Volatile Rates, Fragile Growth:

Global Financial Risk and Productivity Dynamics*

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Abstract

We demonstrate empirically that increased U.S. interest rate volatility forecasts a significant decline in the trends of GDP, consumption, and investment, with the drop being more pronounced in emerging economies than in advanced ones. Using a small open economy model with endogenous growth and financial crises, we rationalize this decline and the cross-country differences. In our model large adverse interest rate shocks disproportionally reduce firm values, tightening borrowing constraints and amplify economic slowdowns. This mechanism allows higher volatility to raise the likelihood of severe shocks, to stifle innovation, and slow trend growth. Our results reveal the critical role of global financial risk in shaping productivity trends in less financially developed emerging markets.

Keywords: Endogenous Growth, Stochastic Interest Rate Volatility, Financial Frictions, Long-Term Productivity Trends, Global Financial Risk Cycle

JEL Classifications: F32,F41,G15,O16

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1 Introduction

Policymakers from emerging market economies (EMEs) often express concerns about the effects of rising U.S. interest rates on their economies. However, it is not only the increase in interest rates that has contractionary effects on EMEs, but also the uncertainty surrounding global interest rates (Carrière-Swallow and Céspedes, 2013). The literature has long theorized that global risk in interest rates (Rey, 2015) contributes to the excess volatility in GDP and consumption observed in EMEs relative to developed economies. In this paper, we provide new insights by arguing that an increase in the volatility of U.S. interest rates not only affects business cycle fluctuations in EMEs but also influences the level and volatility of the long-term productivity trend that underpins their stationary fluctuations. We establish a novel link between U.S. interest rate dynamics and long-run trends in the small open economies, providing an explanation for the different low-frequency responses of advanced and emerging economies.

Using a multivariate time series model, we show that a rise in the stochastic volatility of U.S. real interest rates forecasts a decline in the growth rate of the productivity trend, with more pronounced effects in EMEs. We then introduce a parsimonious small open economy model featuring endogenous growth (Ates and Saffie, 2021) and occasionally binding borrowing constraints (Mendoza, 2010), which is subject to both stationary productivity shocks and first- and second-moment shocks to international interest rates (Fernández-Villaverde et al., 2011). Our model provides an endogenous link between interest rate volatility, firm dynamism, and growth that aligns with our empirical findings. Additionally, the model highlights a financial origin behind the key differences in low-frequency productivity dynamics between EMEs and advanced economies, bridging models of internal financial propagation (Garcia-Cicco et al., 2010) and exogenous trend dynamics (Aguiar and Gopinath, 2007). In our framework, stationary fluctuations endogenously trigger non-stationary dynamics in aggregate productivity via interactions with financial frictions. As a result, the heightened responsiveness of EMEs, relative to advanced economies, to U.S. interest rate risks can be attributed to deeper financial frictions in less developed economies.

Our empirical analysis estimates the impact of stochastic volatility shocks to U.S. interest rates on the trend growth rates of GDP, consumption, and investment. First, we apply the particle filter (Fernández-Villaverde et al., 2011) to estimate a time series of stochastic volatility for U.S. interest

rates. Second, we impose restrictions common to models with balanced growth paths to isolate trend productivity dynamics from other exogenous stationary fluctuations. Third, we estimate two panel VAR models to uncover the impact of U.S. interest rate volatility on the low-frequency dynamics of both emerging and advanced economies. A one-standard-deviation increase in U.S. interest rate volatility predicts a significantly larger decline in the trend growth rate of EMEs compared to advanced economies, with this differential effect persisting for several quarters.

To further explore this pass-through mechanism from interest rate volatility to trend growth, we develop a small open economy model that presents a microfoundation for this connection. In the model, firm entry and expansion in the intermediate goods sector drive growth (Klette and Kortum, 2004). The representative household owns all firms and uses the value of its investments as collateral to borrow from international markets. Because firm values are the present discounted value of future profits, an increase in interest rates reduces firm values, lowering the incentives for firm entry and expansion. Reduced business dynamism, in turn, slows economic growth. Consistent with endogenous sudden-stop models (Mendoza, 2010), a Fisherian deflation mechanism is triggered as lower firm values tighten collateral constraints, further raising the household's discount rate. Increases in interest rate volatility signal, on average, larger shocks in future rates. Due to the asymmetry of borrowing constraints and the predominant role of interest rate shocks in determining collateral values, large interest rate increases are more damaging to collateral and innovation incentives than equivalent decreases. Thus, second-moment shocks to interest rates immediately slow down firm dynamics and reduce the economy's growth rate, with these effects being more pronounced in the presence of severe financial frictions.

We calibrate the model to the Mexican economy by matching long-run productivity growth, firm entry rates, and the relative size of incumbent firms. The interest rate and TFP processes from our empirical analysis guide the stochastic elements of the model. Despite its simplicity, the model replicates the patterns observed in our empirical results. The occasionally binding borrowing constraint introduces state dependence in the effects of interest rate shocks. Specifically, moderate interest rate shocks have symmetric effects on firm values, whereas large shocks display strong asymmetry. Consequently, as interest rate volatility rises, firm values fall, depressing firm entry and expansion efforts, thereby slowing endogenous trend growth. This mechanism helps generate the negative correlation between interest rates and TFP, which is often assumed, directly

or indirectly, as an exogenous channel in the EME literature (Neumeyer and Perri, 2005). In addition, the focus of the model on stationary shocks and financial frictions allows us to reconcile the findings of Aguiar and Gopinath (2007) and Garcia-Cicco et al. (2010).

Finally, in comparing advanced and emerging economies, we find that approximately three-fourths of the differential pass-through from interest rate volatility to trend growth can be attributed to lower financial development (i.e., lower pledgeability of assets), while the remaining portion is explained by higher financial intermediation costs faced by EMEs during periods of elevated interest rate volatility.

Related Literature: Our focus on the role of global interest rates and their volatility connects us to a large body of work in small open economy models. Mendoza (1991), Neumeyer and Perri (2005), and Uribe and Yue (2006) study the importance of changes in the level of interest rates for fluctuations in small open economies. In order to match the empirical effects of interest rates on output, this literature often assumes working capital constraints and an exogenous correlation between TFP and interest rate fluctuations. Our simple model abstracts from both elements, but the internal propagation of the model delivers both the importance of interest rate shocks and the correlation between productivity and interest rates. Fernández-Villaverde et al. (2011), Gruss and Mertens (2009), Carrière-Swallow and Céspedes (2013), Reyes-Heroles and Tenorio (2020), Johri et al. (2022), and Roch et al. (2025) provide evidence for the role of changes in interest rate volatility on the business cycle of emerging economies.[1] We contribute to this literature by showing that interest rate fluctuations not only affect short-run dynamics, but through their effect on trend productivity growth, also trigger hysteresis and low-frequency fluctuations.

Our study is closely related to the literature examining the role of trend shocks to productivity in EME business cycles, which has produced mixed findings (see, for instance, Aguiar and Gopinath (2007), Garcia-Cicco et al. (2010), Chang and Fernández (2013), and Boz et al. (2011)). By linking movements in trend productivity to stationary shocks, models with endogenous growth can reduce reliance on exogenous trend components to explain macroeconomic data. This micro-founded approach aligns more closely with the data and provides a richer framework for policy analysis (Gornemann et al., 2020).[2]

[1] Croce et al. (2012) show that a rise in fiscal uncertainty can lead to a growth slowdown in the U.S. economy.

[2] Some may question the applicability of innovation-driven endogenous growth models to emerging economies. However, these models define innovation broadly, encompassing any process that reduces the marginal cost of produc-

Incorporating endogenous growth improves the capacity of macroeconomic models to account for both business cycle and medium-term dynamics by allowing the productivity trend to respond to stationary shocks (Comin and Gertler, 2006). This addition has been particularly effective in explaining the volatile business cycles and hysteresis observed in EMEs documented, for example, in Cerra and Saxena (2008). For example, Queralto (2020) shows that a model combining financial frictions and endogenous productivity can explain the persistent effects of the Asian financial crisis on the GDP level in affected countries. Similarly, Ates and Saffie (2021) develop a creative-destruction model of endogenous growth (Aghion and Howitt, 1992) featuring firm selection dynamics, offering insights into firm entry selection during Chile's 1998 sudden stop. Meanwhile, Gornemann (2014) highlights the role of medium-term dynamics in the context of sovereign defaults in EMEs. Although some studies have explored models with endogenous financial crises and occasionally binding financial constraints (Benguria et al., 2020; Ma, 2020; Matsumoto, 2022), they do not explicitly link international interest rates to financial collateral. Our model bridges this gap by showing how interest rate shocks influence collateral values, emphasizing the critical role of global risk shocks in shaping low-frequency productivity dynamics.[3]

Within the endogenous growth literature, our work aligns most closely with Aghion et al. (2004), Aghion et al. (2009), and Aghion et al. (2010), who develop theoretical models linking financial constraints to lower long-term growth and greater growth volatility. We build on this tradition by developing a tractable quantitative model that integrates stochastic interest rate volatility, financial development, and growth trend fluctuations into a dynamic stochastic general equilibrium framework suited for quantitative analysis.

In Section 2 we use time series analysis to suggest a link between US interest rate volatility and economic trends in small open economies. Section 3 discusses our economic model, while Section 4 presents its quantitative analysis. Section 5 concludes.

tion—be it through new technologies or process improvements. Moreover, our conclusions remain robust if innovation is interpreted as the costly, forward-looking adoption of frontier technologies. As long as this adoption is endogenous and shaped by interest rate volatility, the mechanisms in our model hold for emerging economies.

[3] Benigno et al. (2020) also connect interest rates to long-run productivity dynamics, arguing that declining interest rates in advanced economies reduce tradable goods production and slow global productivity growth. However, our focus is on stationary shocks rather than secular changes in interest rates.

2 Empirical Analysis

This section provides suggestive evidence linking changes in the volatility of global interest rates–approximated here as U.S. real rates–to persistent changes in economic activity in small open economies using time series models. Specifically, we demonstrate that this relationship is more pronounced for emerging market economies. After describing the data employed, we detail how we extract a time series for the volatility of U.S. real rates. We then outline the multivariate time series model applied to a set of emerging and developed small open economies and present the estimation results.

2.1 Data and Stochastic Volatility in U.S. Real Rates

For the United States, we utilize data on PCE and CPI inflation, real GDP, and Treasury interest rates (3-month, 2-year, 5-year) from FRED. Additionally, we incorporate data on the excess bond premium using the updated series from Gilchrist and Zakrajšek (2012). We pair this with time series data for GDP, consumption, and investment from the IMF's International Financial Statistics for our sample of emerging and developed economies baing our country selection on Vicondoa (2019). The study period runs from 1993 Q1 to 2019 Q4, ending before the COVID-19 pandemic affected macroeconomic conditions. Given missing data for some countries, our panel is unbalanced.

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.[4] 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:

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

$$\log \sigma_t^r = (1 - \rho_\sigma^r)\mu_\sigma^r + \rho_\sigma^r \log \sigma_{t-1}^r + \sigma_r \nu_t^r, \tag{2}$$

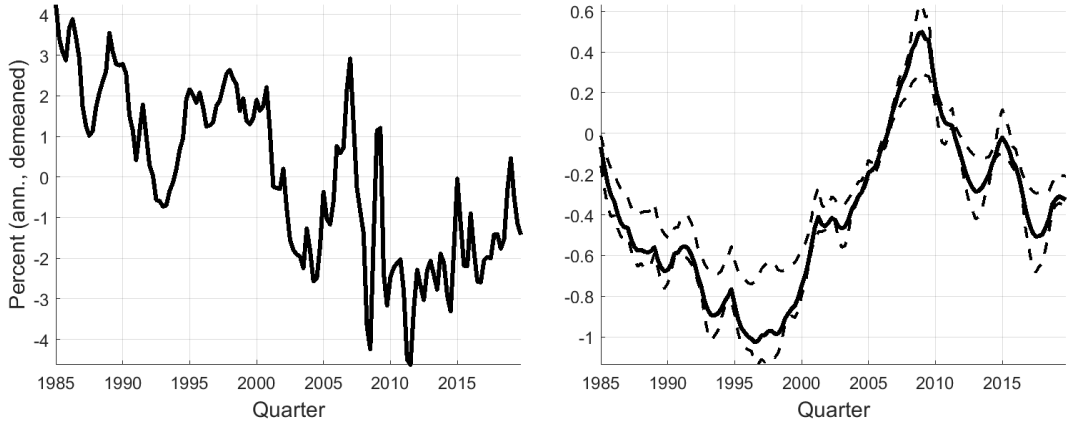
[4]Using the 2-year or 5-year interest rate instead does not significantly alter our core findings, as these series are highly correlated over the sample period.

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

Table 1 presents our parameter estimates.[5] Both the interest rate and its hidden volatility state are highly persistent. Figure 1 displays the real interest rate and the smoothed path of the volatility state.[6] 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 rate and significant fluctuations around this trend. Post-2010, real rates stabilize again, which is reflected in the stochastic volatility process.

ϕ	ρ_σ^r	$10 * \mu_\sigma^r$	$10 * \sigma_r$
0.941	0.967	1.60	0.50
(0.86,1.00)	(0.87,1.01)	(0.72,1.90)	(0.45,0.59)

Table 1: U.S. Interest Rate Model: Estimated Parameters



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

Figure 1: Estimated Series for U.S. Real Rates

2.2 Trend Growth Estimation and Stochastic Volatility Effects

Having derived our measure of time-varying volatility in U.S. interest rates, the next step is to estimate the trend component of GDP. To provide structure for identification, we assume that GDP, consumption, and investment share a common stochastic trend. This assumption mirrors

[5] Standard errors are derived by bootstrapping.

[6] 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.

many growth models, both exogenous and endogenous, where these macroeconomic variables grow at the same rate once temporary disturbances subside. We estimate the growth rate of the stochastic trend a_t for a panel of emerging and advanced economies using a state-space model. Our sample spans 1993Q1 to 2019Q4, with country selection based on Vicondoa (2019).

Formally, we assume the joint process for logged GDP growth (Δy_t), logged consumption growth (Δc_t), and logged investment growth (Δi_t) is:

$$\begin{pmatrix} \Delta y_t \\ \Delta c_t \\ \Delta i_t \end{pmatrix} = \begin{pmatrix} \alpha \\ \alpha \\ \alpha \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} a_t + \begin{pmatrix} 1 \\ a \\ b \end{pmatrix} \Delta\lambda_t + \begin{pmatrix} \sigma_t & 0 & 0 \\ 0 & \sigma_c & 0 \\ 0 & 0 & \sigma_i \end{pmatrix} \epsilon_t^m$$

$$\begin{aligned} a_t &= \rho_a a_{t-1} + \sigma_a \epsilon_t^a \\ \lambda_t &= \rho_\lambda \lambda_{t-1} + \sigma_\lambda \epsilon_t^\lambda. \end{aligned}$$

Here, α represents the joint deterministic trend, and a_t is a stochastic trend following an AR(1) process. λ_t is an AR(1) capturing persistent deviations around the trend, resembling typical business cycles. The parameters a and b gauge the responsiveness of consumption and investment relative to GDP, and σ_t allows for independent growth rate deviations.[7]

We then estimate two panel VARs that include (i) country trends, (ii) U.S. GDP growth, (iii) the excess bond premium, (iv) U.S. real rates, and (v) real rate stochastic volatility. Using a Cholesky decomposition assuming that all other variables do not respond immediately to stochastic volatility changes, we extract a shock to stochastic volatility and track its impact on the accumulated trend. Figure 2 shows the results. We observe a significant decline in the extracted trend for emerging economies following a one standard deviation change in stochastic volatility, while the impact on advanced economies is statistically insignificant.

[7] We tested temporary shocks to the levels of the series but found growth rate shocks fit better for most countries.

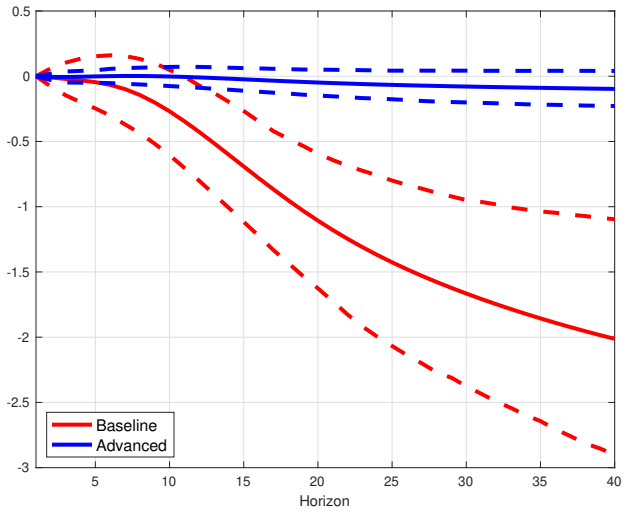


Figure 2: Trend Growth Rate Responses to Stochastic Volatility Shocks

Notes: This figure shows the accumulated response in a_t after a one standard deviation shock to stochastic volatility in the VAR described in the text for the emerging and advanced economy sample, i.e. how much is the level of y_t, c_t, i_t lower after x-quarters after a shock to stochastic volatility.

3 A Simple Model of Endogenous Trend Cycles

3.1 Model Overview

This section introduces a small open economy model that features an occasionally binding borrowing constraint and endogenous growth. In the model, a representative household owns a continuum of intermediate good producers and can use their value as collateral to borrow from the global financial market, where the borrowing terms are influenced by a stochastic interest rate process. The entry, exit, and expansion dynamics of these intermediate producers, following the framework of Klette and Kortum (2004), form the engine of long-run growth. The intermediate goods are sold to a representative final good producer, which operates under the influence of an aggregate efficiency shock. Importantly, the final good is the only tradable product in the economy. Our model builds upon traditional endogenous sudden stop frameworks, extending them in three key ways.

First, the representative household in this economy can post the value of intermediate good-producing firms as collateral when borrowing externally. Second, endogenous technical change links the value of this collateral to innovation decisions made by incumbent and entrant firms.

Third, both the level (first moment) and volatility (second moment) of international interest rates influence firm dynamics, technological innovation, and the severity of financial frictions.

3.2 Households

The representative household chooses consumption C and non-state-contingent bond holdings B each period. It inelastically supplies labor $\bar{L}$ at a wage w and receives lump-sum transfers T from incumbent firms, which it owns. The representative household solves the following problem:

$$\max_{C(s^t),B(s^t)^H} \sum_{t=0}^{\infty} \beta^t \mathbb{E}\left[\frac{1}{1-\gamma}\left[C(s^t)\right]^{1-\gamma} | s_0\right] \tag{3}$$

subject to:

$$C(s^t) + \hat{q}(s^t)B^H(s^t) \leq w(s^t)\bar{L} + B^H(s^{t-1}) + T(s^t) \tag{4}$$

$$\hat{q}(s^t)B^H(s^t) \geq -\phi V(s^t), \tag{5}$$

where $\hat{q}$ denotes the price of debt, which is the reciprocal of the gross interest rate set by financial intermediaries in the economy. The financial constraint prevents households from borrowing more than a fraction ϕ of the value of their collateral, which is equal to the total value of incumbent firms in the economy, V.[8]

3.3 Financial Intermediaries

Households borrow from international financial intermediaries, which are competitive and risk-averse. These intermediaries have a gross funding cost R and lend to households at a price $\hat{q}$. The gross interest rate in international markets follows an AR(1) subject to stochastic volatility given by:

$$R(s^t) - \bar{R} = \rho_R\left(R(s^{t-1}) - \bar{R}\right) + \sigma(s^t)\omega(s^t), \quad \text{where} \quad \omega(s^t) \sim N(0,1), \tag{6}$$

$$\log(\sigma(s^t)) = (1-\rho_\sigma)\mu_\sigma + \rho_\sigma \log(\sigma(s^{t-1})) + \eta_\sigma \nu(s^t), \quad \text{with} \quad \nu(s^t) \sim N(0,1), \tag{7}$$

[8] A key deviation from the literature on endogenous financial crises (Bianchi and Mendoza, 2018) is the use of the household's investment in production as collateral. Using firms' values as collateral is consistent with Private Equity and Venture Capital financing practices. Because the firm's value summarizes future cash flows, this approach also aligns with recent research by Lian and Ma (2021) and Drechsel (2023). Moreover, even traditional bank lending determines the viability of credit based on interviews with entrepreneurs where they describe their projects.

where $\bar{R}$ is the average cost of funds, ρ_R the persistence of the cost of funds, and σ the volatility of the process. The volatility of R follows an AR(1) with mean μ_σ, persistence ρ_σ, and volatility η_σ.

Intermediaries lend at a price $\hat{q}$, derived from the following optimization problem:

$$\max_{b(s^t)} \mathbb{E}\left[\hat{m}(s^{t+1})b(s^t)\middle|s^t\right] - \hat{q}(s^t)b(s^t), \tag{8}$$

where $\hat{m}(s^t, s_{t+1})$ corresponds to the intermediaries' stochastic discount factor. To reflect lenders risk aversion, we assume that the discount factor of financial intermediaries is given by $\hat{m}(s^{t+1}) = 1/(1 + R(s^{t+1}) + \iota_0) + \iota_1(\sigma(s^{t+1}) - \bar{\sigma}))$. This functional form allows international investors to be more risk averse when investing in emerging markets.[9] Thus, the solution to (8) yields the following pricing function:

$$\hat{q}(s^t) = \mathbb{E}\left[\frac{1}{(1 + R(s^{t+1}) + \iota_0 + \iota_1(\sigma(s^{t+1}) - \bar{\sigma}))}\middle|s^t\right], \tag{9}$$

where ι_0 is the average spread and $\iota_1 > 1$ reflects that lenders charge more (less) during high (low) volatility times. This pricing function can reflect risk aversion or increasing costs for financial intermediaries when volatility is high.[10]

3.4 Final Good Producer

The final good producer aggregates a mass Λ of differentiated intermediate goods according to the following technology:

$$\ln Y(s^t) = z(s^t) + \frac{1}{\Lambda}\int_0^\Lambda \ln y_i(s^t), di, \tag{10}$$

[9] The formulation for the stochastic discount factor can be seen as a reduced form structure of endogenous outcomes derived from models in the spirit of Gertler and Karadi (2011) and Gertler and Kiyotaki (2015) when allowing stochastic volatility for interest rates. In Appendix A we present a model with these features and show that increases in the volatility of the funding cost of financial intermediaries lead to higher loan interest rates. Alternatively, our formulation can also be seen as a reduced form version of endogenous time-varying volatility of spreads as a result of volatility in the US interest rate in the context of endogenous default models (De Ferra and Mallucci, 2022).

[10] A similar structure for the discount factor of financial intermediaries has also been used in the literature. See also Arellano and Ramanarayanan (2012), Bianchi et al. (2018), Johri et al. (2022), and Hegarty et al. (2023).

where $Y(s^t)$ is the unique final good, $y_i(s^t)$ is the final good producer's demand for variety i, and $z(s^t)$ is an aggregate efficiency shock that follows:

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

where ρ_z is the persistence of the aggregate efficiency shock and η_z its volatility.

3.5 Intermediate Good Producers

There is a continuum of intermediate goods indexed by i uniformly distributed in $[0, \Lambda]$. Each intermediate good is produced by the firm with the lowest marginal cost according to the following production function:

$$y_i(s^t) = q_i(s^t) l_i(s^t), \tag{11}$$

where q_i is the efficiency in the production of intermediate goods i, and l_i represents the labor used in production, respectively. The leader of each intermediate good is the producer with the lowest marginal cost, this producer enjoys monopoly rents and competes à la Bertrand with the producer with the second lowest marginal cost. A firm can own and produce several intermediate goods. Firms can expand by becoming leaders in other product lines, contract when they lose their advantage in producing certain intermediate goods, and even exit the market if they lose all their products.

3.5.1 Innovation by Incumbents

The productivity of each intermediate variety evolves endogenously with each innovation. Innovations arise when either an incumbent or a potential entrant successfully improves the existing technology for producing an intermediate good. Thus, when an innovation occurs in variety i the new technological leader has access to a productivity $q_i(s^{t+1}) = (1+\sigma)\tilde{q}_i(s^t)$, where $\tilde{q}_i(s^t)$ is the technology that the former leader had and $\sigma > 0$ is the innovation step size.

An incumbent firm can attempt to innovate and become the new leader in an intermediate product that she does not currently own. To model the innovation technology, we follow Ates

and Saffie (2021)'s discrete time version of Klette and Kortum (2004). In particular, a firm with n products can use research labor $L_r(s^t)$ to generate a success probability $x(s^t)$ per product line according to the following production function:

$$x(s^t) = \xi \left(\frac{L_r(s^t)}{n} \right)^{\theta} \equiv \xi \left(l_r(s^t) \right)^{\theta}. \tag{12}$$

The expansion and destruction probabilities are governed by binomial processes. Therefore, a firm with n products that optimally chooses an innovation rate $x(s^t)$ will win k new products with probability:

$$\mathbb{B}(k, n, x(s^t)) = \binom{n}{k} x(s^t)^k \left(1 - x(s^t)\right)^{n-k}, \tag{13}$$

and lose $\tilde{k}$ products when facing the aggregate creative destruction rate $\Delta(s^t)$ according to:

$$\mathbb{B}(\tilde{k}, n, \Delta(s^t)) = \binom{n}{\tilde{k}} \Delta(s^t)^{\tilde{k}} \left(1 - \Delta(s^t)\right)^{n-\tilde{k}}. \tag{14}$$

Lastly, an incumbent firm is subject to a fixed innovation cost $F(s^t)$, which is contingent upon achieving a successful innovation in a product line, and scales with the size of the economy ($F(s^t) = A(s^t)F$). The discrete time problem of an incumbent firm is given by:

$$\begin{aligned} V_n(s^t) &= \max_{x_n(s^t)} n \left[\pi(s^t) - w(s^t)\alpha \left(\frac{x_n(s^t)}{\xi} \right)^{\frac{1}{\theta}} - (1-\alpha) x_n(s^t) F(s^t) \right] \\ &+ \mathbb{E}\left[m(s^{t+1}) \sum_{\tilde{k}=0}^{n} \mathbb{B}\left(\tilde{k}, n, \Delta(s^t)\right) \sum_{k=0}^{n} \mathbb{B}\left(k, n, x_n(s^t)\right) V_{n-\tilde{k}+k}(s^{t+1}) \middle| s_t \right], \end{aligned} \tag{15}$$

where $m(s^{t+1})$ denotes the stochastic discount factor of the household that owns the firms, and α is a parameter that determines the relative weight of variable and fixed costs of innovation.[11] We denote firm's profits by $\pi(s^t)$ and the equilibrium wage by $w(s^t)$. Note that, because firms are atomistic we can assume that the two binomial processes are independent and, therefore, separable. The combination of the two binomial processes characterizes the probability distribution of a firm with n products to transition in only one period to any number of products in $[0, 2n]$

[11] The innovation investment at time t materializes in product transitions at time $t+1$. Entry of new firms also takes one period to materialize.

instead.[12]

We also allow for an efficiency loss in each variety by depreciating the technology of leaders and followers in every product line at a rate of δ. This depreciation can capture either actual losses in production efficiency or changes in the taste of the consumer as the time passes. Because the depreciation affects every producer within a variety, the relative technological gap remains unaffected.

3.6 Entry of New Firms

To capture entry of new firms, define $M(s^t) \in [0,1]$ as the innovation effort to start a new business. We assume that when an entrepreneur invests $\kappa M(s^t)$ units of labor she succeeds with probability $M(s^t)^\nu$ in becoming a single-product firm next period. As with incumbent firms, there is also a fixed cost F associated to a successful innovation. The entrepreneur solves the following problem:

$$\max_{M(s^t)} \left(M(s^t)\right)^\upsilon \mathbb{E}\left[m(s^{t+1})V_1(s^{t+1})\middle| s_t\right] - \alpha\kappa M(s^t)w(s^t) - (1-\alpha)\left(M(s^t)\right)^\nu F(s^t). \tag{16}$$

The result of this optimization determines the number of new single-product firms in the economy.

3.7 Equilibrium Characterization

The parsimony of the model allows us to unveil the link between interest rate volatility, innovation, and the endogenous trend of productivity. In order to characterize the innovation decisions of firms we need to determine the relevant discounting and the production decision of intermediate good producers. To start, the stochastic discount factor of the household is given by

$$m(s^t, s_{t+1}) = \beta \frac{C(s_{t+1})^{-\gamma}}{C(s^t)^{-\gamma} - \phi\mu(s^t)}, \tag{17}$$

where $\mu(s^t)$ represents the Lagrange multiplier associated with the household's borrowing constraint (5). Household consumption is a function of the income of households, in addition to bond-holding allocations, which are influenced by the borrowing constraint that the representa-

[12] See Appendix B for a detailed description of how to calculate the firm size distribution of the economy.

tive household faces. The value of the collateral that households can post is a function of the value of firms in the economy.

Because the intermediate goods producers act as monopolists, we need the demand for intermediate goods in order to solve for the production decision of intermediate firms. The demand for each variety is given by:

$$y_i(s^t) = \frac{Y(s^t)}{\Lambda p_i(s^t)}. \tag{18}$$

Using this unit elastic demand and assuming Bertrand monopolistic competition at the intermediate good level, we can show that profits and labor per product are independent of the product-specific efficiency $q_i(s^t)$. In particular, we have:

$$\pi(s^t) = \frac{\sigma}{1+\sigma}\frac{Y(s^t)}{\Lambda}, \tag{19}$$

$$l(s^t) = \frac{Y(s^t)}{\Lambda w(s^t)\,(1+\sigma)}. \tag{20}$$

Because firm's decisions are independent of the productivity level of the intermediate products in their portfolio, this framework preserves the proportionality of the value function that has made the Klette and Kortum (2004) so popular in the creative destruction literature. In fact, we can guess and verify that $V_n(s^t) = nV_1(s^t)$. This means that every firm invests the same amount per product. By replacing the guess, factoring the future value of a product and using the properties of the binomial distribution, Equation (15) simplifies to:

$$\begin{aligned} V_1(s^t) &= \max_{x(s^t)} \pi(s^t) - w(s^t)\alpha\left(\tfrac{x(s^t)}{\xi}\right)^{\frac{1}{\theta}} - (1-\alpha)x(s^t)F(s^t) \\ &\quad + \mathbb{E}\left[m(s^{t+1})\left(1-\Delta(s^t)+x(s^t)\right)V_1(s^{t+1})\big|\, s_t\right]. \end{aligned} \tag{21}$$

Therefore, the optimal innovation effort per product line is independent of the total number of products that the firm has:

$$x^*(s^t) = \left[\frac{\theta}{\alpha}\xi^{\frac{1}{\theta}}\frac{\mathbb{E}\left[m(s^{t+1})V_1(s^{t+1}) - (1-\alpha)F(s^t)\big|\, s_t\right]}{w(s^t)}\right]^{\frac{\theta}{1-\theta}}. \tag{22}$$

Having characterized the value of each intermediate product line, we can solve for the mass of new firms:

$$M^*(s^t) = \left[\frac{\upsilon}{\alpha\kappa} \frac{\mathbb{E}\left[m(s^{t+1}) V_1(s^{t+1}) - (1-\alpha) F(s^t) \middle| s_t \right]}{w(s^t)} \right]^{\frac{1}{1-\upsilon}}, \tag{23}$$

The endogenous creative destruction rate is composed by the innovation of incumbent firms and new entrants, therefore:

$$\Delta(s^t) = \frac{\left(M^*(s^t)\right)^{\upsilon}}{\Lambda} + x^*(s^t) \tag{24}$$

Having the aggregate rate of creative destruction we can derive the endogenous productivity growth in the economy. In fact, replacing Equation (11) in Equation (10) we obtain:

$$Y(s^t) = e^{z(s^t)} A(s^t) l(s^t), \tag{25}$$

where $A(s^t)$ is the endogenous productivity level defined by:

$$\ln A(s^t) = \frac{1}{\Lambda} \int_0^{\Lambda} \ln q_i(s^t) di. \tag{26}$$

Endogenous productivity growth is generated by creative destruction. Moreover, the productivity of an intermediate good production only increases by a factor $(1+\sigma)$ when it is subject to the creative destruction rate $\Delta(s^t)$:

$$\begin{aligned} & \ln(A(s^t, s_{t+1})) - \ln(A(s^t)) = \Delta(s^t) \ln(1+\sigma) + \ln(1-\delta) \\ \text{or} \quad & \frac{A(s^t, s_{t+1})}{A(s^t)} = 1 + g\left(s^t, s_{t+1}\right) = (1+\sigma)^{\Delta(s^t)} (1-\delta), \end{aligned} \tag{27}$$

where $g\left(s^t, s_{t+1}\right)$ is the growth rate of the endogenous productivity index. When a shock triggers fluctuations in $\Delta(s^t)$, we will observe fluctuations in the endogenous productivity growth rate. Note that, endogenous productivity increases if and only if creative destruction overtakes the depreciation rate δ. Thus, this feature allows the model to potentially generate a negative growth rate.

We can further characterize the equilibrium by combining Equations (25) and (20) to solve for the equilibrium wage:

$$w(s^t) = \frac{e^{z(s^t)} A(s^t)}{\Lambda (1+\sigma)}. \tag{28}$$

Appendix C renders the model stationary by normalizing the growing variables using the productivity index. It also summarizes the full system of dynamic equations that characterizes the stochastic solution of the model.

It remains to characterize the optimality conditions for the representative household's problem. The first order conditions yield the following equilibrium conditions:

$$C(s^t)^{-\gamma} = \mu(s^t) + \beta \hat{R}(s^t) \mathbb{E}\left[C(s^{t+1})^{-\gamma} | s^t \right] \tag{29}$$

$$C(s^t) + \hat{q}(s^t) B^H(s^t) \leq w(s^t)\bar{L} + B^H(s^{t-1}) + \Lambda e(s^t) - \kappa \alpha M(s^t) w(s^t) - (1-\alpha) \left(M(s^t) \right)^{\nu} F(s^t), \tag{30}$$

with $\hat{R}(s^t) = 1/\hat{q}(s^t)$. Equation (29) corresponds to the Euler equation of bond holdings and Equation (30) describes the budget constraint of the household replacing the expression for lump-sum transfers from firms in the economy. Note that Equation (21) implies $e(s^t) = \pi(s^t) - w(s^t)\alpha \left(\frac{x(s^t)}{\xi} \right)^{\frac{1}{\theta}} - (1-\alpha) x(s^t) F(s^t)$.

Lastly, the borrowing constraint faced by the representative household is

$$\hat{q}(s^t) B^H(s^t) \geq -\phi \Lambda V_1(s^t), \tag{31}$$

where the total value of firms in the economy V is equal to the mass of differentiated intermediate goods Λ times the value of owning one product line V_1. This is a consequence of the linearity of the value of a firm in the number of product lines it owns.

3.8 Trend Dynamics and Interest Rates

Equation (27) shows that stationary distortions affecting the endogenous rate of creative destruction (Δ) can trigger permanent changes in the level of the productivity index defined in Equation (26). Because that index determines the long-run growth rate of the economy, every non-stationary variable is normalized by it. Thus, fluctuations in the creative destruction rate generate hysteresis

in output and consumption. In fact, in this class of models, stationary shocks can trigger non-stationary dynamics due to the internal propagation of the model. To understand the drivers of these endogenous trend dynamics we need to study how different shocks affect the determinants of building blocks of creative destruction and, thus, how aggregate shocks drive firm entry and the expansion decision of incumbents. Equations (22) and (23) provide guidance when studying these drivers.

The dynamics of the two components of creative destruction are due to two endogenous objects: the dynamics of the stochastic discount factor of the household and the relative future value of a product normalized by the current wage of the economy. Let us focus first on the effect of a TFP shock. Because TFP shocks are very persistent, they have only fairly small effect on the household's stochastic discount factor. Consequently, TFP shocks typically do not significantly influence productivity growth through this channel. Regarding the second channel, Equation (28) shows that a TFP shock directly increases wages, increasing the denominator of the relative future value of a product normalized by the current wage. Nevertheless, as seen in Equation (21) the value of owning a product is given by the expected discounted value of profits nets of innovation costs, and both profits and R&D costs increase with a TFP shock. Once again, given the persistence of TFP shocks, the ratio of future profits and future output to current wages conditional on a TFP shock is relatively stable. Thus, TFP shocks are not a promising channel to generate endogenous trend dynamics.

In contrast to a TFP shock, an interest rate shock does not directly impact either profits or the cost of innovation.[13] Therefore, the numerator and denominator of the relative future value of a product normalized by the current wage of the economy are mostly unaffected by an interest rate shock. Nevertheless, the interest rate shock generates fluctuations in the stochastic discount factor of the household. Equation (29) illustrates this. Specifically, we see that increases in the financing cost faced by households leads to a decline in the term $\frac{C(s^{t+1})^{-\gamma}}{C(s^t)^{-\gamma}-\mu(s^t)}$, implying that firm will discount the future more heavily. Hence, the innovation intensity of incumbent and entrants fall (see equations (22) and (23)), negatively impacting the creative destruction rate of the economy. Thus, an interest rate shock has a direct impact on the innovation rate of the economy and constitutes

[13]Interest rate shocks do not affect profits or wages because we abstract from working capital constraints. With a working capital constraint, an interest rate shock affects wages and values similarly to a TFP shock. Consequently, the effect of interest rate shocks working through working capital constraints on endogenous trend dynamics is small.

the main driver of the endogenous productivity trend.

It is important to note that both TFP and interest rate shocks can influence the rate of creative destruction by triggering current or future tightening of the collateral constraint (31). When the constraint is binding, households are forced to delever, which reduces current consumption and increases the discounting of future returns. This, in turn, lowers the value of firms, further tightening the constraint and potentially leading to a Fisherian deflationary spiral. Thus, while interest rate shocks are the main drivers of trend dynamics, large (TFP or interest rate) shocks that increase the likelihood of future crises can have permanent effects, mediated by the discount factor, on the creative destruction rate.

In light of the importance of interest rate shocks and the potential triggering of Fisherian deflationary dynamics, we can understand the mechanism that links interest rate volatility and the trend of productivity. To understand this it is helpful to consider an initial situation where the borrowing constraint is slack. As volatility increases, households anticipate that future interest rate fluctuations will be larger in magnitude. While significant interest rate reductions increase the value of firms, larger interest rate hikes can decrease it by a larger magnitude (in absolute value). Specifically, interest rate reductions have a direct effect on the value of collateral, whereas interest rate hikes not only impact collateral value but can also trigger the Fisherian deflation mechanism. Therefore, even in the absence of concurrent interest rate shocks, and increase in interest rate volatility is sufficient to slow down innovation due the asymmetry between the effects of large interest rate hikes and reductions.

4 Quantitative Analysis

In this section, we demonstrate that, despite its simplicity, the model replicates the differential sensitivity of the productivity trend to interest rate volatility between emerging and advanced economies. First, we calibrate the model for both Mexico (an emerging economy) and a financially advanced version of this model economy. Importantly, all shock processes are common to both economies, with the only calibration difference being the level of financial frictions. Second, using generalized impulse responses, we show that, consistent with the analysis in Section 2, the response of the productivity trend to interest rate risk in emerging markets is an order of mag-

nitude 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 20 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 and used to match time series dynamics of the Mexican economy. Table 2 shows the externally calibrated values. First, we estimate the process of the U.S. interest rate directly from the data, as described in Section 2. We set the average interest rate to 4% annually, 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 also standard in the macro literature. 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. This is, without any investment in the creation of new firms and expansion by incumbents, the efficiency index would shrink at rate δ.

Parameter	Symbol	Value	Source
Average US Interest Rate	$\bar{R}$	$(1.04)^{0.25} - 1$	Estimation, US data
Persistence of Interest Rate	ρ_R	0.91	Estimation, US data
Average Interest Rate Volatility	μ_σ	0.17	Estimation, US data
Persistence of Interest Rate Volatility	ρ_σ	0.94	Estimation, US data
Volatility of Interest Rate Volatility	η_σ	0.12	Estimation, US 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	Max A contraction

Table 2: Externally Calibrated Parameters

Table 3 presents a summary of our 9 internally calibrated parameters. The step size σ is set to 0.22, which implies an average annualized growth rate close to 2%, consistent with Mexican data. We set the cost level of entry κ to 31, which generates an annualized 10% entry rate, consistent with Mexican empirical evidence. 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.[14] 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. Lastly, we set ι_1 to 17.4 in order to generate spread sensitivity that is consistent with the hike in Mexican spreads during the Great Recession.

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 D provides a detailed description of the solution method.

[14] 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).

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	1/3
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	17.4	Spread Sensitivity	$\frac{\text{Spread}_{08}-\text{Spread}_{07}}{\sigma_{08}-\bar{\sigma}}$

Table 3: Internally Calibrated Parameters

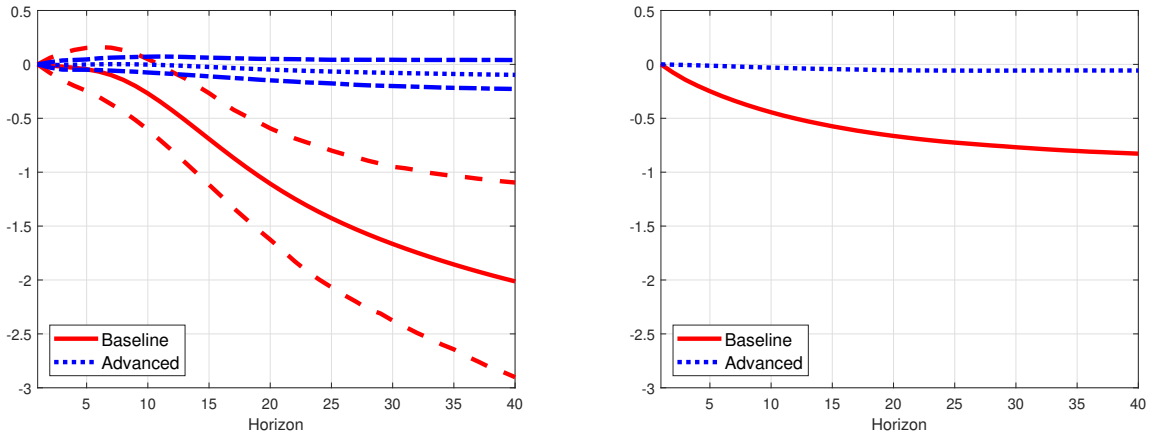
To highlight the importance of heterogeneous financial frictions, we recalibrate only three parameters from Table 3. Our goal is to study the implications of interest rate volatility on growth of an advanced economy. For concreteness, the reader can think of this open advanced economy as resembling Canada.

We recalibrate the parameters governing discount factor of international lenders (ι_0 and ι_1) and we 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 $\iota_0 = 0.004$ and $\iota_1 = 2.17$ so that the average quarterly spread is 0.38% and the spread sensitivity to US interest rate volatility is consistent with what was observed for Canadian spreads during the Great Recession.

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 estimate 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, 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 estimation with data simulated for both calibrations, using the same underlying sequence of shocks.

Figure 3 presents the impulse response functions of the trend component to a one standard deviation stochastic volatility shock, comparing the empirical and model-simulated approaches. The responses in panel (b) of Figure 3 reveal two key patterns: (1) the trend component in the developed 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 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 40% (at its trough) of its empirical counterpart. Because these responses were not a target of our calibration, we consider 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.



(a) Empirical (b) Model

Figure 3: Impulse Response Functions to a US Interest Rate Volatility Shock

Notes: Panel (a) presents the impulse response functions of the accumulated trend to a one standard deviation stochastic volatility shock of the U.S. interest rate, for advanced (blue dotted line) and emerging (red solid line) economies. These responses are estimated following the approach described in Section 2. Panel (b) estimates responses following a similar approach but using model-simulated data.

4.3 Risk Matters: Asymmetric Responses to Interest Rate Shocks

The results shown in Figure 3 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 stochastic 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.[15] 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 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 the household also diminishes. This further tightens the borrowing constraint, reinforcing the cycle and generating significant nonlinearities that contribute to the aforementioned amplification. Conversely, when households experience an interest rate cut, the amplification mechanism is much weaker, as the multiplier is bounded by 0. 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.[16] 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 perfect 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

[15] 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.

[16] 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.

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.

Table 4 presents the standardized differences in responses to symmetric interest rate shocks for endogenous trend growth and the expected discounted value of a product line (normalized by wage) under the two calibrations. Since our focus is on assessing response asymmetry, we present the difference in absolute value responses (i.e., response to interest rate hikes minus response to interest rate cuts in absolute terms). The standardized shock sizes are selected such that, given average volatility, their likelihood of occurrence is approximately 51% (0.66 standard deviations), 32% (1 standard deviation), 10% (1.65 standard deviations), and 5% (2 standard deviations).

Table 4: Asymmetry in Responses and Interest Rate Shocks

Shock Size	g		$\mathbb{E}\left(\frac{m(s^{t+1})V(s^{t+1}))}{w(s^t)}\right)$		$\Pr(\lvert\Delta R\rvert \geq$ Shock Size)		
	Baseline	Advanced	Baseline	Advanced	Low σ_t	Average σ_t	High σ_t
0.66	0.00	0.01	-0.01	0.01	29.1%	50.9%	63.1%
1.0	-0.01	0.01	0.00	0.00	11.3%	32.2%	47.1%
1.65	0.04	0.01	0.04	0.01	0.8%	9.9%	23.0%
2.0	0.06	0.03	0.06	0.02	0.2%	4.8%	14.9%

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

The first column of Table 4 presents the magnitude of the interest rate shock (in absolute value), expressed in standard deviations. Columns 2 and 3 report the difference in standardized responses to interest rate hikes and cuts for the endogenous growth rate under the baseline and advanced economy calibrations, respectively. Similarly, columns 4 and 5 present the same concept for the expected discounted value of a product line, normalized by wages. Lastly, columns 7 through 9 display the probability of observing a shock of at least that magnitude, given a specific level of volatility.

The results reveal two key patterns. First, the asymmetry in the responses of the growth rate and the discounted expected value of a product increases with the size of the interest rate shock: for smaller shocks, the responses to interest rate hikes and cuts are relatively symmetric. However, this symmetry breaks down for larger shocks (e.g., 2 standard deviations). Second, asymmetries

are more pronounced in the baseline calibration. Specifically, in the baseline case, the asymmetry grows more sharply with the size of the shocks, whereas in the advanced economy calibration, the increase is much milder.

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, 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. This contrasts with much of the literature on uncertainty shocks (Bloom, 2009; Vavra, 2014), where second-moment shocks are often assumed to be correlated with first-moment realizations.

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 5 presents selected long-run moments for our baseline and advanced economy calibrations across the two volatility regimes.

Table 5: Volatile Rates and Volatile Trends: Deterministic Volatility

Moment	Mexico		Advanced Mexico	
	SV	No SV	SV	No SV
$\sigma(g)/\mathbb{E}(g)$	0.17	0.10	0.14	0.14
$\sigma(CA/Y)$ %	2.78	2.52	0.73	0.67
$\mathbb{E}(B^H/Y)$ %	-32.78	-34.40	-54.32	-54.41
Spread %	1.00	0.40	1.00	0.40
Prob. Crisis %	2.75	3.50	1.35	1.27

Notes: SV denotes the scenario with stochastic volatility in the world interest rate. In the No SV case, we set the variance of the world interest rate to be equal to its long-run average.

For emerging economies, the results in Table 5 indicate a substantial reduction in the coefficient of variation of trend growth by approximately 40%, highlighting the significant role that volatility shocks play in driving fluctuations. In contrast, the advanced economy experiences no 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 con-

sumption 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 a full 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 may not be volatility itself but rather their response to it. The next section delves deeper into 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 6 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 20%, while the volatility of the

current account relative to GDP falls by nearly 40%. 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.[17]

Table 6: Financial Frictions and Business Cycles

Moment	Mexico	Relaxed Constraint Mexico	Advanced Mexico
$\mathbb{E}(\text{Spread})$ %	1.00	1.00	0.40
$\sigma(g)/\mathbb{E}(g)$	0.17	0.14	0.14
$\sigma(CA/Y)$ %	2.78	1.71	0.73
$corr(\text{Domestic Spread}, g)$	-0.40	0.47	0.66
Prob. Crisis %	2.75	1.50	1.35
$\mathbb{E}(B^H/Y)$ %	-32.78	-52.37	-54.32

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 nearly the entire 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 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 (David et al., 2014).

A key feature of our model, closely linked to financial frictions, is the occurrence of Sudden Stops—episodes marked by sharp reversals in the current account, accompanied by 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, Sudden Stops in our model have persistent effects on output due to the inclusion of endogenous growth. This persistence aligns with findings from other models that integrate financial frictions into growth dynamics (Queralto, 2020; Ates and Saffie, 2021).

Appendix E presents event studies comparing Sudden Stops in emerging and advanced economies,

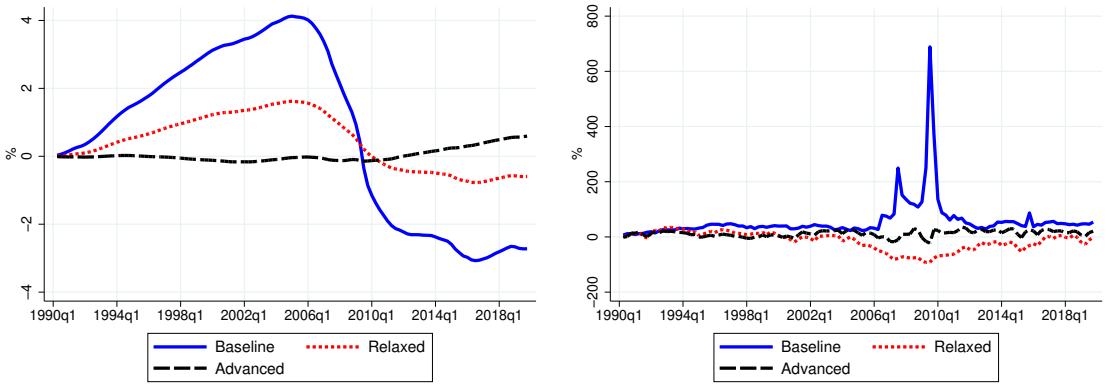
[17] We define the domestic spread as the difference between the domestic interest rate and the rate charged by intermediaries: $\mathbb{E}\left[R^B(s^{t+1}) - \hat{R}(s^t)\right] = \mu(s^t)/\mathbb{E}[\lambda(s^{t+1})|s^t]$.

using calibrations derived from our model. Our results highlight the crucial role of financial frictions in explaining why emerging markets experience more frequent and severe Sudden Stops, with greater hysteresis effects than their advanced economy counterparts.

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 volatility and interest rate shocks depicted in Figure 1. Specifically, we simulate 10,000 series from the TFP process—each combined with the actual observed path of global volatility and interest rates—for 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 4 presents the average trend deviations for productivity levels and the Lagrange multiplier of the borrowing constraint across all economies.[18]



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

Figure 4: Deviations from Trend Based on Actual Interest Rate and Volatility Time Series

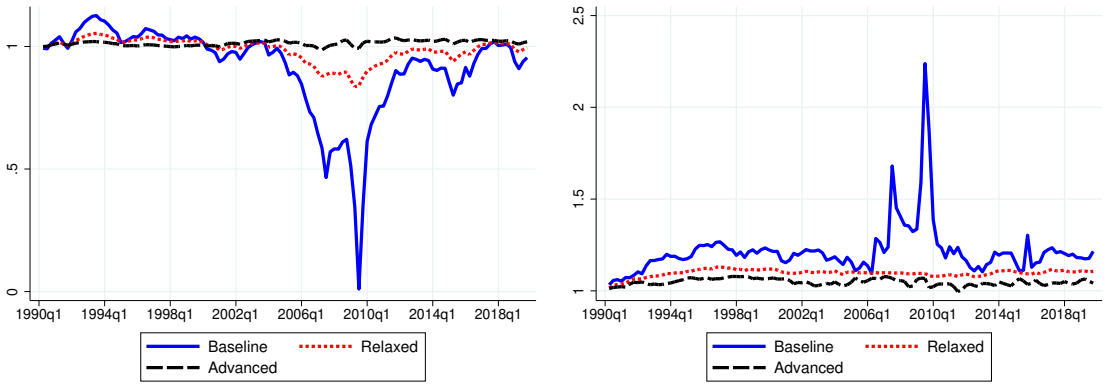
The first panel of Figure 4 illustrates that the average growth trajectories of the three types of economies differ significantly. The period of low volatility and declining interest rates between 1990 and 2006 spurred rapid productivity accumulation in emerging markets, whereas advanced

[18] We construct these series by computing the log difference between the stochastic trend $A_t = \Pi_{i=0}^{t}(1+g_i)$ 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 indeterminacy in cases where the multiplier is 0, where $\mu_t = A_t^{-\gamma}\tilde{\mu}_t$ and $\bar{\mu}_t = \bar{A}_t^{-\gamma}\bar{\tilde{\mu}}$.

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 3% below its productivity trend.

The second panel of Figure 4 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 F, 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, 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.

To further explore the interaction between global financial risk and idiosyncratic shocks, Figure 5 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. Notably, the underlying 10,000 time series of productivity are identical for all three economy types.

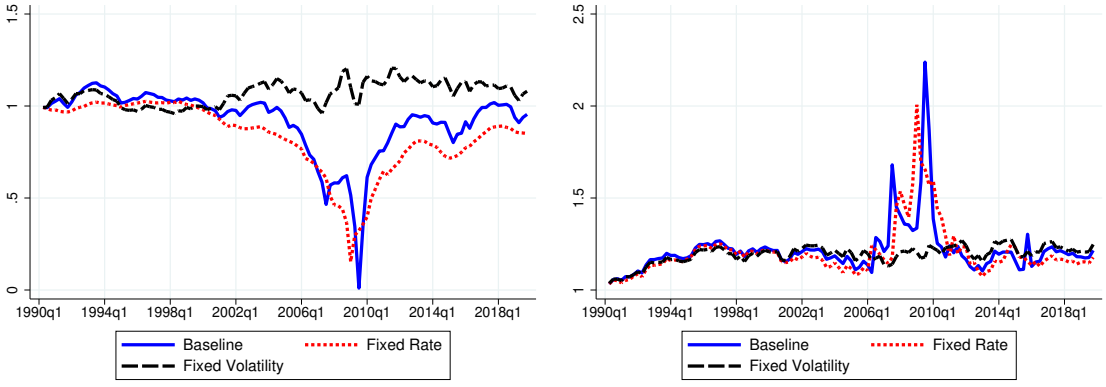


(a) Growth Rate g - Average

(b) Growth Rate g - Standard Deviation

Figure 5: Deviations from Trend Based on Actual Interest Rate and Volatility Time Series

The first panel of Figure 5 is consistent with our previous analysis, showing that endogenous productivity growth remains positive in the early period for emerging markets. Interestingly, the dispersion of the growth rate, presented in the second panel, 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 Appendix G, our empirical estimates of country-level productivity trends align with these observed patterns.



(a) Growth Rate g - Average

(b) Growth Rate g - Standard Deviation

Figure 6: Average and Standard Deviation of Growth Rate g For Different Time Series Scenarios

Finally, Figure 6 decomposes the dynamics presented in Figure 5 for the baseline emerging market calibration by setting either the interest rate shocks or their volatility to their mean. The de-

composition 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 5 highlights the importance of the collateral constraint in shaping both the average growth and the dispersion of productivity dynamics in emerging markets, Figure 6 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.

5 Conclusion

This paper provides new empirical and theoretical evidence linking global financial risk—specifically, uncertainty in U.S. interest rates—to long-term productivity trends, particularly in emerging markets. We demonstrate that volatility shocks have disproportionately large effects on trend growth in emerging economies compared to advanced ones, primarily due to financial frictions that amplify the impact of uncertainty shocks. Limited collateral pledgeability and heightened risk aversion among international lenders create an environment where financial volatility leads to deep and persistent economic downturns.

A key finding of our analysis is the asymmetric response of trend growth to interest rate fluctuations. Large interest rate hikes generate significantly sharper declines in growth than equivalent interest rate cuts, a pattern exacerbated during periods of heightened financial risk. This asymmetry arises because households facing tightening borrowing conditions adjust their consumption and savings behavior in anticipation of more extreme future financing costs, leading to a slowdown in investment and innovation. These dynamics unfold through endogenous mechanisms, without requiring exogenous trend shocks or an artificially imposed correlation between productivity and interest rates.

Decomposing the effects of borrowing constraints and lender risk aversion reveals that financial development plays a crucial role in shaping the impact of volatility shocks. We find that most

of the differential response to financial risk stems from weaker financial infrastructure in emerging markets. When borrowing constraints are relaxed, growth volatility declines substantially, and the frequency of financial crises is reduced. This suggests that rather than focusing solely on external shocks, emerging economies should prioritize financial deepening to mitigate the effects of global uncertainty.

The economic consequences of volatile interest rates are not limited to short-term fluctuations. The real-world sequences of interest rate and volatility shocks reveal that while emerging markets may benefit from high trend growth during periods of low volatility, they are also highly vulnerable to severe productivity losses when financial risk escalates. These downturns are often prolonged by self-reinforcing deleveraging cycles and Fisherian deflation, which tighten borrowing constraints even further. In contrast, economies with more developed financial systems experience a more stable growth trajectory, as they can better absorb financial shocks without triggering systemic crises.

These findings underscore the importance of financial development and risk management in shaping economic resilience. Macroprudential policies—such as enhanced collateral frameworks, countercyclical capital buffers, and stronger financial institutions—can play a critical role in reducing the vulnerability of emerging markets to financial volatility. Future research should explore how policy frameworks tailored to different financial structures can enhance resilience to global uncertainty shocks. Additionally, expanding this framework to analyze the role of firm dynamics and sectoral heterogeneity could offer deeper insights into how financial frictions shape aggregate productivity trends.

Ultimately, this paper highlights the critical role of financial constraints in determining how economies respond to global financial risk. While volatility is an unavoidable feature of the global financial landscape, the way economies react to it—through financial policies, institutional reforms, and risk management strategies—shapes their long-run growth prospects. Strengthening financial systems may be the most effective strategy for ensuring that periods of financial turbulence do not translate into long-term economic stagnation.

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Appendices

Appendix A 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.

A.1 Model Setup

The optimization problem of an individual bank is

$$\begin{aligned} V_{i,t} &= \max_{L_{i,t}, D_{i,t}} E_t \left[\Lambda_{t,t+1} \left((1-\sigma) N_{i,t+1} + \sigma V_{i,t+1} \right) \right] \\ \text{subject to} \quad & V_{i,t} \geq \theta L_{i,t} \\ & N_{i,t} = R^l_{t-1} L_{i,t-1} - R^d_{t-1} D_{i,t-1} \\ & N_{i,t} + D_{i,t} = L_{i,t} \end{aligned}$$

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

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

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

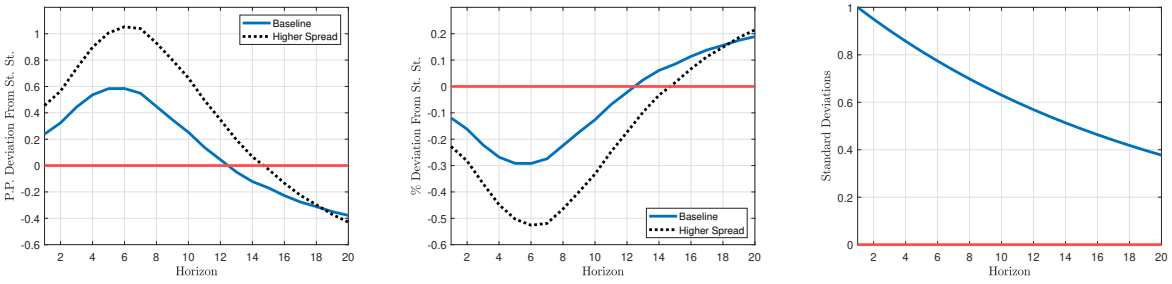
A.2 Quantitative Results

We calibrate the model to match features of the U.S. economy. Table 7 presents the externally calibrated parameters, along with their corresponding values and sources in the data.

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

Table 7: Calibration Summary

The rest of the parameters, Ω, ψ, ν, and θ, are set internally such that equilibrium conditions are satisfied. Figure 7 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.



Loan Interest Rate R^l Loans L_t Stochastic Volatility σ_t

Figure 7: Impulse Response Functions to a Stochastic Volatility Shock

The impulse response functions of the baseline case presented in Figure 7 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 B 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 $\mathbb{I}^+(a) \geq a$.[19] 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 $\tilde{n}$.[20] The BGP distribution can be found by iterating in these laws of motion until the mass of firms in each product category is constant.

[19] 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.

[20] 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 C Dynamic System of Equations

C.1 Representative Household & Financial Intermediation

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

C.2 Final Good Producer

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

C.3 Intermediate Good Producer

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

C.4 Entry

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

C.5 Aggregate Variables

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

C.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 D 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 using 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.

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).[21] 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:

$$M_j(z, R, \sigma_r, B) = \left[\frac{x_j(z, R, \sigma_r, B)^{\frac{1-\theta}{\theta}}}{\xi^{\frac{1}{\theta}}\theta} \frac{\nu}{\kappa} \right]^{\frac{1}{1-\nu}} \tag{32}$$

$$g_j(z, R, \sigma_r, B) = (1+\sigma)^{x_j(z,R,\sigma_r,B) + \frac{M_j(z,R,\sigma_r,B)^\nu}{\Lambda}} (1-\delta) - 1 \tag{33}$$

$$\Delta_j(z, R, \sigma_r, B) = x_j(z, R, \sigma_r, B) + \frac{M_j(z, R, \sigma_r, B)^\nu}{\Lambda} \tag{34}$$

$$l_{rj}(z, R, \sigma_r, B) = \left(\frac{x_j(z, R, \sigma_r, B)}{\xi} \right)^{\frac{1}{\theta}} \tag{35}$$

$$l_j(z, R, \sigma_r, B) = \frac{(1 - \kappa M_j(z, R, \sigma_r, B))}{\Lambda} - l_{rj}(z, R, \sigma_r, B) \tag{36}$$

$$Y_j(z, R, \sigma_r, B) = z l_j(z, R, \sigma_R, B) \tag{37}$$

[21] 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.

$$\pi(z, R, \sigma_r, B) = \frac{\sigma}{\Lambda(1+\sigma)} Y_j(z, R, \sigma_r, B) \tag{38}$$

$$\begin{aligned} t_j(z, R, \sigma_r, B) = \Lambda(\pi_j(z, R, \sigma_r, B) - \alpha w(z) l_{rj}(z, R, \sigma_r, B) - (1-\alpha) F x_j(z, R, \sigma_r, B)) \\ - \alpha\kappa M_j(z, R, \sigma_r, B) w(z) - (1-\alpha) M_j(z, R, \sigma_r, B)^{\nu} F \end{aligned} \tag{39}$$

$$w(z) = \frac{\exp(z)}{\Lambda(1+\sigma)} \tag{40}$$

$$c_j(z, R, \sigma_r, B) = w(z) + B - B'_j(z, R, \sigma_r, B)(1 + g_j(z, R, \sigma_r, B))\hat{q}(R, \sigma_r) + t_j(z, R, \sigma_R, B) \tag{41}$$

Lastly, compute the discounted expected marginal utility

$$\beta \frac{\beta}{\hat{q}(R, \sigma_r)} \mathbb{E}\left[u_j(z', R', \sigma'_r, B'_j(z, R, \sigma_r, B))\right] (1 + g_j(z, R, \sigma_r, B))^{-\gamma}, \tag{42}$$

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:

$$\begin{aligned} V_{1,k+1}(z, R, \sigma_r, B) = \pi_j(z, R, \sigma_r, B) - \alpha w(z) \left(\frac{x_j(z, R, \sigma_r, B)}{\xi}\right)^{\frac{1}{\theta}} - (1-\alpha) x_j(z, R, \sigma_r, B) F \\ + \mathbb{E}\left[m_j(z, R, \sigma_r, B)(1 - \Delta_j(z, R, \sigma_r, B) + x_j(z, R, \sigma_r, B))\left(1 + g_j(z, R, \sigma_r, B)\right) V_{1,k}(z, R, \sigma_r, B)\right] \end{aligned} \tag{43}$$

Until $||V_{1,k+1}(z, R, \sigma_r, B) - V_{1,k}(z, R, \sigma_r, B)|| <$ 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

$$c_{j+1}(z, R, \sigma_r, B) = w(z) + B + \phi\Lambda(V_{1,j}(z, R, \sigma_r, B)) + t_j(z, R, \sigma_R, B) \tag{44}$$

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

tion:

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

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

$$u_{j+1}(z,R,\sigma_r,B) = \beta\frac{\beta}{\hat{q}(R,\sigma_r)}\mathbb{E}\left[u_j(z',R',\sigma_r',B_j'(z,R,\sigma_r,B))\right](1+g_j(z,R,\sigma_r,B))^{-\gamma} \tag{46}$$

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:

$$m_{j+1}(z,R,\sigma_r,B) = \beta\frac{c_{j+1}(z,R,\sigma_r,B'(z,R,\sigma_r,B))^{-\gamma}}{c_{j+1}(z,R,\sigma_r,B)^{-\gamma}-\phi\mu_{j+1}(z,R,\sigma_r,B)}(1+g_j(z,R,\sigma_r,B))^{-\gamma} \tag{47}$$

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:

$$V_{1,k+1}(z,R,\sigma_r,B) = \pi_j(z,R,\sigma_r,B) - \alpha w(z)\left(\frac{x_j(z,R,\sigma_r,B)}{\xi}\right)^{\frac{1}{\theta}} - (1-\alpha)x_j(z,R,\sigma_r,B)F$$
$$+\mathbb{E}\left[m_{j+1}(z,R,\sigma_r,B)(1-\Delta_j(z,R,\sigma_r,B)+x_j(z,R,\sigma_r,B))\left(1+g_j(z,R,\sigma_r,B)\right)V_{1,k}(z,R,\sigma_r,B)\right] \tag{48}$$

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:

$$x_{j+1}(z,R,\sigma_r,B) = \left[\frac{\theta}{\alpha}\xi^{\frac{1}{\theta}}\frac{\mathbb{E}\left[m_{j+1}(z,R,\sigma_r,R)\left(1+g_j(z,R,\sigma_r,R)\right)V_{1,j+1}(z,R,\sigma_R,B)-(1-\alpha)F\middle|\, s_t\right]}{w(z)}\right]^{\frac{\theta}{1-\theta}} \tag{49}$$

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).

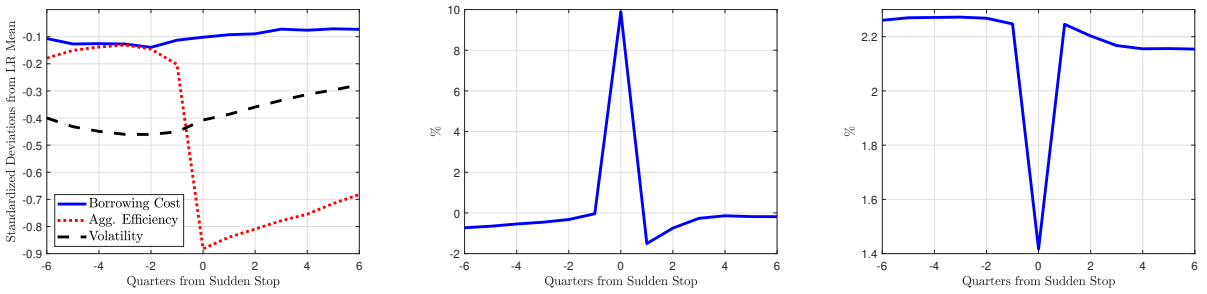
Appendix E Persistent Effects of Sudden Stops

We conduct an event analysis around Sudden Stops endogenously generated by the model under both the baseline and advanced economy calibrations. Using a time window of 10 quarters before and after each event, we average relevant time series.[22] Figure 8 illustrates the Sudden Stop dynamics for the baseline scenario.

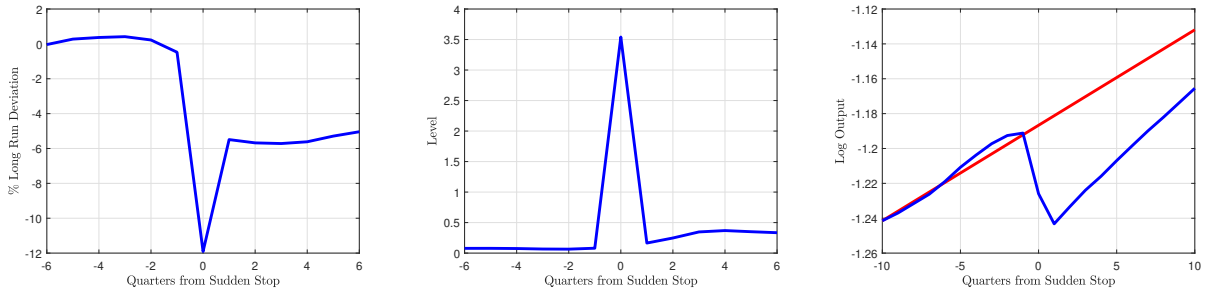
Our focus is on the dynamics of five key variables: the value of a product line, the Lagrange multiplier, the current account-to-GDP ratio, the endogenous trend, and log GDP (in levels). Panel (a) shows the evolution of the model's three shocks around the event. In our framework, Sudden Stops typically occur under three conditions: (1) borrowing costs are below their long-run average, (2) interest rate volatility is low, and (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.[23] 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.

[22] 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.

[23] 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.



(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

Figure 8: Sudden Stop Dynamics - Emerging Economy

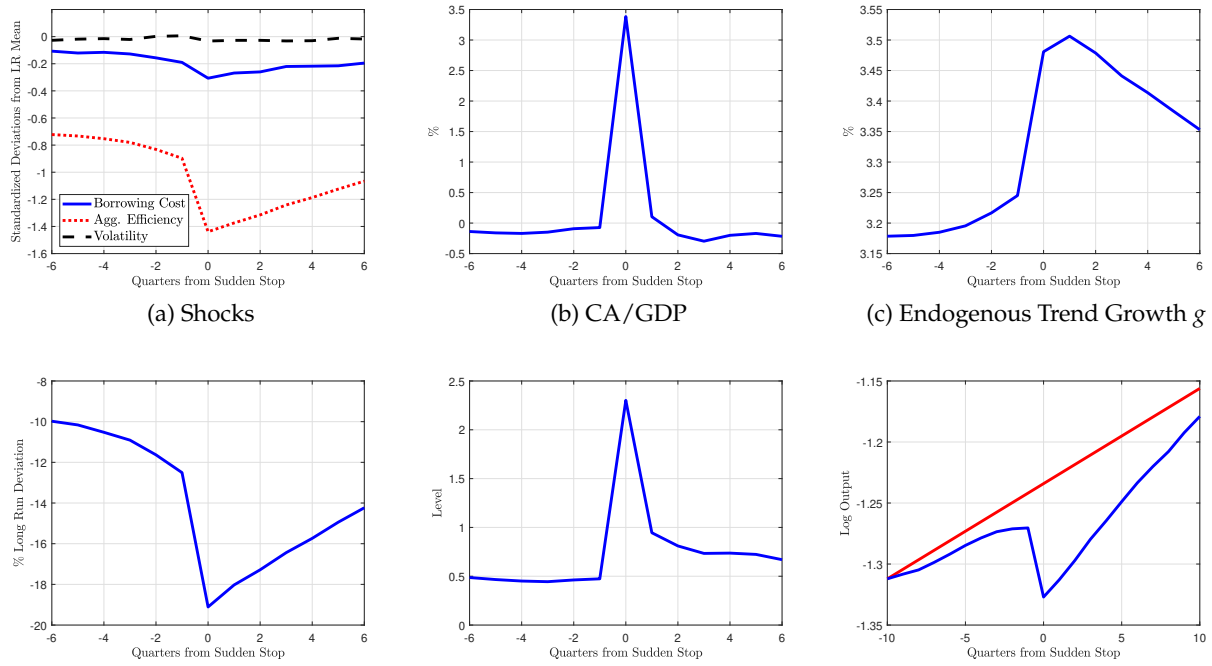
Notes: Sudden Stops are defined as events where the borrowing constraint binds and where the current account-to-GDP ratio is two standard deviations above its long-run mean. The three shocks of the model are standardized by their corresponding long-run means and standard deviations. CA/GDP denotes the 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.[24] 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.

To assess the role of financial frictions in the severity of Sudden Stops, we conduct a similar event analysis using the advanced economy calibration. Figure 9 presents the Sudden Stop

[24]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.

dynamics for this scenario.



(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

Figure 9: Sudden Stop Dynamics - Advanced Economy

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.

This analysis contrasts the dynamics of Sudden Stops between advanced and emerging economies, highlighting both the likelihood and severity of these events. The results in Figure 9 reveal that Sudden Stops in advanced economies are triggered by a much more adverse sequence of shocks compared to the baseline scenario. Specifically, the aggregate efficiency level that leads to a Sudden Stop is nearly 1.5 standard deviations below its long-run average, almost 50% larger than in the emerging economy case. Moreover, Sudden Stops in advanced economies also occur when borrowing costs are lower than their long-run average, and lower than in the baseline calibration. These findings highlight the stronger resilience of advanced economies: not only are financial crises less frequent, but they require a significantly worse deterioration in economic conditions to materialize.

In terms of severity, Sudden Stops in advanced economies are far milder than in emerging

economies. While the current account reversal is substantial, it is about one third of the size seen in emerging economies. Trend growth experiences small ajdustments. As in the baseline scenario, the value of a product line declines and recovers slowly. Finally, although GDP declines are also milder, the persistent drop in aggregate efficiency causes long-run GDP losses to start accumulating several quarters before the Sudden Stop occurs.

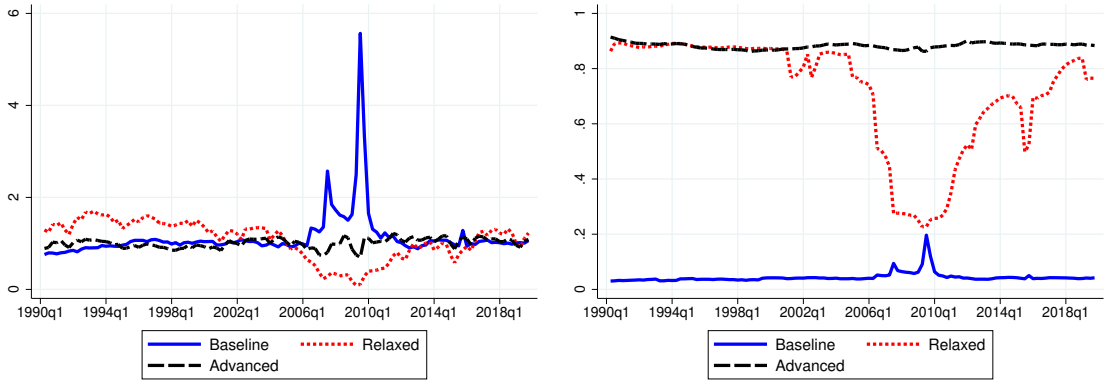
Overall, our results demonstrate that financial frictions play a critical role in shaping both the likelihood and severity of Sudden Stops across advanced and emerging economies. The framework not only captures realistic crisis dynamics but also illustrates how financial crises can have lasting effects on output and the economy's long-run trend.

It is important to distinguish between the crises driven by U.S. interest rate volatility and the 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 F Additional Simulation Results: Binding Borrowing Constraints

Figure 10 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 10: Borrowing Constraint Multiplier & Binding Probability Based on Actual Interest Rate and Volatility Time Series



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

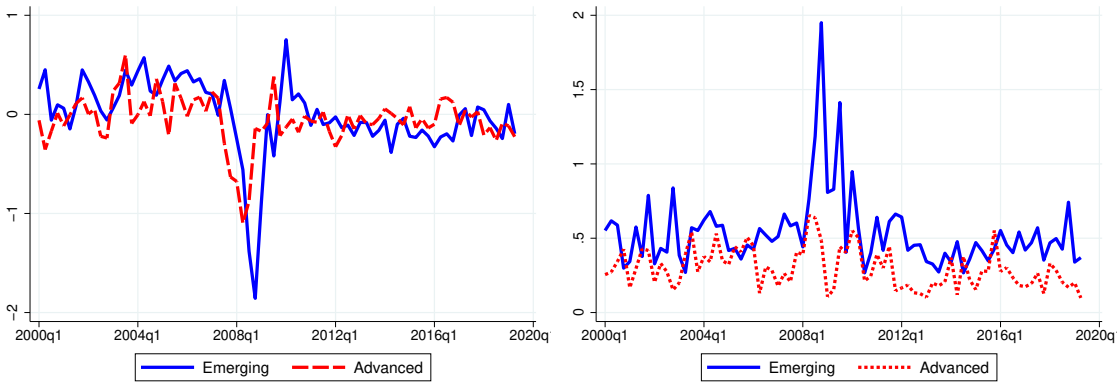
(b) Prob. of Binding Constraint $\Pr(\tilde{\mu}_t > 0)$

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.

Appendix G Empirical Estimates of Trend Growth Rate

In this section, we present selected moments for our empirical estimates of the stochastic trend growth rate. Our estimation method is detailed in Section 2. Figure 11 displays the cross-sectional averages and standard deviations for the panel of emerging and advanced economies in our sample.

Figure 11: Cross-Sectional Moments of the Stochastic Trend Growth Rate



(a) Cross-Sectional Average

(b) Cross-Sectional Standard Deviation

Consistent with our model predictions depicted in Figure 5, the panel of emerging markets exhibits higher average trend growth but greater cross-country dispersion during the Risk-Off period. Furthermore, as the model predicts, the dispersion of trend growth within emerging markets rises sharply during the Great Financial Crisis and remains elevated relative to advanced economies in the years that followed.