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 Amer-
ica. 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.

C11, C23, E44, E52, Q02
Panel Vector Autoregressions, Exogenous Block, Bayesian Estimation, Cross-Border flows

∗The views expressed in this paper are those of the authors and do not necessarily represent those of the
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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 (Bank for International Settlements (2018), Chart E4). Even though the surge in cross-border flows to Latin America was not as sharp as that to Asia EMEs, the region experienced an increase in access to funding for banks and non-bank corporates from abroad, both in terms of bank credit and bond issuance in international capital markets. However, since 2013 cross-border credit to Latin America has slowed down in line with a moderation in the growth rates of credit granted by local banks (Bank for International Settlements (2018), Chart E2).

Cycles in cross-border flows and in the cost of external borrowing for the region may translate to the cost of borrowing of non-financial firms and through that mechanism to variables in the real economy. For instance, easier and cheaper access to international financing translates into lower costs of financing investment for those firms that have direct access to borrowing from abroad. In addition, cheaper external funding costs for banks would translate into higher domestic credit and investment for firms funded through local banks. This second channel can be observed through an increase in the loan-to-deposit ratios in Latin America (with the exception of Chile). 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.

In this work we empirically quantify the transmission mechanism of global financial shocks on macroeconomic and financial variables. We quantify the effect of changes in global financial conditions on cross-border flows and domestic financial and macroeconomic variables. We calculate the effect on access to different types of international financing to each Latin American country in the sample, their effect on the behavior of the domestic banking system and the transmission to the real economy through the link between bank credit, investment and output. We use a sample of Latin American countries to compare the amplitude and propagation of
global financial shocks to domestic variables. For that purpose we 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 model is motivated by the 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. In this scenario, the use of a
counter-cyclical macroprudential policy helps to stabilize the value of the banks balance sheet
and reduces the impact of global financial shocks on the domestic economy.

The empirical approach considers a hierarchical Bayesian Panel VAR (Ciccarelli and Re-
bucci, 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.

Our results are qualitatively consistent with the transmission mechanism depicted by Aoki
et al. (2018). That is, 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. 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. 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. 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.
The increase in the cost of foreign funding is propagated to the cost of domestic funding, as it increases the cost of external liabilities for domestic banks. Domestic banks reduce loan supply and their exposure to non-core funding, as observed through the decline in the loan-to-deposit ratio. 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 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). Extreme portfolio flow surges and retrenchments are mainly driven by global risk (Forbes and Warnock, 2012), although portfolio flows to emerging economies have been mainly driven by interest rate differentials, especially after the Global Financial Crisis (Ahmed and Zlate, 2014). Global banks seem to have a key role in the transmission of external shocks (Cetorelli and Goldberg, 2012; Bruno and Shin, 2014). However, most work focuses on a static analysis of global vs domestic factors, whereas our work considers the dynamic response of domestic financial and real variables to changes in capital flow patterns. Our estimation sheds light on the impact of global financial shocks on different types of capital inflows and how it translates to domestic macroeconomic variables.

Also, our work relates to the literature that analyzes the effect on bilateral cross border bank flows that consider monetary policy shocks (Correa et al., 2018) and of uncertainty shocks (Choi and Furceri, 2019) in the source and recipient countries. They find that global banks follow a reallocation pattern towards safer counter parties after an increase in the US monetary
policy rate and in global uncertainty. We extend it by including also the effect of cross-border flows to non-banks and analyze how it compares to the transmission mechanism of cross-border bank flows to the domestic real economy.

As previously mentioned, our work tries to quantify empirically the transmission mechanism from global financial shocks to domestic financial and macroeconomic variables. Thus, it also relates to theoretical models that attempt to explain this transmission mechanism. 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, which is further amplified through the exchange rate depreciation and the currency mismatch between external funding in dollars and loans in domestic currency. Other models that consider transmission mechanism of capital flows in an environment with price rigidity and financial frictions in small open economies find the optimal use of monetary and macroprudential policies to 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 describes the empirical model used for the analysis, section 3 presents the Gibbs Sampling algorithm for estimating the model, section 4 shows the data description, section 5 discusses the main results and section 6 concludes.

2 The model

We assume in this section that each economy can be modeled as an individual Vector Autorregressive (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.

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:

\[
y_{n,t} = \sum_{l=1}^{P} B'_{n,l} y_{n,t-l} + \sum_{l=0}^{P} B^*_{n,l} y^*_{t-l} + \Delta_n z_t + u_{n,t} \tag{1}
\]
where $y_{nt}$ 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, $u_{nt}$ is a $M_1 \times 1$ vector of reduced form shocks such that $u_{nt} \sim N(0, \Sigma_n)$, $E(u_{nt}u'_{nm,t}) = 0, n \neq m \in \{1, \ldots, N\}$, $p$ 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

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

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

The complete system (1)-(2) is a Panel VAR with an exogenous block. 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 B.

### 2.1 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:

$$p(\beta_n | \beta, O_n, \tau) = N(\beta, \tau O_n)$$

with $\beta$ as the common mean and $\tau$ as the overall tightness parameter. The covariance matrix $O_n$ takes the form of the typical Minnesota prior (Litterman, 1986), i.e. $O_n = diag(\sigma^2)$ such that

$$o_{ij,l} = \begin{cases} \frac{1}{\phi_3} & , i = j \\ \frac{\sigma^2}{\phi_3} & , i \neq j \\ \phi_2, & \text{exogenous} \end{cases}$$

where $i, j \in \{1, \ldots, M_1\}$ and $l = 1, \ldots, p$.
and where $\hat{\sigma}_j^2$ 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:

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

(5)

In a standard Bayesian context, $\overline{\beta}$ and $\tau$ 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) we assume an inverse-gamma prior distribution for $\tau$, so that

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

(6)

Finally, we assume the non-informative prior:

$$p(\overline{\beta}) \propto 1$$

(7)

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

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

(8)

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

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

(9)

where

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

See Pérez Forero (2015) for a similar application for Latin America.
and similarly $\hat{\sigma}_j^2$ 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 the covariance matrix of error terms, so that:

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

(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:

$$p(\tau_X) = IG\left(\nu_X, \frac{s_X^2}{2}\right) \propto \tau_X^{-\nu_X/2} \exp\left(-\frac{1}{2} s_X^2/\tau_X\right)$$

(11)

3 Bayesian Estimation

Given the specified priors (19) and the joint likelihood function ($B.1$), we combine efficiently these two pieces of information in order to get the estimated parameters included in $\Theta$. Using the Bayes’ theorem we have that:

$$p(\Theta | Y) \propto p(Y | \Theta) p(\Theta)$$

(12)

Our target is now to maximize the right-hand side of equation (12) in order to get $\Theta$. The common practice in Bayesian Econometrics (see e.g. Koop (2003) and Canova (2007) among others) is to simulate the posterior distribution (20) in order to conduct statistical inference. This is since any object of interest that is also a function of $\Theta$ 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.

3.1 A Gibbs sampling routine

In general, in every Macro-econometric model it is difficult to sample from the posterior distribution $p(\Theta | Y)$. 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 (20) appropriately. 

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

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

1. Draw \( p(\beta^* | \Theta/\beta^*, y^*, y_n) \). If the candidate draw is stable keep it, otherwise discard it.

2. For \( n = 1, \ldots, N \) draw \( p(\beta_n | \Theta/\beta_n, y^*, y_n) \). If the candidate draw is stable keep it, otherwise discard it.

3. Draw \( p(\Sigma^* | \Theta/\Sigma^*, y^*, y_n) \).

4. For \( n = 1, \ldots, N \) draw \( p(\Sigma_n | \Theta/\Sigma_n, y^*, y_n) \).

5. Draw \( p(\tau_X | \Theta/\tau_X, Y) \).

6. Draw \( p(\beta | \Theta/\beta, Y) \). If the candidate draw is stable keep it, otherwise discard it.

7. Draw \( p(\tau | \Theta/\tau, Y) \).

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 \( \Theta \).

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 the 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 C 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

\[ p(\tau) \propto \tau^{-1/2} \]  \hspace{1cm} (13)

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

Regarding the Minnesota-style 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, \( \phi_1 \) is related with a priori difference between own lags and lags of other variables; \( \phi_2 \) is related with the a priori heteroskedasticity coming from exogenous variables; 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 autoregressive parameter of 0.9 for the prior mean of the first lag of the own variable in each VAR equation.

4 Data Description and Identification Strategy

4.1 Data Description

4.2 Identification of structural shocks

We use sign restrictions in order to compute the impulse responses using the output of the Gibbs Sampling estimation of the Panel VAR model, taking into account that the exogenous block serves also as an extension of the information set for the econometrician, as it mitigates the risk associated with the presence of the omitted variable bias for the domestic block.

\footnote{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.}
4.3 Identification assumptions

The identification of Global Financial shocks is as follows: we have two types of restrictions, as 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 reflects a tighter monetary policy, reflected in a rise in long term interest rate, ii) a reduction in uncertainty given by this policy action, reflected in a fall in the VIX, iii) a fall in commodity prices derived from a tight monetary policy. We do not restrict the remaining variables, neither in the exogenous block, nor in the domestic block.

<table>
<thead>
<tr>
<th>Var / Shock</th>
<th>Name</th>
<th>Global Financial shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic Block</td>
<td>( y )</td>
<td>?</td>
</tr>
<tr>
<td>Consumer Price Index</td>
<td>( CPI_{US} )</td>
<td>?</td>
</tr>
<tr>
<td>Industrial Production</td>
<td>( IP_{US} )</td>
<td>?</td>
</tr>
<tr>
<td>LIBOR 3-month</td>
<td>( LIBOR3M )</td>
<td>( \leq 0 )</td>
</tr>
<tr>
<td>10-year yield (TB)</td>
<td>( 10y )</td>
<td>( \geq 0 )</td>
</tr>
<tr>
<td>VIX</td>
<td>( VIX )</td>
<td>( \leq 0 )</td>
</tr>
<tr>
<td>Commodity prices</td>
<td>( P_{com} )</td>
<td>( \leq 0 )</td>
</tr>
</tbody>
</table>

Table 1: Identifying Restrictions

The identification restrictions shown in Table 1 are only associated with a particular shock. As a result, the remaining shocks 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 (?).
4.3.1 The algorithm

In this stage we use as an input the estimation output from 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\(^3\):

1. Set first \( K = 2,000 \) number of draws.

2. Draw \((\beta_k^*, \Sigma_k^*)\) from the posterior distribution (foreign block) and get \((A_0^*)_k = (P^*)^{-1}\) from the Cholesky decomposition of \(\Sigma_k^* = P^* (P^*)'\).

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

4. Construct the matrix:

\[
\bar{Q}^* = \begin{bmatrix}
I_{k^*} & 0_{(k^* \times M_2 - k^*)} \\
0_{(M_2 - k^* \times k^*)} & Q^*
\end{bmatrix}
\]

That is, a subset of \(k^* < n^*\) variables in \((y^*)\) 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 \(X \sim N(0, I_{M_1})\) and get \(Q\) such that \(QR = X\), i.e. an orthogonal matrix \(Q\) that satisfies the QR decomposition of \(X\). The random matrix \(Q\) has the uniform distribution with respect to the Haar measure on \(O(n)\).

7. Construct the matrix:

\[
\bar{Q} = \begin{bmatrix}
I_k & 0_{(k \times M_1 - k)} \\
0_{(M_1 - k \times k)} & Q
\end{bmatrix}
\]

\(^3\)See Uhlig (2005), among others.
That is, a subset of $k < n$ variables in $(y)$ are going to be slow and therefore they do not rotate. This how we impose zero restrictions in this case.

8. Compute the matrices $\mathbf{A}_{n,0} = (\mathbf{A}_{n,0})_k \mathbf{Q}$ and $\mathbf{A}^*_0 = (\mathbf{A}^*_0)_k \mathbf{Q}^*$, then recover the system (14) 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.

5 Results

Our results are qualitatively consistent with the transmission mechanism depicted by Aoki et al. (2018). Figure 1 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.
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. 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. Hence, we observe a reduction in the loan-to-deposit ratio.

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.

![Graphs of Inflation, GDP, TotalClaims, Debt, IntRate, Depreciation](image)

**Figure 2: 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 2 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-banks 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.

Finally, the reaction of the loan-to-deposit ratio is also consistent with the arguments described above. Those countries with higher reliance on financing through the banking sector, such as Peru, show the largest reduction in the loan-to-deposit ratio.

6 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 ?, 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.

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.
A Data Description

In this section we present the plots from the data described in section 4, the one that covers the period 2001:12-2017:01. The variables in figures are already transformed, i.e. we show how they enter to the empirical model.

A.1 Domestic variables

Figure 3: Brazilian Data
Figure 4: Chilean Data

Figure 5: Colombian Data
Figure 6: Mexican Data

Figure 7: Peruvian Data
A.2 Exogenous variables

Figure 8: Exogenous Data

B The Panel VAR as a linear regression model with normality

B.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:

$$
\begin{bmatrix}
I_{M_1} & -B_{n,0}' \\
0 & I_{M_2}
\end{bmatrix}
\begin{bmatrix}
y_{n,t} \\
y_t^*
\end{bmatrix}
= \sum_{l=1}^{p}
\begin{bmatrix}
B_{n,l}' & B_{n,l}'^* \\
0 & \Phi_{l}^*
\end{bmatrix}
\begin{bmatrix}
y_{n,t} \\
y_t^*
\end{bmatrix} +
\begin{bmatrix}
\Delta_{n} \\
\Delta^*
\end{bmatrix}
\begin{bmatrix}
\Sigma_{n} & 0 \\
0 & \Sigma^*
\end{bmatrix}
\begin{bmatrix}
u_{n,t} \\
u_t^*
\end{bmatrix}
$$

System (1) represents the small open economy in which its dynamics are influenced by the big economy block (2) through the parameters $B_{n,l}'$ and $\Phi_{l}^*$. 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

$$Y_n = X_n B_n + U_n$$  \hspace{1cm} (15)

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 (15) can be re-written such that

$$y_n = (I_{M_1} \otimes X_n) \beta_n + u_n$$

where $y_n = vec(Y_n)$, $\beta_n = vec(B_n)$ and $u_n = vec(U_n)$ with

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

Under the normality assumption of the error terms, we have the likelihood function for each country

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

which is
\[ p (y_n \mid \beta_n, \Sigma_n) = (2\pi)^{-M_1(T_n-p)/2} |\Sigma_n \otimes I_{T_n-p}|^{-1/2} \times \exp \left( -\frac{1}{2} (y_n - (I_{M_1} \otimes X_n) \beta_n)' (\Sigma_n \otimes I_{T_n-p})^{-1} (y_n - (I_{M_1} \otimes X_n) \beta_n) \right) \] (16)

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 \( K^* = M_2p + W \) and the corresponding parameter matrix \( \Phi^* (K^* \times M_2) \), and in particular:

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

The regression model can then be re-written such that

\[ y^* = (I_{M_2} \otimes X^*) \beta^* + u^* \]

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

\[ u^* \sim N (0, \Sigma^* \otimes I_{T^*-p}) \]

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

\[ p (y^* \mid \beta^*, \Sigma^*) = N ((I_{M_2} \otimes X^*) \beta^*, \Sigma^* \otimes I_{T^*-p}) \]

which is

\[ p (y^* \mid \beta^*, \Sigma^*) = (2\pi)^{-M_2(T^*-p)/2} |\Sigma^* \otimes I_{T^*-p}|^{-1/2} \times \exp \left( -\frac{1}{2} (y^* - (I_{M_2} \otimes X^*) \beta^*') (\Sigma^* \otimes I_{T^*-p})^{-1} \times (y_n - (I_{M_2} \otimes X^*) \beta^*) \right) \] (17)
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

\[
p(y, y^* | \Theta) \propto |\Sigma^*|^{-T^*/2} \prod_{n=1}^N |\Sigma_n|^{-T_n/2} \times \exp \left( -\frac{1}{2} \sum_{n=1}^N \left( y_n - (I_{M_1} \otimes X_n) \beta_n \right)' (\Sigma_n \otimes I_{T_n-p})^{-1} \times \right. \\
\left. \left( y_n - (I_{M_1} \otimes X_n) \beta_n \right) - \frac{1}{2} \left( y^* - (I_{M_2} \otimes X^*) \beta^* \right)' (\Sigma^* \otimes I_{T^*-p})^{-1} \times \right. \\
\left. \left( y_n - (I_{M_2} \otimes X^*) \beta^* \right) \right)
\]

(18)

### B.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 \( \Theta \), such that:

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

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

\[
p(\Theta) \propto \prod_{n=1}^N p(\Sigma_n) p(\beta_n | \overline{\beta}, O_n, \tau) p(\tau) \\
= \prod_{n=1}^N |\Sigma_n|^{-\frac{1}{2}(M_1+1)} \times \\
\tau^{-\frac{NM_1K_1}{2}} \exp \left( -\frac{1}{2} \sum_{n=1}^N (\beta_n - \overline{\beta})' (\tau^{-1}O_n)^{-1} (\beta_n - \overline{\beta}) \right) \times \\
\tau^{-\frac{\nu+2}{2}} \exp \left( -\frac{1}{2} s \right) \times \\
|\Sigma^*|^{-\frac{1}{2}(M_2+1)} \times \\
\tau_X^{-\frac{M_2K_2^*}{2}} \exp \left( -\frac{1}{2} (\beta^* - \overline{\beta^*})' (\tau_X^{-1}O_X)^{-1} (\beta^* - \overline{\beta^*}) \right) \times \\
\tau_X^{-\frac{\nu_X+2}{2}} \exp \left( -\frac{1}{2} s_X \right)
\]

(19)
B.3 Posterior distribution of parameters

Given (B.1) and (19), the posterior distribution (12) takes the form:

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

\[
\prod_{n=1}^{N} |\Sigma_n|^{-\frac{T_n + M_1 + 1}{2}} \times \exp \left( -\frac{1}{2} \sum_{n=1}^{N} \left( y_n - (I_{M_1} \otimes X_n) \beta_n \right)' \left( \Sigma_n \otimes I_{T_n - p} \right)^{-1} \left( y_n - (I_{M_1} \otimes X_n) \beta_n \right) 
- \frac{1}{2} \left( y^* - (I_{M_2} \otimes X^*) \beta^* \right)' \left( \Sigma^* \otimes I_{T^* - p} \right)^{-1} \left( y^* - (I_{M_2} \otimes X^*) \beta^* \right) 
+ \tau^{-1} \left( \Sigma^* - \tau \Sigma^* \right) \left( \beta^* - \Sigma^* \beta^* \right) + s \right) \frac{1}{\tau} \times 
\tau^{-\frac{(NM_1 + s_1)\tau}{2}} \exp \left( -\frac{1}{2} \left( \beta_n - \beta \right)' O_n^{-1} \left( \beta_n - \beta \right) + s \right) \frac{1}{\tau} \times 
\tau^{-\frac{(M_2 K + s_X)\tau}{2}} \exp \left( -\frac{1}{2} \left( \beta^* - \beta^* \right)' O_X^{-1} \left( \beta^* - \beta^* \right) + s_X \right) \frac{1}{\tau} \right) 
\]

C 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: \( p(\beta^* \mid \Theta / \beta^*, y^*) \): Given the likelihood (B.1) and the prior

\[ p(\beta^* \mid \beta^*, \tau) = N(\beta^*, \tau O_X) \]

then the posterior is Normal

\[ p(\beta^* \mid \Theta / \beta^*, y^*) = N(\tilde{\beta}^*, \tilde{\Lambda}^*) \]

with

\[ \tilde{\Lambda}^* = (\Sigma^{-1} \otimes X^* X^* + \tau_X^{-1} O_X^{-1})^{-1} \]

\[ \tilde{\beta}^* = \tilde{\Lambda}^* (\Sigma^{-1} \otimes X^* (y^*) + \tau_X^{-1} O_X^{-1} \beta^*) \]
2. Block 2: \( p(\beta_n \mid \Theta/\beta_n, y_n) \): Given the likelihood (B.1) and the prior

\[
p(\beta_n \mid \beta, \tau) = N(\beta, \tau O_n)
\]

then the posterior is Normal

\[
p(\beta_n \mid \Theta/\beta_n, y_n) = N(\tilde{\beta}_n, \tilde{\Delta}_n)
\]

with

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

\[
\tilde{\beta}_n = \tilde{\Delta}_n \left( \left( \Sigma_n^{-1} \otimes X_n' \right) y_n + \tau^{-1}O_n^{-1} \beta \right)
\]

Block 3: \( p(\Sigma^* \mid \Theta/\Sigma^*, y^*) \): Given the likelihood (B.1) and the prior

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

Denote the residuals

\[
U^* = Y^* - X^* B^*
\]

as in equation (15). Then the posterior variance term is Inverted-Wishart centered at the sum of squared residuals:

\[
p(\Sigma^* \mid \Theta/\Sigma^*, y^*) = IW \left( U'^*U^*, T^* \right)
\]

Block 4: \( p(\Sigma_n \mid \Theta/\Sigma_n, y_n) \): Given the likelihood (B.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 (15). Then the posterior variance term is Inverted-Wishart centered at the sum of squared residuals:

\[ p(\Sigma_n | \Theta/\Sigma_n, y_n) = IW \left( U_n'U_n, T_n \right) \]

Block 5: \( p(\tau_X | \Theta/\tau_X, Y) \): Given the priors

\[ p(\tau_X) = IG(s, v) \propto \tau_X^{-\frac{v+2}{2}} \exp \left( -\frac{1}{2} \frac{s}{\tau_X} \right) \]

\[ p(\beta_n | \beta, O_n, \tau) = N (\beta, \tau O_n) \]

then the posterior is

\[ p(\tau_X | \Theta/\tau_X, Y) = IG \left( \frac{M_2K + v_X}{2}, \frac{\sum_{n=1}^N (\beta_n - \beta)' O_n^{-1} (\beta_n - \beta) + s_X}{2} \right) \]

Block 6: \( p(\beta | \Theta/\beta, Y) \): Given the prior

\[ p(\beta_n | \beta, O_n, \tau) = N (\beta, \tau O_n) \]

by symmetry

\[ p(\beta | \beta_n, O_n, \tau) = N (\beta, \tau O_n) \]

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

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

with

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

\[ \overline{\beta} = \overline{\Delta} \left[ \sum_{n=1}^N \tau^{-1} O_n^{-1} \beta_n \right] \]
Block 7: $p(\tau | \Theta/\tau, Y)$: Given the priors

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

$$p(\beta_n | \bar{\beta}, O_n, \tau) = N(\bar{\beta}, \tau O_n)$$

then the posterior is

$$p(\tau | \Theta/\tau, Y) = IG \left( \frac{NM_1K + v}{2}, \frac{\sum_{n=1}^{N} (\beta_n - \bar{\beta})' O_n^{-1} (\beta_n - \bar{\beta}) + s}{2} \right)$$

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

D Impulse responses details

For each draw of $\Theta$ from the posterior distribution, we compute the companion form of the compact model as in equation (15). Then we compute the median value and the 68% credible interval for each impulse response. Results are shown below.
Figure 9: Global Financial shocks effects in Brazil, median value and 68% confidence interval
Figure 10: Global Financial shocks effects in Chile, median value and 68% confidence interval
Figure 11: Global Financial shocks effects in Colombia, median value and 68% confidence interval
Figure 12: Global Financial shocks effects in Mexico, median value and 68% confidence interval
Figure 13: Global Financial shocks effects in Peru, median value and 68% confidence interval
E  Posterior distribution of hyperparameters

Figure 14: Posterior distribution of $\sqrt{\tau_X}$
Figure 15: Posterior draws of $\tau_X$
Figure 16: Posterior distribution of $\sqrt{\tau}$
Figure 17: Posterior draws of $\tau$
References


