News, sovereign debt maturity, and default risk

Online Appendix

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In this online appendix we discuss data sources, explain the calibration of the productivity process and sudden stops, derive the transition probabilities with signals about productivity change, and present details of the computational methods. It also contains multiple robustness checks. In particular, with present the results of a model at quarterly frequency, a model with preferences capturing wealth effects on labor supply (non-GHH), alternative calibration of sudden stop probabilities, models with exogenous maturity, larger grid for TFP shocks and debt level, a model with non-informative news, a model with positive recovery of the debt in default, and discuss the calibration of the preference shocks.

1 Data sources

- GDP per capita: We use the "GDP per capita (constant 2010 US$)" ("NY.GDP.PCAP.KD") from the World Development Indicators (WDI) provided by the World Bank.[1] For the volatility and correlations, we HP filter the data for the entire horizon with available data.
- Debt-to-GDP ratio: For debt-to-output ratios, we use the variable "DT.DOD.DECT.GN.ZS" from the WDI, which gives external debt stocks (% of GNI) for the entire period for which we have available data on spreads and maturity.
- Consumption per capita: We use the variable "NE.CON.PRVT.PC.KD," provided by the WDI, which gives households' final consumption expenditure per capita (constant 2010 US$). We compute the persistence and volatility of this variable in the same way with

[1] This dataset can be accessed via: https://databank.worldbank.org/source/world-development-indicators.

the GDP per capita, namely by HP filtering the log consumption per capita for the entire period using a smoothing parameter of 1600. Our trade balance is computed as the output per capita net of consumption per capita.

- Maturity: For Colombia the data is from "Ministerio de Hacienda y Credito Publico" and for Brazil, it is from "Secretaria de Tesouro Nacioal". These data are reported monthly and we take the median across months within each year. For Mexico (2007-2010) we use "Average term to maturity for foreign debt" from OECD, in their Finance/Central Government Debt Category.

- Duration: For the duration of debt for Colombia we use data from "Ministerio de Hacienda y Credito Publico", as we do for the maturity for this country. This measure of duration follows the Macaulay definition, as we use for our computations in the model. For Brazil and Mexico, we compute the duration using the maturity data described above for these countries (call m), together with the "Average interest on new external debt commitments, official (%)" provided by the International Debt Statistics ("DT.INR.OFFT", call r_o). In particular, we use the following equation to compute the Macaulay measure of duration for these two countries:

$$\text{Duration} = \frac{\sum_{t=1}^{m} t \times \left(\frac{1}{1+r_o}\right)^t}{\sum_{t=1}^{m} \left(\frac{1}{1+r_o}\right)^t}.$$

- 1 and 10 year spreads: We first obtain monthly Brazil, Colombia and Mexico zero coupon one and ten year U.S. dollar sovereign yields from the Bloomberg database. Specifically, we use USD Brazil Sovereign (FMC 802) Zero coupon one year yield ("F80201Y"), and ten year yield ("F80210Y Index"); USD Mexico Sovereign (FMC 804) Zero coupon one year yield ("F80201Y") and ten year yield ("F80210Y"); USD Colombia Sovereign (FMC 803) Zero coupon one year yield ("F80201Y"), and ten year yield ("F80210Y").

  In order to aggregate the monthly yields into yearly, we take median within each year. The spreads are then obtained by subtracting one- and ten-year US Treasury constant maturity rates provided in the FRED database. The indices for the US rates are "DGS1" and “DGS10”, respectively.

- EMBI+ spread: Monthly data from 1998 to 2018 obtained from the Global Economic Monitor (GEM) of the World Bank.[2] The series is J.P. Morgan Emerging Markets Bond Spread (EMBI+, series code EMBIG), and we use the following available countries: Argentina, Brazil, Colombia, Ecuador, Mexico, Panama, Peru, Philippines, Russian Federation, Turkey, Venezuela, and South Africa. In Table 4 where we compare EMBI+ with the model implications, we take mean across a year to convert monthly entries into annual.

- Labor productivity: We use yearly data from the International Labor Organization.[3] The variable we use is real output per worker in constant dollars of the year 2010 (indicator GDP_205U_NOC_NB). The countries we use are Argentina, Brazil, Colombia, Ecuador, Mexico, Panama, Peru, Philippines, Russian Federation, Turkey, Venezuela, and South Africa.

Calibration of the productivity process

We calibrate the parameters for the labor productivity process and the Frisch elasticity in our model to match moments for Colombia. For this we use data from the International Labor Organization for Colombia for the years 1991 to 2017.[4] In particular we use the following data: employment to population ratio for individuals over 15 years old, and real GDP per capita in constant dollars of the year 2010. We take logs and linearly detrend those (log) variables.

We assume labor productivity A_t follows an AR(1) process and use the properties of the GHH preferences with constant Frisch elasticity. In particular, in our economy wages are equal to labor productivity. Then, the optimality conditions for labor supply imply that $\ell_t = A_t^{1/\theta}$ and

[2]The data can be accessed here: https://databank.worldbank.org/source/global-economic-monitor-(gem).
[3]The data can be accessed here: https://ilostat.ilo.org/.
[4]The data can be accessed here: https://ilostat.ilo.org/.

output is $Y_t = A_t^{1+\frac{1}{\theta}}$. Taking logs and computing the variance, we have,

$$\begin{aligned} Var\left(\log(Y_t)\right) &= \left(1+\frac{1}{\theta}\right)^2 Var\left(\log(A_t)\right) \\ Var\left(\log(\ell_t)\right) &= \left(\frac{1}{\theta}\right)^2 Var\left(\log(A_t)\right) \end{aligned}$$

Then, we calibrate parameter θ, which is the inverse of the Frisch elasticity, using the following moments for Colombia:

$$\theta = \sqrt{\left(\frac{Var(GDP\, per\, capita)}{Var(Emp.\, Pop.\, ratio)}\right)} - 1$$

Since $\log(Y_t) = \left(1+\frac{1}{\theta}\right)\log(A_t)$ The autocorrelation of productivity can be inferred directly from the autocorrelation of GDP per capita.

Finally, the variance of the innovation of the AR(1) process can be pinned-down using the variance of GDP per capita, the Frisch elasticity and the autocorrelation parameter.

2 Transition probabilities with signals about productivity change

First, we show how to obtain equation (3) in the main text. Note that using Bayes' rule we can write

$$\Pr(A_{t+1} = A_i | A_t = A_l, s_t = j) = \frac{\Pr(A_{t+1} = A_i, A_t = A_l, s_t = j)}{\Pr(A_t = A_l, s_t = j)}.$$

Using Bayes' rule again, we write the numerator as

$$\Pr(s_t = j, A_{t+1} = A_i, A_t = A_l) = \Pr(s_t = j | A_{t+1} = A_i, A_t = A_l)\Pr(A_{t+1} = A_i, A_t = A_l).$$

Recall that using Bayes' rule,

$$\Pr(A_{t+1} = A_i, A_t = A_l) = \Pr(A_{t+1} = A_i | A_t = A_l)\Pr(A_t = A_l),$$

so

$$\Pr(s_t = j, A_{t+1} = A_i, A_t = A_l) = \Pr(s_t = j | A_{t+1} = A_i, A_t = A_l) \Pr(A_{t+1} = A_i | A_t = A_l) \Pr(A_t = A_l).$$

Replacing in the original expression, we obtain

$$\Pr(A_{t+1} = A_i | A_t = A_l, s_t = j) = \frac{\Pr(s_t = j | A_{t+1} = A_i, A_t = A_l) \Pr(A_{t+1} = A_i | A_t = A_l) \Pr(A_t = A_l)}{\Pr(A_t = A_l, s_t = j)}.$$

Note that using Bayes' rule the denominator can be written as

$$\Pr(A_t = A_l, s_t = j) = \Pr(s_t = j | A_t = A_l) \Pr(A_t = A_l).$$

Replacing the denominator we obtain the expression in equation (3),

$$\Pr(A_{t+1} = A_i | A_t = A_l, s_t = j) = \frac{\Pr(s_t = j | A_{t+1} = A_i, A_t = A_l) \Pr(A_{t+1} = A_i | A_t = A_l)}{\Pr(s_t = j | A_t = A_l)}.$$

In order to reach to the expression for the joint transition probability given in equation (4) in the main text, note that

$$\begin{gathered}\Pr(A_{t+1} = A_i, s_{t+1} = k | A_t = A_l, s_t = j) = \Pr(A_{t+1} = A_i | A_t = A_l, s_t = j) \times \\ \Pr(s_{t+1} = k | A_{t+1} = A_i, A_t = A_l, s_t = j).\end{gathered}$$

Since with our structure of signals and shocks the probability of $s_{t+1} = k$ depends only on the value of A_{t+1}, this can be written as,

$$\Pr(A_{t+1} = A_i, s_{t+1} = k | A_t = A_l, s_t = j) = \Pr(A_{t+1} = A_i | A_t = A_l, s_t = j) \Pr(s_{t+1} = k | A_{t+1} = A_i).$$

Using $\Pr(s_{t+1} = k | A_{t+1} = A_i) = 1/N_s$, this gives the expression in equation (4) in the main text,

$$\Pr(A_{t+1} = A_i, s_{t+1} = k | A_t = A_l, s_t = j) = \Pr(A_{t+1} = A_i | A_t = A_l, s_t = j)/N_s.$$

3 Computational details

3.1 Basics

We use the numerical method proposed in Dvorkin et al. [2018] to solve our model. This approach uses value function iteration on a discretized grid for debt and productivity. We use a different debt grid for each maturity m_i, evenly spaced. We use 81 points for the debt grid and 35 points for the productivity grid. The price function is solved for 41 equally-spaced points on this grid, and the implied function is linearly interpolated in the other parts of the algorithm. Since default usually happens in the steeper region of the price function, we have an uneven grid for productivity that is finer below the median. Namely, this grid has 25 evenly-spread points below the median productivity (including the median), and 10 evenly-spread points above.

We iterate our solution algorithm until the price functions of the debt in good standing in two consecutive iterations are close enough. Our distance measure computes the maximum absolute difference between each entry of the price matrices across two iterations relative to the corresponding level of the price in the earlier iteration. We declare convergence when this error is lower than 10^{-3}.[5]

We use the solutions for our price and policy functions to run the simulations for 1500 countries (paths) for 400 years. We drop the first 100 periods in these simulations. For second order moments, we take averages across each sample. For the first-order moments, we take the sample-specific before taking the cross-sample mean. This is the same approach as we follow for the data.

3.2 Computation of model variables

Spreads. For a country with productivity shock A, signal s, debt rollover shock a, and a debt portfolio choice (b', m'), the yield for a bond with maturity n is

$$YTM(A, s, a, b', m'; n) \equiv \left(\frac{1}{q(A, s, a, b', m'; n) - q(A, s, a, b', m'; n-1)} \right)^{\frac{1}{n}} - 1.$$

[5]Given the very large number of state variables in our model, the average absolute error is two orders of magnitude smaller, that is, lower than 10^{-5}.

We use this yield to compute the spread as $YTM(A, s, a, b', m'; n) - r$. We compute the model counterpart of EMBI+ using the borrowing price of the economy:

$$\text{EMBI} = \tilde{r} - r,$$

where r is the risk-free price and $\tilde{r}$ is the uniform discount rate that would correspond to the unit price of the chosen portfolio:

$$\sum_{t=1}^{m'} \left(\frac{1}{1+\tilde{r}}\right)^t = q(A, s, a, b', m'; m'). \tag{1}$$

Duration and maturity. We use the Macaulay definition to compute the duration of a bond in our model as a weighted sum of future promised payments:[6]

$$\text{Duration} = \frac{\sum_{t=1}^{m'} t \times \left(\frac{1}{1+\tilde{r}}\right)^t}{\sum_{t=1}^{m'} \left(\frac{1}{1+\tilde{r}}\right)^t},$$

where $\tilde{r}$ is the discount rate for the new portfolio given in (1). For maturity, we simply use the maturity of the new portfolio, m'.

3.3 Solution using dynamic discrete choice approach

3.3.1 Model specification

We use the method proposed in Dvorkin et al. [2018], which discretizes the grid for debt level, in addition to the discrete maturity choice. In particular, we assume that choice of debt maturity should a natural number, $m' \in \{1, 2, \ldots, \mathcal{M}\}$. The level of assets are on a discrete grid of $\mathcal{N}$ points. Accordingly, we define vectors for assets and maturity as:

$$b = [b_1, b_2, \ldots, b_{\mathcal{N}}, b_1, b_2, \ldots, b_{\mathcal{N}}, \ldots, b_1, b_2, \ldots, b_{\mathcal{N}}]'$$

[6] This is similar to Hatchondo and Martinez [2009] and Sánchez et al. [2018], and consistent with the measures of duration in our data.

$$m = [m_1, m_1, \ldots, m_1, m_2, m_2, \ldots, m_2, \ldots, m_{\mathcal{M}}, m_{\mathcal{M}}, \ldots, m_{\mathcal{M}}]'.$$

Hence, the country has to choose among $\mathcal{J} = \mathcal{M} \times \mathcal{N}$ different options to pick as its portfolio.

There is a random vector $\boldsymbol{\epsilon}$ of size $\mathcal{J}+1$, whose j^{th} component adds to the value corresponding one particular discrete choice j that the government can take ($\mathcal{J}$ alternatives for portfolio, plus the option to default). We label the elements of the random vector $\boldsymbol{\epsilon}$ as ϵ_j. For convenience we assign the last component ($\epsilon_{\mathcal{J}+1}$) to the choice of default. $\boldsymbol{\epsilon}$ is i.i.d. over time and it follows a multivariate distribution with joint cumulative density function $F(\boldsymbol{\epsilon}) = F(\epsilon_1, \epsilon_2, ..., \epsilon_{\mathcal{J}+1})$.

In this structure, the value before making the default decision is given by:

$$V(A, s, a, b_i, m_i, \boldsymbol{\epsilon}) = \max \left\{ V^G(A, s, a, b_i, m_i, \boldsymbol{\epsilon}), V^D(A, s, \epsilon_{\mathcal{J}+1}) \right\},$$

where V^G and V^D correspond to the values in good standing and default, respectively. We index with i the portfolio that the country brings to the current period.

The value in case of repaying, and in the absence of a sudden stop shock is:

$$V^G(A, s, 1, b_i, m_i, \boldsymbol{\epsilon}) = \max_{j,\ell} \frac{1}{1-\gamma} \left(c_{ij} - \frac{\ell^{1+\theta}}{1+\theta} \right)^{1-\gamma} + \beta E_{A',s',a'|A,s,1} E_{\boldsymbol{\epsilon}'} V(A', s', a', b_j, m_j, \boldsymbol{\epsilon}') + \epsilon_j$$

subject to

$$c_{ij} = A\ell + b_i + q(A, s, 1, b_j, m_j; m_i - 1)b_i - q(A, s, 1, b_j, m_j; m_j)b_j$$
$$j \in \{1, 2, ..., \mathcal{J}\}.$$

In case of a sudden stop shock ($a = 0$), the value is:

$$V^G(A, s, 0, b_i, m_i) = \max_{\ell} \frac{1}{1-\gamma} \left(A\ell + b_i - \frac{\ell^{1+\theta}}{1+\theta} \right)^{1-\gamma} + \beta E_{A',s',a'|A,s,0} E_{\boldsymbol{\epsilon}'} V(A', s', a', b_i, m_i - 1, \boldsymbol{\epsilon}') + \epsilon_{\tilde{j}}$$

where

$$b_{\tilde{j}} = b_i,\ m_{\tilde{j}} = m_i - 1.$$

The value in case of default is:

$$V^D(A, s, \epsilon_{\mathcal{J}+1}) = \max_{\ell} \frac{1}{1-\gamma}\left(\min(A,\phi)\ell - \frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma} + \beta E_{A',s'|A,s} E_{\boldsymbol{\epsilon}'}\left[(1-\lambda)V^D(A', s', \epsilon'_{\mathcal{J}+1}) + \lambda V(A', s', 1, 0, 1, \boldsymbol{\epsilon}')\right] + \epsilon_{\mathcal{J}+1}.$$

We denote the policy for the level and maturity of the assets with $B(A, s, a, b_i, m_i, \boldsymbol{\epsilon})$ and $M(A, s, a, b_i, m_i, \boldsymbol{\epsilon})$, respectively. The default decision is represented by $D(A, s, a, b_i, m_i, \boldsymbol{\epsilon})$, which takes value 1 (0) if the country chooses to default (repay).

With this specification, the unit price of a bond with maturity n, of a country with productivity A, new debt $-b'$, and maturity m is

$$q(A, s, a, b_j, m_j; n) = \frac{E_{A',s',a'|A,s,a} E_{\boldsymbol{\epsilon}'}}{1+r}\left\{\left[\left(1 - D(A', s', a', b_j, m_j, \boldsymbol{\epsilon}')\right) \times \left(1 + q(A', s', a', B(A', s', a', b_j, m_j, \boldsymbol{\epsilon}'), M(A', s', a', b_j, m_j, \boldsymbol{\epsilon}'); n-1)\right)\right]\right\}.$$

Since the realization of the $\boldsymbol{\epsilon}$ shocks plays a role in the actual decisions on default and portfolio, one can think of the policy functions ex-ante as probabilities. In particular, denote the ex-ante default probability as:

$$\mathbf{D}(A, s, a, b_i, m_i) = E_{\boldsymbol{\epsilon}} D(A, s, a, b_i, m_i, \boldsymbol{\epsilon}),$$

and the ex-ante probability of choosing a particular portfolio j, conditional on not defaulting, as $\mathbf{G}_{A,s,a,b_i,m_i}(b_j, m_j)$. Dvorkin et al. [2018] shows that we can write the equilibrium bond price in this structure as:

$$
\begin{aligned}
q(A,s,a,b_j,m_j;n) \quad = \quad & \frac{E_{A',s',a'|y,a}}{1+r}\Bigg\{ \big(1-\mathbf{D}(A',s',a',b_j,m_j)\big) \times \\
& \left[1+\sum_{k=1}^{\mathcal{J}} q(A',s',a',b_k,m_k;n-1)\mathbf{G}_{A',s',a',b_j,m_j}(b_k,m_k)\right]\Bigg\}.
\end{aligned}
$$

Next, we specify the distribution of $\boldsymbol{\epsilon}$. In particular we assume a Generalized Extreme Value distribution for this vector:

$$
F(\boldsymbol{x}) = \exp\left[-\left(\sum_{j=1}^{\mathcal{J}} \exp\left(-\frac{x_j}{\rho\,\sigma}\right)\right)^{\rho} - \exp\left(-\frac{x_{\mathcal{J}+1}}{\sigma}\right)\right].
$$

In this distribution, ρ determines the correlation between the components of the vector 1 to $\mathcal{J}$, namely those that correspond to the portfolio choice. σ increases the variance of the shocks. With this specification on the distribution of the shocks, we can write the policy functions for default is: $\mathbf{D}(A,s,a,b_i,m_i) =$

$$
\frac{\exp\Big(\max_\ell \frac{1}{1-\gamma}\Big(\min(A,\phi)\ell - \frac{\ell^{1+\theta}}{1+\theta}\Big)^{1-\gamma} + \beta E_{A',s'|A,s}\left[(1-\lambda)\mathbf{V}^{\mathbf{D}}(A',s') + \lambda\mathbf{V}(A',s',1,0,1)\right]\Big)^{1/\sigma}}{X + \exp\Big(\max_\ell \frac{1}{1-\gamma}\Big(\min(A,\phi)\ell - \frac{\ell^{1+\theta}}{1+\theta}\Big)^{1-\gamma} + \beta E_{A',s'|A,s}\left[(1-\lambda)\mathbf{V}^{\mathbf{D}}(A',s') + \lambda\mathbf{V}(A',s',1,0,1)\right]\Big)^{1/\sigma}},
$$

where, in case of no sudden stop shock ($a=1$),

$$
X = \Big(\sum_{j=1}^{\mathcal{J}} \exp\left(\max_\ell \frac{1}{1-\gamma}\left(c_{ij} - \frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma} + \beta E_{A',s',a'|A,s,1}\mathbf{V}(A',s',a',b_j,m_j)\right)^{\frac{1}{\rho\sigma}}\Big)^{\rho},
$$

and in case of sudden stop shock ($a=0$),

$$
X = \exp\left(\max_\ell \frac{1}{1-\gamma}\left(c_{i\tilde{j}} - \frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma} + \beta E_{A',s',a'|A,s,0}\mathbf{V}(A',s',a',b_{\tilde{j}},m_{\tilde{j}})\right)^{\frac{1}{\sigma}}.
$$

with $b_{\tilde{j}} = b_i$ and $m_{\tilde{j}} = m_i - 1$. Similarly, the probability of choosing particular portfolio in case of not receiving a sudden stop shock, and conditional on not defaulting, is:

$$\mathbf{G}_{A,s,a,b_i,m_i}(b_j,m_j)=\frac{\exp\left(\max_\ell \frac{1}{1-\gamma}\left(c_{ij}-\frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma}+\beta E_{A',s',a'|A,s,1}\mathbf{V}(A',s',a',b_j,m_j)\right)^{\frac{1}{\rho\sigma}}}{\sum_{k=1}^{\mathcal{J}}\exp\left(\max_\ell \frac{1}{1-\gamma}\left(c_{ik}-\frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma}+\beta E_{A',s',a'|A,s,1}\mathbf{V}(A',s',a',b_k,m_k)\right)^{\frac{1}{\rho\sigma}}},$$

where the ex-ante value in good standing without a sudden stop shock is: $\mathbf{V}(A,s,1,b_i,m_i)=$

$$\begin{aligned}=\quad&\sigma\log\Big[\Big(\sum_{j=1}^{\mathcal{J}}\exp\left(\max_\ell\frac{1}{1-\gamma}\left(c_{ij}-\frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma}+\beta E_{A',s',a'|A,s,1}\mathbf{V}(A',s',a',b_j,m_j)\right)^{\frac{1}{\rho\sigma}}\Big)^{\rho}+\\&+\exp\left(\max_\ell\frac{1}{1-\gamma}\left(\min(A,\phi)\ell-\frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma}+\beta E_{A',s'|A,s}\left[(1-\lambda)\mathbf{V}^{\mathbf{D}}(A',s')+\lambda\mathbf{V}(A',s',1,0,1)\right]\right)^{1/\sigma}\Big]\end{aligned}$$

and with a sudden stop is: $\mathbf{V}(A,s,0,b_i,m_i)=$

$$\begin{aligned}=\quad&\sigma\log\Big[\exp\left(\max_\ell\frac{1}{1-\gamma}\left(c_{i\tilde{j}}-\frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma}+\beta E_{A',s',a'|A,s,0}\mathbf{V}(A',s',a',b_{\tilde{j}},m_{\tilde{j}})\right)^{\frac{1}{\sigma}}+\\&+\exp\left(\max_\ell\frac{1}{1-\gamma}\left(\min(A,\phi)\ell-\frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma}+\beta E_{A',s'|A,s}\left[(1-\lambda)\mathbf{V}^{\mathbf{D}}(A',s')+\lambda\mathbf{V}(A',s',1,0,1)\right]\right)^{1/\sigma}\Big]\end{aligned}$$

with $b_{\tilde{j}}=b_i$ and $m_{\tilde{j}}=m_i-1$.

Finally the ex-ante value in case of default is:

$$\mathbf{V}^{\mathbf{D}}(A,s)=\max_\ell\frac{1}{1-\gamma}\left(\min(A,\phi)\ell-\frac{\ell^{1+\theta}}{1+\theta}\right)^{1-\gamma}+\beta E_{A',s'|A,s}\left[(1-\lambda)\mathbf{V}^{\mathbf{D}}(A',s')+\lambda\mathbf{V}(A',s',1,0,1)\right].$$

This method gives us two parameters of the distribution of the ϵ shocks, one related to the overall volatility of shocks, σ, and one related to the correlation between the portfolio choice components, ρ. In Section **??**, we explain how we calibrate these parameters, and in the Online Appendix we discuss this calibration in more detail.

4 Calibration of Sudden Stops

We take the estimated values for the sudden stop process from Dvorkin et al. [2018], which we reproduce here. We define a sudden stop as in Comelli [2015], and use a dummy variable, SS, which takes the value 1 if there is a sudden stop and 0 otherwise. Since sudden stops are periods of zero or negative capital inflows into the borrower country due to factors exogenous to the country's fundamentals (productivity and levels of debt), we estimate the following regression:

$$SS_{t,i} = \alpha_0 + \alpha_1 SS_{t-1,i} + \alpha_2 (GDP\ cycle)t,i + \alpha_3 (demean\ Debt/GDP)_{t,i}. \tag{2}$$

As the variables ($GDP\ cycle$) and ($demean\ Debt/GDP$) have mean zero, we can obtain the probability of entering into a sudden stop episode, conditional on not being in a sudden stop, as α_0. Similarly, the probability of staying in a sudden stop conditional on being in a sudden stop is $\alpha_0 + \alpha_1$.

Table 1 shows the estimated values of α_0 and $\alpha_0+\alpha_1$ for several specifications of the regression, where the average value of these parameters across specifications are 0.12 and 0.42, respectively. We use these in our model. Moreover, Figure 1 shows that the estimated sudden stops are highly correlated across different countries, suggesting that these episodes are due to changes external to the country and not a reflection of the availability of credit due to countries' fundamentals.

Table 1: Estimation of sudden stop probability

Regression type	Weight	Obs	R^2	α_0	$\alpha_0 + \alpha_1$
Linear reg., controlling by HP cycle and debt-to-GDP	No	457	0.1	0.11	0.42
Linear reg., controlling only by HP cycle	No	971	0.09	0.14	0.44
Linear reg., controlling by HP cycle and debt-to-GDP	Yes	457	0.1	0.11	0.4
Linear reg., controlling only by HP cycle	Yes	971	0.12	0.13	0.44
Probit reg., controlling by HP cycle and debt-to-GDP	No	457	0.1	0.11	0.41
Probit reg., controlling only by HP cycle	No	971	0.08	0.14	0.43
Probit reg., controlling by HP cycle and debt-to-GDP	Yes	457	0.09	0.11	0.39
Probit reg., controlling only by HP cycle	Yes	971	0.11	0.13	0.43
Average of all specifications			0.10	0.12	0.42

Note: When we use weights in regressions, we weight by employment from the Penn World Table to proxy for the size of the country.

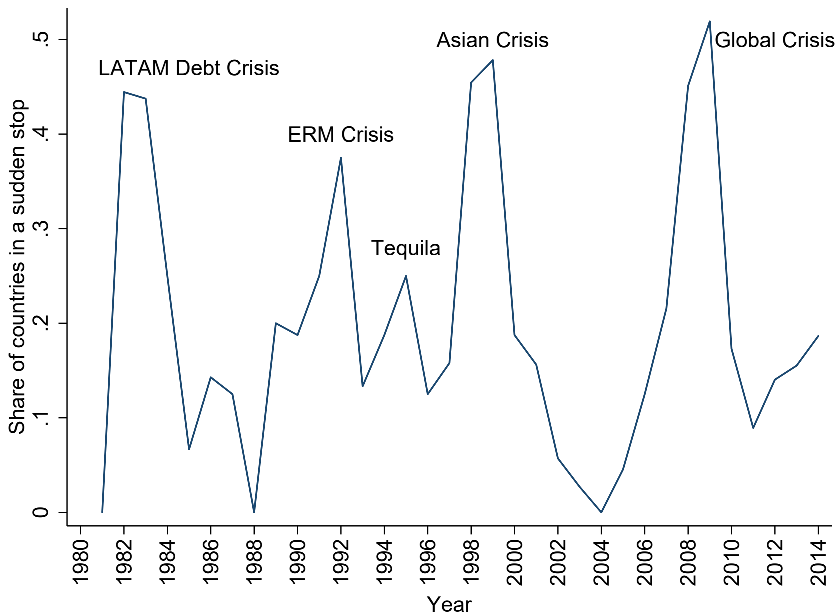


Figure 1: Evolution of Sudden Stop events

5 Calibrating the model at quarterly frequency

In our paper, we calibrate the model at an annual frequency. A parameterization at a higher frequency (shorter time periods) increases the size of possible maturity states and maturity choices, hence making the computation of the model more challenging. Moreover, at the quarterly frequency, the conditional distribution of productivity is more concentrated around specific values due to the higher persistence, and we need to specify a larger grid for productivity, which increases the size of the problem even further.

We devote this section to check the robustness of our results to doing a quarterly frequency analysis (without recalibrating the model to hit the targets due to the much larger computational costs). Table 2 shows the unconditional moments for the baseline economy at the annual frequency and for the quarterly economy with the same set of parameters. The table shows that the moments from both economies are similar with only a few exceptions (e.g., the default rate is smaller in the quarterly model).

In addition, we simulate data and estimate the same structural VAR as in Section 2 of our paper. Figure 2 shows the results of the IRFs for the quarterly VAR estimated using model-

Table 2: Model moments, annual frequency (benchmark) and quarterly frequency

Moments	Benchmark model (annual)	Quarterly model
Debt/output	24.8	20.9
Default rate	2.0	1.4
Std. Dev. EMBI+ (%)	3.7	2.9
Std. Dev. $(log(c))$ / Std. Dev.$(log(y))$	0.98	0.99
Corr. $(log(c), log(y))$	0.97	0.99
Maturity (years)	8.6	12.9
Maturity (years, good times)	8.8	13.6
Maturity (years, bad times)	8.2	12.3
Duration (years)	4.40	5.80
Duration (years, good times)	4.54	6.21
Duration (years, bad times)	4.20	5.40
Corr$(dur, \log(y))$	0.35	0.56
EMBI+ (%)	2.57	1.61
corr$(EMBI+, log(y))$	-0.39	-0.52

Note: The table compares the targeted (Table 2 of paper) and non-targeted moments (Table 4 of paper) implied by the benchmark model and the quarterly calibration.

simulated data. Both the shape and the magnitude of the responses to the different shocks are comparable. These results suggest that the yearly frequency we use in our baseline model and in the VARs estimated with the simulated data at this frequency, and the quarterly frequency we use for the VAR of Section 2, bear no impact on our analysis.

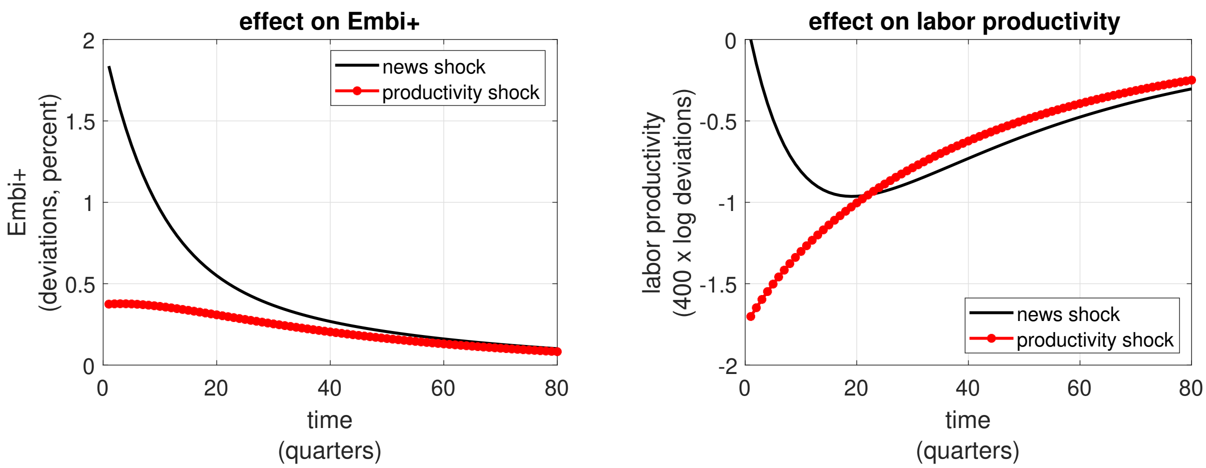
6 Model without GHH preferences

In our paper, we assume GHH preferences, hence abstracting away from any wealth effects on the labor supply. In this section we look at the implications of deviating from this assumption by using the following functional form for the preferences over consumption and leisure:

$$u(c, \ell) = \frac{c^{1-\gamma}}{1-\gamma} - \nu \frac{\ell^{1+\theta}}{1+\theta}.$$

One challenge that arises in this specification is that the optimal labor supply of the household, differently from the model with GHH preferences, depends not only on the realization of the pro-

Figure 2: Impulse responses for the structural VAR using model simulated data from quarterly model



Note: annualized rates.

ductivity shock, but also on net borrowing, that is, the total resources available for consumption other than the labor income. In particular, the maximization over the labor supply, taking as given the net borrowing (denoted by N here) reads:

$$\max_{\ell} \frac{(A\ell + N)^{1-\gamma}}{1-\gamma} - \nu\frac{\ell^{1+\theta}}{1+\theta}$$

For instance, the net borrowing for a country with states, debt $(-b)$, maturity (m), productivity (A) and signal (s), without a sudden stop, and the portfolio choice (b', m') would be:

$$b - q(A, s, b', m'; m')b' + q(A, s, b', m'; m-1)b$$

In order to mitigate the additional computational burden of computing the optimal labor supply for each of the combinations of (b, m, A, s, b', m'), we define a grid of net borrowing, $\mathbf{N}$, of 1000 points. We find the optimal labor supply for each of the points of this vector before starting the iterations to obtain the model equilibrium using the first order condition:

$$\ell^{1+\frac{\theta}{\gamma}}A + N\ell^{\frac{\theta}{\gamma}} - \nu^{-\frac{1}{\gamma}}A^{\frac{1}{\gamma}} = 0$$

In solving the model, when evaluating the objective function for a given portfolio combination (b', m') of the country, we use the implied net borrowing (given the states) to interpolate over the grid $\mathbf{N}$ to get the optimal labor supply.

Table 3 shows how several moments computed with the model-simulated data change with this type of preferences. We compare two values for the labor supply elasticity, a high labor supply elasticity, $\theta = 0.54$, shown in the second column, and a low labor supply elasticity, $\theta = 9$, shown in the third column. The first column shows our benchmark economy with GHH preferences.

These two alternative economies have reasonable levels of debt, default, and spreads. The main issue with non-GHH preferences is generating the correct volatility of consumption given the volatility of income, as seen in the first row, second column, of Table 3. Interestingly, the non-GHH model also displays the wrong correlation between output and duration.

7 Alternative calibration of Sudden Stops

We model sudden stops as a 2-state Markov process. In Appendix D we detail the estimation of the parameters of this process. Our estimates imply a 0.12 probability of entering a sudden stop in a period, conditional on not being in a sudden stop. The probability of staying in a sudden stop in a period is 0.42.

Our modelling of sudden stops is close to that in Bianchi, Hatchondo, and Martinez [2018]. They model a rollover crisis as a sudden increase in the risk aversion of lenders that increases spreads by 200 basis points on average. In their words, "we obtain 3 episodes of a high risk premium every 20 years with an average duration of each episode equal to 1.25 years" (pp. 2643). Bianchi, Hatchondo, and Martinez [2018] calibrate their setup to a yearly frequency, and model these shocks as a 2-state Markov process, with an entry probability of 0.15 and a probability of staying in that regime of 0.2 (Table 2). These numbers are comparable to the values of 0.12 and 0.42, respectively, that we currently use in the benchmark calibration of the 2-state Markov process for the sudden stop shock.

As a robustness check, we ran our baseline model under the Markov transition process of

Table 3: Wealth effects of news shocks and labor supply

	Benchmark $\theta = 0.54$	no GHH $\theta = 0.54$	no GHH $\theta = 9.0$
Std. Dev. $(log(c))$ / Std. Dev.$(log(y))$	0.98	0.41	1.38
Std. Dev. $(log(TB/y))$ / Std. Dev.$(log(y))$	0.25	1.19	1.33
Corr. $(log(c), log(y))$	0.97	-0.25	0.41
Corr. $(TB/y, log(y))$	0.18	0.93	0.32
Maturity (years)	8.57	3.36	5.10
Duration (years)	4.40	2.12	2.91
Corr$(dur, \log(y))$	0.35	-0.35	0.06
1-year spread (%)	1.78	1.22	1.48
1-year spread (%, good times)	0.44	0.86	0.77
1-year spread (%, bad times)	3.56	1.65	2.35
10-year spread (%)	2.28	1.30	1.69
10-year spread (%, good times)	1.71	1.14	1.43
10-year spread (%, bad times)	3.03	1.49	2.00
EMBI+ (%)	2.57	1.36	1.83
Std. Dev. EMBI+ (%)	3.66	1.48	2.45
corr$(EMBI+, log(y))$	-0.39	-0.02	-0.23
Default rate (%)	1.99	1.18	1.51
Face value of debt / GDP (%)	24.8	22.4	23.5

Note: The table compares the targeted (Table 2 of paper) and non-targeted moments (Table 4 of paper) implied by the benchmark model and two alternatives featuring preferences with wealth effects. The first of these alternatives haS a high labor supply elasticity ($\theta = 0.54$) and the second one has a low labor supply elasticity ($\theta = 9$).

Bianchi, Hatchondo, and Martinez [2018] for sudden stops. We find that the moments in our benchmark calibration and this alternative calibration are very similar, as we report in Table 4 below, so we conclude that our results are robust to the calibration of sudden stops shocks within the range of values used in the literature.

Table 4: Alternative sudden stop calibration

	Benchmark	Alternative SS calibration
Std. Dev. $(log(c))$ / Std. Dev.$(log(y))$	0.98	0.99
Std. Dev. $(log(TB/y))$ / Std. Dev.$(log(y))$	0.25	0.25
Corr. $(log(c), log(y))$	0.97	0.97
Corr. $(TB/y, log(y))$	0.18	0.17
Maturity (years)	8.57	7.98
Duration (years)	4.40	4.16
Corr$(dur, \log(y))$	0.35	0.44
1-year spread (%)	1.78	1.75
1-year spread (%, good times)	0.44	0.42
1-year spread (%, bad times)	3.56	3.50
10-year spread (%)	2.28	2.18
10-year spread (%, good times)	1.71	1.63
10-year spread (%, bad times)	3.03	2.90
EMBI+ (%)	2.57	2.45
Std. Dev. (%)	3.66	3.54
corr$(EMBI+, log(y))$	-0.39	-0.40
Default rate (%)	1.99	1.89
Face value of debt / GDP (%)	24.8	24.6

Note: The table compares the targeted (Table 2 of paper) and non-targeted moments (Table 4 of paper) implied by the benchmark model and an alternative calibration of Sudden Stops. Alternative sudden stop calibration corresponds set an entry probability into a sudden stop regime of 0.15 and a probability of staying in that regime of 0.2. These are the numbers used in Bianchi, Hatchondo, and Martinez [2018].

8 Model with exogenous maturity

Our model features sovereign debt maturity choice. In this section we highlight the role of debt endogeneity by contrasting our model implications with those that arise from fixing the maturity of the government bonds at any given level.

In Table 5 of this appendix, we show the results from models fixing the maturity at three different levels. One maturity level we impose is 9 years, which is roughly the average in the model. We also try maturities at 5 and 13 years. The table shows that some key moments implied by the model are sensitive to the imposed maturity level. Among the targeted moments, the debt level and default rates increase with the imposed maturity. In particular, changing the fixed maturity from 5 years to 13 years, the debt/output ratio increases from 18.8 percent to 29.6 percent, and the default rate increases from 1.1 percent to 2.7 percent. The standard deviation of the EMBI+ spread also increases with the imposed maturity. This suggests that the level we impose as the fixed maturity would affect the calibrated parameters targeting these moments, namely the discount rate (β) and the parameters of the cost function of default (ϕ_1 and ϕ_2). As for the non-targeted moments, there are also stark changes with the imposed maturity. For instance, the consumption volatility becomes larger than output volatility for low enough maturity imposed in the model. Spreads also increase with the level of fixed maturity, in line with the higher default rate.

Table 5: Model moments, benchmark and fixed maturity

Moments	Benchmark	Fixed maturity		
		5 yrs	9 yrs	13 yrs
Debt/output	24.8	18.8	24.9	29.6
Default rate	2.0	1.1	2.1	2.7
Std. Dev. EMBI+ (%)	3.7	2.7	3.8	4.6
Std. Dev. $(log(c))$ / Std. Dev.$(log(y))$	0.98	1.03	0.98	0.96
Corr. $(log(c), log(y))$	0.97	0.95	0.97	0.98
Duration (years)	4.40	2.76	4.45	5.88
Duration (years, good times)	4.54	2.77	4.49	5.95
Duration (years, bad times)	4.20	2.74	4.38	5.76
Corr$(dur, \log(y))$	0.35	0.06	0.24	0.37
1-year spread (%)	1.78	1.05	1.85	2.41
1-year spread (%, good times)	0.44	0.15	0.38	0.75
1-year spread (%, bad times)	3.56	2.14	3.80	4.75
EMBI+ (%)	2.57	1.37	2.62	3.72
corr$(EMBI+, log(y))$	-0.39	-0.44	-0.41	-0.33

Note: The table compares the targeted (Table 2 of paper) and non-targeted moments (Table 4 of paper) implied by the benchmark model and three alternatives featuring exogenous maturity levels at 5, 9 and 13 years.

Nevertheless, the table shows that fixing maturity at the benchmark average level gives implications that are more in line with those generated by our endogenous-maturity benchmark. However, without solving our model with endogenous maturity, we do not know which maturity we should impose to replicate the moments of a model with maturity choice.[7]

9 Alternative grid sizes for TFP and debt

We solve our model using 81 points for the debt grid and 35 points for the TFP grid. We also checked the sensitivity of our results to denser grids by running our model with higher number of grid points of these two variables. In particular, Table 6 compares our benchmark results with two alternative computations. The first alternative increases the number of points on the TFP grid from 35 to 70 points. The second alternative, in addition to having 70 points for the TFP grid, increases the number of points on the debt grid from 81 to 121 points.

The table illustrates that the model predictions are not sensitive to having more points for the discrete grids. This includes the cyclicality and volatility of consumption, debt maturity and duration, the default rate and the debt levels. The level, volatility and the cyclicality of the EMBI+ spreads are also stable between our benchmark and the alternatives with more grid points. The robustness results on spreads are especially informative, as Hatchondo et al. [2010] show that these spreads statistics can be sensitive to the grid sizes used in numerical solutions.

10 Non-informative news

Table 6 in the paper shows how the variance of productivity explained by news falls as news precision decreases from $\eta = 0.74$ to $\eta = 0.5$. In the extreme case of non-informative news, by construction, news cannot explain any fraction of the variance of productivity. Moreover, in an estimated structural VAR using model-simulated data, productivity does not react to news shocks, as expected. Thus, a model without news shocks clearly cannot explain the estimated effect of news on productivity and EMBI+. This is the reason why we introduce news shocks in

[7] A similar argument is also made in Sánchez et al. [2018].

Table 6: Model moments and the size of grids

Moments	Benchmark	Denser TFP grid	Denser debt and TFP grid
Std. Dev. $(log(c))$ / Std. Dev.$(log(y))$	0.98	0.98	0.98
Std. Dev. $(log(TB/y))$ / Std. Dev.$(log(y))$	0.25	0.25	0.25
Corr. $(log(c), log(y))$	0.97	0.97	0.97
Corr. $(TB/y, log(y))$	0.18	0.19	0.18
Maturity (years)	8.57	8.66	8.49
Duration (years)	4.40	4.44	4.37
Corr$(dur, \log(y))$	0.35	0.33	0.41
1-year spread (%)	1.78	1.77	1.75
1-year spread (%, good times)	0.44	0.40	0.39
1-year spread (%, bad times)	3.56	3.55	3.52
10-year spread (%)	2.28	2.28	2.23
10-year spread (%, good times)	1.71	1.70	1.68
10-year spread (%, bad times)	3.03	3.03	2.96
EMBI+ (%)	2.57	2.55	2.50
Std. Dev EMBI+ (%)	3.66	3.51	3.45
corr$(EMBI+, log(y))$	-0.39	-0.40	-0.39
Default rate (%)	1.99	1.99	1.96
Face value of debt / GDP (%)	24.8	25.3	25.3

Note: In the benchmark we use 81 points for the debt grid and 35 points for the TFP grid. In the first alternative reported in the table, we increase the number of points on the TFP grid to 70. In the second alternative, we also increase the number of points on the debt grid to 121 (keeping the TFP grid at 70 points).

our analysis.

However, the literature on quantitative sovereign default models has shown that news are not needed to match many moments of emerging market economies. Does the introduction of news worsen the fit of a standard sovereign default model? To answer the question, in Table 7 we illustrate how some of the moments typically studied in this literature behave as we shut down the informativeness of news. The fit of most non-targeted moments, which is very good in a model without news, is not made worse by the extra information about future TFP in news shocks, and the model with the news shock has the clear advantage that it can account for the dynamic relationship between the EMBI+ and TFP and the reaction of these variables to news shocks as estimated in the structural empirical VAR.

Table 7: Model moments, benchmark and non-informative news

Moments	Benchmark model	non-informative news model
Debt/output	24.8	24.0
Default rate	2.0	2.1
Std. Dev. EMBI+ (%)	3.7	2.9
% Variance of prod. explained by news (10 yrs ahead)	18.9	0.0
Std. Dev. $(log(c))$ / Std. Dev.$(log(y))$	0.98	0.99
Corr. $(log(c), log(y))$	0.97	0.98
Maturity (years)	8.6	8.9
Maturity (years, good times)	8.8	9.1
Maturity (years, bad times)	8.2	8.7
Duration (years)	4.40	4.5
Duration (years, good times)	4.54	4.66
Duration (years, bad times)	4.20	4.4
Corr$(dur, \log(y))$	0.35	0.31
EMBI+ (%)	2.57	2.59
corr$(EMBI+, log(y))$	-0.39	-0.55

Note: The table compares the targeted (Table 2 of paper) and non-targeted moments (Table 4 of paper) implied by the benchmark model with precision parameter $\eta = 0.74$ and the non-informative news model with $\eta = 1/7$.

11 Positive recovery of debt in default

In our benchmark model we assume that the debt in default has a value of zero. That is, when the country defaults it endures a random period of financial market exclusion with possibly a loss of productivity, but upon reentry to financial markets, the debt is zero. We now relax the assumption of zero recovery of the debt in default and set a recovery rate of 65% and an extension of maturity of the new restructured debt of 3 years, which as discussed in Dvorkin et al. [2018], is in line with the data on restructurings.[8]

In this way, countries re-access financial markets after default with their debt restructured. We use simulated data from this model for normal times and default periods to estimate the same structural VAR of Section 2. In order to present the details on the EMBI+ measure for our model with recovery, we need to introduce additional notation for the equilibrium bond prices.

With positive recovery, the price of a bond of maturity $n > 0$ of a country with productivity A, new debt $-b'$, and maturity $m' > 0$ is

$$\begin{aligned} q(A, s, b', m'; n) = & \frac{E_{A',s',a'|A,s}}{1+r} \Big\{ \Big[\big(1 - D(A', s', a', b', m')\big) \times \\ & \big(1 + q(A', s', B(A', s', a', b', m'), M(A', s', a', b', m'); n-1)\big) \Big] + \\ & \big(D(A', s', a', b', m')\big) \left[q^D(A', s', b', m'; n)\right] \Big\}. \end{aligned}$$

where the last term in the right captures what happens with the bonds in case of default. In particular, upon default, the lenders no longer hold a bond in good payment status but a bond in default, with price q^D.

The price of a bond in default is simply

$$q^D(A, s, b', m'; n) = \frac{E_{A',s'|A,s}}{1+r} \{(1-\lambda) q^D(A', s', b', m'; n) + \lambda \frac{n}{m'} q(A', s', b^R, m^R; m^R)\},$$

where, λ represents the probability of returning to financial markets after default, $m^R = m + \varrho$

[8] We slightly adjusted the calibration of the benchmark economy, because this positive recovery leads to larger borrowing and default rates using the same parameters as in our previous benchmark calibration.

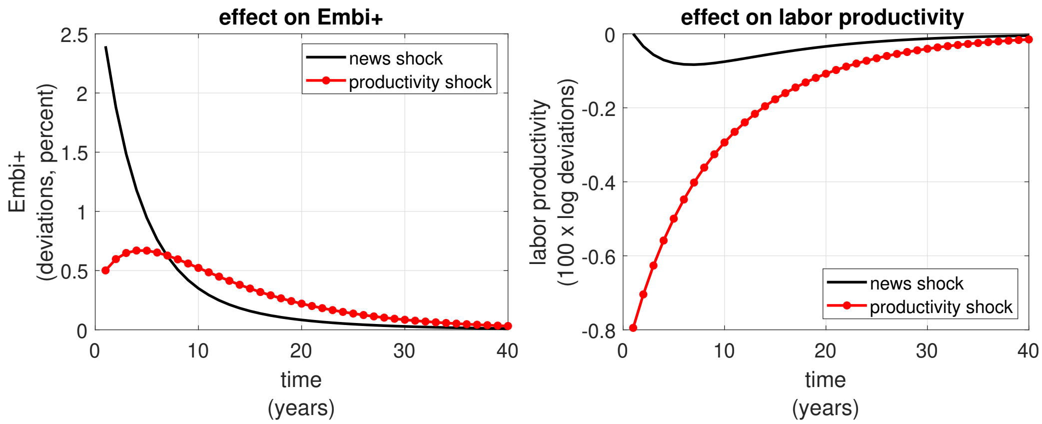


Figure 3: IRFs from Structural VAR with simulated data from model with debt recovery after default.

is the maturity of the restructured debt, and b^R is such that the face value haircut to total debt is $(1-\varphi)$; i.e., $b^R \times m^R = \varphi \times b \times m$. In our calculations for this exercise we assume $\varrho = 3$ and $\varphi = 0.65$.

In order to compute the model counterpart of the EMBI+ spread, we derive the discount rate $\tilde{r}$ from the unit price of a portfolio:

$$q(A, s, a, b', m'; m') = \sum_{t=1}^{m'} \left(\frac{1}{1+\tilde{r}} \right)^t . \tag{3}$$

During default periods, we replace the left-hand variable by $q^D(A, s, b', m'; m')$. Finally, to get the EMBI+ spread, we use EMBI+ $= \tilde{r} - r$, where r is the risk-free rate.

Figure 3 shows the impulse response functions for the model with positive recovery. The counterpart of this figure in our benchmark economy with no recovery is Figure 6 in the draft. As we can see in the figure, the dynamic behavior of the EMBI+ spread and labor productivity are largely similar across models, with the news shock having a large impact on the EMBI+ spreads and a lower, yet non-negligible, impact on productivity.

12 Calibration of extreme value shocks

We now show our strategy to calibrate parameters σ and ρ for the distribution of the ϵ (extreme value) shocks. We follow our previous work [Dvorkin et al., 2018] and calibrate these parameters to match the standard deviation of debt, and the correlation of duration with GDP. Due to the way the ϵ shocks enter the model (affecting primarily the choice of maturity and debt), they have a direct impact on these variables.[9]

Figure 4 shows the effects of changes in the values of σ and ρ on the standard deviations of debt, maturity and duration, and their correlations with GDP. As the parameter values increase, the ϵ shocks play a more important role in the choice of debt and maturity, thus being more decoupled from the borrower's fundamentals. On the one hand, as shown in the left panels of the figure, larger values of σ and ρ increase the variance of duration, maturity and debt. On the other hand, the right panels show that larger values for these parameters decrease the correlation of duration, maturity, and debt, with GDP.

While Figure 4 shows that the values of σ and ρ have significant effects on second order moments of debt and maturity, Table 8 shows that other moments are much less affected. Column number (2) shows that decreasing the value of σ and ρ to half of their values in the benchmark calibration has only small effects. Column (3) shows that even increasing σ by a factor of 10 and ρ by a factor of 4 to its maximum value also has only a small impact. The positive effect on the spread volatility is expected because these parameters correspond to the choice of maturity and debt, but even in this case the impact is not that large, with the standard deviation of the EMBI+ spread increasing from 3.7% to 4.5%.

Therefore, as these parameters substantially affect the second order moments of duration, maturity, and debt, while having little impact on other variables of interest, we deem our calibration strategy to be reasonable.

[9] The moment most influenced by these parameters are the standard deviation of debt, maturity and duration, and the correlation of these variables with output. In our calibration we chose two of these variables, but in this section we show figures for all of them.

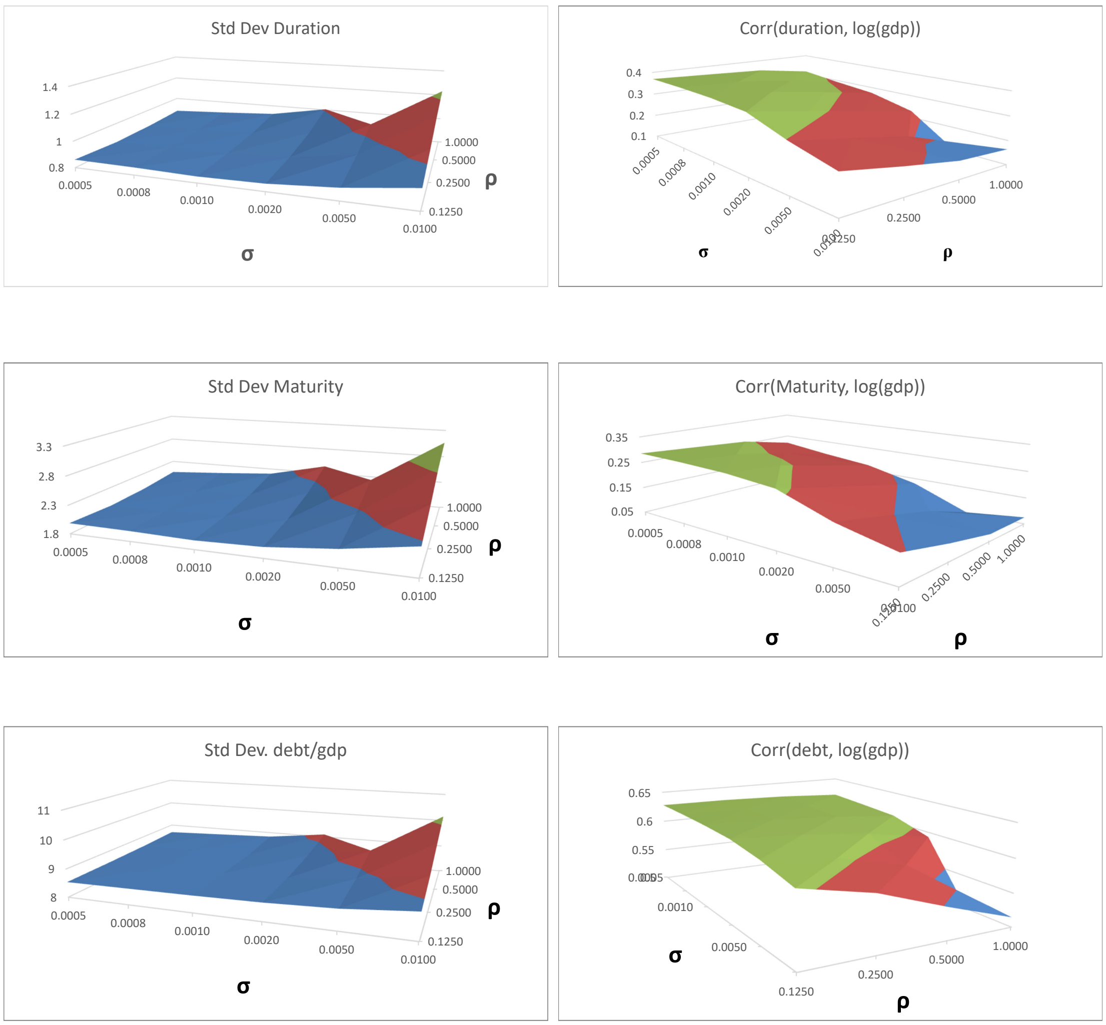


Figure 4: Calibration of ρ and σ

Note: The figure shows the moments implied by the model with alternative values for parameters ρ and σ, keeping the rest of the parameters as in the benchmark.

Table 8: Model moments for different values of σ and ρ

Moments	(1) Benchmark $\sigma = 0.001$, $\rho = 0.25$	(2) $\sigma = 0.0005$ $\rho = 0.125$	(3) $\sigma = 0.01$ $\rho = 1.0$
Debt/output	24.8	24.6	26.8
Default rate	2.0	1.9	2.0
EMBI+ (%)	2.6	2.5	2.6
corr($EMBI+, log(y)$)	-0.39	-0.39	-0.30
Std. Dev. EMBI+ (%)	3.7	3.6	4.5
Std. Dev. ($log(c)$) / Std. Dev.($log(y)$)	0.98	0.99	0.99
Corr. ($log(c), log(y)$)	0.97	0.97	0.96
Duration (years)	4.40	4.32	5.02
Duration (years, good times)	4.54	4.47	5.13
Duration (years, bad times)	4.20	4.11	4.87
Corr(dur, $\log(y)$)	0.35	0.37	0.16
1-year spread (%)	1.78	1.75	1.68
1-year spread (%, good times)	0.44	0.43	0.43
1-year spread (%, bad times)	3.56	3.49	3.33

Note: The table compares targeted (Table 2 of paper) and non-targeted moments (Table 4 of paper) implied by the benchmark model and two alternatives featuring $\sigma = 0.0005$, $\rho = 0.125$ and $\sigma = 0.01$, $\rho = 1$.

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