Comparing the Transmission of Monetary Policy Shocks in Latin America: A Hierarchical Panel VAR *

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Abstract

This paper assesses and compares the effects of monetary policy shocks across Latin American countries that put in practice the Inflation Targeting scheme (Brazil, Chile, Colombia, Mexico and Peru). An estimated Hierarchical Panel VAR allows us to use the data efficiently and, at the same time, exploit the heterogeneity across countries. Monetary shocks are identified through an agnostic procedure that imposes zero and sign restrictions. We find a real short run effect of monetary policy on output (with a peak around 12-15 months); a significant medium run response of prices with the absence of the so-called *price puzzle* and a hump-shaped response of the exchange rate, i.e. weak evidence of the so-called *delayed overshooting puzzle* phenomenon. Nevertheless, we find some degree of heterogeneity on the impact and propagation of monetary shocks across countries. In particular, we find stronger effects on output and prices in Brazil and Peru relative to Chile, Colombia and Mexico and a stronger reaction of the exchange rate in Brazil, Chile and Colombia relative to Mexico and Peru. Finally, we present a weighted-averaged impulse response after a monetary shock, which is representative for the region.

JEL Classification: E43, E51, E52, E58

Key words: Panel Vector Autoregressions, Sign Restrictions, Bayesian Hierarchical models

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1 Introduction

After some years of the Financial Liberalization episode in 1990s, many Latin American economies have adopted the Inflation Targeting (IT) framework for monetary policy (see Mishkin and Savastano (2001) and Quispe-Agnoli (2001) for a deep discussion of the different existing alternatives at that moment), thus following the lead of many developed countries such as New Zealand, Sweden, etc. Among Latin American countries, the most successful were Brazil, Chile, Colombia, Mexico and Peru[1]. One of the main features of the adopted scheme is the fact that the monetary authority uses the short-term interest rate as the main policy instrument. In this paper we explore the effectiveness of monetary policy actions through interest rates for the IT period in each of these countries. That is, we evaluate to what extent monetary policy can cause i) real short run effects in economic activity and ii) significant movements in prices in the medium run. In addition, by comparing these dynamic effects across Latin American ITers (LA5 Countries), we study to what extent they differ in terms of impact and propagation. The latter is a relevant exercise for policy design, since it delivers important information about the transmission mechanism of monetary policy in Latin America.

Inflation Targeting adoption in Latin America has been widely discussed in the past. For instance, Corbo (2000) and Corbo and Schmidt-Hebbel (2001) study the stabilization and disinflation period previous to the adoption of IT. In the same line, Broto (2008) finds that IT adoption is associated with a lower level and volatility of inflation. Moreover, Chang (2008) study the implementation of an Inflation Targeting in Latin America and find a significant deviation from the tradition scheme because of Foreign Exchange Intervention and Reserve accumulation. This is a particular case for Latin American

[1] Coincidentally and according to the Global Projection Model (GPM) of the International Monetary Fund (IMF)(Carabenciov et al., 2013), the block named 'Latin America' includes these five economies as the most representative of the region, i.e. the LA5 countries as in Canales-Kriljenko et al. (2010).

Economies, where the Financial System is partially dollarized[2]. Despite that considerable deviation, monetary policy has been working well and inflation expectations remain anchored to the target. In more recent references, we have that Hosftetter (2011) discusses the potential benefits of adopting a monetary union among Latin America ITers; De Mello and Moccero (2011) find that the IT regime has been associated with great responsiveness of the monetary authority to inflation expectations and, at the same time, lower interest rate volatility but in output; Barajas et al. (2014) estimate regime switching taylor rules for these countries and find that there is a period of parameter instability between 2008-2009 and finally, Mariscal et al. (2014) focus their attention on the credibility of the IT framework studying the evolution of expectations and asking to what extent they are well anchored. They find an increase in monetary policy credibility during the IT period, despite expectations are not fully anchored.

On the empirical side, there exists SVAR-based evidence about the effects of monetary shocks for these LA5 countries separately. Céspedes et al. (2005), Soares-Sales and Tannuri-Pianto (2007), Mendonca et al. (2008), Catão and Pagan (2010), Rocha Lima et al. (2011) Glocker and Towbin (2012) cover the case of Brazil and Parrado (2001), Mies et al. (2002), Catão and Pagan (2010) cover the case of Chile. In addition, the case of Colombia is studied by Echavarría et al. (2007), Ramírez-Vigoya and Rodríguez-Zambrano (2013). Finally, Gaytán-González and González-García (2006), Garcia-Andrés and Torre-Cepeda (2013) cover the case of Mexico and Winkelried (2004), Bigio and Salas (2006), Castillo et al. (2011) and Pérez-Forero and Vega (2014), among others study the case of Peru. It turns out that the impulse responses from these different exercises cannot be easily compared, since the empirical strategy used can be different in several aspects such as the set of variables included, the de-trending procedure used, the identification

[2]Deviations were also caused by the occurrence of the Global Financial Crisis in 2008-09 and the implementation of Macro-Prudential policies (see e.g. Moreno (2011), Terrier et al. (2011), De-Gregorio (2012) and Céspedes et al. (2014), among others).

assumptions, the effective sample included, etc. In addition, we observe mixed results in terms of the significance of the responses of variables such as output, prices and even with common patters as the so-called *price puzzle*. Given this evidence, it clear that we need a different approach in order to get comparable impulse responses across countries.

In this paper we present a unified framework that allows us to compare the impulse responses derived from monetary shocks. In short, the empirical strategy used is as follows. We estimate a Bayesian Hierarchical Panel VAR (see Ciccarelli and Rebucci (2006), Canova and Pappa (2007), Jarociński (2010) and Canova and Dallari (2013)), and we identify policy shocks by imposing zero and sign restrictions. It turns out that comparison across countries is fair, since we apply the same set of identification restrictions to the same set of variables in all these countries. We also control for external variables since, they are an important source of macroeconomic fluctuations in emerging markets (see e.g. Maćkowiak (2007)), especially when the Global Financial Crisis is in the middle of the sample of analysis.

Our main findings are that, on average a monetary policy tightening in LA5 countries produces a significant fall in output in the short run (with a peak around 12-15 months) and on prices in the long run (with a significant response after two years). In addition, we find evidence against the so-called *price puzzle*. Moreover, conditional on the existence of a standard liquidity effect after a monetary policy shock, there exists a mild *delayed overshooting* phenomenon, i.e. a hump-shaped response of the exchange rate, which is in line with the so-called *delayed overshooting puzzle*[3]. Nevertheless, we find some degree of heterogeneity on the impact and propagation of monetary shocks across countries. This is the most important contribution of the paper. In particular, we find stronger effects on output and prices in Brazil and Peru relative to Chile, Colombia and Mexico and a

[3]This literature started with Eichenbaum and Evans (1995) and continued by Kim (2005) and Almuth and Uhlig (2008). Recently Kim et al. (2014) have shown that this was a particular phenomenon for the United States in the decade of 1980.

stronger reaction of the exchange rate in Brazil, Chile and Colombia relative to Mexico and Peru. In line with a textbook approach, the effectiveness of monetary policy is also related with credibility and proper communication, characteristics that are strongly associated with the Inflation Targeting scheme. On the other hand, the exchange rate response can be associated with the intensity of Foreign-Exchange Intervention policies.

The document is organized as follows: section 2 describes the econometric model, section 3 describes the estimation procedure, section 4 explains the identification strategy, section 5 discusses the main results, and section 6 concludes.

2 The Hierarchical Panel VAR model

We assume in this section that each economy can be modeled as an individual Vector Autorregressive (VAR) model. Then we combine efficiently the information of these five economies in order to perform the estimation.

2.1 Setup

Consider the set of countries $n = 1, \ldots, N$, where each country n is represented by a VAR model:

$$y_{n,t} = \sum_{l=1}^{p} B'_{n,l} y_{n,t-l} + \Delta'_n z_t + \Gamma'_n z_{n,t} + u_{n,t} \quad \text{for } t = 1, \ldots, T_n \tag{1}$$

where $y_{n,t}$ is a $M \times 1$ vector of endogenous variables, z_t is a $W \times 1$ vector of exogenous variables common to all countries, $z_{n,t}$ is a $Q_n \times 1$ vector of exogenous variables specific to each country $n \in \{1, \ldots, N\}$, $u_{n,t}$ is a $M \times 1$ vector of reduced form shocks such that $u_{n,t} \sim N(0, \Sigma_n)$, $E(u_{n,t} u_{m,t}) = \mathbf{0}$, $n \neq m \in \{1, \ldots, N\}$, p is the lag length and T_n is the sample size for each country $n \in \{1, \ldots, N\}$.

The latter model can be expressed in a more compact form, so that:

$$Y_n = X_n B_n + Z_n \Gamma_n + U_n \tag{2}$$

Where we have the data matrices $Y_n\,(T_n \times M)$, $X_n\,(T_n \times K)$, $Z_n\,(T_n \times Q_n)$, $U_n\,(T_n \times M)$, with $K = Mp + W$ and the corresponding parameter matrices $B_n\,(K \times M)$ and $\Gamma_n\,(Q_n \times M)$. In particular

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

The model in equation (2) can be rewritten such that

$$\mathbf{y}_n = (I_M \otimes X_n)\,\beta_n + (I_M \otimes Z_n)\,\gamma_n + \mathbf{u}_n$$

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

with

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

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

$$p\left(\mathbf{y}_n \mid \beta_n, \gamma_n, \Sigma_n\right) = N\left((I_M \otimes X_n)\,\beta_n + (I_M \otimes Z_n)\,\gamma_n, \Sigma_n \otimes I_{T_n}\right) \tag{3}$$

The statistical model described by (3) has a joint likelihood function. Denote $\Theta = \left\{\{\beta_n, \gamma_n, \Sigma_n\}_{n=1}^{N}, \overline{\beta}, \tau\right\}$ as the set of parameters, then the likelihood function is

$$p\,(Y \mid \Theta) \propto \prod_{n=1}^{N} |\Sigma_n|^{-\frac{T_n}{2}} \times \exp\begin{pmatrix} -\frac{1}{2}\sum_{n=1}^{N}\left(\mathbf{y}_n - (I_M \otimes X_n)\,\beta_n + (I_M \otimes Z_n)\,\gamma_n\right)' \times \\ \left(\Sigma_n^{-1} \otimes I_{T_n}\right)\left(\mathbf{y}_n - (I_M \otimes X_n)\,\beta_n + (I_M \otimes Z_n)\,\gamma_n\right) \end{pmatrix} \tag{4}$$

2.2 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:

$$p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) = N\left(\overline{\beta}, \tau O_n\right), \; n = 1, \ldots, N \tag{5}$$

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

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

where

$$i, j \in \{1, 2, \ldots, M\} \;\text{ and } l = 1, \ldots, p \tag{7}$$

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

$$p\left(\gamma_n\right) \propto 1 \tag{8}$$

and

$$p\left(\Sigma_n\right) \propto \left|\Sigma_n\right|^{-\frac{1}{2}(M+1)} \tag{9}$$

In a standard Bayesian context, τ and $\overline{\beta}$ 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 τ and $\overline{\beta}$ 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 τ, so that

$$p(\tau) = IG\left(\frac{v}{2}, \frac{s}{2}\right) \propto \tau^{-\frac{v+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\tau}\right) \tag{10}$$

Finally, we assume the non-informative prior:

$$p\left(\overline{\beta}\right) \propto 1 \tag{11}$$

As a result, our statistical model presented has five parameter blocks, so that:

$$\Theta = \left\{\{\beta_n, \gamma_n, \Sigma_n\}_{n=1}^{N}, \overline{\beta}, \tau\right\} \tag{12}$$

and the joint prior is given by (5), (8), (9), (10) and (11), so that

$$\begin{aligned} p(\Theta) \quad &\propto \quad \prod_{n=1}^{N} p(\Sigma_n)\, p\left(\beta_n \mid \overline{\beta}, O_n, \tau\right) p(\tau) \\ &= \quad \prod_{n=1}^{N} |\Sigma_n|^{-\frac{1}{2}(M+1)} \times \\ &\quad\; \tau^{-\frac{NMK}{2}} \exp\left(-\frac{1}{2}\sum_{n=1}^{N}\left(\beta_n - \overline{\beta}\right)'\left(\tau^{-1}O_n^{-1}\right)\left(\beta_n - \overline{\beta}\right)\right) \times \\ &\quad\; \tau^{-\frac{v+2}{2}} \exp\left(-\frac{1}{2}\frac{s}{\tau}\right) \end{aligned} \tag{13}$$

3 Bayesian Estimation

Given the specified priors and the likelihood function (3), 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:

$$p(\Theta \mid Y) \propto p(Y \mid \Theta)\, p(\Theta) \tag{14}$$

Given (4) and (13), the posterior distribution (14) takes the form:

$$\begin{aligned} p(\Theta \mid Y) \;\propto\; & \prod_{n=1}^{N} |\Sigma_n|^{-\frac{T_n+M+1}{2}} \times \\ & \exp\left(\begin{array}{c} -\frac{1}{2}\sum_{n=1}^{N} \left(\mathbf{y}_n - (I_M \otimes X_n)\,\beta_n - (I_M \otimes Z_n)\,\gamma_n\right)' \times \\ \left(\Sigma_n^{-1} \otimes I_{T_n}\right)\left(\mathbf{y}_n - (I_M \otimes X_n)\,\beta_n - (I_M \otimes Z_n)\,\gamma_n\right) \end{array} \right) \times \\ & \tau^{-\frac{(NMK+v)}{2}} \exp\left(-\frac{1}{2}\left[\sum_{n=1}^{N} \left(\beta_n - \overline{\beta}\right)' O_n^{-1} \left(\beta_n - \overline{\beta}\right) + s\right] \frac{1}{\tau} \right) \end{aligned} \tag{15}$$

Our target is now to maximize the right-hand side of equation (15) 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 (15) in order to conduct statistical inference. This is since any object of interest that is also a function of Θ can be easily computed given the simulated 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 $p(\Theta \mid Y)$. 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 (15) appropriately.

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

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

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

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 values. Moreover, in order to reduce the serial correlation across draws, we set a thinning factor of 1000, i.e. given the remaining $1,000,000$ draws, we take 1 every 1000 and discard the remaining ones. As a result, we have 1000 draws for conducting inference. Specific details about the Data Description and how we conduct inference and assess convergence can be found in Appendices C and 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

$$p(\tau) \propto \tau^{-1/2} \tag{16}$$

by setting $v = -1$ and $s = 0$ in (10).

Regarding the Minnesota-stye prior, we do not have any information about the value of the hyper-parameters. Thus, we set a conservative $\phi_1 = \phi_2 = \phi_3 = 1$ in equation (6). More specifically, $\phi_1 = 1$ means that there is no *a priori* difference between own lags and lags of other variables; $\phi_2 = 1$ means that there is no *a priori* heteroskedasticity coming from exogenous variables; and $\phi_3 = 1$ means that the shrinking pattern of coefficients is linear.

4 Structural Shock Identification

As in every econometric problem, identification of causal effects is crucial for obtaining reliable results. In this regard, the orthogonalization of shocks in Vector Autoregressive models is one of the most popular and effective way to achieve this task. That is, the impulse response function derived from an orthogonal shock depicts the causal effect of interest, since by definition this shock is independent of any other economic force in the system.

In the statistical model (1), the error term $u_{n,t} \sim N(0, \Sigma_n)$ corresponds to the reduced form. In particular, the covariance matrix Σ_n is in general non-diagonal, i.e. shocks $u_{n,t}$ are non-orthogonal. Consequently, a shock in any component of $u_{n,t}$ will result in a meaningless impulse response function, because we would be shocking correlated variables. It is therefore necessary to have shocks that are independent (orthogonal) across equations, since this will allow us to isolate the causal effect of interest, i.e. monetary policy shocks, through the structural form of the model. Nevertheless, the structural form (SVAR) cannot be achieved without making additional economic assumptions, i.e. *the identification problem in econometrics*. Rubio-Ramírez et al. (2010) provide an extensive explanation about the issue of Identification in SVARs. According to them, a SVAR model can be exactly-identified, over-identified or even partially-identified. The latter will be the case in our model. Thus, in this section we describe our identification strategy and the algorithm that will capture the mentioned effect.

4.1 Identification assumptions

The identification of monetary shocks is fairly standard. We have two types of restrictions, as it is displayed 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). In this case, as it is standard in the literature, we assume that the Gross Domestic Product (Y) and the Consumer Price Index (P) are *slow* variables, so that they do not react to monetary shocks contemporaneously. 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 monetary shock produces i) the typical liquidity effect, i.e. a negative response of money (M) after a contractionary shock and ii) a negative response of the exchange rate (E), meaning that the Uncovered Interest Rate Parity (UIP) holds. Last but not least, we do not impose any sign to the response of the EMBI nor to the response of Gross Domestic Product (Y) and the Consumer Price Index (P) for the subsequent periods.

Identification restrictions in Table 1 are only associated with one particular shock. As a result, the other $M-1$ shocks are unidentified. This is not a 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. The only limitation of the latter is the fact

Variable / shock	Name	MP shock ($h=0$)	MP shock ($h=1,2$)
Gross Domestic Product	Y	0	?
Consumer Price Index	P	0	?
Interbank rate	R	$\geqslant 0$	$\geqslant 0$
Monetary Base	M	$\leqslant 0$	$\leqslant 0$
Exchange Rate	E	$\leqslant 0$	$\leqslant 0$
EMBI Spread	EMBI	?	?

Table 1. *Identification Restrictions*

that we cannot perform a historical decomposition analysis, because we would need to make additional assumptions in order to identify the remaining $M-1$ shocks properly. However, since this is out of the scope of this paper, we keep the partially-identified model as our main setup.

4.2 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:

1. Set $K = 1000$ and $k = 0$.
2. Draw Θ from the posterior distribution $p(\Theta \mid Y)$.
3. For each country $n = 1, \ldots, N$ and the average draw a rotation matrix $\overline{\mathbf{Q}}_n$ and compute the impulse responses set $F\left(\Theta, \{\overline{\mathbf{Q}}_n\}_{n=1}^{N}\right)$.
4. If impulse responses satisfy sign restrictions for all countries and the average, keep the draw and set $k = k + 1$. If not, discard it and go to next step.
5. If $k < K$ return to Step 2, otherwise stop.

It is worth to remark that in step 3 for each country $n = 1, \ldots, N$ we do:

1. Given Σ_n, compute the Cholesky factor $\mathbf{P}_n$ such that $\mathbf{P}_n\mathbf{P}_n' = \Sigma_n$.

2. Draw $\mathbf{X}_n \sim N(0, I)$ and get $\mathbf{Q}_n$ such that $\mathbf{Q}_n\mathbf{R}_n = \mathbf{X}_n$, i.e. an orthogonal matrix $\mathbf{Q}_n$ that satisfies the QR decomposition of $\mathbf{X}_n$. The random matrix $\mathbf{Q}_n$ has the uniform distribution with respect to the Haar measure on $O(n)$ (Arias et al., 2014).

3. Given β_n, compute the companion form matrix $\mathbf{A}_n$ such that the impulse-response function is

$$f(\beta_n, \Sigma_n, h) = \left[\mathbf{J}(\mathbf{A}_n)^h \mathbf{J}'\right] \mathbf{P}_n, \quad h = 0, 1, \ldots, \infty$$

where $\mathbf{J} = \left[\begin{array}{cccc} I & \mathbf{0} & \ldots & \mathbf{0} \end{array} \right]$ is a selection matrix that is conformable.

4. Construct the matrix:

$$\overline{\mathbf{Q}}_n(M \times M) = \left[\begin{array}{cc} I_k & \mathbf{0}_{(k \times M-k)} \\ \mathbf{0}_{(M-k \times k)} & \mathbf{Q}_n \end{array} \right]$$

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

5. Compute the impulse response set $F\left(\Theta, \{\overline{\mathbf{Q}}_n\}_{n=1}^N\right) = \left\{ \{f(\beta_n, \Sigma_n, h)\, \overline{\mathbf{Q}}_n\}_{h=0}^{\overline{h}} \right\}_{n=1}^N$.

Finally, for the case of the average responses, we compute the companion form using $\overline{\beta}$ and compute the Cholesky factor from $\overline{\Sigma} = (1/N)\sum_{n=1}^N \Sigma_n$. After the simulation of the $K = 1000$ draws we will have a collection of draws of $F\left(\Theta, \{\overline{\mathbf{Q}}_n\}_{n=1}^N\right)$. Therefore, the computation of confidence intervals simply consists on capturing the corresponding percentiles after sorting draws (Casella and Robert, 2004).

5 Results

After simulating the posterior distribution and getting the structural shocks, we are now ready to tackle the main theme of this paper. First of all, according to our identification assumptions in Table 1, we are agnostic about the response of output and prices after the realization of a monetary policy shock, since we only set a zero to the initial response. Figure 1 depicts the response of the included variables for each country in a horizon of 5 years (60 months). Error bands for each country impulse responses can be found in Appendix D.

The upper-left panel depicts the response of output (Y), providing evidence of real effects in the short run derived from monetary policy. All countries reach the maximum response after the first year, with the majority around 12-15 months and with Brazil reaching the maximum before 24 months. Regarding the magnitude of the effect, we observe that the real effects are larger in Peru and Brazil relative to Chile, Colombia and Mexico. It is worth to mention that these effects are directly comparable, since we normalize the raise in interest rate (R) to 1.

Regarding the response in the price level (P), we observe in Figure 1 that the largest response belongs to Brazil, in second place to Peru and then Chile, Colombia and Mexico. One of the most valuable result in this exercise is the fact that we do not observe any symptom that suggests the presence of the so-called *price puzzle*, meaning that the information set included in the model and the identification restrictions are enough to isolate monetary policy shocks in each for these five countries.

Finally, the response of the exchange rate (E), even though is partially influenced by the imposed sign restrictions in Table 1, depicts interesting results. First, it can be observed that currencies react very differently to monetary policy shocks. Countries such as Brazil, Chile or Colombia exhibit larger responses than Mexico and Peru. This can be in part by the fact that Foreign Exchange Intervention practices differ across countries.

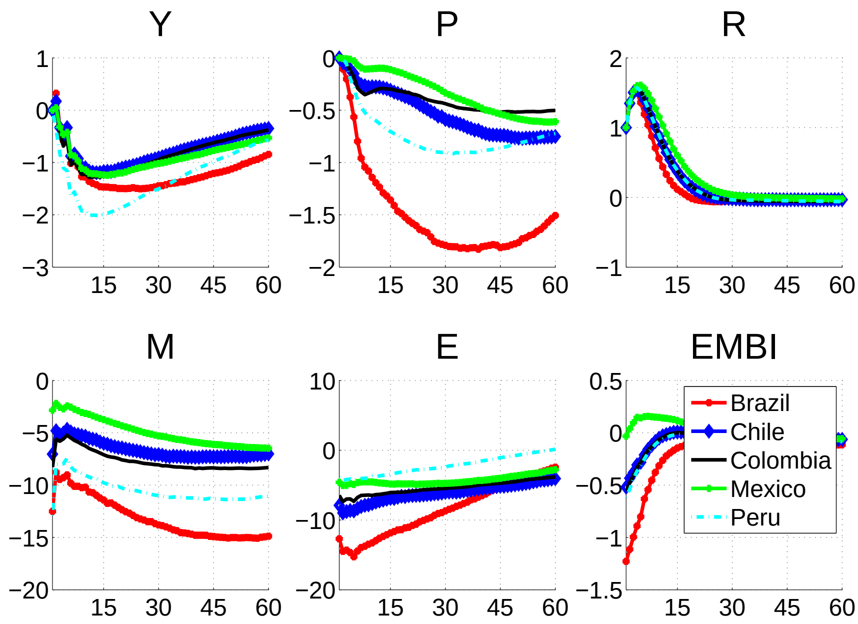

Figure 1. *Comparison of Monetary shocks in LA5 countries; median values*

Therefore, a similar movement in interest rates (R) can produce heterogeneous responses regarding exchange rates (E), i.e. some currencies float more than others. Of course, the reason of why some countries intervene more in the market than other is related with the degree of dollarization of the financial system, i.e. countries with a higher degree of dollarization are more vulnerable to external shocks. Having said that, it is fair enough to affirm that as long as the inflation expectations remain anchored, Inflation Targeting still works despite foreign exchange intervention.

The observed heterogeneity in impulse responses across countries is one of the most important outputs that can be obtained through the Panel VAR methodology. In addition, this setup allows us to explore the average response for the N countries included in the estimation. That is, it is possible to compute the impulse responses based on the vector $\overline{\beta}$, which is a weighted average of coefficients of N countries (see details in Appendix A). In this regard, Figure 2 depicts this average response, where we observe a significant short run effect on output (Y) with a peak around 12-15 months and significant medium

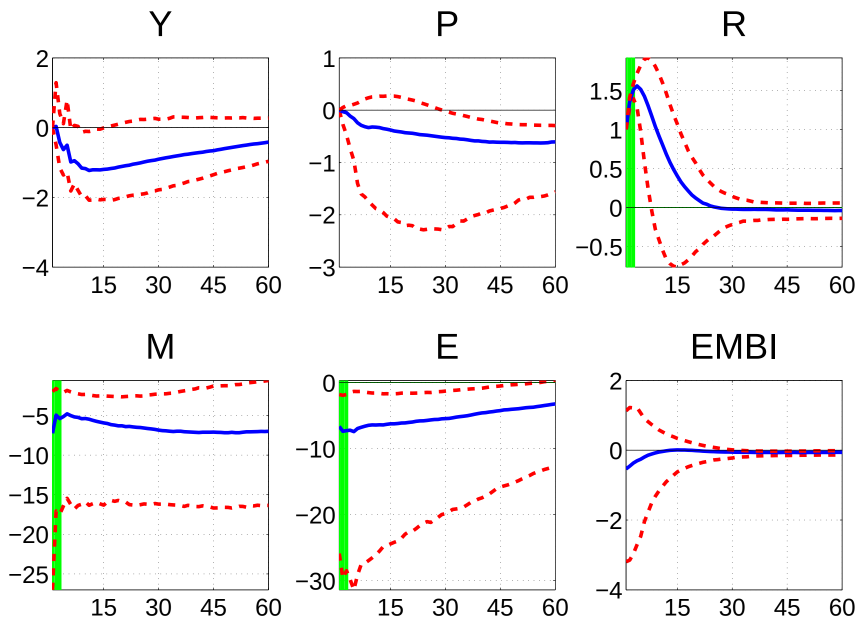

Figure 2. *Average Monetary shock in LA5 countries; median value and 68% bands*

run effect on prices (P). Green bars indicate the imposed sign restrictions for a horizon of three months. Given the zero and sign restrictions, the responses of the monetary base (M) and the exchange rate (E) are significant not only for the first three months, but for the whole horizon of 60 months. Some specific aspect deserves attention, and is the fact that the exchange rate reaches its maximum after three months, giving us mild evidence of the so-called *delayed overshooting puzzle*(Eichenbaum and Evans, 1995)[4]. The latter suggests some type of financial friction that deserves to be modeled for the Latin American case, and this can be part of a future agenda.

6 Concluding Remarks

We have estimated a Bayesian Hierarchical Panel VAR for the LA5 countries (Brazil, Chile, Colombia, Mexico and Peru) and have identified monetary policy shocks through

[4] Eichenbaum and Evans (1995) points out that the empirical response of the exchange rate is not as described in Dornbusch (1976), since the maximum is not reached immediately.

a mixture of zero and sign restrictions. By comparing the impulse response functions of identified shocks, we have found that policy shocks are qualitatively similar across LA5 countries. Nevertheless, we find some degree of heterogeneity on the impact and propagation of monetary shocks across countries. This is the most important contribution of the paper. In particular, we find stronger effects on output and prices in Brazil and Peru relative to Chile, Colombia and Mexico and a stronger reaction of the exchange rate in Brazil, Chile and Colombia relative to Mexico and Peru. In line with a textbook approach, the effectiveness of monetary policy is also related with credibility and proper communication, characteristics that are strongly associated with the Inflation Targeting scheme. On the other hand, the exchange rate response can be associated with the intensity of Foreign-Exchange Intervention policies.

Moreover, in contrast to the majority of previous studies for individual countries, the identification restrictions are enough to avoid the so-called *price puzzle*, at least for the Inflation Targeting period of analysis. We have also presented the weighted-averaged impulse response after a standard monetary shock for LA5 countries, where we find a significant short run effect on output (with a peak around 12-15 months) and significant effect on prices after two years. This result is important for policy design, since it provides reliable information about monetary policy lags and the scope and horizon of monetary actions, which is also relevant for forecasting procedures. In addition, we find weak evidence of the so called *delayed overshooting puzzle* (Eichenbaum and Evans, 1995).

Our results suggest that monetary policy works well under Inflation Targeting for LA5 countries, even though the events such as the Global Financial Crisis and the Macro-prudential Policy measures implementation are included in the sample of analysis. For the latter point, it was crucial to control for external variables. In this regard, the future research agenda should include the effect of external shocks in a Panel VAR setup, so that it would be possible to capture the heterogeneous responses after a common external shock, such as the Global Financial Crisis of 2008-2009.

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A Gibbs Sampling algorithm 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: $p\left(\beta_n \mid \Theta/\beta_n, \mathbf{y}_n\right)$: Given the likelihood (3) 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

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

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

2. Block 2: $p\left(\gamma_n \mid \Theta/\gamma_n, \mathbf{y}_n\right)$: Given the likelihood (3) and the prior

$$p\left(\gamma_n\right) \propto 1$$

   then the posterior is Normal:

$$p\left(\gamma_n \mid \Theta/\gamma_n, \mathbf{y}_n\right) = N\left(\widetilde{\gamma}_n, \widetilde{\Gamma}_n\right)$$

   with

$$\widetilde{\Gamma}_n = \left(\Sigma_n^{-1} \otimes Z_n' Z_n\right)^{-1}$$

$$\widetilde{\gamma}_n = \widetilde{\Gamma}_n \left(\left(\Sigma_n^{-1} \otimes Z_n' \right) \left(\mathbf{y}_n - \left(I_M \otimes X_n \right) \beta_n \right) \right)$$

3. Block 3: $p\left(\Sigma_n \mid \Theta/\Sigma_n, \mathbf{y}_n\right)$: Given the likelihood (3) and the prior

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

Denote the residuals

$$U_n = Y_n - X_n B_n - Z_n \Gamma_n$$

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

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

4. Block 4: $p\left(\overline{\beta} \mid \Theta/\overline{\beta}, Y\right)$: Given the prior

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

by symmetry

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

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

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

with

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

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

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

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

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

then the posterior is

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

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

B The posterior distribution of prior hyper-parameters

The posterior distribution of the parameter τ represents the tightness of the prior distribution of VAR coefficients. We have used a uniform prior distribution for τ in equation (16) (see Gelman (2006)), which is not much informative and therefore it lets the data speak. All in all, we find a considerable amount of shrinkage and a well identified posterior density of the parameter.

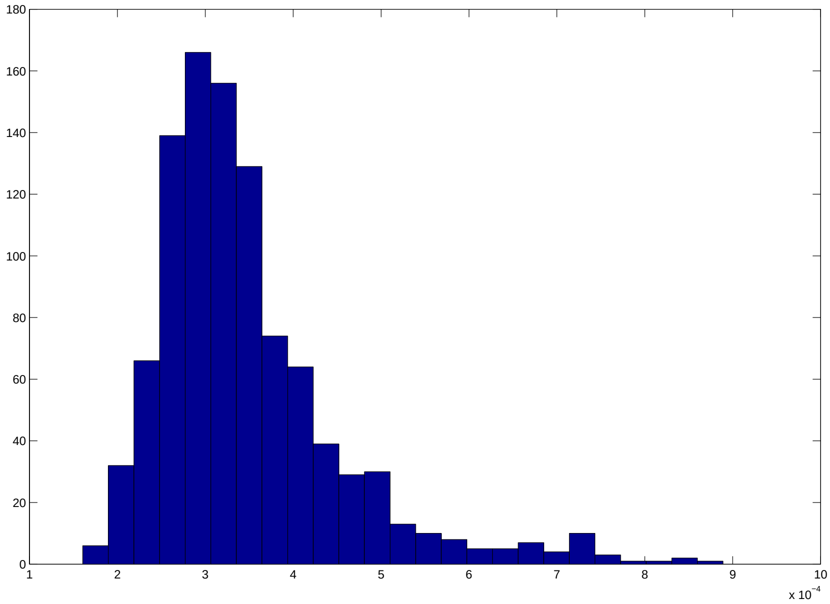

Figure B.1. *Posterior Distribution of* $\sqrt{\tau}$

C Data Description

C.1 Endogenous variables

We include the set of endogenous variables ($\mathbf{y}_n$) for each country:

- Monthly Economic Activity Index (seasonally adjusted)[5], in logs (Y)[6]
- Consumer Price Index, in logs (P).
- Interbank Rate in domestic currency, in % (R).
- Monetary Base (seasonally adjusted) in domestic currency, in logs (M).
- Exchange Rate (Domestic currency per US dollar), in logs (E).
- EMBI Spread, in % (EMBI).

[5]Seasonal adjustment was performed using TRAMO-SEATS.

[6]For Brazil we use the Monthly Industrial Production Index calculated by the IBGE, for Chile we use the IMACEC, for Colombia we also use a Industrial Production Index released by the Banco de la República, for Mexico we use the IGAE and for Peru we use the Monthly GDP Index released by the Banco Central de Reserva del Perú.

Data is in monthly frequency and it was taken from each country Central Bank website.

Country	Sample
Brazil	1999:06-2013:12
Chile	1999:09-2013:12
Colombia	1999:06-2013:12
Mexico	1999:06-2013:12
Peru	2002:02-2013:12

Table C.1. *Effective sample for each country: Inflation Targeting period*

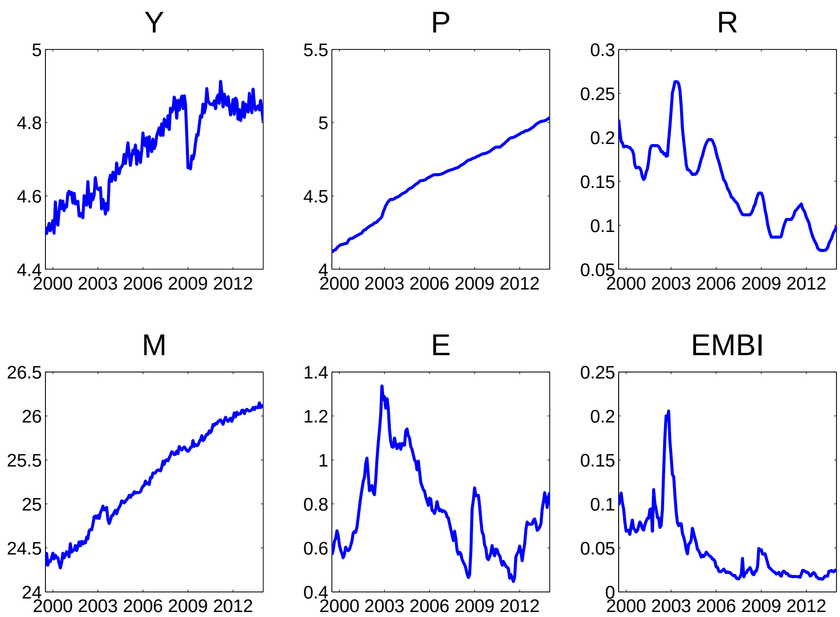

Figure C.1. *Brazilian Data*

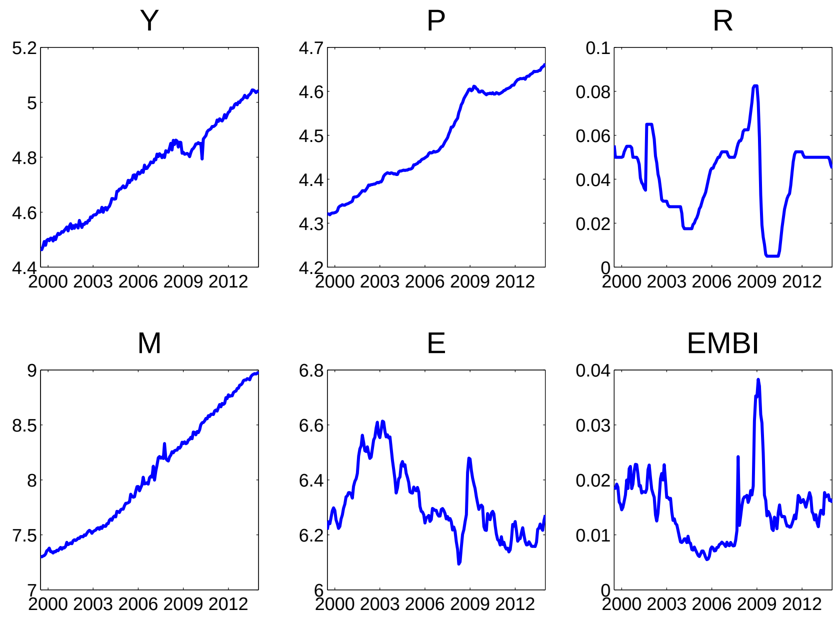

Figure C.2. *Chilean Data*

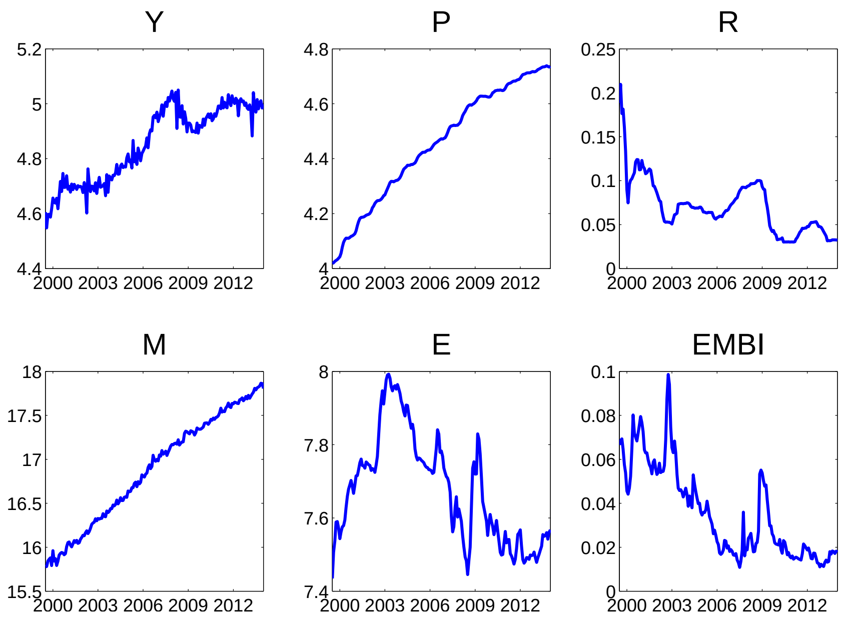

Figure C.3. *Colombian Data*

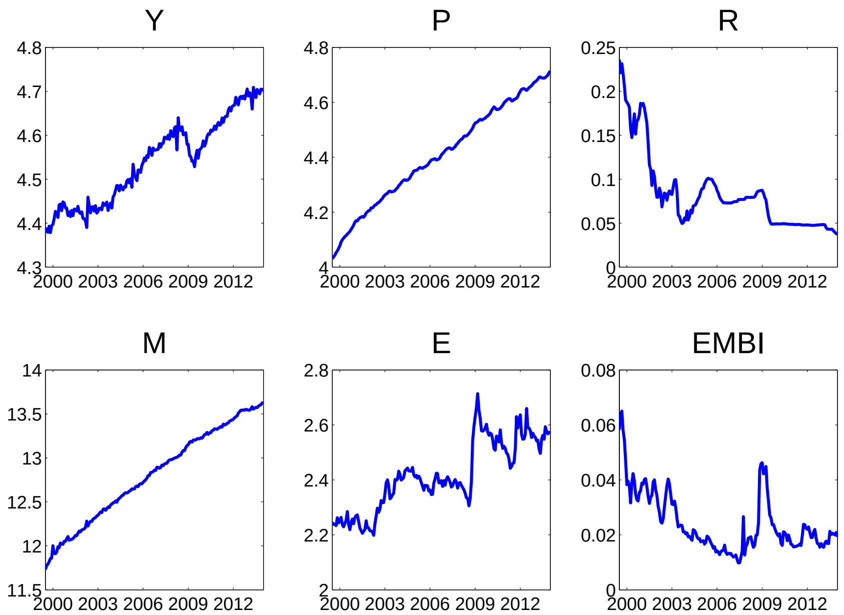

Figure C.4. *Mexican Data*

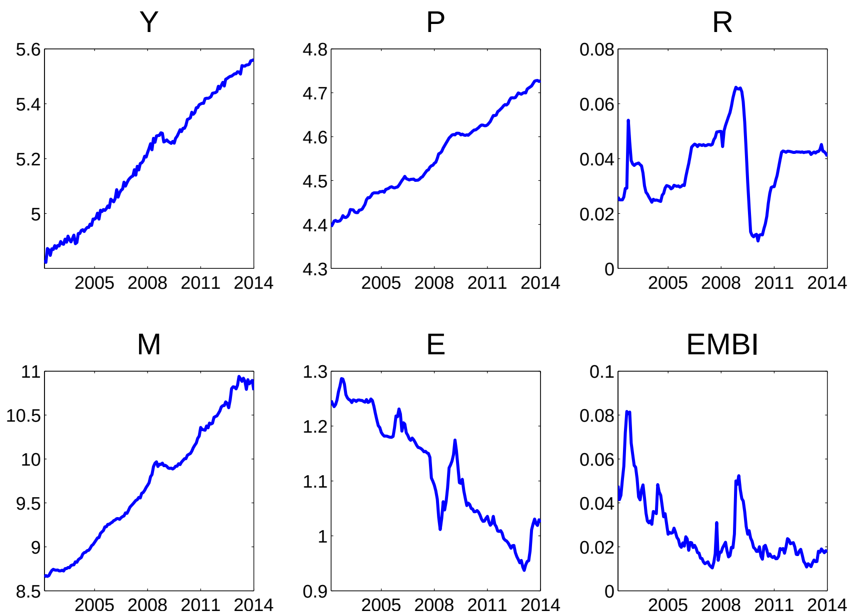

Figure C.5. *Peruvian Data*

C.2 Exogenous variables

As we pointed out in the introduction, the inclusion of external variables is crucial for avoiding the omitted-variables bias. This is even more important in the case of emerging markets (Maćkowiak, 2007) such as Latin American economies, since they are strongly influenced by fluctuations in Oil and Commodity prices, and also by the evolution of the economies of their trade partners. Here we know that trade patterns are different across LA5 countries, but at least the relevance of the U.S. economy is part of the conventional wisdom. As a result, the following exogenous variables ($\mathbf{z}_t$) are included:

- Industrial Production Index of the U.S. (SA), in logs.
- Commodity prices (All commodities), in logs.
- Oil Prices Index (WTI), in logs.
- Consumer Price Index index of the U.S., in logs.
- Federal Funds Rate (FFR), in %.
- A Spread indicator between long and short term interest rate, as in Carrera et al. (2014), in %.
- A constant (c) and a linear time trend (t).

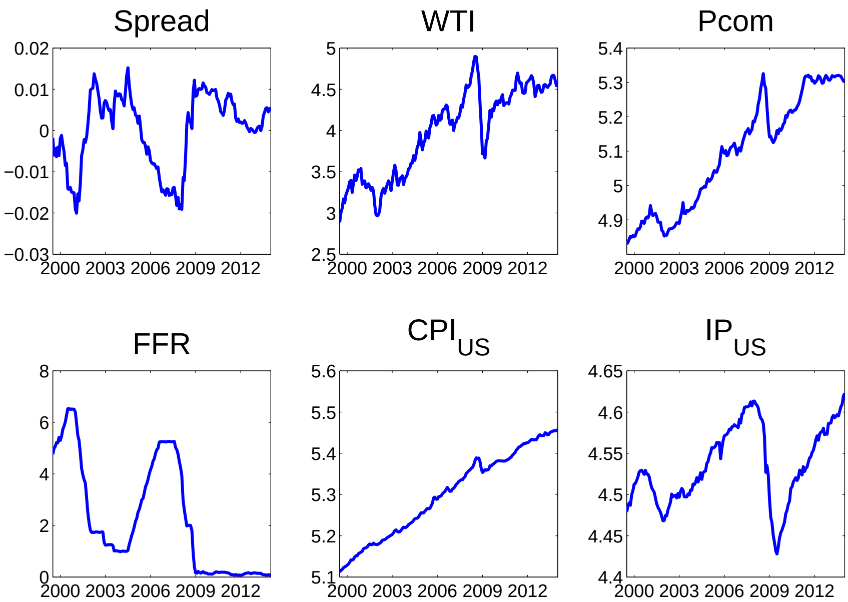

Figure C.6. *Exogenous Variables Data*

Data is in monthly frequency and it was taken from the Federal Reserve Bank of Saint Louis website (FRED database). Interest rates were taken from the H.15 Statistical Release of the Board of Governors of the Federal Reserve System website.

D Individual Impulse Responses

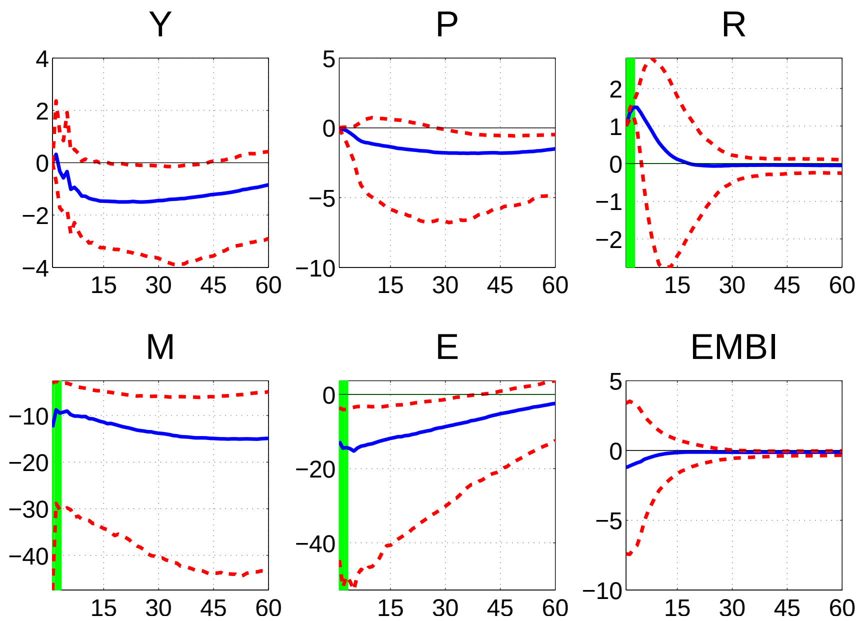

Figure D.1. *Monetary shock in Brazil; median value and 68% bands*

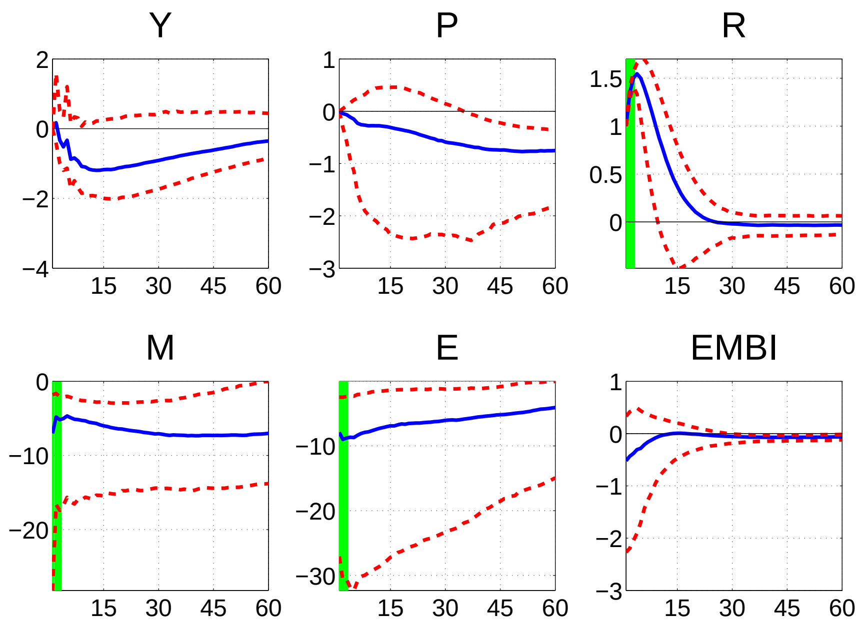

Figure D.2. *Monetary shock in Chile; median value and 68% bands*

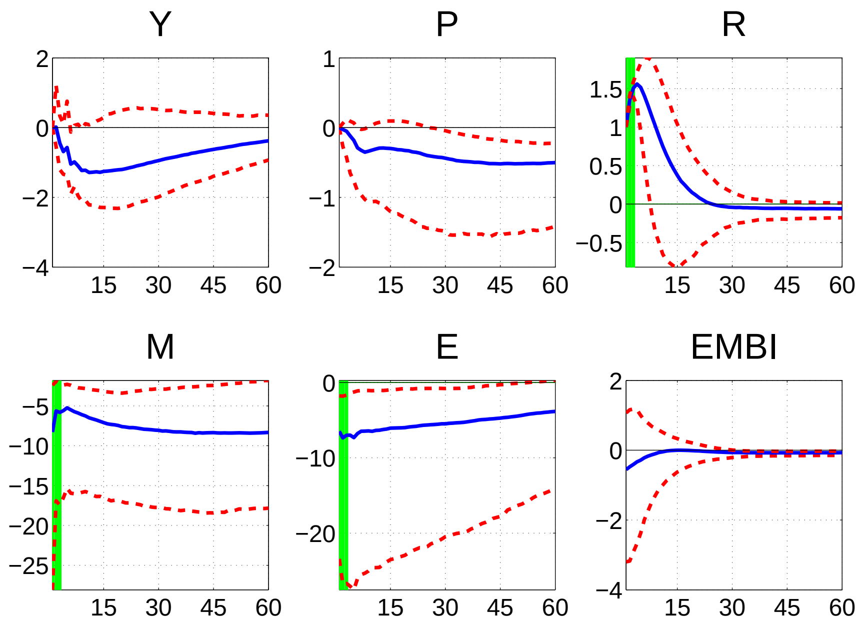

Figure D.3. *Monetary shock in Colombia; median value and 68% bands*

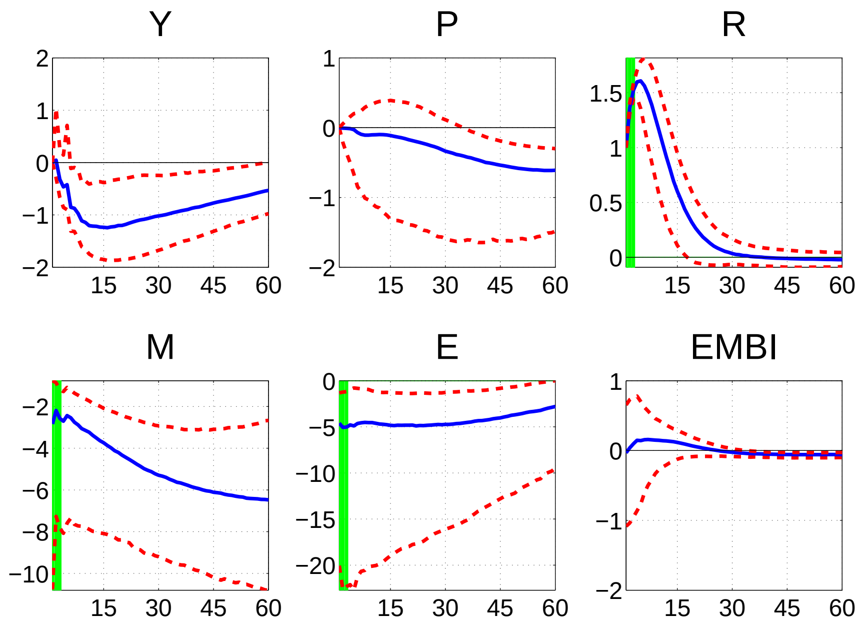

Figure D.4. *Monetary shock in Mexico; median value and 68% bands*

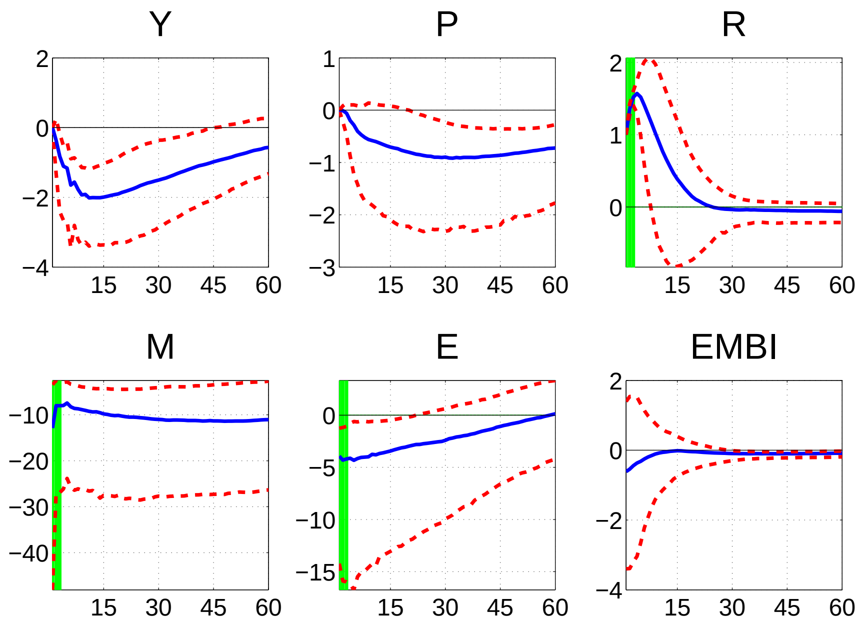

Figure D.5. *Monetary shock in Peru; median value and 68% bands*