, Colombia, Mexico and Peru), we consider both domestic macroeconomic and financial variables. We include standard macroeconomic variables such as real GDP, inflation, exchange rate and monetary policy rate. Also, in each block we include the credit-to-GDP ratio as a financial variable to capture the evolution of the financial deepness in each country. In addition, we consider the different types of cross-border loans and bonds described above. This data is mostly obtained from each country's central bank and the loan-to-book ratio for banks comes from the Bankscope/ Fitch Connect database, where we consider an aggregate measure for all banks in each country in the sample.

The external block, which is common to all Latin American countries, includes macroeconomic and financial variables as well. We consider real GDP and inflation for the United States as indicators of world economic activity and inflationary pressures. We also include the commodity price index to control for the commodity price cycle. We consider the VIX as an indicator of global financial risk and uncertainty. We include two different measures related with interest rates: the 3 month Libor rate and the spread between 10 and 2 years of the US Treasury bond to account for changes in the interest rate structure at different maturities and the slope of the yield curve. This data comes from the FRED database.

The Figures plotting the transformed data used in the empirical model can be found in the appendix E. In the domestic block, real GDP, the exchange rate and prices are calculated as

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year on year percentage variation and multiplied by 100. Monetary policy rates are expressed as percentage points. All types of cross-border flow variables are expressed as percentage of GDP and multiplied by 100. In the external block that is common for all countries, prices, real GDP and commodity price index are calculated as year on year percentage variation multiplied by 100. Finally, Interest rates measures are included in percentages (%) and VIX is included in levels.

3 Empirical Approach

We assume in this section that each economy can be modeled as an individual Vector Autoregressive (VAR) model with an exogenous block. Then we combine efficiently the information of these four economies 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.

3.1 A Panel VAR model with an Exogenous Block

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 domestic variables, z_t is a $W \times 1$ vector of exogenous variables common to all countries, $u_{n,t}$ is a $M_1 \times 1$ vector of reduced form shocks such that $u_{n,t} \sim N\left(\mathbf{0}, \Sigma_n\right)$, $E\left(u_{n,t} u'_{m,t}\right) = \mathbf{0}, n \neq m$ $\in \{1, \ldots, N\}$, 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 $u_t^* \sim N\left(\mathbf{0}, \Sigma^*\right)$ and $E\left(u_t^* u'_{n,t}\right) = \mathbf{0}$ for each $n = 1, \ldots, N$, which means that the external variables are not influenced by the evolution of the domestic ones.

The complete system (1)-(2) is a Panel VAR with an exogenous block (Gondo and Pérez Forero, 2018). That specification will allow us to isolate the effect of external shocks on domestic economies. Further details regarding the matrix manipulations can be found in Appendix A.

3.2 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:

$$p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) = N\left(\overline{\beta}, \tau O_n\right) \tag{3}$$

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

$$o_{ij,l} = \begin{cases} \frac{1}{l^{\phi_3}} & , i = j \\ \frac{\phi_1}{l^{\phi_3}}\left(\frac{\widehat{\sigma}_j^2}{\widehat{\sigma}_i^2}\right) & , i \neq j \\ \phi_2 & , exogenous \end{cases} \tag{4}$$

where

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

and where $\widehat{\sigma}_j^2$ 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:

$$p\left(\Sigma_n\right) \propto |\Sigma_n|^{-\frac{1}{2}(M_1+1)} \tag{5}$$

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In a standard Bayesian context, $\overline{\beta}$ and τ would be hyper-parameters that are supposed to be calibrated. In turn, 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 do not want to impose any particular tightness for the prior distribution of coefficients, we want to get it from the data. Following Gelman (2006) and Jarociński (2010)[2] we assume an inverse-gamma prior distribution for τ, so that

$$p\left(\tau\right) = IG\left(\frac{\upsilon}{2}, \frac{s}{2}\right) \propto \tau^{-\frac{\upsilon+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\tau}\right) \tag{6}$$

Finally, we assume the non-informative prior:

$$p\left(\overline{\beta}\right) \propto 1 \tag{7}$$

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

$$p\left(\beta^*\right) = N\left(\overline{\beta^*}, \tau_X O_X\right) \tag{8}$$

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

$$o_{ij,l}^* = \begin{cases} \dfrac{1}{l^{\phi_3^*}} & , i = j \\ \dfrac{\phi_1^*}{l^{\phi_3^*}}\left(\dfrac{\widehat{\sigma}_j^2}{\widehat{\sigma}_i^2}\right) & , i \neq j \\ \phi_2^* & , exogenous \end{cases} \tag{9}$$

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

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

the covariance matrix of error terms, so that:

$$p\left(\Sigma^{*}\right) \propto \left|\Sigma^{*}\right|^{-\frac{1}{2}(M_2+1)} \tag{10}$$

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:

$$p\left(\tau_X\right) = IG\left(\frac{\upsilon_X}{2}, \frac{s_X}{2}\right) \propto \tau_X^{-\frac{\upsilon_X+2}{2}} \exp\left(-\frac{1}{2}\frac{s_X}{\tau_X}\right) \tag{11}$$

3.3   Bayesian Estimation

Given the specified priors ($A.6$) 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 the Bayes' theorem we have that:

$$p\left(\Theta \mid Y\right) \propto p\left(Y \mid \Theta\right) p\left(\Theta\right) \tag{12}$$

Our target is now to maximize the right-hand side of equation (12) 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 ($A.7$) 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 posterior. In this section we describe a Markov Chain Monte Carlo (MCMC) routine that helps us to accomplish this task.

3.3.1   A Gibbs sampling routine

In general, in every Macro-econometric model it is difficult to sample from the posterior distribution $p\left(\Theta \mid Y\right)$. The latter is a consequence of the complex functional form that the likelihood function (or posterior distribution) might take, given the specified model. Typically, the Metropolis-Hasting algorithm is the canonical routine to do that. However, in this case we

will show that there exists an analytical expression for the posterior distribution, therefore it is possible to implement a Gibbs Sampling routine, which is much simpler than the mentioned Metropolis-Hastings. In this process, it is useful to divide the parameter set into different blocks and factorize ($A.7$) 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.

Algorithm 1

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

1. Draw $p\left(\beta^* \mid \Theta/\beta^*, \mathbf{y}^*, \mathbf{y}_n\right)$. If the candidate draw is stable keep it, otherwise discard it.

2. For $n = 1, \dots, N$ draw $p\left(\beta_n \mid \Theta/\beta_n, \mathbf{y}^*, \mathbf{y}_n\right)$. If the candidate draw is stable keep it, otherwise discard it.

3. Draw $p\left(\Sigma^* \mid \Theta/\Sigma^*, \mathbf{y}^*, \mathbf{y}_n\right)$.

4. For $n = 1, \dots, N$ draw $p\left(\Sigma_n \mid \Theta/\Sigma_n, \mathbf{y}^*, \mathbf{y}_n\right)$.

5. Draw $p\left(\tau_X \mid \Theta/\tau_X, Y\right)$.

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 $p\left(\tau \mid \Theta/\tau, Y\right)$.

8. If $k < K$ set $k = k + 1$ and return to Step 1. Otherwise stop.

A complete cycle of all these steps produces a draw k for the entire parameter set Θ. Under regular conditions the algorithm will converge rapidly to the ergodic posterior distribution. In this case, given the linearity and normality of the model, and also the absence of complicated and non-regular conditional posteriors in each block, convergence is achieved wit a reasonable number of draws. The estimation setup is described in the next subsection.

3.3.2 Estimation setup

We run the Gibbs sampler for $K = 1,050,000$ and discard the first $50,000$ draws in order to minimize the effect of initial the values. Moreover, in order to reduce the serial correlation across draws, we set a thinning factor of 50, i.e. given the remaining $1,000,000$ draws, we take 1 every $1,000$ 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 respectively.

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

$$p(\tau) \propto \tau^{-1/2} \tag{13}$$

by setting $v = -1$ and $s = 0$ in (6).

Regarding the Minnesota-stye prior, we do not have any information about the value of the hyper-parameters. Thus, we set a conservative $\phi_1 = 0.5$, $\phi_2 = 1$ and $\phi_3 = 2$ in equation (4). More specifically, ϕ_1 is related with *a priori* difference between own lags and lags of other variables; ϕ_2 is related with the *a priori* heteroskedasticity coming from exogenous variables[3]; and $\phi_3 = 2$ means that the shrinking pattern of coefficients is quadratic. It is worth to mention 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 (9). Finally, the exogenous block has a standard Minnesota Prior, and we set an autorregressive parameter of 0.9 for the prior mean of the first lag of the own variable in each VAR equation.

3.4 Identification of the Global Financial shock

The transmission mechanism of a Global Financial shock must be identified. That is, we need to isolate this shock from the rest of the effects that explain data fluctuations, i.e. the shock

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[3]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.

needs to be orthogonal. In the context of VAR and Panel VAR models it is standard to impose some restrictions with the purpose of pinning down the effects derived from orthogonal shocks. In our case, we impose some restriction in order to compute the impulse responses of the Global Financial shock using the output of the Gibbs Sampling estimation of the Panel VAR model. It is important to remark that we also take into account that the included exogenous block serves also as an extension of the information set for the econometrician, so that this mitigates the risk associated with the potential existence of the omitted variable bias for the estimated parameters that belong to the domestic block.

3.4.1 Identification assumptions

The identification of Global Financial shocks is as follows: we have two types of restrictions as it is shown in Table 1. 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). 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.

In this case we assume that the Global Financial shock produces i) a change in the slope of the yield curve, which indicates a tighter monetary policy, where this restriction is reflected in a rise in spread of interest rates; ii) a reduction in uncertainty given by this policy action (which can also be related with the monetary policy normalization), where this restriction is reflected in a fall in the VIX, iii) a fall in commodity prices derived from a tighter monetary policy in advanced economies. The identified shock can be interpreted as part of the monetary policy normalization in advanced economies, where they previously implemented the unconventional monetary policies through the compression of the spreads associated with the yield curve (Baumeister and Benati, 2013). In this context, we have to remember that the normalization process started in May of 2013 wit the so-called *Tapering*, and this do not necessarily implied an effective movement in the short term interest rate. Therefore, we do not impose any restriction in the three-month LIBOR rate, and we focus our attention in the slope of the yield curve. On the other hand, It is also important to stress that we do not restrict the remaining variables of

the system, neither in the exogenous block, nor in the domestic block. The results are discussed in the next section, where we also provide some alternative interpretations of the identified shock from the point of view of the domestic economies.

Var / Shock	Name	Global Financial shock
Domestic Block	$\mathbf{y}$	?
Consumer Price Index	CPI_{US}	?
Industrial Production	IP_{US}	?
LIBOR 3-month	$LIBOR3M$	?
SPREAD (Long-Short)	$SPREAD$	$\geqslant 0$
VIX	VIX	$\leqslant 0$
Commodity Prices	$Pcom$	$\leqslant 0$

Table 1: Identifying Restrictions for a Global Financial Shock

The identification restrictions shown in Table 1 are solely associated with a Global Financial shock. As a result, the remaining structural shocks of the system are unidentified. However, it turns out that this is not a 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).

3.4.2 The algorithm

In this stage we use as an input the estimation output from subsection 4.3.1, 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[4]:

Algorithm 2

1. Set first $K = 2,000$ number of draws.

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

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 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 $\mathbf{Q}\mathbf{R} = \mathbf{X}$, 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).

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 rotate. This 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 ($A.1$) 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.

3.5 Results

Our results are qualitatively consistent with the transmission mechanism depicted by Aoki *et al.* (2018). Figure 3 shows that an increase in the foreign interest rate translates into lower external funding for banks and thus into lower credit growth. growth and higher domestic interest rates, as banks would try to partially substitute away from external to domestic financing. Similar to the theoretical model, this effect is amplified through an exchange rate depreciation due to capital outflows, which increases the relative cost of external funding.
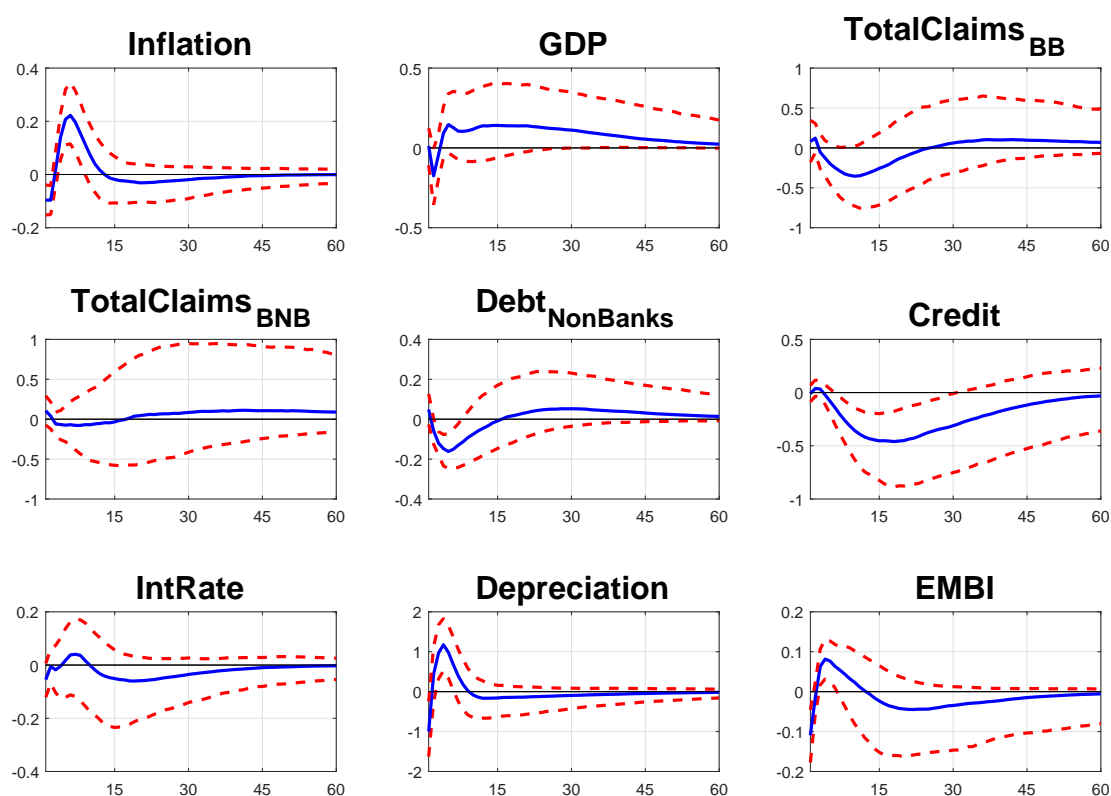

Figure 3: Global Financial Shock: Average Effect in LATAM

In contrast to the theoretical model, we additionally capture other forms of cross-border flows and international funding to emerging markets, such as (i) cross-border flows from global banks to non banks, which consider credit lines for domestic firms in banks abroad, and (ii) debt issuance by non-financial corporates in international capital markets. All types of cross-border flows from advanced countries to Latin America fall after an increase in the foreign interest rate.

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However, there is a larger reduction in flows from global banks to domestic banks relative to those from global banks to non-financial firms. In terms of international capital market funding, the increase in foreign interest rate which translates into higher cost of external funding for non-financial corporates also generates a reduction in debt issuance abroad, but the magnitudes are quantitatively smaller.

In the case of banks, the increase in foreign interest rates affect the cost of foreign funding. Therefore, this leads to a reduction in the proportion of foreign liabilities relative to deposits as a source of funding, which reflects into a reduction in the non-core funding ratio. However, the partial substitution from external to domestic funding leads to an increase in the cost of domestic funding, as banks need to increase domestic interest rates to increase demand for deposits. This higher cost is transferred to their customers through a higher loan rate, therefore reducing credit growth.

In terms of the real economy, we observe some reduction in GDP growth, although it is not significant for most countries in the sample. The increase in inflation is related to the pass through effect from exchange rate depreciation into prices. Thus, monetary policy reacts by increasing the domestic interest rates to contain inflationary pressures, further increasing the cost of domestic funding. This result can also be interpreted as a supply shock that hits the domestic economy, given the effect on exchange rates, prices, output and financial variables. However, given that many different forces might generate qualitative effect that resemble a standard supply shock, we stress the idea that the origin of the shock is external, and should not necessarily be compared as a typical rise in prices derived from domestic causes.
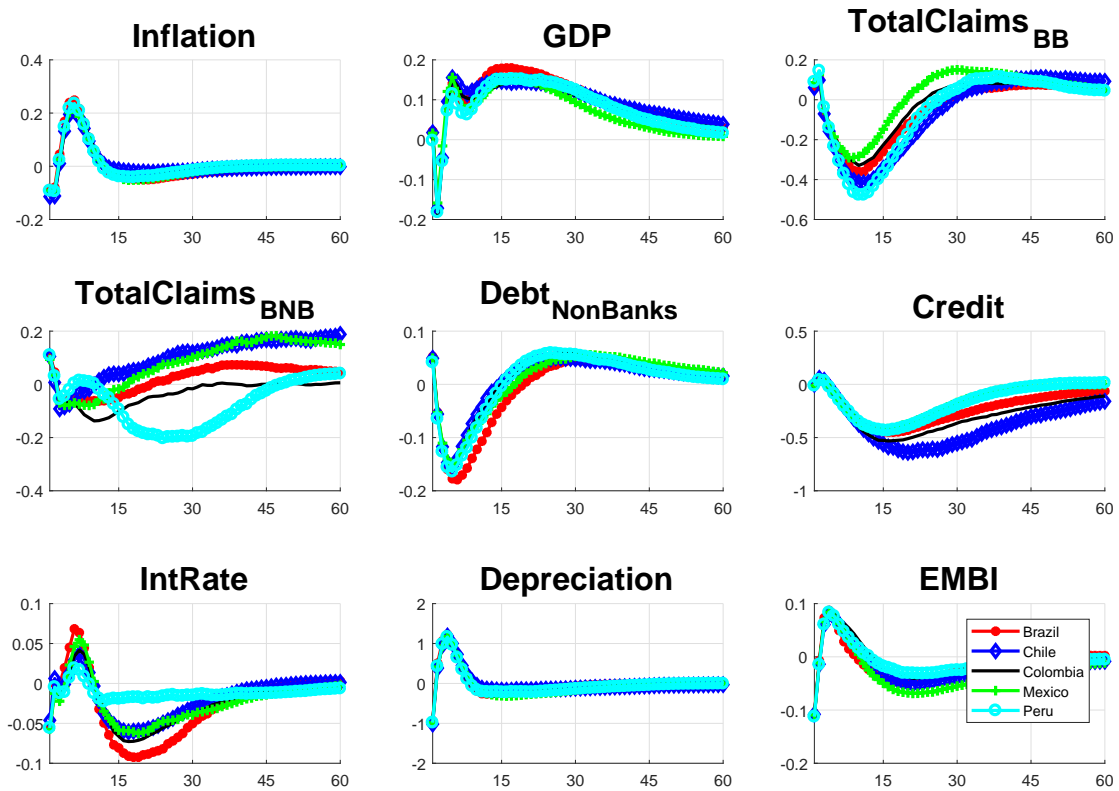
Figure 4: Global Financial shocks comparison

Additionally, our results show some heterogeneity, especially in the case of the effect on cross-border flows to the non-bank sector. Figure 4 the impulse response functions for each Latin American country separately to a foreign interest rate shock. The results are qualitatively similar to the average effects described previously. However, it is important to stress that the differences are mainly shown in the reaction of financial variables. First, cross-border flows from global banks to non-banks in Colombia show the largest drop, about twice the magnitude of that observed for other countries at its peak. In the case of Peru, the reduction in flows to non-bans takes longer to reach its bottom, by more than one year than the rest of the countries in the region.

Second, international debt issuance of non-banks show a larger reduction for the case of Brazil and Mexico. This result could be related to the higher degree of depth of capital markets in those countries and to the higher number of corporates that have access to capital markets abroad.

Third, cross-border bank to bank flows show a larger drop for Peru whereas the smaller reduction is observed in the case of Mexico. This result could also be related to the degree of development and depth of capital markets in each country. Capital market funding in Peru is relatively small and underdeveloped so firms mostly rely on bank funding. In contrast, a higher degree of development and depth of capital markets in Mexico reduces the reliance of private sector firms of financing through the banking sector.

4 Extension: Exploiting Heterogeneity contained in the data

We have found that cross-border flows react significantly to Global Financial shocks, but with some heterogeneity across countries and type of flows. The mentioned evidence suggests that the determinants of these cross-border flows might be different across these dimensions. For that reason, we also evaluate the presence of commonalities and heterogeneity in the pattern of cross-border flows across countries. Thus, we propose a Multi-Country model with lagged inter-dependencies and time varying parameters (Canova and Ciccarelli, 2009)[5]. We abstract from the possible presence of Stochastic Volatility, since the current setup is already computationally demanding. Using Cross-border flows data, the purpose of this exercise is to identify a common component, country and variable specific components for Latin America, since we want to exploit the interaction among countries and also take into account the institutional changes present in the sample of analysis.

4.1 A Time Varying Multi-Country Panel VAR model

The statistical model employed has the form:

$$y_{it} = D_{it}(L) Y_{t-1} + F_{it}(L) Z_t + c_{it} + e_{it} \tag{14}$$

where $i = 1, \ldots, N$ refers to countries and $t = 1, \ldots, T$ refers to time periods. In addition, y_{it} is a $M \times 1$ vector of endogenous variables for each country i and $Y_t = (y_{1t}', y_{2t}', \ldots, y_{Nt}')'$.

Equation (14) can be rewritten in a compact form as

$$Y_t = W_t \delta_t + E_t, \quad E_t \sim N(0, \Omega) \tag{15}$$

where $\delta_t = \left(\delta_{1,t}', \delta_{2,t}', \ldots, \delta_{N,t}' \right)'$ and δ_{it} are vectors containing the coefficients that belong to the lagged and exogenous variables. Canova and Ciccarelli (2009) suggest to reduce the dimension-

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[5]See also Canova *et al.* (2007), Canova and Ciccarelli (2012) and Canova *et al.* (2012), Canova and Ciccarelli (2013).

ality of this model as follows:

$$\delta_t = \Xi_1\theta_{1t} + \Xi_2\theta_{2t} + \Xi_3\theta_{3t} + \Xi_4\theta_{4t} + u_t \tag{16}$$

where Ξ_1, Ξ_2, Ξ_3, Ξ_4 are matrices filled with ones and ones. In particular, θ_{1t} captures movements in coefficients that are common across countries and variables; θ_{2t} captures movements in coefficients which are common across countries; θ_{3t} captures movements in coefficients which are common across variables; θ_{4t} captures movements in coefficients which are common across exogenous variables. Finally, u_t captures all the un-modeled features of the coefficient vector[6]. The factorization (16) significantly reduces the number of parameters to be estimated. In other words, it transforms an over-parametrized panel VAR into a parsimonious SUR model, where the regressors are averages of certain right-hand side variables. In fact, substituting (16) in ($F.2$) we have

$$Y_t = \sum_{i=1}^{4} \mathcal{W}_{it}\theta_{it} + \upsilon_t$$

where $\mathcal{W}_{it} = W_t\Xi_i$ capture respectively, common, country-specific, variable-specific and exogenous-specific information present in the data, and $\upsilon_t = E_t + W_t u_t$. To complete the model, we specify the law of motion $\theta_t = \theta_{t-1} + \eta_t$, with $\eta_t \sim N(0, B_t)$ and where B_t is block-diagonal.

To summarize, the empirical model has the state-space form:

$$Y_t = (W_t\Xi)\theta_t + \upsilon_t \tag{17}$$

$$\theta_t = \theta_{t-1} + \eta_t \tag{18}$$

where $\upsilon_t \sim N(0, \sigma_t)$; $\sigma_t = (1 + \sigma^2 X_t' X_t)$ and $\eta_t \sim N(0, B_t)$. To compute the posterior distributions, we need prior densities for the parameters $(\Omega, \sigma^2, \overline{B}, \theta_0)$.

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[6]See details in appendix F.

4.2 Priors

Following the references we set conjugated priors, i.e. such that the posterior distribution has the same shape as the likelihood function. In particular, given the normality assumption for the shocks, the variance and covariance parameters have an Inverse-Gamma distribution[7] or Inverse-Wishart distribution for the multivariate case. In addition, since we are going to use the Kalman filter and smoother for simulating the posterior distribution of latent factors, it is reasonable to assume the initial point as normally distributed.

$$p\left(\Omega^{-1}\right) = Wi\left(z_1, Q_1\right)$$

$$p\left(\sigma^2\right) = IG\left(\frac{\zeta}{2}, \frac{\zeta s^2}{2}\right)$$

$$p\left(b_i\right) = IG\left(\frac{\varpi_0}{2}, \frac{\delta_0}{2}\right), \quad i = 1, \ldots, 4$$

$$p\left(\theta_0\right) = N\left(\overline{\theta}_0, \overline{R}_0\right)$$

where the latter implies a prior for $\theta_t = N\left(\theta_{t-1|t-1}, R_{t-1|t-1} + B_t\right)$.

4.3 Bayesian Estimation

4.3.1 A Gibbs Sampling routine

Analytical computation of the posterior distribution $(G.3)$ is impossible. However, we can factorize $p\left(\psi \mid Y^T\right)$ into different parameter blocks according to $(G.1)$. The latter allows us to specify the cycle[8]:

Algorithm 3

1. Simulate $\{\theta_t\}_{t=1}^T$ from $p\left(\theta_t \mid Y^T, \psi_{-\theta_t}\right)$

2. Simulate Ω^{-1} from $p\left(\Omega^{-1} \mid Y^T, \psi_{-\Omega}\right)$

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[7] See e.g. Zellner (1971) and Koop (2003).
[8] See details in appendix H.

3. Simulate b_i from $p\left(b_i \mid Y^T, \psi_{-b_i}\right)$

4. Simulate σ^2 from $p\left(\sigma^2 \mid Y^T, \psi_{-\sigma^2}\right)$

where $\overline{\theta}_{t|T}$ and $\overline{R}_{t|T}$ are the one-period ahead forecasts of θ_t and the variance-covariance matrix of the forecast error, respectively, calculated through the Kalman Smoother, as described in Chib and Greenberg (1995). Finally, the posterior of σ^2 is simulated using a Random-Walk Metropolis-Hastings step since it is non-standard, and we take into account the fact that the proposal distribution is not symmetric. Under regularity conditions, cycling through the conditional distributions $(H.1) - (H.2) - (H.3) - (H.4)$ will produce draws from the limiting ergodic distribution.

4.3.2 Estimation setup

In order to analyze the determinants of capital flows, we include for each of the five countries the financial variables for the sample 2001-2017: i) Bank-to-bank flows, ii) Bank-to-nonbank flows and iii) Debt-to-nonbank flows. We also include as exogenous variables i) the Spread between long and short term interest rates, ii) the commodity prices and iii) the VIX index. All the variables were standardized previous to the estimation as in Canova and Ciccarelli (2009).

We run the presented Gibbs sampler for $K = 150,000$ draws and discard the first $100,000$ 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 10, i.e. given the remaining $50,000$ draws, we take 1 every 10 and discard the remaining ones. As a result, we have $5,000$ draws for conducting inference. We set $\varpi_0 = 10^4$, $\delta_0 = 1$, $z_1 = NM + 5$, $Q_1 = diag\left(Q_{11}, \ldots, Q_{1N}\right)$ where Q_{1i} is the residual covariance matrix of the time invariant VAR for the i-th country, $\zeta = 1$, $s^2 = \hat{\sigma}^2$ where $\hat{\sigma}^2$ is the average of the estimated variances of NM independent $AR(p)$ models. Moreover, $\overline{\theta}_0 = \hat{\theta}_0$ is the OLS estimation of the time-invariant version of the model and $\overline{R}_0 = I_{dim(\theta_t)}$. Given the calibrated value of c_σ, the acceptance rate of the metropolis-step is around 0.4. Finally, we set $\gamma_1 = 0$ and $\gamma_2 = 1$, meaning that η_t has a constant variance.

4.4 Results

The results show the different common factors across different types of cross-border flows to the 5 Latin American countries in our sample. Figure 5 shows the common factor to all variables and all countries. This indicator captures the co-movement across countries and type of variables, which we can interpret as an indicator of the part of capital flows that is explain by the so-called "push" factors. The results are statistically significant and in line with the global trend of capital flows to emerging market economies in the last 15 years.

First, we observe a large surge in capital flows during the period 2004-2007, in line with improved perception of fundamentals in emerging economies and good commodity price cycle. We also capture the sharp reduction during the Global Financial Crisis (2008-2009). We also observe a large recovery in the period 2010-2011, in line with the global trend of capital flows from advanced to emerging economies.

The subsequent fall in 2011-2016 is associated to two main factors: (i) the reduction in commodity prices, given that all countries in our sample are commodity exporters, and (ii) taper tantrum and the gradual normalization of monetary policy in the US in the latter part of the sample.
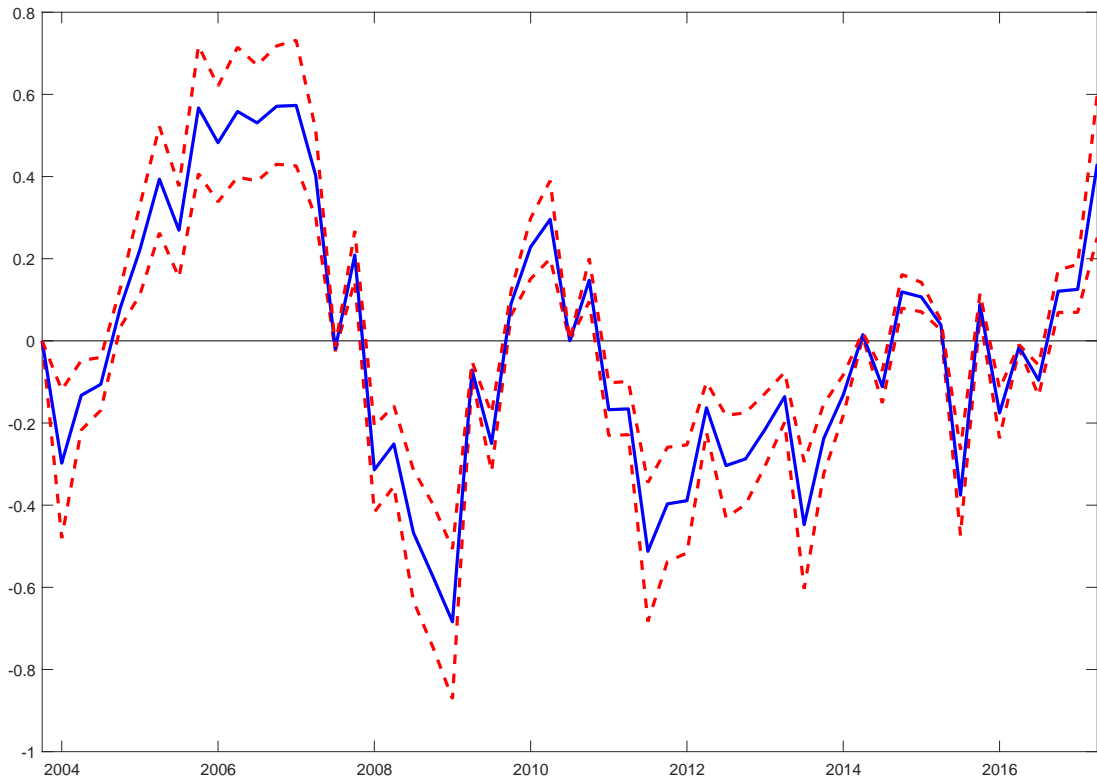
Figure 5: Common Latin America Cross-Border Indicator, median value and 68% c.i.

Despite evidence of some common trend across countries and types of capital flows, we find evidence that there also exists some heterogeneity. Figure 6 shows the results for country-specific trends. We can relate this different patterns across countries to the so-called "pull" factors in the literature. The results show that cross-border flows were very close to the average inflows and outflows for Chile and Mexico, which do not show sharp episodes of capital flow booms or busts. However, at the end of the sample, we observe that there have been lower inflows to these countries relative to others in the sample, such as Colombia and Peru, where growth perspectives and macroeconomic fundamentals have been relatively stronger.
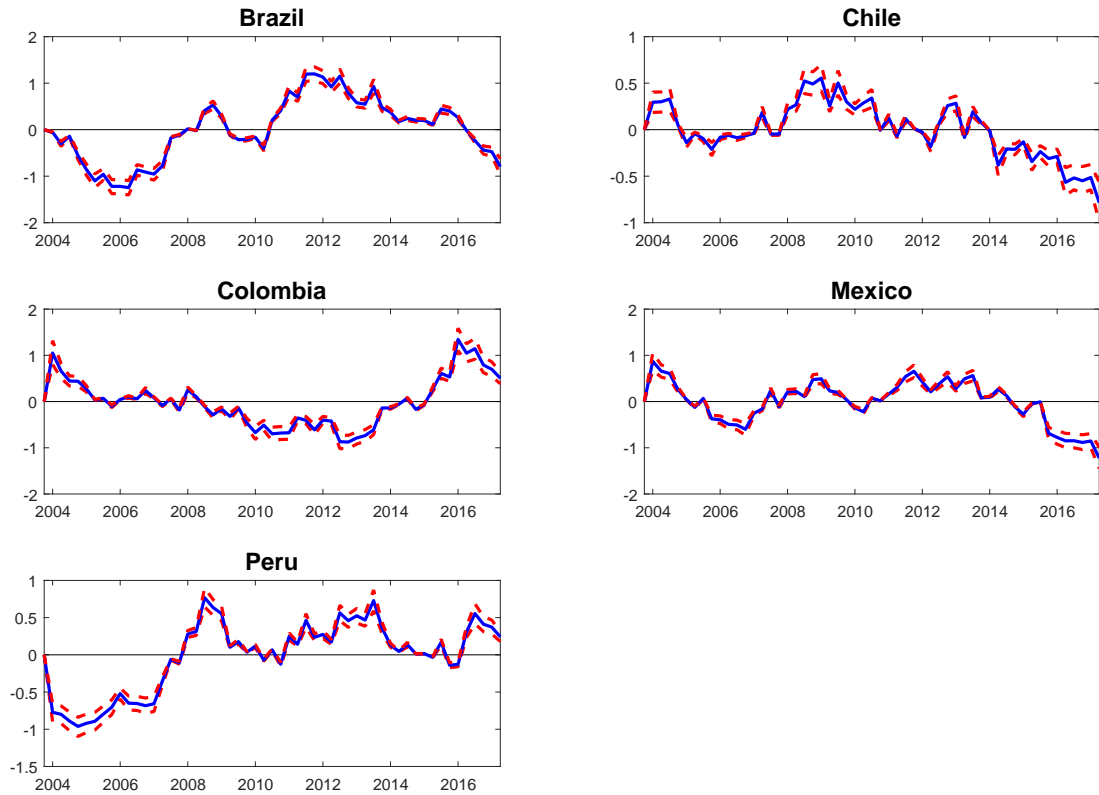
Figure 6: Country-Specific Cross-Border Indicators, median value and 68% c.i.

Finally, Figure 7 shows the common factor across each type of cross-border flow for the sample of countries. This result captures the fact that there could be heterogeneity between funding through bank lending and bond issuance. We observe that capital flows coming from global banks show an increasing trend after the Global Financial Crisis of 2008-2009. In particular, bank to bank flows are especially relevant for our first exercise, as most global funding comes through credit provided by global banks to local banks. The access to international funding through debt securities in 2012-2013 is in line with the general trend of non-financial corporates in emerging market economies issuing bonds in international capital markets after the GFC until the taper tantrum. Also, this result shows that higher funding through this type of flows is modest, which is in line with our motivation where higher bond issuance is more relevant in emerging Asia than in Latin America.

Figure 7: Capital Flow specific Indicators, median value and 68% c.i.

((a)) Bank-to-Bank

((b)) Bank-to-NonBank

((c)) Debt to non-banks

((d)) External shocks
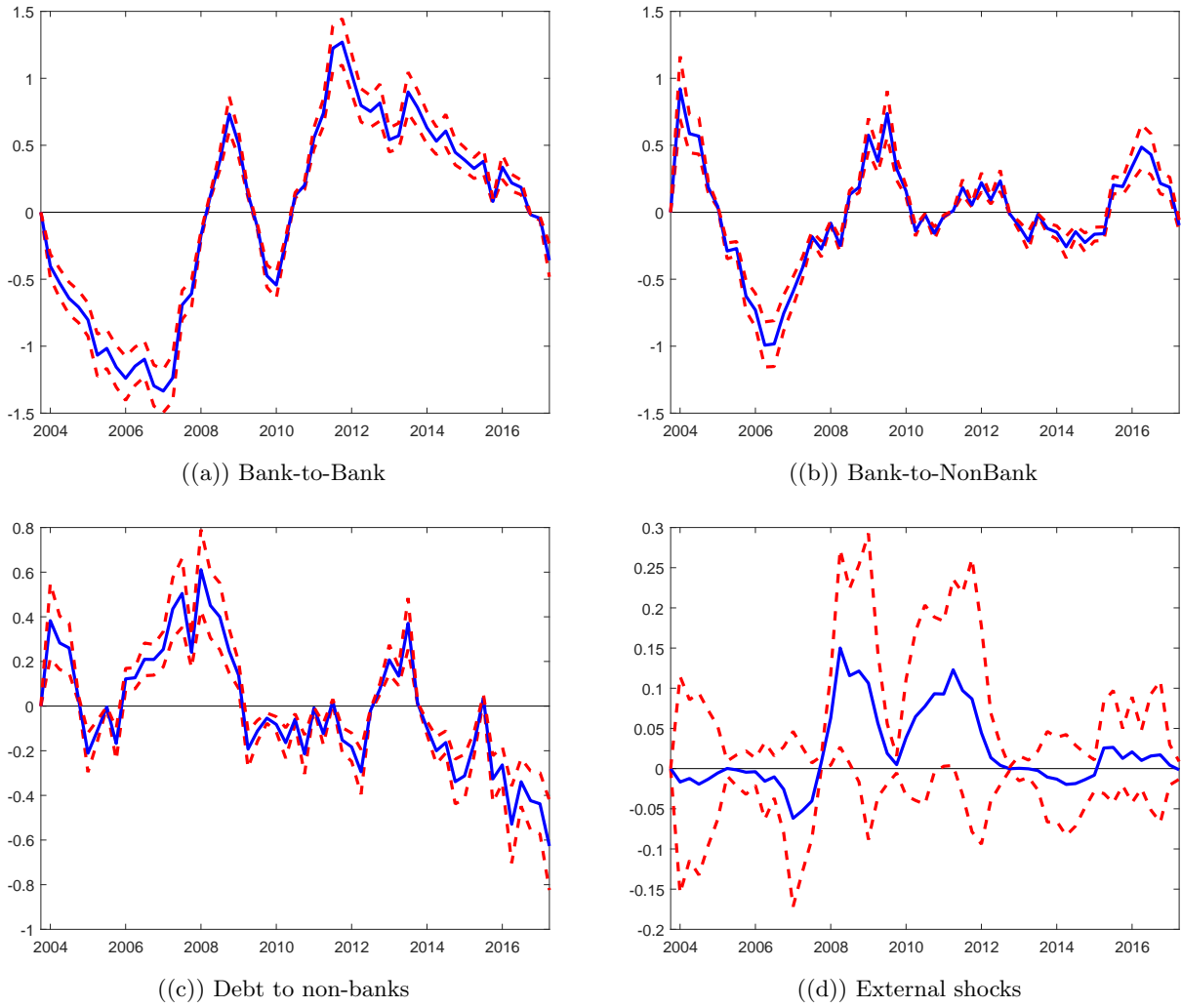
In addition, external factors only have a significant role during the crisis episode (2008-2009) and the peak of commodity prices (2011-2012). All in all, our results from this exercise stress the idea that heterogeneity matters for the determination of capital flows. This heterogeneity can be captured through our model, and this is important for disentangling the role of specific countries and specific type of variables.

5   Concluding Remarks

We have estimated a Bayesian Hierarchical Panel VAR (see Ciccarelli and Rebucci (2006), Jarociński (2010), Canova and Pappa (2011) and Pérez Forero (2015)), where we have extended the standard approach by including an exogenous block that is common for all countries (Gondo and Pérez Forero, 2018), and we have identified structural shocks by imposing zero and sign restrictions. In particular, we calculated the response of domestic financial and macroeconomic variables to exogenous shocks to VIX and long-term foreign interest rates. We considered the possibility of heterogeneous responses between bank and non-bank cross-border flows, and from flows coming from the US and from the rest of AEs.

We quantified the effect of changes in global financial conditions on cross-border flows and domestic financial and macroeconomic variables, motivated by the transmission mechanisms considered in DSGE models such as Aoki *et al.* (2018), and find consistent results. An increase in foreign interest rates translate into lower external funding for banks and thus into lower credit growth and higher domestic interest rates, as banks would try to partially substitute away from external to domestic financing. This effect is amplified through an exchange rate depreciation due to capital outflows, which increases the relative cost of external funding. Thus, there is a larger reduction in cross-border flows, with a quantitatively larger drop in flows from global banks to domestic banks relative to those from global banks to non-financial firms.

The effect on the cost of foreign funding propagates to that of domestic funding through the increase in the cost of external liabilities of the banking sector. For indicators of the real economy, we observe some reduction in GDP growth, although it is not significant for most countries in the sample. The increase in inflation reflects a pass through effect from exchange rate depreciation to prices. Thus, an increase in the monetary policy rate follows to control inflationary pressures.

We also observe a significant heterogeneity in cross-border flows determinants for the region using a time varying coefficients Panel VAR model (Canova and Ciccarelli, 2009). This means that, besides a common component that represents the synchronization of all countries, there

exist country-specific and variable specific indicators, together with an exogenous component, that are able to explain part of the observed cross-border flows.

Further work could explore the evolution of this mechanism before and after the Global Financial Crisis. As previously mentioned, cross-border flows to EME increased significantly, and thus there could have been a change not only in the size and composition of cross-border flows, but also on the propagation and amplification mechanism towards domestic financial sector variables and to macroeconomic variables as well. Another extension could include a comparison with the transmission mechanism of other types of global financial shocks, such as an increase in foreign interest rates in a context of high volatility in financial markets and its implications.

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A The Panel VAR as a linear regression model with normality

A.1 Linear regression model

The model described by (1) and (2) can be expressed in a more compact form for each country $n \in \{1, \ldots, N\}$, so that:

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

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.

Reduced form estimation is performed by blocks as in Zha (1999), since they are independent. 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

$$
Y_n = X_n B_n + U_n \tag{A.2}
$$

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

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

The model in equation $(A.2)$ 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 normality assumption of the error terms, we have the likelihood function for each country

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

which is

$$p(\mathbf{y}_n \mid \beta_n, \Sigma_n) = (2\pi)^{-M_1(T_n - p)/2} |\Sigma_n \otimes I_{T_n - p}|^{-1/2} \times$$
$$\exp\left(-\frac{1}{2}(\mathbf{y}_n - (I_{M_1} \otimes X_n)\beta_n)'(\Sigma_n \otimes I_{T_n - p})^{-1}(\mathbf{y}_n - (I_{M_1} \otimes X_n)\beta_n)\right) \tag{A.3}$$

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^* $(T^* \times M_2)$, X^* $(T^* \times K^*)$, U^* $(T^* \times M_2)$, with $K^* = M_2 p + W$ and the corresponding parameter matrix Φ^* $(K^* \times M_2)$, and in particular:

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

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The regression model can then be re-written such that

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

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

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

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

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

which is

$$p\left(\mathbf{y}^* \mid \beta^*, \Sigma^*\right) = (2\pi)^{-M_2(T^*-p)/2} \left|\Sigma^* \otimes I_{T^*-p}\right|^{-1/2} \times$$

$$\exp\left(\begin{array}{c} -\tfrac{1}{2}\left(\mathbf{y}^* - (I_{M_2} \otimes X^*)\, \beta^*\right)'\left(\Sigma^* \otimes I_{T^*-p}\right)^{-1} \times \\ \left(\mathbf{y}_n - (I_{M_2} \otimes X^*)\, \beta^*\right) \end{array} \right) \tag{A.4}$$

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

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

$$\tag{A.5}$$

A.2 Prior distribution of parameters

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

$$\Theta = \left\{ \{\beta_n, \Sigma_n\}_{n=1}^{N}, \beta^*, \Sigma^*, \tau, \overline{\beta}, \tau_X \right\}$$

so that the joint prior is given by (3), (5), (6), (7), (8), (10) and (11):

$$
\begin{aligned}
p\left(\Theta\right) \propto & \prod_{n=1}^{N} p\left(\Sigma_n\right) p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) p\left(\tau\right) \\
= & \prod_{n=1}^{N} |\Sigma_n|^{-\frac{1}{2}(M_1+1)} \times \\
\tau^{-\frac{N M_1 K}{2}} \exp & \left(-\frac{1}{2} \sum_{n=1}^{N} \left(\beta_n - \overline{\beta}\right)' \left(\tau^{-1} O_n\right)^{-1} \left(\beta_n - \overline{\beta}\right)\right) \times \\
& \tau^{-\frac{v+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\tau}\right) \times \\
& |\Sigma^*|^{-\frac{1}{2}(M_2+1)} \times \\
\tau_X^{-\frac{M_2 K^*}{2}} \exp & \left(-\frac{1}{2} \left(\beta^* - \overline{\beta^*}\right)' \left(\tau_X^{-1} O_X\right)^{-1} \left(\beta^* - \overline{\beta^*}\right)\right) \times \\
& \tau_X^{-\frac{v_X+2}{2}} \exp\left(-\frac{1}{2}\frac{s_X}{\tau_X}\right)
\end{aligned}
\tag{A.6}
$$

A.3 Posterior distribution of parameters

Given (A.1) and (A.6), the posterior distribution (12) takes the form:

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

$$\prod_{n=1}^{N}\left|\Sigma_n\right|^{-\frac{T_n+M_1+1}{2}} \times \exp\left(\begin{array}{c} -\frac{1}{2}\sum\limits_{n=1}^{N}\left(\mathbf{y}_n-\left(I_{M_1}\otimes X_n\right)\beta_n\right)'\left(\Sigma_n\otimes I_{T_n-p}\right)^{-1} \\ \left(\mathbf{y}_n-\left(I_{M_1}\otimes X_n\right)\beta_n\right) \\ -\frac{1}{2}\left(\mathbf{y}^*-\left(I_{M_2}\otimes X^*\right)\beta^*\right)'\left(\Sigma^*\otimes I_{T^*-p}\right)^{-1} \\ \left(\mathbf{y}_n-\left(I_{M_2}\otimes X^*\right)\beta^*\right) \end{array}\right) \times \qquad \text{(A.7)}$$

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

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

B Gibbs sampling details

The algorithm described in subsection 4.3.1 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: $p\left(\beta^* \mid \Theta/\beta^*, \mathbf{y}^*\right)$: 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

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

with

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

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

2. **Block 2:** $p\left(\beta_n \mid \Theta/\beta_n, \mathbf{y}_n\right)$: 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

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

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

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

Denote the residuals

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

as in equation $(A.2)$. Then the posterior variance term is Inverted-Wishart centered at the sum of squared residuals:

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

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

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

Denote the residuals

$$U_n = Y_n - X_n B_n$$

as in equation ($A.2$). Then the posterior variance term is Inverted-Wishart centered at the sum of squared residuals:

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

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

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

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 $n = 1, \ldots, N$:

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

with

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

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

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

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

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

then the posterior is

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

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

C Impulse responses details

For each draw of Θ from the posterior distribution, we compute the companion form of the compact model as in equation $(A.2)$. Then we compute the median value and the 68% credible interval for each impulse response. Results are shown below.
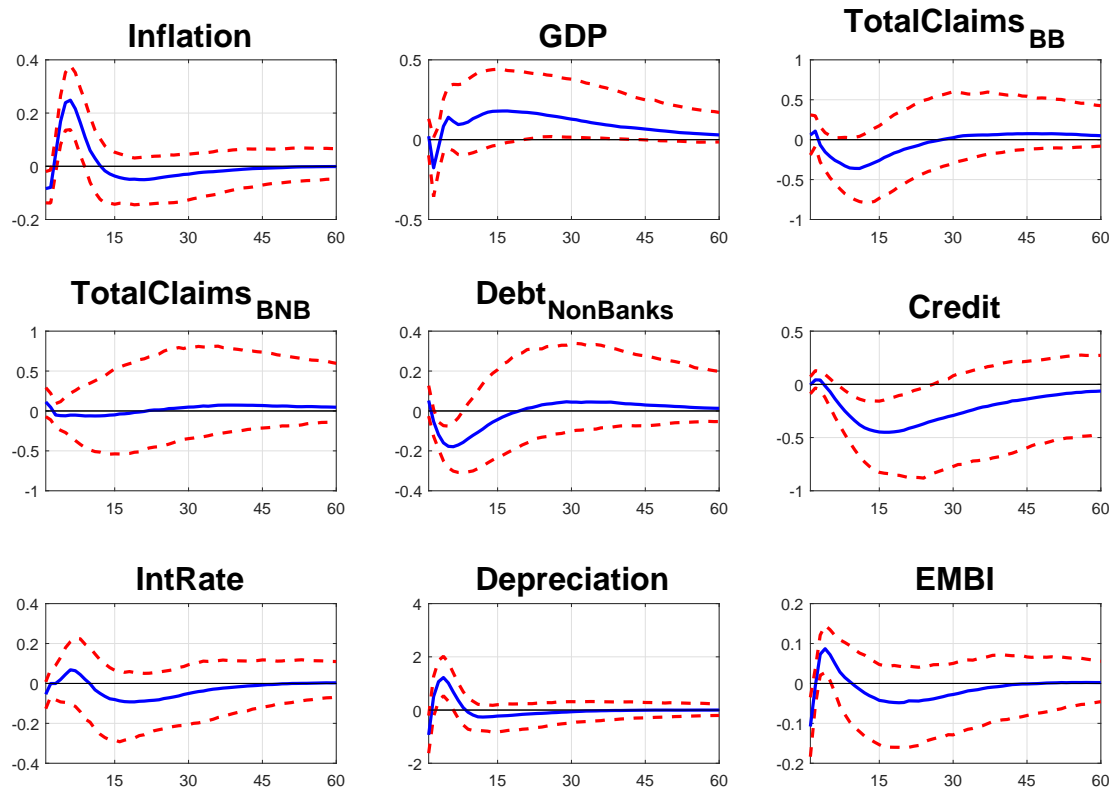
Figure C.8: Global Financial shocks effects in Brazil, median value and 68% c.i.
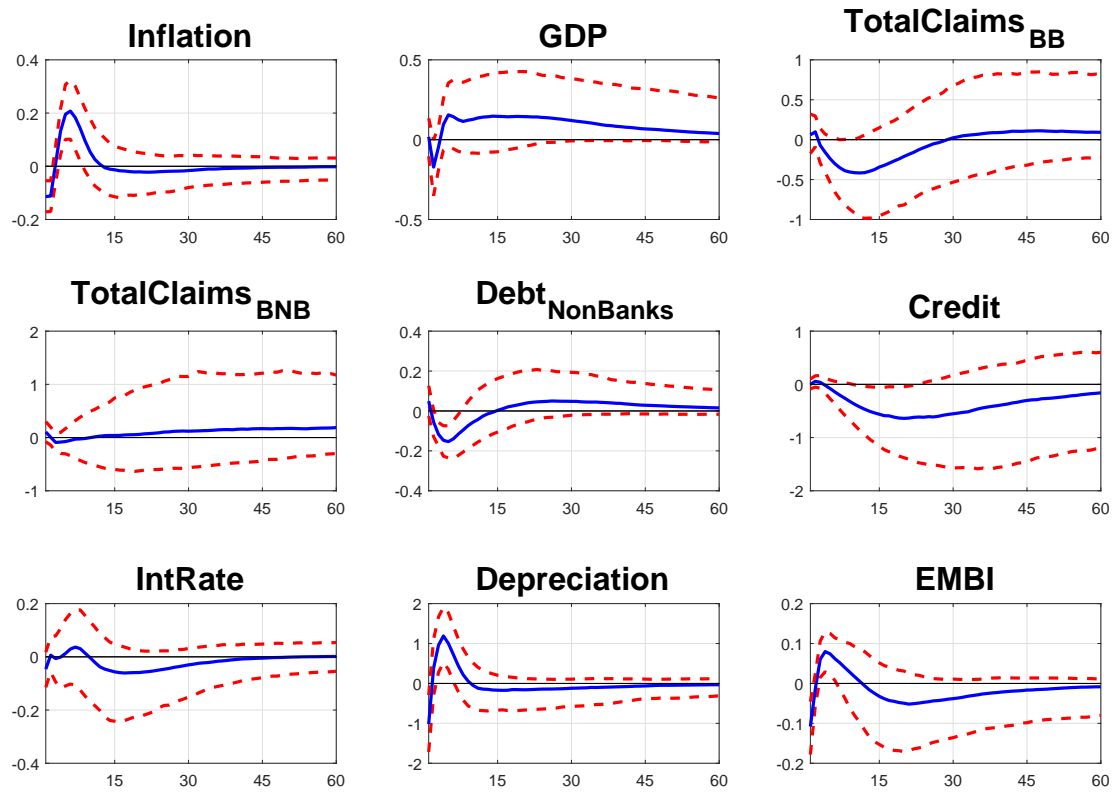
Figure C.9: Global Financial shocks effects in Chile, median value and 68% c.i.
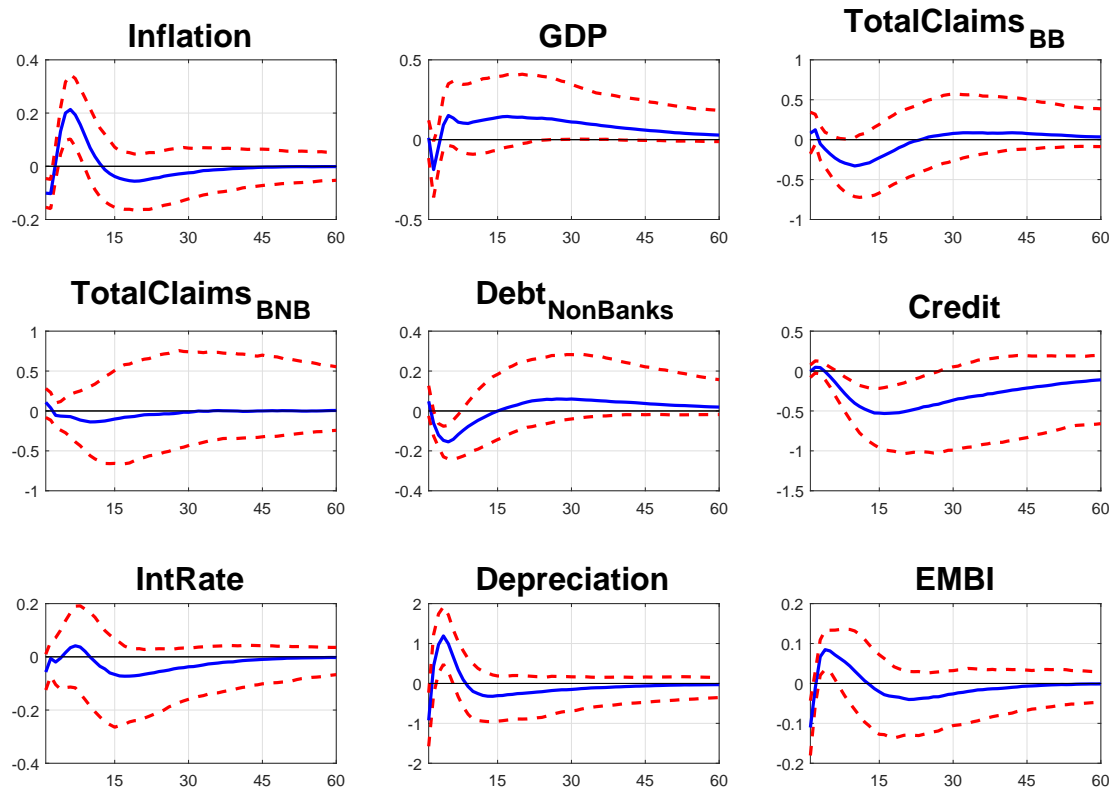
Figure C.10: Global Financial shocks effects in Colombia, median value and 68% c.i.
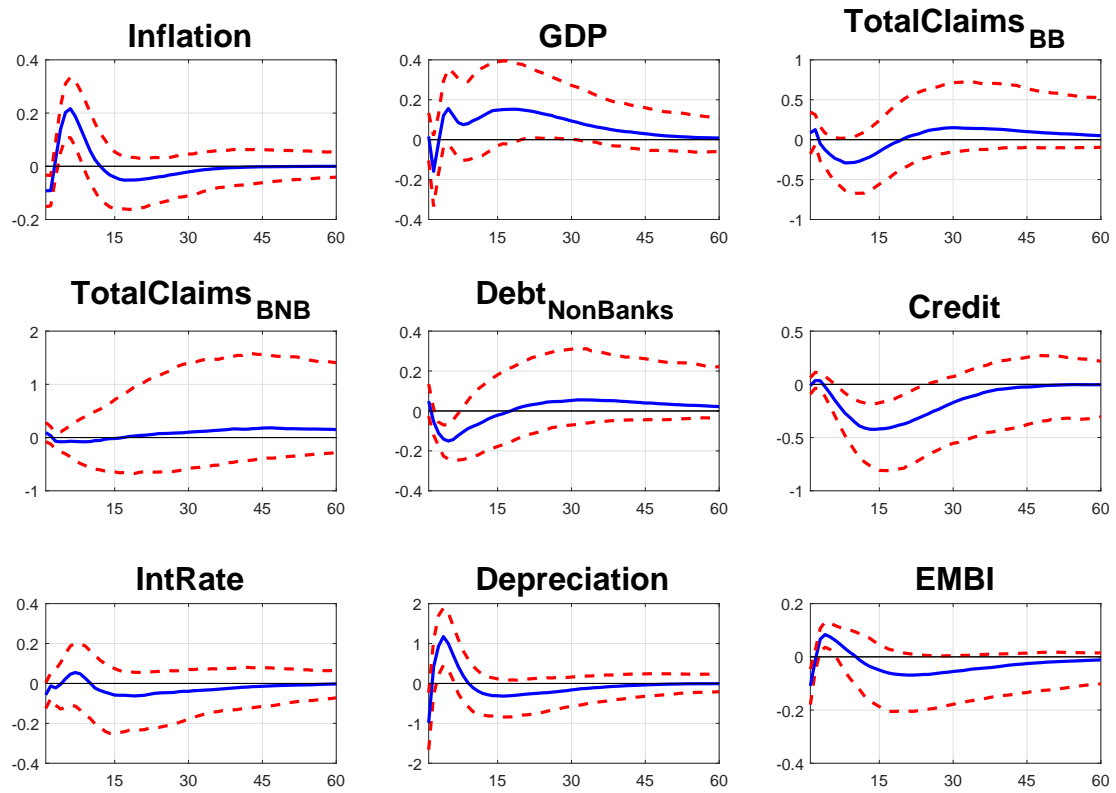
Figure C.11: Global Financial shocks effects in Mexico, median value and 68% c.i.
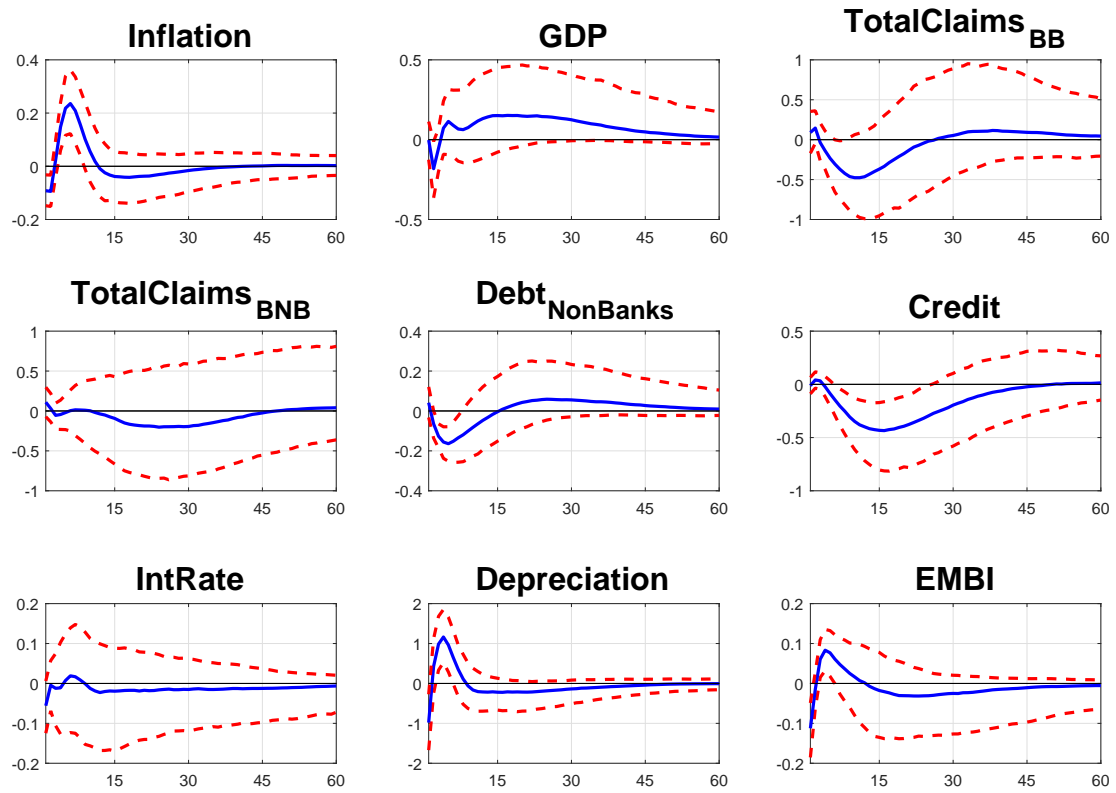
Figure C.12: Global Financial shocks effects in Peru, median value and 68% c.i.

D Posterior distribution of hyperparameters in the Panel VAR
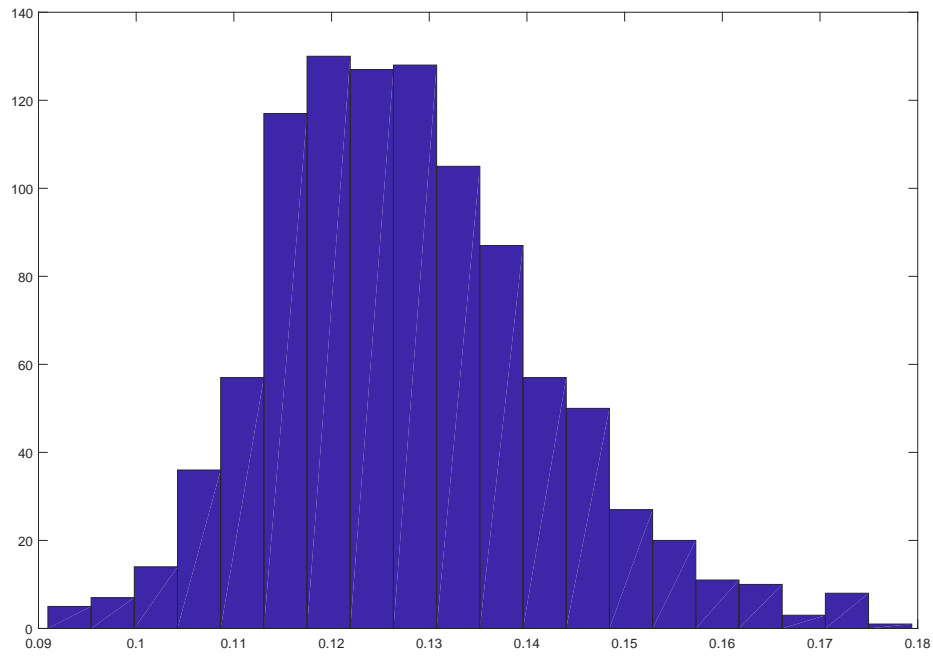
Figure D.13: Posterior distribution of $\sqrt{\tau_X}$
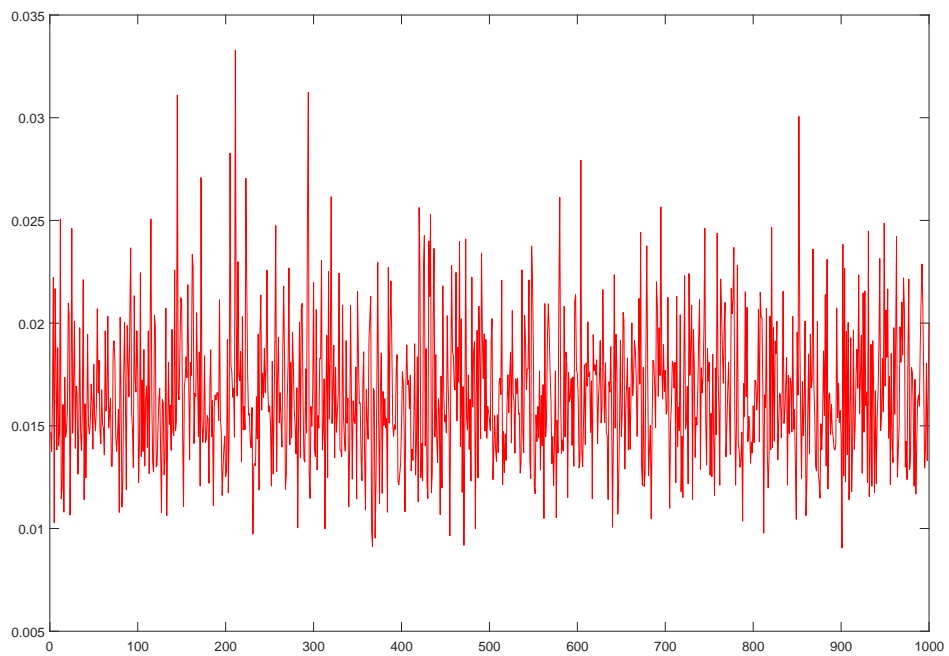
Figure D.14: Posterior draws of τ_X
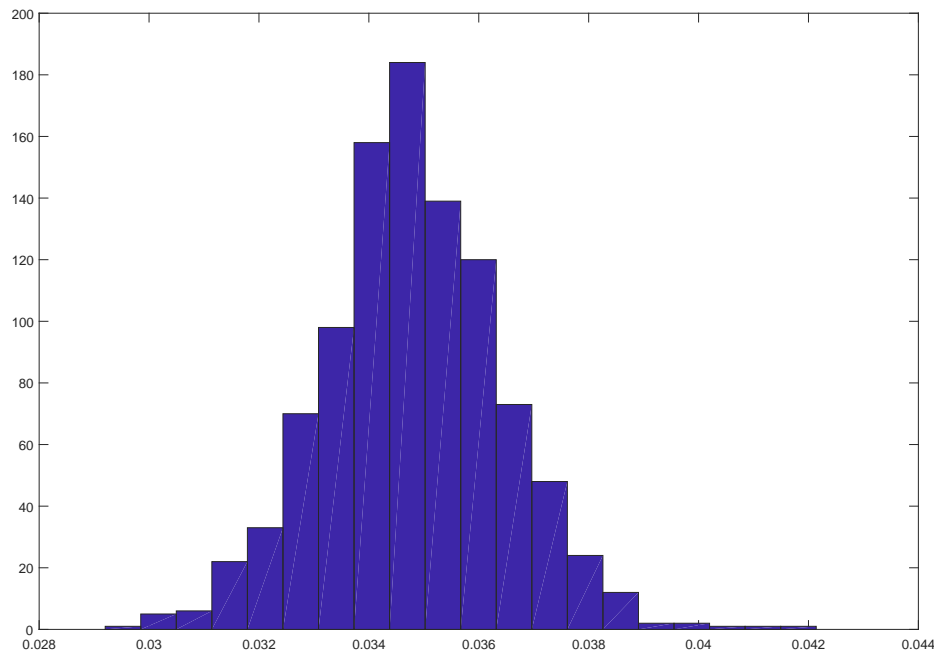
Figure D.15: Posterior distribution of $\sqrt{\tau}$
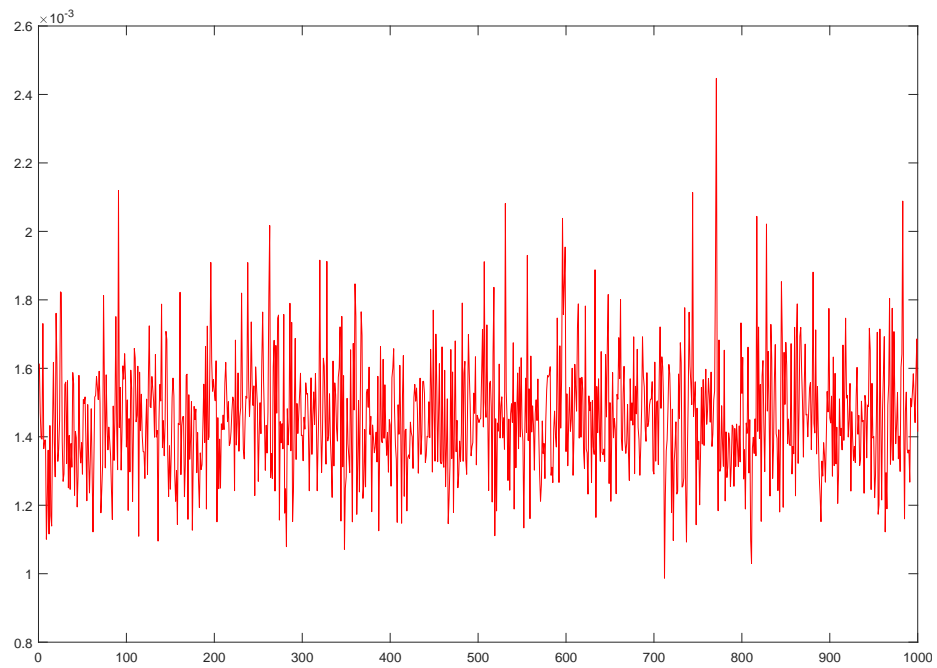
Figure D.16: Posterior draws of τ

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E   The Transformed Data
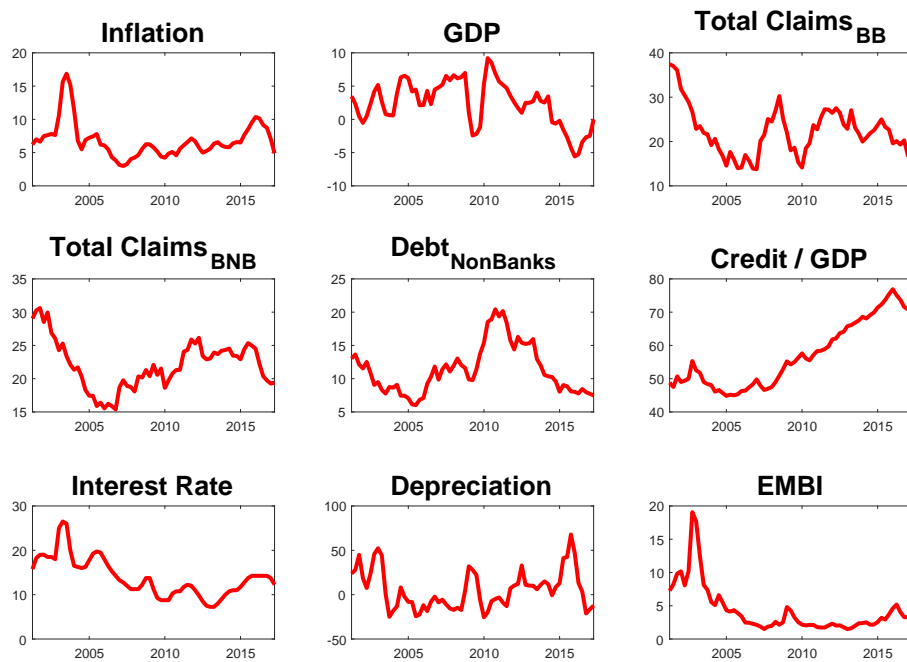
Figure E.17: Brazilian Data
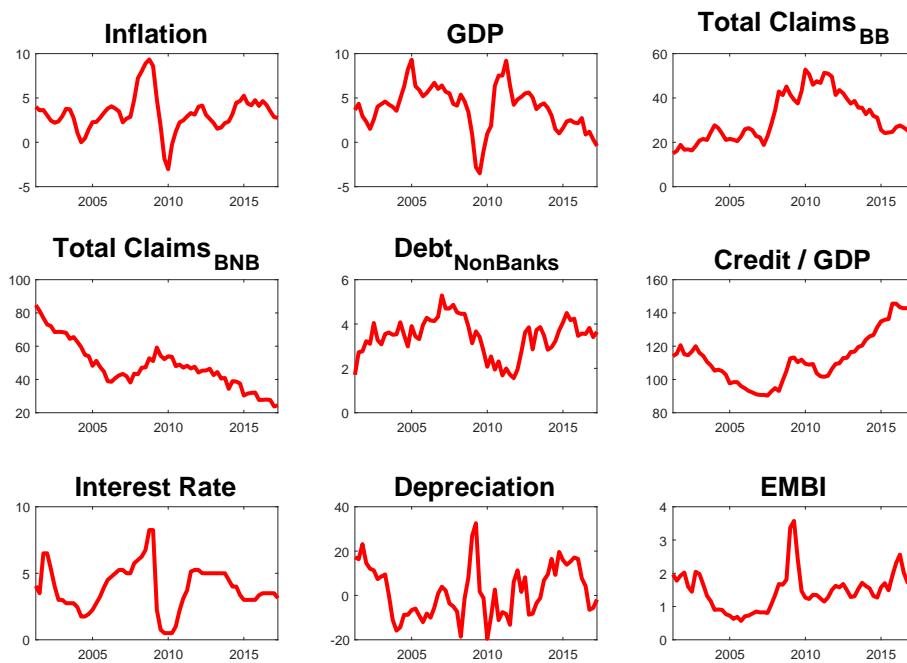
Figure E.18: Chilean Data
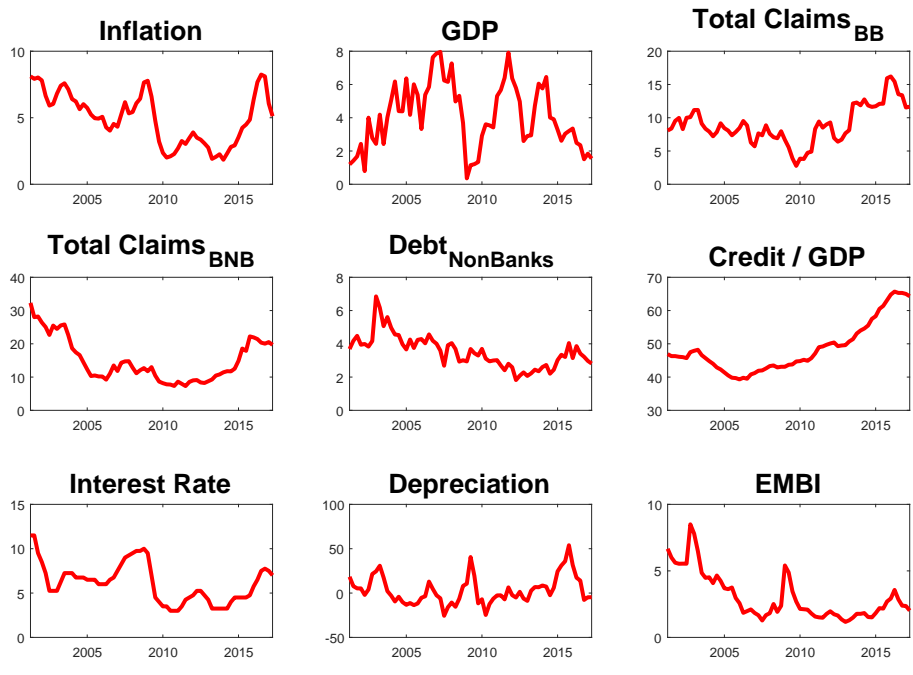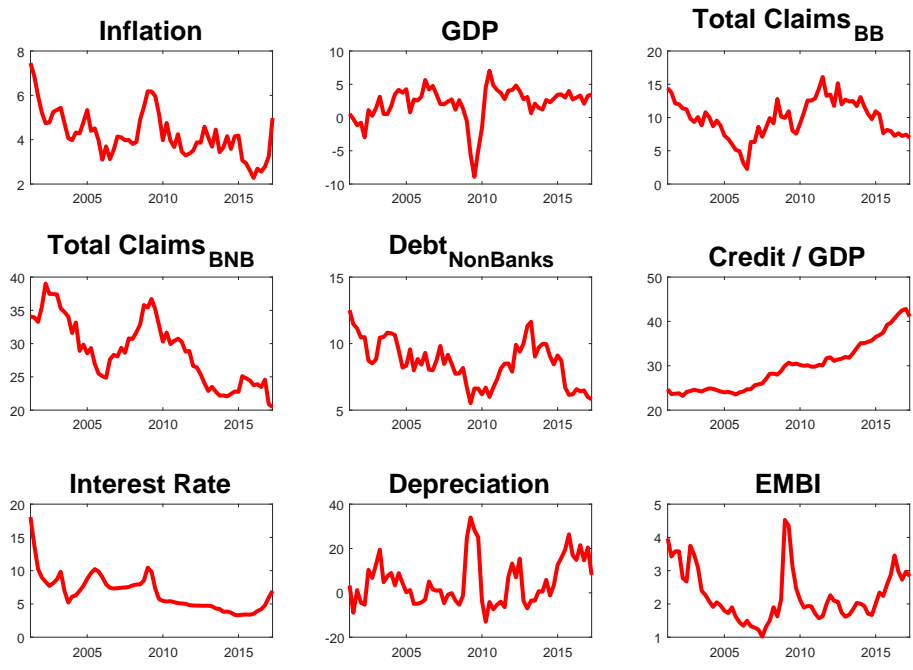
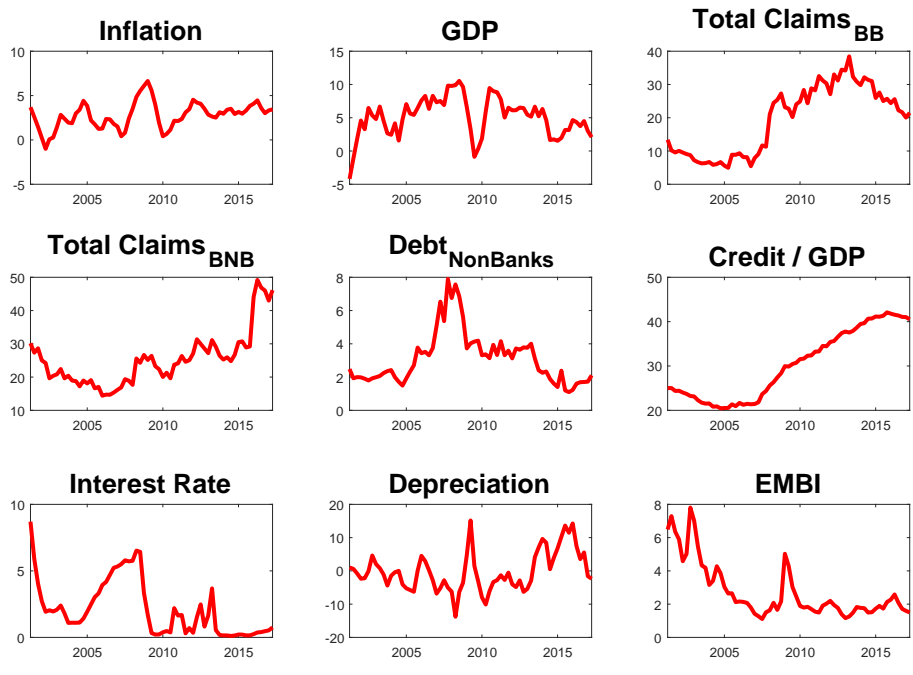Figure E.19: Colombian Data

Figure E.20: Mexican Data
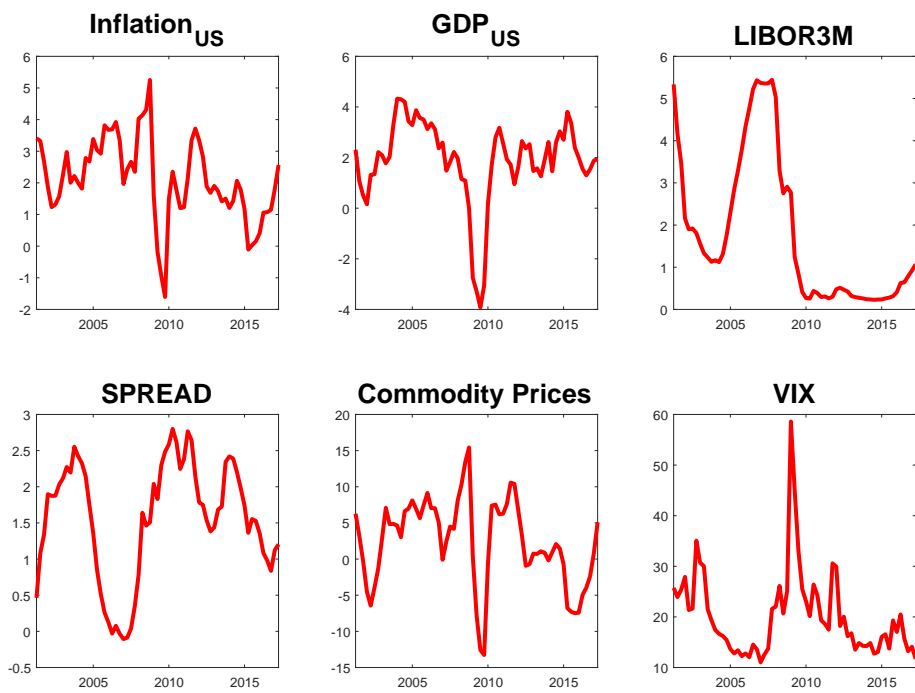
Figure E.21: Peruvian Data

Figure E.22: Exogenous Data

F   The extended Time Varying Multi-Country Panel VAR model

The statistical model employed has the form:

$$y_{it} = D_{it}(L) Y_{t-1} + F_{it}(L) Z_t + c_{it} + e_{it} \tag{F.1}$$

where $i = 1, \ldots, N$ refers to countries and $t = 1, \ldots, T$ refers to time periods. In addition, y_{it} is a $M \times 1$ vector of endogenous variables for each country i and $Y_t = (y'_{1t}, y'_{2t}, \ldots, y'_{Nt})'$.

We define the polynomials

$$D_{it}(L) = D_{it,1} + D_{it,2}L + \cdots + D_{it,p}L^{p-1}$$

$$F_{it}(L) = F_{it,0} + F_{it,1}L + \cdots + F_{it,q}L^q$$

where $D_{it,j}$ are $M \times NM$ matrices for each lag $j = 1, \ldots, p$. Moreover, Z_t is a $M_2 \times 1$ vector of exogenous variables common to all countries and $F_{it,j}$ are $M \times M_2$ matrices for each lag $j = 0, \ldots, q$, c_{it} is a $M \times 1$ vector of intercepts and e_{it} is a $M \times 1$ vector of random disturbances.

Notice that cross-unit lagged inter-dependencies are allowed whenever the $NM \times NM$ matrix $D_t(L) = [D_{1t}(L), D_{2t}(L), \ldots, D_{Nt}(L)]'$ is not block diagonal. Notice also that coefficients in (14) are allowed to vary over time and that dynamic relationships are unit-specific. All these features add realism to the econometric model. However, this comes at the cost of having an extremely large number of parameters to estimate (we have $k = NMp + M_2(1 + q) + 1$ parameters per equation). For that reason, we specify a more parsimonious representation of the latter model in order to proceed to the estimation.

Equation (14) can be rewritten in a compact form as

$$Y_t = W_t \delta_t + E_t, \quad E_t \sim N(0, \Omega) \tag{F.2}$$

where $W_t = I_{NM} \otimes X'_t$; $X'_t = \left(Y'_{t-1}, Y'_{t-2}, \ldots, Y'_{t-p}, Z'_t, Z'_{t-1}, \ldots, Z'_{t-q}, 1 \right)$; $\delta_t = \left(\delta'_{1,t}, \delta'_{2,t}, \ldots, \delta'_{N,t} \right)'$

and δ_{it} are $Mk \times 1$ vectors containing, stacked, the M rows of matrix D_{it} and F_{it}, while Y_t and E_t are $NM \times 1$ vectors. Notice that since δ_t varies with cross-sectional units in different time periods, it is impossible to estimate it using classical methods. Even in the case of constant co-efficients, the amount of degrees of freedom needed to conduct proper inference is tremendously large. For that reason, Canova and Ciccarelli (2009) suggest to reduce the dimensionality of this problem as follows:

$$\delta_t = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t} + \Xi_3 \theta_{3t} + \Xi_4 \theta_{4t} + u_t \tag{F.3}$$

where Ξ_1, Ξ_2, Ξ_3, Ξ_4 are matrices of dimensions $NMk \times 1$, $NMk \times N$, $NMk \times M$, $NMk \times 1$ respectively. θ_{1t} captures movements in coefficients that are common across countries and variables; θ_{2t} captures movements in coefficients which are common across countries; θ_{3t} captures movements in coefficients which are common across variables; θ_{4t} captures movements in coefficients which are common across exogenous variables. Finally, u_t captures all the un-modeled features of the coefficient vector[9].

The factorization (16) significantly reduces the number of parameters to be estimated. In other words, it transforms an over-parametrized panel VAR into a parsimonious SUR model, where the regressors are averages of certain right-hand side variables. In fact, substituting (16) in ($F.2$) we have

$$Y_t = \sum_{i=1}^{4} \mathcal{W}_{it} \theta_{it} + \upsilon_t$$

where $\mathcal{W}_{it} = W_t \Xi_i$ capture respectively, common, country-specific, variable-specific and exogenous-specific information present in the data, and $\upsilon_t = E_t + W_t u_t$.

To complete the model, we specify $\theta_t = [\theta_{1t}', \theta_{2t}', \theta_{3t}', \theta_{4t}']'$ so that we have the law of motion:

$$\theta_t = \theta_{t-1} + \eta_t, \quad \eta_t \sim N(0, B_t)$$

---

[9]See details in Canova and Ciccarelli (2009).

where B_t is block-diagonal with:

$$B_t = \gamma_1 B_{t-1} + \gamma_2 \overline{B}$$

where γ_1 and γ_2 are scalars and a $\overline{B}$ is block-diagonal matrix.

To summarize, the empirical model has the state-space form:

$$Y_t = (W_t \Xi)\, \theta_t + \upsilon_t \tag{F.4}$$

$$\theta_t = \theta_{t-1} + \eta_t \tag{F.5}$$

where $\upsilon_t \sim N(0, \sigma_t)$; $\sigma_t = \left(1 + \sigma^2 X_t' X_t\right)$ and $\eta_t \sim N(0, B_t)$. To compute the posterior distributions, we need prior densities for the parameters $\left(\Omega, \sigma^2, \overline{B}, \theta_0\right)$.

G Posterior Distribution of the TVP-Panel VAR

The posterior distribution of model parameters is the efficient combination of prior information with the observed data. Denote the parameter vector as

$$\psi = \left(\Omega^{-1}, \{b_i\}_{i=1}^4, \sigma^2, \{\theta_t\}_{t=1}^T\right) \tag{G.1}$$

Given the normality assumption of the error term υ_t, the likelihood function of the Multi-Country Panel VAR model ($F.4$) is equal to

$$L\left(Y^T \mid \psi\right) \propto \left(\prod_{t=1}^T \sigma_t^{-NM/2}\right) |\Omega|^{-T/2} \exp\left[-\frac{1}{2}\sum_{t=1}^T (Y_t - W_t \Xi \theta_t)\, (\sigma_t \Omega)^{-1}\, (Y_t - W_t \Xi \theta_t)'\right] \tag{G.2}$$

where $Y^T = (Y_1, Y_2, \ldots, Y_T)$ denotes the data, and $\sigma_t = \left(1 + \sigma^2 X_t' X_t\right)$.

Using the Bayes' rule, we have the posterior distribution:

$$p\left(\psi \mid Y^T\right) \propto L\left(Y^T \mid \psi\right) p\left(\psi\right) \tag{G.3}$$

In the next section we will explain how to obtain the optimal estimates of model parameters in a tractable way. So far, we have identified our object of interest, and the next step is to proceed to the estimation.

H   A Gibbs Sampling for the TVP-Panel VAR

Analytical computation of the posterior distribution ($G.3$) is impossible. However, we can factorize $p\left(\psi \mid Y^T\right)$ into different parameter blocks according to ($G.1$). The latter allows us to specify the cycle:

Algorithm 3 (extended)

1. Simulate $\{\theta_t\}_{t=1}^T$ from $p\left(\theta_t \mid Y^T, \psi_{-\theta_t}\right)$ such that

$$\theta_t \mid Y^T, \psi_{-\theta_t} \sim N\left(\bar{\theta}_{t|T}, \overline{R}_{t|T}\right), \ t \leq T \tag{H.1}$$

2. Simulate Ω^{-1} from $p\left(\Omega^{-1} \mid Y^T, \psi_{-\Omega}\right)$ such that

$$\Omega^{-1} \mid Y^T, \psi_{-\Omega} \sim Wi\left(z_1 + T, \left[\frac{\sum_t \left(Y_t - W_t \Xi \theta_t\right)\left(Y_t - W_t \Xi \theta_t\right)'}{\sigma_t} + Q_1^{-1}\right]^{-1}\right) \tag{H.2}$$

3. Simulate b_i from $p\left(b_i \mid Y^T, \psi_{-b_i}\right)$ such that

$$b_i \mid Y^T, \psi_{-b_i} \sim IG\left(\frac{\varpi^i}{2}, \frac{\sum_t \left(\theta_t^i - \theta_{t-1}^i\right)'\left(\theta_t^i - \theta_{t-1}^i\right) + \delta_0}{2\xi_t}\right) \tag{H.3}$$

where $\xi_t = \gamma_1^t + \gamma_2 \frac{1-\gamma_1^t}{1-\gamma_1}$.

4. Simulate σ^2 from $p\left(\sigma^2 \mid Y^T, \psi_{-\sigma^2}\right)$ such that

$$\sigma^2 \mid Y^T, \psi_{-\sigma^2} \propto L\left(Y^T \mid \psi\right) p\left(\sigma^2\right) \tag{H.4}$$

where $\bar{\theta}_{t|T}$ and $\overline{R}_{t|T}$ are the one-period ahead forecasts of θ_t and the variance-covariance matrix

of the forecast error, respectively, calculated through the Kalman Smoother, as described in Chib and Greenberg (1995). We also have $\varpi^1 = T + \varpi_0$, $\varpi^2 = TM + \varpi_0$, $\varpi^3 = TN + \varpi_0$, $\varpi^4 = T + \varpi_0$.

The posterior of σ^2 is simulated using a Random-Walk Metropolis-Hastings step, since it is non-standard. That is, at each iteration l we draw a candidate $(\sigma^2)^*$ according to

$$\left(\sigma^2\right)^* = \exp\left[\ln\left(\sigma^2\right)^{l-1} + c_\sigma \varepsilon\right]$$

with $\varepsilon \sim N(0,1)$ and c_σ is a parameter for scaling the variance of the proposal distribution. In particular, this is chosen such that the acceptance rate is between $0.2 - 0.4$. Moreover, the acceptance probability at each draw l is given by:

$$\alpha = \min\left\{\frac{L\left(\left(\sigma^2\right)^*, \psi^l_{-\sigma^2} \mid Y^T\right) p\left(\left(\sigma^2\right)^*\right) \varrho\left(\left(\sigma^2\right)^{l-1} \mid \left(\sigma^2\right)^*\right)}{L\left(\left(\sigma^2\right)^{l-1}, \psi^l_{-\sigma^2} \mid Y^T\right) p\left(\left(\sigma^2\right)^{l-1}\right) \varrho\left(\left(\sigma^2\right)^* \mid \left(\sigma^2\right)^{l-1}\right)}, 1\right\}$$

where we take into account the fact that the proposal distribution is not symmetric.

Under regularity conditions, cycling through the conditional distributions $(H.1)-(H.2)-(H.3)-(H.4)$ will produce draws from the limiting ergodic distribution.

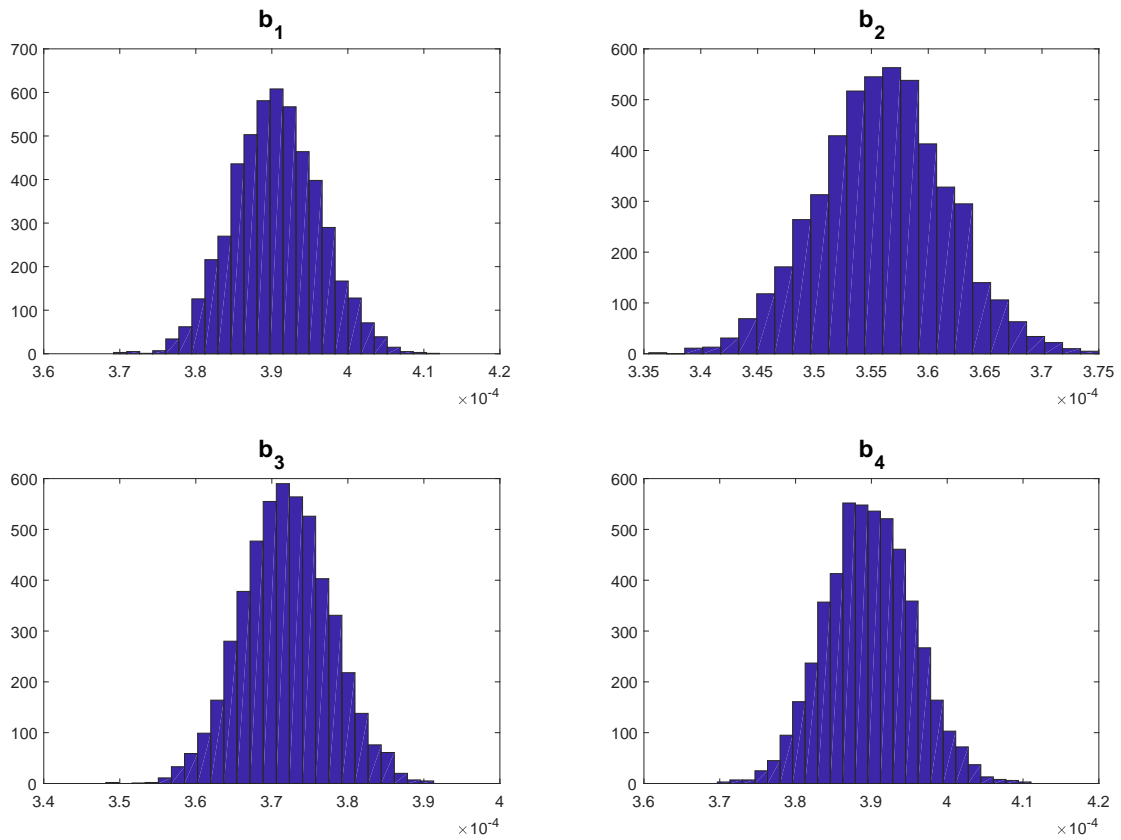# I Posterior distribution of hyperparameters in the TVP-Panel VAR

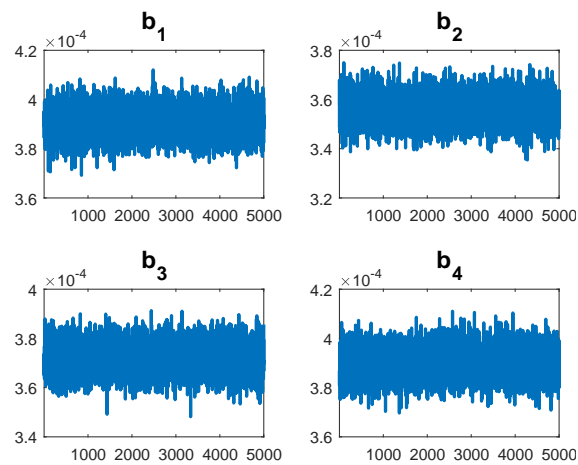Figure I.23: Posterior distribution of variance parameters

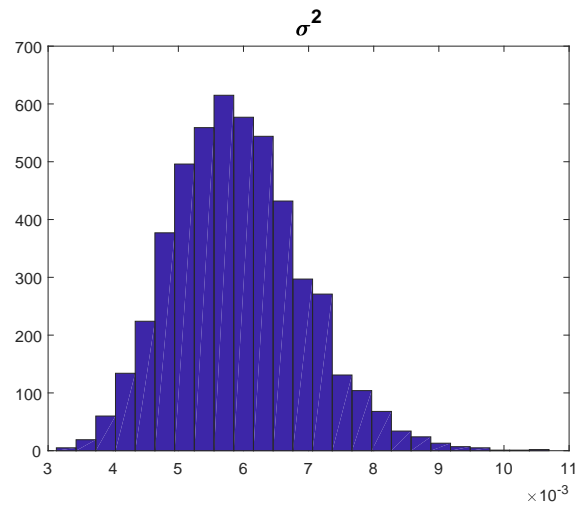Figure I.24: Posterior draws of variance parameters
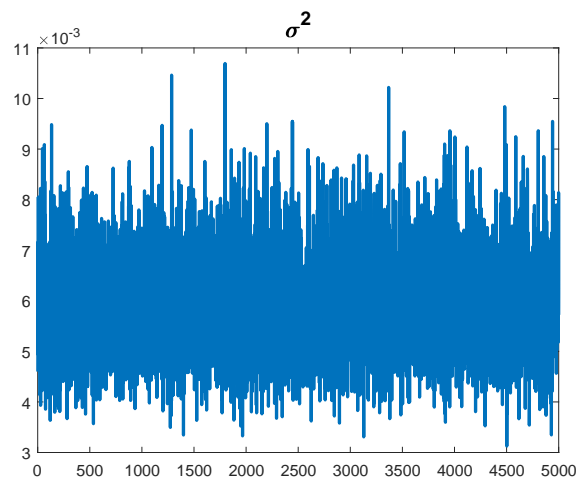
Figure I.25: Posterior distribution of σ^2

Figure I.26: Posterior draws of σ^2

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