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VOLATILE RATES, FRAGILE GROWTH: GLOBAL FINANCIAL RISK AND PRODUCTIVITY DYNAMICS

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ABSTRACT

We document that rising volatility in U.S. interest rates, a key dimension of global financial risk, notably depresses the trend of economic activity in emerging market economies (EMEs) but not in advanced economies (AEs). Using a panel state-space model, we show that a one standard-deviation shock to U.S. monetary policy uncertainty permanently lowers the level of GDP in EMEs by about 25 basis points after three years, with negligible effects in AEs. We rationalize this fact in a small open economy model where firms borrow against future profits to finance innovation. Higher volatility compresses firm values, tightens collateral constraints, and endogenously slows productivity growth, especially when financial frictions are severe.

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1 Introduction

Emerging markets are vulnerable to shifts in global financial conditions. When risk appetite deteriorates, signaled by rising measures like the VIX or widening credit spreads, capital flows to emerging economies reverse sharply, exchange rates depreciate, and output contracts (Rey, 2015; Miranda-Agrippino and Rey, 2020). This sensitivity to global financial volatility is a defining feature of emerging market business cycles. Yet these economies also exhibit substantially greater volatility in their trend of economic growth than advanced economies (Aguiar and Gopinath, 2007). Are these two facts connected? Does financial market volatility affect not only short-run fluctuations but also the trajectory of long-run productivity growth?

This paper provides evidence that it does. We estimate a panel state-space model for two groups of small open economies, seven emerging markets and six advanced economies, over the period 1993 to 2019. The model provides estimates of the time-varying growth rate of country-specific trends in GDP, consumption, and investment growth while decomposing each trend into two components: one driven by global financial uncertainty and one capturing all other sources of trend variation. Our baseline measure of global financial risk is an innovation to U.S. monetary policy uncertainty, constructed from the text-based index of Husted et al. (2020) and orthogonalized to U.S. macroeconomic and policy variables. Our approach allows us therefore to identify how shocks to U.S. interest rate risk affect the persistent component of growth, separately from transitory business cycle fluctuations.

We find that shocks to U.S. interest rate uncertainty generate persistent declines in the trend of economic activity in emerging market economies (EMEs), with no comparable effect in advanced economies (AEs). A one-standard-deviation uncertainty shock that raises perceived volatility of future U.S. interest rates lowers the level of the productivity trend in EMEs by about 25 basis points after three years. The effect is robust across multiple measures of global financial uncertainty and persists even after controlling for the level of interest rates, U.S. GDP growth, and other global conditions. Advanced economies exhibit essentially no response.

To explain these different responses, we develop a small open economy model with three key ingredients: endogenous productivity growth through innovation and firm entry, occasionally binding collateral (borrowing) constraints with firm value as collateral, and stochastic volatility in

world interest rates. The mechanism operates through firms' productivity-enhancing investment. Households own firms and can borrow internationally, but only up to a fraction of the present value of their firms' future profits. When interest rate volatility rises, the expected present value of these profits falls, both because risk-averse households discount the future more heavily and because large adverse interest rate shocks, which become more likely during high-volatility periods, trigger sharp contractions when borrowing constraints bind. Lower firm values reduce investment in innovation by incumbents and entry by new firms, depressing productivity growth.[1]

Crucially, the mechanism is asymmetric and relies on occasionally binding borrowing constraints. A large positive interest rate shock forces households to deleverage when the collateral constraint binds, sharply reducing consumption and raising the marginal utility of wealth. This amplifies the decline in firm valuations through a Fisherian deflation channel: falling asset values tighten the borrowing constraint endogenously, creating a feedback loop between financial conditions and real activity. Conversely, an equally large negative shock provides limited stimulus, since when the constraint is already slack relaxing it further has no effect, because its shadow value is zero. This asymmetry implies that, even holding constant the interest rate, higher volatility lowers expected firm value and depresses innovation, and the effect is stronger when the constraint binds more frequently. In our quantitative exercise, we allow the borrowing rate of our model economy to vary as well with the level of uncertainty, in line with previous work, to move the model closer to the data. However, we show that the just described asymmetry is key to reproduce the empirical patterns.

Calibrated to Mexico, the model replicates the differential response of emerging and advanced economies without targeting it. In the quantitative analysis, emerging and advanced economies share the same technology, preferences, and exposure to the world interest rate and volatility processes; they differ only in financial development parameters that govern how much collateral can be pledged and how strongly borrowing costs respond to volatility, namely the average spread, the sensitivity of spreads to risk, and the share of firm value that is collateralizable. Three counterfactual experiments isolate the sources of the asymmetry. First, eliminating interest rate volatility reduces the coefficient of variation of trend growth in emerging markets by about 30 percent while

[1] Our emphasis on the value of firms is consistent with the cross-country evidence in Lakdawala et al. (2021). They show that rising US monetary policy uncertainty predicts declining asset valuations abroad, especially in emerging market economies.

having negligible effects on advanced economies. Second, adjusting only financial development parameters, the fraction of firm value that can be collateralized and the sensitivity of borrowing costs to volatility, substantially narrows the gap in trend volatility between emerging and advanced economies. Third, the borrowing constraint itself explains roughly 60 percent of emerging markets' excess trend volatility, with the remaining 40 percent reflecting higher and more volatile risk premia.

The model also matches observed patterns in the cross-sectional distribution of growth rates. During periods of elevated U.S. interest rate volatility, not only does average trend growth fall in emerging markets, but dispersion across countries rises sharply: some countries experience severe slowdowns while others are less affected. Advanced economies exhibit stable, low dispersion throughout. When we simulate many emerging economies facing common global financial shocks but idiosyncratic productivity draws, the model replicates this pattern. Cross-country dispersion in trend growth spikes during high-volatility periods in emerging markets but remains flat in advanced economies, because the nonlinear amplification from binding constraints varies with countries' idiosyncratic states.

Related Literature. Our contribution intersects three research areas.

First, volatility shocks in open economies. Classic open economy models (Mendoza, 1991; Neumeyer and Perri, 2005; Uribe and Yue, 2006) studied how fluctuations in world interest rate *levels* affect emerging markets, often through working capital constraints or exogenous productivity correlations. More recent work examines second-moment shocks directly. Fernández-Villaverde et al. (2011) demonstrate that interest rate volatility produces asymmetric real effects through precautionary savings. Carrière-Swallow and Céspedes (2013) show uncertainty shocks generate larger output contractions in emerging than advanced economies. Bhattarai et al. (2020), Reyes-Heroles and Tenorio (2020), and Roch et al. (2025) extend this evidence to U.S. policy uncertainty and financial channels. Gruss and Mertens (2009) and Johri et al. (2022) emphasize volatility's role in Sudden Stops. Our empirical contribution shows second-moment shocks affect not just short-run output but also the *trend* component of growth. We measure this using multiple uncertainty proxies, the VIX, macroeconomic uncertainty (Jurado et al., 2015), and stochastic volatility in Treasury yields, and find robust evidence of persistent trend effects in emerging markets. Our theoretical contribution explains this through a mechanism linking volatility to firm valuation and innova-

tion.

Second, the global financial cycle. Rey (2015) argues global risk drives capital flows and undermines monetary autonomy. Miranda-Agrippino and Rey (2020) show U.S. monetary shocks propagate worldwide, while Chari et al. (2022) document differential effects across financial institutions. Zhou (2024) and Gerding et al. (2014) highlight heterogeneity from investor types and capital market structure. We isolate a distinct channel: internal financial frictions amplify volatility's impact on firm investment and productivity, so identical external shocks generate divergent outcomes.

Third, productivity trends and endogenous growth. Aguiar and Gopinath (2007) argue emerging market cycles reflect shocks to the trend. Garcia-Cicco et al. (2010), Chang and Fernández (2013), and Boz et al. (2011) show both trend and stationary shocks matter. We bridge these views: *stationary* global financial shocks generate *persistent* trend movements through financial amplification and endogenous productivity. Our model builds on the dynamic version of Klette and Kortum (2004) developed by Ates and Saffie (2021) amenable to dynamic stochastic general equilibrium models, and Mendoza (2010) who emphasizes collateral constraints. Gornemann et al. (2025) develop R&D-driven productivity dynamics for real exchange rates, emphasizing technology diffusion rather than our collateral-based innovation channel. Benigno et al. (2025) show secular interest rate declines slow growth through misallocation; we isolate second-moment, volatility, effects.[2]

Standard policy prescriptions, reserve accumulation, exchange rate flexibility, macroprudential tools, address symptoms of external shocks rather than underlying vulnerability. Our analysis suggests deeper reforms are needed: strengthening financial institutions to expand collateralizable assets, improving credit market efficiency to reduce risk premia volatility, and fostering financial development broadly. Without such reforms, even successful stabilization of average borrowing costs may leave emerging markets exposed to persistent growth reversals when global uncertainty rises.

Section 2 presents the empirical evidence. Section 3 develops the model. Section 4 presents the quantitative analysis. Section 5 concludes.

[2]In closed economies, Jordà et al. (2024) and Garga and Singh (2021) show monetary shocks generate persistent output effects when firms adjust innovation.

2 Empirical Evidence: Volatility and Permanent Output Losses

This section provides empirical evidence that U.S. interest rate uncertainty has persistent effects on economic performance across countries. Using a multivariate panel time series framework, we estimate the impact of monetary policy uncertainty shocks on the trend components of GDP, consumption, and investment growth for both emerging and advanced economies. Our results reveal a clear pattern: uncertainty shocks systematically reduce the stochastic trend in emerging markets, while advanced economies are much less affected. This divergence is consistent with a volatility-driven propagation mechanism that is stronger in financially constrained environments.

2.1 Intuition of our approach

In principle, to capture long-lasting effects of uncertainty shocks on economic activity it would be enough to regress GDP growth on many lags of the shocks and cumulate the effects, similar to a local projection. We augment this approach with a few additional restrictions to strengthen its empirical power. In line with both exogenous and endogenous growth models, we assume that GDP, consumption, and investment in country j share a common stochastic trend

$$A_{j,t} = \exp\left(\sum_{s=-\infty}^{t} \hat{a}_{j,s}\right),$$

where $\hat{a}_{j,s}$ denotes the time-varying trend growth rate.[3] As a result, we can write the growth rate of logged GDP ($\Delta y_{j,t}$), logged consumption ($\Delta c_{j,t}$), and logged investment ($\Delta i_{j,t}$) in country j as

$$\begin{pmatrix} \Delta y_{j,t} \\ \Delta c_{j,t} \\ \Delta i_{j,t} \end{pmatrix} = \begin{pmatrix} \alpha_j \\ \alpha_j \\ \alpha_j \end{pmatrix} + \begin{pmatrix} \Delta \tilde{y}_{j,t} \\ \Delta \tilde{c}_{j,t} \\ \Delta \tilde{i}_{j,t} \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \hat{a}_{j,t}.$$

Here α_j denotes the country-specific average growth rate, and a tilde indicates the growth rate of the de-trended series. The terms $\Delta \tilde{y}_{j,t}$, $\Delta \tilde{c}_{j,t}$, and $\Delta \tilde{i}_{j,t}$ are stationary cycle components, while $\hat{a}_{j,t}$ captures the highly persistent, common movement in the three series that we label the

[3] Many approaches have made use of this common trend restriction; see Bocola and Gornemann (2013) for a summary of some of the relevant work.

stochastic trend. The common trend assumption allows us to extract additional information from the co-movement of the three observed series, and imposing some version of stationarity on the de-trended component further strengthens the inference.

To make further progress we assume that $\hat{a}_{j,t}$ is the sum of the effects of uncertainty shocks and a residual component,

$$\hat{a}_{j,t} = a_{j,t} + \sum_{s=0}^{n_\sigma} \eta_s \sigma_{t-s}^{MU},$$

where σ_t^{MU} denotes the monetary policy uncertainty shock at time t, and $a_{j,t}$ captures all other movements in trend growth. We estimate the coefficients $\{\eta_s\}$ directly. The cumulative sum $\sum_{s=0}^{t} \eta_s$ then measures the effect of an increase in interest rate uncertainty t periods ago on the *level* of the stochastic trend, expressed in percent.

2.2 Data and our proxies for interest rate uncertainty

We compile quarterly macroeconomic data from 1993Q1 to 2019Q4 for two country groups. The emerging market sample includes Argentina, Brazil, Chile, Mexico, the Philippines, South Africa, and Turkey. The advanced economy group consists of Australia, Canada, Denmark, New Zealand, Norway, and Sweden. We collect real GDP, consumption, and investment, from the IMF's International Financial Statistics (IFS) database.[4] Due to missing observations, the panel is unbalanced. Our selection of countries is typical for the emerging market business cycles literature and matches the one in, for example, Vicondoa (2019).

Our primary proxy for interest rate uncertainty is derived from the text-based monetary policy uncertainty index in Husted et al. (2020), which we residualize following their work using a VAR approach. This procedure constructs an innovation that is orthogonal to contemporaneous shocks to U.S. macroeconomic and policy variables, so our monetary policy uncertainty shock captures unexpected movements in perceived U.S. interest rate risk conditional on those fundamentals. In robustness checks, we also consider the following alternative uncertainty proxies: (1) the VIX index; (2) macro uncertainty from Jurado et al. (2015); and (3) the stochastic volatility of real U.S. T-bill rates following Fernández-Villaverde et al. (2011).

[4]Gross fixed capital formation is used as our investment measure for consistency and coverage.

2.3 Time series model

Based on our discussion above, we estimate a panel state-space model to isolate the effects of uncertainty shocks on low-frequency trend growth. The joint process for country j is

$$\begin{pmatrix} \Delta y_{j,t} \\ \Delta c_{j,t} \\ \Delta i_{j,t} \end{pmatrix} = \begin{pmatrix} \alpha_j \\ \alpha_j \\ \alpha_j \end{pmatrix} + A^* \left(\begin{pmatrix} \Delta y_{j,t-1} \\ \Delta c_{j,t-1} \\ \Delta i_{j,t-1} \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \hat{a}_{j,t-1} \right) + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \hat{a}_{j,t} + B \cdot Z_t^{US} + \Sigma_j \epsilon_{j,t}^m,$$

$$\begin{aligned} \hat{a}_{j,t} &= a_{j,t} + \sum_{s=0}^{n_\sigma} \eta_s \sigma_{t-s}^{MU}, \\ a_{j,t} &= \rho_a a_{j,t-1} + \sigma_{j,a} \epsilon_{j,t}^a. \end{aligned}$$

In Z_t^{US} we control for current and lagged U.S. GDP growth and the excess bond premium from Gilchrist and Zakrajšek (2012), as well as n_σ growth rates of our series for U.S. interest rate uncertainty to capture transitory effects. Including Z_t^{US} in the measurement equations ensures that the estimated response to σ_t^{MU} can be interpreted as the effect of a global risk shock, holding U.S. macroeconomic and credit conditions fixed. Σ_j is a 3×3 diagonal matrix and shocks $(\epsilon_{j,t}^m, \epsilon_{j,t}^a)$ are drawn from a joint normal distribution. The deterministic trend α_j and the variances of shocks are country specific, while other parameters are imposed to be the same across countries in the panel, a restriction often made in the literature on panel VARs for emerging market economies, see for example Uribe and Yue (2006), Akıncı (2013), and Vicondoa (2019). To capture persistence in trend responses, we set $n_\sigma = 12$ quarters.[5]

Estimation proceeds by casting the model into state space form and estimating it via maximum likelihood using the Kalman filter, which also provides us with time series for the country trends. Standard errors are obtained via bootstrap, re-estimating the entire state-space model in each replication, so confidence intervals for the impulse responses account for uncertainty about both the trend and its response to uncertainty. The uncertainty process σ_t^{MU} is common across all countries in a given panel: each emerging and advanced economy is exposed to the same sequence of global monetary policy uncertainty shocks. Differences in estimated responses therefore reflect

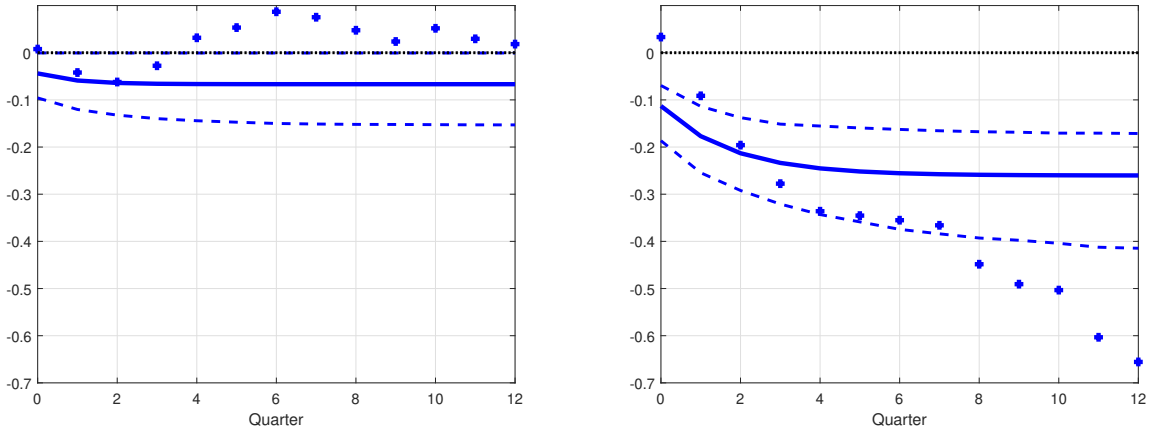
[5] For the baseline estimation we impose more structure on B to deal with the large number of coefficients.

differences in internal propagation, not differences in the shock process itself.

2.4 Results

Figure 1 shows the estimated cumulative impulse response of the stochastic trend to a one-standard-deviation monetary policy uncertainty shock, that is, $\sum_{s=0}^{t} \eta_s$. On the left, we see that for the advanced economies the effect is barely significant (dots). Emerging markets instead experience a sharp and persistent decline in the trend of economic activity (dots on the right in the figure). These effects last for multiple years and are economically meaningful: at a horizon of twelve quarters, the point estimate for EMEs is around -0.65, implying that a one-standard-deviation uncertainty shock lowers the level of the stochastic trend by about 65 basis points relative to baseline, while the corresponding response for AEs is close to zero.

Figure 1: Trend Response to Monetary Policy Uncertainty Shock



(a) Advanced Economies (b) Emerging Market Economies

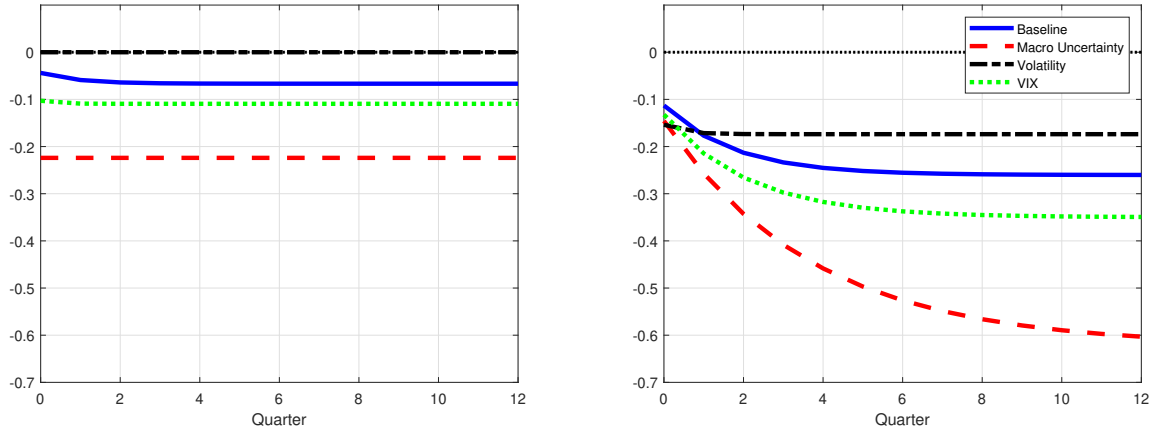
Notes: The solid line shows the point estimate when the functional form for η_s is imposed; bands represent one-standard-deviation confidence intervals. Dots denote the point estimate when no functional form is imposed.

As the unrestricted η_s can lead to noisy movements, we also report the results of imposing a flexible functional form on them. While this is not necessary for our main results, it generates smoother impulse response functions and allows us to focus on the core implications. It also should make our results more robust to picking up short term variations into the trend. Following Barnichon and Matthes (2018), we set $\eta_s = a \exp\left(-\frac{s-b}{c}\right)$ and estimate a, b, c together with the other parameters of the time series model. These results are shown as the lines in Figure 1, and we

report error bands based on them. We continue to see a sizable decline for the emerging market economies by 25 basis points and a smaller, barely significant one for the advanced economies.

Figure 2 confirms that our findings are robust across alternative uncertainty proxies. Here we replace the monetary policy uncertainty shocks by each of the following alternative uncertainty proxies in turn: (1) the VIX index; (2) macro uncertainty from Jurado et al. (2015); and (3) the stochastic volatility of real U.S. T-bill rates following Fernández-Villaverde et al. (2011).[6] We focus on the parametric case in the figures. While unsurprisingly magnitudes vary, we see that the key takeaways survive. Effects are noticeably larger for the emerging markets than for the advanced economies in each case. For measures pertaining to interest rate uncertainty more narrowly, the permanent effect on the stochastic trend for advanced economies seems negligible.[7]

Figure 2: Trend Response to Monetary Policy Uncertainty Shock, Robustness: Shock Proxies



(a) Advanced Economies

(b) Emerging Economies

Notes: This figure plots the cumulative response of the estimated stochastic trend to a one-standard-deviation global uncertainty shock for advanced economies (panel a) and emerging economies (panel b). The "Baseline" line reproduces the response to the monetary policy uncertainty innovation used in Figure 1. The other lines report responses when the uncertainty shock is instead proxied by (i) the VIX index, (ii) macroeconomic uncertainty from Jurado et al. (2015), and (iii) the stochastic volatility of the U.S. real short rate following Fernández-Villaverde et al. (2011). All responses are estimated under the parametric restriction on η_s and include the same set of U.S. controls as in the baseline specification.

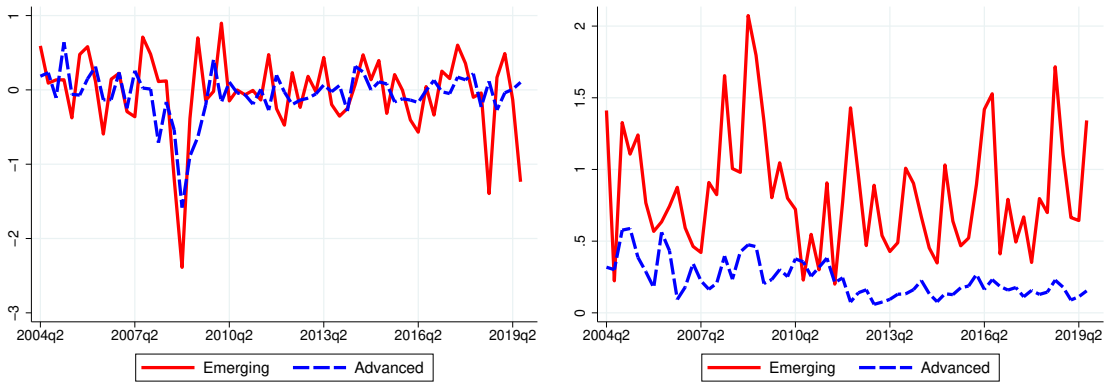
[6]The volatility measure employed in Figure 2 is the stochastic volatility of the U.S. real interest rate (Fernández-Villaverde et al., 2011). Appendix A.1 describes the estimation procedure and results.

[7]We also performed a long list of robustness checks with respect to the structure of the empirical model itself: (i) we allowed U.S. growth and the excess bond premium to enter the trend component directly; (ii) we varied restrictions imposed on B; (iii) we removed some or all U.S. controls or added U.S. interest rates. In all these cases our main results were robust. See the appendix for some details.

2.5 Empirical estimates of trend growth

We now examine the cross-sectional dynamics of estimated trend growth across countries. Figure 3 displays the average and standard deviation of country-specific trend growth (demeaned) for EMEs and advanced economies over quarters with full data coverage. For each quarter, we subtract the country mean and compute the within-group average and dispersion.

Figure 3: Cross-Sectional Moments of the Stochastic Trend Growth Rate



(a) Cross-Sectional Average (b) Cross-Sectional Standard Deviation

Notes: This figure shows cross-sectional moments of the estimated country-specific stochastic trend growth rates for advanced economies and emerging market economies. In each quarter, we subtract each country's average trend growth (over the sample) from its filtered trend growth rate and then compute, within each group, the cross-sectional average (panel a) and cross-sectional standard deviation (panel b). The underlying trends are obtained from the panel state-space model described in Section 2, using common global uncertainty shocks and U.S. controls for all countries.

Two patterns stand out. First, average trend growth among advanced economies is relatively stable. Emerging markets, by contrast, exhibit much larger fluctuations in trend growth, especially during and after the Global Financial Crisis. Second, EMEs show persistently greater cross-sectional dispersion, with a sharp spike during 2008–2009 that remains elevated for years.

These patterns are consistent with our model's amplification mechanism: common volatility shocks generate disproportionately heterogeneous outcomes in financially constrained economies. While advanced economies maintain trend co-movement due to deeper financial systems and lower risk premia, EMEs, facing tighter borrowing constraints, experience deeper and more persistent idiosyncratic trend shocks. In Section 4 we show that the calibrated model reproduces both the lower average trend growth and the higher cross-sectional dispersion of EMEs in periods of elevated U.S. interest rate volatility.

3 A Small Open Economy with Volatility-Driven Trend Dynamics

3.1 Model Overview

We develop a small open economy model in which volatility in global interest rates, beyond changes in their level, drives persistent fluctuations in long-run productivity growth. The mechanism operates through occasionally binding collateral (borrowing) constraints and endogenous firm dynamics. A representative household owns a continuum of intermediate good producers and can borrow externally by pledging shares in firms as collateral. The borrowing terms depend not only on the level of global interest rates but also on their volatility, introducing a channel through which financial conditions affect growth.

The engine of long-run growth is creative destruction among intermediate good producers. Firms expand, contract, or exit through innovation and competition following the framework of Klette and Kortum (2004). These firms sell differentiated intermediate goods to a final good producer, which aggregates inputs into a single tradable final good under an aggregate efficiency shock.

Our model extends traditional endogenous Sudden Stop frameworks in three key ways. First, collateral is based on the value of firms' future profits, directly tying innovation dynamics to borrowing capacity. Second, endogenous technical change determines the evolution of firm value through productivity-enhancing investment and firm entry. Third, both the level (first moment) and volatility (second moment) of international interest rates influence firm dynamics, collateral values, and innovation incentives. Together, these elements generate an endogenous link from second-moment financial shocks to persistent trend growth outcomes. The key equilibrium objects are the household's stochastic discount factor and the economy-wide creative destruction rate, which together determine the evolution of aggregate productivity and thus the trend.

3.2 Households

The representative household chooses consumption C and non-state-contingent bond holdings B each period. Labor supply $\bar{L}$ is inelastic and remunerated at wage w. In addition to labor income, the household receives lump-sum transfers T from incumbent firms, which it owns.

The household solves:

$$\max_{C(s^t),B(s^t)^H} \sum_{t=0}^{\infty} \beta^t \mathbb{E}\left[\frac{1}{1-\gamma}\left[C(s^t)\right]^{1-\gamma}\Big|s_0\right] \tag{1}$$

subject to:

$$C(s^t) + \hat{q}(s^t)B^H(s^t) \leq w(s^t)\bar{L} + B^H(s^{t-1}) + T(s^t), \tag{2}$$

$$\hat{q}(s^t)B^H(s^t) \geq -\phi V(s^t), \tag{3}$$

where $\hat{q}(s^t)$ denotes the price of debt, defined as the reciprocal of the gross interest rate set by international financial intermediaries. The household faces a collateral constraint: it cannot borrow more than a fraction ϕ of the total value of the incumbent firms $V(s^t)$, which it owns.

This structure departs from traditional models of endogenous financial crises (Bianchi and Mendoza, 2018), where collateral is typically tied to tradable income or assets. Instead, consistent with private equity and venture capital practices, the household uses the value of future firm cash flows as collateral. This formulation aligns with recent empirical evidence on earnings-based borrowing constraints (Lian and Ma, 2021; Drechsel, 2023), and mirrors the credit assessment processes observed in traditional banking, where firm project valuations often determine creditworthiness.

3.3 Financial Intermediaries

Households borrow from competitive, risk-averse international financial intermediaries. Intermediaries face a stochastic gross funding cost R, and lend to households at a price $\hat{q}$. The gross interest rate evolves according to an AR(1) process with stochastic volatility:

$$R(s^t) - \bar{R} = \rho_R\left(R(s^{t-1}) - \bar{R}\right) + \sigma(s^t)\omega(s^t), \quad \omega(s^t) \sim N(0,1), \tag{4}$$

$$\log(\sigma(s^t)) = (1-\rho_\sigma)\mu_\sigma + \rho_\sigma \log(\sigma(s^{t-1})) + \eta_\sigma \nu(s^t), \quad \nu(s^t) \sim N(0,1), \tag{5}$$

where $\bar{R}$ denotes the average cost of funds, ρ_R and ρ_σ govern the persistence of the interest rate and its volatility, and $\sigma(s^t)$ denotes the conditional standard deviation of the funding shock.

Intermediaries set lending rates by solving:

$$\max_{b(s^t)} \mathbb{E}\left[\hat{m}(s^{t+1})b(s^t)\middle|s^t\right] - \hat{q}(s^t)b(s^t), \tag{6}$$

where $\hat{m}(s^{t+1})$ is the intermediaries' stochastic discount factor. To capture their risk sensitivity to volatility, we assume:

$$\hat{m}(s^{t+1}) = \frac{1}{1 + R(s^{t+1}) + \iota_0 + \iota_1\left(\sigma(s^{t+1}) - \bar{\sigma}\right)},$$

where ι_0 captures a baseline spread and $\iota_1 > 0$ captures the degree to which spreads widen in response to higher volatility.

This reduced-form specification is consistent with models of intermediary frictions under stochastic volatility, such as Gertler and Karadi (2011) and Gertler and Kiyotaki (2015). Appendix B presents a formal model with these features, showing how increased volatility in funding costs raises loan spreads. Alternatively, this structure is consistent with ambiguity aversion (see Bianchi et al. (2018a)), and similar reduced-form pricing structures have been employed in Arellano and Ramanarayanan (2012), Bianchi et al. (2018b), Johri et al. (2022), and Hegarty et al. (2023).

The solution to (6) yields the bond pricing function:

$$\hat{q}(s^t) = \mathbb{E}\left[\frac{1}{1 + R(s^{t+1}) + \iota_0 + \iota_1\left(\sigma(s^{t+1}) - \bar{\sigma}\right)}\middle|s^t\right], \tag{7}$$

where expected spreads rise with volatility, even when the mean interest rate remains unchanged. Foreign intermediaries' pricing rule determines the wedge between the exogenous world cost of funds and the domestic borrowing rate, while households discount cash flows using their own stochastic discount factor; the two objects capture different sources of risk and are linked through the bond price $\hat{q}(s^t)$.

3.4 Final Good Producer

The final good producer aggregates a mass Λ of differentiated intermediate goods into a single homogeneous final output using a Cobb-Douglas-like technology:

$$\ln Y(s^t) = z(s^t) + \frac{1}{\Lambda} \int_0^{\Lambda} \ln y_i(s^t)\, di, \tag{8}$$

where $Y(s^t)$ denotes the final good, $y_i(s^t)$ is the demand for intermediate variety i, and $z(s^t)$ is an aggregate efficiency shock.

The aggregate efficiency shock follows an AR(1) process:

$$\ln z(s^t) = \rho_z \ln z(s^{t-1}) + \epsilon_t, \quad \epsilon_t \sim N(0, \eta_z^2),$$

where ρ_z governs the persistence and η_z the volatility of aggregate productivity innovations. The final good is the only tradable output in the economy and serves as the numeraire for international borrowing and lending.

3.5 Intermediate Good Producers

A continuum of intermediate goods, indexed by $i \in [0, \Lambda]$, is produced by firms operating under monopolistic competition. Each intermediate good is produced according to:

$$y_i(s^t) = q_i(s^t) l_i(s^t), \tag{9}$$

where $q_i(s^t)$ denotes the efficiency (productivity) of variety i, and $l_i(s^t)$ denotes labor input.

The firm with the lowest marginal cost for each variety is the technological leader, earning monopoly rents through Bertrand competition against the second-best producer. Firms can operate multiple product lines simultaneously, expanding by innovating into additional varieties or contracting when losing technological leadership. Firms exit the market if they lose control of all their product lines. This structure generates endogenous firm dynamics through innovation and creative destruction, linking micro-level competition to macroeconomic productivity growth.[8]

[8]Our quantitative results do not hinge on the specific Klette–Kortum style structure. Any forward-looking endogenous growth model in which firms invest in innovation and creative destruction generates a similar link between firm

3.5.1 Innovation by Incumbents

The productivity of each intermediate good evolves endogenously through innovation. Innovations arise when either an incumbent or a potential entrant successfully improves upon the existing technology for producing a given variety. When an innovation occurs for variety i, the new technological leader gains access to:

$$q_i(s^{t+1}) = (1+\sigma)\tilde{q}_i(s^t),$$

where $\tilde{q}_i(s^t)$ denotes the previous leader's technology level, and $\sigma > 0$ is the innovation step size.

Incumbent firms can actively attempt to innovate and capture new product lines. Following the discrete-time version of Ates and Saffie (2021) based on Klette and Kortum (2004), a firm with n products can allocate research labor $L_r(s^t)$ to generate a per-product success probability:

$$x(s^t) = \xi \left(\frac{L_r(s^t)}{n}\right)^{\theta} \equiv \xi \left(l_r(s^t)\right)^{\theta},$$

where $l_r(s^t)$ denotes research labor per product.

The expansion and destruction of a firm's product portfolio follow binomial processes. Specifically, a firm with n products has probability:

$$\mathbb{B}(k, n, x(s^t)) = \binom{n}{k} x(s^t)^k (1 - x(s^t))^{n-k}, \tag{10}$$

of winning k new products through innovation, and probability:

$$\mathbb{B}(\tilde{k}, n, \Delta(s^t)) = \binom{n}{\tilde{k}} \Delta(s^t)^{\tilde{k}} (1 - \Delta(s^t))^{n-\tilde{k}}, \tag{11}$$

of losing $\tilde{k}$ products to creative destruction, where $\Delta(s^t)$ is the economy-wide creative destruction rate. Incumbent firms face a fixed innovation cost $F(s^t)$ per product line successfully innovated, which scales with the economy's size as $F(s^t) = A(s^t)F$.

values, innovation, and the trend. We adopt this framework because it can be disciplined using firm-level dynamics such as the distribution of firm sizes and exit rates.

Given these dynamics, the incumbent's value function with n products solves:

$$V_n(s^t) = \max_{x_n(s^t)} n\left[\pi(s^t) - w(s^t)\alpha\left(\frac{x_n(s^t)}{\xi}\right)^{1/\theta} - (1-\alpha)x_n(s^t)F(s^t)\right] + \mathbb{E}\left[m(s^{t+1})\sum_{\tilde{k}=0}^{n}\mathbb{B}(\tilde{k}, n, \Delta(s^t))\sum_{k=0}^{n}\mathbb{B}(k, n, x_n(s^t))V_{n-\tilde{k}+k}(s^{t+1})\Big|s_t\right], \tag{12}$$

where $\pi(s^t)$ denotes per-product profits, $w(s^t)$ the wage, and $m(s^{t+1})$ the household's stochastic discount factor.

Because firms are atomistic, the two binomial processes (expansion and destruction) are independent, and the transitions over firm size are separable. A firm with n products can thus transition within one period to any size in $[0, 2n]$.[9]

We also allow for a depreciation rate δ of each product line's technology, capturing gradual efficiency losses or evolving consumer preferences. Depreciation affects all producers symmetrically within a variety and thus does not alter the relative technology gap between leaders and followers.

3.6 Entry of New Firms

Firm entry is modeled analogously to incumbent innovation. Let $M(s^t) \in [0, 1]$ denote the aggregate entrepreneurial effort directed toward starting new businesses. Entrepreneurs invest $\kappa M(s^t)$ units of labor, and successfully create a new single-product firm in the next period with probability $M(s^t)^\nu$.

As with incumbent innovation, entry entails a fixed cost $F(s^t)$, which scales with the economy's size. Entrepreneurs choose $M(s^t)$ to maximize expected net returns:

$$\max_{M(s^t)} \left(M(s^t)\right)^\nu \mathbb{E}\left[m(s^{t+1})V_1(s^{t+1})\Big|s_t\right] - \alpha\kappa M(s^t)w(s^t) - (1-\alpha)\left(M(s^t)\right)^\nu F(s^t), \tag{13}$$

where $V_1(s^{t+1})$ is the expected value of operating a single product line next period.

The optimal solution $M^*(s^t)$ determines the endogenous entry rate of new firms in the economy. Together with incumbent innovation, firm entry shapes the creative destruction rate and thus the economy's long-run growth dynamics.

[9] See Appendix D for a detailed derivation of the firm size distribution dynamics.

3.7 Equilibrium Characterization

The parsimony of the model enables a clear mapping between interest rate volatility, firm innovation, and the endogenous evolution of productivity.

Household Discounting. The stochastic discount factor of the household, reflecting both consumption growth and financial frictions, is:

$$m(s^t, s_{t+1}) = \beta \frac{C(s^{t+1})^{-\gamma}}{C(s^t)^{-\gamma} - \phi\mu(s^t)}, \tag{14}$$

where $\mu(s^t)$ is the Lagrange multiplier on the collateral constraint (3). Consumption depends not only on current income but also on access to borrowing, which is endogenously determined by the value of firm collateral.

Intermediate Good Production. Intermediate good producers face a unit-elastic demand curve:

$$y_i(s^t) = \frac{Y(s^t)}{\Lambda p_i(s^t)}, \tag{15}$$

where $p_i(s^t)$ is the price of variety i. Under Bertrand monopolistic competition, per-product profits and labor demand become independent of the variety-specific productivity $q_i(s^t)$. Specifically:

$$\pi(s^t) = \frac{\sigma}{1+\sigma} \frac{Y(s^t)}{\Lambda}, \tag{16}$$

$$l(s^t) = \frac{Y(s^t)}{\Lambda w(s^t)(1+\sigma)}. \tag{17}$$

Because firm-level decisions are independent of individual q_i, the value function is proportional to the number of products: $V_n(s^t) = nV_1(s^t)$.

Firm Value and Innovation. Given proportionality, the value of controlling a single product line satisfies:

$$V_1(s^t) = \max_{x(s^t)} \left\{ \pi(s^t) - w(s^t)\alpha \left(\frac{x(s^t)}{\xi} \right)^{1/\theta} - (1-\alpha)x(s^t)F(s^t) + \mathbb{E}\left[m(s^{t+1}) \left(1 - \Delta(s^t) + x(s^t)\right) V_1(s^{t+1}) \middle| s_t \right] \right\}, \tag{18}$$

where $\Delta(s^t)$ is the economy-wide creative destruction rate.

The optimal incumbent innovation effort per product line is:

$$x^*(s^t) = \left[\frac{\theta}{\alpha} \xi^{1/\theta} \frac{\mathbb{E}\left[m(s^{t+1}) V_1(s^{t+1}) - (1-\alpha) F(s^t) \middle| s_t \right]}{w(s^t)} \right]^{\theta/(1-\theta)}. \tag{19}$$

Similarly, the mass of new entrant firms is determined by:

$$M^*(s^t) = \left[\frac{\nu}{\alpha\kappa} \frac{\mathbb{E}\left[m(s^{t+1}) V_1(s^{t+1}) - (1-\alpha) F(s^t) \middle| s_t \right]}{w(s^t)} \right]^{1/(1-\nu)}. \tag{20}$$

In equilibrium, incumbent innovation and entry jointly pin down the creative destruction rate, and changes in the stochastic discount factor and in the normalized value of future firm profits propagate into $\Delta(s^t)$ through (19) and (20).

Productivity Growth. The aggregate creative destruction rate combines entry and incumbent innovation:

$$\Delta(s^t) = \frac{(M^*(s^t))^\nu}{\Lambda} + x^*(s^t). \tag{21}$$

Substituting into the production function, aggregate output evolves according to:

$$Y(s^t) = e^{z(s^t)} A(s^t) l(s^t), \tag{22}$$

where $A(s^t)$ is the endogenous productivity index:

$$\ln A(s^t) = \frac{1}{\Lambda} \int_0^\Lambda \ln q_i(s^t)\, di. \tag{23}$$

The law of motion for productivity satisfies:

$$\ln(A(s^t, s^{t+1})) - \ln(A(s^t)) = \Delta(s^t) \ln(1+\sigma) + \ln(1-\delta), \tag{24}$$

where δ captures technological depreciation. Productivity growth can be negative if creative de-

struction is insufficient to offset depreciation. The endogenous productivity index $A(s^t)$ corresponds to the common stochastic trend estimated in Section 2: changes in $A(s^t)$ map into permanent changes in the level of GDP, consumption, and investment.

Labor Market and Wage Determination. Combining (22) and (17), the equilibrium wage satisfies:

$$w(s^t) = \frac{e^{z(s^t)} A(s^t)}{\Lambda(1+\sigma)}. \tag{25}$$

Household Optimality Conditions. The household's first-order conditions are:

$$C(s^t)^{-\gamma} = \mu(s^t) + \beta \hat{R}(s^t) \mathbb{E}\left[C(s^{t+1})^{-\gamma} \middle| s^t \right], \tag{26}$$

$$C(s^t) + \hat{q}(s^t) B^H(s^t) \leq w(s^t)\bar{L} + B^H(s^{t-1}) + \Lambda e(s^t) - \kappa\alpha M(s^t) w(s^t) - (1-\alpha)(M(s^t))^{\nu} F(s^t), \tag{27}$$

where $\hat{R}(s^t) = 1/\hat{q}(s^t)$ and $e(s^t)$ captures firm net earnings per product, derived from (18). The collateral constraint remains:

$$\hat{q}(s^t) B^H(s^t) \geq -\phi \Lambda V_1(s^t), \tag{28}$$

where $V(s^t) = \Lambda V_1(s^t)$ is the total collateral value.

Stationarity and Solution. Appendix E renders the model stationary by normalizing growing variables by the productivity index $A(s^t)$ and summarizes the full system of stochastic equilibrium conditions.

3.8 Trend Dynamics and Interest Rates

Equation (24) shows that stationary distortions affecting the endogenous creative destruction rate $\Delta(s^t)$ can trigger permanent shifts in the level of the productivity index $A(s^t)$, defined in (23). Since $A(s^t)$ governs the long-run growth rate of the economy, any fluctuations in $\Delta(s^t)$ generate hysteresis in output and consumption. In this class of models, stationary shocks can thus produce non-stationary trend dynamics through internal propagation.

Understanding the drivers of these endogenous trends requires analyzing how aggregate shocks affect the determinants of creative destruction—namely, firm entry and incumbent innovation decisions, characterized by (19) and (20). Two key endogenous objects mediate this transmission: (i) the stochastic discount factor of the household, and (ii) the relative expected future value of a product normalized by the current wage.

Effects of TFP Shocks. Consider first a total factor productivity (TFP) shock. Because TFP shocks are highly persistent, they have only a modest effect on the household's stochastic discount factor. Consequently, they typically exert limited influence on innovation through discounting channels.

Regarding the second margin, equation (25) shows that a positive TFP shock increases wages, raising the denominator of the normalized value of future firm profits. However, as equation (18) highlights, both firm profits and productivity-enhancing investment costs also rise with TFP. Given the persistence of TFP shocks, the ratio of future expected profits to current wages remains relatively stable in states where the collateral constraint is slack. Thus, in normal times TFP shocks are not a promising source of endogenous trend fluctuations in this model. When a sufficiently adverse TFP realization pushes the economy into the constrained region, however, the Fisherian deflation channel becomes operative: falling asset values tighten the borrowing constraint, raise the marginal utility of wealth, and depress firm values, thereby dampening innovation and reducing trend growth. In this case TFP shocks can have persistent effects on the trend, but only insofar as they trigger binding financial constraints.

Effects of Interest Rate Shocks. By contrast, interest rate shocks directly affect the household's stochastic discount factor without significantly impacting firm profits or the cost of productivity-enhancing investment.[10] Specifically, an increase in financing costs reduces the term $\frac{C(s^{t+1})^{-\gamma}}{C(s^t)^{-\gamma}-\mu(s^t)}$ in the Euler equation (26), implying that firms discount future profits more heavily. As a result, innovation effort by incumbents and entrants falls (as implied by (19) and (20)), reducing the creative destruction rate $\Delta(s^t)$ and slowing productivity growth. These shocks to the world interest rate process correspond to the orthogonalized global risk innovations we estimate in Section 2:

[10] We abstract from working capital constraints, which would otherwise induce some direct effect of interest rates on wages and firm values. With working capital frictions, interest rate shocks would affect wages similarly to TFP shocks, diminishing their role in generating trend dynamics.

they change the cost of external funds without directly altering domestic technology or preferences. Thus, interest rate shocks constitute a primary driver of endogenous trend dynamics in the model.

Collateral Constraints and Amplification. Both TFP and interest rate shocks can further influence trend growth through collateral constraints. When the borrowing constraint (28) binds, households are forced to delever, lowering current consumption and raising the discount rate applied to future returns. This spiral reduces firm values, tightens borrowing conditions further, and can trigger a Fisherian deflationary spiral. Accordingly, while interest rate shocks are the main force shaping trend dynamics, large TFP shocks that elevate financial stress can also have permanent effects via collateral channels.

The Role of Volatility Shocks. Finally, even absent realized interest rate shocks, volatility shocks matter. Consider an economy where the borrowing constraint is slack. An increase in interest rate volatility raises the expected magnitude of future interest rate fluctuations. Due to the asymmetric nature of the borrowing constraint, large upward rate shocks (tightenings) reduce firm collateral values more severely than downward shocks (easings) expand them.

Specifically, interest rate hikes reduce the value of firm collateral and may trigger a binding constraint, whereas interest rate cuts provide only limited relief. As a result, volatility alone, by skewing expected outcomes, reduces expected firm values and depresses innovation incentives today. This asymmetry arises because the borrowing constraint binds more frequently in bad states than it is slack in good states. Even holding the average world interest rate fixed, higher volatility raises the probability of constraint binding, lowers expected firm values, and depresses innovation incentives, with stronger effects in economies where constraints bind more often. Second-moment shocks to financial conditions can therefore endogenously slow trend productivity growth, even without contemporaneous changes in average funding costs.

4 Quantitative Analysis

In this section, we demonstrate that the model replicates the differential sensitivity of the productivity trend to interest rate volatility between emerging and advanced economies. First, we cali-

brate the model to Mexico (an emerging economy). Then, by adjusting a few parameters from the Mexican calibration, we construct a second calibration that captures a financially more advanced economy. Importantly, all shock processes are common to both economies, with the only calibration difference being the level of financial frictions. Next, using generalized impulse response functions, we show that, consistent with the analysis in Section 2, the response of the productivity trend to interest rate risk in emerging markets is substantially larger than that in advanced economies. Third, we identify asymmetries in firms' value responses and in the endogenous trend to large interest rate shocks of the same absolute magnitude as the key driver of this differential response. Finally, we establish that the difference in asymmetry between emerging and advanced economies stems from their differing levels of financial development. As a result, the same aggregate interest rate risk can propagate very differently, particularly when international investors exhibit higher risk aversion towards emerging markets and the capacity to collateralize future cash flows is more constrained.

4.1 Calibration: Heterogeneous Financial Frictions

We calibrate our model to match features of Mexico, at a quarterly frequency. The model has 21 parameters to calibrate. We divide these parameters into two groups. The first set of 11 parameters is externally calibrated to common values in the literature or directly estimated from the data. Table 1 shows the externally calibrated values. First, we estimate the process of the U.S. interest rate, as described in Appendix A.1. We set the average interest rate at 4% annually (Mendoza, 1991), which is equivalent to roughly 1% every quarter. We set the parameters for the aggregate efficiency process ρ_z and η_z following Neumeyer and Perri (2005).

We set the innovation curvature of incumbents and entrants equal to 0.5, a value standard in the endogenous growth literature (Akcigit and Kerr, 2018). We assume a CRRA utility function with a curvature of $\gamma = 2$, which is standard in calibrations of Sudden Stop models. The last externally calibrated parameter is the depreciation of ideas, which is set to be equal to 1.5% every quarter. From a growth perspective, this value implies a lower bound for productivity growth of -1.5% per quarter. That is, without any investment in the creation of new firms and expansion by incumbents, the efficiency index would shrink at rate δ. This value is roughly consistent with our bottom 1% trend growth estimates for a panel of emerging economies.

Table 1: Externally Calibrated Parameters

Parameter	Symbol	Value	Source
Average U.S. Interest Rate	$\bar{R}$	$(1.04)^{0.25} - 1$	Mendoza (1991)
Persistence of Interest Rate	ρ_R	0.91	Estimation, U.S. data
Average Interest Rate Volatility	μ_σ	0.17	Estimation, U.S. data
Persistence of Interest Rate Volatility	ρ_σ	0.94	Estimation, U.S. data
Volatility of Interest Rate Volatility	η_σ	0.12	Estimation, U.S. data
Persistence of TFP Shock	ρ_z	0.95	Neumeyer and Perri (2005)
Volatility of TFP Shock	η_z	0.02	Neumeyer and Perri (2005)
Innovation Curvature Cost by Incumbents	θ	0.50	Akcigit and Kerr (2018)
Innovation Curvature Cost by Entrants	υ	0.50	Akcigit and Kerr (2018)
Utility Function Curvature	γ	2	Standard
Depreciation of Ideas	δ	0.015	Estimation, lower tail of trend growth

Notes: This table reports externally calibrated parameters, their symbols, numerical values, and data or literature sources. Interest rate and volatility parameters are estimated using U.S. data as described in Appendix A.1.

Table 2 presents a summary of our 10 internally calibrated parameters. The step size σ is set to 0.22, which implies an average annualized growth rate close to 2%, consistent with Neumeyer and Perri (2005). We set the cost level of entry κ to 31, which generates an annualized 10% entry rate, consistent with Mexican empirical evidence.[11] The R&D cost level ξ is set to 0.49 so that the average incumbent firm size relative to entrants is 3. Regarding the fixed cost structure of innovation, we set $\alpha = 0.8$ so that total labor R&D costs account for two-thirds of total R&D costs (Moris and Shackelford, 2020), and $F = 0.21$ so that total R&D expenses relative to firm value amount to 5%, where $F = F(s^t)/A(s^t)$. The mass of products Λ is normalized to 3, ensuring a unit mass of firms in the balanced growth path. We set the discount factor β to 0.98, generating an implied net-foreign-assets-to-GDP ratio close to 33% annually, in line with the long-run average for Mexico presented in Lane and Milesi-Ferretti (2017). We calibrate the collateral coefficient of the borrowing constraint ϕ to 0.62, so that the model produces an annual probability of a crisis close to 3%, consistent with the Sudden Stops literature.[12] We set ι_0, the parameter governing the average spread charged by the representative financial intermediary, to 0.01, to match a 1% quarterly spread in line with Mexico's average EMBI spread between 1994 and 2019. Lastly, we set ι_1 to 14.58 in order to generate a spread sensitivity that is consistent with the hike in the Mexican

[11] According to Mexico's National Institute of Statistics and Geography (INEGI), the annualized entry rate is close to 9% between 2019 and 2021. Because the pandemic had a negative effect on firm creation, we opt for a more conservative entry rate (10%). For more details see https://www.inegi.org.mx/temas/dn/#informacion_general.

[12] We define a crisis or a Sudden Stop as an event where the current account-to-GDP ratio is two standard deviations above its long-run mean and where the borrowing constraint binds. This definition is standard and widely used in the literature (Mendoza, 2010; Bianchi et al., 2016).

EMBI spread during the Great Recession.[13]

Due to the nonlinear nature of a model featuring occasionally binding constraints, we rely on global methods to solve it. We employ a hybrid method that combines time iteration with value function iteration. Appendix F provides a detailed description of the solution method.

Table 2: Internally Calibrated Parameters

Parameter	Symbol	Value	Main Identification	Target
Step Size	σ	0.22	Annual Growth Rate	2%
Cost Level Entry	κ	31	Annual Entry Rate	10%
Cost Level R&D	ξ	0.49	Avg. Firm Size Relative to Entrants	3
Variable Cost Share R&D	α	0.80	R&D Wage Bill to Total R&D Costs	2/3
Fixed Cost R&D	F	0.21	Total R&D Costs to Firm Value	5%
Mass of Products	Λ	3	Unit Mass of Firms	N/A
Discount Factor	β	0.98	Annual Debt-to-GDP Ratio	33%
Borrowing Constraint	ϕ	0.62	Annual Prob. of Crisis	3%
Financial Intermediary Average Price	ι_0	0.01	Average Spread	1%
Financial Intermediary Price Sensitivity	ι_1	14.58	Spread Sensitivity	$\frac{\text{Spread}_{09Q1}-\text{Spread}_{08Q1}}{\sigma_{09Q1}-\bar{\sigma}}$

Notes: This table reports internally calibrated parameters, their symbols, values, main identification roles, and calibration targets. All parameters are calibrated using the Mexico (emerging economy) benchmark; the advanced economy calibration changes only ϕ, ι_0, and ι_1 while keeping all other parameters fixed.

To highlight the importance of heterogeneous financial frictions, we recalibrate only three parameters from Table 2. Our goal is to study the implications of interest rate volatility on growth in an advanced economy.

We recalibrate the parameters governing the pricing rule of international lenders (ι_0 and ι_1) and jointly recalibrate the pledgeability of firms' values (ϕ). We set $\phi = 0.92$ so that the economy experiences a financial crisis with a 1% probability, consistent with targets used for developed economies (Bianchi and Mendoza, 2020). We set $\iota_0 = 0.002$ and $\iota_1 = 2.16$ so that the average quarterly spread is 0.25% and the spread sensitivity to U.S. interest rate volatility is consistent with what was observed for spreads of a panel of advanced economies during the Great Recession.[14] All other parameters in Tables 1 and 2 are held fixed across the two calibrations; only ϕ, ι_0, and ι_1

[13] Mexico's annual EMBI spread increased by 2.5 percentage points between 2008Q1 and 2009Q1. The associated spike in U.S. real interest rate volatility (relative to its trend) was close to 20%. We map this increase to our stochastic volatility grid. In this way, we set $\iota_1 = \frac{\Delta \text{Spread}}{\Delta \sigma} \approx \frac{0.006}{0.0004}$.

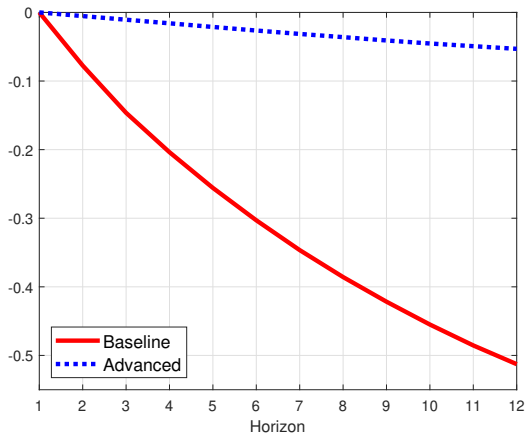
[14] To set ι_1 we calculate the change in the five-year mean CDS spreads (relative to the United States) between 2008 and 2009 for a group of advanced economies. We follow a process identical to the one described for our baseline calibration. Our sample includes Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom. Our data were obtained from Markit.

differ between the emerging and advanced economies.

4.2 Model Meets Data: Stochastic Volatility and Endogenous Trend Dynamics

We use the main empirical fact described in Section 2 to validate the calibrated model. In particular, we compute generalized impulse response functions from model-simulated data, following the approach of Gilchrist et al. (2014), where the shock is a one standard deviation increase in the volatility of the world interest rate (the model-equivalent of the U.S. real interest rate). We estimate the responses of the accumulated trend by simulating two economies: one that experiences a volatility shock in period T and one that does not, and calculating the difference between the two time series. We simulate this exercise 10,000 times for 390 periods in each case, discarding the first 350 periods to eliminate any dependence on initial conditions. We perform this exercise with data simulated for both calibrations, using the same underlying sequence of shocks. Figure 4 presents the impulse response functions of the trend component to a one standard deviation stochastic volatility shock computed using model-simulated data.

Figure 4: Trend Growth Rate Impulse Response Functions to a World Interest Rate Volatility Shock



Notes: This figure presents impulse response functions of the accumulated productivity trend to a one standard deviation stochastic volatility shock of the world interest rate, for the baseline (red solid line) and advanced (blue dotted line) model calibrations. Responses are computed from model-simulated data using the generalized impulse response procedure described in Section 4.2.

The responses in Figure 4 reveal two key patterns: (1) the trend component in the advanced economy (i.e., where the average spread is lower and the financial sector is more developed) experiences significantly less negative effects from a stochastic volatility shock than its emerging economy counterpart, and (2) the magnitude of the decline for the advanced economy calibration

is consistent with the empirical findings, while the decline for the baseline calibration is about 0.25 percentage points larger than its empirical counterpart, at a three-year horizon. Because these responses were not a target of our calibration, we view it as a success that our parsimonious model is able to explain the dynamics of trend growth in response to stochastic volatility shocks in U.S. interest rates.[15]

4.3 Risk Matters: Asymmetric Responses to Interest Rate Shocks

The results shown in Figure 4 indicate that volatility shocks have persistent effects on the economy's trend, with more pronounced impacts on emerging economies. The central question is to understand the mechanism linking financial risk and trend dynamics. By definition, periods of high interest rate volatility are characterized by greater fluctuations in interest rates. Conditional on an interest rate hike (or drop), the average magnitude of an interest rate increase (or decrease) is larger when volatility is higher.[16] In other words, during periods of high financial risk, interest rate shocks are, on average, larger but symmetric (i.e., hikes and drops are of equal absolute size). Interestingly, this symmetry in interest rate fluctuations does not necessarily result in symmetric responses in productivity growth within our framework. In fact, an interest rate hike may induce a much larger adjustment in the trend growth rate than an interest rate cut of the same absolute magnitude.

Financial frictions are crucial to explaining the asymmetric response of the economy to large interest rate shocks. When the collateral constraint binds, an interest rate hike triggers additional household deleveraging, which reduces present consumption, increases the discounting of future values, and ultimately decreases both the trend growth rate and the value of all product lines. Our model incorporates a Fisherian deflationary mechanism that amplifies this cycle: as the value of the product line declines, the collateral value of households' assets also diminishes. This further tightens the borrowing constraint, reinforcing the cycle and generating significant nonlinearities

[15] Given our pricing formulation described in Equation (7), a volatility shock has a level effect on the interest rate perceived by households in the economy. In Appendix C we quantitatively explore the role of a pure change in interest rate volatility. Our findings suggest that the role of volatility itself is roughly 30% of the total response.

[16] To clarify, the average hike conditional on $\sigma(s^t)$ is $\mathbb{E}[\omega(s^t)\sigma(s^t)|\omega(s^t) > 0, \sigma(s^t), s^t]$. We use the same notation as in Section 3. Since $\omega(s^t) \sim N(0,1)$, we apply the truncated normal formula for a conditional expectation and find that $\mathbb{E}[\omega(s^t)\sigma(s^t)|\omega(s^t) > 0, s^t] = \sigma(s^t)\frac{\phi(0)}{1-\Phi(0)}$. Conditional on an interest rate hike, the expected increase is positively correlated with interest rate volatility $\sigma(s^t)$. The same reasoning applies to interest rate cuts.

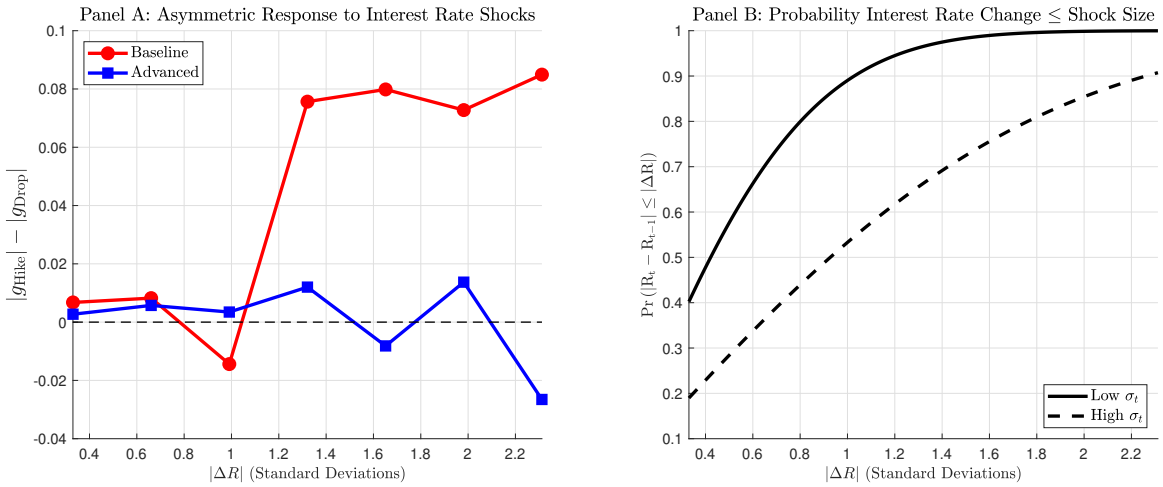
that contribute to the amplification. Conversely, when households experience an interest rate cut, the amplification mechanism is much weaker, as the multiplier is bounded below by zero. Thus, a more volatile interest rate environment foreshadows a persistent period of large interest rate swings. Due to the asymmetric effects of these swings, the expected value of a firm declines when volatility rises, even in the absence of a concurrent interest rate shock.[17] This decline in expected firm value explains the slowdown in innovation efforts by both incumbents and entrants.

To assess the effect of symmetric interest rate changes, we compute impulse response functions to U.S. real interest rate shocks using an approach similar to the one in Section 4.2. We vary the magnitude of shocks while maintaining their symmetry (i.e., equal absolute sizes for hikes and cuts). Each simulation consists of 390 periods (discarding the first 350 to eliminate dependence on initial conditions), repeated 5,000 times for each shock scenario. We then compute the average on-impact response for both the baseline and advanced economy calibrations at the moment the interest rate shock materializes, ensuring that both scenarios are subjected to the same underlying shock sequence.

Figure 5 summarizes these results. Panel A shows the standardized difference in the on-impact response of the endogenous trend growth rate to symmetric interest rate shocks under the two calibrations. Because we are interested in asymmetry, we plot the difference in absolute responses, that is, the absolute on-impact response to a rate increase minus the absolute on-impact response to a rate decrease. Interest rate shocks are expressed in standard deviations relative to the average level of interest rate volatility. Panel B reports, for each shock size, the probability that the absolute change in the interest rate exceeds that threshold, under two volatility regimes: a low-volatility environment (one standard deviation below the average) and a high-volatility environment (one standard deviation above the average). This provides a measure of how likely it is to observe a given shock under each volatility regime.

[17] Note that in a model without an occasionally binding constraint, the economy would benefit from dispersion in interest rate shocks. In fact, because the discount factor is concave with respect to the interest rate, by Jensen's inequality, interest rate hikes have lower absolute effects on the discount factor than interest rate drops of the same magnitude.

Figure 5: Asymmetry in Impulse Responses to Symmetric Interest Rate Shocks



Notes: The asymmetry in responses is presented as $|g^{\text{Hike}}| - |g^{\text{Cut}}|$, where g^{Hike} (g^{Cut}) corresponds to the on-impact response of the trend growth rate g (standardized with respect to its long-run mean and standard deviation) to an interest rate hike (cut). Interest rate shocks are expressed in standard deviations. Low (High) σ_t corresponds to interest rate volatility that is one standard deviation below (above) its long-run average.

Figure 5 reveals two key patterns. First, the asymmetry in the responses of the growth rate increases with the size of the interest rate shock: for smaller shocks, the responses to interest rate hikes and cuts are relatively symmetric, but this symmetry breaks down for larger shocks (e.g., above one standard deviation). Second, asymmetries are much more pronounced in the baseline calibration. We do not observe marked asymmetries for the advanced economy calibration; for very large shocks the asymmetry even goes in the opposite direction.

Panel B of Figure 5 shows that the region where such asymmetries are likely to arise is much larger when volatility is high. In particular, an increase in the real interest rate of at least one standard deviation occurs with about 10% probability in the low-volatility regime, but with almost 50% probability in the high-volatility regime.

Given these asymmetries, an increase in interest rate risk leads the representative household to anticipate that future interest rate shocks will, on average, be larger in absolute terms. For the emerging market case, this implies that future growth will be lower on average. As a result, the household adjusts its consumption and savings behavior in the present, leading to an immediate decline in the endogenous productivity trend, even in the absence of a first-moment shock.

To further investigate the role of volatility shocks in shaping the dynamics of emerging and advanced economies, we conduct an experiment in which we eliminate these shocks and set the

volatility of the world interest rate to its ergodic mean. This allows us to isolate the effects of volatility on long-run growth moments and assess the extent to which financial systems in both types of economies are affected. Table 3 presents selected long-run moments for our baseline and advanced economy calibrations across the two volatility regimes.

Table 3: Volatile Rates and Volatile Trends: Deterministic Volatility

Moment	Mexico		Advanced Mexico	
	SV	No SV	SV	No SV
$\sigma(g)/\mathbb{E}(g)$	0.18	0.13	0.11	0.12
$\sigma(CA/Y)$ %	3.08	2.92	1.11	0.91
$\mathbb{E}(B^H/Y)$ %	-32.49	-33.83	-54.05	-54.23
Spread %	1.00	1.00	0.25	0.25
Prob. Crisis %	2.68	3.23	1.61	1.60

Notes: SV denotes the scenario with stochastic volatility in the world interest rate. In the No SV case, the volatility process is shut down and the standard deviation of the world interest rate is fixed at its long-run (ergodic) mean. All moments are computed from long simulated samples under each regime.

For emerging economies, the results in Table 3 indicate a substantial reduction in the coefficient of variation of trend growth by approximately 30%, highlighting the significant role that volatility shocks play in driving fluctuations. In contrast, the advanced economy does not experience a meaningful change in the volatility of the growth rate, suggesting that volatility shocks have markedly different effects on long-term growth in emerging versus advanced economies.

Notably, in the absence of stochastic volatility, both economies benefit from more stable consumption paths, as evidenced by the decline in current account-to-GDP volatility. This outcome is not trivial, as the absence of volatility reduces the need for precautionary savings, incentivizing households to take on more debt. This effect is particularly pronounced in emerging economies, where households end up with higher debt levels and increased exposure to Sudden Stops—the probability of these events rises by nearly half of a percentage point.

Despite this more aggressive risk-taking behavior, emerging economies still experience net benefits from the removal of interest rate volatility, as indicated by the decline in current account dispersion. These findings suggest that the primary challenge for emerging economies is not only volatility itself but also their response to it. The next section studies in greater detail the role of financial factors in shaping the risk-taking behavior of economic agents.

4.4 Financial Risk and Financial Frictions

The previous section highlighted the asymmetric responses of trend growth to volatility shocks in global interest rates across different economies. These asymmetries primarily arise from the interaction between borrowing constraints and borrowing costs (i.e., higher spreads). In this section, we aim to disentangle the individual contributions of these two factors to the dynamics of trend growth.

We begin by constructing an alternative economy that serves as an intermediate case between the baseline calibration (which represents an emerging economy) and the advanced economy calibration. Specifically, we relax the borrowing constraint in the baseline economy by setting the collateral coefficient, ϕ, equal to that of the advanced economy while keeping all other parameters unchanged. We refer to this calibration as the "relaxed constraint" case. The key distinction between the baseline and relaxed constraint calibrations lies in the latter's increased collateral pledgeability, which aligns it with that of an advanced economy. This adjustment allows us to isolate the effects of the borrowing constraint on long-run economic outcomes. Any remaining differences between the long-run outcomes of the relaxed constraint and advanced economy scenarios can then be attributed to the impact of higher spreads.

Table 4 presents selected long-run moments for the three economies. Relaxing the borrowing constraint leads to significant changes in long-run economic dynamics. Growth volatility, measured by the coefficient of variation, declines by approximately 22%, while the volatility of the current account relative to GDP falls by nearly 50%. While standard small open economy models typically assume a negative correlation between domestic spreads and productivity growth (Neumeyer and Perri, 2005), our model endogenously generates this correlation for emerging markets.[18]

When analyzing the relative contributions of international risk aversion (ι_0 and ι_1) and differences in pledgeability (ϕ), we find that relaxing the borrowing constraint accounts for a large share (roughly 60 percent) of the difference in the coefficient of variation of endogenous trend growth between emerging and advanced economies. While emerging markets exhibit cycles consistent with low-frequency fluctuations (Aguiar and Gopinath, 2007), our findings demonstrate

[18] We define the domestic spread as the difference between the domestic interest rate and the rate charged by intermediaries: $\mathbb{E}\left[R^B(s^{t+1}) - \hat{R}(s^t)\right] = \mu(s^t)/\mathbb{E}[\lambda(s^{t+1})|s^t]$.

that stationary shocks, when combined with financial frictions, can also generate these dynamics (Garcia-Cicco et al., 2010). Moreover, our framework provides a financial microfoundation for why returns remain highly risky in emerging economies, even under a common global risk factor (Gerding et al., 2014).

Table 4: Financial Frictions and Business Cycles

Moment	Mexico	Relaxed Constraint Mexico	Advanced Mexico
$\mathbb{E}(\text{Spread})$ %	1.00	1.00	0.25
$\sigma(g)/\mathbb{E}(g)$	0.18	0.14	0.11
$\sigma(CA/Y)$ %	3.08	1.49	1.11
$corr(\text{Domestic Spread}, g)$	-0.54	0.49	0.49
Prob. Crisis %	2.68	1.50	1.61
$\mathbb{E}(B^H/Y)$ %	-32.49	-52.80	-54.05

Notes: This table reports long-run simulated moments for three calibrations: the baseline (Mexico), the relaxed constraint economy (same as Mexico except for ϕ set to its advanced-economy value), and the advanced economy (Mexico with higher pledgeability and lower, less volatility-sensitive spreads). All moments are computed under stochastic volatility in the world interest rate.

A key feature of our model, which is closely tied to financial frictions, is the occurrence of Sudden Stops. These episodes involve sharp reversals in the current account together with severe contractions in consumption and output. These events emerge due to occasionally binding collateral constraints and endogenous collateral values, which activate a Fisherian deflation mechanism during periods of financial stress (Mendoza, 2005; Mendoza, 2010). Unlike standard business cycle fluctuations with exogenous growth, Sudden Stops in our model feature persistent effects on productivity and output. Appendix G presents event studies of Sudden Stops for our emerging economy calibration. Our results highlight the persistent effects of Sudden Stops on the trend and economic activity, as well as providing a rationale for slow recoveries following this type of event. This persistence aligns with findings from other models that integrate financial frictions into growth dynamics (Queralto, 2020; Guerron-Quintana and Jinnai, 2019; Benguria et al., 2022) and with the hysteresis documented in the empirical literature (Cerra and Saxena, 2008).

4.5 Volatile Rates and Fragile Growth

The calibrated model demonstrates that shocks to global interest rates can have markedly different effects on emerging and advanced economies. To illustrate the economic magnitude of these differences, we use the actual path of the U.S. real interest rate and its volatility (see Figure 9 in

Appendix A.1). Specifically, we simulate 10,000 series from the TFP process. We then feed each TFP sequence, combined with the actual observed path of global volatility and interest rates, into the three economies analyzed in this section. Since all economies face the same sequence of shocks, the only variation across models arises from the internal propagation mechanisms unique to each economy.

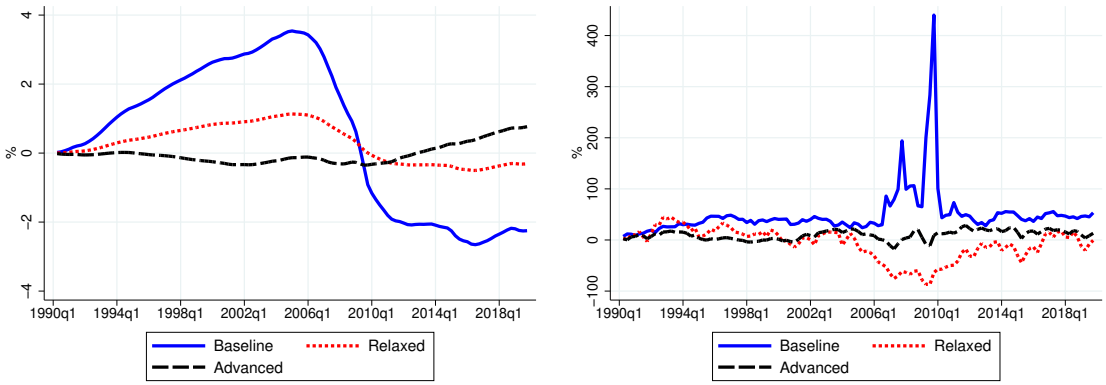
Figure 6 presents the average trend deviations for productivity levels and the Lagrange multiplier of the borrowing constraint across all economies.[19] The first panel illustrates that the average growth trajectories of the three types of economies differ significantly. The period of low volatility and declining interest rates between 1990 and 2006 spurred rapid productivity accumulation in emerging markets, whereas advanced economies benefited much less from reduced global risk. By 2006, emerging market productivity had risen 4% above its trend, while advanced economies exhibited negligible productivity gains. The intermediate economy (Relaxed), which features a relaxed collateral constraint compared to emerging markets, highlights the crucial role of financial frictions in explaining the differences between emerging and advanced economies. However, the end of the low-volatility regime in 2006 triggered substantial productivity losses for emerging markets. All accumulated gains were erased, and by 2018, the average emerging market economy had fallen nearly 2% below its productivity trend.

The second panel of Figure 6 underscores the role of the occasionally binding borrowing constraint. The sharp decline in accumulated productivity observed in 2006 for the average emerging market coincides with an unprecedented increase in the multiplier. Specifically, adverse volatility and interest rate shocks led to a severe deleveraging cycle in emerging markets, significantly hindering productivity growth. Economies that could collateralize a larger share of their income experienced considerably less economic distress. Interestingly, as shown in Appendix H, the multiplier remains predominantly positive for the advanced and relaxed economies, whereas emerging markets strive to avoid hitting the constraint. The Fisherian deflation effect is so strong in emerging markets that precautionary motives keep them far from the constraint under normal conditions. As a result, during low-risk periods, they are able to borrow substantially more,

[19] We construct these series by computing the log difference between the stochastic trend $A_t = \prod_{i=0}^{t}(1+g_i)$ and its deterministic equivalent $\bar{A}_t = (1+\bar{g})^t$, where $\bar{g}$ represents the ergodic mean of the trend growth rate. For the Lagrange multiplier, we compute percentage differences rather than log differences to avoid issues in cases where the multiplier is zero, where $\mu_t = A_t^{-\gamma}\tilde{\mu}_t$ and $\bar{\mu}_t = \bar{A}_t^{-\gamma}\bar{\tilde{\mu}}$.

whereas advanced economies operate with a marginally binding constraint. When international risk rises, the combination of interest rate and TFP shocks can trigger deep financial crises in emerging markets, necessitating aggressive deleveraging. In contrast, advanced economies respond with a moderate increase in precautionary savings, allowing them to maintain some slack in their constraints and better prepare for riskier periods.

Figure 6: Deviations from Trend Based on Actual Interest Rate and Volatility Time Series



(a) $\ln A_t - \ln \bar{A}_t$ (b) $\frac{\mu_t - \bar{\mu}_t}{\bar{\mu}_t}$

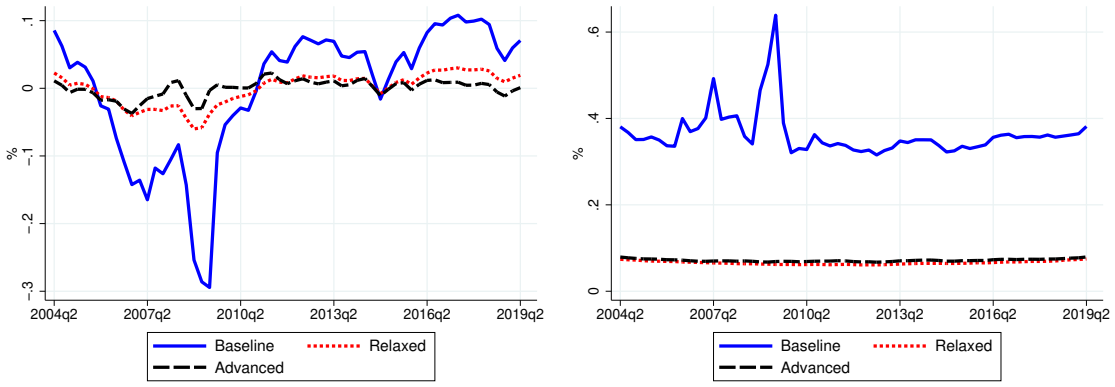
Notes: This figure shows, for the three calibrations (Mexico, relaxed constraint, and advanced Mexico), the average deviation of productivity and of the Lagrange multiplier from their deterministic trends when all economies are subjected to the same path of U.S. real interest rates and volatility. Panel (a) reports $\ln A_t - \ln \bar{A}_t$; panel (b) reports percentage deviations of the multiplier from its deterministic counterpart. Averages are taken across 10,000 simulated TFP paths.

To further explore the interaction between global financial risk and idiosyncratic shocks, Figure 7 depicts the average growth rate and the cross-sectional dispersion of the growth rate for all three types of economies across the 10,000 simulations. We construct these series following the same approach described in Section 2.5 and consider the same time window as in the empirical analysis.

The first panel of Figure 7 is consistent with our empirical analysis presented in Figure 3, showing that endogenous productivity growth is substantially more volatile for emerging economies. The model performs reasonably well in explaining the dynamics of the average trend growth rate of an emerging economy. The second panel presents the dispersion of the growth rate, and suggests that even during high-growth periods, emerging markets exhibit less co-movement than advanced economies. This divergence becomes even more pronounced during periods of heightened volatility. As shown in Section 2.5, our empirical estimates of country-level productivity

trends align with these observed patterns.

Figure 7: Average and Dispersion of Trend Growth



(a) Growth Rate g – Average

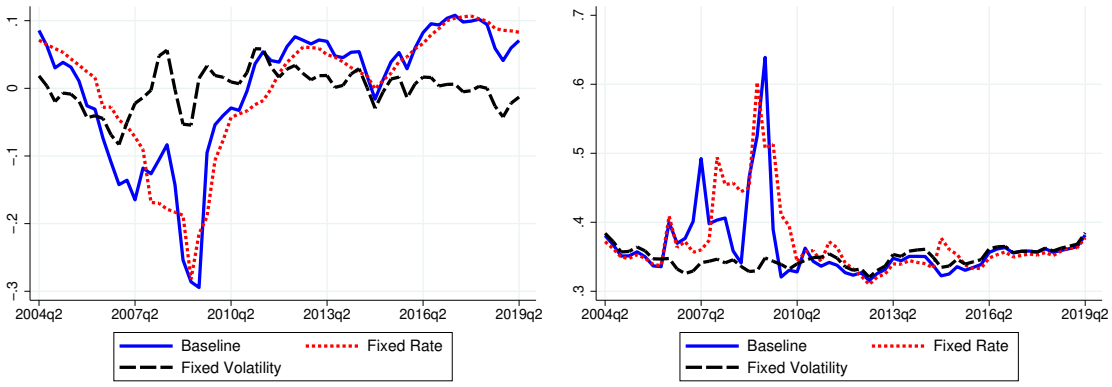
(b) Growth Rate g – Standard Deviation

Notes: For each quarter in the sample window, we compute the cross-sectional average and standard deviation of the trend growth rate g across simulated economies, using the same sample window and construction as in Section 2.5. Panel (a) reports the cross-sectional average; panel (b) reports the cross-sectional standard deviation, for Mexico, relaxed constraint Mexico, and advanced Mexico.

Finally, Figure 8 decomposes the dynamics presented in Figure 7 for the baseline emerging market calibration by setting either the interest rate shocks or their volatility to their mean. The decomposition reveals that global financial risk, rather than actual interest rate shocks, is the primary driver of productivity dynamics in emerging markets. Specifically, when interest rate volatility is held constant at its mean, the average emerging market does not experience a collapse in endogenous growth, and the dispersion across emerging markets disappears.

Thus, while Figure 7 highlights the importance of the collateral constraint in shaping both the average growth and the dispersion of productivity dynamics in emerging markets, Figure 8 demonstrates that the primary driver of these dynamics is aggregate risk. This underscores the crucial interaction between the collateral constraint and aggregate risk in explaining how the same idiosyncratic TFP shocks can generate entirely different dynamics in emerging versus advanced economies.

Figure 8: Average and Standard Deviation of Growth Rate g for Different Interest Rate Scenarios



(a) Growth Rate g – Average

(b) Growth Rate g – Standard Deviation

Notes: This figure reports, for the baseline (Mexico) calibration, the cross-sectional average and standard deviation of the trend growth rate g under three scenarios: (i) full model with stochastic interest rates and volatility, (ii) interest rate volatility fixed at its mean, and (iii) interest rate level fixed at its mean while volatility follows its stochastic process. Panel (a) shows the cross-sectional average; panel (b) shows the cross-sectional standard deviation. All constructions mirror those in Figure 7.

5 Conclusion

This paper provides new empirical and theoretical evidence linking global financial risk to productivity trends, particularly in emerging markets. We focus on uncertainty in U.S. interest rates, orthogonalized to the level of rates, U.S. activity, and credit spreads, as a core measure of global financial risk. On the empirical side, we show that a one standard deviation increase in interest rate volatility lowers the level of the productivity trend in emerging market economies by about 25 basis points after three years, with essentially no effect in advanced economies. On the theoretical side, a small open economy model with collateral constraints and endogenous innovation can account for this asymmetric response even when advanced and emerging economies are exposed to the same global shock process.

A key finding of our analysis is the asymmetric response of trend growth to interest rate fluctuations. Large interest rate hikes generate substantially sharper declines in trend productivity than cuts of the same absolute size increase it, and this asymmetry becomes more pronounced when financial risk is elevated. The mechanism operates through occasionally binding collateral constraints and a Fisherian deflation channel. Interest rate hikes compress firm values, tighten borrowing constraints, and trigger deleveraging, which raises the effective discount rate and re-

duces innovation and entry. Interest rate cuts relax constraints only weakly when they are already slack. These nonlinearities imply that higher volatility in world interest rates lowers the expected value of firms and slows trend productivity growth, even if the average level of interest rates is unchanged. In the quantitative model, advanced and emerging economies share the same preferences, technology, and shock processes; they differ only in the tightness of collateral constraints and the level and volatility sensitivity of spreads faced by borrowers.

Our quantitative results highlight the importance of these financial frictions. Removing stochastic volatility in world interest rates reduces the coefficient of variation of trend growth in the emerging market calibration by about 30 percent, while leaving the advanced economy almost unaffected. Decomposing the role of financial frictions shows that relaxing the collateral constraint alone accounts for a large share, roughly 60 percent, of the excess trend volatility observed in emerging markets, with the remaining difference explained by higher and more volatility-sensitive risk premia. The model also generates Sudden Stops with persistent effects on productivity and output, as financial crises trigger deleveraging cycles and Fisherian deflation that slow innovation and entry well beyond the initial shock.

Feeding the historical path of the U.S. real interest rate and its volatility into the calibrated model reveals the economic magnitude of these mechanisms. During the period of low volatility and falling rates before the mid 2000s, emerging economies accumulate sizable gains in trend productivity relative to advanced economies. When global financial risk rises, however, emerging markets experience a large and persistent reversal: the same shock sequence that advanced economies absorb with modest trend effects generates deep and long-lasting productivity shortfalls in financially constrained economies. The model also replicates the higher cross-sectional dispersion of trend growth observed in the data for emerging markets during high-risk periods, even though all countries face the same global shocks.

These findings underscore the central role of financial development in shaping the long-run consequences of global financial risk. If emerging markets and advanced economies are hit by the same volatility shocks, differences in collateral pledgeability and the behavior of risk premia determine whether volatility translates into persistent productivity losses or is absorbed without long-run damage. Stabilizing the average level of borrowing costs is therefore not sufficient. Reducing the sensitivity of spreads to volatility and expanding the set of collateralizable assets,

through stronger legal enforcement, deeper financial markets, and more robust institutions, is crucial for limiting the impact of risk on trend growth.

From a policy perspective, this suggests that standard tools for managing external shocks, such as reserve accumulation or exchange rate flexibility, address symptoms rather than the underlying source of fragility. Macroprudential policies and institutional reforms that strengthen balance sheets, broaden collateral frameworks, and dampen the volatility of domestic risk premia are essential for making growth less sensitive to global financial risk. Future work could embed such policy instruments into environments with heterogeneous sectors and firms, or richer cross-country heterogeneity, to study how specific regulatory and institutional changes alter the mapping from global risk to trend productivity.

Ultimately, volatility in global financial conditions is an unavoidable feature of the world economy. Our results show that the way this volatility interacts with domestic financial frictions determines whether it leaves temporary business cycle fluctuations or persistent scars on productivity and growth. Strengthening financial systems is therefore central to ensuring that periods of financial turbulence do not translate into long-run stagnation, especially for emerging markets.

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Appendices

Appendix A Empirical Appendix

In this section we provide additional details on the data construction and empirical methods underlying the results in Section 2. We describe how we measure U.S. interest rate uncertainty, outline the estimation of stochastic volatility in real interest rates, and report supporting evidence and robustness checks that validate our empirical implementation.

A.1 Data and Stochastic Volatility in U.S. Real Rates

For the United States, we utilize data on PCE inflation, and Treasury interest rates (3-month, 2-year, 5-year) from FRED. We construct a demeaned quarterly time series for the U.S. real interest rate, measured as the real 3-month T-bill rate, for the period of interest.[20] Following Fernández-Villaverde et al. (2011), we adjust nominal rates by the total change in the PCE index over the current and prior three quarters. We estimate the stochastic volatility of the U.S. real interest rate using the particle filter methodology described by Fernández-Villaverde et al. (2011). Specifically, we filter a sequence σ_t from the following model, estimated by maximum likelihood:

$$R_t - \bar{R} = \phi(R_{t-1} - \bar{R}) + \sigma_t^r \varepsilon_t^r, \tag{29}$$

$$\log \sigma_t^r = (1 - \rho_\sigma^r)\mu_\sigma^r + \rho_\sigma^r \log \sigma_{t-1}^r + \sigma_r \nu_t^r, \tag{30}$$

where $\bar{R}$ represents the sample mean of the real interest rate.

Table 5 presents our parameter estimates.[21] Both the interest rate and its hidden volatility state are highly persistent. Figure 9 displays the real interest rate and the smoothed path of the volatility state.[22] Notably, the hidden volatility state shows substantial variation over time. Volatility declines from 1985 to 2000, corresponding to the relative stability in real rates during this period. Afterward, volatility rises over the next decade, paralleling a persistent decline in the average

[20] Using the 2-year or 5-year interest rate instead does not significantly alter our core findings, as these series are highly correlated over the sample period.

[21] Standard errors are derived by bootstrapping.

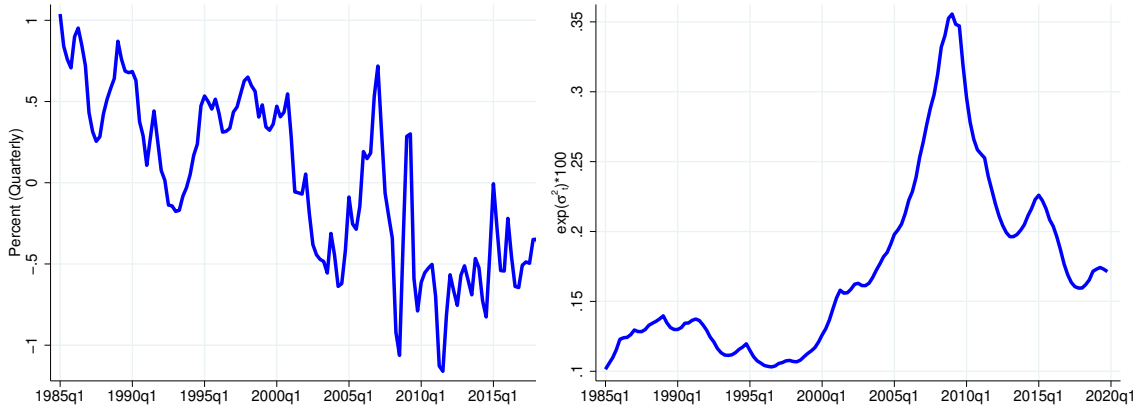
[22] Error bands are generated via Monte Carlo simulation of the smoothed path. The asymmetry in the bands reflects the asymmetry in confidence intervals for the persistence parameters among other things.

rate and significant fluctuations around this trend. Post-2010, real rates stabilize again, which is reflected in the stochastic volatility process.

Table 5: U.S. Interest Rate Model: Estimated Parameters

ϕ	ρ_σ^r	μ_σ^r	σ_r
0.9115	0.9387	−6.3516	0.1181
(0.88,0.93)	(0.88,0.95)	(−6.61,−6.09)	(0.02,0.20)

Figure 9: Estimated Series for U.S. Real Rates



(a) U.S. Real Interest Rate

(b) U.S. Real Interest Rate Stochastic Volatility

A.2 Time Series Models

Here we gather more details on the estimated time series models.

Our baseline specification is:

$$\begin{pmatrix} \Delta y_{j,t} \\ \Delta c_{j,t} \\ \Delta i_{j,t} \end{pmatrix} = \begin{pmatrix} \alpha_j \\ \alpha_j \\ \alpha_j \end{pmatrix} + A \cdot \left(\begin{pmatrix} \Delta y_{j,t-1} \\ \Delta c_{j,t-1} \\ \Delta i_{j,t-1} \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \hat{a}_{j,t-1} \right) + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \hat{a}_{j,t} + B \cdot Z_t^{US} + \Sigma_j \epsilon_{j,t}^m$$

$$\begin{aligned} \hat{a}_{j,t} &= a_{j,t} + \left(\sum_{s=0}^{n_\sigma} \eta_s \sigma_{t-s}^{MU} \right) \\ a_{j,t} &= \rho_a a_{j,t-1} + \sigma_{j,a} \epsilon_{j,t}^a. \end{aligned}$$

For most of our results we also impose $\eta_s = a \cdot \exp\left(-\frac{s-b}{c}\right)$. When we estimate the model, we impose that $\rho_a \in (-1, 1)$ and that Σ_j is diagonal. We assume that all innovations are drawn from a joint normal distribution and that shocks to the trend $(\epsilon^a_{j,t})$ are independent from $\epsilon^m_{j,t}$. To reduce the number of parameters to estimate in our baseline results we also set

$$B \cdot Z^{US}_t = B_1 \cdot (\Delta Y^{US}_t, \Delta Y^{US}_{t-1}, EBP_t, EBP_{t-1}) + \begin{pmatrix} b^y_2 \\ b^c_2 \\ b^i_2 \end{pmatrix} \left(\sum_{s=0}^{n^s_\sigma - 1} \eta^v_s \Delta \sigma^{MU}_{t-s} \right)$$

and impose the same parametric form as discussed above on the η^b_s. So, while we leave the response to US growth (ΔY^{US}_t) and the excess bond premium (EBP_t) unrestricted we impose some restrictions on the transitory effects of the uncertainty shock. Relaxing the latter by allowing B to be fully unrestricted leads to similar point estimates for the η_s but wider error bands.

To compute standard errors we repeat the estimation on model simulated data 1000 times and compute the percentiles of interest. In order to simulate the US variables in this process, we fit a VAR to the US time series.

In addition to using different time series proxies for uncertainty we also performed various variations of the main specification to assess robustness and found our main result survives. As already noted we allowed for different restrictions on B. We also dropped some or all of the US controls. We estimated the model both with and without the parametric restrictions on the η_s.

Finally, we separated the effect of the US variables on the trend from other, transitory effects, by estimating:

$$\begin{pmatrix} \Delta y_{j,t} \\ \Delta c_{j,t} \\ \Delta i_{j,t} \end{pmatrix} = \begin{pmatrix} \alpha_j \\ \alpha_j \\ \alpha_j \end{pmatrix} + A \cdot \left(\begin{pmatrix} \Delta y_{j,t-1} \\ \Delta c_{j,t-1} \\ \Delta i_{j,t-1} \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \hat{a}_{j,t-1} \right) + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \hat{a}_{j,t} + \tilde{B} \cdot \tilde{Z}^{US}_t + \Sigma_j \epsilon^m_{j,t}$$

$$\begin{aligned}\hat{a}_{j,t} &= a_{j,t} + \left(\sum_{s=0}^{n_\sigma} \eta_s \sigma_{t-s}^{MU}\right) + C \cdot (\Delta Y_t^{US}, EBP_t) \\ a_{j,t} &= \rho_a a_{j,t-1} + \sigma_{j,a} \epsilon_{j,t}^a.\end{aligned}$$

Here

$$\begin{aligned}\tilde{B} * Z_t^{US} &= \tilde{B}_1 * (\Delta Y_t^{US} - \Delta Y_{t-1}^{US}, \Delta Y_{t-1}^{US} - \Delta Y_{t-2}^{US}, EBP_t - EBP_{t-1}, EBP_{t-1} - EBP_{t-2}) \\ &+ \begin{pmatrix} b_2^y \\ b_2^c \\ b_2^i \end{pmatrix} \left(\sum_{s=0}^{n_\sigma^s - 1} \eta_s^v \Delta \sigma_{t-s}^{MU}\right).\end{aligned}$$

In this way we impose a separation between permanent and transitory effects of US variables. Results on the η_s are again robust. We use the smoothed estimate for $a_{j,t} + \left(\sum_{s=0}^{n_\sigma} \eta_s \sigma_{t-s}^{MU}\right) + C \cdot (\Delta Y_t^{US}, EBP_t)$ as our estimate of the country trend whenever we display them in the main text to allow more explicitly for other US effects on the trend.

Appendix B A Simple Model with a Financial Accelerator

In this appendix, we characterize a simple model following Gertler and Karadi (2011), Gertler and Kiyotaki (2015), and Akinci et al. (2022), where financial intermediaries in the economy face stochastic volatility in deposit rates. The rest of the features of the model are standard in this literature.

B.1 Model Setup

The optimization problem of an individual bank is

$$\begin{aligned}V_{i,t} &= \max_{L_{i,t}, D_{i,t}} \mathbb{E}_t \left[\Lambda_{t,t+1} \left((1-\sigma) N_{i,t+1} + \sigma V_{i,t+1}\right)\right] \\ \text{subject to} \quad & V_{i,t} \geq \theta L_{i,t} \\ & N_{i,t} = R_{t-1}^l L_{i,t-1} - R_{t-1}^d D_{i,t-1} \\ & N_{i,t} + D_{i,t} = L_{i,t}\end{aligned}$$

We assume that the loan demand is given by $L(R_t^l) = A - B \cdot R_t^l$. The bond interest rate follows the stochastic process:

$$\begin{aligned} R_t^d &= R^d + \rho_1(R_{t-1}^d - R^d) + \sigma_{t-1}\epsilon_t \\ \log \sigma_t &= \log \bar{\sigma} + \rho_2(\log \sigma_t - \log \bar{\sigma}) + \bar{\sigma}\eta_t. \end{aligned}$$

Lastly, $\Lambda_{t,t+1}$ is the relevant discount factor and $\Lambda_{t,t+1} = \frac{1}{R_t^d}$.

B.2 Quantitative Results

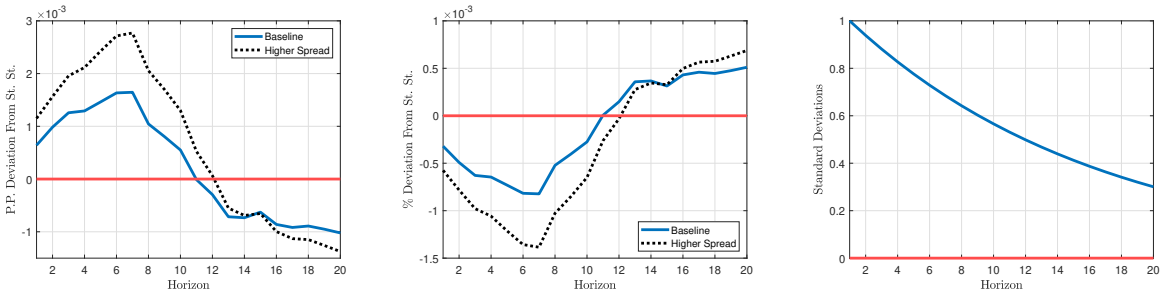
We calibrate the model to match features of the U.S. economy. Table 6 presents the externally calibrated parameters, along with their corresponding values and sources in the data. The parameters for the stochastic process of the real interest rate and volatility are the ones presented in Section A.1.

Table 6: Calibration Summary

Parameter	Symbol	Value	Source
Deposit Rate	R^d	1.005	US data
Demand Parameters	A, B	Internal	$L = 1$
Exit Probability	$1 - \sigma$	0.03	US data
Leverage Ratio	L/N	5	US data
Loan Rate	R^l	1.0075	US data

The rest of the parameters, Ω, ψ, ν, and θ, are set internally such that equilibrium conditions are satisfied. Figure 10 presents the impulse response functions of the model in response to a one standard deviation increase in interest rate volatility. Responses appear as percentage point deviations from their corresponding steady state values. We also add the responses of an alternative calibration (black dotted line). This calibration assumes that the average loan-deposit rate spread is higher than in the baseline scenario ($R^L = 1.0085$). This assumption is consistent with an economy that features a larger value of the parameter ι, which rules the average spread faced by agents in the economy.

Figure 10: Impulse Response Functions to a Stochastic Volatility Shock



Loan Interest Rate R^l | Loans L_t | Stochastic Volatility σ_t

The impulse response functions of the baseline case presented in Figure 10 show that an increase in interest rate volatility leads to an increase in the borrowing costs faced by agents in the economy, which ultimately leads to a decrease in borrowing. Interestingly, the exercise also shows that an economy that has a larger average loan-deposit spread is also more sensitive to a volatility shock: loan rates increases and lending declines are more pronounced relative to the baseline.

Appendix C Financial Intermediation, Risk Aversion and Volatility

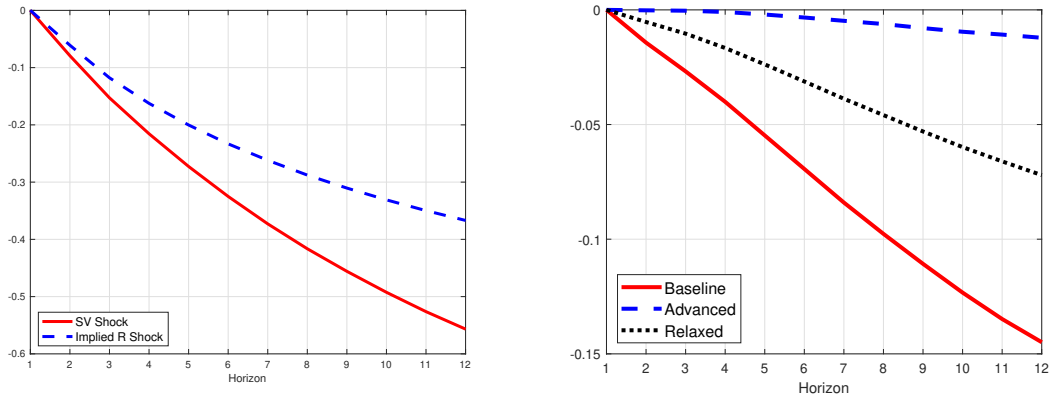
As seen in Equation (7), a change in the volatility state has a level effect on the interest rate, in addition to altering the dispersion of interest rate innovations. To separate these effects, we build a counterfactual in which the only shock corresponds to the level effect coming from ι_1 in Equation (7). In this setup, the only impact is a direct effect on the price of debt, fully isomorphic to a first-moment shock in interest rates. By comparing the impulse response to this shock with the baseline response to a volatility shock, we can decompose the effect into first- and second-moment components. Furthermore, we replicate this exercise for the three calibrations examined in the main text (baseline, advanced, and relaxed constraint economies).[23]

To generate the isomorphic interest rate, we proceed as follows. We begin by generating a cross-section of stochastic volatility shocks, as used in Section 4.2. For each of these sequences, we compute the implied interest rate that would produce the same observed movement in the price $\hat{q}(s^t)$. We then compute impulse responses to this implied interest rate shock. The first panel

[23] See Section 4 more details about the calibration or the economies studied.

of Figure 11 presents the cumulative trend responses to the full stochastic volatility shock and to the implied interest rate shock for the baseline model. The second panel shows the difference in responses between the baseline and the two counterfactual models, where in each case we calculate the model-specific implied R sequence. Because the second panel nets out the level effect, these differences can be interpreted as the pure second-moment effect on interest rates.

Figure 11: Cumulative Trend Responses, Stochastic Volatility and Interest Rate Shocks



(a) Cumulative Responses (b) Differential Responses (SV − Implied R)

Notes: Panel (a) presents the cumulative trend responses to a one standard deviation volatility shock for stochastic volatility shock and the implied interest rate shock (for the baseline calibration). Panel (b) presents the difference between the cumulative trend responses to the the stochastic volatility shock and the implied interest rate shock and for the baseline, advanced and relaxed constraint economies.

The results in the first panel of Figure 11 show that the pure volatility explains roughly 30% of the total response to a volatility shock. While the level effect varies across models with different ι_1, the pure second-moment effect can only differ due to the internal propagation mechanisms within each model. The second panel of Figure 11 confirms that the collateral constraint plays a key role in this propagation. Interestingly, there remains an important difference between the advanced and relaxed economies, which differ only in their average spread and in the first-moment channel of stochastic volatility. This difference arises from the fact that the relaxed economy features a different ergodic distribution and a distinct frequency and severity of Sudden Stops. Thus, more volatile rates can still trigger relatively asymmetric effects through the interaction of the two channels.

Appendix D Calculating the Firm Size Distribution

Because there is a continuum of products we can use the law of large numbers to track the distribution of firms. In particular, denote by $\Omega_n(s^t)$ the mass of firms with n products. The law of motion of this distribution is characterized by a system of dynamic equations that only depend on the innovation rate of incumbents and the mass of entrants:

$$\begin{aligned}
\Omega_1(s^t) &= \left(M^*(s^{t-1})\right)^v + \sum_{n=1}^{\infty} \Omega_n(s^{t-1}) \sum_{k=0}^{1} \mathbb{B}\left(k, n, x^*(s^{t-1})\right) \mathbb{B}\left((k+n-1, n, \Delta(s^{t-1})\right) \\
\Omega_{\tilde{n}>1}(s^t) &= \sum_{n=\mathbb{I}^+(\frac{\tilde{n}}{2})}^{\tilde{n}} \left\{ \Omega_n(s^{t-1}) \sum_{k=\tilde{n}-n}^{n} \mathbb{B}\left(k, n, x^*(s^{t-1})\right) \mathbb{B}\left(k-(\tilde{n}-n), n, \Delta(s^{t-1})\right) \right\} \\
&+ \sum_{n=\tilde{n}+1}^{\infty} \left\{ \Omega_n(s^{t-1}) \sum_{k=0}^{\tilde{n}} \mathbb{B}\left(k, n, x^*(s^{t-1})\right) \mathbb{B}\left(k-(\tilde{n}-n), n, \Delta(s^{t-1})\right) \right\},
\end{aligned}$$

where $\mathbb{I}^+(a)$ refers to the integer closest to a such that $\mathbb{I}^+(a) \geq a$.[24] The first equation has two terms, the first one tracks the entry of new firms with one product while the second term tracks firms that used to have more than 1 product and contracted to exactly 1 product. The second line shows an analogous law of motion for categories of firms with more than one product where the first component are firms that started with less than $\tilde{n}$ products and had net gains that left them at $\tilde{n}$, while the second term reflects firms that were above $\tilde{n}$ and experienced net losses that left them exactly at $\tilde{n}$.[25] The BGP distribution can be found by iterating in these laws of motion until the mass of firms in each product category is constant.

[24] A firm with n products can become a firm with $n' \in [0, 2n]$ in one period, so, at most it can double its size in one period.

[25] The condition that ensures that the mass of products is always equal to one is given by $\sum_{n=1}^{\infty} n\Omega_n(s^t) = \Lambda$.

Appendix E Dynamic System of Equations

E.1 Representative Household & Financial Intermediation

$$
\begin{aligned}
\tilde{m}(s^t, s_{t+1}) &= \beta \frac{\tilde{C}(s_{t+1})^{-\gamma}}{\tilde{C}(s^t)^{-\gamma} - \phi\tilde{\mu}(s^t)} (1 + g(s^t, s_{t+1}))^{-\gamma} \\
\tilde{C}(s^t)^{-\gamma} &= \tilde{\mu}(s^t) + \frac{\beta}{\hat{q}(s^t)} \mathbb{E}\left[\tilde{C}(s^{t+1})^{-\gamma} | s^t\right] (1 + g(s^t, s_{t+1}))^{-\gamma} \\
\tilde{C}(s^t) + \hat{q}(s^t)\tilde{B}^H(s^t)(1 + g(s^t, s_{t+1})) &= \tilde{w}(s^t) + \tilde{B}^H(s^{t-1}) + \tilde{T}(s^t) \\
\hat{q}(s^t)\tilde{B}^H(s^t)(1 + g(s^t, s_{t+1})) &\geq -\phi\Lambda\tilde{V}_1(s^t) \\
\hat{q}(s^t) &= \mathbb{E}\left[\frac{1}{(1 + R(s^{t+1}) + \iota_0 + \iota_1(\sigma(s^{t+1}) - \bar{\sigma}))} \middle| s^t\right].
\end{aligned}
$$

E.2 Final Good Producer

$$
\tilde{Y}(s^t) = e^{z(s^t)} l(s^t).
$$

E.3 Intermediate Good Producer

$$
\begin{aligned}
l(s^t) &= \frac{\tilde{Y}(s^t)}{\tilde{w}(s^t)\Lambda(1 + \sigma)} \\
\tilde{\pi}(s^t) &= \frac{\sigma}{\Lambda(1 + \sigma)} \tilde{Y}(s^t) \\
\tilde{V}_1(s^t) &= \tilde{\pi}(s^t) - \alpha\tilde{w}(s^t) \left(\frac{x(s^t)}{\xi}\right)^{\frac{1}{\theta}} - (1 - \alpha)x(s^t)F + \\
&\quad \mathbb{E}\left[\tilde{m}(s^{t+1})(1 - \Delta(s^t) + x(s^t)) \left(1 + g\left(s^t, s_{t+1}\right)\right) \tilde{V}_1(s^{t+1}) | s^t\right] \\
x^*(s^t) &= \left[\frac{\theta}{\alpha} \xi^{\frac{1}{\theta}} \frac{\mathbb{E}\left[\tilde{m}(s^{t+1}) \left(1 + g\left(s^t, s_{t+1}\right)\right) \tilde{V}_1(s^{t+1}) \middle| s_t\right] - (1 - \alpha)F}{\tilde{w}(s^t)}\right]^{\frac{\theta}{1-\theta}} \\
l_r(s^t) &= \left(\frac{x(s^t)}{\xi}\right)^{\frac{1}{\theta}}.
\end{aligned}
$$

E.4 Entry

$$M^*(s^t) = \left[\frac{v}{\alpha\kappa}\frac{\mathbb{E}\left[\tilde{m}(s^{t+1})\left(1+g\left(s^t,s_{t+1}\right)\right)\tilde{V}_1(s^{t+1})|s^t\right]-(1-\alpha)F}{\tilde{w}(s^t)}\right]^{\frac{1}{1-v}}.$$

E.5 Aggregate Variables

$$\begin{aligned}
1+g(s^t,s_{t+1}) &= (1+\sigma)^{\Delta}(1-\delta) = (1+\sigma)^{x^*(s^t)+\frac{(M^*(s^t))^v}{\Lambda}}(1-\delta)\\
\tilde{T}(s^t) &= \Lambda\left[\tilde{\pi}(s^t)-\tilde{w}(s^t)\alpha\left(\frac{x(s^t)}{\xi}\right)^{\frac{1}{\theta}}-(1-\alpha)x(s^t)F\right]-\kappa\alpha M^*(s^t)\tilde{w}(s^t)-(1-\alpha)\left(M^*(s^t)\right)^v F\\
\tilde{w}(s^t) &= \frac{e^{z(s^t)}}{\Lambda(1+\sigma)}\\
1 &= \Lambda\left(l(s^t)+l_r(s^t)\right)+\kappa M^*(s^t).
\end{aligned}$$

E.6 Exogenous Shocks

$$\begin{aligned}
\ln z(s^t) &= \rho_z \ln z(s^{t-1})+\epsilon_t, \quad \text{with} \quad \epsilon_t\sim N(0,\eta_z^2)\\
R(s^t)-\bar{R} &= \phi_R\left(R(s^{t-1})-\bar{R}\right)+\sigma(s^t)\omega(s^t), \quad \text{with} \quad \omega(s^t)\sim N(0,1),\\
\log(\sigma(s^t)) &= (1-\rho_\sigma)\mu_\sigma+\rho_\sigma\log(\sigma(s^{t-1}))+\eta_\sigma\nu(s^t), \quad \text{with} \quad \nu(s^t)\sim N(0,1),
\end{aligned}$$

Appendix F Solution Method

Our solution algorithm for the decentralized equilibrium follows a combination of the time-iteration method employed in Bianchi et al. (2016) with value function iteration. We extend it in order to update guesses for the continuation value of a product line.

We discretize the processes for aggregate efficiency z, interest rate R and volatility σ_r following Tauchen (1986). We consider grids of 7 points for aggregate efficiency, 21 points for the interest rate, and 9 points for interest rate volatility. Our bond holdings grid consists of 60 points, and is skewed towards larger debt holdings.[26]

In what follows we drop the superscript H from bond holdings B^H in order to save notation. All functions presented below are stationary, unless otherwise noted. We start with a conjecture for the bond holdings policy function, B', defined over the state space (z, R, σ_r, B).[27] We also make a guess for innovation intensity $x(z, R, \sigma_r, B)$.

The steps of the solution algorithm are the following:

1. Start iteration j with a guess for $B'_j(z, R, \sigma_r, B)$ and innovation intensity $x_j(z, R, \sigma_r, B)$. Using these guesses construct:

$$M_j(z, R, \sigma_r, B) = \left[\frac{x_j(z, R, \sigma_r, B)^{\frac{1-\theta}{\theta}}}{\xi^{\frac{1}{\theta}}\theta} \frac{\nu}{\kappa} \right]^{\frac{1}{1-\nu}} \tag{31}$$

$$g_j(z, R, \sigma_r, B) = (1+\sigma)^{x_j(z,R,\sigma_r,B) + \frac{M_j(z,R,\sigma_r,B)^\nu}{\Lambda}} (1-\delta) - 1 \tag{32}$$

$$\Delta_j(z, R, \sigma_r, B) = x_j(z, R, \sigma_r, B) + \frac{M_j(z, R, \sigma_r, B)^\nu}{\Lambda} \tag{33}$$

$$l_{rj}(z, R, \sigma_r, B) = \left(\frac{x_j(z, R, \sigma_r, B)}{\xi} \right)^{\frac{1}{\theta}} \tag{34}$$

$$l_j(z, R, \sigma_r, B) = \frac{(1 - \kappa M_j(z, R, \sigma_r, B))}{\Lambda} - l_{rj}(z, R, \sigma_r, B) \tag{35}$$

$$Y_j(z, R, \sigma_r, B) = z l_j(z, R, \sigma_R, B) \tag{36}$$

[26] Since we interpolate policy functions, our results do not vary substantially with more populated grids.

[27] Note that this guess corresponds to a matrix with dimensions $N_z \times N_R \times N_\sigma \times N_B$, where N_z, N_R, N_σ and N_B correspond to the number of elements in the grid of aggregate efficiency, interest rate, volatility of interest rate and debt, respectively.

$$\pi(z, R, \sigma_r, B) = \frac{\sigma}{\Lambda(1+\sigma)} Y_j(z, R, \sigma_r, B) \tag{37}$$

$$\begin{aligned} t_j(z, R, \sigma_r, B) = \Lambda(\pi_j(z, R, \sigma_r, B) - \alpha w(z) l_{rj}(z, R, \sigma_r, B) - (1-\alpha) F x_j(z, R, \sigma_r, B)) \\ - \alpha\kappa M_j(z, R, \sigma_r, B) w(z) - (1-\alpha) M_j(z, R, \sigma_r, B)^{\nu} F \end{aligned} \tag{38}$$

$$w(z) = \frac{\exp(z)}{\Lambda(1+\sigma)} \tag{39}$$

$$c_j(z, R, \sigma_r, B) = w(z) + B - B'_j(z, R, \sigma_r, B)(1 + g_j(z, R, \sigma_r, B))\hat{q}(R, \sigma_r) + t_j(z, R, \sigma_R, B) \tag{40}$$

Lastly, compute the discounted expected marginal utility

$$\beta \frac{\beta}{\hat{q}(R, \sigma_r)} \mathbb{E}\left[u_j(z', R', \sigma'_r, B'_j(z, R, \sigma_r, B))\right] (1 + g_j(z, R, \sigma_r, B))^{-\gamma}, \tag{41}$$

where $u_j(z, R, \sigma_r, B) = c_j(z, R, \sigma_r, B)^{-\gamma}$.

2. Using the above guesses compute guess for the value of a product line and the stochastic discount factor. For the value or a product line we iterate over the following value function:

$$\begin{aligned} V_{1,k+1}(z, R, \sigma_r, B) = \pi_j(z, R, \sigma_r, B) - \alpha w(z) \left(\frac{x_j(z, R, \sigma_r, B)}{\xi}\right)^{\frac{1}{\theta}} - (1-\alpha) x_j(z, R, \sigma_r, B) F \\ + \mathbb{E}\left[m_j(z, R, \sigma_r, B)(1 - \Delta_j(z, R, \sigma_r, B) + x_j(z, R, \sigma_r, B))\left(1 + g_j(z, R, \sigma_r, B)\right) V_{1,k}(z, R, \sigma_r, B)\right] \end{aligned} \tag{42}$$

Until $||V_{1,k+1}(z, R, \sigma_r, B) - V_{1,k}(z, R, \sigma_r, B)|| < \text{tol}$. $V_{1,j}(z, R, \sigma_r, B)$ is the converged value function.

3. Assume the borrowing constraint binds. Note that when the constraint binds we have that consumption is

$$c_{j+1}(z, R, \sigma_r, B) = w(z) + B + \phi\Lambda(V_{1,j}(z, R, \sigma_r, B)) + t_j(z, R, \sigma_R, B) \tag{43}$$

We then check whether this assumption holds by calculating the residual of the Euler equa-

tion:

$$\mathcal{R}(z,R,\sigma_r,B) = u_{j+1}(z,R,\sigma_r,B)$$
$$-\beta\frac{\beta}{\hat{q}(R,\sigma_r)}\mathbb{E}\left[u_j(z',R',\sigma_r',B_j'(z,R,\sigma_r,B))\right](1+g_j(z,R,\sigma_r,B))^{-\gamma}. \tag{44}$$

If $\mathcal{R}(z,R,\sigma_r,B) > 0$, we keep the values for $c_{j+1}(z,R,\sigma_r,B)$, and we set $B'_{j+1}(z,R,\sigma_r,R) = -\frac{\phi\Lambda V_{1,j}(z,R,\sigma_r,B)}{(1+g_j(z,R,\sigma_r,B))\hat{q}(R,\sigma_r)}$, $\mu_{j+1}(z,R,\sigma_r,B) = \mathcal{R}(z,R,\sigma_r,B)$. Otherwise, the constraint does not bind for that point of the state space and we discard $c_{j+1}(z,R,\sigma_r,B)$ and $B'_{j+1}(z,R,\sigma_r,R)$. We then numerically solve for the value of $c_{j+1}(z,R,\sigma_r,B)$ that satisfies

$$u_{j+1}(z,R,\sigma_r,B) = \beta\frac{\beta}{\hat{q}(R,\sigma_r)}\mathbb{E}\left[u_j(z',R',\sigma_r',B_j'(z,R,\sigma_r,B))\right](1+g_j(z,R,\sigma_r,B))^{-\gamma} \tag{45}$$

We then set $B'_{j+1}(z,R,\sigma_r,B) = \frac{w(z)+B+t_j(z,R,\sigma_R,B)-c_{j+1}(z,R,\sigma_r,B)}{(1+g_j(z,R,\sigma_r,B))\hat{q}(R,\sigma_r)}$ and $\mu_{j+1}(z,R,\sigma_r,B) = 0$.

4. Using the updated guesses $c_{j+1}(z,R,\sigma_R,B)$ and $B'_{j+1}(z,R,\sigma_R,B)$, compute an updated guess for the stochastic discount factor:

$$m_{j+1}(z,R,\sigma_r,B) = \beta\frac{c_{j+1}(z,R,\sigma_r,B'(z,R,\sigma_r,B))^{-\gamma}}{c_{j+1}(z,R,\sigma_r,B)^{-\gamma}-\phi\mu_{j+1}(z,R,\sigma_r,B)}(1+g_j(z,R,\sigma_r,B))^{-\gamma} \tag{46}$$

5. Recompute the value of a product line using the updated stochastic discount factor. This is, use value function iteration over the value of a product line:

$$V_{1,k+1}(z,R,\sigma_r,B) = \pi_j(z,R,\sigma_r,B) - \alpha w(z)\left(\frac{x_j(z,R,\sigma_r,B)}{\xi}\right)^{\frac{1}{\theta}} - (1-\alpha)x_j(z,R,\sigma_r,B)F$$
$$+\mathbb{E}\left[m_{j+1}(z,R,\sigma_r,B)(1-\Delta_j(z,R,\sigma_r,B)+x_j(z,R,\sigma_r,B))\left(1+g_j(z,R,\sigma_r,B)\right)V_{1,k}(z,R,\sigma_r,B)\right] \tag{47}$$

Until $||V_{1,k+1}(z,R,\sigma_r,B) - V_{1,k}(z,R,\sigma_r,B)|| < \text{tol}$. $V_{1,j+1}(z,R,\sigma_r,B)$ is the converged value function.

6. Update guess for innovation intensity of incumbents:

$$x_{j+1}(z,R,\sigma_r,B)=\max\left\{\left[\frac{\theta}{\alpha}\xi^{\frac{1}{\theta}}\frac{\mathbb{E}\left[m_{j+1}(z,R,\sigma_r,R)\left(1+g_j(z,R,\sigma_r,R)\right)V_{1,j+1}(z,R,\sigma_R,B)-(1-\alpha)F\middle|s_t\right]}{w(z)}\right]^{\frac{\theta}{1-\theta}},0\right\} \tag{48}$$

7. Check for convergence. If $||B'_{j+1}(z,R,\sigma_r,B)-B'_j(z,R,\sigma_r,B)||<\epsilon$ and $||x_{j+1}(z,R,\sigma_r,B)-x_j(z,R,\sigma_r,B)||<\epsilon$ then the problem is solved. Otherwise, discard $B'_j(z,R,\sigma_r,B)$ and $x'_j(z,R,\sigma_r,B)$, and use $B'_{j+1}(z,R,\sigma_r,B)$ and $x'_{j+1}(z,R,\sigma_r,B)$ as new guesses for the problem (go back to step 1).

Appendix G Persistent Effects of Sudden Stops

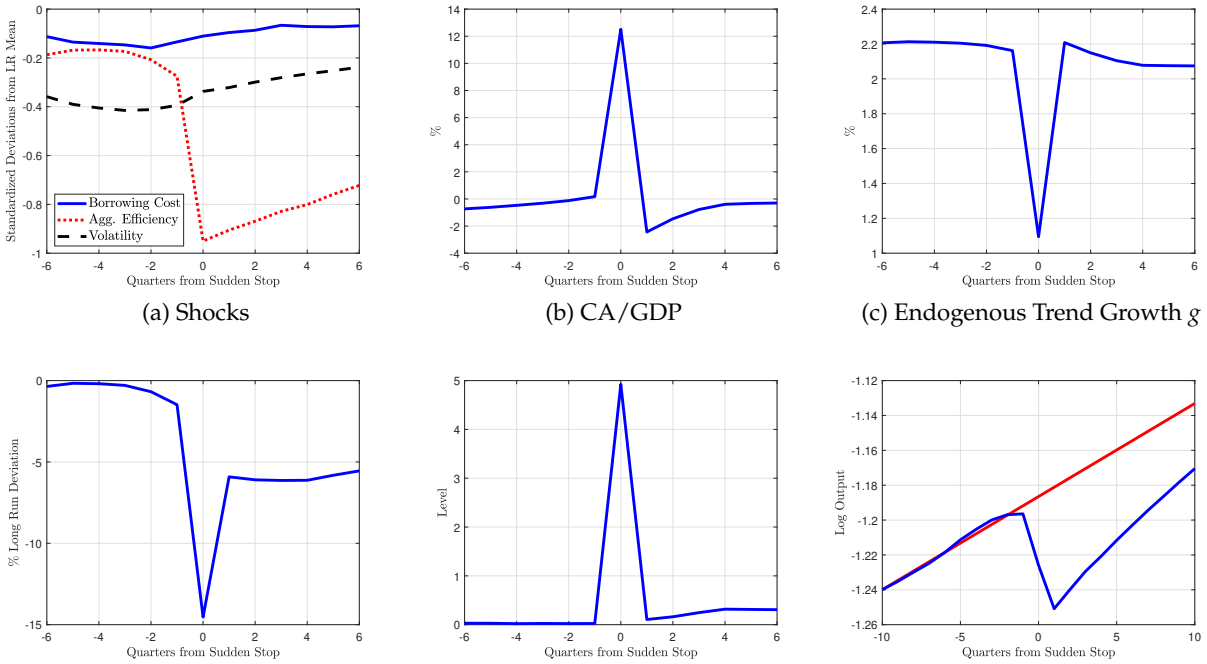
We conduct an event analysis around Sudden Stops endogenously generated by the model under the baseline calibration. Using a time window of 10 quarters before and after each event, we average relevant time series.[28] Figure 12 illustrates the Sudden Stop dynamics for the baseline scenario.

Our focus is on the dynamics of five key variables: the value of a product line, the Lagrange multiplier, the current account-to-GDP ratio, the endogenous trend, and log GDP (in levels). Panel (a) shows the evolution of the model's three shocks around the event. In our framework, Sudden Stops typically occur under three conditions: (1) borrowing costs are below their long-run average, (2) interest rate volatility is low and below its long-run average, and (3) a sudden, significant drop in aggregate efficiency takes place. Low and stable borrowing costs promote excessive borrowing, as households do not fully internalize the consequences of their borrowing decisions, leading to overborrowing.[29] These episodes are particularly pronounced when borrowing conditions are favorable. Because efficiency shocks are persistent, the combination of high leverage and a protracted decline in productivity triggers sharp adjustments in borrowing, as depicted in panel (b), where a steep current account reversal follows.

[28] We define a Sudden Stop as an episode where the current account-to-GDP ratio exceeds its long-run average by two standard deviations and the borrowing constraint binds.

[29] This behavior is characteristic of models with occasionally binding borrowing constraints and endogenous collateral values. See Bianchi (2011) and Bianchi and Mendoza (2018) for a detailed analysis of pecuniary externalities in endowment and production models.

Figure 12: Sudden Stop Dynamics - Emerging Economy



(a) Shocks (b) CA/GDP (c) Endogenous Trend Growth g

(d) Value of a Product Line V_1 (e) Lagrange multiplier μ (f) Log GDP

Notes: Sudden Stops are defined as events where the borrowing constraint binds and where the current account-to-GDP ratio is two standard deviations above its long-run mean. The three shocks of the model are standardized by their corresponding long-run means and standard deviations. CA/GDP denotes the current account-to-GDP ratio, and log GDP corresponds to the log of GDP in levels. The red solid line in the log GDP panel denotes the average trend, which is constructed by averaging the linear growth using the trend growth rate 10 quarters before a Sudden Stop.

Panel (c) depicts the trend growth response: a decline of approximately 1 percentage point (annualized), followed by a rapid recovery. However, as shown in panel (d), the value of a product line experiences a sharp drop and fails to return to its pre-Sudden Stop level. This persistent decline is driven by both the sustained low aggregate efficiency and the increased likelihood of a binding borrowing constraint post-event (panel (e)). A depressed product line value also implies that collateral values remain below their long-run average, contributing to the sluggish recovery.[30] Finally, panel (f) clearly demonstrates the long-lasting consequences, or hysteresis, of a Sudden Stop: output suffers an abrupt and permanent deviation from its pre-event trend.

It is important to distinguish between the crises driven by U.S. interest rate volatility and the

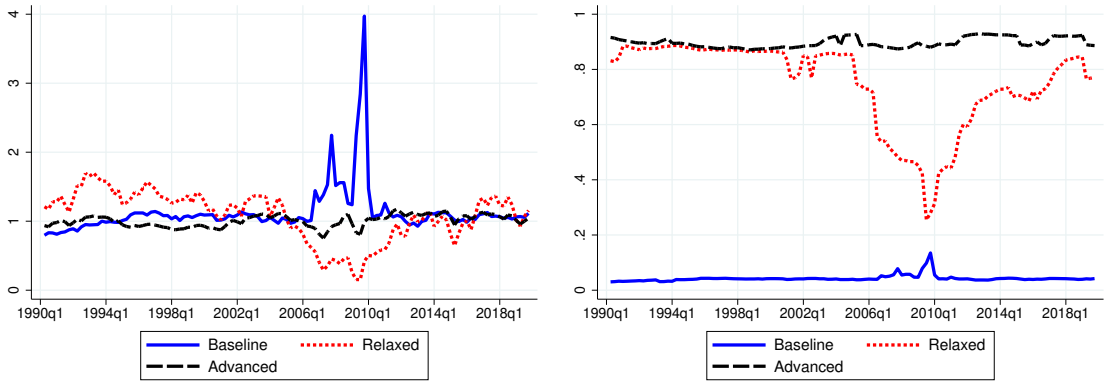
[30]Our framework is notable for generating both slow recoveries and borrowing constraints that bind for several periods after the Sudden Stop, a novel feature typically seen in models with capital accumulation, where capital is used as collateral for borrowing.

Sudden Stops analyzed in this appendix. In the main text, we focus on how increased volatility in U.S. interest rates negatively impacts growth, as agents anticipate larger future interest rate shocks. This is because adverse rate shocks tend to be more damaging than rate reductions are beneficial for growth in emerging economies. However, as shown here, Sudden Stops are different. These events involve a sharp current account reversal and are typically triggered by large negative TFP shocks. Not every instance of a binding borrowing constraint leads to a Sudden Stop; the multiplier can bind without causing a major crisis. Sudden Stops are more closely linked to deep contractions in aggregate efficiency and borrowing needs for consumption smoothing, whereas the main text centers on the dynamics of interest rate volatility and its asymmetric effects on growth due to a binding constraint, without requiring a sharp current account reversal.

Appendix H Additional Simulation Results: Binding Borrowing Constraints

Figure 13 displays simulations of the Lagrange multiplier and the probability of a binding borrowing constraint across three scenarios: baseline, advanced economy calibrations, and an intermediate case with a relaxed borrowing constraint. These simulations incorporate actual interest rate and interest rate volatility data and follow the methodology outlined in Section 4.5. To facilitate comparison, Lagrange multipliers are normalized by their respective ergodic means.

Figure 13: Borrowing Constraint Multiplier & Binding Probability Based on Actual Interest Rate and Volatility Time Series



(a) Average Multiplier $\tilde{\mu}$

(b) Prob. of Binding Constraint $\Pr(\tilde{\mu}_t > 0)$

Notes: This figure shows, for the three calibrations (baseline, relaxed constraint, and advanced), the average normalized Lagrange multiplier and the probability of observing a binding borrowing constraint when all economies are subjected to the same path of U.S. real interest rates and volatility. Averages are taken across 10,000 simulated TFP paths.

As detailed in Section 4.5, our emerging economy calibration highlights strong precautionary motives among households, as the probability of a binding borrowing constraint remains below 10% during periods of low risk. However, in times of heightened interest rate uncertainty, this probability rises significantly, accompanied by a substantial increase in the effective multiplier. In the other two scenarios, economies generally operate near the borrowing limit, with episodes of increased volatility prompting deleveraging, thereby moving away from the endogenous borrowing limit. The behavior of advanced economies is consistent with the relatively painless amplification triggered by a shock that forces deleverage.