Interest Rate Volatility and Sudden Stops: An Empirical Investigation*

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First draft: September 2015
This draft: June 2017

Abstract

Using a multi-country regime-switching vector autoregressive (VAR) model we document the existence of two regimes in the volatility of interest rates at which emerging economies borrow from international financial markets, and study the statistical relationship of such regimes with episodes of sudden stops. Periods of high volatility tend to be persistent and are associated with high interest rates, the occurrence of sudden stops in external financing, and large declines in economic activity. Most strikingly, we show that regime switches drive the countercyclicality of interest rates in emerging markets documented in previous literature (Neumeyer and Perri, 2005) and that high-volatility regimes forecast sudden stops 6 and 12 months ahead.

JEL classification: E3, E43, F34, F4, G12, G15, O11, O16
Keywords: Volatility, interest rates, emerging market economies, sudden stops, Markov regime switching.

*The authors would like to thank Mark Aguiar, Neil Ericsson, Oleg Itskhoki, Nobu Kiyotaki, Enrique Mendoza, Nils Goernemann, Andrea Raffo, Chris Sims, Mark Watson, Emre Yoldas and participants at the Macroeconomics and the International Macroeconomics workshop at Princeton University for useful comments. Both authors gratefully acknowledge financial support from the International Economics Section. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System, The Boston Consulting Group or of any other person associated with the Federal Reserve System or The Boston Consulting Group.

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1 Introduction

Business cycles of emerging economies (EMEs) differ from those of developed small open economies. Economic fluctuations in EMEs are in part driven by external factors reflected in the evolution of international interest rates that domestic borrowers face (Neumeyer and Perri, 2005; Uribe and Yue, 2006; Maćkowiak, 2007; García-Cicco et al., 2010; Chang and Fernández, 2013). In particular, recent research has found that the business cycle in EMEs is significantly affected by shocks to the volatility of external interest rates and not only by changes in their levels (Fernández-Villaverde et al., 2011). In addition, EMEs are subject to infrequent and sharp current account reversals typically followed by deep recessions—the so called *sudden stops* in capital inflows (Dornbusch et al., 1995; Calvo, 1998; Calvo et al., 2004; Eichengreen et al., 2008).

Recent events in the world economy have highlighted the continuing relevance of these two phenomena in affecting economic activity in EMEs and new studies have shown that global risk factors—that is, external to country-specific characteristics—play a relevant role in explaining reversals of capital flows into EMEs (Eichengreen and Gupta, 2016).[1] Hence, to better cope with volatile capital flows, we need a comprehensive understanding of how these flows interact with shocks to factors reflecting global risks—for instance, changes in the volatility of external interest rates. However, the literature has not yet provided an empirical assessment of this interaction. Such interplay seems particularly relevant in present times, when economic policy in advanced economies and political events have shaken global financial markets.

In this paper, we document the existence of two regimes in the volatility of interest rates at which EMEs borrow and study the statistical relationship of these regimes with sudden stops for a large sample of EMEs. First, we estimate a multi-country regime-switching vector autoregressive (VAR) model of interest rates and output with data from this sample of countries. The model we propose allows for stochastic regime switches in external volatility that follow a Markov structure. We follow the methodology developed

[1] See Blanchard et al. (2010), Claessens et al. (2010), and Gourinchas and Obstfeld (2012).

by Hamilton (1990) to estimate the model using optimal Bayesian learning about the underlying state. Second, using the estimated regime probabilities, we analyze the association between volatility regimes and the occurrence of sudden stops. Finally, we extend the empirical literature on sudden stops by carrying out an event analysis of interest rate volatility around these events.

We estimate our regime-switching model and document the presence of considerable and persistent heteroskedasticity of interest rates in EMEs, and show that increases in volatility are contemporaneous with abrupt declines in economic activity and increases in the levels of the interest rate.[2] Moreover, our model specification allows us to show that the countercyclicality of interest rates in emerging markets documented in previous literature (Neumeyer and Perri, 2005) has its origin in the negative co-movement of the long-run means of output and interest rates across regimes, rather than displaying a relation at higher frequencies. Conditional on being in a regime of high mean and volatility of interest rates, these are procyclical.

Furthermore, by exploiting the nonlinear nature of the regime-switching process proposed, we provide novel evidence on the fact that the high-volatility regime is associated with a larger likelihood of experiencing a sudden stop and that it predicts this type of episodes. We find that the occurrence of a sudden stop, conditional on being in a high-volatility state, is significantly greater than the unconditional occurrence, thus proving the joint manifestation of such events in our data, and that regimes of high volatility tend to be followed by sudden stops 6 and twelve 12 months ahead.

Finally, our event analysis shows that sudden stop episodes are preceded by lower-than-normal levels of interest rates, slow increases in volatility, and output above trend. Calvo et al. (1993) identified the importance of external factors, such as the international interest rate and the occurrence of recessions in advanced economies, in inducing capital

[2]These results are in line with those by Fernández-Villaverde et al. (2011) who estimate a stochastic volatility model, instead of a Markov regime-switching one, for four EMEs in Latin America. See Fernández-Villaverde and Rubio-Ramírez (2010) for details on the differences between these two types of models.

outflows in emerging markets.[3] We add to the existing literature by carrying out the first formal analysis measuring the evolution of external interest rates and volatility around sudden stops, and showing that external volatility increases before sudden stops and remains high throughout these events.[4]

The results in this paper contribute to the empirical international business cycle literature in multiple respects. First, we propose a specific model of movements in volatility of interest rates in EMEs, namely a regime-switching structrue, and provide evidence of significant and persistent heteroskedasticity by means of regime switches. Second, we provide novel evidence that increases in volatility in interest rates are contemporaneous to large declines in economic activity. To our knowledge, this is the first paper to estimate this type of processes for a large sample of EMEs and provide evidence of time-varying volatility in interest rates and the joint occurrence of high-volatility regimes and sudden stops. Perhaps surprisingly, the literature that studies the implications of regime changes in interest rates in small open-economy models (Neumeyer and Perri, 2005; Gruss and Mertens, 2009; Chatterjee and Eyigungor, 2016), as well as the effects of shocks to uncertainty measured by the volatility in asset prices (Carrière-Swallow and Céspedes, 2013), appears to have ignored regimes switches in the volatility of interest rates. Third, by showing that the countercyclicality of interest rates in emerging markets reported by Neumeyer and Perri (2005) has a relevant low-frequency component, we highlight the need to account for significant nonlinearities whens studying EMEs business cycles.

The remainder of the paper is organized as follows. Section 2.1 presents the data used in our empirical analysis. Section 2.2 proposes a statistical model that allows for time-varying interest rate volatility and provides evidence of the existence of multiple regimes for our sample of emerging economies. Section 2.3 analyzes the timing and joint occurrence of different regimes in the volatility of interest rates and sudden stops. Section 2.4 carries out the event-window analysis of the evolution of first and second

[3]See Eichengreen et al. (2008) and Forbes and Warnock (2012).

[4]See Eichengreen and Gupta (2016) for a recent account of sudden stops.

moments of the interest rates around episodes of sudden stops. Section 3 concludes.

2 Interest rates, volatility, and sudden stops: Empirical Evidence

2.1 Sources of data

We follow the recent literature on open-economy business cycles and use J.P. Morgan's Emerging Market Bond Index Plus (EMBI+) spread as the variable for the interest rate. This index tracks the return of a set of U.S. dollar-denominated debt instruments issued by emerging markets that meet certain liquidity and credit rating criteria.[5] We follow Fernández-Villaverde et al. (2011) and Neumeyer and Perri (2005) in using the 90-day Treasury bill interest rate as the risk-free rate upon which to add the country spreads. As these authors do, we use the percent increase of the U.S. consumer price index (CPI) over the past 12 months to approximate the expected future inflation of the U.S. dollar, which is then subtracted from the Treasury bill rate to have a return in real terms. The data for the EMBI+ rate was obtained from Global Financial Data, and the Treasury Bill rate and the CPI from the Federal Reserve Bank of St. Louis' FRED system. As in Fernández-Villaverde et al. (2011), we study interest rates at a monthly frequency to avoid smoothing out the time-varying volatility.

The variable for output is the quarterly gross domestic product (GDP), which was obtained from the IMF's International Financial Statistics (IFS) database. All GDP measurements were retrieved at constant prices and were seasonally adjusted using the U.S. Census Bureau's X-13-ARIMA-SEATS filter. The series were detrended using the Hodrick-Prescott filter with a smoothing parameter of 1,600, which is the typical value

[5] A possible limitation of the EMBI+ spread is that the portfolios are composed primarily of bonds and loans issued by sovereign entities, and their return on secondary markets may not reflect the cost of borrowing faced by households and the corporate sector of the respective countries. However, according to Neumeyer and Perri (2005), there is evidence that in Argentina, the return on the index and the prime corporate rate have a similar magnitude, and they are highly correlated.

used for quarterly data. To study the time series comovement of output and interest rates, the filtered GDP series were linearly interpolated to a monthly frequency.

Finally, we rely on the sudden stop episodes identified in Márquez-Padilla and Zepeda-Lizama (2013) to relate these to the different regimes we consider. This paper extends the analysis of Calvo et al. (2008) to more recent years, including the financial crisis starting in 2008. In line with the literature, Márquez-Padilla and Zepeda-Lizama (2013) identify a sudden stop as a period in which the capital flows to the economy fall at least two standard deviations below the country-specific mean. A sudden stop begins when the capital flows fall below one standard deviation under the mean, and it ends when the flows reach the same mark after hitting the trough. Márquez-Padilla and Zepeda-Lizama (2013), as well as Calvo et al. (2008), use IFS data to build a monthly proxy of capital flows to the countries in their sample.[6]

Table 1 shows the data available for every country. The first column indicates that the countries that compose the EMBI+ enter and exit the sample in different dates as a consequence of varying credit ratings and liquidity of their instruments. We also observe a few countries that have interrupted interest rate series. In the maximum likelihood estimations of the model, we employ all data available for each country by assuming that the fragments of time series of a single country are independent random draws from the same stochastic process. Next, the second column of the table shows the availability of GDP data. We only study countries that have quarterly GDP data in constant prices for at least 10 years. Finally, the third column indicates the periods for which Márquez-Padilla and Zepeda-Lizama (2013) provide monthly indicators of sudden stops.

Columns (6) of Table 1 shows the samples of countries that we use for the empirical

[6]The capital account data reported to the IMF by its member countries are only available at a quarterly frequency. Calvo et al. (2008) build, instead, a monthly proxy for the capital flows to each country by using the monthly trade balance minus the change in international reserves. To avoid the presence of seasonal effects, they filter this variable by calculating a 12-month moving average. The list of events we use in this paper is taken from Márquez-Padilla and Zepeda-Lizama (2013), who use backward-looking country-specific means and standard deviations of this proxy for capital flows. The authors use at least 24 months of data to start the moving calculations of these moments.

Table 1: Data available and country samples

	EMBI+ (1)	GDP (2)	Sudden stops (3)	Sample 1 (4)	Sample 2 (5)	Sample 3 (6)
Argentina	Dec/93-Apr/14	Jan/90-Apr/14	Jan/84-Dec/11			
Brazil	Jan/94-Apr/14	Jan/95-Jul/14	Dec/83-Dec/11	X	X	X
Bulgaria	Dec/97-Dec/08 Jan/10-Apr/14	Jan/96-Oct/13	Dec/98-Dec/11		X	X
Chile	May/99-Apr/14	Jan/80-Jul/14	Dec/83-Dec/11		X	X
Colombia	Feb/97-Nov/97 May/99-Apr/14	Jan/94-Jan/11	Dec/83-Dec/11		X	X
Ecuador	Feb/95-Apr/14	Jan/91-Oct/13	Dec/83-Dec/11	X	X	X
Egypt	May/02-Apr/14		Dec/83-Dec/11			X
El Salvador	Apr/02-Apr/14		Dec/94-Dec/11			X
Hungary	Jan/99-Apr/14	Jan/95-Jul/14	Aug/93-Dec/11		X	X
Indonesia	Apr/04-Apr/14	Jan/97-Apr/14	Dec/83-Dec/11		X	X
Korea	Dec/93-May/04	Jan/60-Oct/14	Dec/83-Dec/11	X	X	X
Malaysia	Oct/96-Apr/14	Jan/88-Jul/14	Dec/83-Dec/11	X	X	X
Mexico	Dec/97-Apr/14	Jan/80-Jul/14	Dec/83-Dec/11	X	X	X
Pakistan	Jun/01-Apr/14		Dec/83-Dec/11			X
Peru	Dec/97-Apr/14	Jan/79-Jul/14	Dec/83-Dec/11	X	X	X
Phillipines	Dec/97-Sep/98 May/99-Apr/14	Jan/81-Oct/14	Dec/83-Dec/11	X	X	X
Poland	Oct/95-May/06, Dec/08-Apr/14	Jan/95-Oct/14	Jun/90-Dec/11		X	X
Russia	Dec/97-Apr/14	Jan/95-Jul/14	Dec/98-Dec/11		X	X
South Africa	Dec/94-Nov/97 Apr/02-Apr/14	Jan/60-Apr/14	Dec/83-Dec/11	X	X	X
Turkey	Jun/96-Nov/97 Jul/99-Apr/14	Jan/87-Jul/14	Dec/83-Dec/11	X	X	X
Ukraine	Aug/01-Apr/14		Dec/01-Dec/11			X
Uruguay	May/01-Apr/14		Dec/83-Dec/11			X
Venezuela	Dec/93-Apr/14	Jan/97-Oct/13	Dec/83-Aug/08	X	X	X
Total				10	17	23

exercises. Sample 1 includes the countries that have been typically studied in the literature of emerging market business cycles (e.g., Neumeyer and Perri, 2005; Uribe and Yue, 2006; Aguiar and Gopinath, 2007; Fernández-Villaverde et al., 2011), which we use as a benchmark group. Sample 2 extends the group of countries to all of those for which there is GDP data available. It includes some former Soviet republics, as well as smaller emerging markets. Finally, Sample 3 is composed of all the countries for which there are sudden stop indicators and available interest rate data. Even though Argentina is typically studied in the literature, we exclude it from these samples because the extreme volatility of its interest rates creates a bias in the estimates obtained by pooling the rest of the countries. Nonetheless, we perform a separate statistical analysis with the Argentinian data and provide a discussion of the results later.

2.2 Regime switching in external interest rate volatility

In this section, we provide empirical evidence of the existence of two regimes in the volatility of interest rates for a sample of emerging economies. Then, we carry out exercises to test the robustness of our finding when we consider cases in which other moments of the data are also subject to regime switches.

2.2.1 Model specification and estimation

We estimate a multicountry model of GDP and interest rates in which the volatility of the latter variable is allowed to stochastically switch across low and high regimes following a Markov process. To analyze the interaction between regime changes in the output and interest rate series, we assume a general VAR specification of the joint evolution of GDP and interest rates under the possibility of regime switches not only in the volatility, but also in the matrices that parameterize the VAR process. This assumption also allows us to conduct robustness exercises regarding such regime switches. For the remainder of the section, we express each country's GDP as the logarithmic deviation from its trend. We refer to this variable as the output gap.

Let us denote by $y_{i,t}$ and $r_{i,t}$ the observed output gap and interest rate, respectively, of country i in month t. We assume that these variables follow a first-order VAR with time-varying parameters:

$$\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix} = A_{s_{i,t}} + B_{s_{i,t}} \begin{pmatrix} y_{i,t-1} \\ r_{i,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon^y_{i,t} \\ \epsilon^r_{i,t} \end{pmatrix}, \tag{1}$$

where we have made explicit that the matrices $A_{s_{i,t}}$ and $B_{s_{i,t}}$ depend on the regime that prevails in the country during the current month, denoted by $s_{i,t}$. In our baseline estimation we consider the case in which these matrices are equal across regimes. For each country, the draws of the innovations vector $(\epsilon^y_{i,t}, \epsilon^r_{i,t})'$ are independent across time, and they are distributed Gaussian, with zero-mean and a covariance matrix that depends on the prevailing regime:

$$\Sigma_{s_{i,t}} = \begin{pmatrix} (\sigma^y_{s_{i,t}})^2 & \rho_{s_{i,t}} \cdot \sigma^y_{s_{i,t}} \cdot \sigma^r_{s_{i,t}} \\ \rho_{s_{i,t}} \cdot \sigma^y_{s_{i,t}} \cdot \sigma^r_{s_{i,t}} & (\sigma^r_{s_{i,t}})^2 \end{pmatrix}.$$

We assume that there are only two regimes, $\{s_L, s_H\}$, and denote the corresponding Markov transition matrix as

$$\Pi = \begin{pmatrix} \pi_L & 1-\pi_L \\ 1-\pi_H & \pi_H \end{pmatrix}.$$

We use a likelihood approach to estimate the parameters of the matrices A_s, B_s, Σ_s, and Π for $s \in \{s_L, s_H\}$. To compute the likelihood of the data with random regimes, we follow Hamilton (1990) to make optimal inference about the regime that prevails at any given period for each country. More specifically, we follow the next steps to estimate the model.

First, we make Bayesian inference about the underlying state for a specific country i. Let $x_{i,t} = (y_{i,t}, r_{i,t})$ denote the data observed for the country at month t, and $\Omega_{i,t} = \{x_{i,t}, x_{i,t-1}, \ldots, x_{i,0}\}$ denote the history of data observed until then. We assume that the data $x_{i,t}$ at time t have a Gaussian distribution, conditional on the history of data, $\Omega_{i,t-1}$, a given regime, $s_{i,t} = j$, and the parameters of the model, $\theta \equiv \{A_s, B_s, \Sigma_s, \Pi\}$. Let $\eta_{j,i,t} = f(x_{i,t}|s_{i,t} = j, \Omega_{i,t-1}; \theta)$ denote the density under regime j, and $\xi_{j,i,t|t} = \Pr(s_{i,t} = j|\Omega_{i,t}; \theta)$ denote the probability that regime j prevails at time t given history $\Omega_{i,t}$.

Consider column vectors $\boldsymbol{\xi}_{i,t|t}$ and $\boldsymbol{\eta}_{i,t}$, whose j-th elements are given by $\xi_{j,i,t|t}$ and $\eta_{j,i,t}$, respectively. Hamilton (1990) shows that the optimal Bayesian update of the state probabilities given the realization of the data can be defined recursively as follows:

$$\boldsymbol{\xi}_{i,t|t} = \frac{\Pi' \boldsymbol{\xi}_{i,t-1|t-1} \odot \boldsymbol{\eta}_{i,t}}{f(x_{i,t}|\Omega_{i,t-1}; \theta)} \quad \text{and} \quad f(x_{i,t}|\Omega_{i,t-1}; \theta) = \mathbf{1}'(\Pi' \boldsymbol{\xi}_{i,t-1|t-1} \odot \boldsymbol{\eta}_{i,t}),$$

where $\odot$ denotes element-wise multiplication and $\mathbf{1}$ a vector of ones. To carry out our estimation, we need to start this iterative procedure and choose an initial distribution of the state. We assume that the initial state is distributed according to the ergodic distribution implied by the transition matrix Π.

Given the optimal Bayesian update of the state probabilities, we proceed to form the likelihood for country i in the second step of the estimation. Conditional on time $t-1$ data, and having estimated state probabilities $\xi_{i,t-1|t-1}$, we can find the density of the data at time t:

$$f(x_{i,t}|\Omega_{i,t-1}; \theta) = \sum_j \sum_{j'} \pi_{j,j'} \xi_{j,i,t-1|t-1} \eta_{j',i,t},$$

where j and j' denote the possible states at times $t-1$ and t, respectively. Therefore, the log-likelihood of country i's data $x_{i,T}, x_{i,T-1}, \ldots, x_{i,1}$ is

$$\mathcal{L}(x_{i,T}, x_{i,T-1}, \ldots, x_{i,1}|x_{i,0}; \theta) = \sum_{t=1}^{T} \log f(x_{i,t}|\Omega_{i,t-1}; \theta).$$

Relying on the country-specific likelihoods, we can proceed to construct the joint likelihood of the multi-country model. We assume that every country's time series is ruled by the same statistical model, parameterized by the same θ. The time series of each country is an independent realization of a stochastic process that is governed by the regime-switching VAR given by equation (1). Whenever a country displays breaks in its data, we consider the separate portions of data as independent draws from the same VAR model to form the likelihood.

Because the realizations of time series across countries are assumed to be independent, the likelihood of the multi-country model is simply

$$\mathcal{L}(\{x_{i,T}, x_{i,T-1}, \ldots, x_{i,1}\}_{i\in I} | \{x_{i,0}\}_{i\in I}; \theta) = \sum_{i\in I} \mathcal{L}(x_{i,T}, x_{i,T-1}, \ldots, x_{i,1} | x_{i,0}; \theta).$$

Finally, we estimate the parameters of the model by maximum likelihood. Given the data from the different countries, we use standard optimization algorithms to find the parameter values θ that maximize the multi-country likelihood. The standard errors are calculated by inverting the Hessian matrix that is part of the output from the optimization algorithm.

2.2.2 Results

We report the results of different estimations that depend on the assumptions imposed on parameters across regimes for the general VAR process previously described. In our baseline estimation, we consider the case in which all the parameters governing the VAR are set equal across regimes, except for the volatility of the interest rate shocks, σ_s^r.

We focus first on the standard set of countries considered in the literature. We label this set as Sample 1. This first estimation delivers the following result:[7]

$$\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix} = \begin{pmatrix} 0.0005 \\ 0.0004 \end{pmatrix} + \begin{pmatrix} 0.9651 & -0.0085 \\ 0.0185 & 0.9699 \end{pmatrix} \begin{pmatrix} y_{i,t-1} \\ r_{i,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{i,t}^y \\ \epsilon_{i,t}^r \end{pmatrix}, \tag{2}$$

[7] The standard errors of these estimates can be found in first column of Table 2.

where the covariance and transition matrices are composed of

$$\sigma^y = 0.0064, \quad \rho = -0.0305, \quad \pi_L = 0.9709,$$
$$\sigma^r_L = 0.0059, \quad \sigma^r_H = 0.0415, \quad \pi_H = 0.7857.$$

First, we note that both the output gap and the interest rate processes are highly persistent, which is consistent with the fact that we consider variables at a monthly frequency. We also see that the cross-correlations at this frequency are relatively small, which implies that the expected dynamic feedback between both shocks is low.

The ergodic means of the output gap and the interest rate can be obtained by inverting the estimated VAR matrices:

$$\mathbb{E}\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix} = (\mathbb{I} - \hat{B})^{-1}\hat{A} = \begin{pmatrix} 0.0086 \\ 0.0177 \end{pmatrix}, \tag{3}$$

where $\mathbb{I}$ denotes the identity matrix.

The first component shows that the ergodic mean of the output gap is close to zero, as expected. The second component is, however, surprisingly low, because it indicates that the ergodic mean of the interest rate faced by emerging markets is 1.77% per annum. During the early 2000s, and in the years following the financial crisis, the real return paid by the U.S. Treasury bill was negative, reaching levels below negative 3.5% for a few months in 2008 and 2011. Thus, the interest rate faced by emerging markets, which is composed of the Treasury Bill rate plus the EMBI+ spread, is significantly low for these periods. As a consequence, the estimated long-run mean of the real interest rate of the model is low relative to the common wisdom regarding interest rates in emerging markets.

Next, we notice that the estimated volatility of interest rates changes drastically between regimes: the standard deviation increases seven fold from the low-volatility state to the high-volatility state. The estimated transition probabilities imply that the expected duration of periods of low and high volatility are 34.38 months and 4.67 months, respectively. The ergodic distribution of the Markov process is $P = (0.8805, 0.1195)$, meaning that the countries in the baseline sample spend most of their time in the low-volatility regime. Therefore, the transition to a high-volatility state is relatively unlikely, and when it does occur, the expected length of the regime is short.

Figure 1 depicts, for six countries in Sample 1, the output gap, the interest rate, and the smoothed regime probabilities obtained from the maximum likelihood estimation of the model. The shaded areas indicate the sudden stops identified by Márquez-Padilla and Zepeda-Lizama (2013). As conjectured, we observe that the high-volatility regime occurs rarely. Next, we note that high volatility tends to be contemporaneous with high levels of interest rates and negative output gaps. These findings are consistent with the current literature indicating a positive correlation of volatility and level shocks in emerging market interest rates documented by Fernández-Villaverde et al. (2011), and with the countercyclical interest rate in emerging economies documented in Neumeyer and Perri (2005).

The different graphs in Figure 1 show, in addition, that many of the high-volatility events are accompanied by sudden stops, but the correlation is not perfect, and there is clear heterogeneity in terms of the timing of events across countries. We do not have further evidence of the mechanism driving this correlation: it may either be that situations of distress in international financial markets reduce the volume of lending to emerging markets and sharply increase their borrowing cost, affecting simultaneously the level and volatility of interest rates, or that the fundamentals of the open economies suffer a sharp deterioration, which leads to a withdrawal of funds and an increase of interest rates to compensate for default risk. A better understanding of this mechanims deserves further research in future work.[8]

Table 2 shows the maximum likelihood estimates of the model with different samples and under alternative specifications. The top part of the table shows the parameters

[8]Some research has focused on related questions. For instance, Longstaff et al. (2011) show how global factors influence sovereign credit risks. From a different perspective, Hébert and Schreger (2016) try to identify how country-specific factors, specifically sovereign default, affect asset prices and, therefore, interest rates.

that are common across both regimes. The components of the A and B matrices in (1) are denoted by $\{a_1, a_2\}$ and $\{b_{1,1}, b_{1,2}, b_{2,1}, b_{2,2}\}$, respectively, where the subindices indicate the corresponding locations in the matrices. The middle part of the table presents the estimated parameters that are regime-specific. Finally, the bottom part of the table shows the estimated probabilities that form the transition matrix Π.

The first column of Table 2 repeats the results of the baseline specification using the 10-country Sample 1, shown in equation (2). For the second column, we extend the sample to include 7 additional emerging markets for which we have interest rate and quarterly GDP data (see Table 1). The results obtained for Sample 2 are similar to those for Sample 1. The only notable difference is that the negative correlation between output and interest rate shocks, ρ, has a larger magnitude in absolute value, which emphasizes the countercyclicality of the interest rate in emerging markets emphasized in Neumeyer and Perri (2005).

The third column of Table 2 shows an estimation of the baseline model exclusively for Argentina. This country has been widely used in existing literature as a prototypical EME subject to interest rate shocks.[9] Our results show that this country stands out for several reasons. Probably the most remarkable feature of the estimation for Argentina is that the standard deviation of interest rates in the high-volatility regime is more than 9 times the standard deviation in the low-volatility regime. Moreover, the high-volatility regime is more persistent in Argentina, making the high-volatility episodes longer and more frequent: they last, on average, 11.75 months and they occur 23.89% of the time in the ergodic distribution. Additionally, Figure 2 depicts the smoothed regime probabilities based on the maximum likelihood estimation of the model with Argentina's data. The high levels of volatility and the persistence of such regime in this country are primarily a consequence of the evolution of interest rates during the 2001-2005 period, when the return on Argentinian debt instruments in secondary markets reached levels above 50% per annum.

We do not include Argentina in the multi-country estimation for multiple reasons.

[9]For example, Neumeyer and Perri (2005) and Fernández-Villaverde et al. (2011).

Table 2: Maximum likelihood estimates of the regime switching model

	Baseline model			Fixed effects		Extended model		
	Sam. 1	Sam. 2	Arg.	Sam. 1	Sam. 2	Sam. 1	Sam. 2	Arg.
Common parameters								
a_1	0.0005	0.0002	-0.0005	–	–	–	–	–
	(0.0002)	(0.0001)	(0.0008)					
a_2	0.0004	0.0002	0.0017	–	–	–	–	–
	(0.0002)	(0.0002)	(0.0019)					
$b_{1,1}$	0.9651	0.9657	0.9704	0.9635	0.9630	0.9564	0.9611	0.9667
	(0.0055)	(0.0043)	(0.0130)	(0.0056)	(0.0055)	(0.0053)	(0.0042)	(0.0104)
$b_{1,2}$	-0.0085	-0.0022	0.0003	-0.0137	-0.0131	0.0273	0.0269	0.0411
	(0.0026)	(0.0017)	(0.0034)	(0.0033)	(0.0032)	(0.0029)	(0.0019)	(0.0042)
$b_{2,1}$	0.0185	0.0116	0.0569	0.0162	0.0149	0.0283	0.0231	0.0120
	(0.0072)	(0.0059)	(0.0214)	(0.0075)	(0.0078)	(0.0066)	(0.0056)	(0.0221)
$b_{2,2}$	0.9699	0.9712	0.9694	0.9619	0.9620	0.9718	0.9715	0.9707
	(0.0043)	(0.0034)	(0.0208)	(0.0055)	(0.0055)	(0.0045)	(0.0036)	(0.0265)
σ^y	0.0064	0.0056	0.0080	0.0064	0.0063	0.0056	0.0050	0.0059
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
ρ	-0.0305	-0.0624	-0.2636	-0.0362	-0.0588	0.0300	-0.0050	-0.0622
	(0.0272)	(0.0239)	(0.0659)	(0.0305)	(0.0345)	(0.0242)	(0.0193)	(0.0705)
Regime-dependent parameters								
σ^r_L	0.0059	0.0058	0.0107	0.0060	0.0059	0.0062	0.0061	0.0102
	(0.0001)	(0.0001)	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0006)
$a_{1,L}$	–	–	–	–	–	0.0001	0.0001	-0.0018
						(0.0002)	(0.0001)	(0.0006)
$a_{2,L}$	–	–	–	–	–	0.0002	0.0001	0.0014
						(0.0002)	(0.0002)	(0.0023)
σ^r_H	0.0415	0.0443	0.0970	0.0416	0.0425	0.0379	0.0416	0.0913
	(0.0024)	(0.0022)	(0.0095)	(0.0024)	(0.0026)	(0.0018)	(0.0018)	(0.0086)
$a_{1,H}$	–	–	–	–	–	-0.0111	-0.0109	-0.0229
						(0.0006)	(0.0004)	(0.0019)
$a_{2,H}$	–	–	–	–	–	0.0075	0.0082	0.0128
						(0.0025)	(0.0024)	(0.0157)
Transition probabilities								
π_L	0.9709	0.9768	0.9733	0.9729	0.9723	0.9794	0.9827	0.9775
	(0.0055)	(0.0036)	(0.0135)	(0.0051)	(0.0052)	(0.0037)	(0.0026)	(0.0101)
π_H	0.7857	0.7651	0.9150	0.7817	0.7786	0.8608	0.8526	0.9217
	(0.0348)	(0.0308)	(0.0404)	(0.0362)	(0.0362)	(0.0240)	(0.0213)	(0.0325)

Asymptotic standard errors reported in parenthesis. These were estimated using a numerical second derivative matrix of the log-likelihood function.

One of the main reasons is that a large share of changes in interest rates in Argentina during this period can be explained by changes in fundamentals, mainly sovereign default (see Hébert and Schreger (2016)). Thus, Argentinian households and firms were not actually facing these interest rates for their marginal borrowing decisions during the crisis. As we have mentioned, the EMBI+ spread corresponds to loans that are traded in secondary markets, that are typically long or medium term, and that are issued by the government under sovereign immunity. Thus, it is more likely that the external borrowing of the private sector collapsed during the period of debt restructuring that followed Argentina's sovereign default of December 2001, and that no new borrowing took place at the secondary market rates.

To verify the robustness of the baseline specification, we estimate a model that allows for country-specific long-run means in output and interest rates in the form of a distinct (but fixed) A_i matrix for each country, while pooling the data together to estimate the B, Σ_s and Π matrices. The results for Samples 1 and 2 are presented in the fourth and fifth columns of Table 2 and are denoted as "fixed effects" estimates. We do not observe any considerable difference between the fixed effects and the baseline estimations of the model. The estimated components of the A_i matrices display some cross-country variation and, as expected, their values lie in the region around the corresponding common matrix of the baseline model. The existence of multiple regimes in the volatility of interest rates remains statistically significant after allowing more parameters for this type of regime dependence.

The results of the baseline model suggest that regime switches in volatility might be accompanied by increases in the mean levels of interest rates and declines in output. Suggestive evidence of these facts can be clearly seen in Figure 1. Thus, we estimate an extended model that allows for regime dependence of the A_s matrix of the VAR model (1) in addition to regime dependence of interest rate volatility, σ_s^r.

The results of this exercise are presented in the last part of Table 2. The estimates in column 6, corresponding to Sample 1, confirm our intuition. The first thing we observe is that, indeed, the maximum likelihood estimates of the A_s matrix are regime-dependent.

Assuming that there are no further changes of regime, one can estimate the implied long-run means of $(y_{i,t}, r_{i,t})'$ using expression (3), as follows:

$$\mathbb{E}\left[\left.\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix}\right| s_{i,\tau} = s_L \ \forall \tau \right] = \begin{pmatrix} 0.0141 \\ 0.0196 \end{pmatrix}, \quad \text{and}$$
$$\mathbb{E}\left[\left.\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix}\right| s_{i,\tau} = s_H \ \forall \tau \right] = \begin{pmatrix} -0.2341 \\ 0.0313 \end{pmatrix}.$$

Regarding the output gap process, the long-run means deviate considerably from zero. In the low-volatility state, the mean is 1.41%, but when the state changes to the high regime, the mean output gap turns negative, down to negative 23.41%. Given that the VAR is highly persistent, the output gap never reaches that level in our sample. Nonetheless, this feature induces a sharp decline in output in the periods following a switch to the high-volatility state, whereas the growth that follows a switch to the low-volatility state is much slower. The considerable asymmetry between the long-run means of output gap evidences the presence of a negative skew in the evolution of output shocks in our sample.

Regarding the long-run mean of interest rates, however, we observe that the high-volatility regime is characterized by higher levels of interest rate shocks, as was previously conjectured: the mean of the interest rate goes from 1.96% to 3.13% between the low- and high- volatility regimes. This increase during volatile times is consistent with the positive correlation of volatility and level shocks to the interest rate found by Fernández-Villaverde et al. (2011) for a smaller sample of emerging markets.

By allowing for changes in the mean of the output process, the estimated standard deviation for the output shocks falls from 0.0064 in the baseline model to 0.0056 in the extended one. The remaining variation of the output series is explained by the slow convergence to the mean of the regime that prevails at the time. Something similar happens to the estimates of interest rate variance, particularly in the high-volatility state. Given the fact that in this regime the expected interest rate is higher, then a lower share of the movement in the variable can be attributed to exogenous shocks and a higher share corresponds to the slow convergence to the higher mean, thus reducing the estimated volatility of the regime. However, notice that the existence of multiple regimes in the volatility of interest rates remains statistically significant after allowing for this type of change in their levels.[10]

In addition, by allowing for regime-specific long-run means of output and interest rates, the contemporaneous correlation of the shocks to these variables turns slightly positive. This results implies that, conditional on remaining in the same regime, the interest rate in the baseline group of emerging markets is slightly pro-cyclical, as observed in most small developed economies (Neumeyer and Perri, 2005). However, the changes in regimes are the ones inducing a negative correlation of the interest rate and output across time because the first variable increases when the high-volatility regime prevails, which also induces a gradual reduction of the output gap.

Even though the estimated coefficients of the transition matrix change with respect to our baseline model, the ergodic distribution remains similar, $P = (0.8709, 0.1291)$. However, the expected durations of the low- and high-volatility episodes are longer than in the baseline estimation, reaching 48.48 months and 7.18 months, respectively.

The seventh column of Table 2 presents the results for Sample 2. We do not observe large differences with respect to the results reported for Sample 1. The eighth column shows the results corresponding to Argentina, where we see an even larger variation in the regime-dependent long-run means of output and interest rates:

$$\mathbb{E}\left[\left.\begin{pmatrix} y_t \\ r_t \end{pmatrix}\right| s_\tau = s_L \ \forall \tau\right] = \begin{pmatrix} 0.0138 \\ 0.0544 \end{pmatrix}, \text{ and}$$
$$\mathbb{E}\left[\left.\begin{pmatrix} y_t \\ r_t \end{pmatrix}\right| s_\tau = s_H \ \forall \tau\right] = \begin{pmatrix} -0.3094 \\ 0.3076 \end{pmatrix}.$$

[10]Notice that changes in the A_s matrix and in the volatility of interest rates across regimes are driven by the same latent stochastic process. Hence, regime switches reflect more general changes in the VAR process than simply differences across interest rate volatility levels. See Jurado et al. (2015) for more details on how these different regimes might not reflect changes in actual uncertainty.

Under the low-volatility regime, the long-run mean of the output gap is 1.38%, and the interest rate remains at 5.44%, which is relatively low. However, in the high-volatility state, the long-run mean of the output gap is negative 30.94%, and the interest rate fluctuates around a mean of 30.76%. Again, the introduction of regime switching in long-run means reduces the estimated negative correlation between output and interest rate shocks, which, in the case of Argentina, turns slightly positive.

In summary, our results provide evidence of statistically significant regime switches in the volatility of interest rates for a large sample of emerging economies. The volatility changes across regimes are robust to alternative specifications of our VAR model of output and interest rates. Moreover, when allowing for regime-specific changes in the means of output and interest rate processes, we find that high volatility regimes are associated with sharp output declines and interest rate increases, which drive most of the negative co-movement between these time series. Lastly, the estimated regime probabilities provide suggestive evidence that high-volatility regimes occur at the same time as sudden stop episodes for some of the countries considered in our sample. We now turn to a more formal treatment of the relation between occurrences of high-volatility regimes and sudden stops.

2.3 The timing of volatility regimes and sudden stops

In this section, we perform a formal test of the association between high-volatility states and sudden stop episodes that is apparent in Figure 1. We will consider as high-volatility states those in which the smoothed regime probability derived from the estimation of the baseline Markov-switching model lies above 50%.

We first consider the case of contemporaneous occurrence of high-volatility regimes and sudden stops. To test for this joint event, we compare the unconditional and conditional frequencies of sudden stops. The results of our test are shown in Table 3.[11] The first row of column 1 shows that the unconditional probability—or, equivalently, the prevalence—of sudden stops in Sample 1 is 14.67% of the periods. However, if we condition on high-volatility states, the probability of sudden stops increases to 20.89%, as shown in the second row of the table. The difference between the conditional and unconditional probability, 6.21 percentage points, is significantly different from zero at a 5% level. In Sample 2, the conditional probability of a sudden stop is also higher than the unconditional one, but the difference between both is smaller, at only 4.43 percentage points.

Next, we explore whether the occurrence of high volatility predicts the occurrence of sudden stops in the near future. The third and fourth rows of Table 3 show the probability of a sudden stop, conditional on high-volatility states 6 and 12 months previously, respectively. First, we see that there is an increase in the probability of a sudden stop when we condition on high volatility 6 months ahead. The difference with respect to the unconditional probability is 10.01 percentage points, and it is significant at a one percent level. Similarly, there is a positive and significant difference between the probability of a sudden stop conditional on high volatility 12 months ahead and its unconditional counterpart, but the difference is considerably smaller, at 4.95 percentage points. The results are similar in Sample 2, but the magnitude of the difference between conditional and unconditional probabilities is lower. The results strongly suggest that high-volatility periods tend to precede sudden stops, especially at a 6 month distance. It is important to highlight that this result provides absolutely no evidence of any causality direction across interest rate volatility, output and sudden stops.[12]

[11] The statistic to test for the difference in frequencies is

$$Z = \frac{\hat{p}_a - \hat{p}_b}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_a} + \frac{1}{n_b}\right)}},$$

where $\hat{p}_a$ and $\hat{p}_b$ denote the frequencies of sudden stop periods in samples a and b, respectively, n_a and n_b denote the size of the samples, and $\hat{p} = \frac{\hat{p_a} n_a + \hat{p_b} n_b}{n_a + n_b}$ is the estimate of the common frequency under the null hypothesis that $p_a = p_b$.

[12] See Hébert and Schreger (2016) and Stangebye and Gu (2017) for two examples in which causality

We run an analogous exercise as previously, but using a forward-lagged indicator of high-volatility states. Now, we are asking what is the probability of a sudden stop having occurred 6 or 12 months in the past, conditional on a high-volatility state being prevalent in the current month. The fifth and sixth rows of Table 3 show the results of this exercise. Even though the difference between conditional and unconditional probabilities is positive, their magnitude is small, and we cannot reject the null hypothesis of them being equal to zero. The difference becomes even smaller at a 12-month distance, and the results are weaker when we include the remaining countries in Sample 2. Therefore, in these samples, there does not seem to be a significant association between the occurrence of sudden stops and rises in volatility 6 or 12 months ahead.

In summary, our results formally show that sudden stops occur more frequently when the volatility of interest rates is high. Moreover, our analysis suggests that a high probability of highly volatile interest rates is a good predictor of sudden stops 6 and 12 months ahead. The inverse relation is not found in the data for our sample of countries - the occurrence of a sudden stop does not predict future increases in the volatility of interest rates, at least when considering a 12-month horizon.

2.4 Sudden stop event windows

The results of the previous sections suggest that sudden stops are associated with increases in interest rates and in their volatility. In this section, we formalize this argument by showing event studies of these variables around the beginning of such episodes. We compare the average behavior or interest rates, volatility, and the output gap around 61 sudden stop events that are observed in the countries of Sample 3 against the corresponding behavior in regular times. In this set of countries, sudden stops take place every 73.9 months, and they last for 10.8 months, on average (see Table 4).

Figure 3 shows the mean deviation of the interest rate around the month in which a sudden stop episode begins, denoted by t, from its country-specific mean in non-sudden

operates in opposite directions.

stop periods. We use country-specific means to control for the fact that some countries have a higher prevalence of sudden stops and their interest rates are, on average, higher, even in the absence of crises. Each period $t+s$ represents the average of the observations in the s-th month preceding or following the beginning of the sudden stop. In the figure, we observe that during the 12 months preceding a sudden stop, the interest rate is slightly below its normal times level, by less than one percentage point. In contrast, during the 12 months following the beginning of the sudden stop, the interest rate speedily increases to around 2% above the normal times level. Finally, in the following months, the interest rate reverts back to its ordinary level, which is reached around the 16th period.[13]

Let us now analyze whether there is a pattern in the volatility of interest rates around sudden stops. Figure 4 shows the episode window for the 7-month centered moving standard deviation of the interest rate. We see that prior to a sudden stop, interest rate volatility remains close to its normal times level, and in the preceding 6 months, it starts to increase gradually. Volatility reaches a peak in the month when the sudden stop begins, and it remains relatively high until it hits another peak at the 12th month. However, as we observe in the different panels of Figure 1, the second rise in volatility usually corresponds to sharp declines in the interest rate that occur at the end of the sudden stop episodes. In fact, most of the countries in our sample experienced a sudden rise of interest rate levels and volatility in the last months of 2008 and an abrupt return to normal levels at the beginning of 2010. Many of these countries faced capital account reversals simultaneously, which might partly explain the pattern observed in our event windows. Nonetheless, this behavior is not specific to the recent financial crisis; other countries experienced similar dynamics for different sudden stop episodes, including Ecuador in 1999–2000, Korea in 1997–1998, and the Philippines 1999–2001, to name a few cases.

The slow speed at which volatility changes in the sample could be a mechanical

[13] We have verified that these patterns are robust to the alternative groups of countries that we have studied in the previous section (i.e., Samples 1 and 2).

consequence of our averaging across 7 months of interest rate data. Figure 5 shows the event studies of volatility using different window lengths to calculate the standard deviation of interest rates. The blue dash-dotted line corresponds to a 3-month centered moving standard deviation of interest rates. We observe, indeed, sharper increases of volatility at the beginning of the sudden stop period and 12 months after, but the magnitudes are not considerably different from those obtained with the baseline 7-month calculation. The red dashed line shows the calculation of the event studies using the 11-month centered moving standard deviation. The patterns are similar to the alternative calculations, but the evolution tends to be smoother, as expected. In summary, the results of this analysis are robust to the length of the window for which we choose to calculate the moving volatility of interest rates.

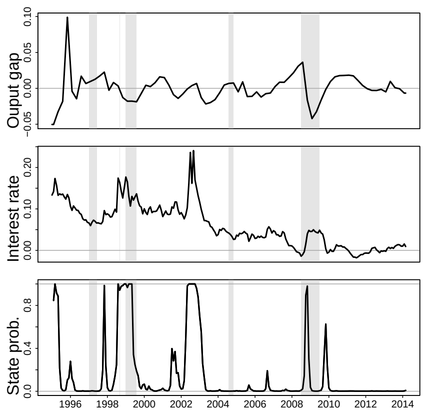
Finally, Figure 6 presents the event window for output. For this exercise, we constrain the analysis to the countries in Sample 2 due to data availability. Similar to previous literature (e.g., Korinek and Mendoza, 2013), we find that output tends to be above average in the months preceding a sudden stop, but it experiences a sharp decline at the beginning of the sudden stop crisis. This drop is then typically followed by a slow recovery that lasts around 24 months.

3 Conclusions

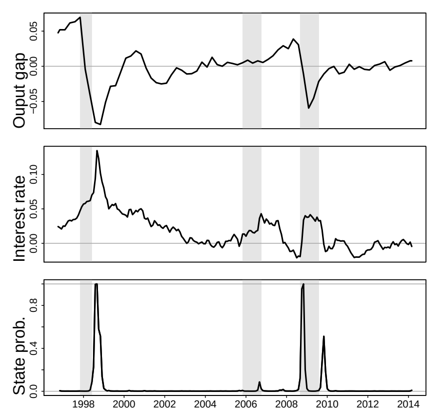
Our estimation provides evidence of regime switches in interest rate volatility for a group of emerging markets. Furthermore, we show that these regimes are closely related to the occurrence of sudden stops. The empirical association between the occurrence of sudden stops and fluctuations in interest rates, volatility, and output that we observe in the data does not necessarily imply causal relations. However, a better understanding of this empirical correlation is very relevant given the current state of the world economy in which global uncertainty is high and capital flows freely across countries. A natural next step for this research is to explore causality between these variables.

A comprehensive understanding of the empirical relation between interest rates, their volatility, and output in emerging markets also contributes to the growing theoretical literatures modeling sovereign default (Johri et al., 2015), and optimal macroprudential policy (e.g., capital controls) in countries facing the risks of shocks to volatility and sudden stops (Jeanne and Korinek, 2010; Bianchi and Mendoza, 2013). For instance, in Reyes-Heroles and Tenorio (2015), we consider a benchmark model of endogenous sudden stops to analyze optimal macroprudential policy in the presence of shocks to the first and second moments of the borrowing rate. Our analysis relies on analogous empirical estimates to the ones in this paper to assess the quantitative effect of changes in the volatility of interest rates on the dynamics of leverage, the occurrence of endogenous sudden stops, and the need for macroprudential management of international capital flows. Chatterjee and Eyigungor (2016) provides another example of a theoretical model that relies on this type of estimates to understand the effects of political turnover on sovereign default risk.

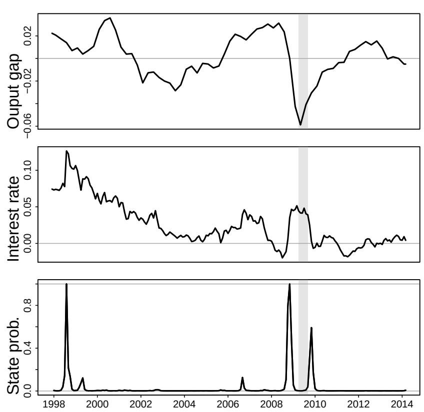
Figure 1: Output gap, interest rates, and smoothed regime probabilities. The shaded areas indicate the occurrence of sudden stops.



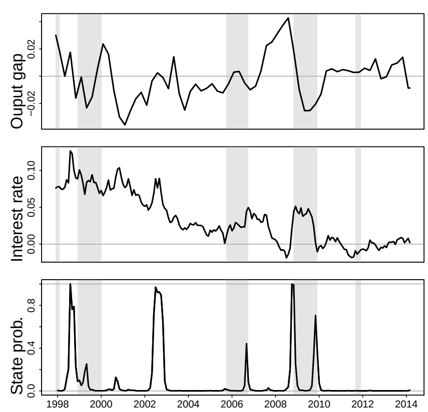
(a) Brazil



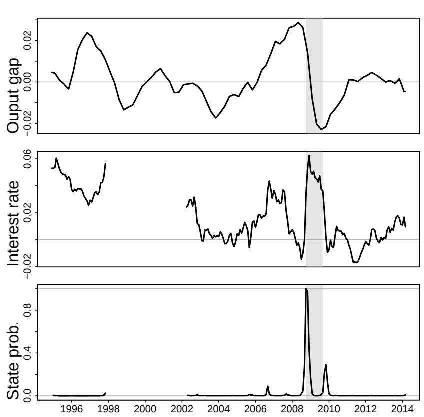
(b) Malaysia



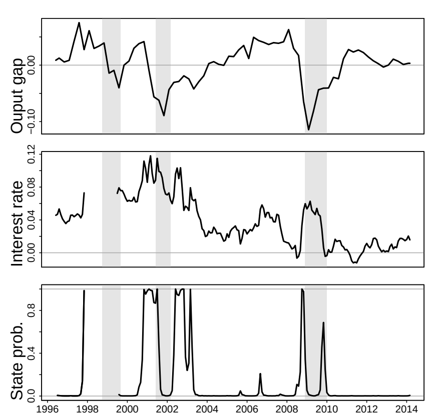
(c) Mexico



(d) Peru



(e) South Africa



(f) Turkey

Table 3: Prevalence of sudden stops for different volatility windows

Probability of sudden stop	Sample 1 Prob.	Sample 1 Diff.	Sample 2 Prob.	Sample 2 Diff.
Unconditional	0.1467	–	0.1425	–
Conditional on high volatility	0.2089	0.0621**	0.1869	0.0443*
Conditional on high volatility at $t-6$	0.2468	0.1001***	0.2172	0.0746***
Conditional on high volatility at $t-12$	0.1962	0.0495*	0.1667	0.0241
Conditional on high volatility at $t+6$	0.1835	0.0368	0.1667	0.0241
Conditional on high volatility at $t+12$	0.1519	0.0052	0.1313	-0.0112

Note: ***, ** and * denote significance at the 1, 5, and 10 percent levels. All the differences are with respect to the unconditional probability of the respective sample.

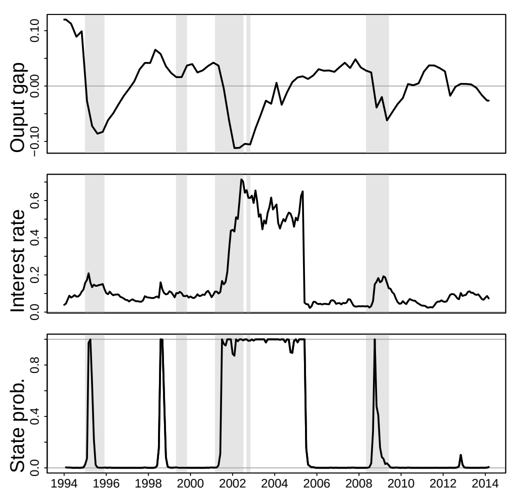


Figure 2: Argentina: output gap, interest rates, and smoothed regime probabilities. The shaded areas indicate the occurrence of sudden stops.

Table 4: Sudden stop episodes in the data

	Episodes	Num. of episodes	Avg. length (months)	Avg. freq. (months)
Argentina	Jan/95-Dec/95, May/99-Nov/99, Mar/01-Jul/02, Sep/02-Nov/02, May/08-Jun/09	5	10.6	43.4
Brazil	Jan/97-Jun/97, Sep/98-Sep/98, Jan/99-Aug/99, Aug/04-Nov/04, Jul/08-Jul/09	5	6.4	43.4
Bulgaria	Nov/05-Apr/06, Oct/08-Feb/10	2	11.5	78.5
Chile	Aug/98-May/99, Apr/06-Jun/07, Oct/09-Sep/10	3	12.3	72.3
Colombia	May/98-Nov/98, Jan/99-Jun/00, Mar/08-Feb/09	3	12.3	72.3
Ecuador	Jul/99-Oct/00	1	16.0	217.0
Egypt	Apr/11-Dec/11	1	9.0	217.0
El Salvador	Aug/96-Jul/97, Feb/99-Apr/99, Sep/99-Oct/99, May/02-Sep/02, May/09-Oct/10	5	8.0	41.0
Hungary	Dec/96-May/97, Mar/10-Feb/11	2	9.0	108.5
Indonesia	Dec/97-Nov/98, Dec/99-Feb/01, Oct/11-Dec/11	3	10.0	72.3
Korea	Sep/97-Nov/98, Apr/01-Dec/01, Nov/05-Jan/06, Jul/08-Jun/09, Oct/10-Apr/11	5	9.2	43.4
Malaysia	Dec/94-Nov/95, Nov/97-Jun/98, Nov/05-Oct/06, Sep/08-Aug/09	4	11.0	54.3
Mexico	Dec/94-Mar/95, Apr/09-Sep/09	2	5.0	108.5
Pakistan	Sep/95-Nov/95, Jun/98-Jan/99, Dec/03-Aug/04, Jul/08-Mar/09	4	7.3	54.3
Peru	Jul/97-Feb/98, Dec/98-Jan/00, Oct/05-Oct/06, Nov/08-Dec/09, Sep/11-Dec/11	5	10.6	43.4
Philippines	Jun/97-Jul/99, Oct/99-Jun/01	2	23.5	108.5
Poland	Apr/99-Sep/00, Nov/08-Sep/09	2	14.5	108.5
Russia	Oct/05-Apr/06, May/08-Sep/09	2	12.0	78.5
South Africa	Oct/08-Sep/09	1	12.0	217.0
Turkey	Mar/94-Jan/95, Oct/98-Sep/99, Jun/01-Mar/02, Dec/08-Jan/10	4	11.8	54.3
Ukraine	Oct/04-Mar/05, Oct/08-Jan/10	2	11.0	60.5
Uruguay	Jan/02-May/03, Jun/09-Jan/11	2	18.5	108.5
Venezuela	Jan/00-Apr/01	1	16.0	177.0
Sample 1		30	10.8	71.0
Sample 2		47	11.1	75.1
Sample 3		61	10.8	73.9
All countries		66	10.8	71.6

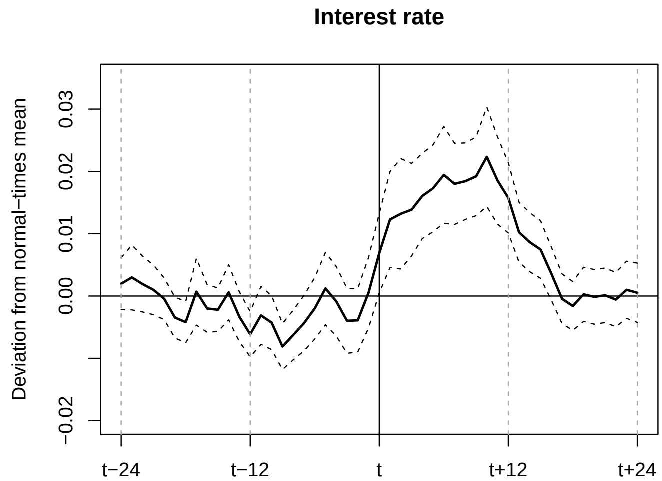


Figure 3: Empirical behavior of the interest rate during sudden stops.
The graph depicts the deviation of the interest rate from the normal-times country-specific mean, using all data available for Sample 3. t denotes the month in which the sudden stop begins. Dotted lines represent one standard error intervals.

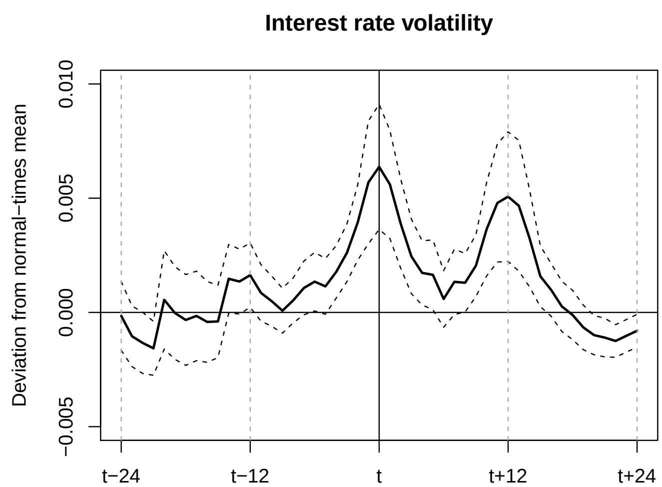


Figure 4: Empirical behavior of interest rate volatility during sudden stops.
The graph depicts the deviation of interest rate volatility from the normal-times country-specific mean, using all data available for Sample 3. Interest rate volatility is measured as the seven-month centered moving standard deviation. t denotes the month in which the sudden stop begins. Dotted lines represent one standard error intervals.

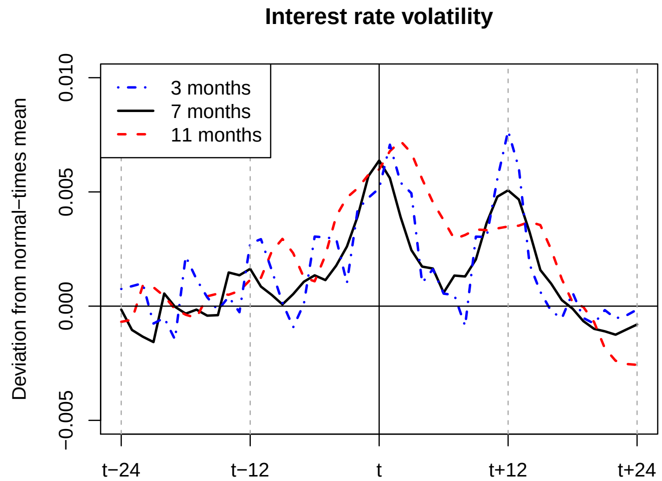


Figure 5: Empirical behavior of interest rate volatility during sudden stops.
The graph depicts the deviation of interest rate volatility from the normal-times country-specific mean. Each line represents the event window using 3, 7 and 11 months to calculate the standard deviation of interest rates. t denotes the month in which the sudden stop begins.

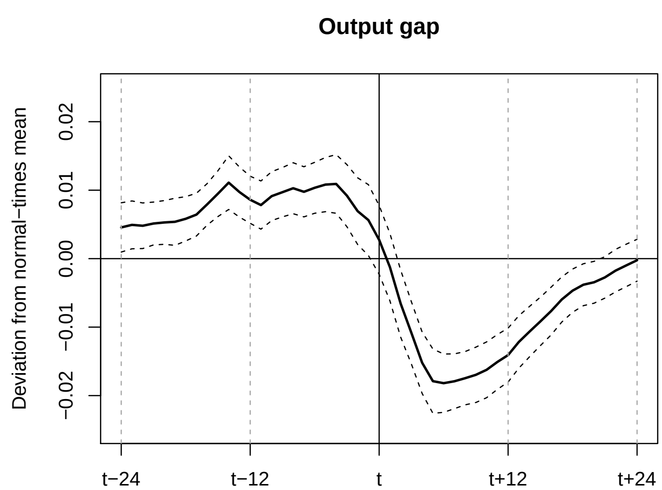


Figure 6: Empirical behavior of the output gap during sudden stops.
The graph depicts the deviation of the output gap from the normal-times country-specific mean, using all data available for Sample 2. t denotes the month in which the sudden stop begins. Dotted lines represent one standard error intervals.

References

Aguiar, M. and Gopinath, G. (2007). Emerging market business cycles: The cycle is the trend. *Journal of Political Economy*, 115(1):69–102.

Bianchi, J. and Mendoza, E. G. (2013). Optimal time-consistent macroprudential policy. NBER Working Papers 19704, National Bureau of Economic Research, Inc.

Blanchard, O. J., Das, M., and Faruqee, H. (2010). The initial impact of the crisis on emerging market countries. *Brookings Papers on Economic Activity*, 41(1):263–323.

Calvo, G. A. (1998). Capital Flows and Capital-Market Crises: The Simple Economics of Sudden Stops. *Journal of Applied Economics*, 1:35–54.

Calvo, G. A., Izquierdo, A., and Meja, L.-F. (2008). Systemic sudden stops: The relevance of balance-sheet effects and financial integration. Working Paper 14026, National Bureau of Economic Research.

Calvo, G. A., Izquierdo, A., and Mejia, L.-F. (2004). On the empirics of sudden stops: The relevance of balance-sheet effects. Working Paper 10520, National Bureau of Economic Research.

Calvo, G. A., Leiderman, L., and Reinhart, C. M. (1993). Capital inflows and real exchange rate appreciation in latin america: The role of external factors. *Staff Papers-International Monetary Fund*, pages 108–151.

Carrière-Swallow, Y. and Céspedes, L. F. (2013). The impact of uncertainty shocks in emerging economies. *Journal of International Economics*, 90(2):316–325.

Chang, R. and Fernández, A. (2013). On the sources of aggregate fluctuations in emerging economies. *International Economic Review*, 54(4):1265–1293.

Chatterjee, S. and Eyigungor, B. (2016). Endogenous political turnover and fluctuations in sovereign default risk. Manuscript, Federal Reserve Bank of Philadelphia.

Claessens, S., DellAriccia, G., Igan, D., and Laeven, L. (2010). Cross-country experiences and policy implications from the global financial crisis. *Economic Policy*, 25(62):267–293.

Dornbusch, R., Goldfajn, I., Valdés, R. O., Edwards, S., and Bruno, M. (1995). Currency crises and collapses. *Brookings Papers on Economic Activity*, pages 219–293.

Eichengreen, B., Gupta, P., and Mody, A. (2008). Sudden Stops and IMF-Supported Programs. In *Financial Markets Volatility and Performance in Emerging Markets*, NBER Chapters, pages 219–266. National Bureau of Economic Research, Inc.

Eichengreen, B. J. and Gupta, P. D. (2016). Managing sudden stops. Policy Research Working Paper Series 7639, The World Bank.

Fernández-Villaverde, J., Guerrón-Quintana, P., Rubio-Ramírez, J. F., and Uribe, M. (2011). Risk matters: The real effects of volatility shocks. *American Economic Review*, 101(6):2530–61.

Fernández-Villaverde, J. and Rubio-Ramírez, J. (2010). Macroeconomics and volatility: Data, models, and estimation. NBER Working Papers 16618, National Bureau of Economic Research, Inc.

Forbes, K. J. and Warnock, F. E. (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics*, 88(2):235–251.

García-Cicco, J., Pancrazi, R., and Uribe, M. (2010). Real business cycles in emerging countries? *American Economic Review*, 100(5):2510–31.

Gourinchas, P.-O. and Obstfeld, M. (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics*, 4(1):226–65.

Gruss, B. and Mertens, K. (2009). Regime Switching Interest Rates and Fluctuations in Emerging Markets. Economics Working Papers 2009/22, European University Institute.

Hamilton, J. D. (1990). Analysis of time series subject to changes in regime. *Journal of econometrics*, 45(1):39–70.

Hébert, B. and Schreger, J. (2016). The Costs of Sovereign Default: Evidence from Argentina. Manuscript, Harvard University.

Jeanne, O. and Korinek, A. (2010). Managing credit booms and busts: A pigouvian taxation approach. NBER Working Papers 16377, National Bureau of Economic Research, Inc.

Johri, A., Khan, S. K., and Sosa-Padilla, C. (2015). Interest Rate Uncertainty and Sovereign Default Risk. Manuscript, University of Notre Dame.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

Korinek, A. and Mendoza, E. G. (2013). From sudden stops to fisherian deflation: Quantitative theory and policy implications. NBER Working Papers 19362, National Bureau of Economic Research, Inc.

Longstaff, F. A., Pan, J., Pedersen, L. H., and Singleton, K. J. (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, 3(2):75–103.

Maćkowiak, B. (2007). External shocks, us monetary policy and macroeconomic fluctuations in emerging markets. *Journal of Monetary Economics*, 54(8):2512–2520.

Márquez-Padilla, C. and Zepeda-Lizama, C. (2013). Sudden stops and the structure of capital flows: The case of emerging and developing countries. Working Paper 2892805, Social Science Research Network (SSRN).

Neumeyer, P. A. and Perri, F. (2005). Business cycles in emerging economies: the role of interest rates. *Journal of Monetary Economics*, 52(2):345–380.

Reyes-Heroles, R. and Tenorio, G. (2015). Managing capital flows in the presence of external risks. Manuscript, Federal Reserve Board.

Stangebye, Z. R. and Gu, G. (2017). The Pricing of Sovereign Risk under Costly Information. Manuscript, University of Notre Dame.

Uribe, M. and Yue, V. Z. (2006). Country spreads and emerging countries: Who drives whom? *Journal of International Economics*, 69(1):6–36.