Lopsided Interest Rates in International Borrowing Markets[*]

Yuanchen Cai[†]   Pablo A. Guerrón Quintana[‡]

Thursday 17th April, 2025

Abstract

This paper studies the macroeconomic consequences of asymmetric interest rate shocks at which small open economies borrow in international financial markets. Empirically, we document that borrowing spreads have two distinct regimes. The first one features stable borrowing rates, i.e., low risk. In contrast, the second phase displays large spreads with significant volatility and –asymmetry, high risk. We fit the spreads to a rich statistical process that allows for changes in the level, volatility, skewness and kurtosis of the spread's distribution. Each of the spread regimes is estimated to be highly persistent. When we embed the estimated spreads in a standard small-open economy model, we find that 1) spread shocks alone explain a large fraction of the volatility in consumption and investment in the data; 2) interest shocks of similar magnitude have stronger contractionary effects in an economy where only low risk exists than in one with changes between high and low risk; 3) the transition from an economy with only low-risk interest rate shocks to one like in the data results in a significant and persistent contraction. The welfare cost of this transition equals 2.4% of consumption. Finally, an unexpected increase in skewness pushes the economy into a recession with output, consumption, and investment dropping by as much as 1%, 2%, and 5%, respectively. This contraction resembles those experienced by developing countries during sudden stop episodes.

***Keywords*—** Borrowing spreads, risk, skewness, business cycles, welfare cost, sudden stops

[*]We thank our discusant Mauricio Calani, Susanto Basu, Mick Devereux, David Lagakos, Johannes Pfeifer, Carolin Pflueger, Helen Rey, Sergio Salgado, Martin Uribe, Rosen Valchev, and seminar participants at Banco de España, Banque de France, Boston College, the Central Bank of Chile, the Reserve Bank of Australia, the Green Line Macro Meeting, SED Cartagena 2023, SITE Stanford 2023, and the 8th International Macroeconomics and Finance Conference for comments. All remaining errors are solely responsibility of the authors.

[†]Boston College, cairs@bc.edu

[‡]Corresponding author. Boston College, pguerron@gmail.com

1 Introduction

Emerging economies borrow internationally at interest rates that fluctuate significantly over their business cycles. During good times, borrowing rates tend to be stable and low. However, interest rates become high, volatile, and positively skewed during times of distress. In this paper, we study empirically and theoretically the impact that such lopsided interest rates have on small open economies.

The asymmetric behavior of international interest rates is observed in Figure 1, which shows Emerging Markets Bond Index Plus (EMBI+) spreads for a sample of countries in Latin America for the period 1998-2020. For completeness, we also report an average EMBI+ spread for a set of countries classified as developing economies. A common feature of these interest rate distributions is positive skewness. Among these countries, Argentina and Ecuador stand out due to their significantly larger right skewness. The inlet shows that even the far right tails of their distributions have a positive mass. These observations are further confirmed in Table 1, which shows that borrowing rates are not only higher in emerging economies, but also display more volatility, positive skewness, and kurtosis than the real U.S. 3-month T-bill rates. In fact, the first four moments of the spread distributions point to significant deviations from normality. These empirical regularities are in sharp contrast to previous empirical and theoretical work that has modeled international borrowing rate shocks as normally distributed (see, for example, Aguiar & Gopinath (2008) and García-Cicco et al. (2010)).

In our work, we focus on a group of developing countries and Argentina. Our choice is guided by two principles. First, by pooling countries, the sample captures common shocks that can be attributed to contagion originating from abroad. Argentina, in turn, is chosen because it has faced wild fluctuations in international borrowing rates and its business cycles have been extensively studied in previous studies (see, for example, Neumeyer & Perri (2005)). Figure 2 plots the monthly series of the international risk-free real interest rate (3-month T-bill rate) and Argentina's EMBI+ country spread for the period 1998-2020; Figure 3 plots the same variables but for the average country in the sample. While the international risk-free real rate is generally low and stable, the country spread is characterized by two distinct phases: high-risk episodes when spreads are significantly higher and more volatile (e.g., the early 2001-mid 2005 economic turmoil) and low-risk episodes when spreads are low and relatively stable in the late 1990s or 2005-2007. Therefore, the positive skewness of the interest rate distribution can be attributed to episodes with high and more volatile spreads.

As stressed by G. Calvo et al. (2006), the sharp increases in spreads are part of what they call Systemic Sudden Stops. That is, periods in which economic activity collapses, there is a reversal of net exports, and high borrowing interest rates affect several emerging economies around the same time. Two examples of these episodes are the Tequila and Russian crises. Although the former crisis started in Mexico, it quickly affected countries such as Argentina and Turkey. Furthermore, Ecuador, Turkey, and Argentina were casualties of the Russian crisis in the late 1990s. Figure 4 shows the adverse impact on economic indicators of a typical sudden stop. The SOE's GDP goes from being 3% above trend before the crisis to being 4 p.p. below trend at the start of the episode. The impact on consumption and investment is even larger. As we shall see momentarily, these systematic sudden stops motivate us to model fluctuations in interest rates as exogenous events.

In the first part of this paper, we fit a rich time series process to the EMBI+ spreads in Argentina (Arg) and the pooled developing countries (Dev). As we discuss in Section 2, the empirical model is a mixture of two Normal-Laplace (N-L) distributions with a first-order Markov process governing the switching between the two distributions. Each of these distributions captures the spread dynamics around low-risk or high-risk times. The estimated process replicates well the first four moments of the borrowing spreads in our sample. If we look at the estimation for the Dev countries, the model's skewness and kurtosis are 1.16 and 2.33, respectively, and their empirical counterparts are 1.48 and 1.6. Importantly, we find that a process with only one N-L distribution fails to match the right skewness of the empirical distribution of spreads. This is so in spite of the N-L distribution's ability to generate right skewness by itself. The estimation further reveals that the Markov regimes are highly persistent. For example, the probability of switching from the low-risk state to the high-risk state is less than 1% per month.

Next, we embed the estimated process for the EMBI into a canonical small open economy model (Neumeyer & Perri (2005)). Because we need to capture highly nonlinear events, the model is solved using projection methods and the Smolyak algorithm. To calibrate the model, we take some parameter values from the literature while we calibrate the rest to match the moments of the ergodic distribution generated by the model to their empirical counterparts. We then feed simulated interest rates to the model to compute impulse response functions to study the impact of changes in interest rate risk on macroeconomic outcomes in the small open economy.

The lessons from the theoretical exercise can be summarized as follows. First, the model does a good job in matching non-targeted moments such as the autocorrelation function of the net exports-to-GDP ratio. Moreover, interest rate shocks alone explain a sizable fraction of the volatility of consumption and investment in Argentina and the pool of developing economies. This is so even though the only frictions in the model are costly adjustments of investment and debt. Our finding is in sharp contrast with those in Aguiar & Gopinath (2008), who find that interest rate shocks fail to replicate even the correlations and volatilities of emerging economies, and those in Mendoza (2010), who make the case for collateral constraints to explain sudden stop episodes.

Second, we find that a similarly sized interest rate shock has more contractionary effects on an economy with a single low-risk regime versus the benchmark economy. The reason is that interest rates are low in the single-regime version, resulting in high levels of indebtedness compared to the alternative model. Facing large interest rate shocks, the former economy needs to deleverage heavily, which is only possible by a large contraction in the economy.

Finally, the transition from the single-regime economy with low risk to one like the pooled developing countries' is characterized by a prolonged recession. Indeed, consumption collapses by nearly 20% at the trough of the recession, while output falls by approximately 5%. Importantly, the steep contraction resembles the one observed during sudden stop episodes (G. A. Calvo (1998) and Mendoza (2010)). In the long run, because the country is buffeted by larger and more volatile interest rate shocks, the economy ends up with lower debt. The welfare cost of transitioning from the low-risk regime to one similar to the pooled developing countries' EMBI is equal to 2.4% of consumption in the low-risk regime.

The reader may wonder why our study focuses on exogenous fluctuations in borrowing interest rates. One reason is the nature of systematic sudden stops. As noted above, these episodes start in one country and quickly spread to other economies. So, from Argentina's perspective, the Tequila crisis resulted in an exogenous change in its international borrowing conditions. Another reason is that it is well documented in the literature that exogenous shocks to borrowing interest rates are important drivers of business cycle fluctuations in emerging economies. This point is made using RBC-type models in Neumeyer & Perri (2005) and Fernández-Villaverde et al. (2011). Using a Vector Autoregression approach and panel data, Uribe & Yue (2006) estimate that about two-thirds of the fluctuations in country spreads are explained by innovations that are exogenous to the country's economic activity. Furthermore, Longstaff et al. (2011) finds that the main driver of the variation in sovereign credit spreads is "more related to the US stock and high-yield markets than they are to local economic measures."

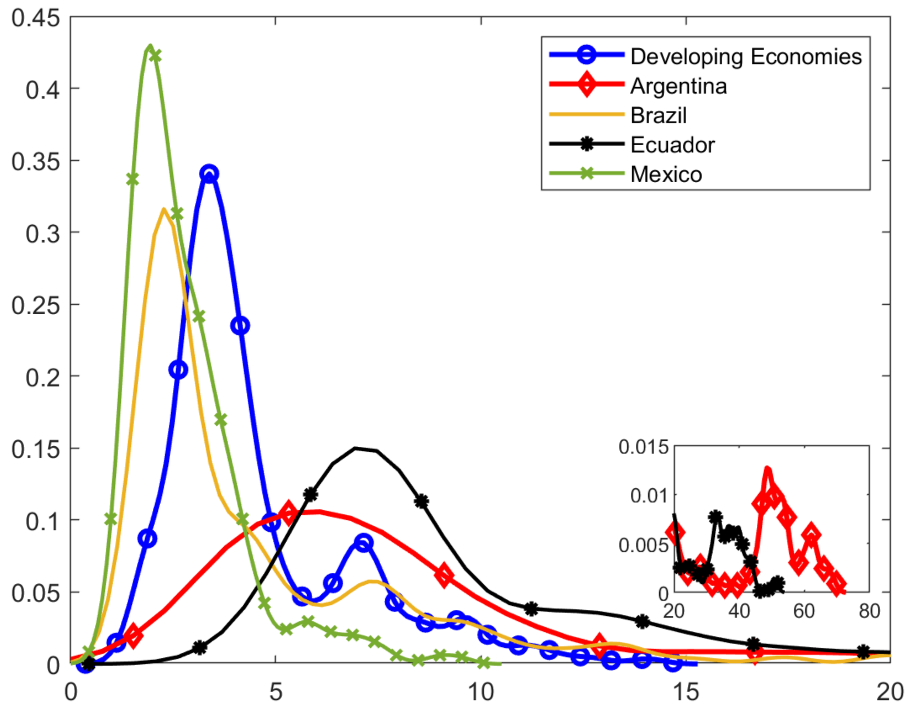


Figure 1: Distribution of EMBI Spreads

Table 1: Moments of EMBI Spreads and T-bill rate

	Mean	Std.	Skewness	Kurtosis
Developing Economies	0.0037	0.0018	1.4033	1.6425
Argentina	0.0110	0.0116	1.6418	1.1529
Brazil	0.0037	0.0028	1.8354	3.4858
Ecuador	0.0089	0.0063	2.1389	3.9157
Mexico	0.0023	0.0011	1.8081	4.1067
Real US 3-M T-bill	-0.0002	0.0014	0.4741	-0.3330

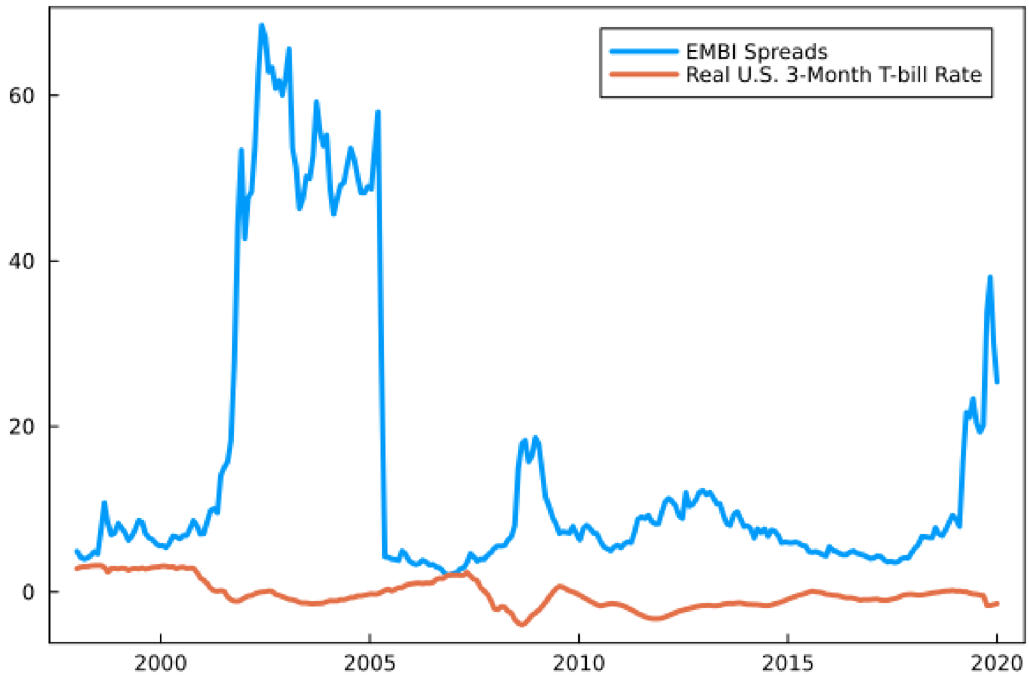


Figure 2: Argentina: Risk-free Rate and Country Spreads

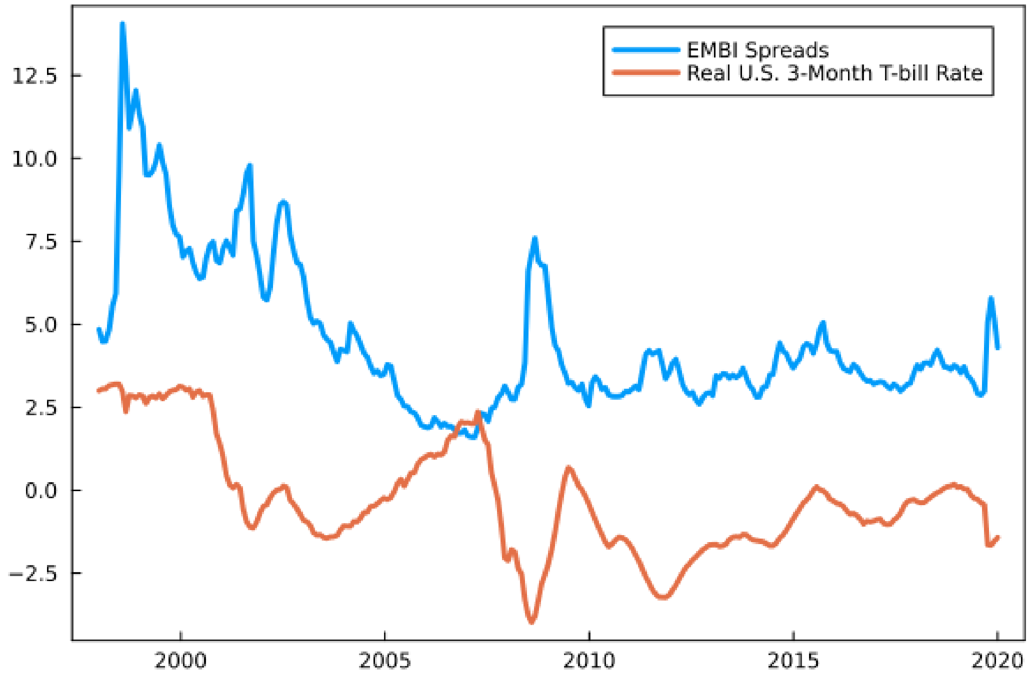


Figure 3: Developing Economies: Risk-free Rate and Country Spreads

As the European debt crisis of the 2010s taught us, lopsided borrowing costs are a broader problem that affects other small open economies beyond those falling under the "developing country" umbrella. Indeed, credit default swap (CDS) spreads for countries such as Greece, Ireland, Italy, Portugal, and Spain displayed significant asymmetric behavior during the Great Recession and particularly so at the peak of the debt crisis in 2011. As shown in Table 16 in the Appendix, the CDS in these European countries have moments that are comparable to those in Table 1. As a result, those CDS spreads can be described by the mixture of low-risk and high-risk regimes.[1] Using a broader sample of advanced economies and emerging economies, Born et al. (2020) show that the interest rate spreads between these two sets of countries tend to behave similarly in the last two decades. In fact, they report that the skewness of spreads in advanced economies is about 60% higher than that of emerging economies during the period 2008-2018. Taken together, these facts imply that the lessons learned from our study apply directly not only to emerging economies but also to advanced ones.

The remainder of the paper is organized as follows. The related literature is reviewed next. Section 2 discusses the data, the empirical strategy, and the results of fitting the empirical model to the data. The model including optimality conditions is presented in Section 3. That section also discusses how skewness shocks affect the small open economy's decisions to borrow internationally. Section 4 presents the calibration exercise. The results from simulating our model are in Section 5.

[1] Guerrón-Quintana et al. (2021) advocate the use of nonlinear empirical models to capture departures from normality in the European CDS spreads.

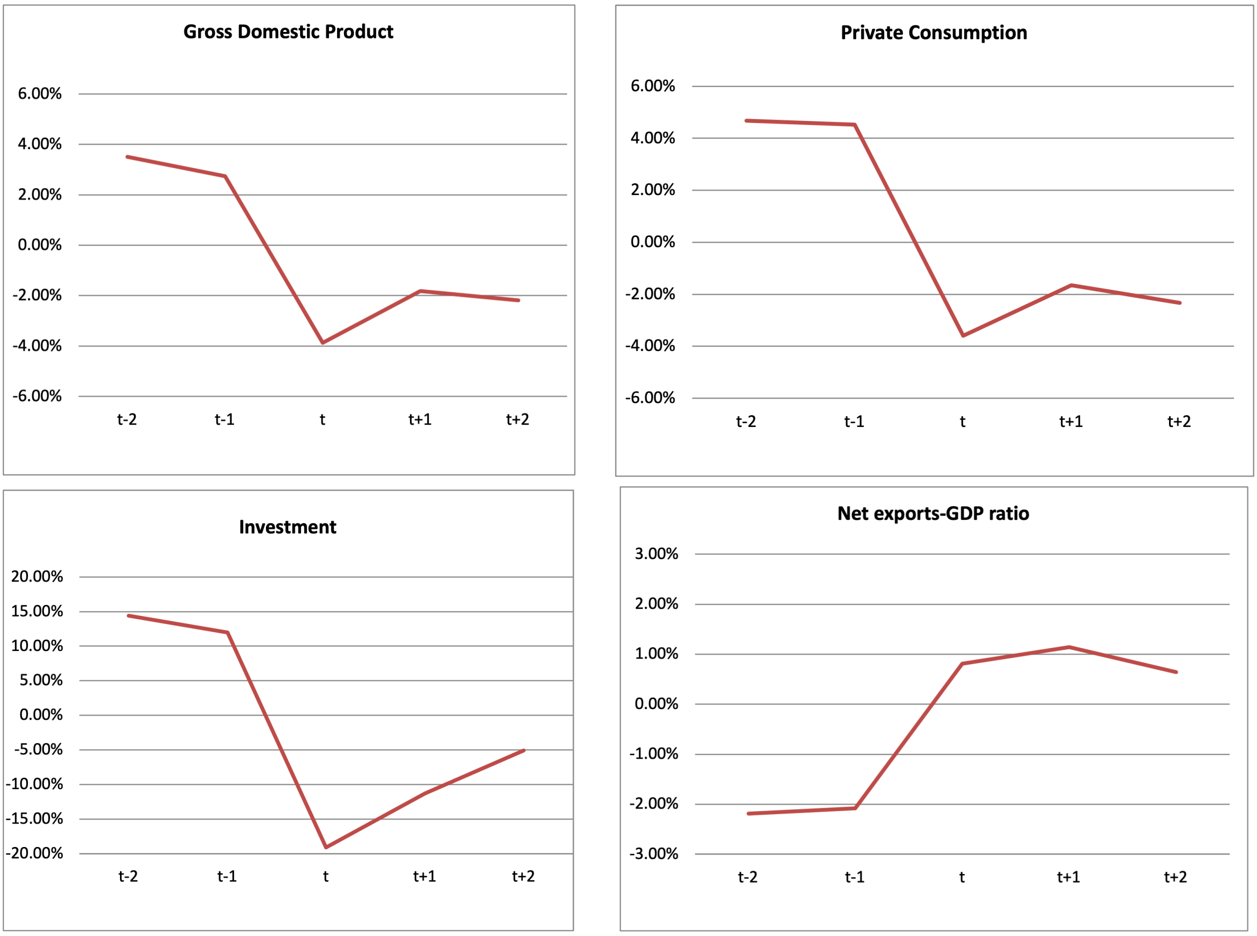


Figure 4: Sudden Stops in Data from Mendoza (2010)

Literature Review

This paper is related to several strands of literature. First and foremost, it contributes to a growing literature that studies time-varying skewness. Guvenen et al. (2014) and Busch et al. (2022) provide evidence on business cycle variations in micro-skewness of labor income risk. Salgado et al. (2019) finds empirical evidence of procyclicality of the skewness of the growth rates of employment, sales, and productivity based on firm-level data. Their quantitative modeling exercises also show that a pure negative skewness shock to firms' productivity growth has a persistent negative effect on real economic activities. Our paper is most closely related to Gordon & Guerrón-Quintana (2017) and Kent & Phan (2019), who study asymmetry in business cycles in emerging economies. The first paper shows that the asymmetry can arise from the interactions between sovereign default and capital accumulation. The later authors assume that productivity shocks are asymmetric.

This paper also builds on the large body of literature studying time-varying volatility/uncertainty shocks – for a recent survey of the literature, see Fernández-Villaverde & Guerrón-Quintana (2020). Bloom (2009) initiated the modern version of this literature with his study of uncertainty and firm dynamics. Fernández-Villaverde et al. (2011) studies on the real effects of time-varying volatility of interest rates at which small open economies borrow. We use their model and incorporate a

Markov regime-switching process with two states – a high-risk state and a low-risk state. The impact on consumption, investment, output, etc. of a change in the skewness of interest rates when the economy switches from one state to another is then examined.

Finally, this paper is linked to the literature that studies how small risks of rare disasters can generate real macroeconomic effects and explain asset pricing puzzles (Barro, 2006; Gabaix, 2011; Gabaix, 2012; Gourio, 2012; Wachter, 2013). Our paper shows changes in the tail-risk, as a result of time-varying skewness, have an impact on consumption, investment, output, etc. of small open economies, confirming the intuition of the "rare disasters" literature.

2 Empirical Model of EMBIs

In this section, we describe the empirical model and the estimation strategy to capture the salient features of the interest rate spreads for Argentina (Arg) and the sample of developing economies (Dev).

2.1 Modeling the Interest Rate Process

As we learned from Figure 2 and Figure 3, international borrowing rates display episodes with high rates and more volatility and episodes with relatively low rates and less volatility. This motivates us to model the law of motion of interest rates with a Markov switching process with two regimes. More specifically, the real interest rates faced by the small open economy in international markets at time t, r_t, is assumed to follow a regime switching AR(1) process

$$\begin{aligned} r_t &= \rho_{St} r_{t-1} + \epsilon_t \\ \epsilon_t &= \mu_{St} + \sigma_{St} Z_t + \frac{E_{1,t}}{\alpha_{St}} - \frac{E_{2,t}}{\beta_{St}}, \end{aligned} \tag{1}$$

where $S_t = \{H, L\}$ is assumed to follow a first-order, two-state Markov process with transition probability $Pr(S_t = j|S_{t-1} = i) = p_{ij}$ and transition matrix $\mathbf{P} = \begin{bmatrix} p_{11} & 1-p_{11} \\ 1-p_{22} & p_{22} \end{bmatrix}$. Z_t follows a standard normal distribution and $E_{1,t}$, and $E_{2,t}$ are standard exponential distributions. In addition, we impose that $Z_t, E_{1,t},$ and $E_{2,t}$ are independent of each other. Effectively, conditional on being in regime S_t, the innovations to the real interest rate process ϵ_t follow a Normal-Laplace distribution specified by $NL(\mu_{St}, \sigma^2_{St}, \alpha_{St}, \beta_{St})$ (see Reed (2006)). The choice to model ϵ_t with a normal-Laplace distribution rests on the need to deviate from standard assumptions of Gaussian shocks, since skewness of the interest rate distribution is different in the two risk states. As shown in Figure 16 in the Appendix, the skewness of the N-L distribution is determined by the relative values of α and β. The distribution is right skewed if α is smaller than β. In contrast, larger values of α lead to left skewness in the distribution. When $\alpha = \beta = 1$, the Normal-Laplace distribution collapses to a normal distribution with mean μ and standard deviation σ. We provide a more detailed discussion in the Appendix.

The interest in the impact of time-varying skewness in macroeconomics is relatively new. Hence, it is worth briefly discussing alternative approaches to model it. Salgado et al. (2019) uses a mixture of two normally distributed random variables where the distributions have different conditional means and standard deviations. That is, the stochastic process for the shock ϵ is

$$\epsilon \sim \begin{cases} N(\mu^s, \sigma^s) & \text{with prob } p^s \\ N\left(-\frac{p^s}{1-p^s}\mu^s, \sigma^s\right) & \text{with prob } 1-p^s. \end{cases} \tag{2}$$

Similarly to our approach, the authors use a regime where risk is low and another one where risk is high. Moreover, most of the skewness is generated from the switching across regimes. Compared to our method, theirs has 2 fewer parameters, resulting in matching 2 fewer moments than us.

Alternatively, shocks can be generated from a skewed normal distribution given by

$$skew\mathcal{N}(y \mid \mu, \sigma, \alpha) = \frac{2}{\sqrt{(2\pi)}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}} \int_{-\infty}^{\alpha \frac{y-\mu}{\sigma}} \frac{1}{\sqrt{2\pi}} e^{\frac{-t^2}{2}} \, \mathrm{d}t.$$

This distribution has three parameters: one for location (μ), second for scale (σ) and one for shape (α). This formulation gets closer to our N-L distribution in the sense that it generates skewness and excess kurtosis. Although we have not attempted to estimate it using our data, we suspect that, as in our work, a single regime will undergenerate skewness (for a recent application, see Wolf (2023)).

Lhuissier (2025)introduces a general framework that extends standard Markov-switching dynamic linear factor models to accommodate regime changes in skewness. It replaces the typical within-regime normality assumption with a closed skew-normal distribution to capture asymmetry. The baseline model is specified by the state-space representation:

$$x_t = F_{s_t} x_{t-1} + \eta_t, \tag{3}$$

$$y_t = H_{s_t} x_t + \epsilon_t, \tag{4}$$

Here, ϵ_t is normally distributed but state equations errors now follow a closed skew-normal distribution

$$\begin{aligned} \eta_t &\sim \text{closed skew-normal}(\mu_{s_t,\eta}, \Sigma_{s_t,\eta}, \Gamma_{s_t,\eta}, \nu_{s_t,\eta}, \Delta_{s_t,\eta}), \\ \epsilon_t &\sim \mathcal{N}(\mu_{s_t,\epsilon}, \Sigma_{s_t,\epsilon}), \end{aligned}$$

The unobserved regime s_t is a first-order Markov process governed by a transition matrix P. An approximate filtering algorithm, which generalizes Kim (1994)'s method, is presented to estimate the parameters of the model. The approach involves iteratively computing conditional predictive distributions and posterior distributions for the states and regimes while addressing dimensionality challenges through an approximating procedure. The algorithm yields the conditional likelihood function necessary for parameter estimation via maximum likelihood or Bayesian methods.

2.2 Interest Rate Data

The real interest rate r_t at which the small open economy borrows on dollar-denominated loans is decomposed as the international risk-free real rate plus a country spread. The international risk-free real rate is defined as the yield on 3-month Treasury bills minus inflation expectation, which is calculated as the 12-month moving average of US CPI inflation rates in the current and 11 preceding months. The monthly country spread data for Arg and Dev are obtained from J.P. Morgan Emerging Markets Bond Index Plus (EBMI+). Data used to estimate the real interest rate processes are from January 1998 to June 2020.

2.3 Empirical Results

The parameters of $NL(\mu_{St}, \sigma^2_{St}, \alpha_{St}, \beta_{St})$ and the persistence parameters ρ_{St} are estimated by Simulated Methods of Moments. More specifically, we simulate interest rates for 771 periods, discard the first 500 periods as burn-in, and calculate the targeted moments of simulated data in the remaining periods. This process is repeated 1000 times, after which we compute the average across the 1000 simulations for each of the moments. We choose the parameters that minimize the squared distance between the simulated moments and their empirical counterparts.

Ten moments are targeted in total: mean, standard deviation, skewness, kurtosis of the unconditional distribution, and conditional means, conditional standard deviations, and conditional skewness in the high- and low-risk regimes. Periods in which real interest rates are one standard deviation above the median over the sample period are assumed to be in the high-risk regime.[2] The probability of being in the high-risk regime in the next period conditional on being in the high-risk regime in the current period, p_{22}, is set to be equal to the fraction of high-risk periods that are followed by another high-risk period in the data. Likewise, p_{11}, the probability of staying in the low-risk regime in the next period conditional on being in the low-risk regime in the current period, is set to be equal to the fraction of low-risk periods followed by another low-risk period.

The estimated parameters for the N-L distribution and the Markov-Switching process are reported in Tables 2 and 3 for Argentina and the group of developing countries, respectively. As discussed in Reed (2006), the moments of the N-L distribution are functions of the parameters $\mu, \sigma, \alpha,$ and β, so analyzing their estimated values is futile. With this in mind, we see that the spreads are highly persistent in the low regime and to a lesser degree in the high regime. Moreover, the probability of switching from the low regime to the high regime is quite small (less than 1% per month). The

[2] Similar methods to date regimes are used in, for example, Bianchi et al. (2018). Salgado et al. (2019) use the frequency of expansions and recessions to date regimes of high and low skewness.

likelihood of going back to the low regime from the high regime is small (around 4% for developing countries).

Table 2: Argentina: Parameter Estimates

Parameter	St = L	St = H
μ	0.00052813	0.0040988
σ	9.3696e-08	1.498e-07
α	4370353.5378	408.9358
β	2805.3758	112030108.9375
ρ	0.94	0.8
p_{11}	0.99103	-
p_{22}	-	0.95833

Table 3: Developing Economies: Parameter Estimates

Parameter	St = L	St = H
μ	-0.00022585	-0.0010004
σ	0.00019758	1.7823e-05
α	2340.1002	516.1156
β	90357.6321	67357.9295
ρ	0.92017	0.90008
p_{11}	0.99545	-
p_{22}	-	0.96078

The estimated interest rate process replicates the first four unconditional moments of the spreads data reasonably well, as reported in the row labeled Model in Table 4. The next two rows show the implied moments when one regime is active at a time. The results indicate that the high mean in the data is due to the high regime. However, we see that each regime alone fails to generate the large higher moments in the data. In fact, individual regimes would predict counterfactual skewness (high-regime) and kurtosis (low-regime). This means that the regime switching embedded in the benchmark empirical model (equation 1) is critical to replicate the empirical skewness and kurtosis in the data.

For comparison, the last row of Table 4 presents the moments implied by the interest rate process that allows for a single regime. Consistent with the previous literature, the model matches the mean and standard deviation. However, the single-regime spread model significantly underpredicts the third and fourth moments of the spreads. This is so in spite of the N-L distribution being specified to allow for departures from normality.

Before moving to the model section, it is worth briefly discussing how the T-bill rates compare to Dev's spreads in terms of their higher moments. From the data in Tables 4 and 6, one can see that the real T-bill interest rates follow a distribution that has relatively small deviations from normality. For completeness, Table 5 shows the results for Argentina.

In table 4, the low regime has an average annual spread equal to 2.9%($= 0.0024 \times 1200$). The average in the high regime is 11%. The spread at the ergodic mean in the simulated series is 3.72%.

Table 4: Moments for Real Interest Rate Spreads

	Developing Economies			
	Mean	Std.	Skew.	Kurto.
Data	0.0035	0.0026	1.4767	1.5810
Simulation	0.0031	0.0021	1.1609	2.3331
	Individual Regimes			
Low	0.0024	0.0011	0.3366	0.0527
high	0.0092	0.0043	0.5309	0.2832
	One-Regime Process			
	0.0035	0.0027	0.1503	-0.3559

Table 5: Moments for Real Interest Rate Spreads

	Argentina			
	Mean	Std.	Skew.	Kurto.
Data	0.0109	0.0114	1.6684	1.2616
Model	0.0101	0.0091	1.2397	1.4644
	Individual Regimes			
Low	0.0029	0.0009	-0.3378	-0.1562
high	0.0327	0.0040	0.7896	0.8047
	One-Regime Process			
	0.0109	0.0114	0.1755	-0.3079

Table 6: Moments for Real U.S. 3-Month T-bill Rates

	Mean	Std.	Skew.	Kurto.
Data	-0.0002	0.0014	0.4741	-0.3330

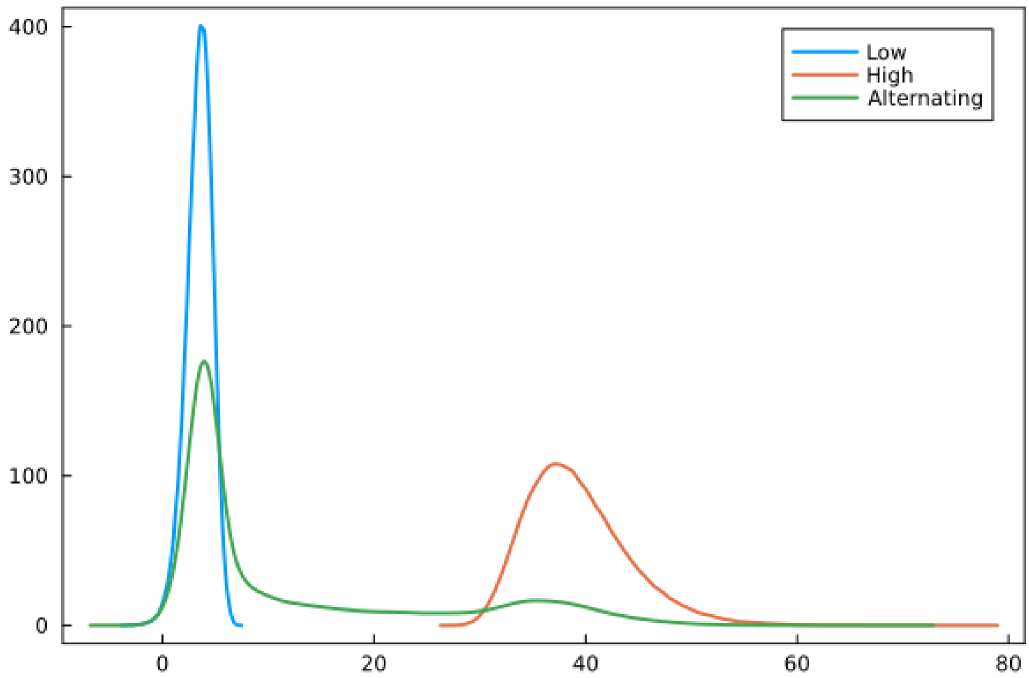


Figure 5: Argentina: Distribution of Simulated Interest Rates

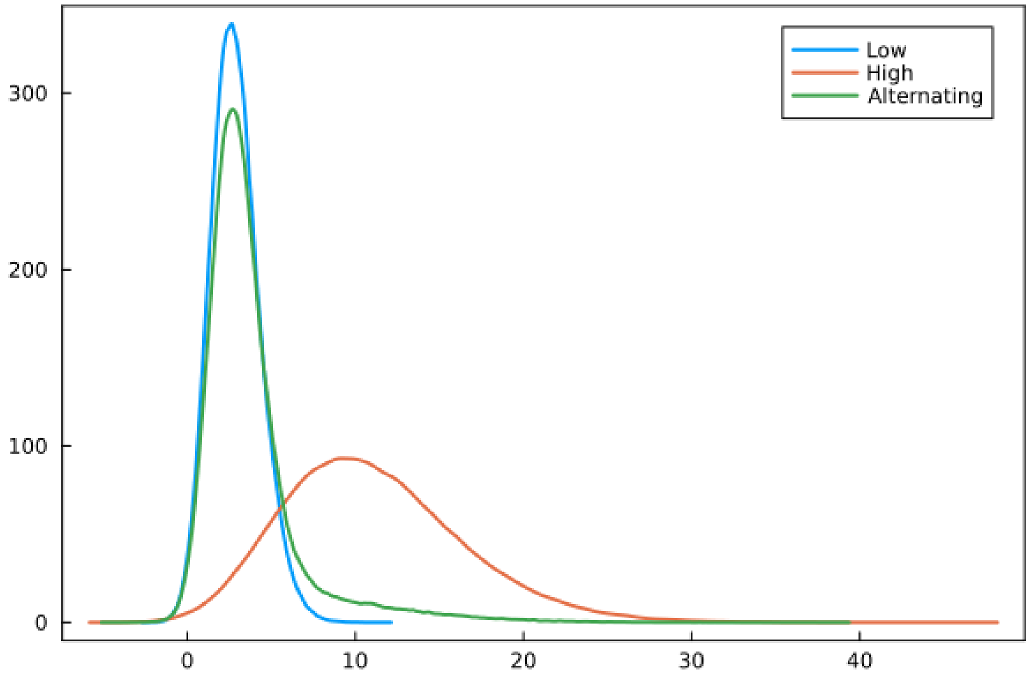


Figure 6: Developing Economies: Distribution of Simulated Interest Rates

3 Model

Our framework is based on the standard small open economy (SOE) model outlined, for example, in Fernández-Villaverde et al. (2011) and Neumeyer & Perri (2005). The economy is populated by a representative household with preferences

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\nu}}{1-\nu} - \omega \frac{H_t^{1+\eta}}{1+\eta} \right) \tag{5}$$

The budget constraint that the household faces is

$$\frac{D_{t+1}}{1+r_t} = D_t - W_t H_t - R_t K_t + C_t + I_t + \frac{\Phi_D}{2}(D_{t+1} - D)^2 \tag{6}$$

where D_t is an internationally traded one-period uncontingent bond, and the convention we follow here is that positive values of D_t denote debt. Following Schmitt-Grohé & Uribe (2003), we include a portfolio adjustment cost, where $\Phi_D > 0$ controls the cost of holding a net foreign asset position and D is the level of debt in the deterministic steady state.[3] r_t is the real interest rate domestic residents of the small open economy borrow at in the international financial market, which follows the process specified by equations (1) and (2). The household also provides labor H_t and earns real

[3]Technically speaking, the portfolio adjustment cost is not necessary given that the nonlinear solution pins down the stochastic steady state of the model. However, in practice, we noticed that the introduction of this cost helps with convergence of the solution.

wage W_t, and invests in physical capital K_t and earns the real rental rate of capital R_t.

The law of motion of capital stock is

$$K_{t+1} = (1-\delta)K_t + I_t - \frac{\phi}{2} I_t \left(\frac{I_t}{I_{t-1}} - 1\right)^2 \tag{7}$$

where δ is depreciation rate and $\phi > 0$ governs capital adjustment cost. The no-Ponzi-game condition is also imposed.

Firms hire labor and rent capital from households and produce consumption goods. The production technology the firms use is

$$Y_t = K_t^{\alpha}(e^{X_t} H_t)^{1-\alpha} \tag{8}$$

$$X_t = \rho_x X_{t-1} + \sigma_x u_{x,t} \tag{9}$$

where X_t is a labor-augmenting productivity shock and $u_{x,t}$ follows a standard normal distribution.

Under perfect competition, $Y_t = W_t H_t + R_t K_t$. Thus, we can write net export NX_t as

$$NX_t = Y_t - C_t - I_t = D_t - \frac{D_{t+1}}{1+r_t} + \frac{\Phi_D}{2}(D_{t+1} - D)^2 \tag{10}$$

A competitive equilibrium is defined as a sequence of prices and allocations such that the representative household and firms optimize and markets clear. The first-order necessary conditions (FONC) are

$$C_t^{-\nu} = \lambda_t \tag{11}$$

$$\frac{\lambda_t}{1+r_t} = \lambda_t \Phi_D (D_{t+1} - D) + \beta \mathbb{E}_t \lambda_{t+1} \tag{12}$$

$$\varphi_t = \mathbb{E}_t \left[(1-\delta)\varphi_{t+1} + \alpha \frac{Y_{t+1}}{K_{t+1}} \lambda_{t+1}\right] \tag{13}$$

$$\omega H_t^{\eta+1} C_t^{\nu} = (1-\alpha) Y_t \tag{14}$$

$$\begin{aligned} \lambda_t &= \varphi_t \left[1 - \frac{\phi}{2}\left(\frac{I_t - I_{t-1}}{I_{t-1}}\right)^2 - \frac{\phi I_t}{I_{t-1}}\left(\frac{I_t - I_{t-1}}{I_{t-1}}\right)\right] \\ &\quad + \beta \mathbb{E}_t \left[\varphi_{t+1} \phi \left(\frac{I_{t+1}}{I_t}\right)^2 \left(\frac{I_{t+1} - I_t}{I_t}\right)\right] \end{aligned} \tag{15}$$

where λ_t is the Lagrangian multiplier associated with debt and φ_t is the Lagrangian multiplier associated with physical capital. The equilibrium is defined by FONC, the law of motion for capital, the country's budget constraint, and the exogenous productivity and interest rate processes.

3.1 Solving the Model

The model is solved using projection methods and the Smolyak algorithm. Since the economy is assumed to follow a Markov-switching process with two regimes, there are two sets of decision rules corresponding to the two risky states. This also means that the time required to solve the model is effectively doubled. To speed up the process, we implement parallel computing in the Julia programming language, which is particularly crucial for the calibration exercise discussed in the next section. The detailed algorithm for solving the model is as follows:

1. Choose an approximation fineness (set to 2 in our solution), as well as the upper and lower bounds on the state variables (capital K_t, debt D_t, productivity Z_t, interest rate r_t and investment in the previous period I_{t-1}). Construct the grid and the associated Chebyshev's polynomials following the Smolyak algorithm.

2. At each collocation point, choose initial guesses for λ_t, I_t and φ_t and compute C_t, H_t, Y_t. Compute the value of I_t by equating the RHS of equation (13) and the value of λ_t calculated from equation (10).[4] Use the result to update the guess for I_t and compute K_{t+1}, D_{t+1}.

3. At each node of the monomial rule, compute r_{t+1}, z_{t+1}. Together with K_{t+1}, D_{t+1}, I_t, approximate λ_{t+1}, I_{t+1}, φ_{t+1} and compute $C_{t+1}, H_{t+1}, Y_{t+1}$ using the model's equilibrium conditions. Given these values, compute the expectation term in equation (11) and the RHS of equation (13).

4. Evaluate the errors of I_t and equations (11) and (13) at every collocation point. Update the guesses and iterate until convergence.

3.2 Understanding Skewness Shocks

Before moving to the calibration and result sections, it is worth spending some time to understand the economics behind skewed shocks to borrowing spreads. To do so, let us start with a simplified version of the Euler equation for bond issuance which ignores the debt adjustment cost:

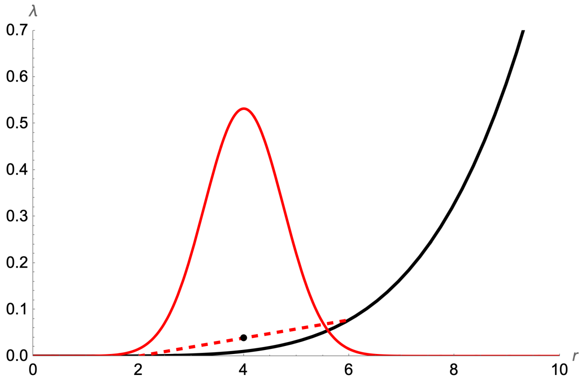
$$\frac{\lambda_t}{1+r_t} = \beta \mathbb{E}_t \lambda_{t+1}.$$

For the sake of argument, assume that everything is constant except consumption and interest rates. Then using the Euler equation for consumption and the budget constraint at $t+1$, the last expression can be approximately rewritten as

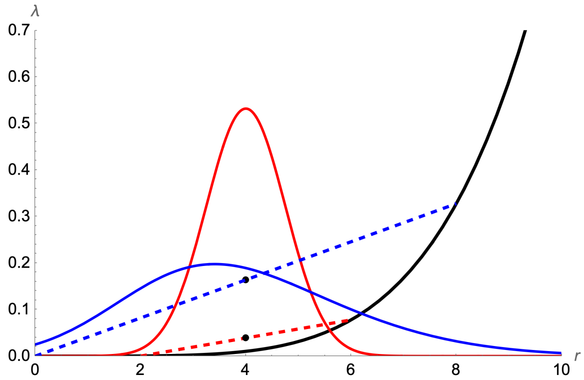
$$\frac{\lambda_t}{1+r_t} \approx \beta \mathbb{E}_t \left[\frac{1+r_{t+1}}{\tilde{D}} \right]^{\nu}. \tag{16}$$

[4] We use the model's linear solution as a more educated guess for the nonlinear version.

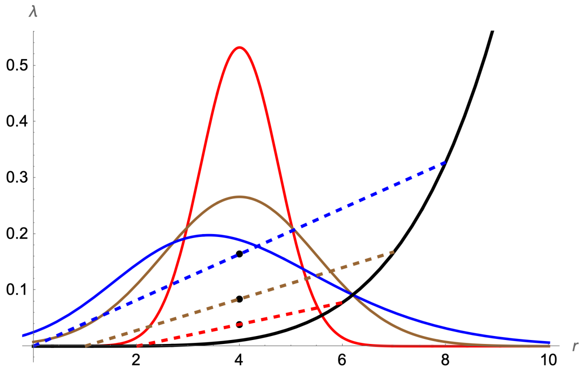
If only the skewness of future interest rates changes, $1 + r_t$ remains unaffected. However, the expectation of future interest rate fluctuations does change. The additional mass in the right tail of the distribution and the convexity of the marginal utility imply that households expect higher interest rates in the future, which in equilibrium results in an increase in marginal utility today, and hence a drop in contemporaneous consumption. This intuition can be visualized in Figure 7, where the interest rates are on the horizontal axis and the marginal utility of consumption on the vertical axis (convex line in black). The black dot along the red dashed line in panel (a) shows the expected marginal utility of consumption when the interest shocks are normally distributed (red bell). In panel (b), we can see the impact on the expected marginal utility of a shift from a normal distribution to a right-skewed distribution (blue bell). Because larger spread shocks are more likely in the future (larger mass on the right side of the distribution), the expected marginal utility is higher (black dot) than under normality. As a consequence, rational agents will reduce consumption by shifting from normally distributed spreads to right-skewed spreads.



a. Normal distribution



b. Skewed distribution



c. Mean-preserving spread distribution

Figure 7: Marginal utility and interest rate distributions

The curious reader may wonder how expected marginal utility behaves when the distribution of interest rates suffers a mean-preserving increase in its volatility, which is the case analyzed in the stochastic volatility literature. This situation is depicted in panel (c) in Figure 7. The brown distribution corresponds to the mean-preserving shift in dispersion. The black dot corresponds to the expected marginal utility when households face greater uncertainty. Looking at the blue and brown dots, we can easily see that volatility shocks have a smaller impact on marginal utility than skewed shocks. The reason is simple. Although volatility shocks increase the likelihood of adverse (right tail) events, they also increase the likelihood of benign shocks (left tail). This "good" feature of volatility shocks partially offsets the adverse ones – the impact is not fully neutralized due to the convexity of marginal utility. In contrast, skewed shocks result only in adverse future shocks, triggering a stronger response in marginal utility, and hence a larger drop in consumption than under mean-preserving volatility shocks.

A more formal way to see the impact of skewness shocks is to take a third order expansion to the right hand side of equation 16 around a constant interest rate $\bar{r}$:

$$\mathbb{E}_t\left[\frac{1+r_{t+1}}{D}\right]^{\nu} \propto \left\{1+\frac{\nu}{1+\bar{r}}\mathbb{E}_t(\Delta r_{t+1})+\frac{1}{2}\frac{\nu(\nu-1)}{1+\bar{r}}\mathbb{E}_t(\Delta r_{t+1}^2)+\frac{1}{6}\frac{\nu(\nu-1)(\nu-2)}{1+\bar{r}}\mathbb{E}_t\Delta(r_{t+1}^3)\right\}.$$

Here, if the risk aversion coefficient satisfies $\nu > 2$, a surprise increase in skewness leads to a large contemporaneous marginal utility and hence to a drop in consumption compared to the pre-shock level. Importantly, for the same-sized change in volatility and skewness, $\mathbb{E}_t\Delta(r_{t+1}^2) = \mathbb{E}_t\Delta(r_{t+1}^3)$, skewness shocks lead to greater increases in marginal utility than volatility shocks if $\nu > 5$. As noted in the discussion above, this is the result of larger interest rate shocks being more likely under rises in skewness than under rises in volatility.

4 Calibration

The parameters in the model are divided into two groups. The first group of parameters is set to be equal to the standard values in the literature (Table 11), while the second group of parameters is calibrated to match selected empirical moments. The discount factor β is set equal to $\frac{1}{1+r}$, where r is the mean interest rates in the sample period. The four parameters in Table 11 – holding cost of debt Φ_D, the parameter that controls the non-stochastic steady-state debt level D, capital adjustment cost ϕ, and standard deviation of productivity shocks σ_x – are chosen to minimize the quadratic distance between four moments of the ergodic distribution of the model and their empirical counterparts. These four moments are the volatility of output σ_y, the relative volatility of consumption to output σ_c/σ_y, the relative volatility of investment to output σ_i/σ_y, and net export as a percentage of output NX/Y.

The empirical moments are computed based on the cyclical components of HP-filtered quarterly data except for net export as a percentage of output, which is the sample average of unfiltered data. To compute model-implied moments, we simulate the model for $T+\tau$ periods starting from the steady state and discard the first T periods as burn-in.[5] Since the model is of monthly frequency, the remaining τ periods are converted into quarterly frequency by summing up 3 periods of value. Specifically, variable X is set equal to $\sum_{s=1}^{3} X_{T+s}$ in the first quarter, $\sum_{s=4}^{6} X_{T+s}$ in the second

[5] T is set to 1000 for Arg and 2500 for Dev, because it takes longer for the model calibrated to Dev to reach the ergodic distribution. τ is set equal to 198 for Arg and 396 for Dev, which correspond to the number of available periods of data used to compute the empirical moments for each country.

quarter, etc. The resulting quarterly simulated data are then HP-filtered and used to compute the second moments of the ergodic distribution. This process is repeated 1000 times and the moments are averaged over the 1000 simulations. The empirical and model-implied moments are reported in Table 12, which clearly shows that the model is successful in matching these targeted moments.

Table 7: Summary Calibration I

	Value	Interpretation
ν	5	Inverse of elasticity of intertemporal substitution
η	1000	Parameter determining elasticity of labor to wages
ω	1	Disutility of labor
δ	0.014	Depreciation rate
α	0.32	Capital share
ρ_x	0.95	Autocorrelation of productivity shocks

Table 8: Argentina: Summary Calibration II

	Value	Interpretation
Φ_D	0.00045	Debt adjustment cost
D	-18	Parameter that controls average value debt
ϕ	150	Capital adjustment cost
σ_x	0.0308	Standard deviation of productivity shocks
β	0.9892	Discount factor

Table 9: Argentina: Empirical and Simulated Moments

	Data	Simulated
σ_y	3.91	3.91
σ_c/σ_y	1.09	1.08
σ_i/σ_y	2.93	2.90
NX/Y	-1.48	-1.40

Table 10: Argentina: Moments

	Mean			Std.		
	Low	High	Alt.	Low	High	Alt.
C	7.1081	11.7995	7.8603	0.0191	0.0133	0.0417
I	1.2976	1.3020	1.3944	0.0250	0.0244	0.1164
Y	8.9897	8.9858	9.1120	0.0379	0.0380	0.0390
H	2.9893	2.9817	2.9879	0.0001	0.0000	0.0002
D*	27.3276	-153.9638	-13.6430	2.0169	3.3970	5.5065
NX*	0.5840	-4.1157	-0.1427	0.2259	0.2661	0.4128

Table 11: Developing Economies: Summary Calibration II

	Value	Interpretation
Φ_D	3e-5	Debt adjustment cost
D	-31	Parameter that controls average value debt
ϕ	30	Capital adjustment cost
σ_x	0.0198	Standard deviation of productivity shocks
β	0.9965	Discount factor

Table 12: Developing Economies: Empirical and Simulated Moments

	Data	Simulated
σ_y	2.60	2.60
σ_c/σ_y	1.32	1.10
σ_i/σ_y	3.88	3.86
NX/Y	0.34	0.37

Table 13: Developing Economies: Moments

	Mean			Std.		
	Low	High	Alt.	Low	High	Alt.
C	8.3904	13.2250	8.6234	0.0056	0.0111	0.0286
I	2.8450	3.1753	2.8442	0.0218	0.0385	0.1002
Y	11.5415	11.9233	11.5214	0.0252	0.0253	0.0260
H	2.9875	2.9809	2.9871	0.0000	0.0001	0.0001
D*	70.4867	-668.8874	11.4626	2.0855	18.1404	5.8853
NX*	0.3061	-4.4770	0.0537	0.2450	0.2952	0.4848

We report the mean and standard deviation of the variables in our model in 13. Three cases are considered: 1) when only the low-risk regime is in place (column *Low*); 2) when only the high-risk regime is in action (column *High*); and 3) when the economy switches back and forth between the 2 regimes (column *Alt*). An important insight from the table is that the second moments in the model critically depend on the regime switching element of the interest rate process. For example, the model with only one regime at a time does not deliver the excess volatility of consumption typical of emerging economies. Furthermore, each regime alone fails to generate the correct signs of the means of debt and net exports simultaneously.

The relative importance of interest rate shocks can be grasped from Table 14. There, we report the first and second moments implied by our model when technology shocks are excluded from the simulation. Spread shocks alone contribute to about 20% of the volatility of output and more than 90% of the volatility of consumption and investment. This is an important finding given the simplicity of the model. In fact, previous work has highlighted the difficulties that similar models have in generating sizable business cycles out of interest rate shocks modeled as autoregressive processes with normally distributed shocks (see, for example, Aguiar & Gopinath (2008)).

Table 14: Developing Economies: Moments without Technology Shock

	Mean			Std.		
	Low	High	Alt.	Low	High	Alt.
C	8.3687	13.2031	8.6019	0.0031	0.0106	0.0280
I	2.8370	3.1651	2.8362	0.0136	0.0340	0.0978
Y	11.5174	11.8967	11.4972	0.0008	0.0022	0.0055
H	2.9875	2.9809	2.9871	0.0000	0.0001	0.0001
D*	73.1629	-666.3026	14.0701	0.3028	17.9490	5.2539
NX*	0.3117	-4.4715	0.0591	0.0584	0.1607	0.4014

Our model does a good job reproducing the autocorrelation function of the net exports-to-GDP ratio as shown in Table 15. However, it fails to deliver the negative correlation with respect to GDP.

Table 15: Developing Economies: Net Exports Moments

NX/Y	Data	Model
Correlation with Y	-0.6856	0.3987
Autocorrelation (1 lag)	0.9409	0.9062
Autocorrelation (2 lag)	0.8856	0.7800
Autocorrelation (3 lag)	0.8279	0.6599
Autocorrelation (4 lag)	0.7733	0.5489

5 Results

To examine the impact of shocks to the interest rate process on real economic outcomes, we compute impulse-response functions. We simulate 1000 economies independently, each of $T + \tau$ periods, where $\tau > 1$. In period T, the economies are hit by a shock and evolve naturally thereafter. The macroeconomic outcomes are averaged across the 1000 economies, and the IRFs are computed as the deviations of a given variable from its value in $T - 1$, the period prior to the shock. Please note that for consumption, investment, and output, deviations are expressed in percentages, while for debt and net export, deviations are expressed in levels.

5.1 Interest Rate Shocks

As a first exercise, we shock our baseline economy with an increase in the borrowing interest rate equal to 696 basis points (bps) annualized, which is the difference between the average interest rate in the low regime and the average interest rate in the high regime. Figure 8 shows the IRFs in the alternating regime following the shock (blue lines). As expected, the model generates a decline in economic activity with large drops in consumption and investment, which together drive down output. The reason behind this contraction is that the small open economy wants to deleverage to reduce the large interest payments coming from higher interest rates. This is achieved by reducing domestic absorption and increasing net exports. For comparison, Figure 9 shows the IRFs for the Argentinean case where the interest rate shock is equal to 3396 bps. Although the responses are qualitatively similar, the larger shock and the more leveraged economy imply that the contraction is stronger in Argentina than in the Dev case.

Our simulations show that an increase of 696 bps in the low regime and the alternating regime is not the same. As shown in Figure 8, while the increase in the borrowing rate generates a drop of 0.7% of output at the trough of the recession in the low regime (orange lines), the same shock drives output down by 0.5% in the alternating regime. At first sight, this finding may seem surprising. However, the economy that spends all its time in the low regime has a substantially larger amount of debt than the one in the alternating economy (about 6 times larger). As a consequence, an interest rate shock of similar magnitude demands significantly larger deleveraging in the low-risk economy, resulting in a larger contraction.

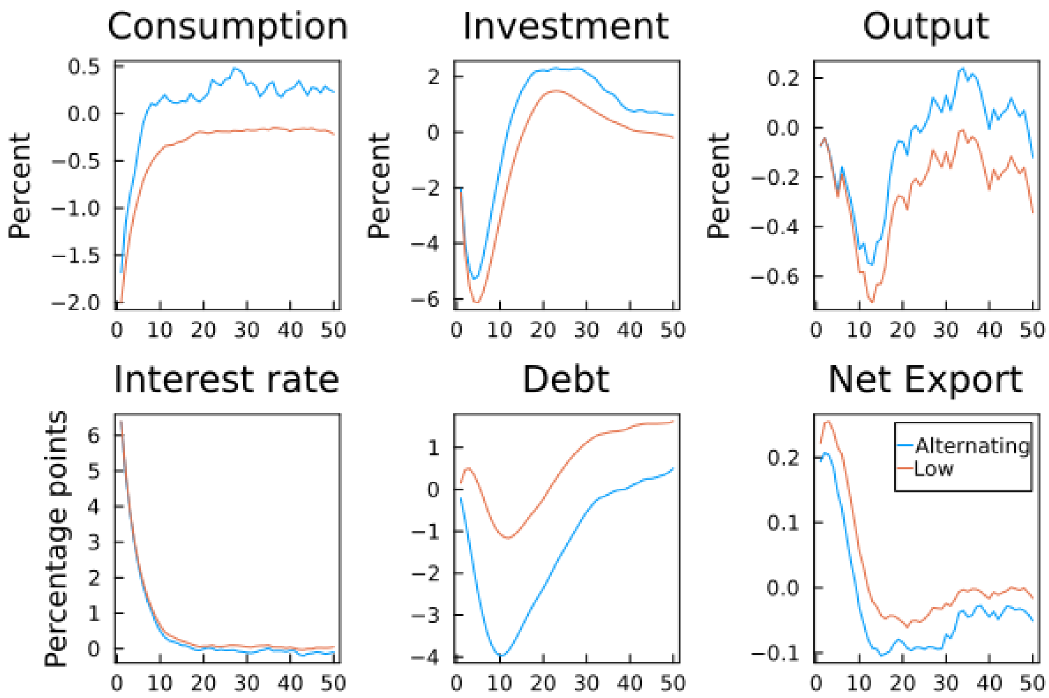


Figure 8: Developing Economies: Impulse Responses to an Increase in Interest Rate

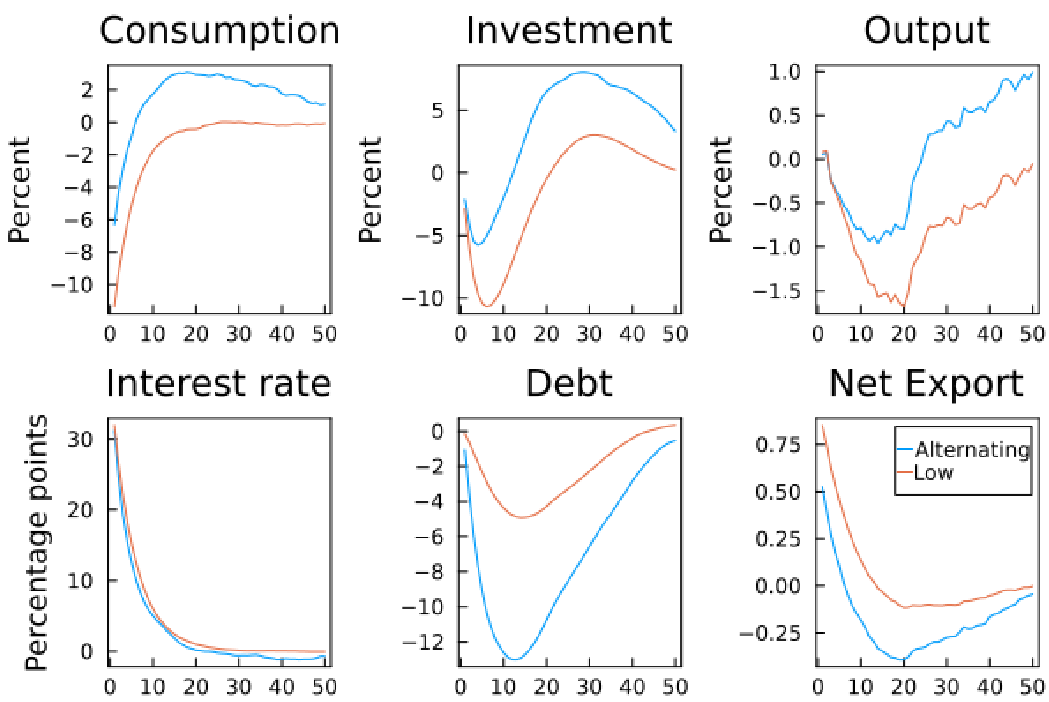


Figure 9: Argentina: Impulse Responses to an Increase in Interest Rate

5.2 TFP Shocks

Figure 11 shows the response of the economy to a one-standard deviation increase in productivity. The dynamics is standard because the core of our model is the RBC framework. We note that, unlike interest rate shocks, regimes have a reduced effect on the impact of productivity shocks on output.

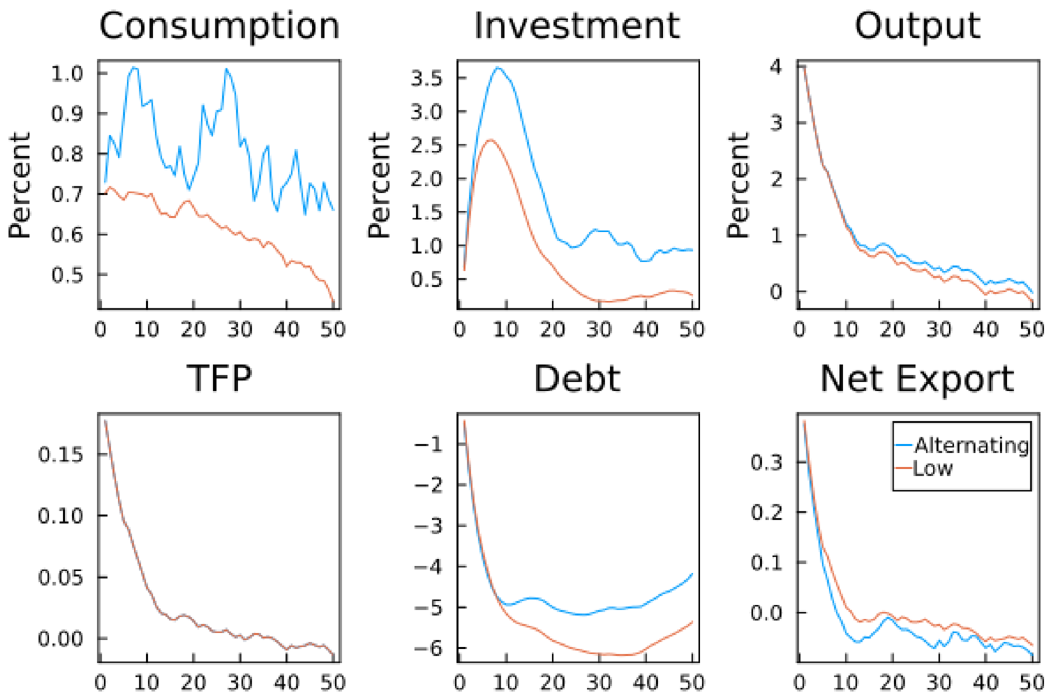


Figure 10: Developing Economies: Impulse Responses to TFP shock

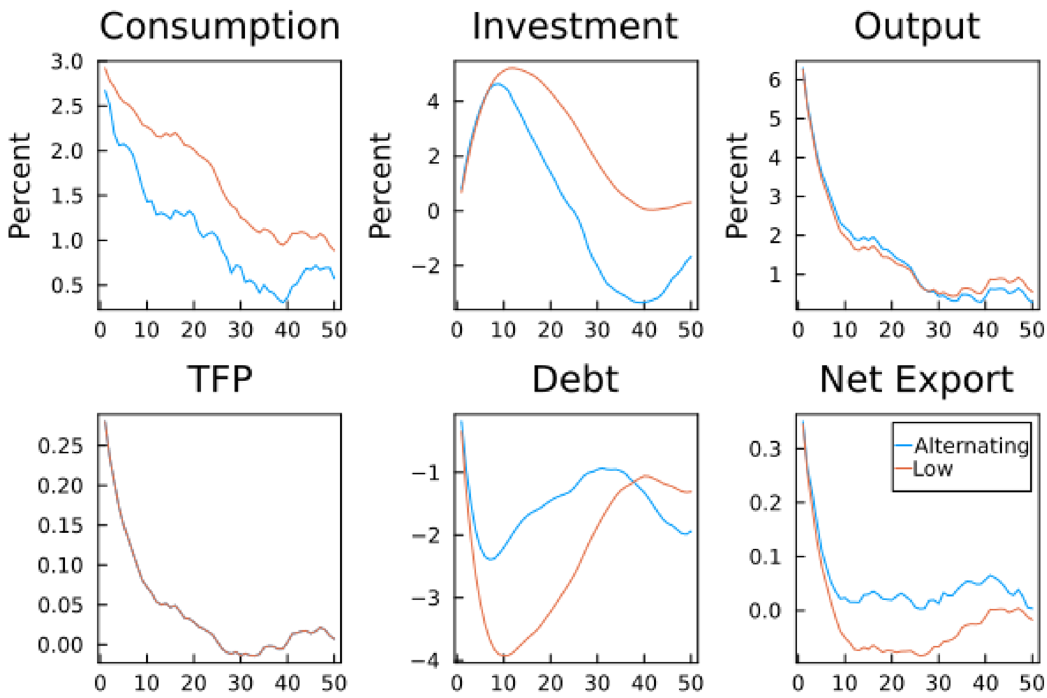


Figure 11: Argentina: Impulse Responses to TFP shock

5.3 Going from Low Risk to Alternating Risk

For the next set of results, we will focus on the dynamics of the model calibrated to the average developing economy. Figure 12 shows the responses of the economy when it moves from a world with only low-risk interest shocks to one in which low- and high-risk regimes coexist. In this exercise, all four moments of the EMBI+ process increase, which corresponds to the SOE moving from the blue distribution in Figure 6 to living on average in a world with the green distribution. To compute these impulse responses, we simulate 1000 independent economies in the low-risk state. In period $T = 1000$, these economies are hit by a shock and enter the high-risk state and evolve naturally thereafter, alternating between the high-risk and the low-risk states governed by the transition probabilities. The macroeconomic outcomes are averaged across the 1000 economies, and the IRFs are computed as the percentage deviation of a given variable from its value in $T = 999$, the period prior to the shock.

The first point to note is that the spreads initially climb by 500 bps. But within a few quarters they settle in a new ergodic distribution with a mean 100 bps higher than that in the past. Following this increase in risk that increases simultaneously the first four moments of the interest rate distribution, the economy experiences a persistent contraction – consumption drops by almost 20% on impact, investment drops by 40% a few quarters after the shock and output drops by 5% at the trough of the recession. The IRFs are qualitatively consistent with the characteristics of business cycles observed in developing economies: 1) the responses of consumption and investment are larger than the responses of output, consistent with the excess volatility of consumption and investment; 2) net export is negatively correlated with domestic absorption.

By comparing the IRFs in Figure 8 (orange lines) with those in this section, one can assess the effects of a permanent increase in risk versus those of a transitory increase in the level of the spreads, which is the shock typically studied in the related literature. In terms of spreads, the initial increase is relatively similar between the two exercises. However, the higher long-term spreads together with higher volatility and greater skewness in the riskier scenario are accompanied by a permanent decline in debt, which reduces the burden of debt service. Looking at economic activity, we see that an unexpected increase in risk brings about a recession with similar qualitative and quantitative characteristics like in a sudden stop episode. This section provides a more comprehensive picture of what an average SOE experiences during such an episode, since these recessions are typically characterized by movements not only in the first moment, but also in the second and third moments of spread shocks. What is surprising behind this result is the absence of financial frictions that the literature uses to generate prolonged contractions (see, for example, Mendoza (2010)).[6] This exercise shows that exogenous fluctuations in an SOE's international borrowing conditions (as a result of contagion or changes in other external factors) alone can have a significant impact on its economic activity if borrowing rates are modeled accordingly to the data.

One thing to note is that consumption converges to a level slightly higher than the pre-shock level in the long run. As we explained above, the reason is that because debt in the alternating regime is quite low, servicing debt in this regime is less expensive than in the low-risk episode. The extra resources are used to increase consumption. In contrast, investment and output settle in ergodic distributions with lower means than before the shock.

[6] Note that the debt adjustment cost is quite small. As a consequence, this cost does not work as a financial friction.

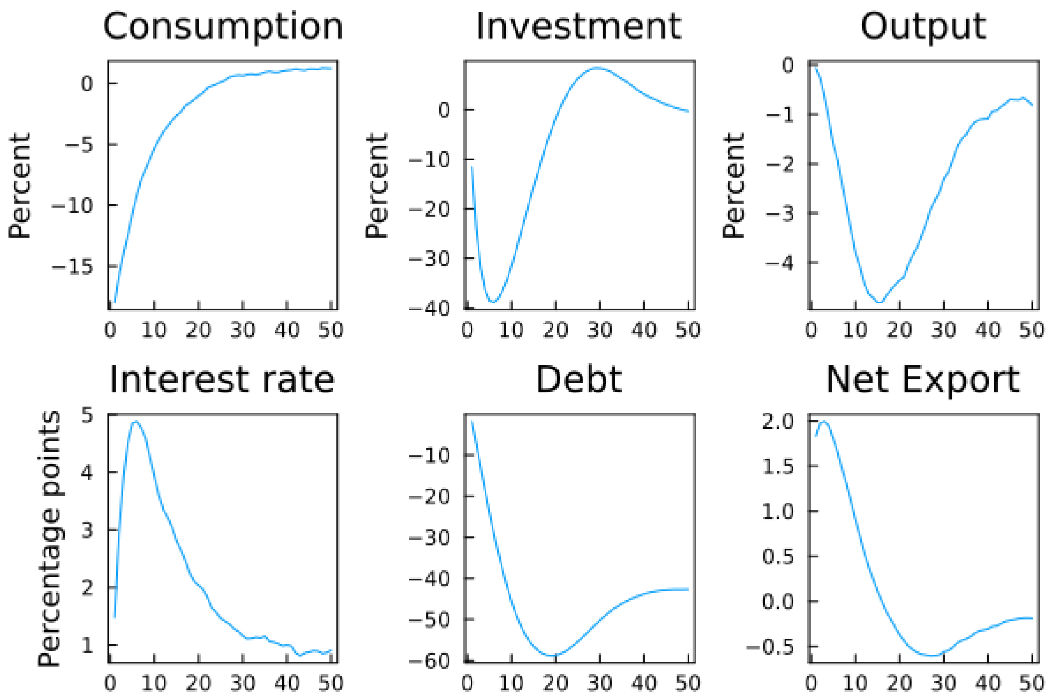


Figure 12: Developing Economies: Impulse Responses to Increase in Risk

We compute the welfare impact of transitioning from the low-risk economy to one with higher risk following the strategy in Otrok (2001). A change in risk impacts the level of consumption and, subsequently, welfare. Our simulations indicate that the welfare loss associated with moving from the low regime to the alternating regime is 2.4% of consumption in the low regime. That is, households are willing to give up that fraction of their consumption in the low regime to avoid the transition.

5.4 Going from Low Risk to a Single Regime

Does switching between low- and high-risk regimes matter? One way to answer this question is to consider the following thought exercise. Starting in the low-regime economy, we let it move to a world in which there is another unique regime. This new regime has interest rate shocks with the same mean, persistence, and volatility of the ergodic distribution of the benchmark regime-switching interest rates (see the last panel in Table 5). Figure 13 displays the transition. The economy experiences a prolonged recession. However, the severity is one order of magnitude lower. At its trough, output is about 1.3 p.p. lower than the mean of the ergodic distribution in the low-risk regime.

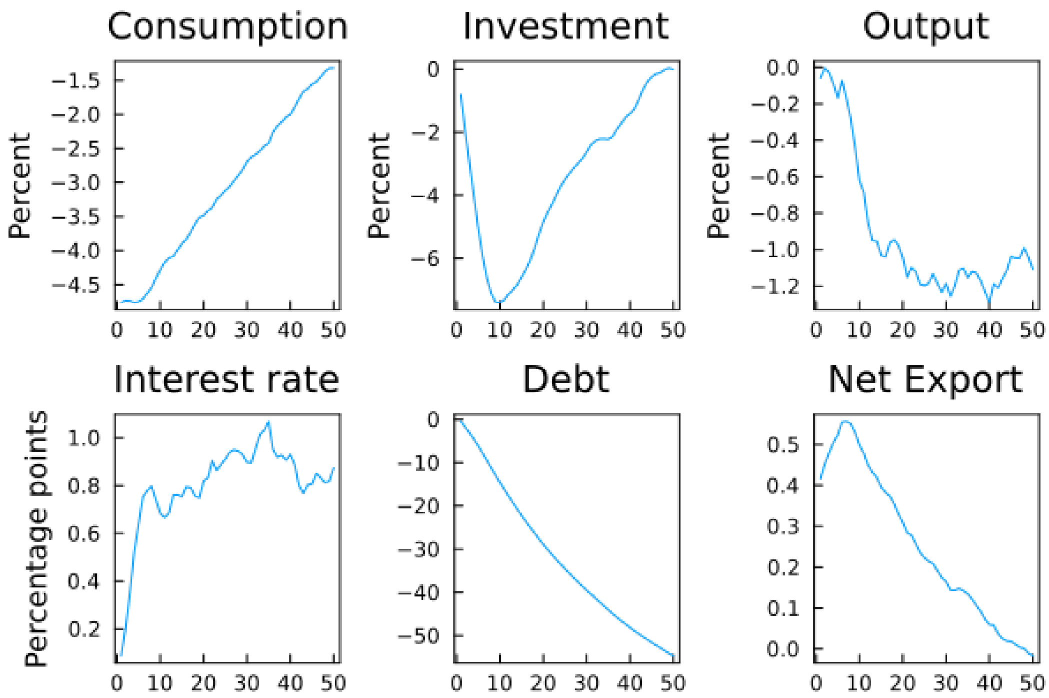


Figure 13: Developing Economies: Impulse Responses to Going from Low Risk to a Single Regime

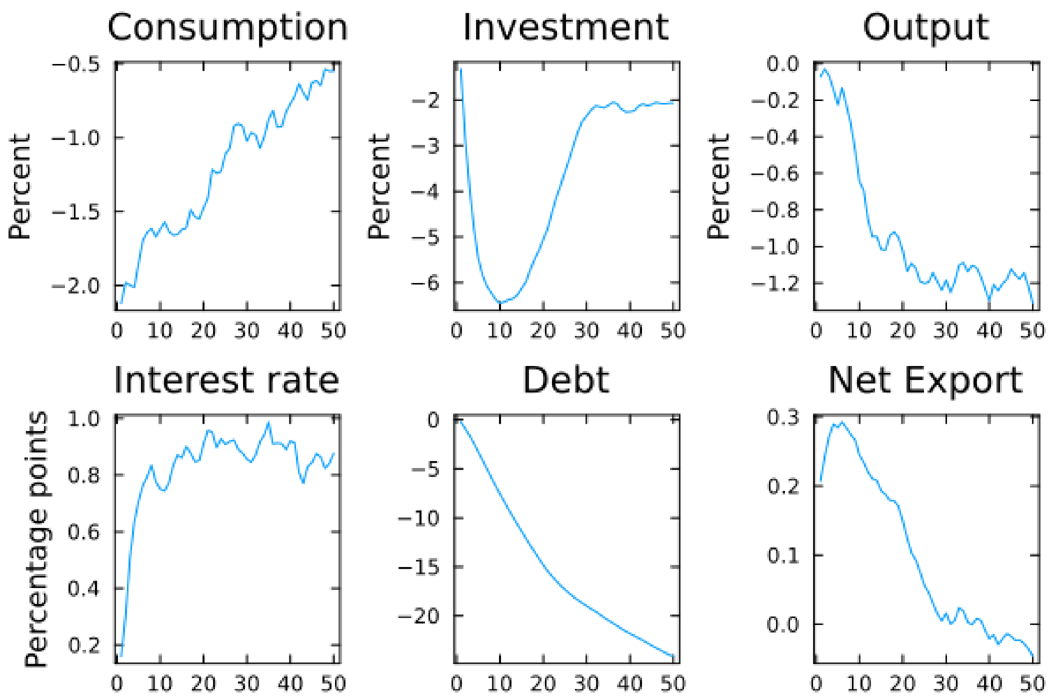


Figure 14: Developing Economies: Impulse Responses to Going from Low Risk to Alternating Regime

5.5 Increase in Skewness

What does an increase in skewness do to the economy? To answer this question, we conduct the following experiment. We start in the low regime with its own policy rules, and the probability of switching to the high regime is set to zero ($p_{11} = 1$). In addition, the exponential shocks in equation 1 are also set to zero ($E_1 = E_2 = 0$) while the scale (σ_1) and the mean (μ_1) of the interest process are changed to match the unconditional mean and volatility of spreads in the data. We simulate this economy 1000 times and at time T we switch to the baseline economy with all shocks and regime switches. The macroeconomic outcomes are averaged across the 1000 simulations and the IRFs are computed as the percentage deviation of a given variable from its value at time T-1.

Figure 15 displays the IRFs to an increase in skewness for the calibration for the pooled developing economies. This shock makes draws from the right tail of the interest rate process more likely, which in turn makes servicing debt more onerous. The optimal response of the planner is to reduce indebtedness by contracting consumption and investment while generating a boost to net exports. Since labor is inelastic, the contraction in domestic absorption is strong enough to induce a drop in GDP. As the third panel in the first row shows, the economy's GDP drops permanently by almost 100 bps.

Another way of thinking about the contractions in consumption and investment is as follows. The larger mass on the right tail of the interest rate distribution translates into higher expected marginal utility and lower contemporaneous consumption, as discussed in Section 3.2. Meanwhile, higher interest rate risk makes the hedge provided by foreign debt against the risk of holding physical capital less attractive. As a result, the planner reduces the holdings of foreign debt and the desired amount of physical capital, reflected in permanently lower levels of investment.

That the model can generate co-movement to non-TFP shocks may seem surprising at first sight. However, co-movement following the skewness shock is the result of two features of the model. First, inelastic labor supply prevents households from drastically increasing their labor offering in response to shocks.[7] Second, the economy has two assets: capital and bonds. The skewed interest rate shocks make bonds riskier, so the household naturally switches to capital. The shifting is limited due to the presence of investment adjustment costs; see Fernández-Villaverde & Guerrón-Quintana (2020) for additional details and other channels to preserve co-movement.

[7] Alternatively, one can use GHH preferences to make labor supply inelastic.

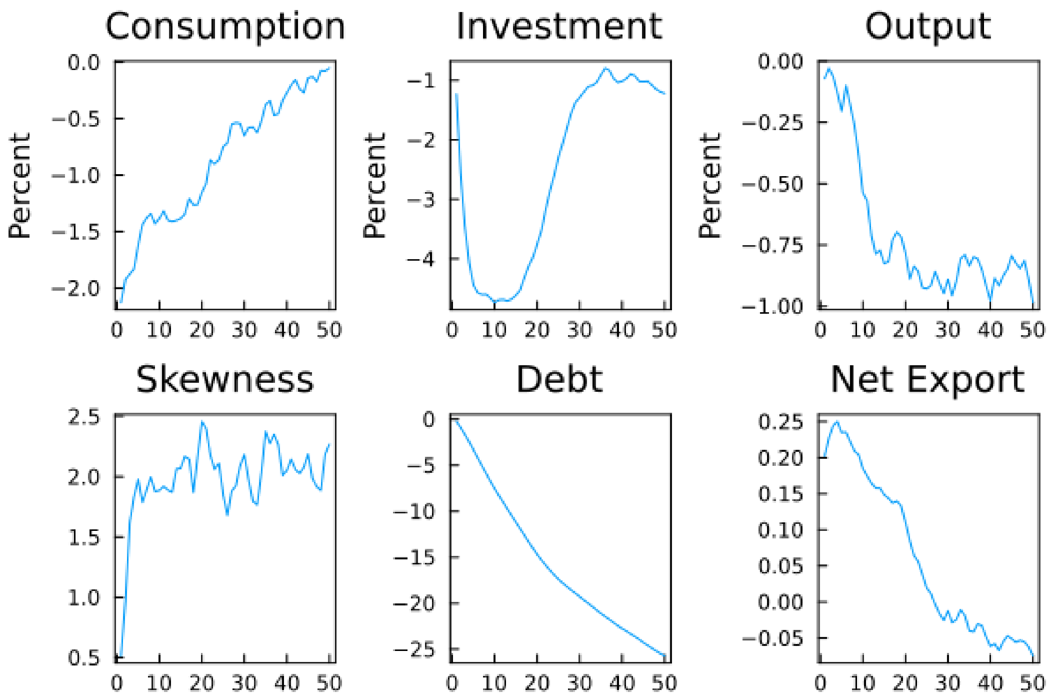


Figure 15: Developing Economies: Impulse Responses to Increase in Skewness

6 Final Remarks

A crucial insight from our work is that the Markov-switching nature of external interest rate shocks is critical to account for business cycles in developing economies. As demonstrated in our analysis, a relatively standard open economy Real Business Cycle model, augmented with our lopsided interest rate process, effortlessly generates the business cycle patterns observed in emerging economies. This finding has significant implications for both theoretical and empirical research in international macroeconomics.

On the theoretical front, our results suggest that the complex dynamics of emerging market business cycles can be largely explained by the nonlinear behavior of interest rates, without necessitating additional financial frictions or exotic assumptions about productivity processes. This parsimony is particularly appealing, as it provides a simpler framework for understanding sudden stops and economic contractions in these economies.

Empirically, our findings call for a reconsideration of the econometric tools used to study the dynamics of economies such as Argentina, Ecuador, or Mexico. Specifically, we advocate for the use of Markov-switching vector autoregressions (MS-VAR) or time-varying vector autoregressions (TV-VAR) in empirical investigations. These methodologies are better equipped to capture the sudden shifts in interest rates that our analysis has shown to be crucial in generating business cycles in emerging economies. Furthermore, our results underscore the importance of modeling higher moments and regime changes in interest rates when analyzing small open economies.

References

Aguiar, M., & Gopinath, G. (2008, April). Emerging Market Fluctuations: The Role of Interest Rates and Productivity Shocks. In K. Cowan, S. Edwards, R. O. Valdés, N. L. S. Editor), & K. Schmidt (Eds.), *Current Account and External Financing* (Vol. 12, p. 345-367). Central Bank of Chile.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *The Quarterly Journal of Economics*, *121*(3), 823–866.

Bianchi, J., Hatchondo, J. C., & Martinez, L. (2018). International reserves and rollover risk. *American Economic Review*, *108*(9), 2629–2670.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, *77*(3).

Born, B., Müller, G., Pfeifer, J., & Wellmann, S. (2020). *Different No More: Country Spreads in Advanced and Emerging Economies* (CESifo Working Paper Series). CESifo.

Busch, C., Domeij, D., Guvenen, F., & Madera, R. (2022). Skewed idiosyncratic income risk over the business cycle: Sources and insurance. *American Economic Journal: Macroeconomics*, *14*(2), 207–42.

Calvo, G., Izquierdo, A., & Talvi, E. (2006). *Phoenix Miracles in Emerging Markets: Recovering without Credit from Systemic Financial Crises* (Tech. Rep.). NBER working paper 12101.

Calvo, G. A. (1998). Capital flows and capital-market crises: The simple economics of sudden stops. *Journal of Applied Economics*, *1*(1), 35-54.

Catherine, S. (2022). Countercyclical labor income risk and portfolio choices over the life cycle. *The Review of Financial Studies*, *35*(9), 4016–4054.

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

Fernández-Villaverde, J., & Guerrón-Quintana, P. A. (2020). Uncertainty shocks and business cycle research. *Review of Economic Dynamics*, *37*, S118-S146. (The twenty-fifth anniversary of “Frontiers of Business Cycle Research”)

Gabaix, X. (2011). Disasterization: A simple way to fix the asset pricing properties of macroeconomic models. *American Economic Review*, *101*(3), 406–09.

Gabaix, X. (2012). Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *The Quarterly journal of economics*, *127*(2), 645–700.

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

Gordon, G., & Guerrón-Quintana, P. (2017). Asymmetric business cycles and sovereign default. *Economics Letters*, *161*, 116–119.

Gourio, F. (2012). Disaster risk and business cycles. *American Economic Review*, *102*(6), 2734–66.

Guerrón-Quintana, P., Khazanov, A., & Zhong, M. (2021). *Nonlinear dynamic factor models* (Tech. Rep.). Boston College.

Guvenen, F., Ozkan, S., & Song, J. (2014). The nature of countercyclical income risk. *Journal of Political Economy*, *122*(3), 621–660.

Justiniano, A., & Primiceri, G. E. (2008). The time-varying volatility of macroeconomic fluctuations. *American Economic Review*, *98*(3), 604–641.

Kent, L., & Phan, T. (2019). Time-varying skewness and real business cycles. *Economic Quarterly*(2Q), 59–103.

Lhuissier, S. (2025, March). *Skewed dynamic linear models with markov-switching: Measuring and forecasting macroeconomic risks.* Retrieved from http://www.stephanelhuissier.eu (Unpublished manuscript, Banque de France)

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

Mendoza, E. G. (2010). Sudden stops, financial crises, and leverage. *American Economic Review*, *100*(5), 1941–1966.

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

Otrok, C. (2001). On measuring the welfare cost of business cycles. *Journal of Monetary Economics*, *47*(1), 61-92.

Ranciere, R., Tornell, A., & Westermann, F. (2008). Systemic crises and growth. *The Quarterly Journal of Economics*, *123*(1), 359–406.

Reed, W. J. (2006). The normal-laplace distribution and its relatives. In *Advances in distribution theory, order statistics, and inference* (pp. 61–74). Springer.

Salgado, S., Guvenen, F., & Bloom, N. (2019). *Skewed business cycles* (Tech. Rep.). National Bureau of Economic Research.

Schmitt-Grohé, S., & Uribe, M. (2003). Closing small open economy models. *Journal of International Economics*, *61*(1), 163-185.

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

Wachter, J. A. (2013). Can time-varying risk of rare disasters explain aggregate stock market volatility? *The Journal of Finance*, *68*(3), 987–1035.

Wolf, E. (2023). *Estimating Growth at Risk with Skewed Stochastic Volatility Models* (Poster presented at 12th ECB conference on forecasting techniques). ECB.

Appendix

A Data

The real interest rate on dollar-denominated debt that domestic residents face on the international financial market is computed as the sum of the international risk-free real rate and a country spread. The international risk-free real rate is defined as the 3-month T-bill rate minus the inflation expectation. Inflation expectation is calculated as the 12-month moving average of US CPI inflation rates in the current and preceding 11 months. Monthly data on 3-month T-bill rates and CPI are obtained from the FRED database. Monthly country spread data for Argentina are obtained from J.P. Morgan Emerging Markets Bond Index Plus (EBMI+).

To compute the four targeted empirical moments – output volatility σ_y, the relative volatility of consumption to output σ_c/σ_y, the relative volatility of investment to output σ_i/σ_y, and net export as a percent of output NX/Y – quarterly national accounts data from 2004Q1 to 2020Q2 are obtained from the National Institute of Statistics and Censuses of Argentina. Consumption is household expenditure on goods and services; investment is gross fixed capital formation plus changes in inventories; net exports are exports of goods and services minus imports of goods and services; output is the sum of consumption, investment, and net exports. σ_y, σ_c/σ_y and σ_i/σ_y are computed based on the cyclical components of HP-filtered quarterly data. NX/Y is the average of net export to GDP ratio over the sample period.

Table 16: Moments of European CDS Spreads

	Mean	Std.	Skewness	Kurtosis
Portugal	0.0023	0.0025	1.9985	3.7385
Italy	0.0014	0.0008	1.7896	2.6257
Ireland	0.0015	0.0019	1.6343	1.4208
Greece	0.0745	0.1253	1.3128	-0.236
Spain	0.0012	0.0011	1.4610	1.4238

Monthly data covering 2008.7 – 2020.9

B The Normal-Laplace Distribution

The probability density function (pdf) of a normal-Laplace distribution $NL(\mu, \sigma^2, \alpha, \beta)$ is

$$f(x) = \frac{\alpha\beta}{\alpha+\beta}\phi\Big(\frac{x-\mu}{\sigma}\Big)\Big[R\Big(\alpha\sigma - \frac{x-\mu}{\sigma}\Big) + R\Big(\beta\sigma + \frac{x-\mu}{\sigma}\Big)\Big] \tag{17}$$

The location parameter $\mu \in \mathbb{R}$ while the scale parameter σ and parameters α and β, which govern the behaviors of the right tail and the left tail, respectively, are positive. R is Mills' ratio:

$$R(z) = \frac{\Phi^c(z)}{\phi(z)} = \frac{1 - \Phi(z)}{\phi(z)} \tag{18}$$

where ϕ and Φ are the pdf and cdf of the standard normal distribution.

The normal-Laplace distribution can be obtained by mixing a normal distribution and a Laplace distribution, therefore a normal-Laplace random variable can be expressed as

$$X = \mu + \sigma Z + \frac{E_1}{\alpha} - \frac{E_2}{\beta} \tag{19}$$

where Z is a standard normal deviate and E_1, E_2 are standard exponential deviates. Z, E_1, E_2 are independent of each other. Equation 19 thus provides a convenient way to simulate pseudorandom numbers from the normal-Laplace distribution. The mean and variance of the normal-Laplace distribution are

$$E(X) = \mu + \frac{1}{\alpha} - \frac{1}{\beta} \tag{20}$$

$$Var(X) = \sigma^2 + \frac{1}{\alpha^2} + \frac{1}{\beta^2} \tag{21}$$

The parameters α and β govern the behavior of the right and left tails, respectively, with small values indicating heaviness in the corresponding tail. This can be seen in figure **??**, which plots probability density functions for $NL(0, 1, \alpha, 1)$ for $\alpha = 1, 0.5, 0.3, 0.1$, and for $NL(0, 1, 1, \beta)$ for $\beta = 1, 0.5, 0.3, 0.1$. The $NL(\mu, \sigma^2, \alpha, \beta)$ distribution will always have a greater heaviness in the tails compared to the $N(\mu, \sigma^2)$ distribution.

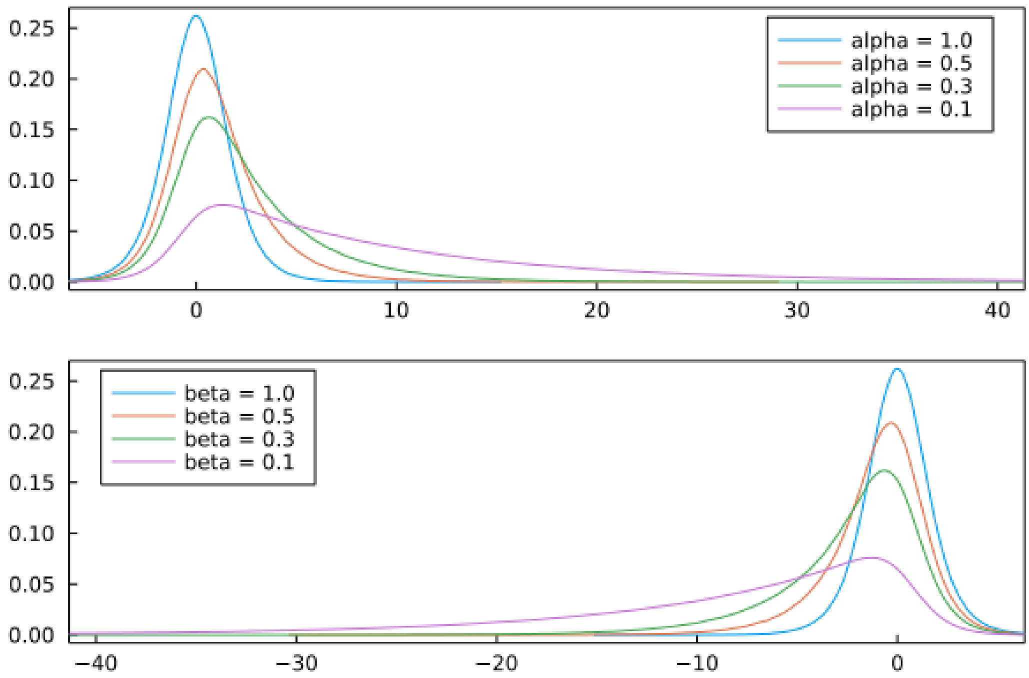


Figure 16: Probability Density Functions of $NL(0, 1, \alpha, 1)$ and $NL(0, 1, 1, \beta)$

B.1 Policy Functions

Figures 17 plot the policy functions for output in the low/high-risk regimes.

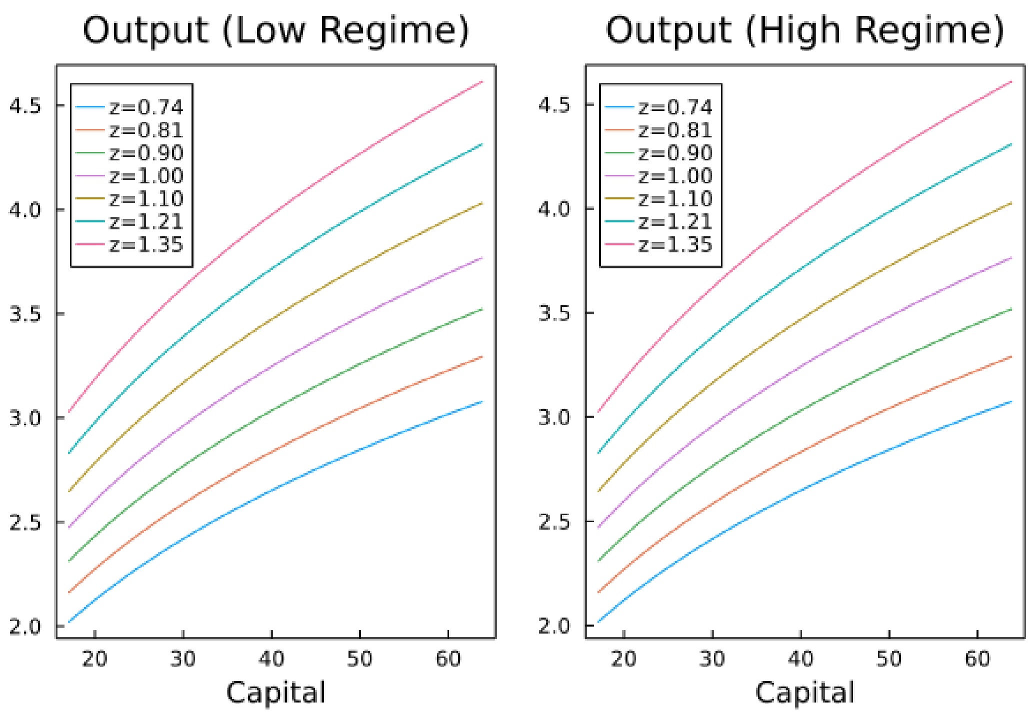


Figure 17: Argentina: Policy Function for Output