FX Volatility LATAM: Common and Idiosyncratic Factors

XXXIX Encuentro de Economistas del BCRP

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The views expressed are those of the author and do not necessarily reflect those of the Central Bank of Peru.

November 23, 2021

Contents

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- In this context, our particular interest is to capture the common volatility component for LATAM currencies, and to determine the fraction of total volatility explained by this factor. This will give us a clear idea on how much of the exchange rate volatility is due to international or domestic factors.

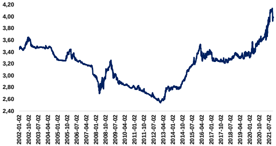
Figure: **Exchange Rate Data - LATAM (2002-2021)**

(a) Brazil

(b) Chile

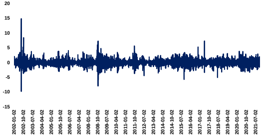
(c) Colombia

(d) Mexico

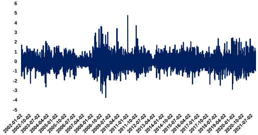


(e) Peru

Figure: **Exchange Rate Returns Data - LATAM (2002-2021)**



(a) Brazil



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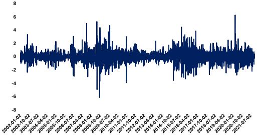

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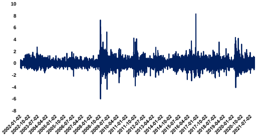
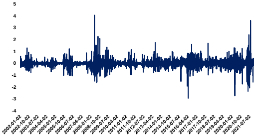


(d) Mexico



(e) Peru

Literature Review

- Synchronization of Currencies Financial Crises: Fratzscher (2009), Coudert *et al.* (2011)
- Co-jumps in volatility: Bollerslev *et al.* (2008), Clements and Lia (2013)
- Stochastic volatility and common drifting: Qu and Perron (2013), Laurini and Mauad (2015), Carriero *et al.* (2016), Lee *et al.* (2017).
- Bayesian Simulation of Linear State-Space Systems: Carter and Kohn (1994), Durbin and Koopman (2002).
- Stochastic volatility and Linear State Space Simulation: Jacquier *et al.* (1994), Kim *et al.* (1998), Del Negro and Primiceri (2015).

Main Findings

- Exchange volatility in LATAM is highly synchronized, although there are domestic factors that also play a role.
- The estimated global factor is highly correlated with other global measures of uncertainty, such as the VIX.
- Our estimated common factor explains a large portion of total volatility for each country under study, especially during the GFC of 2008, the Taper Tantrum of 2013 and the recent Covid-19 Pandemic episode.
- In most of the cases, a higher idiosyncratic volatility can be related with electoral periods.

A Stochastic Volatility Model for the ER daily returns

Let: $r_{i,t} = 100 * (e_{i,t} - e_{i,t-1})/e_{i,t-1}$ for each $i = 1, \ldots, N$:

$$r_{i,t} = \alpha_i + exp(\frac{b_i h_t}{2} + \frac{h_{i,t}}{2})v_t, \qquad v_{i,t} \sim i.i.d.N\,(0,1)$$

where the common volatility factor h_t is given by:

$$h_t = h_{t-1} + \eta_t, \qquad \eta_t \sim i.i.d.N\left(0, \sigma_\eta^2\right)$$

and the idiosyncratic volatility $h_{i,t}$ is given by:

$$h_{i,t} = h_{i,t-1} + \epsilon_{i,t}, \qquad \epsilon_{i,t} \sim i.i.d.N\left(0, \sigma_{\epsilon_i}^2\right)$$

- b_i: Loading parameter
- α_i: intercept coefficient
- t: daily frequency

Table of Contents

Bayesian Estimation

- The model can be re-written as a state-space system with an exogenous component and time varying matrices (Kim and Nelson, 1999), so that:

$$y_t = D_t\alpha_t + Z_t X_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, H_t)$$

$$\alpha_t = A_t\alpha_{t-1} + R_t\eta_t, \qquad \eta_t \sim N(0, Q_t)$$

- Posterior simulation of vector α_t is performed following Carter and Kohn (1994) and Durbin and Koopman (2002).
- Because of Stochastic Volatility, the measurement equation is linearly approximated following Kim *et al.* (1998) with the correction of Del Negro and Primiceri (2015), i.e. the error term ε_t follows a $log\chi^2$ distribution and its approximated using a mixture of 7 normals.

Bayesian Estimation

Denote $\psi = \left(\Theta, \alpha^T\right)$ as the parameter set of the model, then the complete posterior distribution is:

$$p\left(\psi \mid y^T\right) = p\left(\Theta, \alpha^T \mid y^T\right) \propto p\left(\Theta\right) p\left(\alpha_0\right) \prod_{t=1}^{T} p\left(y_t \mid \alpha_t, \Theta\right) p\left(\alpha_t \mid \alpha_{t-1}, \Theta\right)$$

where $\alpha_t = \left[h_t, \{h_{i,t}\}_{i=1}^{N}\right]'$

Priors

- We set the prior distribution as follows:

Parameter	Distribution	Hyper-parameters
$h_{i,0}$	Normal	$N\left(0, V_h\right)$
h_0	Normal	$N\left(0, V_h\right)$
σ_η^2	Inverse-Gamma	$IG\left(d_0 \times \underline{\sigma}^2, d_0\right)$
$\sigma_{\epsilon_i}^2$	Inverse-Gamma	$IG\left(d_0 \times \underline{\sigma}^2, d_0\right)$
b_i	Normal	$N\left(\underline{b}, V_b\right)$
α_i	Normal	$N\left(0, V_\alpha\right)$

Table: Prior Distribution for the parameter set

- where $V_h = 1000$, $V_\alpha = 10$, $\underline{b} = 0.5$, $V_b = \underline{b}/9$, $\underline{\sigma}^2 = 0.1$ and $d_0 = 10$

Data

- We use ER returns data: Brazil, Chile, Colombia, Mexico and Peru
- Frequency: Daily
- Sample: 2002/01/02 - 2021/10/31
- Source: Reuters

Gibbs Sampling

1. Simulate $\{h_{i,t}\}_{t=1}^{T}$ from $p\left(h_{i,t} \mid r_i^T, \psi_{-h_{i,t}}\right)$ for each $i = 1, \ldots, N$: SS-Volatility
2. Simulate $\{h_t\}_{t=1}^{T}$ from $p\left(h_t \mid r^T, \psi_{-h_t}\right)$: SS-Volatility
3. Simulate σ_η^2 from $p\left(\sigma_\eta^2 \mid r^T, \psi_{-\sigma_\eta^2}\right)$: Inverse-Gamma
4. Simulate $\sigma_{\epsilon_i}^2$ from $p\left(\sigma_{\epsilon_i}^2 \mid r_i^T, \psi_{-\sigma_{\epsilon_i}^2}\right)$ for each $i = 1, \ldots, N$: Inverse-Gamma
5. Simulate b_i from $p\left(b_i \mid r_i^T, \psi_{-b_i}\right)$ for each $i = 1, \ldots, N$: Metropolis-Hastings step
6. Simulate α_i from $p\left(\alpha_i \mid r_i^T, \psi_{-\alpha_i}\right)$ for each $i = 1, \ldots, N$: Conditional Linear Regression
7. Simulate s_i from $p\left(s_{ii} \mid r_i^T, \psi_{-s_i}\right)$ for each $i = 1, \ldots, N$: Discrete Distribution

Estimation Setup

- We run the Gibbs sampler for $K = 100,000$ and discard the first $50,000$ draws in order to minimize the effect of initial values.
- In order to reduce the serial correlation across draws, we set a thinning factor of 50. As a result, we have $1,000$ draws for conducting inference.
- The acceptance rate of the metropolis-step associated with b_i is around 25% for each $i = 1, \ldots, N$.

Contents

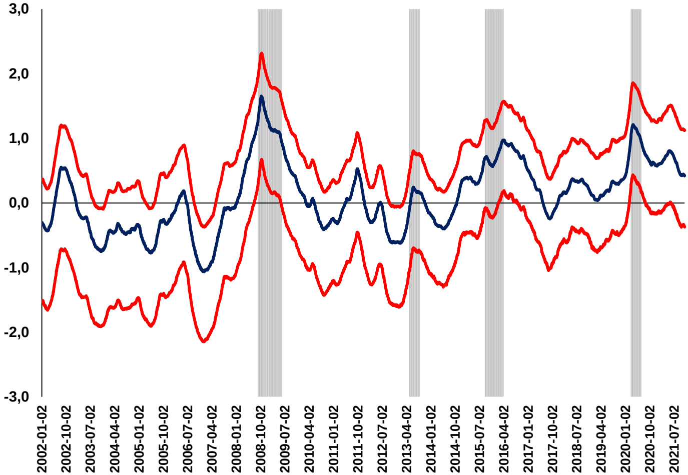
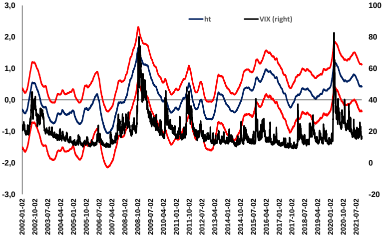
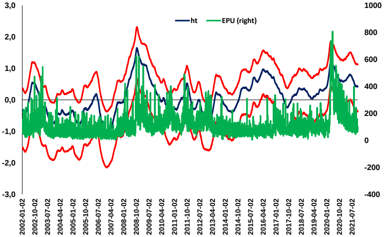


Figure: Log-Common Factor Volatility (h_t)

Figure: **Log-Common Factor Volatility and Volatility Indexes**



(a) VIX



(b) EPU-US

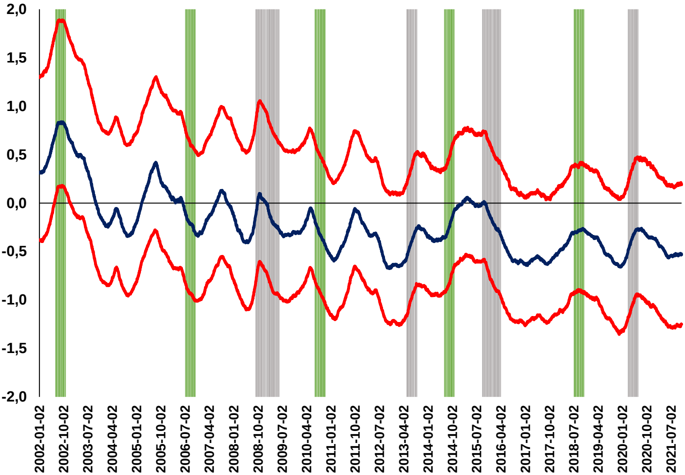


Figure: Log-Idiosyncratic Volatility - Brazil

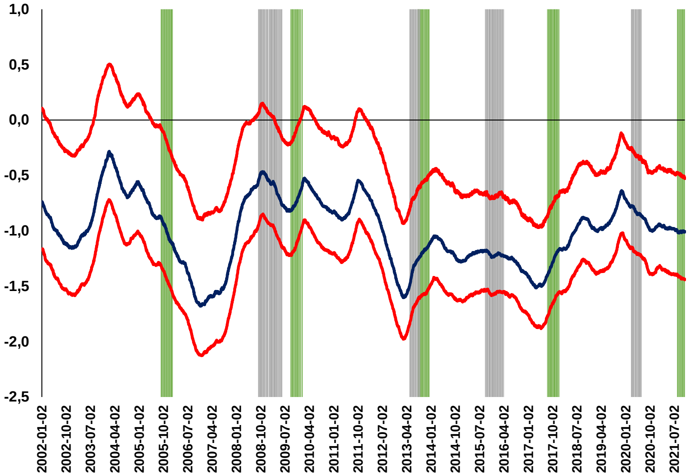


Figure: Log-Idiosyncratic Volatility - Chile

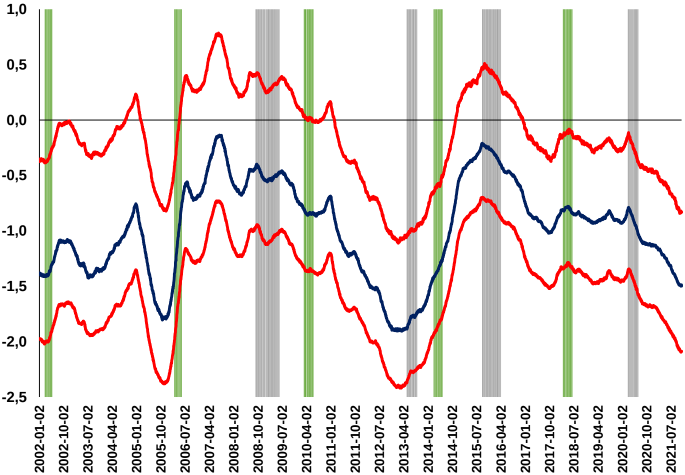


Figure: Log-Idiosyncratic Volatility - Colombia

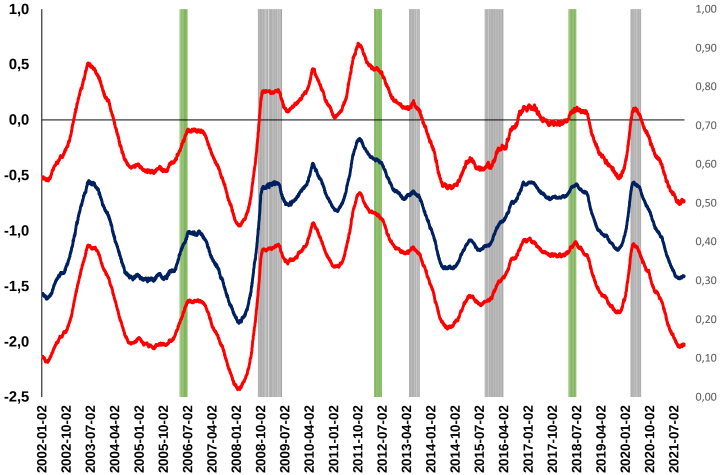


Figure: Log-Idiosyncratic Volatility - Mexico

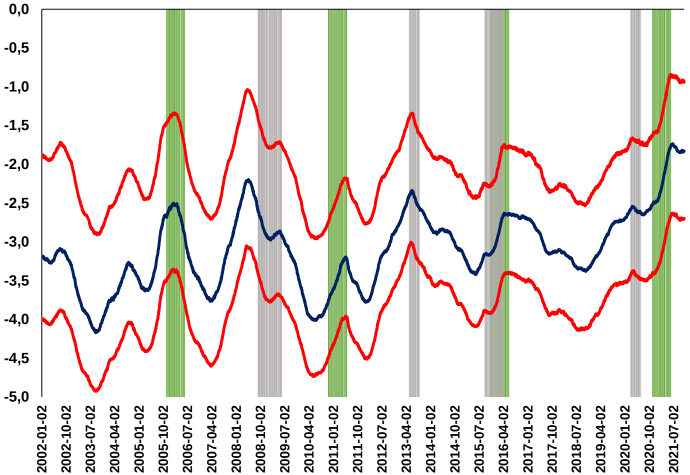
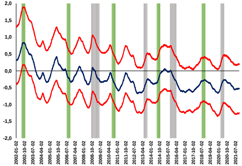
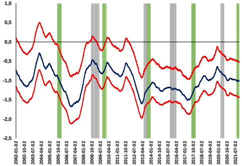


Figure: Log-Idiosyncratic Volatility - Peru

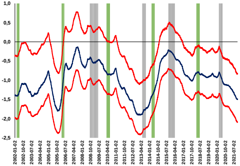
Figure: **Log-Idiosyncratic Volatility**



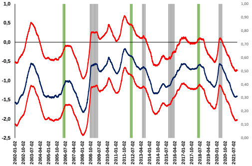
(a) Brazil



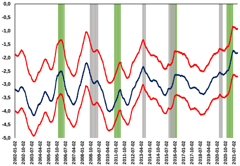
(b) Chile



(c) Colombia



(d) Mexico



(e) Peru

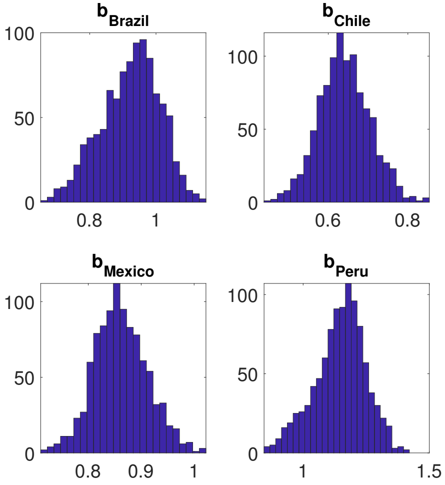


Figure: Posterior Distribution of Loading parameters (b_i)

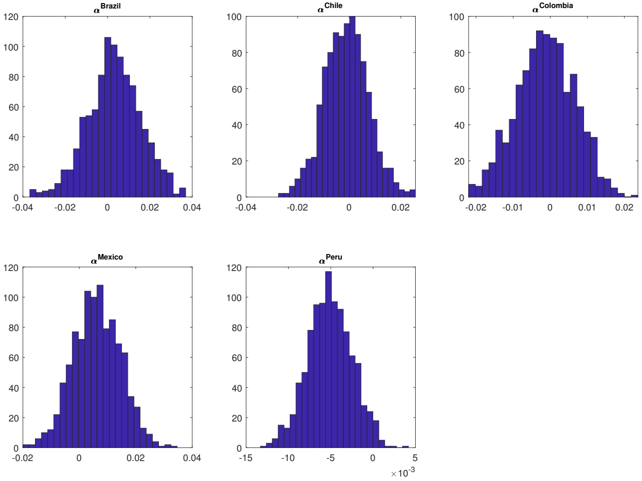


Figure: Posterior Distribution of Intercept coefficients (α_i)

Contents

An Indicator of Relative Contribution

- With the aim of capturing the relative contribution of each factor, we construct for each $i = 1, \ldots, N$ an indicator as follows

$$I_{i,t} = \frac{exp\left(\frac{b_i * h_t}{2}\right)}{exp\left(\frac{h_{i,t}}{2}\right)} \tag{1}$$

- When $I_{i,t} > 1$, the contribution of the global factor is relatively higher with respect to the idiosyncratic one.
- We can test the null hypothesis that $H_0 : I_{i,t} = 1$ for each case.

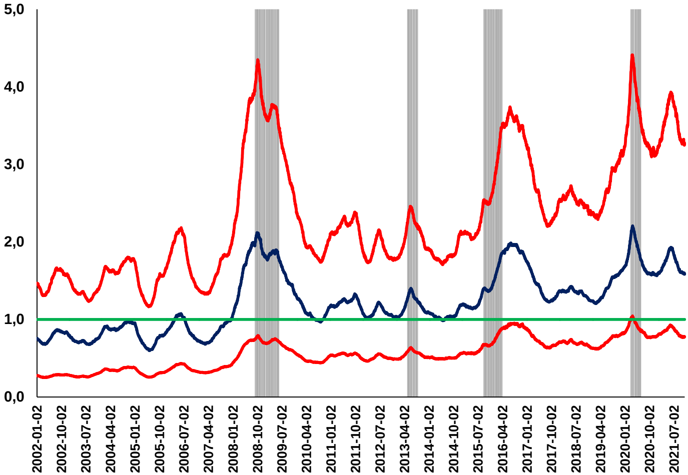


Figure: Relative Contribution Indicator - Brazil

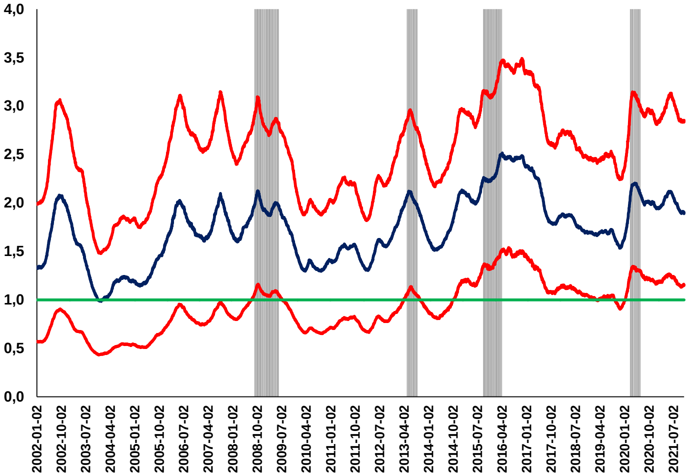


Figure: Relative Contribution Indicator - Chile

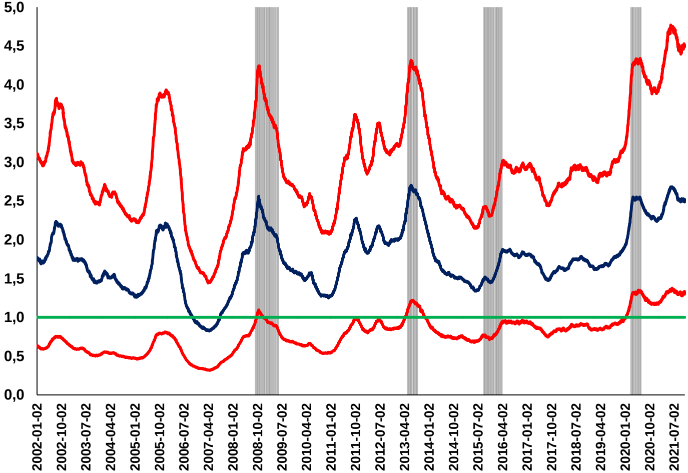


Figure: Relative Contribution - Colombia

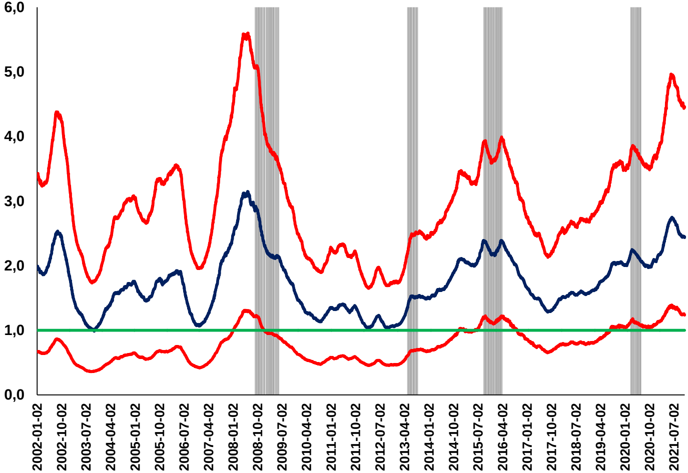


Figure: Relative Contribution - Mexico

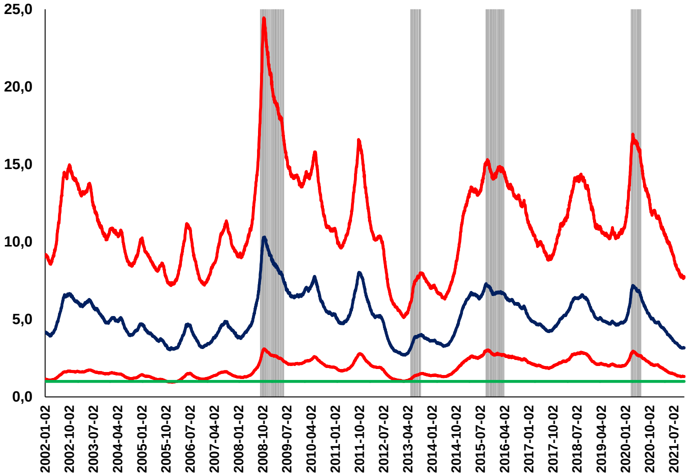
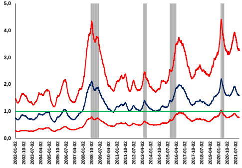
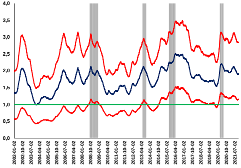


Figure: Relative Contribution - Peru

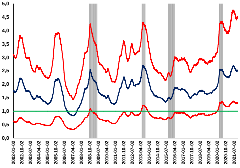
Figure: **Relative Contribution Indicator**



(a) Brazil



(b) Chile



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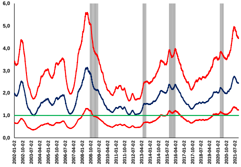

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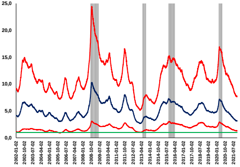

(e) Peru

Final Remarks

- Exchange volatility in LATAM is highly synchronized, although there are domestic factors that also play a role.
- The estimated global factor is highly correlated with other global measures of uncertainty, such as the VIX.
- Our estimated common factor explains a large portion of total volatility for each country under study, especially during the GFC of 2008, the Taper Tantrum of 2013 and the recent Covid-19 Pandemic episode.
- In most of the cases, a higher idiosyncratic volatility can be related with electoral periods.
- **Research Agenda**
    - The differences both in the weight of the global factor and in idiosyncratic volatility deserve a more in-depth explanation. A first idea is related to the specific characteristics of each market, capital flows, as well as to the exchange intervention carried out by each central bank.
    - The comparison of idiosyncratic volatility with local political uncertainty indexes.
    - The comparison between the global factor and DXY volatility.

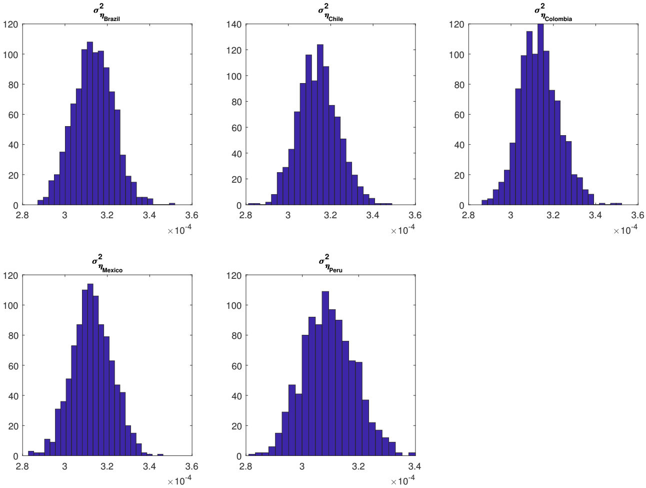

Figure: Posterior Distribution of Variance parameters (σ^2_η)

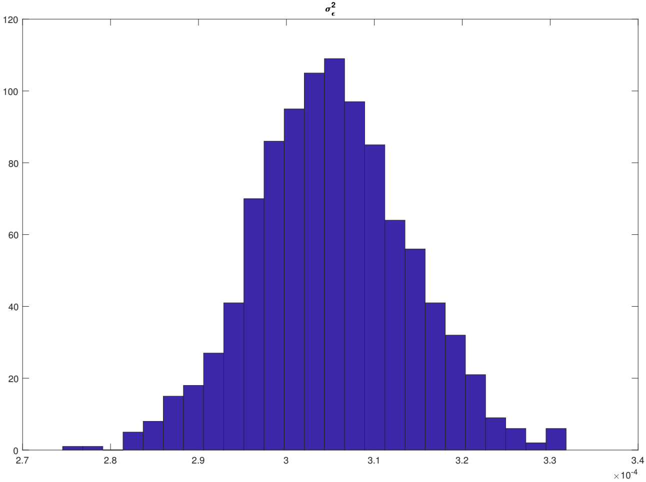

Figure: Posterior Distribution of Variance parameters (σ_η^2)

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