Uncertainty Shocks and Financial Regimes in Emerging Markets*

Luis Gonzalo Llosa† Fernando J. Pérez Forero‡ Vicente Tuesta§

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Abstract

We study the link between financial conditions and economic uncertainty in five emerging markets (Brazil, Chile, Colombia, Mexico, and Peru). In the empirical model, uncertainty is measured as the volatility of the economy's structural shocks and its macroeconomic effect is contingent on the state of financial markets (normal or distress). We find that sudden jumps in uncertainty tighten financial conditions, increasing the likelihood of financial distress. We also find that uncertainty shocks are recessionary at all periods, induce lower interest rates and weaken domestic currencies against the US dollar. Importantly, these responses are larger and more persistent during periods of financial distress.

JEL Classification: C23, E44, F21, F32

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†Universidad de Lima; Email address: lgllosa@ulima.edu.pe

‡Deputy Manager of Monetary Policy Design, Central Reserve Bank of Peru, Jr. Santa Rosa 441, Lima 1, Peru; Email address: fernando.perez@bcrp.gob.pe

§QYPU Multi Family Office y Universidad de Lima; Email address: vtuesta@ulima.edu.pe

1 Introduction

Uncertainty shocks have received considerable attention in the last decade.[1] Events such as the global financial crisis (GFC) or more recently COVID-19 have triggered jumps in uncertainty which have been followed by sharp economic contractions. Additionally, the interaction between financial frictions and uncertainty, with the consequent impact on credit aggregates and asset prices, is identified as the main cause of deep recessions and sluggish recoveries in developed countries. Many authors have called this transmission mechanism the "financial view" (financial frictions and the credit channel).[2]

It is a well-known fact that the financial view is quite relevant for emerging market economies (see e.g. Calvo *et al.* (2006), García-Cicco *et al.* (2010)). Meanwhile, these economies tend to experience higher macro uncertainty than developed economies.[3] Inspired by these observations, in this paper we examine the role of uncertainty shocks in emerging markets through the lens of the financial view. With this objective in mind, we estimate a threshold vector autoregressive model with financial regimes and volatility effects using monthly data (from 2003 to 2021) for five emerging markets (Brazil, Chile, Colombia, Mexico, and Peru). Using this framework, we evaluate how these countries respond to uncertainty shocks under two different financial regimes: normal or crisis.

Our model follows closely Alessandri and Mumtaz (2019), who analyze the response of US economy (output, inflation, interest rates and financial conditions) to an uncertainty shock. In their model, uncertainty shocks are captured by the average volatility of structural shocks and the economy's response is allowed to change depending on financial conditions. We extend this framework by adding variables that play a crucial role under the financial view in emerging economies, namely, VIX index (a proxy for global risk aversion), foreign exchange rates (vis-à-vis the US dollar) and country credit spreads on U.S.

[1] See e.g. Bloom (2009), Leduc and Liu (2016), Bloom *et al.* (2018), Caldara *et al.* (2019), Caggiano *et al.* (2020), Baker *et al.* (2020).

[2] To cite a few examples, Christiano *et al.* (2014), Gilchrist and Zakrajšek (2012), Caldara *et al.* (2016), Alessandri and Mumtaz (2019) and Arellano *et al.* (2019).

[3] For instance, from 2012 to 2019, CBOE's Emerging Market volatility index (VXEEM) is about 40 percent higher than US CBOE's SP500 volatility index (VIX). Also, Bloom (2014) analyze a panel data of 60 countries and finds that developing countries experience about one-third higher macro uncertainty than developed countries.

dollar-denominated sovereign bonds.[4] In our estimated model, country credit spreads are placed at the center of financial conditions, determining whether or not financial markets are in crisis.[5]

We find that emerging market economies have experienced sudden jumps in uncertainty which wreck havoc on financial markets, causing a widening of country credit spreads and increasing the likelihood of a financial crisis. Moreover, higher uncertainty unleashes recessionary forces, depreciates the domestic currency vis-à-vis the US dollar and induces lower interest rates. These responses are larger and more persistent when financial markets fall into crisis. For some countries, this state-contingency also means that large positive shocks to uncertainty have more effect on the economy than other uncertainty shocks (negative or small). Finally, we show that, although uncertainty explains a small share of the business cycle volatility, its importance raises considerably when financial markets are distressed.

This paper is connected to a large body of empirical literature showing that the interaction between uncertainty and financial frictions is an important driver of economic fluctuations, i.e. financial view.[6] Recently, using threshold VAR with time-varying volatility, Alessandri and Mumtaz (2019) find that for the US uncertainty shocks have recessionary effects at all times, but their impact on output is larger when the economy is going through a financial crisis. We show that emerging markets in our sample are, in general, similar to the US in that respect.

Our focus on uncertainty shocks in emerging markets is shared by other papers in the literature. Based on a linear VAR model, Carrière-Swallow and Céspedes (2013) find that, in comparison with developed economies, the economic consequences of shocks to US stock market volatility for emerging markets are much more severe, especially if financial

[4] An inexhaustible reading list highlighting the role of these variables in small open economies will include Uribe and Yue (2006), Mendoza and Yue (2012) and Rey (2018).

[5] To be specific, we say that financial conditions are in crisis when credit spreads are above an endogenously estimated threshold. This view is compatible with the evidence and business-cycle theories showing the impact of country credit spreads on economic activity, e.g. Uribe and Yue (2006), Mendoza and Yue (2012).

[6] One branch derives implications for equilibrium responses to uncertainty shocks in the presence of financial frictions, see Christiano *et al.* (2014), Gilchrist and Zakrajšek (2014), Caldara *et al.* (2016), and Arellano *et al.* (2019). Another branch analyzes the role of time-varying aggregate risk at explaining business cycles, see also Caldara *et al.* (2016) and the papers cited therein.

markets are underdeveloped. Bhattarai *et al.* (2020) use a panel VAR approach and find that increases in US stock market volatility not only cause a fall in economic activity in emerging markets, but also negatively affect the market value of financial assets. Similar results are found by Miescu (2018), who applies an instrumental variable approach in a panel VAR context. The evidence from the afore-mentioned papers is complementary to ours, but there are some aspects in which we differ. First, our notion of uncertainty is related to predictability about the economic environment faced by agents, considering that a regime change might happen in the future. This interpretation of uncertainty provides a more comprehensive picture than that of the US stock market volatility, which is exogenous from emerging markets' point of view.[7] Second, the identification of the financial view applied by Carrière-Swallow and Céspedes (2013) exploits structural cross-sectional differences, which vary very little along the business cycle. In contrast, we apply a different identification based on regime changes triggered by sudden movements in financial conditions.[8]

The document is organized as follows. Section 2 describes the Threshold VAR model used for the empirical analysis. A description of the data is provided in Section 3. A general overview of the Bayesian estimation procedure can be found in Section 4. Section 5 analyzes the results, focusing on the response of variables to an uncertainty shock under different financial regimes. Section 6 presents additional analyses quantifying the importance of uncertainty shocks at explaining emerging markets' business cycles. Finally, section 7 presents the main conclusions.

2 The Model

In this section we specify the dynamic stochastic model used to assess the effects of macro-financial uncertainty in in the presence of regime changes. Specifically, we consider the following two-regime Vector Auto-regressive model (Threshold-BVAR), which closely

[7]In this sense, we are similar to Miescu (2018), who constructs indicators of aggregate uncertainty capturing the deterioration in the agents' ability to predict economic outcomes. Yet, in our case, uncertainty is endogenously determined within the model.

[8]This perspective is akin to emerging markets' business cycles general equilibrium theories, see e.g. Mendoza and Yue (2012), Aoki *et al.* (2018), Akinci and Queraltó (2018), among others.

follows Alessandri and Mumtaz (2019)[9]:

$$
\begin{aligned}
Z_t = &\left(c_1 + \sum_{j=1}^{p} \beta_{1j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{1j} \log \lambda_{t-j} + \Omega_{1t}^{1/2} e_t \right) \tilde{S}_t + \\
&\left(c_2 + \sum_{j=1}^{p} \beta_{2j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{2j} \log \lambda_{t-j} + \Omega_{2t}^{1/2} e_t \right) \left(1 - \tilde{S}_t\right)
\end{aligned} \tag{1}
$$

where Z_t is a N-dimensional vector of variables (defined below) in period t and e_t is a vector of normally independently and identically distributed shocks, $e_t \sim i.i.d.N\,(0, I_N)$. We define $Z_t \equiv [Y_t, P_t, R_t, E_t, F_t, G_t]'$, where Y_t is an indicator of economic activity, P_t is the inflation rate, R_t is the policy interest rate, E_t is the percentage change in the value of the domestic currency, F_t is an indicator of financial conditions and G_t is a proxy of global risk aversion. The time-varying covariance matrices are represented by $\Omega_{it}\ \forall\ i = 1, 2$. Variable λ_t is the time-varying volatility component, which represents uncertainty about Z_t. Finally, $\tilde{S}_t$ is a binary regime indicator which takes the values of zero or one.

The binary regime indicator $\tilde{S}_t$ is defined by:

$$
\tilde{S}_t = 1 \iff F_{t-d} \leq Z^*, \tag{2}
$$

where d is a discrete positive integer representing the lag of financial conditions and Z^* is a threshold parameter. Both are unknown parameters that need to be estimated. Hereafter, $\tilde{S}_t = 1$ refers to periods when financial markets are calm or normal, otherwise financial markets are in crisis.

The covariance matrix for the error term Ω_{it}, with $i = 1, 2$, is time varying according to:

$$
\Omega_{it} = A_i^{-1} H_t A_i^{-1\prime}, \tag{3}
$$

[9]The model departs from the traditional linear Vector Auto-regressive (VAR) models, which have been widely used for dynamic macroeconomic and financial analysis since (Sims, 1980, 1986). Since then, different variants and extensions have been considered using Bayesian techniques, especially because non-linearities also matter for capturing macroeconomic and financial phenomena (Constâncio, 2014). Among these extensions we can find the Time Varying parameter-VAR (Cogley and Sargent, 2005), and with Stochastic Volatility (Primiceri, 2005; Canova and Gambetti, 2009), the Markov Switching (MS)-BVAR (Sims and Zha, 2006) and the Threshold VAR (TVAR) (Balke, 2000). All these variants are equally important, since one size does not fit all.

where the constant matrix A_i for $i = 1, 2$ is lower triangular:

$$A_i = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{i,1} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ \alpha_{i,k} & \alpha_{i,k+1} & \dots & 1 \end{bmatrix} \tag{4}$$

In this context, recall also that $vec\,(A_i) = S_A \alpha_i + s_A$ (Amisano and Giannini, 1997), where α_i is a column vector that contains the set of free parameters $\alpha_{i,k+1}$ in matrix A_i, and where S_A and s_A are matrices governed by 0s and 1s.[10] The latter is a useful transformation to sample the full parameter vector α_i (Canova and Pérez Forero, 2015) and the time-varying matrix H_t is defined by:

$$H_t = \exp(\lambda_t) \times S, \tag{5}$$

where S is a $N \times N$ diagonal matrix that captures the constant heteroskedasticity:

$$S = \begin{bmatrix} s_1 & 0 & \dots & 0 \\ 0 & s_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & s_N \end{bmatrix} \tag{6}$$

with $s_j > 0$ for $j = 1, \dots, N$.

The stochastic variable λ_t follows a stationary first-order auto-regressive process $AR(1)$ with drift:

$$\lambda_t = \mu + F(\lambda_{t-1} - \mu) + \eta_t \tag{7}$$

where $0 < F < 1$ and $\eta_t \sim i.i.d.N(0, Q)$. Notice that this single variable λ_t governs the time-varying volatility (Carriero *et al.*, 2016; Alessandri and Mumtaz, 2019), which is a more parsimonious representation than other specifications where each shock has

[10] The operator $vec\,(.)$ transforms the matrix into a column vector by stacking all its columns consecutively.

a different time varying variance (see e.g. Primiceri (2005), Canova and Pérez Forero (2015), among others).

System (1) - (7) clearly departs from standard linear VAR models.[11] First, it entertains the possibility of stochastic volatility impacting both the expectation of Z_t and its variance, through λ_t and Ω_{it} $\forall$ $i = 1, 2$, respectively. Second, it allows for time-varying parameters which ultimately depends on the realization of $\tilde{S}_t$.[12]

3 Data

We use monthly data for Brazil, Chile, Colombia, Mexico, and Peru. For this group of countries, Y_t is the year-to-year growth rate of an economic activity index (i.e. industrial production), P_t is the year-to-year headline inflation rate, R_t is policy interest rate in domestic currency set by the monetary authority, E_t is the year-to-year percentage of the foreign exchange rate against the US dollar, F_t is J.P. Morgan's country EMBI spread and G_t is the VIX index.[13] These data spans from April 2003 to October 2021. The EMBI spreads are obtained from Bloomberg database and the rest of the data are obtained from International Monetary Fund-International Financial Statistics (IFS) and Central Bank websites.

Variables were ordered in the model from the most exogenous variable to the most endogenous one, i.e. the vector Z_t contains the variables: i) VIX Index, ii) Industrial Production, iii) Inflation, iv) Interest Rate, v) Exchange Rate Depreciation, vi) EMBI spread. Finally, we emphasize that the exogenous volatility serves also as an extension of the information set for the econometrician, as it mitigates the risk associated with the presence of the omitted variable bias, i.e. the path of volatilities essentially capture every pattern that is not captured by the model using the set of variables Z_t.

[11] See Sims (1980, 1986)

[12] These special features are useful is the presence of non-linear dynamics in macroeconomic and financial data. See e.g. Cogley and Sargent (2005), Primiceri (2005), Canova and Gambetti (2009), Sims and Zha (2006) and Balke (2000).

[13] To focus on the cyclical fluctuations of financial conditions, we filter the EMBI spreads using Hodrick and Prescott (1997).

4 Bayesian Estimation

The model can be estimated using Bayesian methods. Specifically, given the pre-specified priors and the joint likelihood function, we can combine efficiently these two pieces of information in order to estimate the parameters as described in Section A in the Appendix. Given the specified priors and the joint likelihood function, we combine efficiently these two pieces of information to get the estimated parameters included in Θ. Using the Bayes' theorem, we have that:

$$p(\Theta \mid Y) \propto p(Y \mid \Theta)\, p(\Theta) \tag{8}$$

Recall that $\Theta = \left\{Z^*, d, \Phi_{1:2}, \alpha_{1:2}, s_{1:N}, \lambda^T, \mu, F, Q\right\}$, where Z^* is the Threshold parameter, d is the lag for the financial conditions the threshold equation, Φ_i are the VAR coefficients for each regime $i = 1, 2$, α_i are the covariance coefficients of matrix A_i for each regime $i = 1, 2$, s_n are the variance parameters of error terms in the VAR system for each equation $j = 1, 2, .., N$, λ^T is the latent volatility component, and $\{\mu, F, Q\}$ are the parameters associated with the *a priori* AR(1) law of motion of λ^T. We use the notation Θ/χ whenever we denote the parameter vector Θ without the parameter χ.

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

1. Draw $p\left(Z^* \mid \Theta/Z^*, Z^T\right)$: Metropolis-Hastings step
2. Draw $p\left(d \mid \Theta/d, Z^T\right)$: Multinomial Distribution
3. Draw $p\left(\Phi_i \mid \Theta/\Phi_i, Z^T\right)$: Normal Distribution, $i = 1, 2$
4. Draw $p\left(\alpha_i \mid \Theta/\alpha_i, Z^T\right)$: Normal Distribution, $i = 1, 2$
5. Draw $p\left(s_j \mid \Theta/s_j, Z^T\right)$: Inverse-Gamma Distribution, $j = 1, \ldots, N$
6. Draw $p\left(\lambda^T \mid \Theta/\lambda^T, Z^T\right)$: Single-Move Kalman Smoother
7. Draw $p\left(\mu \mid \Theta/\mu, Z^T\right)$: Normal Distribution
8. Draw $p\left(F \mid \Theta/F, Z^T\right)$: Truncated Normal Distribution
9. Draw $p\left(Q \mid \Theta/Q, Z^T\right)$: Inverse-Gamma Distribution

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

5 Main Results

In this section, we present our main results. We emphasize that uncertainty tends to rise simultaneously with financial distress, corroborating the relevance of the financial view in emerging markets. Moreover, uncertainty in emerging markets reflects both local and global factors, but the latter plays a much more important role. Regarding the impact of uncertainty on emerging market economies, our results show that increases in uncertainty have recessionary effects, depreciate the domestic currency against the US dollar and (in most cases) induce lower interest rates. Inflation responses are unambiguous across countries, suggesting that demand-side and supply-side effects offset each other. The monetary policy reaction via interest rates is in general counter-cyclical. Importantly, these effects get amplified when the financial markets are in crises.

5.1 Statistical analysis

Let's first explore the statistical properties of the estimated uncertainty, measured by the stochastic volatility variable λ_t. Figure 1 depicts the estimated uncertainty for the five emerging markets and the periods when financial conditions tightened above the estimated thresholds, $\tilde{S}_t = 0$ (gray areas). Note that most economies experienced a significant jump in uncertainty during both the GFC and the recent crisis generated by COVID-19. Importantly, both episodes were characterized by a sudden tightening of global financial conditions followed by significant economic contractions.[14] Another stylized fact that emerges from the estimation is the hefty spillovers from uncertainty to financial conditions. As shown in Figure 1, most events of elevated uncertainty coincide with distressed financial markets. This tight link between uncertainty and financial conditions is at the core of the transmission mechanism of uncertainty to the real sector as emphasized by the literature (Christiano *et al.*, 2014; Gilchrist and Zakrajšek, 2014;

[14]See for example Caggiano *et al.* (2020)

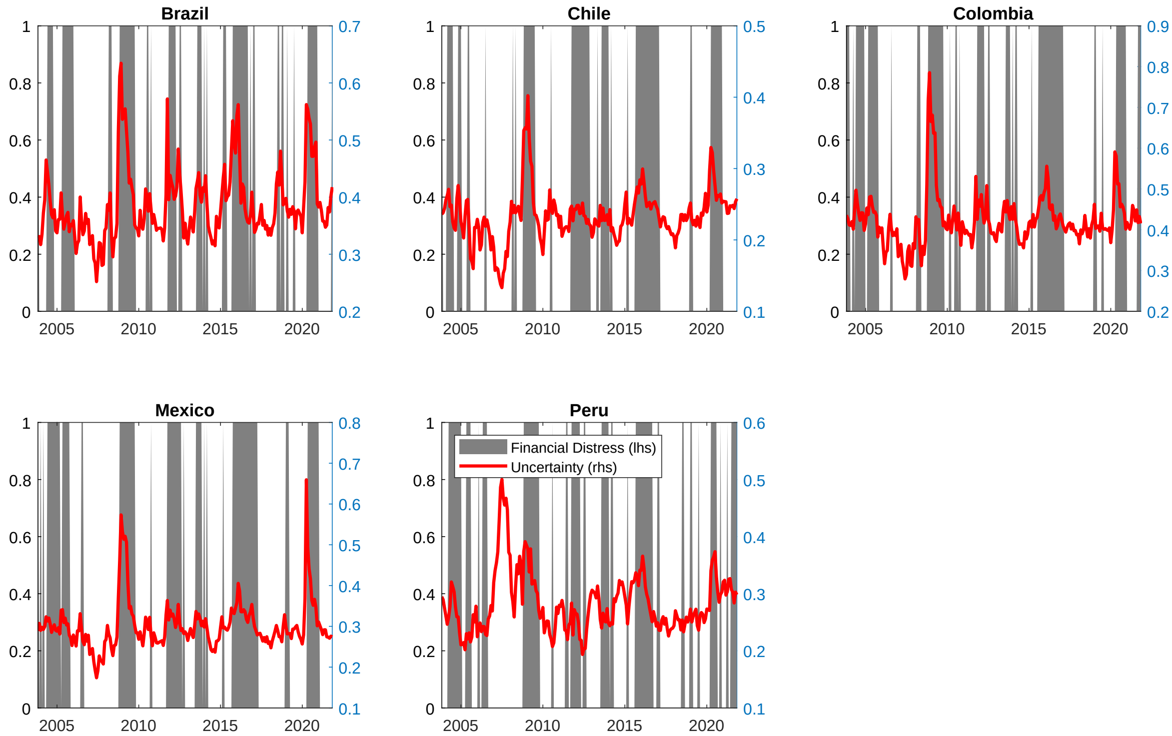

Figure 1: Financial stress regime $1 - S_t$ and economic uncertainty λ_t

Arellano *et al.*, 2019).

Our results also indicate that economic uncertainty in emerging economies reflects both global and idiosyncratic factors. Table 1 reveals that spikes of uncertainty are quite elevated (i.e. positive Skewness), frequent (i.e. excess Kurtosis) and persistent (i.e. positive first and second auto-correlations). Moreover, these spikes tend to occur at the same time (i.e. positive pair-wise correlations) suggesting that emerging markets are prone to contagion of international risk. Idiosyncratic factors seem to be also important as evidenced by the differences in the statistics and the lack of perfect correlation. For example, average uncertainty differs across countries, with Colombia in the upper end and Chile in the lower end of the range. Yet, most of the uncertainty faced by emerging markets comes from a global factor.[15]

[15] To corroborate this, we performed a principal component analysis over the (standardized) uncertainty levels. The results indicate that close to 70 percent of the cross-sectional variability is captured by the first principal component.

Table 1: Economic Uncertainty λ_t - Main Statistics

a. Moments	Brazil	Chile	Colombia	Mexico	Peru
Average	0.39	0.23	0.42	0.30	0.28
Standard deviation	0.06	0.04	0.06	0.06	0.05
Skewness	1.32	0.82	2.04	2.46	1.40
Kurtosis	4.93	6.71	10.70	12.33	5.66
First autocorrelation	0.82	0.87	0.83	0.84	0.90
Second autocorrelation	0.64	0.73	0.64	0.66	0.81

b. Correlations	Brazil	Chile	Colombia	Mexico	Peru
Brazil	1.00	0.77	0.86	0.84	0.10
Chile	0.77	1.00	0.82	0.83	0.03
Colombia	0.86	0.82	1.00	0.91	0.07
Mexico	0.84	0.83	0.91	1.00	0.09
Peru	0.10	0.03	0.07	0.09	1.00

5.2 Impulse responses

This subsection analyzes the estimated impulse response functions. Figure 2 plots the responses of the main endogenous variables (i.e., output, country credit spreads, exchange rate, inflation rate and interest rates) following a positive 1-standard deviation shock to the stochastic innovation appended to the process of λ_t (see equation 7). Periods associated with normal times and financial crises are graphed in black and red, respectively. For each regime the figures plot the median impulse-responses (solid lines) and the 68% confidence bands.

We find that, in all countries, an increase in uncertainty leads to a decline economic activity. More importantly, the sharpest declines are detected under the financial crises regime.[16] In fact, the cross-country average of the ratio of the maximum drop in output in the financial crises regime to the maximum drop in the normal regime is 1.9. This non-linearity shed lights about the important role played by financial conditions in the transmission mechanism of uncertainty shocks. Another important feature of the impulse response functions is that, when uncertainty returns to normality, output growth does

[16]There is also some heterogeneity across-countries in terms of output's sensitivity to uncertainty. Colombia and Brazil stand out as countries where uncertainty shocks cause larger drops in output, without much differences between financial regimes. On the contrary, Chile, Mexico and Peru's outputs display smaller reactions to uncertainty, but larger differences between financial regimes.

not bounce above its pre-shock level as predicted by some theoretical models, e.g. Bloom (2009). This indicates that uncertainty shocks generate a permanent loss in the level of output (relative to trend), an effect that is stronger when financial conditions deteriorate considerably.[17]

Next, we address how do country risk spreads and foreign exchange rates respond to an uncertainty shock. With the exception of Peru, uncertainty leads to a tightening of financial conditions, i.e. widening of country credit spreads. In this sense, economic risk is an important driver of financial conditions, which amplify the effects of uncertainty on the real sector as emphasized by the literature (Christiano *et al.*, 2014; Gilchrist and Zakrajšek, 2014; Arellano *et al.*, 2019; Uribe and Yue, 2006; García-Cicco *et al.*, 2010; Mendoza and Yue, 2012). With respect to the foreign exchange rates, in all countries, uncertainty shocks trigger a depreciation of the domestic currency versus the US dollar, during both normal and financially distressed regimes. It is also interesting to note the differences in the dynamics of exchange rates across countries and regimes. In the cases of Brazil, Colombia and Mexico, the exchange rate depreciation is of greater magnitude and persistence in the financial crisis regime than in the normal regime.[18] The responses of country credit spreads and foreign exchange rates confirm that risk is a prominent driver of asset prices and capital flows in emerging markets as predicted by some economic models, see also Fernández-Villaverde *et al.* (2011) and Cormun and De Leo (2020).

Turning to inflation, we highlight that the responses are quite heterogeneous across countries and regimes. On one hand, the inflation rates of Brazil, Chile and Mexico decrease after an uncertainty shock only if financial conditions are under distress. On the other hand, the Peruvian inflation tends to increase, while the Colombian inflation is almost unresponsive. This mixed evidence suggests that demand-side effects could be partially or completely offset by supply-side effects.[19]

[17]The non-linear response of output and the lack of a V-shaped recovery after an uncertainty shock are also observed in the US, see Alessandri and Mumtaz (2019).

[18]Peru stands out as a case where the exchange rate depreciation is relatively muted. This is expected as its central bank intervenes actively in the market to avoid excessive exchange rate volatility.

[19]Alessandri and Mumtaz (2019) points out that the effects on uncertainty on prices are ambiguous. Business cycle models with strong demand-side effects predict that uncertainty shocks reduce inflation, e.g. Christiano *et al.* (2014). However, uncertainty can also act through supply-side effects as in Fernández-Villaverde *et al.* (2015). In this case, an increase in uncertainty can lead to higher inflation.

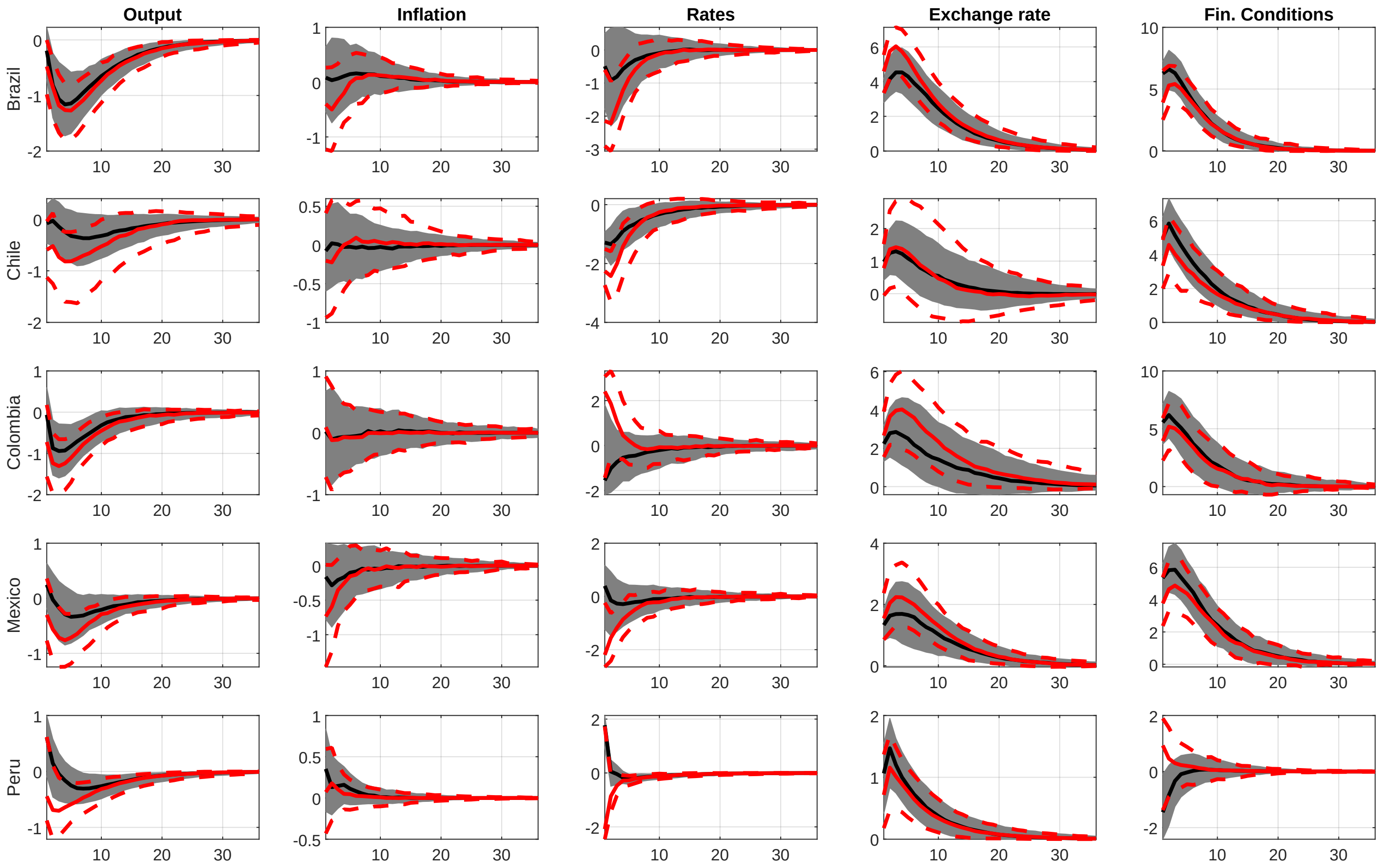

Figure 2: Effects of an one standard deviation uncertainty shock; median values and 68% bands.

Note: Bands for the 'Normal' regime are plotted as gray-shaded areas. Bands for the 'Crises' regime are plotted as red dotted lines.

Finally, regarding the monetary policy reaction to higher uncertainty, we note that most countries react by cutting interest rates, specially under financial crises. This counter-cyclical response is consistent with the responses of output and, to a lesser extent, of inflation.[20]

6 Additional results

6.1 Size and sign asymmetries

We have shown that the responses of emerging market economies to an increase in uncertainty depend on whether the financial markets are calm or distressed. As pointed out by Alessandri and Mumtaz (2019), this state-contingency might also imply a differentiated response conditional on the sign and size of the uncertainty shock. Intuitively, the response of the economy might depend on the initial financial conditions (normal or crises) and whether or not a shock of particular size or sign induces a switch of regime.

To analyze the potential size/sign asymmetries, we calculate the impulse responses of the endogenous variables to (i) small and large uncertainty shocks, defined as one and five standard deviations perturbations, respectively, and (ii) positive and negative uncertainty shocks. We illustrate the asymmetries using the impulse responses for Mexican output and foreign exchange rate.[21]

Figure 3 depicts the response of Mexican output to shocks of different size and sign under the two regimes. The left and right columns show the impulse responses under 'Normal times' and 'Crises', respectively. These results reveal that the responses of output are not linear with respect to the sign of the shock. To appreciate this, note that, for any given regime, the change in output caused by a reduction in uncertainty of a specific size (small or large) is smaller than the change in output caused by an increase in uncertainty of the same size. The impulse responses of output are also not linear with respect to

[20]Colombia, Mexico and Peru depart from this pattern. In the first case, a pro-cyclical interest rate reaction is observed when financial markets are distressed. In the cases of Mexico and Peru, interest rates increase under the normal regime.

[21]We pick Mexico because is the country with more noticeable asymmetries. Results for other countries and variables are relegated to the appendix, see figures C.5 - C.7.

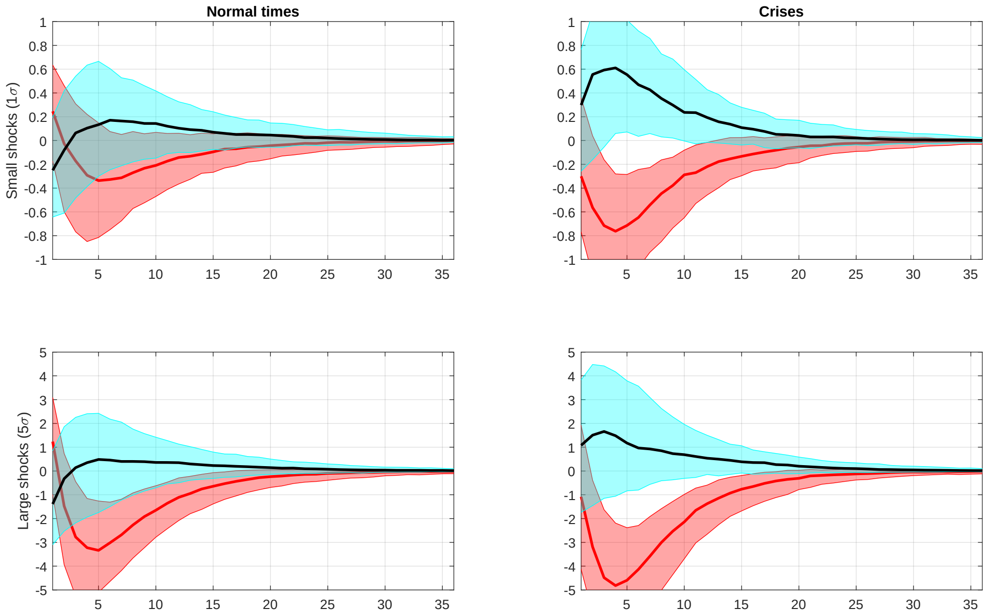

Figure 3: Response of Mexican output.
(Median values and 68% bands)

Note: Bands for the positive and negative shocks are plotted as cyan-shaded and red-shaded areas, respectively. The left (right) column plots the responses under the 'Normal' ('Crises') regime. The top (bottom) row plots the responses to a one (five) standard deviation uncertainty shock.

the size of the shock.[22] One one hand, large positive shocks cause disproportionately more damage to output than smaller shocks of the same sign. On the other hand, output expansions caused by large negative shocks are noticeably closer to the expansions caused by small negative shocks.

Figure 4 focuses on the response of Mexican foreign exchange rate. As highlighted in the previous section, an increase in uncertainty triggers a depreciation of the foreign exchange rate, which is larger if financial markets are in crisis. Similarly, the foreign exchange rate appreciates more forcefully after a reduction in uncertainty if financial markets are distressed. This regime-dependent response holds regardless of the size of the shock. Turning to other possible asymmetries, we first emphasize that the foreign exchange rate responses are almost linear with respect to the sign of shock if the shock is small. To see this, note that, for any given regime, the change in the foreign exchange rate caused by a small increase in uncertainty mirrors the change in the foreign exchange

[22] Recall that, in the absence of non-linear dynamics (e.g. linear VAR), the impulse response function of the "x" standard deviation shock is just x-times the impulse response function of the one standard deviation shock.

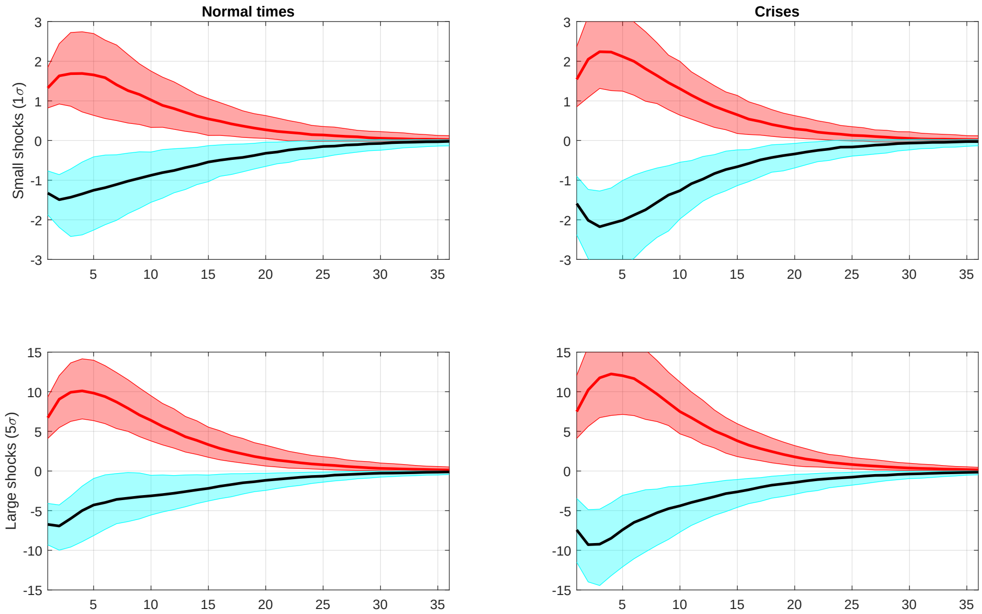

Figure 4: Response of Mexican foreign exchange rate.
(Median values and 68% bands)

Note: Bands for the positive and negative shocks are plotted as cyan-shaded and red-shaded areas, respectively. The left (right) column plots the responses under the 'Normal' ('Crises') regime. The top (bottom) row plots the responses to a one (five) standard deviation uncertainty shock.

rate caused by a small reduction in uncertainty. This linearity breaks down if shocks are large. Specifically, for any given regime, the change in the foreign exchange rate caused by a large increase in uncertainty is of greater magnitude and persistence than the change in the foreign exchange rate caused by a large reduction in uncertainty. We also detect some minor evidence of size asymmetry. In particular, a large positive uncertainty shock causes a disproportionate larger and longer-lasting depreciation of foreign exchange rate than the one caused by a small positive shock.

These results shed more lights on the important linkages between financial markets and the real economy in the transmission of uncertainty shocks (i.e. 'financial view'). Large increases in uncertainty have a particularly damaging effect on output because the economy is pushed towards a financial constraint, which might tighten further through negative valuation effects caused by the foreign exchange rate depreciation. By the same token, large reductions in uncertainty have less meaningful effect on output.

Table 2: Forecast Error Variance Decomposition - 12 months ahead

	Average	Brazil	Chile	Colombia	Mexico	Peru
a. Output						
Normal Times	2.22	5.28	0.99	3.21	0.93	0.68
Financial Crises	3.62	6.53	2.79	5.15	2.08	1.53
b. Inflation						
Normal Times	0.92	1.41	0.66	1.31	0.96	0.27
Financial Crises	1.14	1.63	1.02	1.44	1.32	0.27
c. Interest rate						
Normal Times	4.10	4.75	4.14	6.99	2.72	1.89
Financial Crises	7.72	10.00	9.52	9.69	6.40	3.00
d. Exchange rate						
Normal Times	27.23	83.53	5.75	30.51	12.24	4.11
Financial Crises	44.77	127.61	7.52	65.69	20.19	2.86
e. Fin. conditions						
Normal Times	86.07	124.84	79.05	110.91	113.83	1.70
Financial Crises	62.27	94.69	46.29	85.41	83.56	1.39

Note: Each row shows the fraction of forecast error variance explained by volatility shocks for one of the variables included in the Threshold VAR of Section 2. 'Normal times' refers to periods when financial conditions lie below the endogenously estimated threshold Z^*, see equation (2). 'Financial Crises' refers to periods when financial conditions exceed the threshold.

6.2 Variance decomposition

In this subsection, we quantify the relevance of uncertainty shocks at explaining emerging markets' business cycles using a forecast error variance (FEV) decomposition analysis of the endogenous variables in the Threshold VAR of Section 2. Table 2 reports the fraction of the forecast error variance explained by uncertainty shocks 12 months ahead. Note that for most variables and countries, uncertainty shocks are more prominent during financial crises. For example, on average, 3.6 percent of output's FEV is explained by uncertainty shocks when financial markets are in crises, but this share falls to 2.2 percent when financial markets are calm. Note also that uncertainty shocks explain a larger fraction of the variance of financial variables versus non-financial variables (output and inflation). Finally, there is important heterogeneity in the cross-section, with Brazil standing out as the country where uncertainty shocks matter the most and Peru as the country where they matter the least.

7 Concluding Remarks

Financial frictions in connection with uncertainty shocks are at the center of the discussion of transmission mechanisms in both developed and emerging markets. Furthermore, this connection is present and more pertinent to study when the economy is either in normal times or under financial distress. This paper contributes the afore-mentioned discussion by identifying and analyzing the role of uncertainty shocks in emerging markets through the lens of the financial view (triggered by credit distortions) when the economy is either under financial distress or normal times.

Our results show that the five emerging market economies under study have experienced sudden jumps in economic uncertainty which tend to happen at the same time. Indeed, for the five economies, the regime associated to elevated financial distress coincides with periods in where external financial constraints were tighter, such as GFC and Covid periods. This highlights the presence of a clear relationship between financial constraints and uncertainty shocks in emerging markets.

Like developed markets, our results indicate that uncertainty shocks are recessionary regardless the regime, being their impact larger when the emerging economy is under financial stress. Our findings further emphasize a key role for variables such as credit spreads and exchange rates in both identifying uncertainty shocks and understanding the transmission mechanisms when emerging economies are hit by uncertainty shocks during distressed regimes.

As further research is worth noting that uncertainty is a crucial variable in modern macro-finance literature. It is everywhere and it further affects the behavior of policy makers, consumers, entrepreneurs, and investors. Thus, understanding the stylized facts of economic and financial uncertainty in emerging markets is an unexplored topic worth pursuing.

Finally, central bankers are looking for answers related to how to respond to uncertainty shocks during distressed periods. Likewise, it is relevant to quantify whether the adoption of policy rules, the use of different instruments, and communication strategies have reduced uncertainty. The previous-mentioned concerns open a broad research agenda on the role of Central Banks in affecting both macro and financial uncertainty.

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A Gibbs sampling details

The algorithm described in subsection 4 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, where we closely follow Alessandri and Mumtaz (2019).

1. **Block 1**: Draw $p\left(Z^* \mid \Theta/Z^*, Z^T\right)$: Metropolis-Hastings step (Chen and Lee, 1995)

   We first draw a candidate Z^{can} using a random-walk proposal distribution:

$$Z^{can} = Z^* + \varepsilon^Z \tag{A.1}$$

   where Z^* is the current draw and $\varepsilon^Z \sim N(0, c_Z)$ with $c_Z > 0$ is a constant calibrated to yield and acceptance rate between 0.2 and 0.4. To improve the mixing properties of the MCMC algorithm, we use the modified adaptive proposal distribution used by Haario *et al.* (2001), taking equation (*A*.1) as a starting point. Then, the acceptance probability is given by the transition kernel:

$$\alpha\left(Z^{can}, Z^*\right) = min\left\{1, \frac{p\left(Z^{can} \mid Z^*, \Theta_{-Z^*}\right)}{p\left(Z^* \mid Z^{can}, \Theta_{-Z^{can}}\right)}\right\} \tag{A.2}$$

   where the posterior distribution $p\left(Z^* \mid \Theta_{-Z^*}\right)$ is:

$$p\left(Z^* \mid \Theta_{-Z^*}\right) = L\left(Z^*, \Theta/Z^* \mid Z^T\right) \times p\left(Z^*\right) \tag{A.3}$$

   where $L\left(Z^*, \Theta/Z^* \mid Z^T\right)$ is the likelihood function of the model described in equation (1) and $p\left(Z^*\right)$ is the prior distribution for the parameter set.

2. **Block 2**: Draw $p\left(d \mid \Theta/d, Z^T\right)$: Discrete Multinomial Distribution (Chen and Lee, 1995)

   The conditional posterior distribution for parameter d is a discrete multinomial with conditional probability

$$p\left(d \mid \Theta/d, Z^T\right) = \frac{L\left(d, \Theta/d \mid Z^T\right)}{\sum_{d=1}^{d_{max}} L\left(d, \Theta/d \mid Z^T\right)} \tag{A.4}$$

where we set $d_{max} = 6$ and $L\left(d, \Theta/d \mid Z^T\right)$ is the likelihood function of the model described in equation (1).

3. **Block 3**: Draw $p\left(\Phi_i \mid \Theta/\Phi_i, Z^T\right)$: Normal Distribution, $i = 1, 2$

   Given the Threshold BVAR model in (1), we take the SUR transformation as in Koop and Korobilis (2010). In particular, let $\phi_i = vec\left(\Phi_i\right)$. Given the prior $p\left(\phi_i\right) = N\left(\underline{\phi}_i, \underline{V}_i\right)$, then the posterior distribution of ϕ_i is Normal:

$$p\left(\phi_i \mid \Theta/\phi_i, Z^T\right) = N\left(\overline{\phi}_i, \overline{V}_i\right) I\left(\phi_i\right) \tag{A.5}$$

   where $I\left(.\right)$ is the prior truncation for stationary draws, and

$$\overline{V}_i = \left(\underline{V}_i^{-1} + \sum_{t=p+1}^{T} X_t' \Omega_{it}^{-1} X_t\right)^{-1} \tag{A.6}$$

$$\overline{\phi} = \overline{V}_i \left(\underline{V}_i^{-1} \underline{\phi}_i + \sum_{t=p+1}^{T} X_t' \Omega_{it}^{-1} Z_t\right) \tag{A.7}$$

   where $X_t = x_t' \otimes I_{dim(Z)}$ and $x_t = \left[Z_{t-1}', \ldots, Z_{t-p}'\right]'$. In addition, recall that $\Omega_{it} = A_i^{-1} H_t A_i^{-1\prime}$ as in equation (3) and $H_t = \exp\left(\lambda_t\right) \times S$ as in equation (5).

4. **Block 4**: Draw $p\left(\alpha_i \mid \Theta/\alpha_i, Z^T\right)$: Normal Distribution, $i = 1, 2$

   Consider the reduced-form residual terms $\varepsilon_{it} \sim i.i.d.N\left(0, \Omega_{it}\right)$ of the BVAR model in equation (1), where $\Omega_{it} = A_i^{-1} H_t A_i^{-1\prime}$. Therefore, the standardized innovations are $A_i \varepsilon_{it} = \tilde{\varepsilon}_{it}$. Recall also that $vec\left(A_i\right) = S_A \alpha_i + s_A$, so that (Amisano and Giannini, 1997; Canova and Pérez Forero, 2015):

$$vec\left(A_i \varepsilon_{it}\right) = \left(\varepsilon_{it}' \otimes I\right)\left(S_A \alpha_i + s_A\right) \tag{A.8}$$

As a consequence we can define $\tilde{e}_{it} = (\varepsilon'_{it} \otimes I)\, s_A$ and $\tilde{x}_{it} = -(\varepsilon'_{it} \otimes I)\, S_A$ such that we have the following linear-normal regression model:

$$\tilde{e}_{it} = \tilde{x}_{it}\alpha_i + \tilde{\varepsilon}_{it} \tag{A.9}$$

Given the prior $\alpha \sim N(\mu_\alpha, \Omega_\alpha)$ we sample the posterior

$$p\left(\alpha_i \mid \Theta/\alpha_i, Z^T\right) = N\left(\overline{\alpha}_i, \overline{V}_{\alpha_i}\right) \tag{A.10}$$

with

$$\overline{V}_{\alpha_i} = \left(\Omega_\alpha^{-1} + \sum_{t=p+1}^{T} \tilde{x}'_{it} H_t^{-1} \tilde{x}_{it}\right)^{-1} \tag{A.11}$$

$$\overline{\alpha}_i = \overline{V}_{\alpha_i}\left(\Omega_\alpha^{-1}\mu_\alpha + \sum_{t=p+1}^{T} \tilde{x}'_{it} H_t^{-1} \tilde{e}_{it}\right) \tag{A.12}$$

5. **Block 5**: Draw $p\left(s_j \mid \Theta/s_j, Z^T\right)$: Inverse-Gamma Distribution, $j = 1, \ldots, dim(Z)$

   Variance parameters $s_j > 0$ are simulated using an Inverse-Gamma distribution. Given the prior $s_j \sim IG(d_s \times \underline{s}, d_s)$, the posterior distribution is:

$$p\left(s_j \mid \Theta/s_j, Z^T\right) = IG\left(d_s \times \underline{s} + \sum_{t=p+2}^{T} u_{j,t}^2, d_s + T - p - 1\right) \tag{A.13}$$

   where residuals are defined as $u_{j,t} = A_1\tilde{e}_{1t}S_t + A_2\tilde{e}_{2t}(1 - S_t)$ for $t = p+1, \ldots, T$.

6. **Block 6**: Draw $p\left(\lambda^T \mid \Theta/\lambda^T, Z^T\right)$: Single-Move Kalman Smoother

   Sampling latent volatility λ^T is non-trivial, since it also enters in the model as an exogenous variable with contemporaneous and lagged effects (feedback). Thus, the resulting state space in non-linear, and as a result the popular multi-move method of Kim *et al.* (1998) cannot be used for this purpose. Instead, given the complexity of the system, we need to recall single-move techniques as in Jacquier *et al.* (1994), among others.

$$f\left(\lambda_t \mid \lambda_{-t}, \Theta_{-\lambda^T}, Z^T\right) \propto f\left(\lambda_t \mid \lambda_{-t}, \Theta_{-\lambda_t}\right) f\left(Z_t \mid \lambda_t, \Theta_{-\lambda_t}\right) \tag{A.14}$$

$$\begin{aligned} f\left(\lambda_t \mid \lambda_{-t}, \sigma_\eta, \phi, \mu\right) = & \quad f\left(\lambda_t \mid \lambda_{t-1}, \lambda_{t+1}, \sigma_\eta, \phi, \mu\right) \\ \Rightarrow & \qquad\qquad \lambda_t \sim N\left(\lambda_t^* \upsilon^2\right) \end{aligned} \tag{A.15}$$

$$\lambda_t^* = \mu + \frac{F\left\{\left(\lambda_{t-1} - \mu\right) + \left(\lambda_{t+1} - \mu\right)\right\}}{1 + F^2} \tag{A.16}$$

$$\upsilon^2 = \frac{Q}{1 + F^2} \tag{A.17}$$

Given that $\exp\left(-\lambda_t\right)$ is a convex function, it is then bounded by any linear function in λ_t, so that:

$$\ln f\left(Z_t, \lambda_t, \sigma_\eta, \phi, \mu\right) = const + \ln f^*\left(Z_t, \lambda_t, \sigma_\eta, \phi, \mu\right) \tag{A.18}$$

$$\begin{aligned} \ln f^*\left(Z_t, \lambda_t, \sigma_\eta, \phi, \mu\right) = & \qquad -\frac{1}{2}\lambda_t - \frac{Z_t^2}{2}\left\{\exp\left(-\lambda_t\right)\right\} \\ \leqslant & \quad -\frac{1}{2}h_t - \frac{y_t^2}{2}\left\{\begin{array}{c} \exp\left(-h_t^*\right)\left(1 + h_t^*\right) \\ -h_t \exp\left(-h_t^*\right) \end{array}\right\} \\ = & \qquad \ln g^*\left(y_t, h_t, \sigma_\eta, \phi, \mu, h_t^*\right) \end{aligned} \tag{A.19}$$

$$\begin{aligned} f\left(h_t \mid h_{-t}, \sigma_\eta, \phi, \mu\right) \times f^*\left(y_t, h_t, \sigma_\eta, \phi, \mu\right) \leqslant & \quad f_N\left(h_t \mid h_t^*, \upsilon^2\right) \times \\ & \quad g^*\left(y_t, h_t, \sigma_\eta, \phi, \mu, h_t^*\right) \end{aligned} \tag{A.20}$$

$$f_N\left(h_t \mid h_t^*, \upsilon^2\right) g^*\left(y_t, h_t, \sigma_\eta, \phi, \mu, h_t^*\right) \propto f_N\left(h_t \mid \mu_t, \upsilon^2\right) \tag{A.21}$$

where

$$\mu_t = \lambda_t^* + \frac{\upsilon^2}{2}\left[y_t^2 \exp\left(-\lambda_t^*\right) - 1\right] \tag{A.22}$$

We draw a candidate $h_t^c \sim N\left(\mu_t, \upsilon^2\right)$ and accept it with probability α_λ

$$\alpha_\lambda = \min\left\{1, \frac{f_t^*}{g_t^*}\right\} \tag{A.23}$$

7. **Block 7**: Draw $p\left(\mu \mid \Theta/\mu, Z^T\right)$: Normal Distribution

8. **Block 8**: Draw $p\left(F \mid \Theta/F, Z^T\right)$: Truncated Normal Distribution

9. **Block 9**: Draw $p\left(Q \mid \Theta/Q, Z^T\right)$: Inverse-Gamma Distribution

   Variance parameter $Q > 0$ is also simulated using an Inverse-Gamma distribution. Given the prior $Q \sim IG\left(d_Q \times \underline{Q}, d_Q\right)$, the posterior distribution is:

$$p\left(Q \mid \Theta/Q, Z^T\right) = IG\left(d_Q \times \underline{Q} + \sum_{t=2}^{T} \eta_t^2, d_Q + T - 1\right) \tag{A.24}$$

   where residuals are defined as $\eta_t = (\lambda_t - \mu) - F(\lambda_{t-1} - \mu)$ for $t = 2, \ldots, T$.

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

B Impulse responses details

After performing the MCMC simulation described in previous sections, we collect the posterior draws of all parameter blocks. Then, taking random draws from each block, taking into account that we have achieved convergence, we perform the following steps $\overline{S}$ times in order to get the impulse responses:

1. **Step 1**: Set the number of periods $\overline{H}$ and pick a random draw for the parameter space $\Theta = \left\{Z^*, d, \Phi_{1:2}, \alpha_{1:2}, s_{1:N}, \lambda^T, \mu, F, Q\right\}$ from the estimated posterior distribution.

2. **Step 2**: Pick a random initial point t^* from $t^* \sim U(1, T)$.

3. **Step 3**: Given t^*, Z^*, d and the data vector Z_{t^*}, determine the initial regime S_0 according to equation (2).

4. **Step 4**: Use the same initial value for the two regimes, i.e. $Z_0^\delta = Z_{t^*}$ and $Z_0^0 = Z_{t^*}$ and set also the initial values $\lambda_0^\delta = \lambda_{t^*}$ and $\lambda_0^0 = \lambda_{t^*}$.

5. **Step 5**: Repeat $\overline{L}$ times the following steps:

   (a) For each $t = 1, \dots, \overline{H}$ forecast λ_t^δ and λ_t^0 according to equation (7). In the case of period $t = 1$, set $\eta_1^\delta = \delta$ and $\eta_1^0 = 0$.

   (b) Given the values of λ_t^δ and λ_t^0, for each $t = 1, \dots, \overline{H}$ forecast Z_t^δ and Z_t^0 according to equation (1). Notice that in each case it is necessary to determine the current regime, i.e. S_t^δ and S_t^0, according to equation (2).

   (c) Compute the Impulse response $IRF_{1:\overline{H}} = Z_{1:\overline{H}}^\delta - Z_{1:\overline{H}}^0$.

6. **Step 6**: Take averages over $IRF_{1:\overline{H}}$.

It is important to mention that, given number of draws $\overline{S}$, we compute percentiles for each regimes by splitting the total number of draws according to the initial regime determined in Step 3. In our exercise we set $\overline{S} = 1000$, $\overline{L} = 100$. In addition, we set $\overline{H} = 36$ (three years), $\delta = \sqrt{Q}$ for the normal size and $\delta = 5\sqrt{Q}$ for the large shocks exercise. Moreover, given the Impulse Response function, computation of Variance Contributions is straightforward.

C Figures

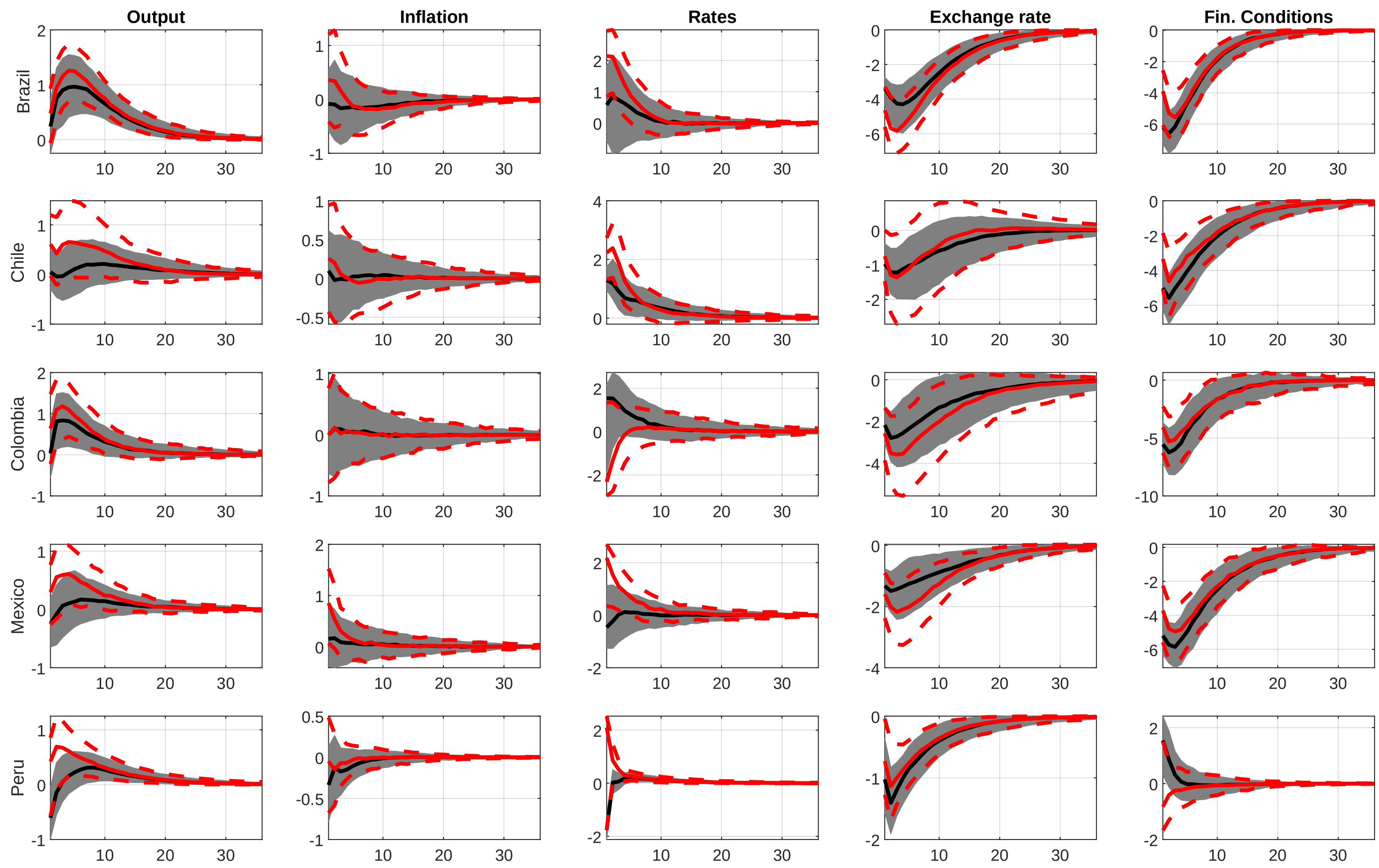

Figure C.5: Effects of a negative one standard deviation uncertainty shock; median values and 68% bands.

Note: Bands for the 'Normal' regime are plotted as gray-shaded areas. Bands for the 'Crises' regime are plotted as red dotted lines.

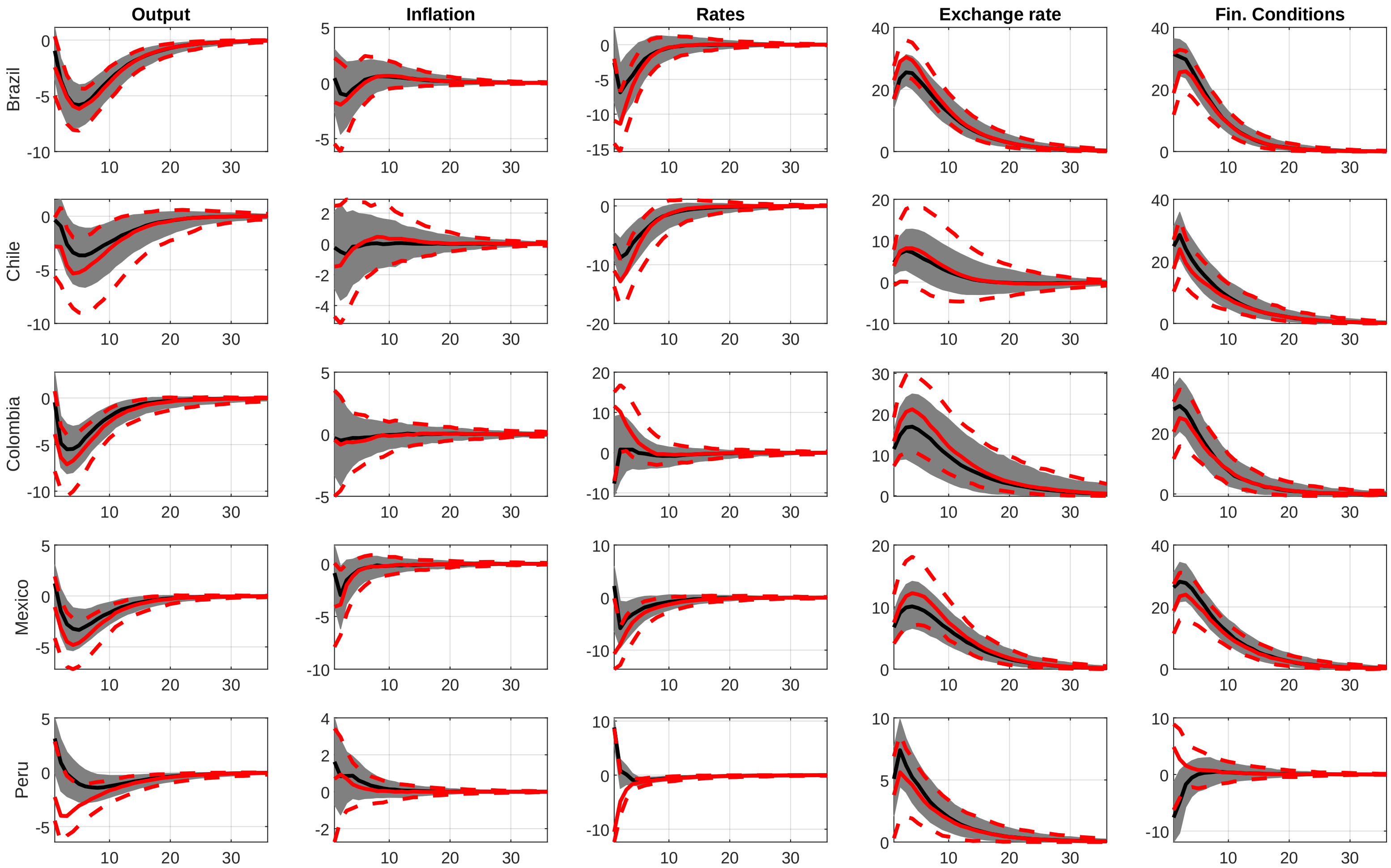

Figure C.6: Effects of a five standard deviation uncertainty shock; median values and 68% bands.

Note: Bands for the 'Normal' regime are plotted as gray-shaded areas. Bands for the 'Crises' regime are plotted as red dotted lines.

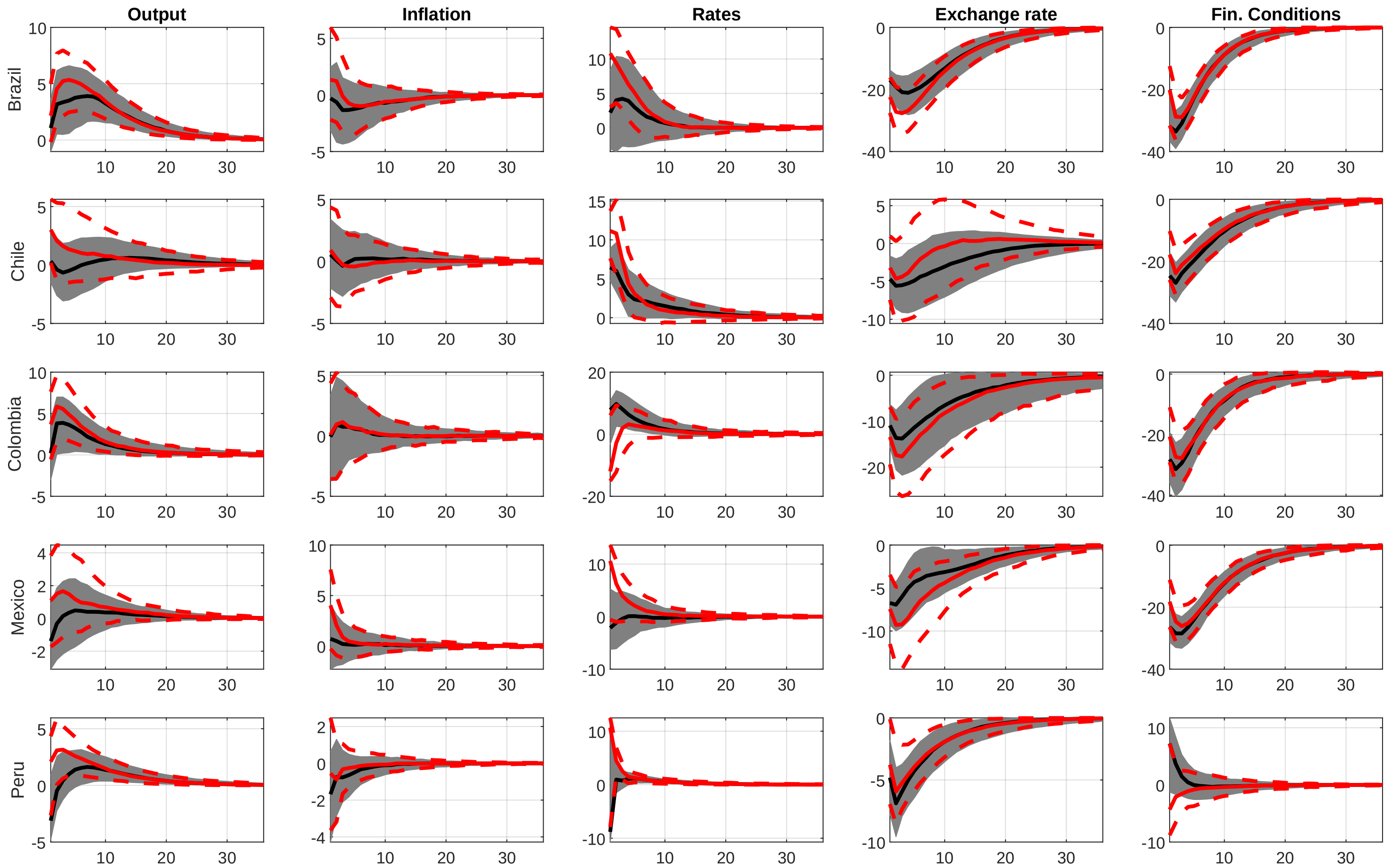

Figure C.7: Effects of a negative five standard deviation uncertainty shock; median values and 68% bands.

Note: Bands for the 'Normal' regime are plotted as gray-shaded areas. Bands for the 'Crises' regime are plotted as red dotted lines.