Nonlinear Impacts of Financial and Uncertainty Shocks: Evidence from Emerging Economies

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Abstract

We analyze the impact of financial and uncertainty shocks in a set of 10 emerging markets (EMs) using a Bayesian hierarchical threshold VAR with volatility-in-mean. We find that, under normal financial conditions, financial shocks are more pervasive in EMs than uncertainty shocks. However, under financial stress periods, uncertainty shocks become more important than financial shocks. This result suggests that, under financial distress periods, financial stress reinforces uncertainty, playing a central role in the business cycles in such countries.

Keywords: Emerging Markets, Bayesian threshold hierarchical VAR, Financial Shocks, Uncertainty Shocks

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1 Introduction

Given the widely observed positive relationship between asset price volatility and credit spreads during the 2007–2009 financial crisis, a growing strand of literature has emphasized the empirical relevance of financial volatility and macroeconomic uncertainty shocks on business cycles (see Bhattarai et al., 2020; Caldara and Kamps, 2017; Carrière-Swallow and Céspedes, 2013; Cuaresma et al., 2020; Jurado et al., 2015). Especially, both financial uncertainty and macroeconomic uncertainty shocks appear to play central roles in advanced economies (AEs) (Caldara et al., 2016; Carriero et al., 2018b; Ludvigson et al., 2015). Notwithstanding, the theoretical literature has advanced in rationalizing the linkage between financial frictions and fluctuations in uncertainty and how it could affect macroeconomic variables (Bai et al., 2011; Christiano et al., 2014; Gilchrist et al., 2014). As the financial market prices the riskiness of firms' assets, riskier assets resulting from higher uncertainty must come up with a rise in credit spreads to compensate bondholders for heightened uncertainty (Gilchrist et al., 2014).

Nevertheless, with very few exceptions (e.g., Alessandri and Mumtaz, 2019; Salzmann, 2020), little attention has been given to an important question that emerges in context of uncertainty shocks: the role of the state of financial conditions in the transmission of the shocks. During tranquil times, it seems reasonable to assume that financial markets can—at least partially—insulate uncertainty shocks, which would result in a potentially lower transmission of the shocks to the real economy, mainly through prices. However, under stressful periods, economic uncertainty may be coupled with a high probability of credit crunch because credit markets may be more exposed to, e.g., moral hazard problems and weaker balance sheet conditions. These problems may reinforce the shock, which might ultimately trigger a crisis. Thus, the economy can have very different responses to uncertainty shocks depending on the state of the financial and credit markets. Not surprisingly, Alessandri and Mumtaz (2019) find that the effects of an exogenous increase in uncertainty during financial distress can be six times larger than in normal times in the US.

This paper contributes to the empirical literature by investigating the presence of state-dependent effects of financial and uncertainty shocks in a sample of 10 emerging markets (EMs) under two different regimes: one with normal financial conditions and another featuring financial distress. We focus on EMs because they are much more prone to financial instability periods, policy reversals, and sudden stops (Calvo et al., 2006; Mendoza, 2010; Neumeyer and Perri, 2005) than AEs, potentially resulting in higher systemic risk and macroeconomic uncertainty. In each country in the sample, we measure uncertainty through the average volatility of the economy's structural shocks, and the financial conditions are proxied by an estimated financial stress index (FSI). As in Galvão and Owyang (2018) and Alessandri and Mumtaz (2019), the two regimes are defined as depending on a threshold value of the FSI, which is a variable that governs the transmission mechanism between the regimes.

The analyses is employed using a Bayesian panel threshold VAR with volatility in mean (BPT-VAR-VM) model that extends the idiosyncratic two-regimes threshold VAR with volatility in mean model proposed by Alessandri and Mumtaz (2019) to a panel context by adding hierarchical layers in the spirit of the Bayesian hierarchical approach advocated by Jarociński (2010) and Mumtaz et al. (2018). Here, we introduce hierarchical structures both in the VAR parameters and volatility process. Such a strategy is important to circumvent the problem of short time series the countries in the sample, because it can efficiently exploit the idiosyncratic information to better estimate the panel statistics. Thus, the model used in this paper features a two-regimes model of stochastic volatility in a multi-country context. Given that the model is heavily parameterized and nonlinear, we compute the posterior distribution of the model by using an adaptive Metropolis-within-Gibbs scheme (Atchadé and Rosenthal, 2005), which helps to ameliorate the difficulties in calibrating the random walk Metropolis step.

Our focus is mainly on the role played by two shocks: a financial shock and a macroeconomic uncertainty shock. The financial shock is a sign identified shock that maximizes forecast error decomposition (FEVD) of a financial stress indicator, in the spirit of Mumtaz et al. (2018). The macroeconomic uncertainty shock is an orthogonal shock to the uncertainty measure equation, which is interpreted as a deterioration in the accuracy of the forecasts of the future economy's condition made by the agents.

We find that, in EMs, the relationship between financial and uncertainty shocks follows a nonlinear state-dependence of the financial conditions, similar to what has been observed in some AEs (Alessandri and Mumtaz, 2019). Financial shocks are likely to reduce the GDP growth in both regimes, while uncertainty shocks have more negative impacts during financial distress. Interesting, in EMs, the relative importance of such shocks in explaining the FEVD of GDP changes substantially between the regimes: uncertainty shocks become more critical than financial shocks during a financial stress regime, contrary to what we observed in normal times. This result suggests that financial frictions reinforce uncertainty shocks, magnifying their effects on the economy.

The macroeconomic impacts of uncertainty and financial shocks have increasingly been analyzed by the literature, mostly focusing on AEs (e.g., Alfaro et al., 2018; Bloom, 2009; Carriero et al., 2018a,b; Jurado et al., 2015; Meinen and Roehe, 2018; Mumtaz, 2018). Similar to Carrière-Swallow and Céspedes (2013); Choi (2018), the present paper contributes to such literature by analyzing EMs, which are more subject to large swings in financial conditions, in a panel context. Here, however, we take into account the state of the financial markets at the same time as we estimate the uncertainty process.

The paper is organized as follows: Section 2 presents the econometric strategy, with estimation details been presented in Section 3. Section 4 discussed the results, and Section 5 presents the concluding remarks.

2 Empirical Methodology

This section presents the BPT-VAR-VM discussing both the idiosyncratic and hierarchical structures of the model.

2.1 Bayesian Panel Threshold VAR with Volatility in Mean

For each country $i \in \{1 \cdots, 10\}$ in the sample, we estimate the following model:

$$\begin{aligned} Y_{it} = &\left(\sum_{j=1}^{L} b_{1,ij} Y_{it-j} + \sum_{j=0}^{J} g_{1,ij} \ln\lambda_{t-j} + c_{1,i} Z_{it} + \Omega_{1,it}^{1/2} u_{it} \right) \mathcal{R}_{it} + \\ &\left(\sum_{j=1}^{L} b_{2,ij} Y_{it-j} + \sum_{j=0}^{J} g_{2,ij} \ln\lambda_{t-j} + c_{2,i} Z_{it} + \Omega_{2,it}^{1/2} u_{it} \right) (1 - \mathcal{R}_{it}) \end{aligned} \tag{1}$$

The idiosyncratic vector of endogenous variables, Y_{it}, is given by the GDP growth rate, y_{it}, investment growth, inv_{it}, quarterly CPI inflation, π_{it}, a monetary policy-related interest rate in log terms, i_{it}, and a financial stress index (FSI), fsi_{it}. The vector Z_{it} contains a constant term and some control variables. It includes the t and $t-1$ observations from (i) the G7 growth, (ii) $\sum_{-i} y_{jt}/9$, and (iii) $\sum_{-i} fsi_{jt}/9$, where $\sum_{-i}$ denotes the summation of certain variable for all countries but i. Such variables aim to control for cross-sectional correlation and spillover effects, so that the shocks of interest in this papers can be viewed as idiosyncratic.[1]

The common stochastic volatility captured by the scalar process λ_{it} is an empirical, unobservable measure of aggregate uncertainty that affects the first moment dynamics of the model. Moreover, $L \in \{1, \cdots, 4\}$, restricted due to data limitation, is the lag length of the VAR, while the lag of the volatility structure, J, is fixed to 1. Note that, as in Alessandri and Mumtaz (2019); Carriero et al. (2018b), volatility enters the VAR contemporaneously with Y_{it}.

The framework allows the parameters to change according to two different states of financial conditions: "normal times" and "bad times." The transition across regimes is governed by the variable $\mathcal{R}_{it}$, which expresses whether the level of the FSI is below or above some idiosyncratic threshold value, fsi_i^*. It is given by the following:

$$\mathcal{R}_{it} = \begin{cases} 1, & \text{if } fsi_{it-d_i} \leq fsi_i^*, \\ 0, & \text{otherwise} \end{cases}$$

where $fsi_{it} \in Y_{it}$. The parameter d_i, where $d_i = 1$, is the (fixed) idiosyncratic delay. We refer to "normal times" as situations in which $\mathcal{R}_{it} = 1$ and "stressful" or "bad times" as situations in which $\mathcal{R}_{it} = 0$.

The covariance of the residuals is regime-dependent, and in regime r, can be factored as follows:

$$\Omega_{r,it} = A_{r,i}^{-1} H_{r,it} A_{r,i}^{-1\prime} \tag{2}$$

where $A_{r,i}$ is a regime dependent triangular matrix. As in Alessandri and Mumtaz (2019), we assume that the idiosyncratic volatility process, $H_{r,it}$, is given by:

$$H_{r,it} = \lambda_{it} S_{r,i} \tag{3}$$

$$S_{r,i} = \text{diag}(s_{r,i1}, s_{r,i2}, s_{r,i3}, s_{r,i4}, s_{r,i5}) \tag{4}$$

$$\ln\lambda_{it} = \alpha_i + F_i \ln\lambda_{it-1} + \eta_{it} \tag{5}$$

where $\eta_{it} \sim N(0, Q_i)$. Under such a formulation, a positive shock to the log-volatility, $\eta_{it} > 0$, shifts upward the covariance matrix of the idiosyncratic residuals, u_{it}, leading to a deterioration in the accuracy of the forecasts of Y_{it+k} made by the agents.

The presence of λ_{it} in equation (1) allows the GDP growth rate, investment growth, CPI inflation, a monetary policy-related interest rate, and the FSI to adjust to a riskier state of the economy endogenously. This feature is important for EMs because these countries are likely to experience sudden, abrupt changes in their variables (see, for example, Calvo et al., 2006; Mendoza, 2010).

2.2 Hierarchical Structure

Similar to Jarociński (2010) and Mumtaz et al. (2018), we introduce a hierarchical structure for some key parameters in the model. Such priors are useful in the context of emerging economies because the cross-sectional information can be used to improve the precision of the country-specific estimates.

[1] Note that the inclusion of Z_{it} into the VAR can also be viewed as expanding the information set with a low computational cost.

Denote $\beta_{i,r} = vec([b_{r,i1}, \cdots, b_{r,1L}, g_{r,i1} \cdots, g_{r,iJ}])$ and collect the non-zero and non-one elements in A_{ri} through the vector $a_{i,r}$. In what follows, a bar over a variable indicates its cross-sectional weighted average. As in Gomes et al. (2020); Mumtaz et al. (2018), we assume a normal prior for the regime-dependent VAR coefficients in the spirit of Jarociński (2010):

$$p(\beta_{r,i}|\bar{\beta}_r, \delta_{\beta,r}) \sim N(\bar{\beta}_r, \delta_{\beta,r}\Lambda_{\beta,i}) \tag{6}$$

where $\Lambda_{\beta,i}$ is a diagonal matrix capturing the scale of the data. The scale associated with the autoregressive coefficients is set following the dummy observation approach by Bańbura et al. (2010), whereas those associated with log-volatility parameters are set in a loose way.

We also assume a normal prior for the regime-dependent covariance components:

$$p(a_{r,i}|\bar{a}_r, \delta_{a,r}) \sim N(\bar{a}_r, \delta_{a,r}\Lambda_{a,i}) \tag{7}$$

in which $\Lambda_{a,i}$ is a diagonal matrix of the scales and λ_a expresses the degrees of pooling, as above. Moreover, following Gomes et al. (2020); Mumtaz et al. (2018), we assume a normal prior for the mean threshold value, which is given by the following:

$$p(fsi_i^*|\bar{fsi}^*, \delta_{fsi}) \sim N(\bar{fsi}^*, \delta_{fsi}\Lambda_{fsi,i}) \tag{8}$$

where $\Lambda_{fsi,i}$ is the scale of the prior, and δ_{fsi} is the corresponding degrees of pooling.

Furthermore, we introduce hierarchical priors for the volatility process. Let $h_{it} = \ln\lambda_{it}$ express the idiosyncratic log-volatility and write its transition equation in terms of deviation from the mean:

$$h_{it} - \mu_i = F_i(h_{it-1} - \mu_i) + \eta_{it} \tag{9}$$

where $\mu_i = \frac{\alpha_i}{1-F_i}$. Given this formulation, we assume a normal prior for μ_i and F_i expressed by:

$$p(\mu_i|\bar{\mu}, \delta_\mu) \sim N(\bar{\mu}, \delta_\mu\Lambda_{\mu,i}) \tag{10}$$

and

$$p(F_i|\bar{F}, \delta_F) \sim N(\bar{F}, \delta_F\Lambda_{F,i}) \tag{11}$$

where, again, $\Lambda_{\mu,i}$ and $\Lambda_{F,i}$ are the scales and λ_μ and λ_F measure the degree of pooling.

Priors for the degrees of pooling are assumed to have an inverse gamma prior, $p(\delta) \sim iG(S_0, V_0)$. Finally, the deterministic terms, $c_{r,i}$, the mean log volatility μ_i, and the standard deviations, S_i, are assumed to be country-specific. Thus, countries can have completely idiosyncratic initial conditions and some degree of heterogeneity in the magnitude of the shocks in the economy.

The parameters $\delta_{\beta,r}, \delta_{a,r}, \delta_{\bar{fsi}}, \delta_F$ captures the degree of heterogeneity in the data associated with the parameters $\beta_{i,r}, a_{i,r}, fsi_i$, and F_i, respectively. For illustration, suppose we are interested in estimating an idiosyncratic parameter ϖ_i using data from other countries by means of a hierarchical normal prior, with the degree of heterogeneity capture by the parameter δ_ϖ. Whenever $\delta_\varpi \to 0$, the posterior of ϖ_i becomes more influenced by the prior, and ϖ_i shrinks to the panel mean, $\bar{\varpi}$, whereas a large δ_ϖ indicates less influence from data coming from other countries on the idiosyncratic parameter ϖ_i. The same kind of reasoning is applied to all aforementioned δ's.

3 Estimation and identification

This section presents the algorithm used to compute the posterior distribution of the parameters of the model. Given the hierarchical and idiosyncratic structures, the algorithm is divided into two blocks. Later we discuss the identification scheme.

The hyperparameters of the priors are set as follows: The idiosyncratic scale matrices for the VAR parameters, $\Lambda_{\beta,i}$, are set using the dummy observation scheme proposed by Bańbura et al. (2010), with the tightness parameter set to 1. The elements of the scale matrices $\Lambda_{a,i}$, associated with the cross-sectional weighted averages $\bar{a}_r$, are set to $100 \times abs(a_{i,ols})$, in which $a_{i,ols}$ is obtained from OLS estimates for each country. Moreover, we set the scale matrices $\Lambda_{fsi,i} = \Lambda_{\mu,i} = \Lambda_{F,i} = 10$.

Finally, as in Jarociński (2010), the degree of pooling in all cases are assumed to have an inverse Gamma prior, $p(\delta) \sim iG(S_0, V_0)$, with hyperparameters set up following the suggestion made by Gelman (2006), so that $S_0 = 0$ and $V_0 = -1$, implying a uniform prior on the standard deviation.

Let's concisely describe how the estimation algorithm operates so that readers not interested in the estimation details below can skip to subsection 3.2. The marginal posterior distributions of the idiosyncratic parameters are approximated using an adaptive Metropolis-Within-Gibbs algorithm. The algorithm is an extension to a panel context of the algorithm used in Alessandri and Mumtaz (2019) to account for the panel structure of the data.

For all idiosyncratic models, we first apply a GLS transformation to account for heteroscedasticity. To draw the idiosyncratic threshold parameter, we follow Chen and Lee (1995) by interpreting the system as a change-point problem. Then, we use a Metropolis step with the adaptation scheme proposed by Atchadé and Rosenthal (2005), setting the target acceptance rate in the range from 0.23 to 0.44. The idiosyncratic stochastic volatility, λ_{it}, is drawn following Alessandri and Mumtaz (2019) but with the previously discussed hierarchical scheme. For each country in the sample, the idea is to represent the model in a nonlinear state-space form and apply the algorithm by Jacquier et al. (1994) for stochastic volatility models. For all remaining parameters, for $\forall t, i$, given a draw from the posterior of the idiosyncratic threshold parameter and λ_{it}, we can separate the data into the two regimes, and sample using the standard Gibbs sampler for hierarchical VAR models with conjugate priors (see, e.g., Gomes et al., 2020; Mumtaz et al., 2018).

3.1 Adaptive Metropolis-Within-Gibbs Sampler

Let Θ be the set of all parameters in the model,

$$\Theta = \left\{ \left\{ \beta_{r,i}, a_{r,i}, c_{r,i}, \Omega_{r,i}, \tilde{fsi}_i^*, d_i, F_i, \alpha_i, S_i, \mu_i^* \right\}_{i=1}^{C}, \bar{\beta}_r, \bar{a}_r, \bar{\tilde{fsi}}^*, \bar{F}, \delta_{\beta,r}, \delta_{a,r}, \delta_{\tilde{fsi}}, \delta_F, \right\}_{r=1}^{2}$$

and let Θ^* denote all the remaining parameters when we are interested in some parameter in Θ. Denote Y_{it} the left-hand side variables on equation (1), let X_{it} be a vector concatenating the left hand variables including log-volatilities, and denote Z_{it} as vector with deterministic terms. The algorithm operates through outer and inner loops as follows:

3.1.1 Inner loop

At some iteration of the Markov Chain, given a draw for all panel parameters,

$$\bar{\beta}_r, \bar{a}_r, \bar{\tilde{f}}si^*, \bar{F}, \delta_{\beta,r}, \delta_{a,r}, \delta_{\tilde{fsi}}, \delta_F,$$

for a country c, the inner loop is given by the following:

1. $p(\beta_{r,i}|\Theta^*)$: Given a draw of λ_{it}, apply a GLS transformations $y_{it} = Y_{it}/\lambda_{it}$, $x_{it} = X_{it}/\lambda_{it}$, and $z_{it} = Z_{it}/\lambda_{it}$ to remove the heteroscedasticity from the variables and take the regime-dependent data $y_{r,i}$, $x_{r,i}$, and $z_{r,i}$ in regime r. Then, draw from the conditional posterior distribution, which is normal, denoted by $N(M_{\beta_r}, V_{\beta_r})$, where:

$$\begin{aligned} V_{\beta_r} &= \left((\delta_{\beta,r}\Lambda_{\beta,i})^{-1} + \Omega_{r,i}^{-1} \otimes x'_{r,i}x_{r,i}\right)^{-1} \\ M_{\beta_r} &= V_{\beta_r}\left((\delta_{\beta,r}\Lambda_{\beta,i})^{-1}\bar{\beta}_r + \Omega_{r,i}^{-1} \otimes x'_{r,i}(y_{r,i} - c_{r,i})\right) \end{aligned}$$

2. $p(c_{r,i}|\Theta^*)$: Draw from the conditional posterior for the deterministic terms, denoted by $N(M_c, V_c)$, where:

$$\begin{aligned} V_c &= \left((\Lambda_{c,i})^{-1} + \Omega_{r,i}^{-1} \otimes z'_{r,i}z_{r,i}\right)^{-1} \\ M_c &= V_i\left((\Lambda_{c,i})^{-1}c_0 + \Omega_{r,i}^{-1} \otimes z'_{r,i}(y_{r,i} - x_{r,i}\beta_{r,i})\right) \end{aligned}$$

3. $p(a_{r,i}|\Theta^*)$: Let $E_{r,it} = Y_{r,it} - X_{r,it}\beta_{r,i} - c_{ri}$ be the residuals in regime r in country i. Following Alessandri and Mumtaz (2019), the model can be restated as $A_{ri}E_{r,it} = H_{ri}^{1/2}U_{r,it}$, where $U_{r,it} \sim N(0,1)$, which is a system of linear equation. The k-th equation is $E_{r,it}(k) = -\zeta E_{r,it}(-k) + H_{ri}^{1/2}(k)U_{r,it}(k)$, where k represents the k-th column and $-k$ denotes columns 1 to $k-1$. The parameter ζ denotes the relevant elements of $a_{r,i}$. Apply a GLS transformation by dividing both sides of the previous equation by $\sqrt{\lambda_{it}s_{ij}}$, where $j = 1, \cdots, K$, denoting the transformed variables by *. Then, given the normal prior assumed for $a_{r,i}$, draw from the normal conditional posterior, given by $N(M_{a_r}, V_{a_r})$, where:

$$\begin{aligned} V_{a_r} &= \left((\delta_{a,r}\Lambda_{a,i}^{(k)})^{-1} + \frac{1}{H_{r,i}(k)}E_{r,it}^*(-k)'E_{r,it}^*(-k)\right)^{-1} \\ M_{a_r} &= V_{a_r}\left((\delta_{a,r}\Lambda_{a,i}^{(k)})^{-1}\bar{a}_r^{(k)} + \frac{1}{H_{r,i}(k)}E_{r,it}^*(-k)'E_{r,it}^*(k)\right) \end{aligned}$$

4. $p(S_{r,i}|\Theta^*)$: Given a draw from the idiosyncratic VAR and the idiosyncratic threshold, the model for the country i can be written as $(A_{1,i}(E_{1,it}))'\mathcal{R}_i + (A_{2,i}(E_{2,it}))'(1-\mathcal{R}_i) = e_{it}$. The associate j-th equation of such a system of equation is given by $E_{ijt} = -\zeta_1 E_{it}(-k)\mathcal{R}_i + (-\zeta_1 E_{it}(-k))(1-\mathcal{R}_i) + e_{ijt}$, where the variance of e_{ijt}, from equation j, is time-varying, and given by $\lambda_{it}s_{ij}$. Applying a GLS transformation, we can use $E_{ijt}^* = E_{ijt}/\sqrt{\lambda_{it}}$ to obtain the transformed residual, e_{ijt}^*, whose variance is given by s_{ij}. Then, in regime r, the conditional posterior for such variance is inverse Gamma, with scale $e_{r,ijt}^{*}{}'e_{r,ijt}^* + S_{0,ij}$ and degrees of freedom $V_{0,i} + T_{r,i}$, where $T_{r,i}$ is the number of observations in regime r.

5. λ_{it}: These variables are drawn using a similar scheme to that of Alessandri and Mumtaz

(2019), but here extended to the panel information by means of the hierarchical prior for the volatilities discussed above. The algorithm follows the approach proposed by Carlin et al. (1992); Jacquier et al. (1994) by applying the Kalman filter to state-space model using the log-volatilities $h_{it} = \ln\lambda_{it}$.

Given a previous draw of the mean log-volatility, $\tilde{\mu}_i$, and from the log-volatility, $\tilde{h}_{it}$, the transition equation for each country in terms of deviations from the mean is given by:

$$\tilde{h}_{it} - \tilde{\mu}_i = F_i(\tilde{h}_{it-1} - \tilde{\mu}_i) + \eta_{it}$$

We then draw the associated parameters by the following steps:

5.1. $p(Q_i|\Theta^*)$: The conditional posterior of Q_i is inverse Gamma with scale $\eta_{it}'\eta_{it} + Q_{0,i}$ and $T_i + V_{Q_{0i}}$ degrees of freedom.

5.2. $p(F_i|\Theta^*)$: The conditional probability distribution for F_i is $N(M_F, V_F)$, where

$$V_F = \left((\delta_F \Lambda_{F,i})^{-1} + \frac{1}{Q_i} h_{it-1}^*{}' h_{it-1}^*\right)^{-1}$$
$$M_F = V_F\left((\delta_F \Lambda_{F,i})^{-1}\bar{F} + \frac{1}{Q_i} h_{it-1}^*{}' h_{it}^*\right)$$

where $h_{it}^* = \tilde{h}_{it} - \tilde{\mu}_i$

5.3. $p(\mu_i|\Theta^*)$: Given a draw for F_i, we can use the relation $\Delta\tilde{h}_{it} = C_i\mu_i + \eta_{it}$, where $\Delta\tilde{h}_{it} = \tilde{h}_{it} - F_i\tilde{h}_{it-1}$, and $C_i = 1 - F_i$. Then, the conditional posterior for μ_i is $N(M_\mu, V_\mu)$, where

$$V_\mu = \left((\Lambda_{\mu,i})^{-1} + \frac{1}{Q_i} C_i' C_i\right)^{-1}$$
$$M_\mu = V_\mu\left((\Lambda_{\mu,i})^{-1}\mu_0 + \frac{1}{Q_i} C_i' \Delta\tilde{h}_{it}\right)$$

where the hyper-parameters are set to $\Lambda_{\mu,i} = 10$ and $\mu_0 = 0$.

5.4. As shown by Carlin et al. (1992), $f(\tilde{h}_{it}|\tilde{h}_{it-1}, \tilde{h}_{it+1}, \Theta^*) \sim N(M_{fi,t}, V_{fi,t})$, where

$$V_{fi,t} = \left(Q_i^{-1} + F_i' Q_i^{-1} F_i\right)^{-1}$$
$$M_{fi,t} = V_{fi,t}\left(\tilde{h}_{it-1} F_i^{-1} Q_i^{-1} + \tilde{h}_{it+1} Q_i^{-1} F_i\right)$$

5.5. h_{it} is draw using the date-by-date independence metropolis scheme as in Jacquier et al. (1994). The acceptance probability is given by the ratio os the conditional probability $f(Y_{it}|\tilde{h}_{it}, \Theta^*)$ and the new vs the old draw, or $\frac{f(Y_{it}|\tilde{h}_{it}^{new}, \Theta^*)}{f(Y_{it}|\tilde{h}_{it}^{old}, \Theta^*)}$, where $f(Y_{it}|\tilde{h}_{it}, \Theta^*)$ uses the idiosyncratic likelihood of the VAR for country i.

6. The idiosyncratic threshold is draw using an adaptive random walk Metropolis-Hastings (MH) algorithm together with the prior (8) and the country-specific joint likelihood. The acceptance ratio is given by the standard MH ratio, $\alpha^i = \min\left(1, \frac{f(Y_{it}|\tilde{fsi*}^{new}, \Theta^*)}{f(Y_{it}|\tilde{fsi*}^{old}, \Theta^*)}\right)$, similar to Chen and Lee (1995). However, the variance of the proposed draws for each country is adapted using the adaptive Random Walk proposed by Atchadé and Rosenthal (2005), with the target acceptance rate set to 0.234. We penalize draws in

which we don't have at least 5% of observations in the bad regime and at least 50% in the good regime.

7. Repeat steps 1 to 3 for $r = \{1, 2\}$.
8. Repeat steps 1 to 7 for $c = \{1, \cdots, C\}$. This step can be done by using parallel computation if more than one worker is available.

3.1.2 Outer loop

Given draws for all idiosyncratic parameters, the outer loop works by draws from the following conditional posterior distributions:

1. $p(\lambda_{\beta,r}|\Theta^*)$: As shown by Jarociński (2010), the conditional posterior is inverse Gamma, with scale given by

$$\sum_{i=1}^{C}\left(\beta_{r,i} - \bar{\beta}_r\right)\Lambda_{\beta,i}^{-1}\left(\beta_{r,i} - \bar{\beta}_r\right)' + S_0$$

and $(C \times K \times (K \times L + (J+1))) + V_0$ degrees of freedom.

2. $p(\lambda_{a,r}|\Theta^*)$: The conditional posterior is inverse Gamma, with scale given by

$$\sum_{i=1}^{C}\left(a_{r,i} - \bar{a}_r\right)\Lambda_{a,i}^{-1}\left(a_{r,i} - \bar{a}_r\right)' + S_0$$

and $\left(C \times \frac{K\times(K-1)}{2}\right) + V_0$ degrees of freedom.

3. $p(\lambda_{\tilde{fsi}}|\Theta^*)$: The conditional posterior is inverse Gamma, with scale given by

$$\sum_{i=1}^{C}\left(\tilde{fsi}_i^* - \bar{\tilde{fsi}}^*\right)\Lambda_{\tilde{fsi},i}^{-1}\left(\tilde{fsi}_i^* - \bar{\tilde{fsi}}^*\right)' + S_0$$

and $C + V_0$ degrees of freedom.

4. $p(\lambda_F|\Theta^*)$: The conditional posterior is inverse Gamma, with scale given by

$$\sum_{i=1}^{C}\left(F_i - \bar{F}\right)\Lambda_{F,i}^{-1}\left(F_i - \bar{F}\right)' + S_0$$

and $C + V_0$ degrees of freedom.

5. $p(\lambda_\mu|\Theta^*)$: The conditional posterior is inverse Gamma, with scale given by

$$\sum_{i=1}^{C}\left(\mu_i - \bar{\mu}\right)\Lambda_{\mu,i}^{-1}\left(\mu_i - \bar{\mu}\right)' + S_0$$

and $C + V_0$ degrees of freedom.

6. $p(\bar{\beta}_r|\Theta^*)$: Given the normal prior, the conditional posterior is normal given by $N(M_{\bar{\beta}_r}, V_{\bar{\beta}_r})$,

where:

$$V_{\bar{\beta}_r} = \left(\frac{1}{\lambda_{\beta,r}} \sum_{i=1}^{C} \Lambda_{\beta,i}^{-1} + \Lambda_{\beta,0}^{-1} \right)^{-1}$$

$$M_{\bar{\beta}_r} = V_{\bar{\beta}_r} \left(\frac{1}{\lambda_{\beta,r}} \sum_{i=1}^{C} \Lambda_{\beta,i}^{-1} \beta_{r,i} + \Lambda_{\beta,0}^{-1} \beta_0 \right)$$

7. $p(\bar{a}_r|\Theta^*)$: Given the normal prior, the conditional posterior is normal given by $N(M_{\bar{a}_r}, V_{\bar{a}_r})$, where:

$$V_{\bar{a}_r} = \left(\frac{1}{\lambda_{a,r}} \sum_{i=1}^{C} \Lambda_{a,i}^{-1} + \Lambda_{a,0}^{-1} \right)^{-1}$$

$$M_{\bar{a}_r} = V_{\bar{a}_r} \left(\frac{1}{\lambda_{a,r}} \sum_{i=1}^{C} \Lambda_{a,i}^{-1} a_{r,i} + \Lambda_{a,0}^{-1} a_0 \right)$$

8. $p(\bar{\tilde{fsi}}^*|\Theta^*)$: Given the normal prior, the conditional posterior is normal given by $N(M_{\bar{\tilde{fsi}}^*}, V_{\bar{\tilde{fsi}}^*})$, where:

$$V_{\bar{\tilde{fsi}}^*} = \left(\frac{1}{\lambda_{\tilde{fsi}}} \sum_{i=1}^{C} \Lambda_{\tilde{fsi},i}^{-1} + \Lambda_{\tilde{fsi},0}^{-1} \right)^{-1}$$

$$M_{\bar{\tilde{fsi}}^*} = V_{\bar{\tilde{fsi}}^*} \left(\frac{1}{\lambda_{\tilde{fsi}}} \sum_{i=1}^{C} \Lambda_{\tilde{fsi},i}^{-1} \tilde{fsi}_i^* + \Lambda_{\tilde{fsi},0}^{-1} \tilde{fsi}_0^* \right)$$

9. $p(\bar{F}|\Theta^*)$: Given the normal prior, the conditional posterior is normal given by $N(M_{\bar{F}}, V_{\bar{F}})$, where:

$$V_{\bar{F}} = \left(\frac{1}{\lambda_F} \sum_{i=1}^{C} \Lambda_{F,i}^{-1} + \Lambda_{F,0}^{-1} \right)^{-1}$$

$$M_{\bar{F}} = V_{\bar{F}} \left(\frac{1}{\lambda_{\beta,r}} \sum_{i=1}^{C} \Lambda_{F,i}^{-1} F_i + \Lambda_{F,0}^{-1} F_0 \right)$$

10. Repeat steps 1, 2, 6, and 7 for $r = \{1, 2\}$.

3.2 Nonlinear Impulse Responses and Identification Scheme

To analyze the (potentially regime-dependent) effects of the shocks of interest, for each country and a given draw for all idiosyncratic parameters, we use the nonlinear (generalized) impulse response (NIRF) proposed by Koop et al. (1996), defined as:

$$NIRF_y(h, \varepsilon_{it}, \mathcal{H}_{t-1}) = E[Y_{t+h}|\varepsilon_{it}, \mathcal{H}_{i,t-1}] - E[Y_{t+h}|\mathcal{H}_{i,t-1}] \tag{12}$$

where h is the length of the simulation horizon, ε_{it} is the shock of interest, and $\mathcal{H}_{t-1}$ is the history in period t. The NIRFs are defined so that the regime can change over the horizon. We focus on the role of two shocks in each regime, namely, financial shocks and uncertainty shocks.

3.2.1 Financial Shocks

Financial shocks in each regime are identified by means of sign restrictions, with restrictions following the spirit of the VAR literature aiming to identify financial and credit shocks in advanced countries (e.g., Fornari and Stracca, 2014; Furlanetto et al., 2017; Mumtaz et al., 2018). However, because we have no prior information regarding the effects of financial shocks on EMs' variables like inflation or the monetary-policy related variable, we impose sign restrictions only on the responses of GDP growth, investment growth, and on the FSI, been agnostic about inflation and the monetary policy responses.[2] Nonetheless, following Mumtaz et al. (2018), we restrict the number of admissible models by imposing a max FEVD restriction on the response of the financial stress indicator. Thus, we assume that a "bad" financial shock, captured by an unanticipated increase in FSI, will not lead to an increase both in the GDP growth nor the investment growth. The selected shocks are those that maximize the FEVD of the FSI. Table 1 summarizes the imposed restrictions.

Table 1: Sign Restrictions

	Financial Shock
GDP growth	≤ 0
Investiment growth	≤ 0
Inflation	-
Policy Rate	-
FSI	> 0 and Max FEVD

3.2.2 Volatility Shocks

As the volatility shock is assumed to be exogenous, we compute the NIRFs of such shocks applying the algorithm proposed by Alessandri and Mumtaz (2019) country-by-country. Thus, for each country in the sample, we simulate shocks to the log-volatility equation given some initial condition and use the estimated paths into the Threshold VAR equation to compute the NIRFs.

3.3 The Average Emerging Economy

The main goal of the paper is to combine the information from all countries in the sample to analyze the average effects of the shocks of interest. One way to make inference for the whole panel is to focus on the "average country" or "typical country" (Gomes et al., 2020; Mumtaz and Sunder-Plassmann, 2021) by focusing on the hierarchical posterior mean parameters, and them using some strategy to average the observations. However, such methodology is not straightforwardly justified in a nonlinear context of a model with stochastic volatility in mean.

Here, similar to Gomes et al. (2020), we compute the NIRFs using the "panel", weighted average statics, while using the idiosyncratic parameters and histories to compute individual for all countries in the sample. Then, we take the sample average of the computed NIRFs. In words, this process conditions the inference on the mean parameters, integrating out the idiosyncratic features in a two-step fashion.

[2]NIRFs with sign restrictions are not straightforward generalizations of their linear counterparts. The algorithm used to compute such functions is presented in the appendix.

3.4 Data

Emerging countries are selected mainly due to data availability. Data comes from many different sources. The countries in the sample Brazil, Chile, Colombia, Malaysia, Philippines, Poland, Russia, Thailand, and Turkey. National account variables for EMs are gathered from IFS, OECD, Euro Stats, ADB, or national statistics agencies in some cases. CPI data are taken from BIS. Monetary policy-related interest rates are taken from BIS or IFS, depending on availability. G7 growth data is taken from FRED. Variables are seasonally adjusted by the X13 filter whenever necessary. The Appendix presents the details.

3.4.1 Financial Stress Index for Emerging Markets

Similar to Soave (2020), our FSI is given by the idiosyncratic dynamic common factor estimated from a time-varying factor augmented VAR (TVP-FAVAR) to purge the macroeconomic shocks from the financial variables. For all countries in the sample, the FSI is estimated from the five sub-indices of financial stress in EMs proposed by Balakrishnan et al. (2011). These sub-indices include a banking sector stress index, a foreign market pressure index, two equity volatility measures, and a measure of sovereign debt stress (EMBI+). In the present paper, we also consider the financial information contained in the interbank rate and the spread between deposit and lending rates in the procedure. Details on financial data and estimation are described in Appendix C. Following Galvão and Owyang (2018), the macro-block of variables includes the GDP growth, CPI inflation, and a monetary policy-related variable are used to purge from the FSI the macroeconomic shocks.

In sum, we follow a two-step strategy in which we first estimate the FSI. Then, we fed the BPT-VAR-VM model with the estimated FSI to search for the periods in which the economy is under financial distress or normal times. We could draw the factors by adding more steps into our Metropolis-in-Gibbs algorithm, but the computational burden in panel context makes such a strategy prohibitive. In this sense, our analyses can be interpreted are conditioning the data to the median of our FSI measure.[3]

4 Results

We ran 1,000,000 replications the algorithm, discarding the first 100,000 as burn-in, and retaining every 50-th draw for inference. An appendix section presenting evidence on the convergence of the algorithm is available upon request. The selected lag length of the VAR is $L = 1$, but the results are fairly similar using $L = 2$.

Figure 1 illustrates the estimated transitions, FSIs, and uncertainty measures for all countries in the sample. In most cases, high uncertainty typically occurs during financial distress periods, although some episodes of financial stress periods are not followed by large spikes in uncertainty, and vice-versa.

Given the country-specific estimated thresholds, we compute the NIRFs for shocks to FSI and uncertainty following the previously described strategy. For concreteness, we focus on the average responses in each regime to the shocks to the FSI and uncertainty, but the idiosyncratic responses are available upon request from the author.

The results for the average effects of financial and uncertainty shocks in EMs are expressed in Figure 2. Blue lines denote to the normal regime, and red lines represent bad

[3]Data used to estimate the FSI are taken from Datastream, BIS, IMF, and GEM, and details are available upon request.

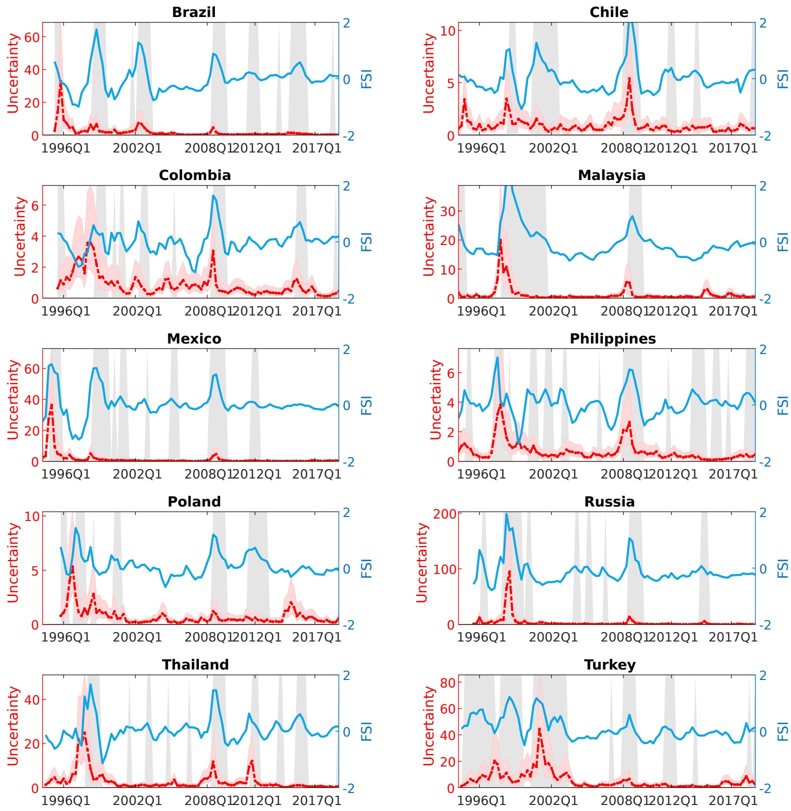

Figure 1: Financial regimes in 10 EMs. Grey areas are the estimated "financial distress periods." Blue lines indicate estimated FSI. Red-dashed lines denote the estimated macroeconomic uncertainty. Red areas are the 68% error band for the uncertainty measure.

regime estimations. We begin by focusing on the GDP responses to different shocks in the two regimes. We find that both shocks may harm the GDP in a nonlinear fashion. In Panel (a) of the figure, we observe that financial stress shocks lead to a reduction in the GDP in both regimes, but the magnitude is strikingly larger in good times compared with bad times.[4] In sharp contrast, the effects of uncertainty shocks on the GDP (Panel (b)) are indistinguishable from zero in normal times, turning to a large negative impact in bad times. These results suggest that, under normal financial conditions, financial shocks are more pervasive for EMs than uncertainty shocks. However, during financial distress, uncertainty shocks become more salient than financial shocks. These findings suggest that the role played by these two shocks changes when the regime changes.

[4]These magnitudes are the converse of those found by Soave (2020), who did not account for stochastic volatility.

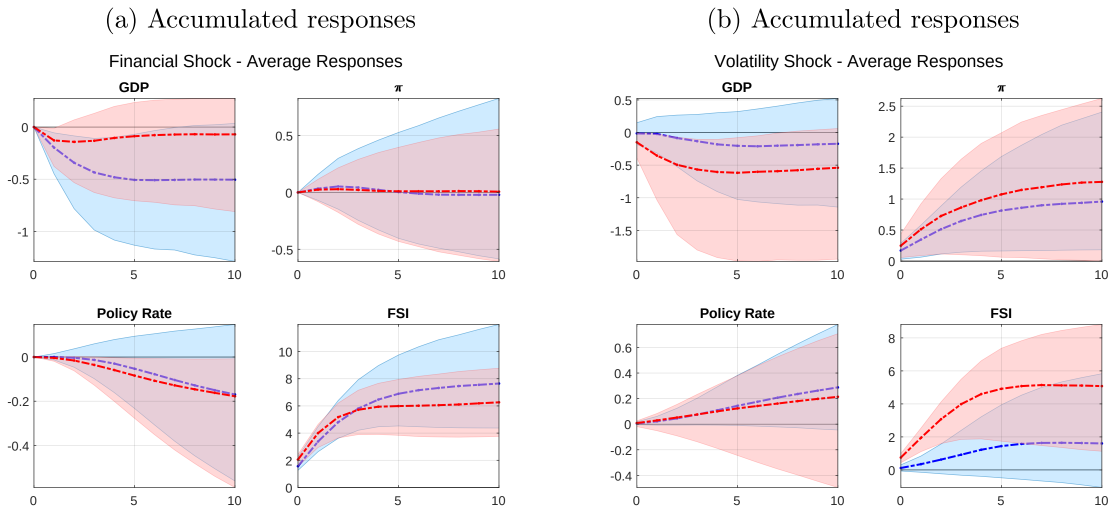

Figure 2: Accumulated NIRFs in the two regimes. Blue-dashed lines are responses in a good regime. Red-dashed lines are responses in a bad regime. The 68% error bands are the areas with transparency.

Although omitted here due to space limitation, our findings also suggest that inflation has an unobvious response to financial shocks in EMs, with a high degree of heterogeneity. In contrast, uncertainty shocks are typically inflationary regardless of the regime.[5]

The FSI responses to financial shocks reveal a similar pattern between regimes. By contrast, the responses of the FSI to volatility shocks are quite different between regimes. During bad times, uncertainty shocks trigger a more substantial increase in financial stress than in normal times in EMs.

To further analyze the previous results, Figure 3 presents the forecast error variance decomposition (FEVD) in the two regimes. For concreteness, we focus on the FEVD of the GDP and FSI only. During normal times, at the median, financial shocks account for about 10% of the FEVD of the GDP, close to the importance of the uncertainty shocks in the long run. However, during crises, the importance of financial shocks reduces to about 5%, whereas the importance of uncertainty shocks magnifies to more than 15% of the GDP FEVD.

For the FSI, while financial shocks explain about 70% of the FEVD in normal times, in bad times, the importance of such shocks reduces to about 50%. In contrast, during normal times, uncertainty shocks explain about 10% of the FSI FEVD and become more than 25% during bad times.

[5]Evidences of the responses of inflation to uncertainty and financial shocks for rich countries can be found, e.g., in Alessandri and Mumtaz (2019); Galvão and Owyang (2018); Meinen and Roehe (2018).

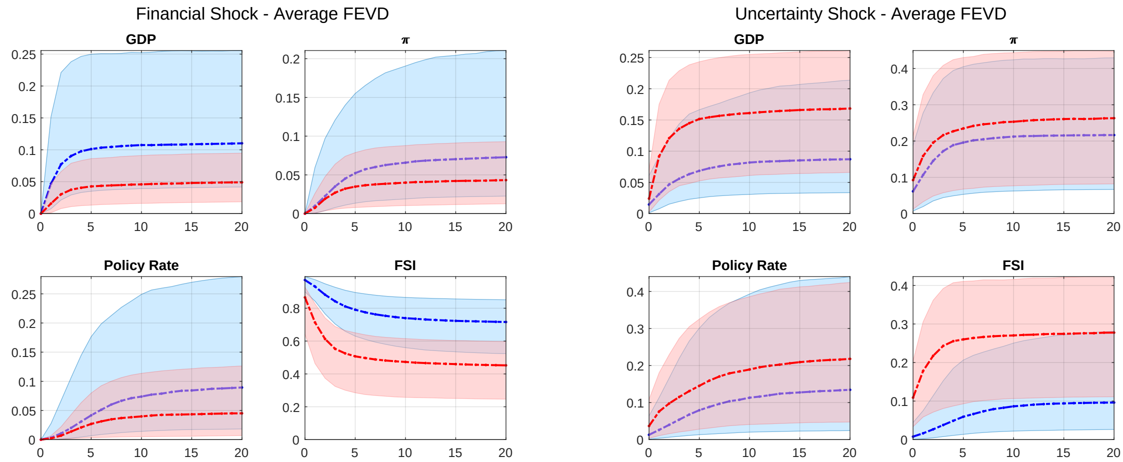

Figure 3: FEVD in the two regimes. Blue-dashed lines are FEVD in the good regime. Red-dashed lines are FEVD in the bad regime. 68% error bands are the areas with transparency.

5 Conclusion

This paper assessed the impacts of financial and uncertainty shocks in EMs using a Bayesian hierarchical threshold VAR with volatility-in-mean model. For a set of 10 EMs, we found that the relative importance of financial and uncertainty shocks varies depending on the state of the financial markets. Under normal financial conditions, financial shocks have a considerable negative effect on the GDP. In contrast, while uncertainty shocks may trigger stress in financial markets, such shocks have only mild effects on the GDP.

However, during financial distress, this relative importance changes. Financial shocks still negatively affect the GDP, but uncertainty shocks take a more prominent negative role than financial shocks.

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A Data

Table 2: Quarterly Macroeconomic Data

Variables			Real Sector	Inflation Measure	Interest Rates					
			GDP Growth/Investment	Consumer Price Index	Central Bank Interest Rate - IFS		Central Bank Interest Rate - BIS		Money Market Rates - IFS	
Country	Time Span		Source	Source	Time Span		Time Span		Time Span	
Brazil*	1995Q1	2019Q2	IFS	BIS	-	-	1995Q1	2019Q2	-	-
Chile*	1995Q2	2019Q2	OECD	BIS	-	-	1995Q2	2019Q2	-	-
Colombia*	1995Q3	2019Q2	IFS	GEM	-	-	1995Q3	2019Q2	-	-
Malaysia	1995Q4	2019Q2	IFS	BIS	-	-	1995Q4	2019Q2	-	-
Mexico	1994Q1	2019Q2	OECD	BIS	-	-	1998Q4	2019Q2	1994Q1	1998Q3
Philippines	1994Q1	2019Q2	IFS	BIS	-	-	1994Q1	2019Q2	-	-
Poland	1995Q3	2019Q2	OECD	BIS	-	-	1995Q3	2019Q2	-	-
Russian Federation	1995Q2	2019Q2	IFS	GEM	-	-	1995Q2	2019Q2	-	-
Thailand**	1998Q1	2019Q2	IFS	BIS	1998Q1	2019Q2	-	-	-	-
Turkey	1998Q3	2019Q2	Eurostats	BIS	1998Q3	2019Q2	-	-	-	-

Notes: GEM: Global Economic Monitor; BIS: Bank for International Settlements; IFS: International Financial Statistics; Observations prior to 1996Q1 taken from Uribe and Schmitt-Grohé (2017). **Interest rate for Thailand is proxied by the Central Bank policy rate from IFS.

Table 3: Financial Stress Index: Variables and Sources

Variables	Bank Stress FSI.1			Bank Stress FSI.2			EMPI FSI.3: NEER, Reserves			Stock Market: FSI.4, FSI.5			Sovereign Spreads FSI.6			Credit Spreads FSI.7		
Country	Source	Time Span		Source	Time Span		Source	Time Span		Source	Time Span		Source	Time Span		Source	Time Span	
Brazil	Datastream	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1994M06	2019M07	IFS	1997M01	2019M07
Chile	Datastream	1995M05	2019M07	Datastream	1996M01	2019M07	GEM	1995M05	2019M07	Datastream	1995M05	2019M07	GEM	1999M05	2019M07	IFS	1995M05	2018M12
Colombia	Datastream	1995M04	2019M07	Datastream	1995M04	2019M07	GEM	1995M04	2019M07	Datastream	1995M04	2019M07	GEM	1997M02	2019M07	IFS	1995M04	2019M07
Malaysia	Datastream	1995M11	2019M07	Datastream	1995M11	2019M07	GEM	1995M11	2019M07	Datastream	1995M11	2019M07	GEM	1996M10	2019M07	IFS	1995M11	2019M07
Mexico	Datastream	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1996M06	2019M07	IFS	1994M01	2019M07
Philippines	Datastream	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1997M12	2019M07	IFS	1994M01	2019M07
Poland	Datastream	1995M01	2019M07	Datastream	1995M01	2019M07	GEM	1995M01	2019M07	Datastream	1995M01	2019M07	GEM	1995M11	2019M07	IFS	1995M01	2019M07
Russian Federation	Datastream	1998M07	2019M07	Datastream	1995M05	2019M07	GEM	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1997M12	2019M07	IFS	1997M01	2019M07
Thailand	Datastream	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1997M12	2018M05	IFS	1994M01	2019M07
Turkey	Datastream	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1994M01	2019M07	Datastream	1994M01	2019M07	GEM	1996M07	2019M07	Datastream/IFS	1997M01	2019M07

Notes: GEM: Global Economic Monitor; IFS: International Financial Statistics; *Missing data for Thailand's EMBI+ is filled using CDS data.

B Nonlinear Impulse Response With Sign Restrictions

Because of the dependence of initial conditions, it's not straightforward to extend the nonlinear impulse response functions from Koop et al. (1996) in light of identification uncertainty. For the standard algorithms to impose sign restrictions, such dependence makes the computation burden grows exponentially.

The algorithm used in the paper works as follows:

1. For $t = t_0$, in which t_0 is the first available observation, given a draw of all parameters in the model and a draw of the unobserved stochastic volatility process, for country i at instant t, form a history $\mathcal{H}\rangle_{t-1}$. It has to include the lags of the VAR equation, the lag of the stochastic volatility equation, and the variable indicating the current state of the economy, $\mathcal{R}_t$.

2. Draw a candidate orthogonal matrix Q_t from algorithm proposed by Rubio-Ramírez et al. (2010). In both regimes, compute covariance matrix $\Omega_{r,it} = A_{r,i}^{-1} H_{r,it} A_{r,i}^{-1\prime}$. Check it $Q\text{chol}(\Omega_{r,it})$ satisfy the restrictions in both regimes. Otherwise, draw a new Q_t;

3. Using the history, check the state of the economy. Draw R pseudo shocks from period 1 to H and compute the forecasts of economy for the R draw. Repeat the process but now augment the equation with the shock of interest with a shock of a certain magnitude in period 1. The impulse response at t is the average difference between the two forecasts.

4. Repeat the above steps until T.

5. Compute the FEVD associated with the impulse response for all t.

6. Repeat the process for S times.

7. The sign identified NIRF in each regime is the one that has the maximum FEVD in S draws in each regime.

8. Given a select NIRF for country i, repeat the process for the rest of the countries in the sample.