# Regime-Switching in Emerging Market Business Cycles: Interest Rate Volatility and Sudden Stops[*]

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**Abstract**

We document the presence of discrete regime-switching in emerging market business cycles, particularly in the volatility of interest rates at which countries borrow internationally, using a multi-country regime-switching vector autoregressive model. We study the statistical relationship of such business cycle 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.

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**Keywords:** Volatility, interest rates, emerging market economies, sudden stops, Markov regime-switching, uncertainty.

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# 1 Introduction

Emerging market economy (EME) business cycles differ from those of developed economies in two key respects. First, external interest rates are a primary driver of the real business cycle: interest rates are markedly countercyclical and economic activity responds to shocks not only to the level, but also to the volatility of interest rates.[1] Second, EMEs are subject to infrequent and sharp current account reversals, which are typically followed by deep recessions: the so-called *sudden stops* in capital inflows.[2]

The vast majority of empirical literature on EME business cycles has relied on linear frameworks to analyze the relationship between interest rates and the real economy. For instance, the effects of shocks to the level of interest rates have been analyzed through the lens of linear autoregressive models, while the analysis of shocks to interest rate volatility has resorted to stochastic volatility models where the variance of shocks drifts gradually.[3]

However, separate literature pioneered by Sims and Zha (2006) has documented the empirical relevance of discrete regime changes in the volatility of shocks driving business cycle dynamics in the United States. This literature has relied on Markov regime-switching models that allow for discrete changes in the volatility of shocks, with sudden jumps interrupted by periods of calm. The literature makes the case for these type of models to be a central tool in applied macroeconomics.[4]

Informed by the work on regime-switching in applied macroeconomics, this paper documents the presence of discrete regime switches in EME business cycles, particularly in the volatility of interest rates at which countries borrow internationally.[5] Our exploration is highly relevant from both positive and normative perspectives. From a positive perspective, our Markov regime-switching framework (i) provides additional flexibility relative to models of stochastic volatility in modeling aggregate dynamics (e.g., asset pricing) and (ii) informs

[1]See Neumeyer and Perri (2005); Uribe and Yue (2006); Maćkowiak (2007); García-Cicco et al. (2010); Chang and Fernández (2013) regarding shocks to levels and Fernández-Villaverde et al. (2011) regarding shocks to volatility.

[2]See Dornbusch et al. (1995); Calvo (1998); Calvo et al. (2004); Eichengreen et al. (2008).

[3]See Neumeyer and Perri (2005), Uribe and Yue (2006) and Fernández-Villaverde et al. (2011).

[4]The results in this literature have become very informative for research on expending the microfoundations of theoretical models. For an example see Bianchi (2013).

[5]Throughout the paper, we refer to the yield of US-dollar denominated sovereign bonds whenever we reference "interest rates".

on how regime changes may align with other type of fundamental shocks (e.g., uncertainty shocks). From a normative perspective (e.g., optimal policy), a benevolent planner facing a regime-switching shock process may want to shape her policies based on the current and expected future regimes.[6]

In this paper we focus on exploring the role of discrete regime switches in EME business cycles from an empirical perspective. We pay particular attention to the presence of regime switches in the volatility of external interest rates, and we characterize the relation between these regimes, economic activity and sudden stops. Our main analysis proceeds in three steps. First, we estimate a multi-country regime-switching vector autoregressive (VAR) model of interest rates and output with data from a broad sample of EMEs. The model we propose allows for stochastic regime switches in parameters determining the levels of observable variables and the volatility of interest rates. Second, using the estimated regime probabilities, we analyze the relationship between volatility regimes and the occurrence of sudden stops. Third, we perform an event analysis of interest rate volatility around sudden stops to characterize its behavior within our sample of 88 EME sudden stops. In the last part of the paper we carry out an additional exercise where we investigate the relationship between high interest rate volatility regimes and global uncertainty shocks.[7]

Using our regime-switching VAR, we document the presence of considerable and persistent interest rate heteroskedasticity in EMEs that is accurately described by a discrete Markov-switching framework. We show that increases in volatility are contemporaneous to abrupt declines in economic activity and increases in the level of interest rates.[8] Furthermore, we show that the countercyclicality of EME interest rates documented in previous literature (e.g., Neumeyer and Perri, 2005) has its origin in the negative co-movement of the ergodic means of output and interest rates across regimes, rather than displaying a relation at a higher frequency.[9] To the extent of our knowledge, this is the first work to investigate the

[6]We address both types of such issues from a theoretical perspective in separate work (Reyes-Heroles and Tenorio, 2017).

[7]See Bloom (2014) for a survey on the recent literature on uncertainty shocks.

[8]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.

[9]This is, conditional on being in a regime of high output and low interest rates, these variables have low (virtually zero) correlation. This result highlights the importance of accounting for significant nonlinearities

empirical role of discrete regime switches in which volatility can vary across states along the EME business cycle.

Next, we provide novel evidence on the relation between interest rate volatility regimes and sudden stop events using the output of our regime-switching model. We identify sudden stop episodes up to 2016 by extending the standard methodology of Calvo et al. (2008). We propose a novel method to rule out "false positives", i.e., episodes in which current account reversals are driven by commodity net export booms, rather than reversals in capital inflows. The Appendix to the paper contains our full list of sudden stops, together with the description of our methodology. When contrasting these sudden stops with the discrete volatility states from our regime-switching VAR, we find that high-volatility regimes tend to be followed by sudden stops six and twelve months ahead. We show, nonetheless, that the relationship between volatility and sudden stops depends heavily on the presence of external debt (EXD) crises in our sample, and that the relationship is weakened (or even overturned at some time horizons) if this type of crises is excluded. A causal analysis goes beyond the scope of this paper, but we find the empirical relation between interest rate volatility regimes, sudden stops and EXD crises to be remarkable.

The third part of the paper presents our event analysis and shows that sudden stop episodes are preceded by lower-than-normal interest rate levels, slow increases in volatility, and output above trend. Calvo et al. (1993) have already identified the importance of external factors, such as the international interest rate and the occurrence of recessions in advanced economies, in inducing capital outflows in EMEs.[10] 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.[11] Again, we find that interest rate levels and volatilities behave considerably different in non-EXD sudden stops, as the impact on these variables is much lower. We would expect the financial tightening in non-EXD sudden stops to be reflected in other asset prices, such as the exchange rate, corporate rates, interbank rates or equity prices. However, such an analysis would go beyond the scope of this paper.

when studying business cycles in EMEs, for which a regime-switching approach is appropriate.

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

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

In the last part of the paper we follow the literature on uncertainty fluctuations to identify global uncertainty shocks and study how these shocks align with our high interest-rate volatility regimes.[12] We show that, indeed, high interest-rate volatility regimes and global uncertainty shocks are statistically dependent. However, we show that the degree of correlation between both types of shocks is relatively low, which means that the country-specificity of our estimated regime probabilities elicits additional information on the state of particular countries that is not captured by global uncertainty shocks.

Our investigation is particularly relevant in the economic context faced by EMEs in the aftermath of the 2008 global financial crisis. After almost a decade of hitherto unseen monetary easing, which kept interest rates and volatility abnormally low around the world, the global recovery is fostering a period of generalized monetary policy re-normalization, increasing borrowing costs and higher volatility.[13] The global conditions faced by EMEs in the near term is highly uncertain and conditions could change rapidly. This could bring non-linear dynamics in the real economy and asset prices, as was observed in some countries in recent months.

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 EMEs. 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 event-window analysis of the evolution of first and second moments of the interest rates around episodes of sudden stops. Section 3 studies the relationship between high interest rate volatility regimes and global uncertainty shocks. Section 4 concludes.

[12]We follow the work of Carrière-Swallow and Céspedes (2013), who in turn follow the seminal contribution by Bloom (2009) on the macroeconomic effects of uncertainty shocks to study the effects of global uncertainty on EMEs, to identify global uncertainty shocks.

[13]Other factors such as the rise of populism and protectionism around the world also threatens to impact the availability of international financing and the access to goods markets for EMEs.

# 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 Global (EMBIG) spread to calculate each country's interest rate. This index tracks the return of a set of US dollar-denominated debt instruments issued by EME sovereign and quasi-sovereign entities that meet certain criteria.[14] We use the yield of the 5-year US Treasury Inflation-Protected Securities (TIPS) as the real rate upon which we add the country spreads.[15] Since we are using the yield of an inflation-linked bond, the rate needs no further inflation adjustment. The data for the EMBIG rate was obtained from J.P. Morgan, and the TIPS data comes from Bloomberg. 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 either from the IMF's International Financial Statistics (IFS) database, national statistical agencies or central banks. All GDP measurements were retrieved at constant prices and were seasonally adjusted using the US 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 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.

[14] Other works in the literature (e.g., Fernández-Villaverde et al., 2011) use the EMBI Plus index instead. We have opted to use the EMBIG index, as Neumeyer and Perri (2005) do, because its less stringent requirements allow for more countries to access the index at any given time. This increases the number of observations (countries and time periods) that are available for our estimation. The results do not vary significantly from those obtained in a previous version of the paper in which we used EMBI Plus spreads.

In general, a potential limitation of using the EMBIG spread to reflect borrowing costs is that the portfolios are composed primarily of bonds and loans issued by sovereign and quasi-sovereign entities, and their return on secondary markets may not reflect the cost of borrowing faced by households and the corporate sector. 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 that they are highly correlated.

[15] Previous works in the literature have used the 90-day Treasury bill rate, discounted by a measure of expected inflation, instead. We believe our approach fits the maturity of EMBI Global bonds better, as the country indexes have median maturities in the 3.7 to 10.0 year range. We thank an anonymous referee for recommending the approach we use in this paper.

We extend the analysis of Calvo et al. (2008) to identify sudden stop episodes until the end of 2016. Following their methodology, we identify a sudden stop as a period in which capital flows to a country fall at least two standard deviations below the country-specific mean. A sudden stop begins when capital flows fall below one standard deviation below mean, and it ends when the flows reach the same mark after hitting the trough. Given the fact that balance of payments data is available only at a quarterly frequency, we follow Calvo et al. (2008) in using IFS data to build a monthly capital flow proxy based on the evolution of the goods trade balance and changes in FX reserves.[16] A novel contribution of this paper is that we overlay a filter to identify false positives by excluding episodes in which the reversal in the capital flows proxy was driven by a sharp expansion in the primary sector trade balance, potentially as a consequence of a terms of trade shock. For this, we use data from Hausmann et al. (2013) to segment the trade balance between primary and manufacturing activities. We provide more details on the construction of sudden stop indicators in the Appendix.

Finally, to verify the robustness of our results, we exclude periods of external debt (EXD) crises from our calculations. In periods for which there is credit rating data available, we consider an EXD crisis any time span in which at least one of the country's long-term foreign currency debt falls to CCC- or below for Standard & Poors and Fitch, or Caa3 or below for Moody's.[17] Credit rating data comes from Bloomberg. For years in which credit rating data is unavailable (1980s and early 1990s for most countries), we use the episodes of sovereign external default and restructuring identified by Reinhart and Rogoff (2009).

Table 1 shows the data available and the country samples we use for our estimations. Column (1) indicates that EMBIG countries enter and exit the index in different dates as a consequence of meeting or not the various index requirements. We also observe a few countries that have interrupted EMBIG spread series. In the maximum likelihood estimations of the model, we employ all data available for each country by assuming that the separate fragments of time series of a single country are independent random draws from the same

[16]For a few exceptions where IFS data was unavailable, we use data from national statistical agencies or central banks. All import, export and FX reserve time series were separately seasonally adjusted using the X-13-ARIMA-SEATS filter.

[17]The CCC-/Caa3 level is described by rating agencies to mean that there are "substantial risks" of credit default. However, according to sovereign debt specialists, rating agencies rarely bring the rating down to the "in-default" D levels, even when a country is already delayed in coupon payments.

stochastic process. Columns (2) and (3) show the periods for which we have GDP data and sudden stops indicators, respectively.

Columns (4)-(6) show the country samples that we use for the empirical exercises. Sample 1 includes the countries that have been typically studied in the literature of EME 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 includes all countries for which there is GDP data available. It includes some former Soviet republics, as well as smaller EMEs. Finally, Sample 3 is composed of all the countries for which we have interest rate data and sudden stop indicators.

## 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 EMEs, and we show the relation of these regimes with the real business cycle. Then, we carry out exercises to test the robustness of our findings to: (a) introducing country-specific fixed effects, (b) allowing other moments of the data to be subject to regime switches, and (c) excluding EXD crises. Our empirical results are robust to all specifications, but the magnitude of interest rate volatility shifts across regimes is considerably lower when EXD crises are removed.

### 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.

Table 1: Data available and country samples

| | EMBIG (1) | GDP (2) | Sudden stops (3) | Sample 1 (4) | Sample 2 (5) | Sample 3 (6) |
|---|---|---|---|---|---|---|
| Argentina | Dec/93-Dec/17 | Mar/90-Mar/17 | Jan/85-Dec/16 | X | X | X |
| Brazil | Apr/94-Dec/17 | Mar/90-Sep/17 | Jan/85-Dec/16 | X | X | X |
| Bulgaria | Jul/94-Nov/13 | Mar/95-Sep/17 | Dec/98-Dec/16 | | X | X |
| Chile | May/99-Dec/17 | Mar/80-Mar/17 | Jan/85-Dec/16 | | X | X |
| China | Mar/94-Feb/17 | | Jan/85-Dec/16 | | | X |
| Colombia | Feb/97-Feb/17 | Mar/94-Mar/17 | Jan/85-Dec/16 | | X | X |
| Dominican Republic | Nov/01-Dec/17 | Mar/07-Sep/17 | Jan/85-Oct/11 | | X | X |
| Ecuador | Feb/95-Dec/17 | Mar/91-Sep/16 | Dec/87-Dec/16 | X | X | X |
| Egypt | Jul/01-Feb/17 | Mar/02-Dec/13 | Jan/85-Dec/16 | | X | X |
| El Salvador | Apr/02-Dec/17 | Mar/90-Sep/17 | Dec/94-Dec/16 | | X | X |
| Hungary | Jan/99-Dec/17 | Mar/95-Mar/17 | Aug/93-Dec/16 | | X | X |
| Indonesia | May/04-Dec/17 | Mar/97-Mar/17 | Jan/85-Dec/16 | | X | X |
| Korea | Dec/93-Mar/04 | Mar/70-Sep/17 | Jan/85-Dec/16 | X | X | X |
| Malaysia | Oct/96-Dec/17 | Mar/88-Mar/17 | Jan/85-Dec/16 | X | X | X |
| Mexico | Dec/93-Feb/17 | Mar/80-Jun/17 | Jan/85-Dec/16 | X | X | X |
| Nigeria | Dec/93-Dec/17* | | Jan/85-Dec/14 | | | X |
| Pakistan | Jun/01-Dec/17** | | Jan/85-Dec/16 | | | X |
| Panama | Jul/96-Feb/17 | | Jan/85-Jan/13 | | | X |
| Peru | Mar/97-Dec/17 | Mar/79-Mar/17 | Jan/85-Dec/16 | X | X | X |
| Philippines | Dec/93-Dec/17 | Mar/81-Mar/17 | Jan/85-Dec/16 | X | X | X |
| Poland | Oct/94-Dec/17 | Jun/95-Sep/17 | Jun/90-Dec/16 | | X | X |
| Russia | Dec/97-Dec/17 | Mar/95-Sep/17 | May/99-Dec/16 | | X | X |
| South Africa | Dec/94-Dec/17 | Mar/70-Dec/16 | Jan/85-Dec/16 | X | X | X |
| Turkey | Jun/96-Dec/17 | Mar/87-Mar/17 | Jan/85-Dec/16 | X | X | X |
| Ukraine | May/00-Dec/17 | Mar/00-Dec/16 | Dec/01-Dec/16 | | X | X |
| Uruguay | May/01-Dec/17 | Mar/97-Sep/17 | Jan/85-Dec/16 | | X | X |
| Venezuela | Dec/93-Dec/17 | Mar/97-Dec/15 | Jan/85-Apr/09 | X | X | X |
| Total | | | | 11 | 23 | 27 |

*No EMBIG data available Apr-07/Jan-11. **No EMBIG data available Jan-03/Mar-04.

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 $B_{s_{i,t}}$ may depend on the regime that prevails in the country during the current month, denoted by $s_{i,t}$. 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 $A_s$, $B_s$, $\Sigma_s$, and $\Pi$ for $s \in \{s_L, s_H\}$. To compute the likelihood of the data with non-observable stochastic 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:

$$\boldsymbol{\xi}_{i,t|t} = \frac{\Pi' \boldsymbol{\xi}_{i,t-1|t-1} \odot \boldsymbol{\eta}_{i,t}}{f(x_{i,t}|\Omega_{i,t-1};\theta)} \quad \text{and} \quad f(x_{i,t}|\Omega_{i,t-1};\theta) = \mathbf{1}'(\Pi' \boldsymbol{\xi}_{i,t-1|t-1} \odot \boldsymbol{\eta}_{i,t}), \tag{2}$$

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 $\Pi$.

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 $\theta$. 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.

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. We use standard optimization algorithms to find the parameter values $\theta$ 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 specifications of 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, $\sigma_s^r$.

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:[18]

$$\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix} = \begin{pmatrix} 0.0005 \\ 0.0009 \end{pmatrix} + \begin{pmatrix} 0.9643 & -0.0076 \\ 0.0254 & 0.9673 \end{pmatrix} \begin{pmatrix} y_{i,t-1} \\ r_{i,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{i,t}^y \\ \epsilon_{i,t}^r \end{pmatrix}, \tag{3}$$

where the covariance and transition matrices are composed of

$$\begin{aligned} &\sigma^y = 0.0072, \quad \rho = -0.0298, \quad \pi_L = 0.9670, \\ &\sigma_L^r = 0.0044, \quad \sigma_H^r = 0.0437, \quad \pi_H = 0.8404. \end{aligned}$$

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

The ergodic means of the output gap and the interest rate can be obtained by inverting

[18] The standard errors of these estimates can be found in Table 2, column (1).

the estimated VAR matrices:

$$\mathbb{E}\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix} = (\mathbb{I} - \hat{B})^{-1}\hat{A} = \begin{pmatrix} 0.0083 \\ 0.0329 \end{pmatrix}, \tag{4}$$

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 by construction. The second component indicates that the ergodic mean of the real interest rate faced by EMEs is 3.29% per annum, which is roughly in the range we expected.

Next, we notice that the estimated volatility of interest rates changes drastically between regimes: the standard deviation increases ten-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 30.3 and 6.3 months, respectively. The ergodic distribution of the Markov process is $P = (0.8288, 0.1712)$, 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 relatively 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 (equation (2)). The shaded areas indicate the sudden stops we identify using the methodology described in the Appendix. 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 EME interest rates documented by Fernández-Villaverde et al. (2011), and with the countercyclical interest rate in EMEs 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 EMEs 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.[19]

Table 2 displays the maximum likelihood estimates of the model with different samples and under alternative specifications. The top part of the table shows the parameters that are common across both regimes. The components of the $A$ and $B$ matrices in equation (1) are denoted by $\{a_1, a_2\}$ and $\{b_{1,1}, b_{2,1}, b_{1,2}, b_{2,2}\}$, 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 $\Pi$.

Column (1) repeats the results of the baseline specification using the 11-country Sample 1, shown in equation (3). For column (2), we extend the sample to include 12 additional EMEs 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, without any remarkable differences.

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 $B$, $\Sigma_s$ and $\Pi$ matrices. The results for Samples 1 and 2 are presented in columns (3) and (4) 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.

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

[19]Some research has focused on related questions. For instance, Uribe and Yue (2006) combine theory and empirics to disentangle the relations between country spreads, the world interest rate, and business cycles in EMEs. Longstaff et al. (2011) show how global factors influence sovereign credit risks. From a different perspective, Hébert and Schreger (2017) try to identify how country-specific factors, specifically sovereign default, affect asset prices and, therefore, interest rates.

Table 2: Maximum likelihood estimates of the regime-switching model

| | Baseline model | | Fixed effects | | Extended model | | Exc. EXD crises | |
|---|---|---|---|---|---|---|---|---|
| | Sam. 1 | Sam. 2 | Sam. 1 | Sam. 2 | Sam. 1 | Sam. 2 | Sam. 1 | Sam. 2 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Common parameters | | | | | | | | |
| $a_1$ | 0.0005 | 0.0004 | – | – | – | – | 0.0010 | 0.0011 |
| | (0.0002) | (0.0001) | | | | | (0.0002) | (0.0001) |
| $a_2$ | 0.0009 | 0.0007 | – | – | – | – | 0.0009 | 0.0009 |
| | (0.0002) | (0.0001) | | | | | (0.0002) | (0.0001) |
| $b_{1,1}$ | 0.9643 | 0.9686 | 0.9644 | 0.9664 | 0.9681 | 0.9699 | 0.9642 | 0.9690 |
| | (0.0047) | (0.0033) | (0.0048) | (0.0033) | (0.0046) | (0.0033) | (0.0049) | (0.0034) |
| $b_{2,1}$ | 0.0254 | 0.0221 | 0.0249 | 0.0232 | 0.0307 | 0.0282 | 0.0267 | 0.0248 |
| | (0.0041) | (0.0033) | (0.0041) | (0.0033) | (0.0040) | (0.0031) | (0.0042) | (0.0032) |
| $b_{1,2}$ | -0.0076 | -0.0066 | -0.0109 | -0.0101 | 0.0119 | 0.0136 | -0.0185 | -0.0222 |
| | (0.0018) | (0.0013) | (0.0021) | (0.0015) | (0.0023) | (0.0017) | (0.0032) | (0.0022) |
| $b_{2,2}$ | 0.9673 | 0.9704 | 0.9607 | 0.9592 | 0.9659 | 0.9638 | 0.9655 | 0.9624 |
| | (0.0035) | (0.0027) | (0.0042) | (0.0030) | (0.0036) | (0.0027) | (0.0038) | (0.0029) |
| $\sigma^y$ | 0.0072 | 0.0061 | 0.0072 | 0.0060 | 0.0068 | 0.0058 | 0.0073 | 0.0060 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $\rho$ | -0.0298 | -0.0287 | -0.0300 | -0.0298 | 0.0129 | -0.0004 | -0.0115 | -0.0132 |
| | (0.0213) | (0.0169) | (0.0220) | (0.0158) | (0.0203) | (0.0149) | (0.0216) | (0.0164) |
| Regime-dep. parameters | | | | | | | | |
| $\sigma^r_L$ | 0.0044 | 0.0041 | 0.0043 | 0.0039 | 0.0047 | 0.0043 | 0.0039 | 0.0038 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $a_{1,L}$ | – | – | – | – | 0.0003 | 0.0001 | – | – |
| | | | | | (0.0002) | (0.0001) | | |
| $a_{2,L}$ | – | – | – | – | 0.0010 | 0.0009 | – | – |
| | | | | | (0.0002) | (0.0001) | | |
| $\sigma^r_H$ | 0.0437 | 0.0452 | 0.0450 | 0.0399 | 0.0478 | 0.0423 | 0.0273 | 0.0313 |
| | (0.0016) | (0.0016) | (0.0018) | (0.0011) | (0.0020) | (0.0013) | (0.0011) | (0.0011) |
| $a_{1,H}$ | – | – | – | – | -0.0071 | -0.0068 | – | – |
| | | | | | (0.0007) | (0.0005) | | |
| $a_{2,H}$ | – | – | – | – | 0.0090 | 0.0089 | – | – |
| | | | | | (0.0025) | (0.0017) | | |
| Transition probabilities | | | | | | | | |
| $\pi_L$ | 0.9670 | 0.9701 | 0.9673 | 0.9724 | 0.9704 | 0.9747 | 0.9655 | 0.9713 |
| | (0.0045) | (0.0032) | (0.0044) | (0.0029) | (0.0039) | (0.0027) | (0.0049) | (0.0032) |
| $\pi_H$ | 0.8404 | 0.8491 | 0.8401 | 0.8485 | 0.8306 | 0.8397 | 0.8560 | 0.8419 |
| | (0.0229) | (0.0165) | (0.0230) | (0.0164) | (0.0221) | (0.0170) | (0.0224) | (0.0185) |

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

that allows for regime dependence of the $A_s$ matrix of the VAR model in equation (1) in addition to regime dependence of interest rate volatility, $\sigma_s^r$.

The results of this exercise are presented in columns (5) and (6) of Table 2. The estimates in column (5), 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 (4), as follows:

$$\mathbb{E}\left[\left.\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix}\right| s_{i,\tau} = s_L \text{ for every period } \tau\right] = \begin{pmatrix} 0.0291 \\ 0.0457 \end{pmatrix}, \quad \text{and}$$
$$\mathbb{E}\left[\left.\begin{pmatrix} y_{i,t} \\ r_{i,t} \end{pmatrix}\right| s_{i,\tau} = s_H \text{ for every period } \tau\right] = \begin{pmatrix} -0.1863 \\ 0.0978 \end{pmatrix}.$$

Regarding the output gap process, the long-run means deviate considerably from zero (significant at the 95% level). In the low-volatility state, the mean output gap is 2.91%, but when the state changes to the high regime, the mean output gap turns negative, down to −18.63%. Given that the VAR is highly persistent, the output gap does not reach 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 increase in output that follows a switch to the low-volatility state is much more gradual. 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 ergodic mean goes from 4.57% to 9.78% 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 EMEs.

By allowing for changes in the mean of the output process, the estimated standard deviation for the output shocks falls from 0.0072 in the baseline model to 0.0068 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.[20]

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 virtually zero. This result implies that, conditional on remaining in the same regime, the interest rate in the baseline group of EMEs is acyclical. 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.

The estimated persistence of the high volatility regime increases with respect to our baseline model, whereas the persistence of the low volatility regime falls. As a result, the ergodic distribution changes to $P = (0.8513, 0.1487)$, which implies that, in the long run, the extended model spends more time in the low volatility state than it does in the baseline model. The expected duration of the low-volatility episodes increases to 33.8 months, whereas the duration of high-volatility episodes falls to 5.9 months.

Column (6) presents the results for Sample 2. We do not observe large differences with respect to the results reported for Sample 1. Again, the introduction of regime-switching in long-run means reduces the estimated negative correlation between output and interest rate shocks.

Finally, we explore whether our results are robust to the removal of EXD crises. These episodes are typically accompanied by a sharp increase in interest rate level and volatility,

[20]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.

and usually induce economic slowdown due to the disruption of private sector financing. Columns (7) and (8) display the model estimates where EXD crisis episodes were excluded.[21] We find that the presence of interest-rate volatility regimes is robust to the removal of EXD crises, but indeed, the change in volatility accross regimes is smaller. For Sample 1 (column 7), volatility only increases 7-fold from 0.0039 to 0.0273, compared with the 10-fold increase in the baseline model (column 1). Moreover, the ergodic mean of the output gap increases vis-à-vis the baseline model to 0.0113, as expected, but the ergodic mean of interest rates also rises, to 0.0346, contrary to our intuition.

In summary, our results provide evidence of statistically significant regime switches in the volatility of interest rates for a large sample of EMEs. 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. Our findings are also robust to the removal of EXD crisis, but the change in volatility between regimes is smaller. Finally, 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 interest rate volatility and sudden stops that is visibly apparent in Figure 1. We prove that the ocurrence of high volatility states in our Markov-switching model is a good predictor of sudden stop episodes 12 and 6 months ahead. We show that the relationship between high-volatility and sudden stops is also present contemporaneously and with lags (i.e., sudden stops ssociated with future volatility), but the relationship is weaker. Nevertheless, we prove that the relation between volatility and sudden stops depends heavily on the presence of EXD crises in our sample.

[21] For the model estimation, we assume that separate non-crisis fragments of a single country's time series are independent random draws of the same stochastic process.

Once these episodes are excluded, the relationship between volatility and sudden stops is weakened and even overturned at some horizons.

First, we explore whether the occurrence of high volatility predicts the occurrence of sudden stops in the near future. We do this by comparing the unconditional probability of a sudden stop against the probability of a sudden stop conditional on a high-volatility episode. We consider as high-volatility episodes those in which the smoothed regime probability derived from the estimation of the baseline Markov-switching model (equation (2)) lies above 50%. The results are shown in Table 3.[22] The first row of column (1) shows that the unconditional probability (i.e., the empirical prevalence) of sudden stops in Sample 1 is 10.37%. However, if we condition on the occurrence of high volatility 12 months before, the probability of sudden stops increases to 14.41%, as shown in the second row of the table. The difference between the conditional and unconditional probability, 4.03 percentage points, is significantly different from zero at the 1% level. In Sample 2 (column 2), the conditional probability of a sudden stop is also higher than the unconditional one, but the difference between both is smaller, at only 1.9 percentage points (significantly different from zero at the 10% level).

The difference between conditional and unconditional probabilities increases considerably at the 6-month ahead horizon (line 3). The results strongly suggest that high-volatility periods tend to precede sudden stops, especially at a 6 month distance.

The fourth row of Table 3 shows the probability of a sudden stop conditional on a high-volatility state occurring contemporaneously. The probability differential remains positive, but it is lower than at the 6-month ahead calculation. That is, a sudden stop is more intensely associated with a high-volatility state taking place 6-months ahead, rather than contemporaneously.

Finally, we run an analogous exercise 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

[22] 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 months in the past, conditional on a high-volatility state being prevalent in the current month. The fifth and sixth rows show the results. For Sample 1 (column 1), even though the difference between conditional and unconditional probabilities is positive and significantly different from zero, their magnitude is smaller than when we condition on preceding volatility. The difference becomes statistically insignificant in Sample 2 (column 2).

We next explore whether our findings are robust to the exclusion of EXD crises. We re-calculate conditional and unconditional probabilities of sudden stops, but now excluding episodes associated with EXD crises. Columns (3) and (4) of Table 3 show that our baseline results are considerably weaker and even overturned at some horizons. In Sample 1 (column 3), high volatility episodes increase the probability of a non-EXD sudden stop six months ahead by only 3.95 percentage points, which is much lower than the 9.88 percentaje point difference in our baseline calculation (column 1). Volatility has no statistically significant predictive power for non-EXD sudden stops at the 12 month-ahead and the contemporaneous windows. Finally, non-EXD sudden stops are less likely to be followed by high-volatility states, as the last two rows of columns (3) and (4) show statitically significant negative differences against the unconditional probability.

The predictive relationship between sudden stops and high volatility episodes, and the lack thereof when EXD crises are excluded, provides no evidence of any causality direction between these variables.[23] However, our empirical results illustrate potential areas of interest for future research.

## 2.4 Sudden stop event windows

The results of the previous sections suggest that sudden stops are associated with increases in interest rate levels and volatility. In this section, we formalize this argument by analyzing event studies of these variables around the beginning of sudden stops. Indeed, we find that sudden stops tend to be preceded by below-average interest rates and abnormally low volatility, that both variables increase considerably a few months prior to the beginning of the sudden stop, and that they remain high thereafter. As in the previous section, we find that

[23]See Hébert and Schreger (2017) and Stangebye and Gu (2017) for two examples in which causality operates in opposite directions.

interest rate levels and volatilities behave considerably different in non-EXD sudden stops, as the impact on these variables is much lower. We would expect the financial tightening in non-EXD sudden stops to be reflected in other asset prices, such as the exchange rate, corporate rates, interbank rates or equity prices. However, such an analysis would go beyond the scope of this paper.

For our event window analysis, we compare the average behavior of interest rates, volatility, and the output gap around the 88 sudden stop events in Sample 3 against the corresponding behavior in regular times. In this set of countries, sudden stops take place every 105.4 months, and they last for 9.8 months, on average (see Table 4). Sample 3 countries spend on average 9.3% of time in sudden stop states, and 10.2% of sudden stops are associated with EXD crises (concentrated in a handful of countries).

Figure 2 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 stop periods. We use country-specific means to control for the fact that some nations 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 following or preceding the beginning of the sudden stop.

In panel (a) of Figure 2 we show the interest rate window analysis for all sudden stops. We observe that during months 24 to 12 preceding the start of a sudden stop, the interest rate is slightly below its normal times level, by less than one percentage point. During the 12 months preceding the sudden stop, the interest rate gradually increases to reach over 1 percentage point above normal-times level. Then, during the 24 months following the beginning of the sudden stop, the interest rate remains between 1 and 2 percentage points above the normal times level. The reversion of the interest rate to normal levels is very sluggish.[24]

Panel (b) of Figure 2 shows, nonetheless, that the interest rates behave differently in non-EXD sudden stops. In this group of sudden stops, below-average interest rates tend to precede sudden stops almost during a 2-year period, and rates revert back to normal levels around the beginning of sudden stops. Again, it is likely that asset prices other than

[24]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).

the external interest rate might be reflecting the tighteining of financial conditions around non-EXD sudden stops, but that analysis goes beyond the scope of this paper.

Next, we analyze whether there is a pattern in the volatility of interest rates around sudden stops. Panel (a) of Figure 3 shows the episode analysis for the 7-month rolling standard deviation of the interest rate (centered window), including all sudden stops. We find that 24 to 12 months prior to a sudden stop, interest rate volatility remains below its normal times level, but in the preceding 12 months, it starts to increase gradually. Volatility reaches a peak approximately 6 months after the sudden stop begins, after which it starts falling quickly.

Consistent with our results from the previous section, we find that the relationship between volatility and sudden stops weakens considerably when we exclude EXD crises (panel (b) of Figure 3). We find again that volatility falls below normal in the months following a non-EXD sudden stop.

We verify that the slow speed at which volatility changes around sudden stops is not a mechanical consequence of our averaging across 7 months of interest rate data. Figure 4 shows the event studies of volatility using different window lengths to calculate the standard deviation of interest rates (including all sudden stop episodes). The blue dash-dotted line corresponds to a 3-month centered moving standard deviation of interest rates. We observe, indeed, sharper increases of volatility preceding the start of the sudden stop period and at the peak approximately 9 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. This implies that our results are robust to the length of the window for which we choose to calculate the moving volatility of interest rates.

Finally, Figure 5 presents the event window for the output gap. 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 the output gap 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 event. After hitting the trough, output has a gradual recovery back to trend, which takes around 24 months. In panel (b), we find that the output gap dynamics are very similar if we exclude EXD crises.

## 3 Interest Rate Volatility and Uncertainty Shocks

In this section we investigate how our high interest-rate volatility regimes from Section 2 relate to global uncertainty shocks. An important challenge faced by the literature on economic uncertainty (e.g. Bloom, 2009; Carrière-Swallow and Céspedes, 2013; Caldara et al., 2016) is that this phenomenon is difficult to measure. Existing work relies on a broad range of proxies, such as measures of implied volatility in financial instruments, to represent the degree of underlying uncertainty at a given point in time. Here, we show that our country-specific interest-rate volatility regimes are not independent from a typical measure of global uncertainty based on implied volatility, as one would naturally expect. However, we also show that our interest-rate volatility regimes bring additional country-specific information, since they are not perfectly correlated with global uncertainty regimes—in some countries less so than others.[25]

One of the most common proxies of economic uncertainty used in the literature is the implied stock-market volatility measured by the VXO.[26] Carrière-Swallow and Céspedes (2013) follow Bloom (2009) and define global uncertainty shocks as periods in which the VXO index spikes up. Here, we replicate their procedure to identify uncertainty shocks along the time-span of our data sample. Like them, we define periods of high uncertainty as those in which the Hodrick Prescott-detrended VXO exceeds its mean by a multiple of its standard deviation. We set that multiple to 1.45 in order to obtain the same uncertainty episodes that Bloom (2009) identified up to 2008.[27]

Figure 7 shows the result of this procedure. The black line is the VXO implied volatility index. The areas shaded in yellow represent the periods identified as uncertainty shocks. In

[25] We thank an anonymous referee for bringing this point to our attention.

[26] The VXO index reflects a market estimate of future volatility based on S&P 100 options. The literature has used the VXO rather than the better-known VIX index, which is based on S&P 500 options, since the latter was introduced later and has a shorter history. However, both indices are highly correlated.

[27] Carrière-Swallow and Céspedes (2013) and Bloom (2009) use 1.65 for the cutoff. We believe that the difference can be attributed to filtering out the VXO series using different time spans.

addition to the episodes that have been previously identified by the literature (i.e., all those preceding the 2008 global financial crisis), we identify the European debt crisis (Aug-Nov 2011) and two bouts of China stock market turbulence (Sep 2015 and Jan-Feb 2016) as uncertainty shocks. In the figure, we overlay the share of countries in our sample of EMEs that are experiencing a high-volatility episode (gray bars). It is visually clear that there is a positive association between global uncertainty and country-level interest-rate volatility, in particular in episodes of broad financial instability (e.g., the 1998 Russian financial crisis or the 2008 global financial crisis). However, there are episodes of high interest rate volatility in EMEs during which the VXO remained at relatively low levels, like around the 1994-1995 Tequila crisis.

In Table 5, we prove more formally that for several countries, uncertainty events and high interest-rate volatility regimes are stochastically dependent. Column (1) shows the *unconditional* prevalence of high interest-rate volatility regimes in each country. Then, Columns (2)-(8) show the prevalence of high interest-rate volatility regimes *conditional* on the ocurrence of a global uncertainty shock at different leads and lags. If the events were stochastically independent, the conditional and unconditional probabilities should be statistically equal. However, as the table shows, for several countries, and for Sample 1 and 2 in the aggregate, the prevalence of volatility regimes increases substantially when global uncertainty is high, and the difference is highly statistically significant.

Nevertheless, despite the statistical dependence of both types of shocks, we believe that our high interest-volatility regimes bring additional information, either specific to the EME sovereign debt asset class, or idiosyncratic to the countries in our sample. The evidence in Table 6 shows that the correlation for both shocks is indeed relatively low and substantially different across countries. For instance, in Colombia, which is displayed in Figure 8, interest rate volatility states are highly correlated with global uncertainty. This means that volatility in the sovereign spread is largely driven by external factors rather than idiosyncratic shocks. In contrast, in Mexico, interest-rate volatility regimes have a low–and even negative–correlation with global uncertainty, since most of the financial turmoil took place in the mid-1990s, when global uncertainty was low, and the country's spread had low volatility even in periods of high global uncertainty, like the 2008 global financial crisis and the 2011 European debt crisis, to name a few.

# 4 Conclusions

Our estimation provides evidence of regime switches in interest rate volatility for a group of EMEs. 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 EMEs 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 (2017), 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 empirical estimates analogous 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.

# 5 Appendix: Sudden stop episode calculation

In this appendix we describe how we identify sudden stop episodes. The literature has defined sudden stops as large and sudden reversals of capital inflows. One strand of the literature has relied on capital account data to directly identify the swings (e.g., Forbes and Warnock, 2012b). Another strand identifies capital flows indirectly by using changes in the trade balance and FX reserves to proxy for capital account movements (e.g., Calvo et al., 2008). We follow the latter approach because it allows for a higher frequency measure of capital flows, as trade balance and FX reserve data is available at a monthly frequency for most EMEs in our sample (capital account is typically available only at a quarterly frequency). This feature of the data implies that we can explore the evolution of the level and volatility of interest rates around sudden stops more precisely.

The downside to this approach is that it assumes that primary and secondary income, as well as balance of payments errors and omissions, remain relatively constant in time. In addition, large swings in commodity prices could generate sharp trade balance moves, that could give rise to sudden stop "false positives". We address this issue using a novel approach (second step, below).

## 5.1 Step 1. Identify sudden stop candidates

The first step is to identify sudden stop candidates. We follow Calvo et al. (2008) in building a monthly capital inflows proxy and identifying sudden stop candidates as those in which the proxy reverses sharply. As in Calvo et al. (2008), we define the capital inflows proxy as:

$$P_{i,t} \equiv \Delta R_{i,t} - (X_{i,t} - M_{i,t}),$$

where $X_{i,t}$ and $M_{i,t}$ denote country $i$'s monthly merchandise exports and imports (respectively) at time $t$, and $\Delta R_{i,t}$ denotes the monthly accumulation of FX reserves (if positive). The rationale behind the proxy is that, whenever capital inflows are increasing, the country can either accumulate FX reserves, $\Delta R_{i,t}$, or incur a trade deficit, $-(X_{i,t} - M_{i,t})$. We use merchandise trade and FX reserve data from the IFS.[28] All of these variables are measured in US dollars and are seasonally adjusted using the US Census Bureau's X-13-ARIMA-SEATS filter.

To mute down potential noise in the capital flows proxy, we calculate the 12-month moving average, $C_{i,t} \equiv \frac{1}{12}\sum_{j=t}^{t-12} P_{i,j}$, before calculating the year-over-year change, $\Delta C_{i,t} \equiv C_{i,t} - C_{i,t-12}$. We define sudden stop candidates as those periods in which $\Delta C_{i,t}$ falls two standard deviations below the mean. The episode begins when $\Delta C_{i,t}$ falls one-standard deviation below mean, and it ends when $\Delta C_{i,t}$ hits that same mark on the way back up. We calculate the mean and standard deviation in an expanding window, and use at least 24 months of data to calculate the first episode in each country. Figure 6 illustrates the process for Argentina. The first five times that $\Delta C_{i,t}$ hits the two standard deviation mark are considered sudden stops, whereas the last one in 2008 is considered a "false positive", based on the second step below.

## 5.2 Step 2. Identify and exclude "false positives"

The second step is to identify "false positives". These are episodes where the reversal in the capital inflow proxy is driven by a boom in net exports of primary goods, which is likely caused by commodity price increases rather than by an actual reversal of capital inflows. Here, we use a novel approach by decomposing each country's trade balance between primary goods, which are sensitive to terms of trade shocks, and manufacturing goods, which are more responsive to shifts in capital inflows. We use annual four-digit export and import data from Hausmann et al. (2013), which is available for most countries for the 1962-2016 period. We use the UNCTAD groups to classify products into primary commodities, precious stones and non-monetary gold (SITC 0 + 1 + 2 + 3 + 4 + 68 + 667 + 971), and manufactured goods (SITC 5 + 6 + 7 + 8 - 667 - 68).

We consider a country as an exporter of primary goods if its cumulative primary good trade balance along the sample period is positive. Conversely, we define a primary good importer if its primary good cumulative trade balance is negative. Relying on these definitions,

[28] With a few exceptions when IFS data is unavailable, we use data from national statistical agencies or central banks

we define the following events: a primary good trade balance "boom" is a year in which the primary good trade balance is more than 1.65 standard deviations above the sample mean; a manufactured good trade balance "boom" is a year in which the manufacturing good trade balance is more than 1.65 standard deviations above its sample mean; and a manufactured good trade balance "crash" is a year in which the manufacturing good trade balance is more than 1.65 standard deviations below its sample mean.

We use these episodes to eliminate sudden stop "false positives". For primary good exporters, we exclude sudden stops that reach the peak capital outflows (the two standard deviation mark) during years in which there is a primary good trade balance boom, as long as there is no manufacturing trade balance boom. We want to avoid excluding a sudden stop like Mexico 1995, in which there was both a sharp reversal of both the primary and manufacturing net exports that led to booms in both categories.

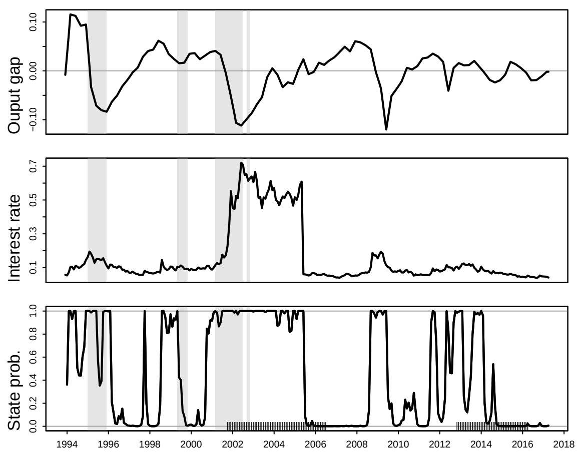
For primary good importers, we exclude sudden stops that reach the peak capital outflows during years in which there is a primary good trade balance boom, as long as it is not associated with a manufacturing good trade balance crash. We want to avoid excluding sudden stops like China 2009, in which a primary good importer faces the withdrawal of external financing and experiences a sharp fall in the manufacturing trade balance, which drives a sharp increase in the primary goods trade balance, since the latter are used as inputs in the production of export goods.

A special consideration is taken for 2008. The first half of the year was characterized by a global boom in commodity prices, which is likely to lead to "false positives" in primary good exporters, while the second half set the stage for the global financial crisis, which is likely to cause "actual" sudden stops in leveraged economies. To account for this, we do not exclude sudden stops that reach peak capital outflows between September and December of 2008, irregardless of whether the country experienced a primary good trade balance boom (which is most likely to have happened in the first part of the year).

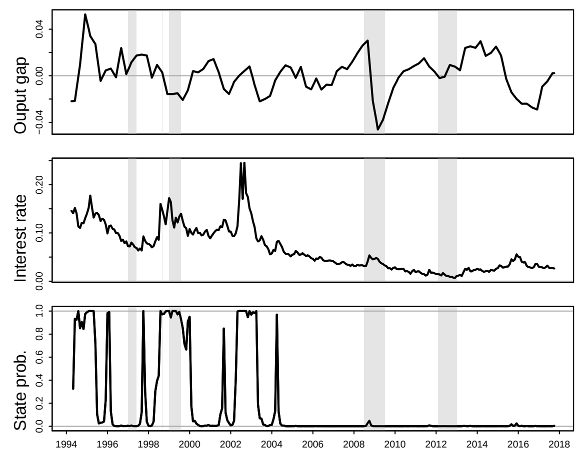
Table 7 shows the list of sudden stop episodes identified with this methodology. The table already excludes "false positives", which represented 28% of the original candidate episodes. In addition to the length of the episode, we indicate whether the sudden stop is associated with an EXD crisis. This occurs when there is at least a one month overlap between the sudden stop and the EXD crisis based either in the credit ratings threshold or on the episodes identified by Reinhart and Rogoff (2009).

Figure 9 shows the share of countries in our sample that are experiencing a sudden stop at every point in time. We verify the previously explored fact that sudden stops tend to be bunched accross countries (e.g., Forbes and Warnock, 2012b), due to financial interconnectedness and the presence of common factors such as commodity trade. We also find that the prevalence of EXD crises has fallen as a fraction of sudden stops in the past decades. This implies that private-sector external financing is now playing a more important role in EME current account dynamics and the vulnerability to sudden stops, as opposed to a few decades ago when most of the international borrowing was conducted directly by governments and was mostly US dollar-denominated.

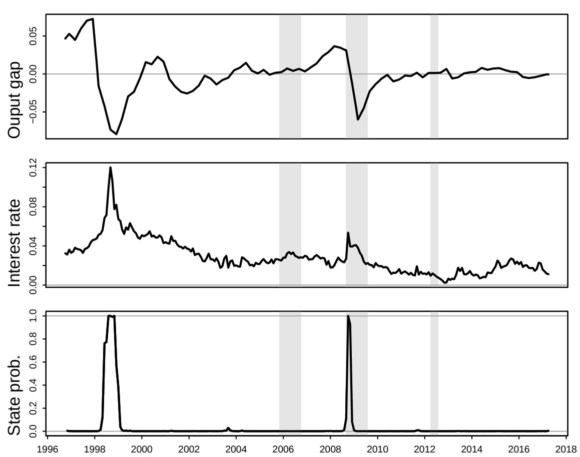
Figure 1: Output gap, interest rates, and smoothed regime probabilities. The shaded areas indicate the occurrence of sudden stops. Vertical lines next to the axis represent EXD crises.



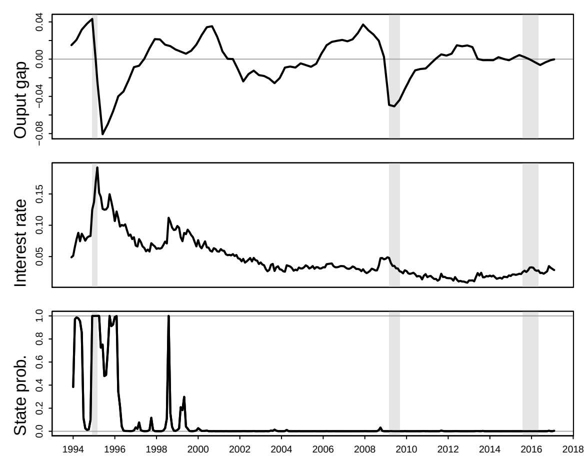

(a) Argentina



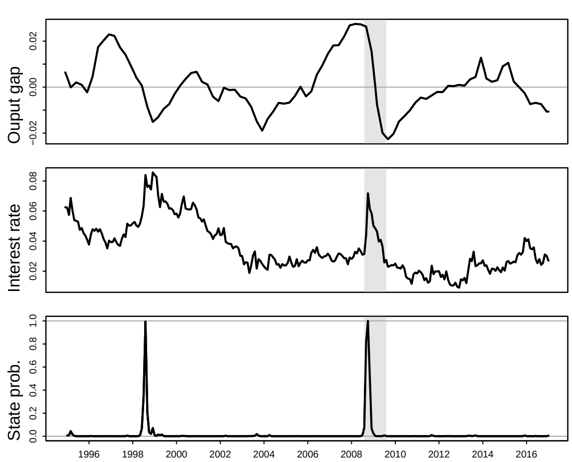

(b) Brazil



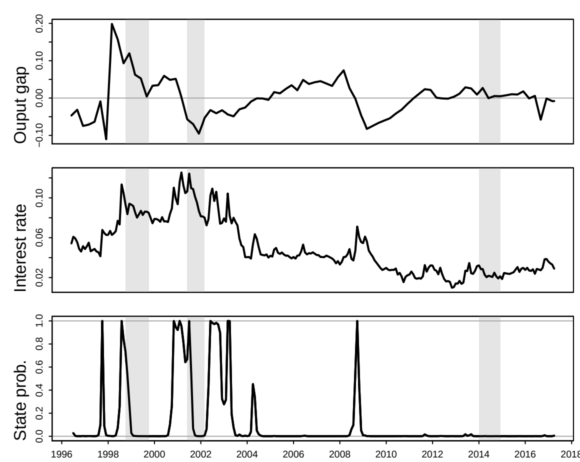

(c) Malaysia




(d) Mexico




(e) South Africa

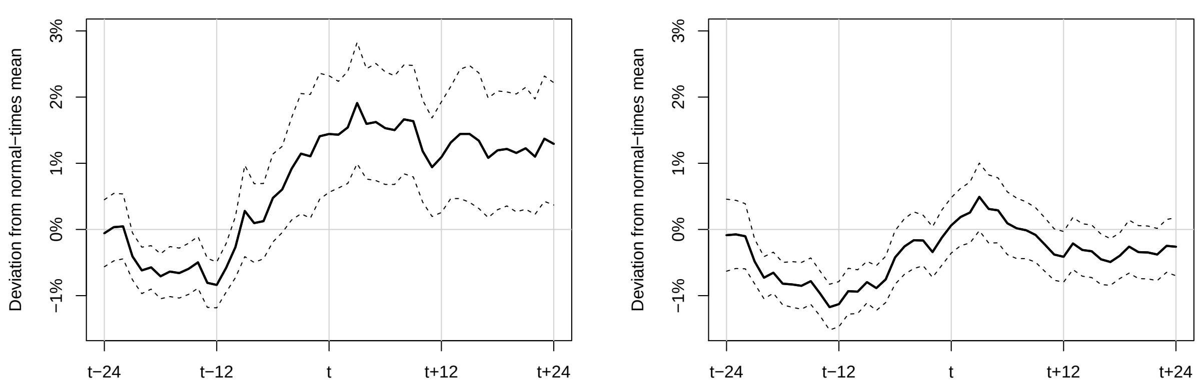



(f) Turkey

Table 3: Prevalence of sudden stops for different volatility windows

| | All events | | Exc. EXD crises | |
|---|---|---|---|---|
| | Sample 1 (1) | Sample 2 (2) | Sample 1 (3) | Sample 2 (4) |
| **Prevalence of sudden stops** | | | | |
| Unconditional | 0.1037 | 0.0924 | 0.0913 | 0.0819 |
| Conditional on high volatility at $t-12$ | 0.1441 | 0.1114 | 0.0847 | 0.0657 |
| Conditional on high volatility at $t-6$ | 0.2025 | 0.1598 | 0.1308 | 0.0976 |
| Conditional on high volatility at $t$ | 0.1751 | 0.1477 | 0.1013 | 0.0759 |
| Conditional on high volatility at $t+6$ | 0.1308 | 0.1097 | 0.0570 | 0.0422 |
| Conditional on high volatility at $t+12$ | 0.1456 | 0.1097 | 0.0823 | 0.0563 |
| **Difference vs unconditional** | | | | |
| Conditional on high volatility at $t-12$ | 0.0403*** | 0.0190* | -0.0065 | -0.0162 |
| Conditional on high volatility at $t-6$ | 0.0988*** | 0.0674*** | 0.0395*** | 0.0157 |
| Conditional on high volatility at $t$ | 0.0714*** | 0.0553*** | 0.010 | -0.0060 |
| Conditional on high volatility at $t+6$ | 0.0271* | 0.0173 | -0.0343** | -0.0397*** |
| Conditional on high volatility at $t+12$ | 0.0418*** | 0.0173 | -0.0090 | -0.0256** |

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.




(a) All episodes (b) Excluding EXD crises

Figure 2: Empirical behavior of the interest rate during sudden stops.
The graphs depict 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.

Table 4: Sudden stops: descriptive statistics

| | Num. episodes (1) | Avg. length (months) (2) | Avg. freq. (months) (3) | %time in ss. (4) | %ss in EXD crisis (5) |
|---|---|---|---|---|---|
| Argentina | 5 | 10.2 | 76.8 | 13.3% | 40.0% |
| Brazil | 7 | 7.7 | 54.9 | 14.1% | 14.3% |
| Bulgaria | 1 | 6.0 | 217.0 | 2.8% | – |
| Chile | 1 | 13.0 | 384.0 | 3.4% | – |
| China | 5 | 12.8 | 76.8 | 16.7% | – |
| Colombia | 2 | 13.5 | 192.0 | 7.0% | – |
| Dominican Republic | 2 | 12.5 | 161.0 | 7.8% | 50.0% |
| Ecuador | 6 | 6.7 | 58.2 | 11.5% | 33.3% |
| Egypt | 4 | 12.3 | 96.0 | 12.8% | – |
| El Salvador | 4 | 5.5 | 66.3 | 8.3% | – |
| Hungary | 3 | 8.3 | 93.7 | 8.9% | – |
| Indonesia | 3 | 12.3 | 128.0 | 9.6% | – |
| Korea | 3 | 9.3 | 128.0 | 7.3% | – |
| Malaysia | 6 | 10.2 | 64.0 | 15.9% | – |
| Mexico | 3 | 7.0 | 128.0 | 5.5% | – |
| Nigeria | 1 | 8.0 | 360.0 | 2.2% | – |
| Pakistan | 4 | 7.5 | 96.0 | 7.8% | 25.0% |
| Panama | 5 | 7.0 | 67.4 | 10.4% | – |
| Peru | 3 | 13.0 | 128.0 | 10.2% | – |
| Philippines | 3 | 15.0 | 128.0 | 11.7% | – |
| Poland | 4 | 8.3 | 79.8 | 10.3% | – |
| Russia | 1 | 17.0 | 212.0 | 8.0% | – |
| South Africa | 1 | 13.0 | 384.0 | 3.4% | – |
| Turkey | 6 | 9.7 | 64.0 | 15.1% | – |
| Ukraine | 1 | 6.0 | 181.0 | 3.3% | – |
| Uruguay | 3 | 12.3 | 128.0 | 9.6% | 66.7% |
| Venezuela | 1 | 15.0 | 292.0 | 5.1% | – |
| Sample 1 | 44 | 9.7 | 93.1 | 10.4% | 11.4% |
| Sample 2 | 73 | 9.9 | 107.0 | 9.2% | 12.3% |
| Sample 3 (All) | 88 | 9.8 | 105.4 | 9.3% | 10.2% |

Table 5: Prevalence of country-specific volatility states conditional on global uncertainty

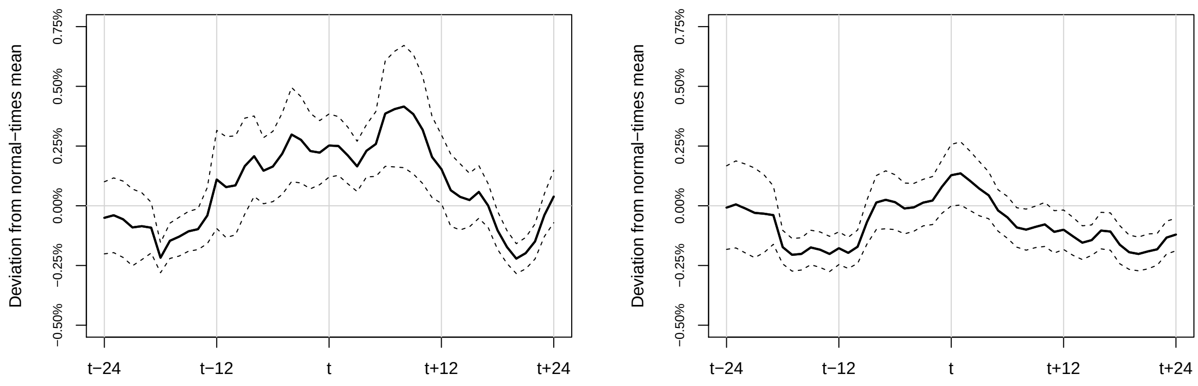
| | Uncond. | Conditional on high global uncertainty at $t+$ (lags/leads) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | $-3$ | $-2$ | $-1$ | 0 | 1 | 2 | 3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Argentina | 0.45 | 0.55* | 0.62*** | 0.66*** | 0.69*** | 0.66*** | 0.55* | 0.45 |
| Brazil | 0.18 | 0.21 | 0.24 | 0.28* | 0.31** | 0.28* | 0.28* | 0.24 |
| Bulgaria | 0.16 | 0.03* | 0.07 | 0.07 | 0.10 | 0.10 | 0.07 | 0.03* |
| Chile | 0.01 | 0.00 | 0.00 | 0.03 | 0.07 | 0.07 | 0.07 | 0.07 |
| Colombia | 0.05 | 0.07 | 0.10 | 0.17* | 0.24*** | 0.24*** | 0.17* | 0.14 |
| Dominican Republic | 0.06 | 0.03 | 0.07 | 0.10 | 0.14 | 0.17 | 0.17 | 0.17 |
| Ecuador | 0.42 | 0.48 | 0.55** | 0.62*** | 0.62*** | 0.62*** | 0.59*** | 0.48 |
| Egypt | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| El Salvador | 0.04 | 0.03 | 0.07 | 0.10 | 0.14 | 0.14 | 0.14 | 0.14 |
| Hungary | 0.02 | 0.00 | 0.03 | 0.07 | 0.10 | 0.10 | 0.10 | 0.10 |
| Indonesia | 0.03 | 0.03 | 0.07 | 0.10 | 0.14 | 0.14 | 0.14 | 0.14 |
| Korea | 0.03 | 0.00 | 0.00 | 0.00 | 0.03 | 0.07 | 0.03 | 0.00 |
| Malaysia | 0.04 | 0.07 | 0.07 | 0.10 | 0.14 | 0.14 | 0.14 | 0.14 |
| Mexico | 0.08 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.03 | 0.00 |
| Peru | 0.09 | 0.07 | 0.10 | 0.14 | 0.21* | 0.28*** | 0.21* | 0.14 |
| Philippines | 0.03 | 0.00 | 0.03 | 0.07 | 0.07 | 0.07 | 0.03 | 0.00 |
| Poland | 0.04 | 0.00 | 0.00 | 0.03 | 0.07 | 0.10 | 0.10 | 0.07 |
| Russia | 0.16 | 0.07 | 0.10 | 0.17 | 0.21 | 0.24 | 0.21 | 0.17 |
| South Africa | 0.02 | 0.00 | 0.00 | 0.03 | 0.07 | 0.14** | 0.14** | 0.10 |
| Turkey | 0.11 | 0.07 | 0.17 | 0.31*** | 0.31*** | 0.34*** | 0.28*** | 0.24** |
| Ukraine | 0.46 | 0.48 | 0.55 | 0.66*** | 0.69*** | 0.66*** | 0.55 | 0.45 |
| Uruguay | 0.11 | 0.21 | 0.21 | 0.24* | 0.28** | 0.31*** | 0.31*** | 0.31*** |
| Venezuela | 0.41 | 0.59*** | 0.59*** | 0.62*** | 0.69*** | 0.72*** | 0.66*** | 0.59*** |
| Sample 1 | 0.17 | 0.18 | 0.22** | 0.26*** | 0.29*** | 0.30*** | 0.27*** | 0.22** |
| Sample 2 | 0.14 | 0.13 | 0.16* | 0.20*** | 0.23*** | 0.24*** | 0.22*** | 0.18*** |

Note: ***, ** and * denote that the difference between conditional and unconditional probabilities is significant at the 1, 5, and 10 percent levels.

Table 6: Cross-correlations of country-specific volatility states and global uncertainty

| | Correlation with high global uncertainty at $t+$ (lags/leads) | | | | | | |
|---|---|---|---|---|---|---|---|
| | $-3$ | $-2$ | $-1$ | 0 | 1 | 2 | 3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Argentina | 0.15** | 0.20*** | 0.22*** | 0.25*** | 0.22*** | 0.15** | 0.07 |
| Brazil | 0.07 | 0.10* | 0.13** | 0.17*** | 0.13** | 0.13** | 0.10* |
| Bulgaria | $-0.10$ | $-0.05$ | $-0.05$ | $-0.01$ | $-0.01$ | $-0.05$ | $-0.10$ |
| Chile | $-0.03$ | $-0.03$ | 0.13* | 0.29*** | 0.29*** | 0.29*** | 0.29*** |
| Colombia | 0.06 | 0.12* | 0.25*** | 0.38*** | 0.38*** | 0.25*** | 0.19*** |
| Dominican Republic | 0.01 | 0.12 | 0.22** | 0.32*** | 0.43*** | 0.43*** | 0.43*** |
| Ecuador | 0.12* | 0.17*** | 0.23*** | 0.23*** | 0.23*** | 0.20*** | 0.12* |
| Egypt | $-0.08$ | $-0.08$ | $-0.08$ | $-0.08$ | $-0.08$ | $-0.08$ | $-0.08$ |
| El Salvador | 0.02 | 0.11 | 0.20*** | 0.30*** | 0.30*** | 0.30*** | 0.31*** |
| Hungary | $-0.04$ | 0.07 | 0.19*** | 0.30*** | 0.30*** | 0.30*** | 0.30*** |
| Indonesia | 0.07 | 0.20** | 0.32*** | 0.45*** | 0.45*** | 0.45*** | 0.45*** |
| Korea | $-0.05$ | $-0.05$ | $-0.05$ | 0.12 | 0.30*** | 0.12 | $-0.05$ |
| Malaysia | 0.08 | 0.08 | 0.15** | 0.22*** | 0.22*** | 0.22*** | 0.22*** |
| Mexico | $-0.09$ | $-0.09$ | $-0.09$ | $-0.09$ | $-0.04$ | $-0.04$ | $-0.09$ |
| Peru | 0.00 | 0.05 | 0.10 | 0.20*** | 0.30*** | 0.20*** | 0.10 |
| Philippines | $-0.05$ | 0.04 | 0.12** | 0.12** | 0.12** | 0.04 | $-0.05$ |
| Poland | $-0.07$ | $-0.07$ | 0.00 | 0.06 | 0.13** | 0.13** | 0.07 |
| Russia | $-0.06$ | $-0.03$ | 0.05 | 0.09 | 0.13** | 0.09 | 0.05 |
| South Africa | $-0.04$ | $-0.04$ | 0.07 | 0.18*** | 0.40*** | 0.40*** | 0.29*** |
| Turkey | $-0.03$ | 0.11* | 0.28*** | 0.28*** | 0.33*** | 0.24*** | 0.19*** |
| Ukraine | 0.15** | 0.21*** | 0.31*** | 0.34*** | 0.31*** | 0.21*** | 0.11 |
| Uruguay | 0.19*** | 0.19*** | 0.24*** | 0.30*** | 0.35*** | 0.35*** | 0.35*** |
| Venezuela | 0.26*** | 0.26*** | 0.29*** | 0.33*** | 0.34*** | 0.28*** | 0.22*** |
| Sample 1 | 0.04 | 0.07 | 0.13 | 0.18 | 0.23 | 0.18 | 0.10 |
| Sample 2 | 0.02 | 0.07 | 0.14 | 0.21 | 0.24 | 0.20 | 0.15 |

Note: ***, ** and * denote that correlation is different from zero at 1, 5, and 10 percent levels.




(a) All episodes

(b) Excluding EXD crises

Figure 3: Empirical behavior of interest rate volatility during sudden stops.
The graphs depict 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.

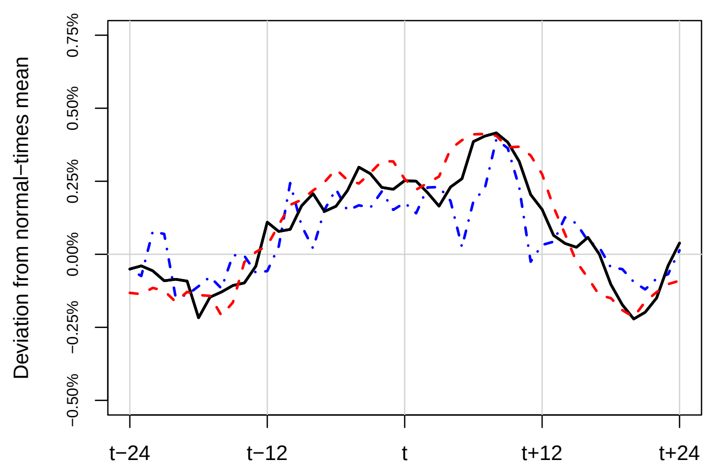
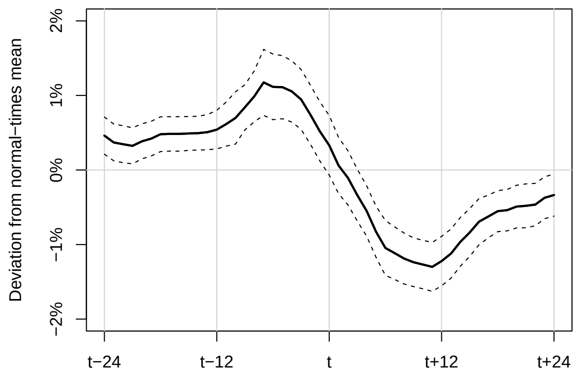
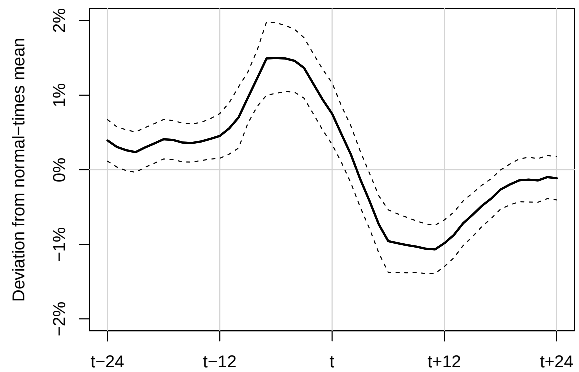



Figure 4: Empirical behavior of interest rate volatility during sudden stops.
The graph depicts the deviation of interest rate volatility from the normal-times country-specific mean. Each line represents the event window using 3, 7 and 11 months to calculate the standard deviation of interest rates. $t$ denotes the month in which the sudden stop begins.




(a) All episodes




(b) Excluding EXD crises

Figure 5: Empirical behavior of the output gap during sudden stops.
The graphs depict 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.

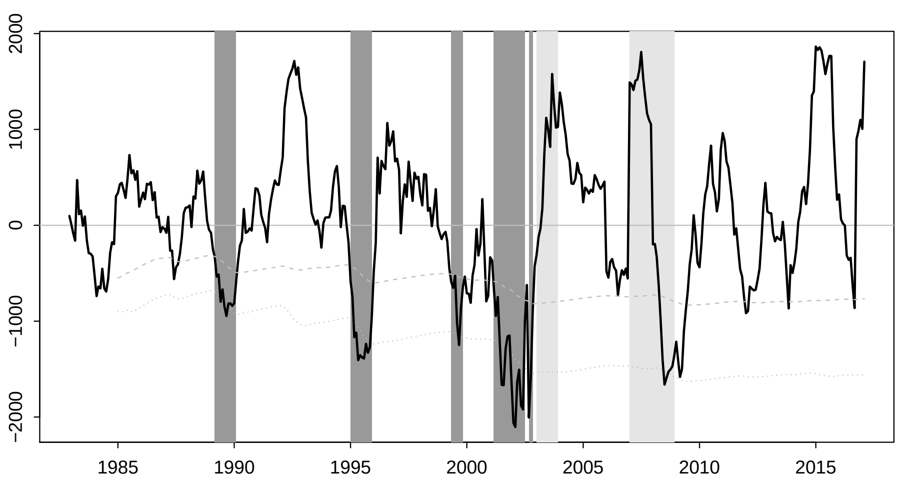



Figure 6: Argentina: change in capital inflows and sudden stop episodes.
The graph depicts the year-over-year change in the smoothed monthly capital inflow proxy for Argentina, measured in US$mn. The dashed and dotted lines represent one and two standard deviations from the mean, respectively. Dark gray shading represents sudden stop episodes; light gray shading represents episodes where false positives are eliminated due to the occurrence of primary good trade balance booms.

Table 7: Sudden stops: list of events

| | Timing | Length (months) | EXD crisis | | Timing | Length (months) | EXD crisis |
|---|---|---|---|---|---|---|---|
| Argentina 1 | Mar/89-Feb/90 | 12 | | Korea 2 | Apr/01-Dec/01 | 9 | |
| Argentina 2 | Jan/95-Dec/95 | 12 | | Korea 3 | Oct/10-Apr/11 | 7 | |
| Argentina 3 | May/99-Nov/99 | 7 | | Malaysia 1 | Dec/87-Oct/88 | 11 | |
| Argentina 4 | Mar/01-Jul/02 | 17 | Y | Malaysia 2 | Mar/93-Nov/93 | 9 | |
| Argentina 5 | Sep/02-Nov/02 | 3 | Y | Malaysia 3 | Dec/94-Nov/95 | 12 | |
| Brazil 1 | Sep/85-Jan/86 | 5 | Y | Malaysia 4 | Nov/05-Oct/06 | 12 | |
| Brazil 2 | Mar/93-Nov/93 | 9 | | Malaysia 5 | Sep/08-Aug/09 | 12 | |
| Brazil 3 | Jan/97-Jun/97 | 6 | | Malaysia 6 | Apr/12-Aug/12 | 5 | |
| Brazil 4 | Sep/98-Sep/98 | 1 | | Mexico 1 | Dec/94-Mar/95 | 4 | |
| Brazil 5 | Jan/99-Aug/99 | 8 | | Mexico 2 | Mar/09-Sep/09 | 7 | |
| Brazil 6 | Jul/08-Jul/09 | 13 | | Mexico 3 | Aug/15-May/16 | 10 | |
| Brazil 7 | Feb/12-Jan/13 | 12 | | Nigeria 1 | Jun/96-Jan/97 | 8 | |
| Bulgaria 1 | Nov/05-Apr/06 | 6 | | Pakistan 1 | Sep/95-Nov/95 | 3 | |
| Chile 1 | Jun/98-Jun/99 | 13 | | Pakistan 2 | May/98-Jan/99 | 9 | Y |
| China 1 | Jul/92-Jun/93 | 12 | | Pakistan 3 | Dec/03-Aug/04 | 9 | |
| China 2 | Nov/97-Jan/99 | 15 | | Pakistan 4 | Jul/08-Mar/09 | 9 | |
| China 3 | Nov/05-Jan/07 | 15 | | Panama 1 | Feb/88-Feb/89 | 13 | |
| China 4 | Jan/09-Jun/09 | 6 | | Panama 2 | May/98-May/98 | 1 | |
| China 5 | Dec/11-Mar/13 | 16 | | Panama 3 | Feb/02-Jun/02 | 5 | |
| Colombia 1 | Jan/99-Jun/00 | 18 | | Panama 4 | Feb/04-Sep/04 | 8 | |
| Colombia 2 | Dec/11-Aug/12 | 9 | | Panama 5 | Oct/09-May/10 | 8 | |
| Dom. Rep. 1 | Feb/94-Feb/95 | 13 | Y | Peru 1 | Jul/97-Feb/98 | 8 | |
| Dom. Rep. 2 | Apr/09-Mar/10 | 12 | | Peru 2 | Feb/99-Nov/99 | 10 | |
| Ecuador 1 | Apr/88-Feb/89 | 11 | Y | Peru 3 | Mar/02-Nov/03 | 21 | |
| Ecuador 2 | Oct/99-Dec/00 | 15 | Y | Philippines 1 | Dec/99-Jun/01 | 19 | |
| Ecuador 3 | Mar/11-Jul/11 | 5 | | Philippines 2 | Mar/12-Feb/13 | 12 | |
| Ecuador 4 | Feb/12-Apr/12 | 3 | | Philippines 3 | Nov/13-Dec/14 | 14 | |
| Ecuador 5 | Feb/14-May/14 | 4 | | Poland 1 | Dec/90-Dec/90 | 1 | |
| Ecuador 6 | Dec/14-Jan/15 | 2 | | Poland 2 | Mar/99-May/00 | 15 | |
| Egypt 1 | Mar/85-Apr/86 | 14 | | Poland 3 | Feb/12-Aug/12 | 7 | |
| Egypt 2 | Jul/89-May/90 | 11 | | Poland 4 | Nov/13-Aug/14 | 10 | |
| Egypt 3 | Mar/91-Mar/92 | 13 | | Russia 1 | May/08-Sep/09 | 17 | |
| Egypt 4 | Apr/11-Feb/12 | 11 | | South Africa 1 | Aug/08-Aug/09 | 13 | |
| El Salvador 1 | Aug/96-Jul/97 | 12 | | Turkey 1 | Aug/87-Oct/87 | 3 | |
| El Salvador 2 | Feb/99-Apr/99 | 3 | | Turkey 2 | May/91-Jan/92 | 9 | |
| El Salvador 3 | May/02-Sep/02 | 5 | | Turkey 3 | Mar/94-Jan/95 | 11 | |
| El Salvador 4 | Dec/13-Jan/14 | 2 | | Turkey 4 | Oct/98-Oct/99 | 13 | |
| Hungary 1 | Dec/96-Apr/97 | 5 | | Turkey 5 | Jun/01-Mar/02 | 10 | |
| Hungary 2 | Mar/10-Feb/11 | 12 | | Turkey 6 | Jan/14-Dec/14 | 12 | |
| Hungary 3 | Mar/12-Oct/12 | 8 | | Ukraine 1 | Oct/04-Mar/05 | 6 | |
| Indonesia 1 | Nov/92-Nov/93 | 13 | | Uruguay 1 | Oct/87-Oct/87 | 1 | Y |
| Indonesia 2 | Dec/97-Nov/98 | 12 | | Uruguay 2 | Jan/02-May/03 | 17 | Y |
| Indonesia 3 | Jun/15-May/16 | 12 | | Uruguay 3 | May/15-Nov/16 | 19 | |
| Korea 1 | Nov/86-Oct/87 | 12 | | Venezuela 1 | Oct/89-Dec/90 | 15 | |

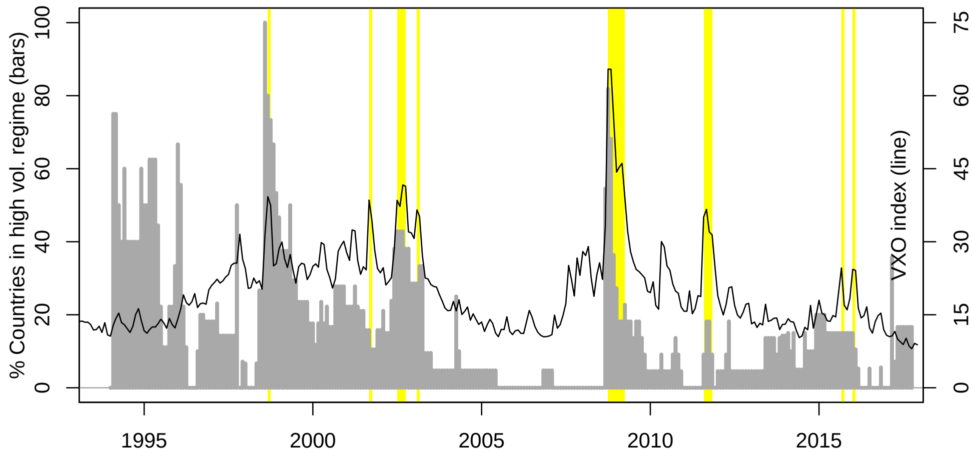
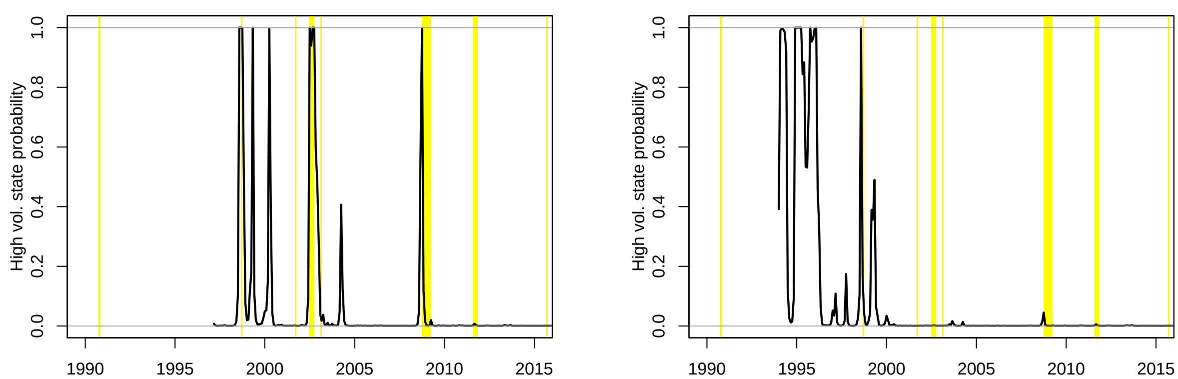



Figure 7: Share of countries in high volatility state and global uncertainty regimes.
Yellow shaded areas represent high uncertainty regimes calculated based on the VXO implied volatility index, following the methodology developed by Bloom (2009)




(a) Colombia

(b) Mexico

Figure 8: Probability of high volatility state and global uncertainty regimes.
Yellow shaded areas represent high uncertainty regimes calculated based on the VXO implied volatility index, following the methodology developed by Bloom (2009)

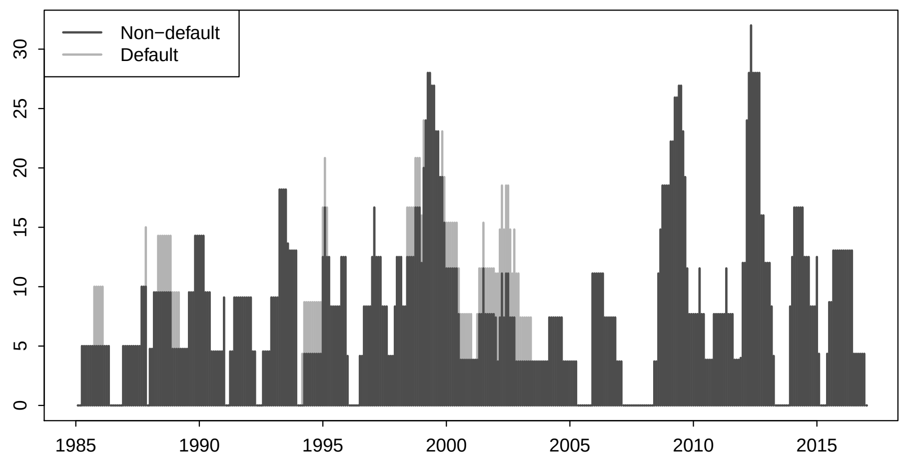



Figure 9: Histogram of sudden stop episodes by month.
The graph depicts the share of countries in our sample experiencing a sudden stop at any given point in time. Light bars indicate EXD crisis related sudden stops.

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