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News, sovereign debt maturity, and default risk*

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Abstract

Leading into a debt crisis, interest rate spreads on sovereign debt rise before the economy experiences a decline in productivity, suggesting that news about future economic developments may play an important role in these episodes. In a VAR estimation, a news shock has a larger contemporaneous impact on sovereign credit spreads than a comparable shock to labor productivity. A quantitative model of news and sovereign debt default with endogenous maturity choice generates impulse responses and a variance decomposition similar to the empirical VAR estimates. The dynamics of the economy after a bad news shock share some features of a productivity shock and others of sudden stop events. However, unlike episodes of sudden stops, long-term debt does not shield the country from bad news shocks, and it may even exacerbate default risk. Finally, an increase in the precision of news allows the government to improve its debt maturity management, especially during periods of high stress in credit markets, and thus face lower yield spreads while increasing the amount of debt.

JEL Classification: F34, F41, G15.

Keywords: Crises, News, Default, Spreads, Maturity, Country Risk, Sovereign Debt.

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1 Introduction

Several financial crises in emerging economies, and more recently the European financial crisis, have highlighted how shifts in expectations about the future path of the economy affect sovereign debt decisions and prices, reinforcing the view that news about future fundamentals are a very relevant driving force in international credit markets. Our paper analyzes the extent to which changes in expectations driven by news matter for country risk dynamics, and how the effect depends on the maturity of sovereign debt.¹

The role of news about future productivity for sovereign credit events is illustrated in Figure 1. The plots in the figure show the evolution of labor productivity and country risk around events of sovereign financial distress.² The sample contains 20 years of data for 12 emerging economies. The analysis focuses on episodes involving significantly high country risk.³ The main takeaway from the figure is that country risk reacts prior to any sharp reduction in productivity, suggesting that bond prices may be responding to news about future productivity.

To complement the suggestive evidence provided by the plots with a more formal empirical analysis, we estimate a panel-VAR following the identification strategy of news shocks introduced by Beaudry and Portier (2006). Our results show that news shocks have a significant contemporaneous effect on country risk, and that such effect is larger than that of a labor productivity shock of similar magnitude.

We consider these empirical VAR results as a motivating starting point to study the role of news for sovereign debt dynamics, and we advance our analysis further by developing a structural model with news, debt maturity choice, and default risk.⁴ Our contributions can be framed in terms of the answers to four questions. We first ask: Does the model replicate the key long run

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¹In this paper, country risk is the risk that a government will default on its debt commitments.

²We measure country risk with the Emerging Market Bond Index Plus (EMBI+) spread. The EMBI+ is a JP Morgan index that tracks total returns for traded foreign currency denominated debt instruments issued by emerging market economies. The EMBI+ covers US dollar-denominated Brady bonds, loans and Eurobonds. The family of EMBI is the most widely used and comprehensive emerging market sovereign debt benchmark. See Financial Times lexicon, definition of EMBI, http://markets.ft.com/research/Lexicon/Term?term=EMBI (accessed October 23, 2019).

³We define a debt crisis, or high country risk event, as a period in which the EMBI+ doubles relative to the previous year.

⁴A number of studies have identified potential issues with the strategy of Beaudry and Portier (2006), as summarized in the survey by Beaudry and Portier (2014).
Figure 1: Labor productivity and country risk (EMBI+ spread) at times of distress

Note: Authors’ calculation using yearly data from the International Labor Organization and The World Bank for Argentina, Brazil, Colombia, Ecuador, Mexico, Panama, Peru, Philippines, Russia, Turkey, Venezuela, and South Africa. Labor productivity is in logs, in deviations from a country-specific log-linear trend, and multiplied by 100. Debt crisis is defined as the period in which the EMBI+ doubles relative to the previous year. The values for EMBI+ and labor productivity are normalized to those of the year before the debt crisis for the median country in the sample.

Debt statistics and dynamics observed in emerging economies? We find that the calibrated model closely mimics the indebtedness and default features documented for emerging countries. Our framework also captures key moments of the debt profile of these economies, such as the level and dynamics of debt duration, maturity, and spreads for different debt maturities. Furthermore, we show that the model closely mimics the dynamics of debt and default risk leading to sovereign debt crises, by comparing the impulse responses of the model with empirical estimates. To compare the impulse responses, we estimate a structural panel-VAR with data for emerging market economies, and we show that the VAR estimated with model-simulated data looks very similar. Thus, a first key contribution of our study is to provide a structural interpretation of the empirical findings using a quantitative dynamic small open economy model of sovereign debt.

Our framework takes into account different sources of macroeconomic fluctuations in small open economies, so every period our model economy receives shocks to productivity, credit markets access (sudden stop), and a noisy signal about next period productivity (news shock). A natural question that arises in this context is then: How different are the debt profile and default risk responses to shocks to productivity, news, and sudden stops? The economic dynamics after a
bad news shock shares some features of a response to a productivity shock and others of sudden stop events. In particular, after the realization of bad news, the country experiences an immediate jump in the default probability as in the case of a bad productivity shock, though significantly smaller. The reason for the smaller response of the default probability is that the anticipation of adverse future fundamentals allows the country to reduce its liabilities ahead of the decline in productivity. The deleveraging, however, is smaller than after a sudden stop episode, so the default probability remains elevated long after the bad news shock occurs. Thus, a second key contribution of our study is that it helps understand how different sources of macro fluctuations affect sovereign debt and default risk dynamics in small open economies.

To moderate the impact of shocks on the economy, sovereigns manage their sovereign debt. The management process involves not only decisions about the total amount of debt but also, crucially, about when the debt is due. Thus, our third question is: Does long debt maturity help shield countries from bad news shocks? Our study is the first to analyze news shocks in a sovereign default model with long-term bonds, so it is well equipped to address the question. Intuitively, as bad news increase the cost of borrowing, countries limit their debt issuance after a bad news shock. Accordingly, after receiving bad news, countries reduce debt in the amount of payments due that period as in the case of a sudden stops. As the due payments are smaller with longer maturity, there is less default in the period of a bad news shock when the country has longer debt maturity. While this intuitive line of thought suggests that long maturity shields countries from bad news shocks, such conclusion would be misleading because the reduced deleveraging in the period of the shock implies that there is higher default in the period after the news shock. In fact, we find that long debt maturity implies a larger default probability in the following years, which yields a higher cumulative default probability.

Finally, having analyzed the role of maturity, a key debt dimension, on a country’s response to news, we use the model to understand the role of a key property of news: What is the role of the precision of news for debt dynamics? In the benchmark calibration, the precision of news is calibrated such that the model replicates the dynamics of labor productivity after a news shock as estimated in the data. We then vary the precision and analyze key changes in the long run statistics of the economy and on the dynamics after a news shock. We find that as news precision
increases, the sovereign manages debt better, increasing the level of indebtedness with similar or even lower spreads, especially during times of distress. These spreads become less negatively related with output because there is more deleveraging in anticipation to bad productivity, and the countries can reduce the volatility of consumption.

1.1 Related literature

Our paper is related to two strands of the literature. First, we borrow from the news and learning literature. Cochrane (1994) and Beaudry and Portier (2006) find that news about total factor productivity or stock prices can explain a significant portion of the forecast variance of consumption, output, and hours worked. Building on the real business cycle literature, Jaimovich and Rebelo (2008, 2009) and Schmitt-Grohe and Uribe (2012) explore the importance of news using log-linear approximation methods. Recently, Kamber et al. (2017) have analyzed the effect of news about future TFP shocks in four advanced small open economies subject to financial frictions. However, these studies abstract from debt default as an equilibrium outcome, a salient feature of emerging markets, and rely on log-linear approximation methods that are not well suited to analyze nonlinear events like debt crises. In addition, Zeev et al. (2017) explore the effects of terms-of-trade shocks and news about them on emerging countries.\footnote{See also Schmitt-Grohe and Uribe (2018).} In contrast to these papers, we focus on how news shocks in emerging economies interact with default risk and debt maturity. We consider a dynamic stochastic quantitative model of endogenous sovereign debt maturity and default, and we employ nonlinear methods, which are crucial in capturing the movements in default risk and yield spreads as they relate to the likelihood of future income or productivity falling below a threshold.

Second, our analysis borrows from the literature on sovereign debt and default. Following the seminal work on international sovereign debt by Eaton and Gersovitz (1981), a large portion of the literature on quantitative models of sovereign debt default has used only one-period debt (Aguiar and Gopinath, 2006; Arellano, 2008; Cuadra et al., 2010; Mendoza and Yue, 2012; Yue, 2010, among others). Models of long debt duration, such as Chatterjee and Eyigungor (2012) and
Hatchondo and Martinez (2009), feature exogenous maturity. In contrast, our quantitative model features endogenous sovereign debt maturity and repayment. Only recent work on quantitative default models allows for endogenous debt maturity, but it does not consider the role of news shocks (Arellano and Ramanarayanan, 2012; Bai et al., 2014; Hatchondo et al., 2016). We consider a quantitative default model that uses the tractable endogenous maturity framework developed in Sánchez et al. (2018), and we solve the model numerically using the techniques proposed by Dvorkin et al. (2018).

A related paper that incorporates news shocks in a sovereign default model is Durdu et al. (2013). The contribution of that study is to link the precision of news to the level of development of the country, and to compare some predictions of the model with the data as the precision of news varies. Instead, we focus on the dynamics created by news shocks relative to productivity and sudden stop shocks, and we explore whether debt maturity management is effective to deal with news shocks. Nevertheless, our last section also analyses the role of the precision of news and complements Durdu et al. (2013) by showing how duration, maturity, and the term structure of interest rate spreads are affected by the precision of news. Hence, our analysis in that section focuses on key debt features that cannot be addressed in Durdu et al. (2013) because they consider a model with only one-period debt. To our knowledge, our paper constitutes the first effort to integrate news about future fundamentals, endogenous debt maturity and default risk in a nonlinear dynamic stochastic quantitative model.

The rest of the paper is organized as follows. Section 2 estimates a panel-VAR to identify the effects of news on sovereign default risk. Section 3 presents the economic environment and the theoretical framework. Section 4 presents the model’s calibration and compares key non-targeted moments from the model with data. Section 5 studies the response of model variables to news shocks and shows that, in our model, bad news may generate a debt crisis. Section 6 concludes.
2 Empirical Evidence

We start our analysis by conducting an empirical study on the effects of news shocks following the seminal work of Beaudry and Portier (2006).\(^6\) News about the future path of productivity has an impact on economic conditions today, which is typically reflected in the contemporaneous behavior of financial variables. For an emerging economy that borrows in international markets, future productivity has important effects on the current and future default decisions. Thus, emerging market interest rates typically react to news about future productivity.

Our analysis deviates from Beaudry and Portier (2006) in two important ways. First, we focus on emerging market economies. We use a multi-country panel data approach to overcome limitations with data availability and increase the number of observations and the precision of our estimates. In contrast, the study of Beaudry and Portier (2006) focuses on the U.S. economy. Second, we look at sovereign borrowing costs, captured in the data by the Emerging Markets Bond Index Plus (EMBI+) spread. In contrast, Beaudry and Portier (2006) look at movements in domestic stock market prices due to news.

Our empirical identification strategy relies on short-run restrictions to the effects of news. Let \(\epsilon_{1,t}\) denote the conventional innovation to productivity and \(\epsilon_{2,t-j}\) denote the news shock, which anticipates the movements in productivity \(j\) periods in advance. Let \(A_t\) denote the state of (log) productivity at time \(t\), and assume that the productivity depends on current and past values of these economic shocks, i.e.,

\[
A_t = [B_{11}(L) B_{12}(L)] \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix},
\]

where the notation follows Barsky and Sims (2011). \(B_{11}(L)\) and \(B_{12}(L)\) are polynomials in the lag operator. The main restriction derived from the theory is \(B_{12}(0) = 0\). Therefore, news shocks do not have a contemporaneous impact on productivity. A simple process that describes

\(^6\)Other papers have also contributed to the recent literature on news shocks. See for example, Jaimovich and Rebelo (2009); Barsky and Sims (2011); Schmitt-Grohe and Uribe (2012); Kurmann and Otrok (2013); Levchenko and Pandalai-Nayar (2015), among others.
the effect of these shocks on productivity is

\[ A_t = \rho A_{t-1} + \sigma_1 \epsilon_{1,t} + \sigma_2 \epsilon_{2,t-j}. \]

This is a special case of equation (1), and shows that the innovation \( \epsilon_{1,t} \) is able to affect productivity contemporaneously, while the innovation \( \epsilon_{2,t} \) cannot, but its impact on productivity, while known today, will be realized in the future. This second type of innovation is what the literature has labeled a news shock.

We aim to identify the effect of news shocks on interest rate spreads and productivity in emerging market economies. For this purpose, we estimate a VAR system that includes measures of these two variables. In particular, we use the EMBI+ spread and labor productivity.\(^7\) Our sample consists of quarterly data from 1995q1 to 2016q4 for eight developing countries: Argentina, Brazil, Colombia, Ecuador, Mexico, Peru, Philippines, and South Africa. The sample is very similar to the one used by Uribe and Yue (2006), but is extended to include more recent years.\(^8\)

The VAR system of order one can be written in reduced form as

\[
\begin{bmatrix}
A_t \\
r_t
\end{bmatrix}
= C_0 + C_1 \begin{bmatrix}
A_{t-1} \\
r_{t-1}
\end{bmatrix} + \begin{bmatrix}
u_{1,t} \\
u_{2,t}
\end{bmatrix},
\]

where \( A_t \) is labor productivity, \( r_t \) is the EMBI+ spread, and \( u_{1,t} \) and \( u_{2,t} \) are the reduced-form disturbances. \( C_0 \) and \( C_1 \) are matrices of coefficients. Following Uribe and Yue (2006), we allow \( C_0 \) to vary by country in our panel –i.e., a country fixed-effect– and we estimate the system equation-by-equation employing the instrumental-variable method they use for dynamic panel data.\(^9\)

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\(^7\)We measure the EMBI+ spread in percentage points and labor productivity in logs and in deviations from a log-linear trend, multiplied by 100. We obtain the EMBI+ and the labor productivity data from the World Bank and the International Labor Organization, respectively. See Appendix A for a complete description. Labor productivity is measured at the yearly frequency in the data, so we obtain quarterly measures using the proportional Denton method and the country’s GDP as the high frequency proxy.

\(^8\)The data availability for the EMBI+ spread limits the sample of countries.

\(^9\)See Uribe and Yue (2006) for a complete description. The estimation uses the procedure of Anderson and Hsiao (1981). Our results are robust to using simple OLS estimators for the panel VAR.
We use the estimated VAR system to extract information about the role of news. To identify the structural shocks, we assume that the reduced-form innovations and the structural shocks follow a linear relationship,

\[
\begin{bmatrix}
  u_{1,t} \\
  u_{2,t}
\end{bmatrix} = \Omega
\begin{bmatrix}
  e_{1,t} \\
  e_{2,t}
\end{bmatrix},
\]

where \( \Omega \) is a matrix of coefficients. Note that equation (1) is a special case of our VAR under our assumed structural relationships. As is well known in the literature, it is not possible to identify all the elements in \( \Omega \) using only information from the reduced-form estimates. Our identification strategy assumes that news shocks cannot affect productivity contemporaneously. In this way, we assume that the element \( \Omega_{12} = 0 \). As is usual in the literature, we also assume that the structural shocks have unit variance. These restrictions are sufficient to identify the effects of news shocks in our empirical model.\(^{10}\)

Figure 2 shows the impulse-response functions of the estimated VAR to news and productivity shocks. The left panel shows the response of the EMBI+ spread to each shock, and similarly, the right panel shows the responses of labor productivity. The dashed lines represent 95 percent confidence bands. In both cases we show the effects of news and current productivity shocks that have a negative impact on productivity. As shown in the left plot, both negative shocks increase the EMBI+ spread in emerging countries, but news shocks have a substantially larger effect on the EMBI+ spread than contemporaneous productivity shocks. The spread response to news is stronger on impact, and decays monotonically and gradually, exhibiting some persistence. The right plot shows that news shocks have the largest impact on labor productivity between one and two years after they occur.

The magnitude of the effects is different for the two types of shocks. Table 1 shows the variance decomposition at different horizons. On the one hand, given our identification strategy, news shocks do not contribute to the variance of productivity one quarter ahead. Nevertheless,

\(^{10}\)We also estimated our VAR specification taking into account the presence of extreme capital flow episodes, or sudden stops, driven by global factors exogenous to the domestic economy. In particular, we included dummy variables that account for periods of global sudden stops and interact them with the coefficients of the lagged variables in the VAR model. The inclusion of these dummy variables changes only slightly the shape and magnitude of the impulse responses.
Figure 2: Impulse responses for the structural VAR

Note: Impulse response functions for the structural VAR model with short-run identification restrictions. Responses are for a one standard deviation shock. Confidence bands computed via bootstrap. Dashed lines encompass the central 95 percent of the simulations.

they are a source of uncertainty in the longer run, accounting for 8 percent of the forecast error variance 2 years ahead and 18 percent 10 years ahead. On the other hand, news shocks account for the bulk of the variance in the EMBI+.

Table 1: Forecast Error Variance Decomposition (Percent)

<table>
<thead>
<tr>
<th></th>
<th>Productivity</th>
<th>EMBI+</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prod Shock</td>
<td>News Shock</td>
</tr>
<tr>
<td>1 quarter</td>
<td>100.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1 year</td>
<td>97.56</td>
<td>2.44</td>
</tr>
<tr>
<td>2 years</td>
<td>92.24</td>
<td>7.76</td>
</tr>
<tr>
<td>5 years</td>
<td>83.78</td>
<td>16.22</td>
</tr>
<tr>
<td>10 years</td>
<td>82.19</td>
<td>17.81</td>
</tr>
<tr>
<td></td>
<td>0.90</td>
<td>99.10</td>
</tr>
<tr>
<td></td>
<td>1.62</td>
<td>98.38</td>
</tr>
<tr>
<td></td>
<td>2.49</td>
<td>97.51</td>
</tr>
<tr>
<td></td>
<td>3.69</td>
<td>96.31</td>
</tr>
<tr>
<td></td>
<td>3.91</td>
<td>96.09</td>
</tr>
</tbody>
</table>

Note: Forecast error variance decomposition for the structural VAR model with short-run identification restrictions at different horizons.

The recent work by Zeev et al. (2017) studies the role of news shocks in emerging market economies. They estimate a VAR with 8 variables, including net exports over GDP, for five emerging economies: Argentina, Brazil, Chile, Colombia, and Peru, and shows that for these emerging economies, news about the future (in their specific case, commodity-terms-of-trade) have a large contribution to the cyclical fluctuations in GDP. Moreover, they find that positive
news about terms of trade has a positive impact on future GDP, net exports and a negative impact on spreads. While the exercise in Zeev et al. (2017) is somewhat different than ours, it does suggest that news are an important source of fluctuations in emerging economies and that spreads react to them. Our empirical evidence agrees with this result. We complement the empirical analysis using a quantitative model of sovereign default allows us to better understand these findings, in particular how and why spreads react to news shocks, thus filling a gap in the literature.

Some papers, including Schmitt-Grohe and Uribe (2012) and Beaudry and Portier (2014), have identified potential issues with this empirical strategy. We use the findings presented above only as a starting point of our study, which we complement with a structural analysis using a model with news, debt maturity and default risk. Therefore, in the next section we present a quantitative model of sovereign debt that incorporates news about the direction of changes in productivity. Consistent with the empirical evidence discussed earlier, the model suggests that news shocks have a large impact on the risk of default and predict a future drop in productivity. Also in line with our empirical findings, the model shows that yield spreads react more to adverse news shocks than to a drop in productivity of similar magnitude. In particular, we simulate data with our quantitative model and use this data to estimate the same empirical VAR we presented in this Section, allowing us to connect our model to our empirical findings. The comparison between the empirical VARs estimated with actual data and VARs estimated with simulated data is common in other other areas of macroeconomics.11 However, to the best of our knowledge, this analysis has not been performed before with models of sovereign default in the tradition of Eaton and Gersovitz (1981).

The close alignment of the model dynamics with the data allows us to use our setup to study the role of news on debt management (i.e., the level and maturity of debt) and the term structure of sovereign bond spreads, and furthermore to understand why the data suggests that news are an important driver of country risk dynamics.

11 See, for instance, the seminal work of Christiano et al. (2005).
3 Model

3.1 Preferences and shocks

We build on the sovereign default setup with maturity choice introduced in Sánchez et al. (2018). Time is discrete, and the small open economy receives a stochastic labor productivity shock, $A_t$, that follows a finite-state first-order Markov chain with state space $A \subset \mathbb{R}_{++}$ and transition probability $\Pr(A_{t+1} = A_i \mid A_t = A_l)$. We discretize the labor productivity space into a grid with $N_A$ points, with $N_A$ large enough so that $\Pr(A_{t+1} = A_i \mid A_t = A_l)$ is sufficiently small for all $l$ and $i$.

In this economy there is a benevolent government that trades bonds in international credit markets to maximize the lifetime utility of the representative household. The discount factor is $\beta \in (0, 1)$ and the period utility is $u(c, \ell)$, a function of consumption, $c$, and labor, $\ell$, with standard properties. Production takes place using a constant returns to scale technology that uses only labor.

3.2 News

Every period, the government receives a signal $s \in \{1, 2, ..., N_s\}$ about the realization of labor productivity next period, where $N_s \leq N_A$ is the number of grid points for the signal. Given $N_s$ and the way we define the news, it will be clear that we need that $\Pr(A_{t+1} = A_i \mid A_t = A_l) < 1/N_s$ for all $l$ and $i$.

We define the sets of values of productivity associated with each signal $j \in \{1, 2, ..., N_s\}$ as

$$\Delta_j(A_l) = \left\{ A_i : (j - 1)/N_s < \sum_{n=1}^{i} \Pr(A_{t+1} = A_n \mid A_t = A_l) \leq j/N_s \right\},$$

where these sets depends on current productivity $A_l$ because there is persistence in labor productivity.

The signal associated with future productivity, $A_i \in \Delta_j(A_l)$, and current productivity, $A_l$, is $S(A' = A_i, A = A_l) = j$. Note that by construction, the news is better the larger the value of
Also, since we assumed that \( \Pr(A_{t+1} = A_i \mid A_t = A_l) \) is sufficiently small for all \( l \) and \( i \), the probability of receiving each signal is approximately the same; i.e., \( \Pr(s_t = j \mid A_t = A_l) \approx 1/N_s \).

News precision is introduced assuming that the probability of realizing a signal \( s \) if the future productivity shock is \( A_i \) and the current one is \( A_l \), is given by:

\[
Pr(s_t = j \mid A_{t+1} = A_i, A_t = A_l) = \begin{cases} 
\eta, & \text{if } j = S(A_i, A_l) \\
\frac{1-\eta}{N_s-1}, & \text{otherwise}.
\end{cases}
\]  

(2)

Note that if \( \eta = 1/N_s \), we have \( \frac{1-\eta}{N_s-1} = 1/N_s \), so the signal is not informative; i.e.,

\[
Pr(s_t = j \mid A_{t+1} = A_i, A_t = A_l) = \frac{1}{N_s} \forall j, A_i, A_l.
\]

We consider cases with \( 1/N_s < \eta < 1 \), so news are informative but imperfect.

After some algebra, it can be shown that the forecast of the probability of receiving a productivity shock \( A_i \) given the current productivity \( A_l \) and the signal \( j \) is

\[
Pr(A_{t+1} = A_i \mid A_t = A_l, s_t = j) = Pr(A_{t+1} = A_i \mid A_t = A_l) \frac{Pr(s_t = j \mid A_{t+1} = A_i, A_t = A_l)}{Pr(s_t = j \mid A_t = A_l)},
\]  

(3)

where the actual transition probability \( Pr(A_{t+1} = A_i \mid A_t = A_l) \) is adjusted by a factor equal to 1 if \( \eta = 1/N_s \) (non-informative signals), and greater than 1 if \( 1/N_s < \eta \leq 1 \) and \( j = S(A_i, A_l) \). In other words, the last term in (3) is larger than one, and thus the signal leads to an upward revision of the probability of \( A_i \) next period given \( A_l \) today, when the signal received points to a realization of future productivity that is in the set that includes \( A_i \).\(^{12}\)

It is also useful to describe the implied joint transition of productivity and signal, which is:

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

(4)

What does news do? News change the probability distribution of next-period productivity given the current level of productivity. Figure 3 shows two cases with different level of precision

\(^{12}\)Appendix B provides the derivation of expressions (3) and (4).
for current productivity $A = 0.913$ and 7 possible values of news, $N_s = 7$. The solid red lines show the unconditional probability distribution, i.e., the distribution of probabilities for next period’s labor productivity in the absence of news. In these cases, on average, labor productivity is expected to increase because current productivity is below the mean and there is mean reversion. The dashed blue lines represent bad news. They correspond to values of tomorrow’s productivity at the bottom 14.2 percent ($1/N_s$) of the unconditional distribution. After the bad news signal is observed, the distribution is very concentrated in these values for productivity; it is much more likely that labor productivity will decrease tomorrow. Notice that the concentration of probability on these points is starker on the right panel than on the left panel, which illustrates the role of higher news precision (larger $\eta$). The long-dashed brown lines represent good news, which is associated with productivity values between the percentiles 71.5 and 85.7 of the unconditional distribution. In this case, the probability of increasing productivity rises. The short-dashed green lines represent signal 3, which corresponds to slightly negative news (productivity values between percentiles 28.6 and 42.8).
3.3 Credit markets

As in Sánchez et al. (2018), at the beginning of the period a country has a debt portfolio characterized by the promised level of per-period payments \( b \) and by the number of periods that those payments will be made (maturity), \( m \). Notice that the portfolio may consist of any number of bonds. Whether the portfolio is composed of one bond or several bonds is irrelevant in this framework. The key restriction is that the profile of payments is fixed, so the portfolio can be characterized with just two state variables, \((b, m)\).

To understand our notation, consider a country that chooses a portfolio characterized by \((b, m)\) for the next period. Given that portfolio, the value of a specific bond that pays \( \tilde{b} \) for \( n \) periods is \( \tilde{b} q(y, b, m; n) \), where \( y \) denotes current income. Default occurs on the entire portfolio, so the price of this bond depends on the characteristics of the entire portfolio \((b, m)\). When the portfolio maturity, \( m \), coincides with the bond maturity, \( n \), the price \( q \) represents the price of the portfolio per unit of yearly payments. Therefore, the market value of the entire portfolio can be written as \( b q(y, b, m; m) \).

To further illustrate the notation, consider the following example. Suppose that the country has the portfolio \( \{b, b, b, b\} \) and that the portfolio is made of three bonds with payment promises

- \( \{b, b, b, 0\} \), \hspace{1cm} \text{(bond 1)}
- \( \{b - b, b - b, b - b, 0\} \), and \hspace{1cm} \text{(bond 2)}
- \( \{0, 0, 0, b\} \). \hspace{1cm} \text{(bond 3)}

The value of each bond would be

- \( \tilde{b} \times q(y, b, 4; 3) \), \hspace{1cm} \text{(bond 1)}
- \( (b - \tilde{b}) \times q(y, b, 4; 3) \), and \hspace{1cm} \text{(bond 2)}
- \( b \times [q(y, b, 4; 4) - q(y, b, 4; 3)] \), \hspace{1cm} \text{(bond 3)}

respectively. Adding the value of these three bonds we obtain the value of the portfolio, \( b \times \)
\(q(y, b, 4; 4)\). These prices provide very useful notation for the country’s choice of maturity.

The country in our setup cannot commit to repaying its obligations, so given an outstanding amount of assets, \(b\) (debt if \(b < 0\)), it has two actions to choose from. The first option is to pay its obligations and thus keep its good credit status. Alternatively, the country may decide not to make its debt payment (default).

A default brings immediate financial autarky and a direct productivity loss to the defaulting country. After the initial default decision, the country remains in autarky for a stochastic number of periods and then returns to international debt markets with no debt balance.\(^{13}\)

In times of good credit status, the country may face a “debt rollover” (sudden stop) shock, \(a\), where \(a = 0\) if the country is facing a disruption in its access to financial markets and is hence impeded from rolling over or changing its debt portfolio, and \(a = 1\) otherwise. When the country experiences this sudden stop event, world financial markets cease to lend to the economy, so the country may only choose between repaying or repudiating its obligations. We introduce sudden stop shocks in our model to get a sufficiently high level of debt maturity in normal times. It is well known that, for borrowers, long-term debt is more costly than short-term debt due to debt dilution. However, borrowers value long-term debt as a way to hedge against rollover crises or sudden stops (see Sánchez et al. (2018) for a discussion.)\(^{14}\) On the empirical side, Calvo et al. (1993); Calvo et al. (2006); Uribe and Yue (2006) and Forbes and Warnock (2012), among others, show that extreme capital flow episodes or sudden stops are a salient feature of emerging market economies and are typically driven by global factors external to the country. Additionally, Aguiar et al. (2016) construct a statistical model of emerging market spreads with unobserved factors that are common to all emerging markets (but orthogonal to individual country’s fundamentals), and label these as global factors.

Thus, the decision to default is influenced by the current level and maturity of debt, by the

\(^{13}\)Dvorkin et al. (2018) show that restructurings that look similar to the data can be endogenously obtained in a model in the tradition of Eaton and Gersovitz (1981).

\(^{14}\)Alternative ways of modeling exogenous variation in the availability of credit include adding risk-averse pricing kernels, as proposed first by Lizarazo (2013), or to introduce exogenous variations in the risk-free rate. More recently, a growing number of quantitative sovereign default studies incorporates sudden stops or rollover crises similar to the ones we have. Two examples are Aguiar et al. (2016) and Bianchi et al. (2018), who develop models in which lenders’ risk aversion may experience a sudden increase.
country's productivity, \(A\), by the news about future productivity, by the costs of default, and by the debt rollover shock (sudden stop).

### 3.4 Decision problem

Each period the state variables for the government consist of the productivity shock, \(A\); the signal about the productivity of next period, \(s\); the sudden stop shock, \(a\); asset level, \(b\); and maturity, \(m\). The government decides, among other things, whether to default on the existing debt or not:

\[
V(A, s, a, b, m) = \max \left[ V^G(A, s, a, b, m), V^D(A, s, b, m) \right].
\]

where the policy function \(D(A, s, a, b, m)\) is 1 if default is preferred and 0 otherwise. If the country does not receive a sudden stop shock \((a = 1)\), and decides not to default, it selects the maturity of the new portfolio, \(m'\), and the debt level, \(b'\). The value in this case is:

\[
V^G(A, s, 1, b, m) = \max_{b', m'} \left[ u(c, \ell) + \beta E_{A', s', a'|A, s} V(A', s', a', b', m') \right]
\]

subject to

\[
c = A\ell + b - \left( q(A, s, b', m'; m) b' + q(A, s, b', m'; m - 1) b \right) \]

\[
b' \in \mathbb{R}_-, m' \in M.
\]

Note that while this notation can be interpreted as retiring all the old debt at market prices and issuing new debt, the same constraint can be rewritten to show the split between new resources added by the change in yearly payments and new resources added by the change in maturity,

\[
c = A\ell + b - \left( q(A, s, b', m'; m') (b' - b) - [q(A, s, b', m'; m') - q(A, s, b', m'; m - 1)] b \right) \]

In contrast, a country that receives a sudden stop shock and therefore has no access to credit markets \((a = 0)\), may pay to its creditors but cannot issue new debt, so the next period payment
will remain at today’s amount $b$ and the maturity will be one year shorter at $m - 1$. Thus, the value today can be expressed as:

$$V^G(A, s, 0, b, m) = \max_\ell u(\ell + b, \ell) + \beta E_{A', s', a'|A, s}V(A', s', a', b, m - 1).$$

The policy functions for the amount of debt and the maturity are $B(A, s, a, b, m)$ and $M(A, s, a, b, m)$. When the country makes only its debt payment, the policies are $B(A, s, a, b, m) = b$ and $M(A, s, a, b, m) = m - 1$. Therefore, if $a = 0$, it must be that $B(A, s, 0, b, m) = b$ and $M(A, s, 0, b, m) = m - 1$.

Default brings immediate financial autarky for a stochastic number of periods and a direct productivity loss to the defaulting country. Formally, the value of default is:

$$V^D(A, s, b, m) = \max_\ell u(\min(A, \phi)\ell, \ell) + \beta E_{A', s', a'|A, s} [(1 - \lambda)V^D(A', s', b, m) + \lambda V(A', s', a', 0, 0)] ,$$

where the parameter $\lambda$ captures the probability of reentry to international capital markets after default. After exclusion, the country reenters with no debt.\(^{15}\)

### 3.5 Equilibrium bond prices

Given the world interest rate $r$, and the existence of risk-neutral lenders, the price of the country’s debt must be consistent with zero expected discounted profits. Thus, the price of a bond of maturity $n > 0$ of a country with productivity $A$ and new debt portfolio $(b', m')$ can be represented by $q(A, s, b', m'; n) =

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

The key term added by long term debt is that the policy function for borrowing, $B$, must be included in the next period prices. This extra term captures the debt dilution mechanism emphasized by Hatchondo et al. (2014). Finally, the endogenous maturity feature adds the policy

\(^{15}\)In a previous version of this paper the country returned to credit markets with a new portfolio with reduced debt and increased maturity to capture the findings in Dvorkin et al. (2018). Since adding these features did not change the analysis of news, the model is now simplified assuming the country gets a fresh start.
function for maturity choice \( M \) into tomorrow’s prices. Thus, this framework also captures debt dilution generated via extensions of maturity, as discussed in Sánchez et al. (2018).

## 4 Quantitative model

To solve the model numerically, we first consider functional forms and perform the calibration. We then explain some of the dynamics of the model with regressions that we run on model-simulated data.

### 4.1 Functional forms

We follow Mendoza and Yue (2012), among others, and use GHH (Greenwood et al., 1988) preferences with a CRRA flow utility function with risk aversion \( \gamma \geq 1; \)

\[
    u(c, \ell) = \frac{1}{1 - \gamma} \left( c - \frac{\ell^{1+\theta}}{1 + \theta} \right)^{1-\gamma},
\]

where the parameter \( \theta \) is the inverse of the Frisch elasticity.

Schmitt-Grohe and Uribe (2012) found that in a macroeconomic model with news shocks for the United States, estimates favor this type of preferences with no wealth effects on labor. In addition, Correia et al. (1995) show that a small-open-economy RBC model with GHH preferences can better match the cyclical moments of small open economies.\(^{16}\)

The GHH specification implies that the labor supply is not affected by actual or expected changes in wealth, and therefore it is an increasing function of the wage only, \( \ell_t = w_t^{1/\theta} \). Since we assumed that production takes place using a constant returns to scale technology that uses only labor, we have that \( w_t = A_t \) and then \( \ell_t = A_t^{1/\theta} \) and output is \( Y_t = w_t \ell_t = A_t^{1+\frac{1}{\theta}} \).

---

\(^{16}\)We also solved the model using preferences with wealth effects. With wealth effects, the dynamics after a news shocks do not changed significantly. The most significant difference is in the ability of the model to fit the high variance of consumption relative to the variance of income observed in emerging markets.
4.2 Calibration

We calibrate the model to a yearly frequency. This assumption reduces the time it takes to solve the model but does not affect our results.\footnote{We also solved the model with a quarterly frequency for our baseline calibration and the results are comparable to the ones we present here.}

First, we set some model parameters at standard values that help keeping our results comparable with the literature. As shown in Table 2, households in the economy have a constant relative risk aversion (CRRA) utility with risk aversion coefficient $\gamma=2$. We set the maximum possible maturity to 20 years, which is significantly larger than the maturity observed for emerging markets.\footnote{Our results are robust to allowing for longer maximum maturities.} We set the yearly risk-free real interest rate to 0.042, which matches the long-run average of 10-year U.S. Treasury bonds. We set the probability of returning to financial markets exogenously to 0.17, which implies an average exclusion period of 6 years. This is number is consistent with the evidence in Tomz and Wright (2013). The parameter $\theta$, which determines the Frisch elasticity, and the parameters for the law of motion for labor productivity are computed using moments of detrended (log) real GDP per capita and (log) employment to population for Colombia and the model specification of the labor supply and output.\footnote{See Appendix A for details.} In this way, we obtain $\theta = 0.538$, which implies a Frisch elasticity of 1.89. This number is close to the one used by Mendoza and Yue (2012). The standard deviation of the innovation in labor productivity is set to 0.0078 and the autocorrelation to 0.9044. These numbers, together with the value of $\theta$, replicate the autocorrelation and volatility of detrended GDP per capita for Colombia.

Using the definition of sudden stop from Comelli (2015), and controlling by fluctuations in the availability of credit due to the country’s own fundamentals, we estimate that the probability of a sudden stop episode starting is 0.12 and the probability of continuing in the sudden stop is 0.42. These events capture episodes in which many countries find it difficult to access international credit markets, and are usually associated with an international financial crisis.\footnote{Figure 11 in Appendix D shows that our sudden stop periods are more global and related to well-known emerging market debt crises. Details on the estimation and results are also presented there.} While we use a very different statistical model to recover the sudden stop process, our results are consistent
with Aguiar et al. (2016) and Bianchi et al. (2018).

### Table 2: Calibrated parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest rate, $r$</td>
<td>0.042</td>
<td>10-year U.S. yield minus PCE inf. (Avg. 1980-2010)</td>
</tr>
<tr>
<td>Risk aversion, $\gamma$</td>
<td>2</td>
<td>Literature</td>
</tr>
<tr>
<td>Redemption prob., $\lambda$</td>
<td>0.17</td>
<td>6 year average exclusion</td>
</tr>
<tr>
<td>Discount factor, $\beta$</td>
<td>0.87</td>
<td>Debt/output 25% (model, 23%)</td>
</tr>
<tr>
<td>Cost of default, $\phi$</td>
<td>0.94</td>
<td>Default rate 2.0% (model, 1.8%)</td>
</tr>
<tr>
<td>Precision of news, $\eta$</td>
<td>0.80</td>
<td>10-yr. variance decomp. of productivity to news shock</td>
</tr>
<tr>
<td>Sudden stop entry prob., $p_{ns,s}$</td>
<td>0.12</td>
<td>Estimated (see Appendix D)</td>
</tr>
<tr>
<td>Sudden stop staying prob., $p_{s,s}$</td>
<td>0.42</td>
<td>Estimated (see Appendix D)</td>
</tr>
<tr>
<td>Labor prod. shock std, $\sigma_A$</td>
<td>0.0078</td>
<td>Estim. using data for Colombia (see Appendix A)</td>
</tr>
<tr>
<td>Labor prod., $\rho_A$</td>
<td>0.904</td>
<td>Estim. using data for Colombia (see Appendix A)</td>
</tr>
<tr>
<td>Inverse of Frisch elasticity, $\theta$</td>
<td>0.54</td>
<td>Estim. using data for Colombia (see Appendix A)</td>
</tr>
</tbody>
</table>

As is standard in the literature, $\beta$ and $\phi$ are calibrated jointly to replicate the debt-to-output ratio and the default rate. We calibrate these parameters to obtain a default rate of 2.0% and a debt-to-output ratio of 25%. These two numbers are consistent with the empirical evidence discussed in Tomz and Wright (2013). In addition to these two parameters, we calibrate the precision of news, $\eta$, to replicate the effect of a news shock on future productivity. Specifically, we search for the value of $\eta$—jointly with $\beta$ and $\phi$—such that the VAR estimated with model-simulated data replicates the following moment: the news shock accounts for 17.8 percent of the forecast error variance of productivity 10 years ahead (see Table 1).

We solve the model numerically using the method developed in Dvorkin et al. (2018), which is helpful to achieve convergence in models with endogenous maturity. Appendix C contains detailed information on the computational method we use.

### 4.3 Model mechanics

The mechanics of the model can be grasped by looking at Table 3. The table contains linear regressions of key variables on income, debt, and news. The regressions are performed on data simulated with the model. An advantage of using simulated data is that we capture the shape of the policy functions around the values of state variables that occur more frequently in equilibrium.
The top panel shows regressions using all observations in the simulation, and the lower panel restricts the attention to economies with higher risk of default (selected on low income). The first three columns of the top panel show that maturity, duration, and borrowing are increasing in income and decreasing in current debt. The next two columns show that as income increases, there is a decrease in yield spreads such that the 10-years minus 1-year term premium increases (steeper spread curve). The opposite result is obtained as debt increases: there is an increase in yield spreads and the term premium decreases. Good and bad news have opposite effects. Bad (good) news decreases (increases) maturity, duration, and borrowing. Bad (good) news also increases (decreases) yield spreads and reduces (increases) the term premium.

Table 3: The effects of news on selected model variables

<table>
<thead>
<tr>
<th></th>
<th>All income levels</th>
<th>Conditional on low income levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Chg log maturity</td>
<td>Chg log duration</td>
</tr>
<tr>
<td>log GDP</td>
<td>0.278</td>
<td>0.288</td>
</tr>
<tr>
<td>log Debt</td>
<td>-0.376</td>
<td>-0.391</td>
</tr>
<tr>
<td>dummy(good news)</td>
<td>-0.032</td>
<td>-0.043</td>
</tr>
<tr>
<td>dummy(bad news)</td>
<td>-0.000</td>
<td>-0.054</td>
</tr>
</tbody>
</table>

Note: Standardized regression coefficients using model-simulated data.

The bottom panel of Table 3 shows the same regressions conditional on lower income, which is generally associated to higher default risk. Some of the mechanics are different because in this
situation countries are basically trying to avoid default. The behavior of spreads and the term premium is the same as before, but the choice of debt maturity differs. As income increases, countries choose to decrease maturity slightly, and reduce borrowing significantly, a strategy consistent with the attempt to avoid default. Starting from the same situation of financial distress, an increase in debt triggers a reduction in maturity as before, but now the change in borrowing is positive, as expected of a country that must rollover more debt. The final difference is that bad news in this situation generates an increase in maturity. Starting from a situation of financial distress, receiving bad news about tomorrow can make repayment conditions very difficult, as we show below. Increasing maturity is a way of making the repayment easier tomorrow, and of reducing the risk of default.

To gain insight into how the effect of news depends on debt maturity, Figure 4 shows default regions for good and bad news for 5- and 10-year maturity bonds. The upper left plot shows the default region (red area) for different values of the labor productivity and the face value of debt under good news for an economy with debt maturity of 5 years, the upper middle plot shows the same for bad news, and the upper right plot shows the difference between these two plots, i.e., the difference in the default probability due to a shift from good to bad news.

The figure suggests that in our model, as expected, countries with more debt and lower productivity choose to default. Also, the top three plots illustrate that a bad signal is associated to a larger default region than a good signal. The broad red band in the right plot shows that the default probability increases dramatically for several states of the economy. Given debt, maturity, and productivity, the realization of bad news changes the country’s decision from repayment to default. This suggests that an economy near its default threshold may experience a substantial increase in its sovereign yield spreads following a negative news shock.

The lower plots present the default region under good and bad news when debt maturity is 10 years. Intuitively, with longer maturity the economy is less exposed to increasing interest rates, so the default region is smaller, as the default threshold shifts toward lower productivity and more debt (worse fundamentals). As we will show later, this does not necessarily mean that long maturity shields the country from a bad news shock once the dynamics in the following periods are also considered.
Figure 4: Default regions and news

Note: Probabilities of default next period conditional current states. We consider a country that is not in sudden stop today. Good (bad) signal corresponds to 6th (2nd) signal.
5 Main Results

This section presents our main results, which we organize around the responses to the four key questions discussed in the introduction, namely: Does the model replicate the debt and macro dynamics in emerging economies? How different are the responses to news shocks from productivity shocks and sudden stop shocks? Does long maturity shield countries from bad news shocks? Finally, what is the role of the precision of news? Next, we address each of these questions.

5.1 Does the model replicate the debt and macro dynamics of emerging economies?

To address this question, we proceed in three steps. First, we compare non-targeted statistics generated with the stationary distribution of the model against their data counterpart. Second, we generate the dynamics of the model before default episodes, and we compare them with literature studying these dynamics. Finally, and key for the goal of this paper, we estimate the VAR with model-simulated data and show that it looks quite similar to the empirical estimation in Section 2.

The non-targeted moments of interest generated by the model and the corresponding empirical statistics for a set of key emerging market economies are shown in Table 4. The model captures well the average level and the pro-cyclicality of the maturity and duration observed in the data. The table also provides information about sovereign interest rate spreads of instruments with different maturities. Consistent with the data, on average the 1-year spread is below the 10-year spread, i.e., the term premium tends to be positive, and yield spreads for all debt maturities tend to behave counter-cyclically, i.e., higher spreads are observed in bad times, both in the model and in the data. The two bottom rows show the EMBI+, which co-moves negatively with output both in the model and in the data.\footnote{The EMBI+ spread is a commonly used measure of sovereign borrowing costs for emerging economies, and it is based on the pricing of a country’s portfolio of sovereign bonds that satisfy minimum liquidity requirements and are mostly denominated in foreign currency.}
### Table 4: Fit of non-targeted moments

<table>
<thead>
<tr>
<th>Moments</th>
<th>Model</th>
<th>Brazil</th>
<th>Colombia</th>
<th>Turkey</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev. ( \log(c) ) / Std. Dev. ( \log(y) )</td>
<td>1.00</td>
<td>1.15</td>
<td>1.15</td>
<td>1.08</td>
</tr>
<tr>
<td>Corr. ( \log(c), \log(y) )</td>
<td>0.94</td>
<td>0.75</td>
<td>0.90</td>
<td>0.92</td>
</tr>
<tr>
<td>Maturity (years)</td>
<td>6.02</td>
<td>6.13</td>
<td>8.91</td>
<td>7.50</td>
</tr>
<tr>
<td>Maturity (years, good times)</td>
<td>6.17</td>
<td>6.25</td>
<td>10.25</td>
<td>7.08</td>
</tr>
<tr>
<td>Maturity (years, bad times)</td>
<td>5.83</td>
<td>5.64</td>
<td>7.90</td>
<td>8.35</td>
</tr>
<tr>
<td>Duration (years)</td>
<td>3.30</td>
<td>3.49</td>
<td>5.08</td>
<td>4.89</td>
</tr>
<tr>
<td>Duration (years, good times)</td>
<td>3.38</td>
<td>3.57</td>
<td>5.79</td>
<td>5.63</td>
</tr>
<tr>
<td>Duration (years, bad times)</td>
<td>3.21</td>
<td>3.18</td>
<td>4.55</td>
<td>4.40</td>
</tr>
<tr>
<td>Corr((dur, \log(y)))</td>
<td>0.22</td>
<td>0.69</td>
<td>0.93</td>
<td>0.69</td>
</tr>
<tr>
<td>1-year spread (%)</td>
<td>1.83</td>
<td>2.04</td>
<td>1.35</td>
<td>1.87</td>
</tr>
<tr>
<td>1-year spread (%), good times</td>
<td>0.98</td>
<td>0.82</td>
<td>0.92</td>
<td>1.96</td>
</tr>
<tr>
<td>1-year spread (%), bad times</td>
<td>2.92</td>
<td>3.43</td>
<td>1.63</td>
<td>1.75</td>
</tr>
<tr>
<td>10-year spread (%)</td>
<td>2.24</td>
<td>4.10</td>
<td>3.26</td>
<td>2.69</td>
</tr>
<tr>
<td>10-year spread (%), good times</td>
<td>1.91</td>
<td>1.69</td>
<td>1.56</td>
<td>2.76</td>
</tr>
<tr>
<td>10-year spread (%), bad times</td>
<td>2.66</td>
<td>6.86</td>
<td>4.39</td>
<td>2.59</td>
</tr>
<tr>
<td>EMBI+ (%)</td>
<td>2.24</td>
<td>4.90</td>
<td>3.41</td>
<td>3.95</td>
</tr>
<tr>
<td>corr((EMBI+, \log(y)))</td>
<td>-0.31</td>
<td>-0.76</td>
<td>-0.85</td>
<td>-0.79</td>
</tr>
</tbody>
</table>

Note: See Appendix A for data sources for Brazil, Colombia and Turkey, and further empirical details. Duration is computed using the Macaulay definition. EMBI+ in the model is the effective yield spread over the risk free rate given the secondary market price of the outstanding debt portfolio of the borrower. Appendix C provides the computational details on the model.
The statistics in Table 4 show that the model describes well the average and cyclical behavior of debt maturity, duration and interest rates spreads at different maturities. Figure 5 illustrates that the model also performs in line with the data leading into an extreme debt distress event, i.e., a sovereign default. The upper left plot suggests that the economy defaults following a declining path for labor productivity, A, hence for output, a similar pattern to that found in the literature (see for instance Mendoza and Yue (2012)). As shown in the upper right panel, the debt-to-GDP ratio increases prior to the default, especially in the year going into the episode, in line with the decline in output. Consistent with the lower output and the increasingly heavy debt burden faced by the economy, the short-term (1-year) interest rate spreads sharply increase before the event. The lower right figure shows that debt duration decreases as the economy approaches default.

Figure 5: Behavior around default

Note: Patterns prior to defaults. Only defaults without any other default in the past and future 10 years are selected. Total debt in upper right plot is the stock of the face value of the debt (−\(b_n\)). Appendix C.2 provides the computation of EMBI and duration in model simulations.

We use model-simulated data to estimate a VAR like the one we specified with the empirical
The impulse responses for the structural VAR using model-generated data, presented in Figure 6, show that our quantitative model of sovereign default with news replicates quite closely the main results found in the empirical VAR analysis regarding the dynamic evolution of spreads and productivity in response to news and contemporaneous shocks (see Figure 2 in Section 2 for the empirical results). The left panel in the figure shows that the EMBI+ spread increases more in response to a bad news shock than to an adverse contemporaneous productivity shock, and the magnitudes of the responses are close to those obtained in the empirical VAR. The right panel highlights that, as in the data, labor productivity declines markedly following a news shock, and then gradually recovers.

Figure 6: Impulse responses for the structural VAR using model generated data

Note: Impulse response functions for the structural VAR with short-run identification restrictions using model generated data. Responses are for a one standard deviation shock.

Table 5 presents the importance of each type of shock in explaining the variation of the EMBI+ spread and labor productivity in our simulations. The model replicates well the empirical forecast error variance decomposition between productivity and news shocks illustrated in Table 1. Our model only targets how much a news shock explains of the variation in labor productivity after 10 years, which is 17.93% in the model vs. 17.81% in the data. Therefore, the close match between the model and the data obtained for the other periods highlights again the ability of our framework to capture the empirical dynamics of news and sovereign debt.

22 The model has a yearly frequency, but results are robust to using a quarterly specification, it just takes much more computing time.
Table 5: Forecast Error Variance Decomposition using model generated data
(Percent)

<table>
<thead>
<tr>
<th></th>
<th>Productivity</th>
<th></th>
<th>EMBI+</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1 year</td>
<td>100.00</td>
<td>0.00</td>
<td>8.23</td>
<td>91.77</td>
</tr>
<tr>
<td>2 years</td>
<td>96.63</td>
<td>3.37</td>
<td>8.78</td>
<td>91.22</td>
</tr>
<tr>
<td>5 years</td>
<td>87.24</td>
<td>12.76</td>
<td>9.74</td>
<td>90.26</td>
</tr>
<tr>
<td>10 years</td>
<td>82.07</td>
<td>17.93</td>
<td>10.23</td>
<td>89.77</td>
</tr>
</tbody>
</table>

Note: Forecast error variance decomposition for the structural VAR with short-run identification restrictions at different horizons using model simulated data.

5.2 How different are the responses to shocks to productivity, news, and sudden stops?

To answer this question, Figure 7 shows the evolution of key debt prices and quantities after the three possible shocks in the model: bad news (solid black line), bad productivity (short-dashed blue line), and a sudden stop (long-dashed red line). We construct these figures taking the stationary distribution as the starting point, so they are representative of the behavior of this economy.

The top-left plot shows the evolution of productivity. To make productivity and news shocks comparable, the bad productivity shock is selected such that the associated immediate drop in labor productivity is similar in magnitude to the decline in next period productivity after a bad news shock—the cumulative loss in productivity is almost the same in both cases. In contrast, a sudden stop shock has no effect on productivity.

In terms of the evolution of debt (top middle plot), the magnitude of the effect of a bad news shock lies between the large deleveraging occurring after a sudden stop shock and the almost no change in debt after a productivity shock. This happens because lenders are somehow reluctant to rollover debt following a news shock. Remember that a sudden stop shock means that lenders do not extend credit to the country. After a bad productivity realization, lenders may be willing to lend to the country because mean reversion indicates that productivity is going to recover.

The top right plot shows the evolution of the default probability around each of the shocks. The productivity shock generates the largest immediate effect on the default probability, followed
by the bad news shock, and the sudden stop shock. The debt maturity is sufficiently long so that the deleveraging of 4 percentage points of output is enough to avoid default after sudden stop shocks. The plots also show that the cumulative defaults generated by bad news is similar to bad productivity shocks.

Figure 7: Impulse responses in the model

Note: For each impulse response, we run the 8000 samples for 140 periods so that we reach the ergodic distribution. We then impose a given shock at period 141. For the “Bad news” impulse response, this shock is the lowest signal (out of seven in total). For the “Bad productivity shock”, the shock is a drop in productivity to maintain a similar cumulative decline in the productivity over the 5 years after the shock. For the “Sudden stop” impulse response, the shock is a sudden stop. We then take averages across samples for each separate impulse response for all variables, except the EMBI and term premium, for which we use the median. We report the deviations from 1 period before the shock hits.

The first two bottom panels show the evolution of spreads. As in our VAR, the largest effect is after the bad news shock. Note that sudden stops reduce the one-period spread, which occurs because of the deleveraging mentioned above. Because of mean reversion and deleveraging, 10-year spreads do not move much, so the term premium (10-minus-1-year yields), shown in the middle panel, decreases significantly after bad news shocks.

Finally, the bottom right panel shows the evolution of debt maturity. After a sudden stop shock, maturity decreases by one year because the country is temporarily unable to borrow
in credit markets. After a bad productivity shock, maturity decreases slightly, as reported in Sánchez et al. (2018). Finally, the effect of a news shock on maturity is small for reasons that will be clear after the next subsection, which analyzes the role of maturity during bad news shocks.

5.3 Does long maturity shield countries from bad news shocks?

To understand the interaction of maturity with news shocks, we computed two alternative economies with different average equilibrium maturities by varying the risk of a sudden stop. The average maturity in the lower maturity model is 3.4 years and in the higher maturity model is 7.8 years.

Figure 8 illustrates how the debt price and quantity responses to news and sudden stop shocks depend on debt maturity. The first column of plots shows how these two economies with different equilibrium maturity react after a bad news shock. For comparison, we also present the evolution after a sudden stop (second column of plots), for which it is well known that economies can protect themselves by borrowing with long maturity. The solid black lines correspond to the economy with lower maturity and the dashed red lines correspond to the economy with higher maturity.

As shown in the upper right panel, long debt maturity helps mitigate an increase in default risk due to a sudden stop shock. On impact, in response to a sudden stop shock, the default probability increases by 2 percentage points with shorter maturity, while remaining almost unchanged with longer maturity. To understand this finding, note that the case of longer maturity is also associated to a smoother debt path around the sudden stop event, as there is less deleveraging on impact because the debt payments are more spread out over time. With a sudden stop, countries must decide whether to default or deleverage. Since with shorter term debt the due payment is larger, the deleveraging is larger and more countries prefer to avoid it by choosing to default.
Figure 8: Impulse responses in the model for different maturity economies

<table>
<thead>
<tr>
<th>Bad news shock</th>
<th>Sudden Stop Shock</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Graph" /></td>
<td><img src="image2" alt="Graph" /></td>
</tr>
<tr>
<td><img src="image3" alt="Graph" /></td>
<td><img src="image4" alt="Graph" /></td>
</tr>
</tbody>
</table>

Note: “Lower maturity” and “Higher maturity” economies correspond to models with the same calibration as in our benchmark, except for the probability of entering sudden stop, which is set at 0.01 in the first case and 0.25 in the second. The average maturity in the lower maturity model is 3.4 years and in the higher maturity model is 7.8 years. The probability of exiting a sudden stop episode is set at 0.42 in both economies, the same as in the benchmark. For each impulse response, we run the 8000 samples for 140 periods, so that we reach the ergodic distribution. We then impose a given shock at period 141. For the “Bad news” impulse response, this shock is the lowest signal (out of seven in total). For the “Sudden stop” impulse response, the shock is a sudden stop. We then take averages across samples. We report the deviations from 1 period before the shock hits.

Compared to the case of long term debt, with short term debt the default risk and debt dynamics after a news shock are more similar to those observed during a sudden stop event. The lower row of plots shows that the dynamics of debt for short and long maturities in response to a news shock are also similar to the case of a sudden stop event, with debt deleveraging associated to a news shock is milder under long term debt.\[^{23}\] The key difference between the response of a long and short maturity economy to news shocks, though, is in the dynamics of the risk of default, where long term debt magnifies the total (cumulative) increase in default risk from an

\[^{23}\]In the case of bad news, the economy keeps deleveraging for several periods, unlike in a sudden stop event, in which the economy immediately increases its leverage (U shaped debt path).
adverse news shock. On impact the default probability due to a news shock increases about the same for long and short debt (4 percentage points), but with long term debt the increase is more persistent, peaking a year after default at almost 6 percentage points.

To understand this finding, consider a country that receives bad news with perfect precision. Immediately, the lenders would restrict the supply of credit because they are aware that productivity will be lower next period, forcing a deleveraging. This deleveraging will be costly, so some countries will prefer to default. But those that do not default in the current period will have low debt in the next period, and will more likely be able to avoid default. In the extreme case that all debt is due today, creditors will be willing to lend exactly until the point they know the country will not default tomorrow. With long term debt, lenders restrict the supply of credit as well, but since less debt was due in the period, the deleveraging is smaller. Because there is less deleveraging, there will be fewer countries defaulting in the current period. But in the next period, when the bad productivity realizes, countries will have excessive debt and many of them will decide to default. So, while long term debt may protect the country from a bad news shock in the period of the event, it will make things worse in the future, when the bad news materializes into a bad productivity outcome.

5.4 What is the role of the precision of news?

We have shown that the calibrated model with news about future fundamentals captures well the average moments and the default dynamics observed in the data. Next, we discuss the role of the precision of news for the behavior of key debt variables. To the best of our knowledge, Durdu et al. (2013) is the only other paper performing a comparison of economies with different news precision in a quantitative model with endogenous default risk. They conclude that economies with higher signal precision behave more similar to richer economies. The analysis in this section complements their work by considering not only the amount of debt but also its maturity, and how each interacts with news shocks and sudden stops.

Figure 9 shows the main moments generated by the model for six news precision levels.
Note: The Figure presents moments from the ergodic distribution of the news shock computed from model-simulated data, and how these moments change with news precision. The model is solved for each precision level shown in the plots.
The first row of plots shows that as the precision of news increases, indebtedness also increases but the default rate remains roughly constant. This means that the country is improving its ability to manage debt. The second row of plots lends support to the intuition that debt management improves with news precision by looking at yield spreads: The plot on the left shows that the average spreads change little when the precision of news increases, but the one on the right shows that in bad times the spreads decrease at both maturity 1 and 10 years. The left plot of the third row provides another way to see the better debt management when news signals become more precise. The negative correlation between yield spreads and income decreases as the precision of news improves. The weaker negative correlation implies that the borrowing costs for the country do not rise as much when economic growth weakens, so debt becomes a more affordable tool to support consumption when the marginal value of consumption is higher.

The correlation between total debt and income increases with the precision of news (right hand-side plot in the third row), as countries take advantage of more informative news by deleveraging more during bad times. The country’s debt management improvement is reflected in the bottom-left plot, which shows that the country is better able to smooth consumption with higher precision of news. Finally, the plot next to it shows that the average maturity is not affected by the precision of news. This is because of the key difference between news shocks and sudden stops shocks that we discussed in the previous section.

Our study also focuses on the dynamics following news shocks around financial crisis, so in Figure 10 we present the effect of the precision of news on the impulse responses to news shocks.
Figure 10: Impulse responses after a bad news shocks in the model for different precisions

Note: “No precision” (“Low precision) economy corresponds to a model with the same calibration as in our benchmark except for the signal precision, η, which is set at 0.145 (0.5). The benchmark has η = 0.8. For each impulse response, we run the 8000 samples for 140 periods so that we reach the ergodic distribution. We then impose a “Bad news” shock, which is the lowest signal (out of seven in total). We then take averages across samples for each separate impulse response for all variables, except the EMBI for which we use the median. We report the deviations from 1 period before the shock hits.

The impulse responses for productivity, EMBI, and default are presented in Figure 10 for three values of precision, η = {0.145, 0.5, 0.8}. The left panel shows the path of labor productivity over 5 years following a negative news shock. As the precision of news decreases, a bad news shock has a lower impact on future labor productivity. Consistent with this effect, the other two plots show that the EMBI spread and the default rate respond less to bad news when the precision is lower.

To further understand the role of news precision, Table 6 shows the variance decomposition for three levels of precision. Clearly, the news shocks account for a larger share of the variance of productivity and EMBI for all forecast horizons as the signal precision increases. Notice in particular the change in the share accounted for productivity in a 10 year horizon, which was the target with used to calibrate the precision in the model. It varies from 1.42 for η = 0.5 to 33.53 for η = 0.9.
Table 6: Variance Decomposition

<table>
<thead>
<tr>
<th></th>
<th>Percent</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Productivity</td>
<td>Embi+</td>
</tr>
<tr>
<td><strong>benchmark</strong> ($\eta = 0.8$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 year</td>
<td>100.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2 years</td>
<td>96.63</td>
<td>3.37</td>
</tr>
<tr>
<td>5 years</td>
<td>87.24</td>
<td>12.76</td>
</tr>
<tr>
<td>10 years</td>
<td>82.07</td>
<td>17.93</td>
</tr>
<tr>
<td><strong>Higher Prec</strong> ($\eta = 0.9$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 year</td>
<td>100.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2 years</td>
<td>92.75</td>
<td>7.25</td>
</tr>
<tr>
<td>5 years</td>
<td>74.95</td>
<td>25.05</td>
</tr>
<tr>
<td>10 years</td>
<td>66.47</td>
<td>33.53</td>
</tr>
<tr>
<td><strong>Lower Prec</strong> ($\eta = 0.5$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 year</td>
<td>100.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2 years</td>
<td>99.80</td>
<td>0.20</td>
</tr>
<tr>
<td>5 years</td>
<td>99.08</td>
<td>0.92</td>
</tr>
<tr>
<td>10 years</td>
<td>98.58</td>
<td>1.42</td>
</tr>
</tbody>
</table>

Note: Forecast Error Variance decomposition of the structural VAR model estimated using model simulated data. The top panel shows the decomposition for the benchmark model, the middle panel corresponds to an economy with higher precision, and the bottom panel corresponds to an economy with lower precision.

6 Conclusions

We provide empirical evidence that news about future productivity significantly affects the dynamics of sovereign debt and yield curve spreads near a debt crisis. Estimating a panel-VAR for several emerging economies, we find that a news shock has a significantly larger contemporaneous impact on sovereign credit spreads than a comparable shock to labor productivity. We rationalize our empirical results developing a quantitative model of news, sovereign debt default, and endogenous maturity. We show that a VAR estimated on simulated data can replicate well our empirical results. The model also closely mimics the debt maturity and business cycles statistics documented for emerging markets.

The dynamics of the economy after a bad news shock share some features of a productivity shock and others of sudden stop events: Similar to productivity shocks, the risk of default increases and yield spreads jump, while similar to sudden stops shocks, countries that avoid
default following news shocks are forced to a significant deleveraging.

We find that the deleveraging after a bad news shock is related to debt maturity in an interesting way. With long term debt, countries need to deleverage less to avoid default in the period they receive bad news. But differently from sudden stop episodes, this small deleveraging means that the country is very likely to default next period, when news are realized. Thus, we find that borrowing at longer maturities does not shield the country from bad news shocks. In contrast, our results suggest that long maturity may exacerbate default risk after bad news shocks.

Finally, our model suggests that higher news precision improves sovereign debt management, as the country experiences a slight decline in the average default rate while increasing indebtedness. The improved debt management is reflected in lower spreads in bad times and less cyclical consumption.

References


Appendix A  Data sources

- GDP per capita: We use the variable “NY.GDP.PCAP.KD” in the World Development Indicators (WDI) database provided by the World Bank,\(^{24}\) which gives the GDP per capita in constant 2005 US$. For the volatility and correlations, we HP filter the available data using a smoothing parameter of 1600.

- 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: For the moments on consumption, we use the variable “NE.CON.PRVT.PC.KD,” provided by the WDI, which gives households’ final consumption expenditure per capita (constant 2005 US$). For the volatility and correlations, the paper follows the same approach as for the GDP per capita, by HP filtering the log consumption per capita for the entire period using a smoothing parameter of 1600. We also use this variable to construct the trade balance by subtracting consumption from output.

- Maturity: The data for Brazil (2005-2014) and Colombia (2001-2014) are from the HAVER database. We take the median across average maturity of debt at the end of each month. For Brazil, the maturity is for external federal public debt (“N233FYDE”), and, for Colombia, it is for the central government external debt (“N223FFDM”). The data for Turkey (2005-2010) is from the OECD database defined as “Average term to maturity for foreign debt”.\(^{25}\)

- Duration: We use the HAVER database for the duration of central government external debt (“N233DUR”) for Colombia, as we do for the maturity for this country. For Turkey we use the duration of foreign debt from the OECD database. Both databases follow the Macaulay definition, which we use for our computations in the model. For Brazil, we compute the duration using the maturity information (\(m\)) described above for this

\(^{24}\)This dataset can be accessed via: https://databank.worldbank.org/source/world-development-indicators.

\(^{25}\)OECD statistics are publicly available at https://stats.oecd.org/
country, together with the official average interest on new external debt commitments (“DT.INR.OFFT”), \( r_o \), provided by the WDI, also following the Macaulay definition:

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

- **1yr and 10yr Spreads**: The yields are US dollar sovereign yields obtained from Bloomberg. The variable name is “GTUSDxyY”, with the indicators of particular maturity bond \( x \in \{1, 10\} \), and country \( y \in \{\text{BR, COL, TR}\} \). The yields are reported daily, and we take the median over year. The yield spreads are computed by subtracting the median over the daily US yields from the same data source, with variable name “H15T1Y” and “GT10” for 1 and 10 year bonds.

- **EMBI+ spread**: Monthly data from 1998 to 2018 obtained from the Global Economic Monitor (GEM) of the World Bank.\(^{26}\) 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 median across a year to convert monthly entries into annual.

- **Labor productivity**: We use yearly data from the International Labor Organization.\(^{27}\) 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.

\(^{27}\) The data can be accessed here: https://ilostat.ilo.org/.
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. 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 output is $Y_t = A_t^{1+\frac{1}{\theta}}$. Taking logs and computing the variance, we have,

$$Var(\log(Y_t)) = \left(1 + \frac{1}{\theta}\right)^2 Var(\log(A_t))$$

$$Var(\log(\ell_t)) = \left(\frac{1}{\theta}\right)^2 Var(\log(A_t))$$

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

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

Since $\log(Y_t) = (1 + \frac{1}{\theta}) \log(A_t)$ 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.

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$^{28}$The data can be accessed here: https://ilostat.ilo.org/.
Appendix B  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

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

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,

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

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,

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

\section*{Appendix C Computational details}

\section*{C.1 Basics}

We solve the model numerically using the method proposed in \textit{Dvorkin et al. (2018)}, which 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 income. In particular, the income grid is spread evenly over 25 points lower or equal to the median income, and evenly over 10 points higher than the median income. We use the Tauchen method to discretize the income process.

For convergence, we use a measure of distance for the price function of debt in good standing in a given iteration that takes into account the maximum absolute distance of the prices across
two iterations relative to the level of the price in a given state. We declare convergence when this error is lower than $10^{-3}$.\footnote{Given the very large number of state variables in our model, the average absolute error is two orders of magnitude smaller, that it, lower than $10^{-5}$.}

After solving for the policy and value functions, we run the simulations for 1500 countries (paths) for 400 years and drop the first 100 periods. The model counterparts to the empirical correlation and standard deviation statistics are averages across samples. For the first-order moments, country-specific means are taken before averaging across countries. This is consistent with our treatment of the data.

C.2 Computation of model variables

Spreads. Consider a country with income $y$, debt rollover shock $a$, and a debt portfolio choice with maturity $m'$ and level $b'$. The yield for a bond with maturity $n$ is

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

Then the spread for maturity $m$ is $YTM(A, s, a, b', m'; n) - r$. In order to compute the model counterpart of EMBI+, we use the borrowing price of the economy:

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

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:

$$\sum_{t=1}^{m'} \left( \frac{1}{1 + \tilde{r}} \right)^{t} = q(A, s, a, b', m'; m'). \quad (6)$$

Duration and maturity. Similar to Hatchondo and Martinez (2009) and Sánchez et al. (2018), and the measures of duration in our data, we use the Macaulay definition to compute in our model the duration of a bond as a weighted sum of future promised payments:
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 (6). For maturity, we simply use the maturity of the new portfolio, \( m' \).

C.3 Solution using dynamic discrete choice approach

C.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, \( m' \in \{1, 2, \ldots, M\} \). The level of assets are on a discrete grid of \( N \) points. Accordingly, we define vectors for assets and maturity as:

\[
\mathbf{b} = [b_1, b_2, \ldots, b_N, b_1, b_2, \ldots, b_N, \ldots, b_1, b_2, \ldots, b_N]'
\]

\[
\mathbf{m} = [m_1, m_1, \ldots, m_1, m_2, m_2, \ldots, m_2, \ldots, m_M, m_M, \ldots, m_M]'.
\]

Hence, the country has to choose among \( J = M \times N \) different options to pick as its portfolio.

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

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

\[
V(A, s, a, b_i, m_i, \epsilon) = \max \{ V^G(A, s, a, b_i, m_i, \epsilon), V^D(A, s, \epsilon_{J+1}) \},
\]

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:

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

subject to

$$c_{ij}(y) = y + b_i + q(A, s, 1, b_j, m_j; m_i - 1)b_i - q(A, s, 1, b_j, m_j; m_j)b_j$$

$$j \in \{1, 2, ..., J\}.$$ 

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

$$V^G(A, s, 0, b_i, m_i) = \max \frac{1}{1-\gamma} \left( y + b_i - \frac{\ell^{1+\theta}}{1+\theta} \right)^{1-\gamma} + \beta E_{A', s', a'|A, s, 0} E\epsilon V(A', s', a', b_i, m_i - 1, \epsilon') + \epsilon_j$$

where

$$b_j = b_i, \ m_j = m_i - 1.$$ 

The value in case of default is:

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

The policy functions for the amount of assets and maturity choices are $B(A, s, a, b_i, m_i, \epsilon)$ and $M(A, s, a, b_i, m_i, \epsilon)$, respectively. We represent the policy for default with $D(A, s, a, b_i, m_i, \epsilon)$, 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 produc-
tivity $A$, new debt $-b'$, and maturity $m$ is

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

Since the realization of the $\epsilon$ 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:

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

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

$$q(A, s, a, b_j, m_j; n) = \frac{E_{A', s', a'|y, a}} {1 + r} \left\{ (1 - D(A', s', a', b_j, m_j)) \times \left[ 1 + \sum_{k=1}^{J} q(A', s', a', b_k, m_k; n - 1) G_{A', s', a', b_j, m_j}(b_k, m_k) \right] \right\}$$

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

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

In this distribution, $\rho$ determines the correlation between the components of the vector 1 to $J$, namely those that correspond to the portfolio choice. $\sigma$ increases the variance of the shocks. With this specification on the distribution of the shocks, we can write the policy functions for
default is: $D(A, s, a, b_i, m_i) = \exp \left( \max_\ell \frac{1}{1-\gamma} \left( \min(A, \phi) \ell - \frac{\ell^{1+\theta}}{1+\theta} \right)^{1-\gamma} + \beta E_{A', s'|A, s} \left[ (1-\lambda) V^D(A', s') + \lambda V(A', s', 1, 0, 1) \right] \right)^{1/\sigma}$

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

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

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

$$X = \exp \left( \max_\ell \frac{1}{1-\gamma} \left( c_{ij} - \frac{\ell^{1+\theta}}{1+\theta} \right)^{1-\gamma} + \beta E_{A', s', a'|A, s, 0} V(A', s', a', b_j, m_j) \right)^{\frac{1}{\rho}}.$$

with $b_j = b_i$ and $m_j = m_i - 1$. Similarly, the probability of choosing particular portfolio in case of not receiving a sudden stop shock, and conditional on not defaulting, is:

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

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

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

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

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

$$= \sigma \log \left[ \exp \left( \max_\ell \frac{1}{1-\gamma} \left( c_{ij} - \frac{\ell^{1+\theta}}{1+\theta} \right)^{1-\gamma} + \beta E_{A', s', a'|A, s, 0} V(A', s', a', b_j, m_j) \right)^{\frac{1}{\rho}} \right] +$$

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

with $b_j = b_i$ and $m_j = m_i - 1.$
Finally the ex-ante value in case of default is:

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

In solving the model, we need to set two parameters governing the distribution of the \( \epsilon \) shocks: one related to the overall volatility of shocks, \( \sigma \), and the one related to the correlation between the portfolio choice components, \( \rho \). We follow Dvorkin et al. (2018) in setting \( \sigma \) at 0.001 and \( \rho \) at 0.25.

**Appendix D  Calibration of Sudden Stops**

For the estimation of sudden stop shocks, we use the sudden stop definition from Comelli (2015) and update the data until 2014. We run the following regression:

\[ SS_{t,i} = \alpha_0 + \alpha_1 SS_{t-1,i} + \alpha_2 (GDP \ cycle)_{t,i} + \alpha_3 (demean Debt/GDP)_{t,i}, \quad (7) \]

where \( SS \) is a dummy variable that is 1 if there is a sudden stop and 0 otherwise. Given that our model already captures fluctuations in credit availability due to income and indebtedness, we want to capture sudden stops when income and debt are in normal levels. Given that the variables \( (GDP \ cycle) \) and \( (demean Debt/GDP) \) have mean zero, we can obtain \( \omega^N = \alpha_0 \) and \( \omega^{SS} = \alpha_0 + \alpha_1 \). The results are shown in Table 7.
Table 7: Estimation of sudden stop probability

<table>
<thead>
<tr>
<th>Regression type</th>
<th>Weight</th>
<th>Obs</th>
<th>R²</th>
<th>ω\textsuperscript{N}</th>
<th>ω\textsuperscript{SS}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear reg., controlling by HP cycle and debt-to-GDP</td>
<td>No</td>
<td>395</td>
<td>0.11</td>
<td>0.11</td>
<td>0.43</td>
</tr>
<tr>
<td>Linear reg., controlling only by HP cycle</td>
<td>No</td>
<td>911</td>
<td>0.10</td>
<td>0.14</td>
<td>0.44</td>
</tr>
<tr>
<td>Linear reg., controlling by HP cycle and debt-to-GDP</td>
<td>Yes</td>
<td>395</td>
<td>0.10</td>
<td>0.12</td>
<td>0.41</td>
</tr>
<tr>
<td>Linear reg., controlling only by HP cycle</td>
<td>Yes</td>
<td>911</td>
<td>0.12</td>
<td>0.14</td>
<td>0.44</td>
</tr>
<tr>
<td>Probit reg., controlling by HP cycle and debt-to-GDP</td>
<td>No</td>
<td>395</td>
<td>0.10</td>
<td>0.11</td>
<td>0.43</td>
</tr>
<tr>
<td>Probit reg., controlling only by HP cycle</td>
<td>No</td>
<td>911</td>
<td>0.09</td>
<td>0.13</td>
<td>0.43</td>
</tr>
<tr>
<td>Probit reg., controlling by HP cycle and debt-to-GDP</td>
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<td>395</td>
<td>0.10</td>
<td>0.11</td>
<td>0.39</td>
</tr>
<tr>
<td>Probit reg., controlling only by HP cycle</td>
<td>Yes</td>
<td>911</td>
<td>0.11</td>
<td>0.13</td>
<td>0.43</td>
</tr>
<tr>
<td>Average of all specifications</td>
<td></td>
<td></td>
<td>0.10</td>
<td>0.12</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Note: In the regressions with weights we use employment for the PWT as a proxy for the size of the country.

To make sure our episodes are not fluctuations in the availability of credit related to the country’s income and indebtedness, which are endogenous in our model, in the next figure we plot the share of the countries in sudden stop for each year. The figure shows that there is bunching of sudden stops, suggesting that these episodes are due to changes external to the country.
Figure 11: Bunching of Sudden Stop events