Determinants of Sovereign Risk

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Abstract

Standard option pricing theory cannot be applied when pricing sovereign debt. In the case of a country, there is no underlying asset that is traded or to which creditors hold claims in the event of default. We propose an empirically tractable model that addresses the distinct features of sovereign risk while retaining the intuition of the standard option pricing framework. In our model, an index of macroeconomic variables drives yield spreads over U.S. Treasuries, the probability of default, and the recovery value conditional on default. Our model predicts that both the level and the volatility of fundamentals matter for default risk. Using data on external sovereign debt prices for a sample of emerging market countries, we find that the volatility of terms of trade has a statistically and economically significant effect on spreads and default probabilities. The ratio of debt to GDP explains variation mainly in the time series of spreads rather than in the cross section. A variable summarizing a country's recent default history has additional explanatory power. Fitting our model to the data, we find that it can account for close to one third of observed spread variation. A one percent increase in the model predicted spread is associated with a 0.73 percent increase in the realized spread. We also find that the model fits better for borrowers of lower credit quality, a result that is consistent with recent findings in the corporate bond literature.

1 Introduction

At an empirical level, there is tremendous variation in the cost of external borrowing faced by emerging market economies. This is true both across countries and over time. A common measure of this cost is a country's yield spread, which is defined as the difference between the interest rate the government has to offer on its external U.S. dollar denominated debt and the rate paid by the U.S. Treasury on debt of comparable maturity.

From the perspective of emerging market sovereign borrowers, it is important to understand what drives these differences in borrowing costs, given the central role external debt plays in the public finances of many of these countries. International investors also need to know the underlying factors determining yield spreads in order to decide if they are adequately compensated for the risk they are taking.

We investigate how much of the variation in sovereign yield spreads can be explained by fundamental factors in the context of a structural model of debt prices. Standard structural models of risky corporate debt pricing cannot be used when pricing sovereign debt. In these models, the firm defaults and is taken over by creditors if firm asset value falls below liabilities. Risky debt is priced as a combination of safe debt and a short position in a put option. In the sovereign case, there is no equivalent of firm asset value with an observable market price. Moreover, even if one could agree on an underlying wealth measure, creditors typically do not hold claims to a country's assets in the event of default. As a result, it is a priori unclear what a country's default threshold would be in terms of such a wealth measure.

We propose a model that addresses the distinct features of the sovereign debt market while retaining the familiar intuition of structural bond pricing models. In our model an index of macroeconomic fundamentals determines default and recovery value. Intuitively, once fundamentals fall below a certain threshold, the cost of repayment becomes too high and the country goes into default. As in standard bond and option pricing models, a higher volatility of the index implies a higher probability of default, a higher value of the put option, and therefore a higher spread.

There are two main parts to the empirical analysis of the paper. We first explore the empirical determinants of spreads and default probabilities in a reduced form framework. As motivated by our model, we focus in particular on the role of volatility. We then fit the model to price bonds directly. We use spread observations on external U.S. dollar denominated debt from J.P. Morgan's Emerging Market Bond Index (EMBI). Spreads are calculated over U.S. Treasuries of comparable maturity and cover a set of 32 emerging market countries from 1994 to 2002.

First, we investigate the extent to which economic fundamentals explain variation in spread levels in a reduced form framework. Motivated by previous studies, we choose the ratio of debt to GDP as our starting point. We consider a number of other macroeconomic fundamentals. We pay particular attention to terms of trade. This is because terms of trade are directly related to a country's ability to generate dollar revenue via exports and make payments on external debt (Bulow and Rogoff (1989)). In addition, terms of trade are plausibly exogenous since they are calculated using world prices. We find that spreads are higher for countries that have recently experienced adverse terms of trade shocks. Moreover, consistent with the predictions of our model, the volatility of terms of trade has a statistically and economically significant effect on spreads. We also find that, even after accounting for macroeconomic fundamentals, spreads are higher for countries that have recently emerged from default. This is consistent with Reinhart, Rogoff, and Savastano (2003), who argue that a key predictor of future default is a country's history of default.

We also find that the ratio of debt to GDP captures a large share of the within country time series variation in spreads but has little explanatory power in the cross section. This suggests that what is important is whether a country's debt level is high relative to its own mean, not whether it is high relative to other countries.

In addition, we examine our model's implication that any variable affecting the probability of default should affect the spread. We estimate the conditional probability of default over the next period in a reduced form logit model following the approach proposed by Shumway (2001) in the context of predicting corporate bankruptcy. Since defaults are rare events, we use a longer sample period that includes observations starting in 1970 in order to increase the power of our estimation. We find that the level of debt to GDP and the volatility of terms of trade are important predictors of default, in line with their effect on spreads.

Second, we fit our model to price bonds directly. Default occurs once the index of fundamentals falls below a threshold. Based on this observation, we estimate both the relative weights on the components of our index and the threshold by running a predictive regression of a default indicator on our set of macroeconomic explanatory variables. This again uses the longer sample period since 1970. We then predict spreads for the shorter sample period since 1994 using our model and the estimated parameters and compare them to observed EMBI spreads. In principle, this approach allows us to identify systematic mispricing in the market, which is something reduced form regressions cannot achieve since they fit the overall mean of observed spreads by construction. We find that our model can account for nearly one third of the variation in observed spreads. In a regression of actual on predicted spreads, we find that a one percent increase in predicted spreads implies a 0.73 percent increase in actual spreads.

We also group bond spread observations by their estimated default probability and compute average levels of observed and model implied spreads for each group. We find that model implied spreads are smaller than actual spreads for all the groups, but that the proportion of the yield spread explained by our model increases significantly with the probability of default. Huang and Huang (2003) find a similar pattern when calibrating structural form models to U.S. corporate bond prices.

There is a large related literature on the empirical determinants of sovereign yield spreads. The literature varies widely in choice of variables and methodology. Several studies model sovereign yield spreads in a reduced form regression context similar to our approach.[1] Although no clear consensus on the determinants of spreads emerges from this literature, the level of debt to GDP is significant in most studies. However, measures of volatility are largely absent from this literature. Two exceptions are Edwards (1984), who includes variability of reserves and finds that it is insignificant, and Westphalen (2001), who finds some limited effect of changes in local stock market volatility on changes in short term debt prices. In the corporate bond context, Campbell and Taksler (2003) find a strong empirical link between equity volatility and yield spreads.

Duffie, Pedersen, and Singleton (2003) consider determinants of the yield spread on Russian dollar-denominated debt between 1994 and 1998. They model sovereign yield spreads using a risk-neutral credit event intensity process, following Duffie and Singleton (1999). Our approach is similar to theirs in that we apply methodology from pricing corporate debt to the case of sovereign bonds.[2]

There is also a large literature on predicting banking and currency crises and sovereign default using macroeconomic fundamentals.[3] Again, the focus of these studies is on level variables, rather than volatility. There are some exceptions: in two recent papers, Catao and Sutton (2002) and Catao and Kapur (2004) predict sovereign default in a hazard model using a similar setup to ours. They identify volatility of terms of trade as an important predictor of default. These studies on default and crisis prediction do not, however, relate the determinants of default to the determinants of spreads.

Very few studies consider whether spreads accurately reflect default risk and loss given default. One exception is Klingen, Weder and Zettelmeyer (2004) who argue that

[1] Edwards (1986), Eichengreen and Mody (1998), Min (1998), Beck (2001), and others explore a large set of macroeconomic variables to explain spreads. Some papers such as Cantor and Packer (1996), and Kamin and von Kleist (1999) instead use credit ratings as a comprehensive measure.

[2] In their recent book on credit risk, Duffie and Singleton (2003) discuss empirical and theoretical work on sovereign risk in more detail.

[3] Early contributions to this literature include Hajivassiliou (1987, 1994). Berg, Borensztein, Milesi-Ferretti, and Pattillo (1999), Kaminsky and Reinhart (1999), Goldstein, Kaminsky, and Reinhart (2000) have concentrated on constructing what they refer to as “early warning systems.” Berg, Borensztein, and Pattillo (2004) provide an overview of this line of research.

returns on emerging market debt have been no higher than returns on U.S. Treasuries over the last thirty years, thus providing investors with inadequate compensation for risk.

The remainder of this paper is organized as follows. Section 2 introduces our theoretical model and discusses why corporate bond pricing models do not apply to the case of sovereign debt. We derive the model implied probability of default and the yield spread. Section 3 describes the data. Section 4 investigates the extent to which macroeconomic fundamentals explain spreads in reduced form regressions. We find that adding volatility of terms of trade improves the fit substantially. Our results are robust to various specification checks. Section 5 turns to default prediction and relates default and spread determinants. Section 6 fits our structural model to the data and finds that it accounts for a substantial fraction of observed spreads. This section also relates our results to recent findings in the corporate bond literature. Section 7 concludes.

2 A model of sovereign spreads

2.1 Motivation

In standard structural corporate bond pricing models,[4] firm asset value jointly determines default and recovery value. If firm assets fall below liabilities, the firm defaults and creditors receive asset value. The bond is priced as a combination of safe debt and a short put option on the asset value of the firm. In the model, leverage and volatility determine both the spread and the default probability.

Pricing sovereign debt is fundamentally different. First, no claim on a country's assets is traded. Consequently, there is no market price with which to measure asset value. More importantly, even if one were to construct such a measure by discounting expected future revenue streams, asset value is not the relevant measure for pricing sovereign debt. Creditors do not "take over" the country in the event of default. Country wealth therefore does not determine default: a country may default even if its wealth exceeds its liabilities. Empirically, emerging market economies often have far lower debt to GDP levels than developed countries yet default much more frequently (Reinhart, Rogoff and Savastano (2003)). The inability of creditors to claim country assets also means that a country's wealth level may not determine the recovery rate following default.

[4] Merton (1974) is arguably the first modern structural bond pricing model. Many other models have followed. Some examples are Black and Cox (1976), Leland (1994), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001). Huang and Huang (2003) provide an overview of this literature. A common feature of these models is that default is related to an underlying process of asset value.

2.2 A default threshold model

We propose a simple and empirically tractable model for pricing sovereign debt. In our model, fundamentals determine both the probability of default and the spread. A country defaults when the cost of repayment becomes "too high." To capture this intuition, we assume that default occurs next period if an index of macroeconomic fundamentals falls below a certain threshold. Intuitively, we think of this index as the country's "ability and willingness to pay."

We consider a discrete time setup. We denote the level of the index in period t by W_t and the default threshold by W^*. For a currently solvent country, default occurs next period if the state variable lies below the threshold:

$$W_{t+1} < W^* : \text{default occurs at } t+1.$$

We assume that the index is lognormally distributed:

$$w_{t+1} = w_t + \phi_{t+1}, \text{ where } \phi_{t+1} \sim N\left(0, \sigma_w^2\right).$$

Lower case letters denote logs and ϕ_{t+1} is the shock to the log index with standard deviation σ_w.

Given these assumptions, the probability of default next period is given by:

$$P_t\left(W_{t+1} < W^*\right) = \Phi\left(-\frac{w_t - w^*}{\sigma_w}\right),$$

where $\Phi(.)$ denotes the c.d.f. of the standard normal. Default is less likely if fundamentals are high and if volatility is low. More precisely, default is less likely if the difference between the state variable and the threshold, scaled by volatility, is larger. Adopting the terminology of the corporate default literature, we refer to this scaled difference as distance to default.[5]

This expression already illustrates the basic intuition of our model: the probability of default depends on the level as well as the volatility of fundamentals. This motivates the inclusion of measures of volatility in our empirical exploration in later sections.

In order to derive bond prices, we need to make an assumption about the payoff to bondholders in default. We assume that bondholders receive face value if the country remains solvent. If the country defaults, we assume that the fractional recovery value depends on the level of the index, i.e. the worse fundamentals are at the time of default,

[5] Duffie and Wang (2003) construct distance to default for firms to measure their probability of default. They refer to it as a volatility adjusted measure of leverage. Vassalou and Xing (2004) also use distance to default to proxy for corporate default risk.

the less creditors receive:[6]

$$\begin{aligned} \text{solvent} &: \; B_{t+1} = D \\ \text{default} &: \; B_{t+1} = \gamma W_{t+1} D, \end{aligned}$$

where B_{t+1} is the payoff to bondholders next period, D is the face value of the bond, and γW_{t+1} is the fractional recovery rate (γ measures the sensitivity of changes in the recovery rate to changes in the index). Intuitively, γ will have a value that makes γW_{t+1} vary between 0 and 1.[7]

If we assume that investors are risk neutral, we can calculate the price and yield spread on the bond given our model. The yield spread on debt is defined as $s_t = -\log\left(\frac{B_t}{D}\right) - r_f$, where B_t is the price of the bond. In the Appendix,[8] we show that the yield spread is given by:

$$\begin{aligned} s_t &= -\log\left(\gamma \exp\left(w_t + \frac{1}{2}\sigma_w^2\right) \Phi\left(\frac{w^* - w_t}{\sigma_w} - \sigma_w\right) + \Phi\left(-\frac{w^* - w_t}{\sigma_w}\right)\right) \\ &\equiv g\left(W_t; W^*, \gamma, \sigma_w\right). \end{aligned}$$

The first part of this expression is equal to the expected payoff to bondholders conditional on default multiplied by the probability of default.[9] The second part is the probability of the country staying solvent in which case creditors receive face value. The spread depends negatively on the level of the state variable and recovery rate, and positively on the threshold and volatility. There are two reasons why higher volatility leads to a higher spread. Higher volatility implies a lower distance to default and a lower expected payoff to bondholders in default.

One limitation of this result is that it assumes that investors are risk neutral, which means that the correct discount rate for the bond is equal to the riskfree rate. In the standard option pricing framework a measure of risk is not necessary since the assumptions of continuous trading and geometric Brownian motion allow for the construction of a perfect hedge. The bond can then be priced using risk neutral probabilities. In discrete time under lognormality, the no arbitrage condition implied by trading of the

[6] Alternatively, one could just assume a fixed recovery rate at the time of default. We will consider this in Section 6.

[7] The need for this parameter is related to the fact that default depends only on the distance to default. If we scale up the index, the threshold, and the volatility of the index by the same amount, distance to default remains unchanged. We will come back to this issue in Section 6.

[8] In the appendix we derive the spread assuming that $\gamma = \frac{\lambda}{W^{**}}$. We discuss the intuition for introducing the additional parameter W^{**} in Section 6.

[9] This is written as the scaled expected level of the index $\gamma E_t\left[W_{t+1}\right]$ multiplied by the adjusted probability of default. The adjustment captures the fact that the expected payoff is calculated only for values of the index that imply default and that higher volatility lowers the expected payoff given default.

underlying asset is sufficient to derive the price.[10] In our case, since the underlying is not traded, we need a direct estimate of the riskiness of the index.[11]

Given an estimate of the covariance of the state variable with the stochastic discount factor σ_{wm}, we can write down the spread on the bond for the case where investors are risk averse:

$$s_t = -\log\left(\gamma \exp\left(w_t + \sigma_{wm} + \frac{1}{2}\sigma_w^2\right)\Phi\left(\frac{w^* - w_t - \sigma_{wm}}{\sigma_w} - \sigma_w\right) + \Phi\left(-\frac{w^* - w_t - \sigma_{wm}}{\sigma_w}\right)\right).$$

The common bond pricing interpretation is that the covariance with the SDF changes the risk neutral drift of the index. The price is then given by the same formula, but with the real default probabilities substituted by risk neutral default probabilities. We can see that risk is priced in the way we would expect. If the state variable tends to be low in bad states of the world, i.e. if the covariance with the SDF is negative, then the bond is more risky. Consequently, the risk neutral probability of default is larger than the real probability of default and the spread is higher. Intuitively, if sovereign defaults tend to occur in bad states of the world, risk averse investors will demand a higher rate of return.[12]

2.3 The index of fundamentals

We now consider what variables should be included in our index. The credit risk we consider is the risk of default on dollar-denominated debt.[13] In the case of a firm, we would calculate the present discounted value of future dollar revenue, compare it to the level of dollar liabilities, and calculate a proxy for leverage. The two components are a measure of liabilities and a measure of repayment capabilities. In the country case, these are commonly measured by dollar-denominated debt and GDP, forming the debt to GDP ratio.

We add a more explicit measure of the government's ability to generate dollar revenue, namely terms of trade. To see why this is relevant, consider an oil exporting country. The country generates dollar revenue by exporting oil and spends dollars on imports. Terms of trade, the relative price of exports and imports, is thus an important determinant of the country's ability to repay dollar-denominated liabilities. Bulow and

[10] This fact was pointed out by Rubinstein (1976). If the underlying were traded, we could use the no arbitrage condition to substitute out the stochastic discount factor and calculate the predicted price taking into account the asset's risk premium.

[11] In future work, we plan to estimate the covariance with the stochastic discount factor directly. This could be done by using high frequency bond return observations in a factor model.

[12] Note that we expect the yield spread also to depend on other factors such as liquidity, taxes, and investor sentiment (Elton, Gruber, Agrawal, and Mann (2001)).

[13] The yield on local currency debt tends to be driven by local inflation risk.

Rogoff (1989) make this point. Other macroeconomic fundamentals we consider include government primary balance, country size and wealth, and the 10-year U.S. Treasury rate.

Turning to measures of volatility, we concentrate on the volatility of terms of trade. Our focus on this measure is motivated by the fact that terms of trade are calculated using world prices and are therefore plausibly exogenous. This may not be the case for some of the other components of the index.

Before turning to the implementation of our model in Section 6, we explore the determinants of spreads in reduced form regressions in the next sections.

3 Data

We restrict ourselves to U.S. dollar-denominated debt instruments issued or guaranteed by emerging market governments. Our measure of yield spreads over U.S. Treasuries comes from J.P. Morgan's Emerging Markets Bond Index Global (EMBI Global). This is a daily series starting in 1994 which currently comprises a sample of 32 emerging market countries. It includes a basket of Brady bonds, loans, and Eurobonds. The average maturity of the debt instruments included in the index is around 12 years. The basic liquidity requirement for inclusion is that the instrument needs to have verifiable daily prices and cash flows. The Data Appendix gives precise details on country and instrument inclusion criteria.

Figure 1 plots the time series of a weighted index of EMBI spreads from 1994 to 2004, measured in basis points. The individual countries are weighted by the governments' total outstanding external debt levels. From the graph, we immediately see that there is substantial variation in average yield spreads. At times of crisis, like the Mexican crisis of 1994-95, the Russian default in the summer of 1998, or the aftermath of the Argentinian default in late 2001, all emerging market sovereign borrowers face substantial increases in their borrowing costs. At any given point in time, there is also tremendous cross sectional variation in the interest rates paid by emerging market governments on their external debt. The summary statistics in Table 1 show that, for countries that are not in default, median daily spreads in 2003 vary from 32 basis points for Hungary to 1130 basis points for Ecuador.[14]

The macroeconomic explanatory variables we use for our analysis come from a variety of sources that we discuss in detail in the Appendix. We use annual cross country data

[14]The spreads can of course be much higher for countries that are in default. The median daily spread for Argentina in 2003 is 5359 basis points. Côte d'Ivoire, Nigeria, and Uruguay are also in default in 2003.

on fundamentals. Debt to GDP is total government external debt divided by GDP. To measure shocks to the terms of trade we construct change in terms of trade as the percentage change of the terms of trade over the previous five years. We measure volatility of terms of trade by calculating the standard deviation of the terms of trade over a ten year backward looking window.

Table 1 shows the considerable variation in the median levels of these macroeconomic explanatory variables for the group of countries we consider. For instance, the median level of external debt as a fraction of GDP ranges from 0.14 for China to 1.16 for Côte d'Ivoire. Volatility of terms of trade also exhibits substantial cross sectional variation. Some countries, such as Hungary, Lebanon, Panama, Poland, or Turkey have an annual terms of trade volatility of less than five percent. On the other hand, Nigeria and Venezuela have annual volatilities well above twenty percent. High terms of trade volatility is to a large extent driven by oil prices. Crude petroleum and refined petroleum products are among the top two export categories for four of the five countries with the highest terms of trade volatility.

We also use our explanatory variables to predict default. Our data on sovereign defaults come from Reinhart, Rogoff, and Savastano (2003). These authors have constructed annual default indicators for different debt categories for a large sample of countries going back to the early nineteenth century. We use their series for default on total debt, which includes foreign currency bonds and foreign currency bank debt. The default indicator variable takes the value one if a country is currently in default and zero otherwise.

We use this default indicator to construct a variable that measures recent default history. Our years since last default variable counts the number of years since the country's last year in default, where the variable is capped at 10 and set equal to 11 if a country has never defaulted. If a country is in default, it is set equal to zero. This variable is motivated by Reinhart, Rogoff, and Savastano (2003), who argue that history of default is an important predictor of future default. We use this variable to explore whether it adds explanatory power beyond what is captured by underlying macroeconomic fundamentals.

Table 2 reports summary statistics for both the regression and default prediction samples. We notice that there is large variation in all of our explanatory variables. Change in terms of trade has a mean of zero, reflecting the fact that on average terms of trade do not trend over the sample period.

We also include several time series variables in our analysis. As proxies for the riskless long and short term world interest rates, we include the 10-year and 6-month U.S. Treasury rates. We also include the U.S. default yield spread, defined as the spread of corporate bonds with a Moody's rating of Baa over U.S. Treasuries. Our liquidity measure is the difference between the 3-month Eurodollar rate and the 3-month Treasury rate. Finally, we include the implied volatility of the S&P500 index (VIX).

4 Empirical determinants of spreads

In this section, we explore how much of the variation in sovereign yield spreads can be explained by macroeconomic fundamentals in a reduced form framework. We use annual averages calculated from our daily spread series. Restricting the sample to the set of observations for which all the variables are available leaves us with 143 observations for 28 countries. The relatively small sample size is due to the fact that EMBI spreads are only available since 1994 and that several of our macroeconomic explanatory variables are only measured at annual frequency.[15] Since we are considering determinants of the spread while the country is not in default, we drop all country-year observations where a country is in default. We use these observations in Section 6 when we estimate recovery values. Summary statistics for our regression sample are reported in Panel A of Table 2.

In Table 3, we report regression results for different specifications. We start by using only the level of debt to GDP to explain spreads. Consistent with the existing literature, we find that debt to GDP is significant. We then add the volatility of terms of trade and find it to be highly significant.[16] The R-squared increases from 13 to 38 percent. Higher terms of trade volatility is associated with higher spreads. Adding the years since last default increases the R-squared to 53 percent, the coefficient is also significant.[17] The coefficient on volatility of terms of trade drops but is still significant. We also find that spreads are lower if terms of trade have deteriorated over the last five years. This is again consistent with our framework since a deterioration in the terms of trade increases the cost of paying off dollar-denominated debt. In summary, we find that all of these explanatory variables have the expected sign and are statistically significant.

[15] We do not have enough observations on terms of trade to calculate volatility for the Dominican Republic and Croatia, Nigeria is in default throughout the sample period, and data on debt is missing for El Salvador.

[16] In order to make point estimates, significance levels, and R-squared's comparable across specifications, all regressions use the same sample as our main specification, reported in column (6).

[17] We consider different specifications using dummies to understand why the years since last default has explanatory power for spreads. The coefficient seems to be identified mainly from the relatively high spreads for countries that have emerged from default one or two years ago as well as the relatively low spreads for countries that have never been in default or have been out of default for ten or more years. Adding dummies in this manner, however, does not increase the fit of the regression. In order to keep our model parsimonious we have decided to use the years since last default to capture this variation.

The economic significance of the explanatory variables in our baseline regression is reported in Panel B of Table 3. The effect on spreads of a one standard deviation increase in the explanatory variables is 90 basis points for debt to GDP, 124 basis points for volatility of terms of trade, -162 basis points for years since last default, and -64 basis points for the change in terms of trade.

Another point to note is that, in our model, high terms of trade volatility increases the probability of default, and thus countries with higher terms of trade volatility should, ceteris paribus, have a higher observed frequency of default and therefore a higher spread. The unconditional correlation between terms of trade volatility and the years since last default is indeed strongly negative (-.48) for our sample. While this number does not control for other covariates, it is at least suggestive that this effect is empirically relevant. This means that the coefficient on the years since last default may be picking up some of the effects of terms of trade volatility. In any case, this would imply that our estimates of the effects of volatility are conservative. In fact, if we do not include years since last default, the economic significance of volatility of terms of trade increases from 124 bps to 187 bps.

We also control for regional effects, country size and wealth. We find that spreads are significantly lower in Eastern Europe and South East Asia than in Latin America. However, the coefficients on our main variables are essentially unchanged when these regional dummies are included. Country size, as measured by the logarithm of GDP, and country wealth, as measured by the logarithm of per capita GDP, are insignificant.

Finally, we control for different time series variables. The 10-year U.S. Treasury rate has a significant negative effect on spreads. This is consistent with the findings of Eichengreen and Mody (1998). These authors also document a negative effect of the 10-year Treasury rate on emerging market spreads using a different dataset over the period 1991-96. In the context of corporate debt, Longstaff and Schwartz (1995) point out the negative correlation between corporate credit spreads and interest rates, which is consistent with their theoretical valuation model for corporate bonds. Duffee (1998) finds that spreads move negatively with three month Treasury bill rates.

The default yield spread, defined as the spread of U.S. corporate bonds with a Moody's rating of Baa over U.S. Treasuries, has a positive and significant effect when included by itself. However, when included with the 10-year Treasury rate, both variables become insignificant. This is not surprising, given the strong negative correlation between these regressors. The 6-month Treasury rate, our measure of liquidity, and the implied volatility of the S&P 500 index are not significant when included with the 10-year Treasury rate.

In summary, we find that spreads are high if the level of debt to GDP is high, if the volatility of terms of trade is high, years since last default are low, terms of trade have deteriorated over the past five years, the 10-year U.S. Treasury rate is low, or the default yield spread is high.

4.1 Spreads in the cross section and time series

In our baseline specification discussed in the previous section, we find that debt to GDP, years since last default, volatility of terms of trade, and the change of terms of trade over the last five years can explain a significant fraction of the variation in spreads in our panel. In this section we investigate whether these variables are identified from cross sectional or time series variation.

Figure 2a plots average spreads against average volatility of terms of trade. Countries with higher volatility of terms of trade tend to have higher spreads. The graph reflects the strong positive correlation of 0.67 between the two. This is in contrast to the weaker correlation of 0.29 between countries' average spread and average level of debt to GDP. This lack of correlation is apparent in Figure 2b. It seems, therefore, that spreads are driven mainly by terms of trade volatility and less by debt to GDP in the cross section. Figure 2c plots country demeaned spreads against debt to GDP. We see that, within a country, debt to GDP moves together with spreads. At 0.56 the two series are highly correlated, and it seems that debt to GDP is better at explaining time series variation in spreads within a country rather than variation across countries.

Next we explore these effects more rigorously by running panel regressions of spreads on explanatory variables, and calculating the between and within estimators when grouping by country. Results are reported in Table 4. We find that in the cross section (between estimates) debt to GDP is only significant at the 20% level when included by itself and even less significant when included with other variables. When adding volatility of terms of trade the R-squared increases substantially from 0.08 to 0.46, while debt to GDP becomes insignificant. Including all the variables from our baseline regression, we find that the years since last default and terms of trade volatility are the only ones that remain significant.

Exploring time series variation, we find that debt to GDP is highly significant and stable across specifications. It explains a large share of the variation in spreads by itself, with an R-squared of 0.31. In the baseline specification in column (6), debt to GDP and change in terms of trade are significant at the 1% level. Volatility of terms of trade and years since last default are significant at the 5% level.

In summary, debt to GDP and change in the terms of trade have little explanatory power in the cross section, but they are successful at explaining the time series. This is consistent with Reinhart, Rogoff, and Savastano's (2003) idea that some countries are more intolerant to high debt levels. In that case it matters if a country's debt to

GDP is high relative to the country specific mean, but it does not matter if it is high relative to other countries. The fact that the change in the terms of trade over the last five years is significant when explaining within country variation is consistent with our default threshold model in Section 2. In the context of our model, we expect the spread to increase when the level of the index decreases (terms of trade deteriorate).

4.2 Robustness checks

As already mentioned, the assumption that volatility of terms of trade is exogenous seems plausible, given that terms of trade are calculated using world prices. Here we provide some additional robustness checks. In the simplest theoretical model, the volatility of the underlying willingness to pay variable is constant over time but can vary across countries. Default occurs if the underlying falls below a threshold. In such a world, we would expect periods of default to be associated with worsening (i.e. declines) in the terms of trade but no change in the observed volatility of terms of trade. If, on the other hand, volatility of terms of trade is endogenous, maybe because there is a third factor that causes simultaneous debt and currency crises and an associated jump in the terms of trade, then we would expect periods of default to be associated with increases in the observed volatility of terms of trade.

In order to address this, we look at the empirical behavior of our calculated terms of trade volatility time series around default events. For our regression sample, we find that in the year *before* default (5 observations), the volatility of terms of trade *falls* slightly on average. The average change in the level of terms of trade is slightly negative at both the one year and the five year horizons. We also find that *during the first year* of default, the volatility of terms of trade tends to fall. Again, the average change in the level of terms of trade is slightly negative at both the one year and the five year horizons.[18] These patterns are inconsistent with an endogeneity story.

We do several other robustness checks. First, we replace the volatility of terms of trade with its one year lag. Next, we drop observations in years preceding a default. We also cluster standard errors by country and by year. Finally, we add country and year fixed effects. Our results are unaffected by these changes.

[18] The first three columns refer to the year before default; the last three refer to the first year of default (percentages).

	mean	min	max	mean	min	max
Δvoltt	−1.2	−7.1	2.5	−3.5	−10.7	0.6
Δtt (1yr)	−0.8	−14.3	8.3	−0.4	−15.7	9.1
Δtt (5yr)	−8.1	−18.7	4.3	−10.8	−17.7	−2.5

5 Default prediction and relation to spreads

We now investigate the empirical determinants of the probability of default. Our dependent variable is a forward looking default indicator, which we construct from the default series in Reinhart, Rogoff, and Savastano (2003).[19] In order to compare the determinants of spreads and default probabilities, we use the same set of explanatory variables as in the previous section. Our terms of trade data go back to 1960, and since we are calculating volatility over a ten year backward looking window, we start our sample in 1970. At 560 observations, the sample used in this section is much larger than the spread regression sample of the previous section. However, there are only 25 defaults or less than 5% of the observations. We winsorize the data, replacing variable values in the top five percentiles of the distribution with the value of the variable at the 95th percentile. Similarly, we replace variable values in the bottom five percentiles of the distribution with the value of the variable at the 5th percentile. Summary statistics are given in Panel B of Table 2. We split the sample into two pieces, non-default and default observations, which are those observations immediately preceding a default. We notice that countries that are about to default have higher debt to GDP, and higher volatility of terms of trade.

Results of logit regressions of our forward looking default indicator on explanatory variables are reported in Table 5.[20] We find that debt to GDP, volatility of terms of trade, and the U.S. default yield spread explain a large share of the variation in default probabilities. Adding volatility of terms of trade to debt to GDP increases the pseudo R squared from 11% to 17%. The direction of the effects of all these variables are consistent with our earlier spread regression results. We also find that, conditional on other explanatory variables, countries in Latin America are more likely to default. We cannot look at regional effects in more detail in the present context because we do not have enough default observations in our sample to identify other regional dummies. In contrast to our results on spread determinants in the previous section, we find that, conditional on other variables, the change in terms of trade over the past five years do not matter for the probability of default. Also, years since last default are now only significant when a time series variable is included.

We find that an increase in the 10-year U.S. Treasury rate is associated with an

[19]The default indicator for a country is equal to one in a given year if the country goes into default over the course of the following year, but is not currently in default. It is set equal to zero if the country is not currently in default and does not default over the next year. If the country is already in default, the variable is coded as a missing value.

[20]Since completing the first draft of this paper, we have become aware of two articles that are related to the results in this section. Catao and Sutton (2002) and Catao and Kapur (2004) investigate empirical determinants of default in a reduced form setting which is similar to our specification.

increase in the probability of default. This is in contrast to its negative effect on spreads discussed in the previous section. We should point out that the result for the default prediction regression is partly driven by the large number of defaults at the beginning of the 1980's, a period of very high nominal and real interest rates in the United States.[21]

In summary, debt to GDP, volatility of terms of trade and the default yield spread affect spreads and probabilities of default in the same way, while change in terms of trade and years since default have no robust effect on the default probability but impact the spread. The 10-year U.S. Treasury rate has opposing effects on spreads and default probabilities.

6 Model estimation

We now turn to fitting our model to the data directly. Using data on default events from 1970 to 2002, we estimate the weights on the individual components of the index and the default threshold. We then use these estimated parameters to calculate model predicted spreads and compare those to observed spreads.

6.1 Estimation of the model parameters from default data

We define a default indicator variable Y_{it+1} that takes the value 1 if country i is in default in period $t+1$, and 0 otherwise. In our model, the probability of default at time $t+1$ conditional on the level of the index at time t is a function of the distance to default, defined as the log difference of the level of the index and the threshold, scaled by volatility. We assume that the logarithm of the index w_{it} for country i at time t is a weighted average of a $k \times 1$ vector of observable fundamentals x_{it}:[22]

$$w_{it} = \beta' x_{it}.$$

In the case of a country, fundamentals continue to be observable once a country enters default. We include observations both in and out of default since in our model the level of the index determines recovery value in default. Empirically, for a given level of fundamentals, a country is more likely to be in default next period if it is currently in default. To capture this effect, we include a dummy d_{it} that is equal to one if the

[21] A more general question is whether the differences in the empirical determinants of spreads in Table 3 and the default predictors in Table 5 might be due to the different sample periods. We cannot fully address this concern since there are only five default observations in the subsample since 1994, resulting in low power.

[22] We assume that the observable variables approximately follow a martingale.

country is currently in default and has coefficient η.[23] Another interpretation is that the dummy picks up the effects of unobservable country characteristics that are different in and out of default.

Since we assume that the index of fundamentals is lognormally distributed, the probability of the country being in default next period is given by:

$$P(Y_{it+1} = 1 \mid x_{it}) = \Phi\left(\frac{w^* - \beta' x_{it} + \eta d_{it}}{\sigma_w}\right).$$

We can estimate the weights as well as the threshold by running a probit regression of country-year default observations on previous period's x_{it}, a default dummy, and a constant.[24]

Results are reported in Table 6, Panel A.[25] We use log debt to GDP and log terms of trade as explanatory variables. Specifically, we use the log terms of trade today relative to average terms of trade over the last 10 years. The coefficients have the signs we would expect, but log terms of trade is not significant. The coefficient on the default dummy is large and highly significant. This implies that once a country has entered default it is more likely to stay in default. The regression constant is an estimate of the default threshold.

In a probit, only the relative magnitude of the coefficients on the explanatory variables is identified. If $\left(\widehat{\beta}, \hat{w}^*, \hat{\sigma}_w\right)$ is an estimate, so is $\left(\nu\widehat{\beta}, \nu\hat{w}^*, \nu\hat{\sigma}_w\right)$ for any $\nu > 0$. This is reflected in the fact that we only have estimates of the weights and the threshold - volatility is assumed to be 1 in a standard probit.[26]

Before we can calculate spreads, we need to pin down the scale of the weights. Intuitively, the scaling factor affects the recovery value that bondholders get in default. It also affects the level of volatility and therefore the expected payoff in default.

To identify β, we impose the restriction $\sum_{j=1}^{k} \beta_j = \kappa$.[27] We get an estimate of κ by

[23] We discuss this issue in more detail when considering the empirical distribution of the distance to default in Figure 3.

[24] In Appendix C we disuss how one could in principle estimate this problem using maximum likelihood. Since the maximum likelihood surface is not concave we do not use this estimation procedure. Instead, we run a simple probit that implicitly assumes that the volatility of the index is constant across countries.

[25] Since we now have included observations in which the country is in default, we cannot directly compare the pseudo R-squared to our logit regression results.

[26] Intuitively, default is a binary event. The only thing that matters is the distance to default, which remains unchanged if the weights, the threshold, and volatility are all rescaled by the same number.

[27] In the corporate bond case, the index is equal to asset value and it enters with coefficient 1. The reason for this is that recovery value moves one for one with asset value in default.

exploiting the relation between the index and the payoff to bondholders in default:

$$\delta_{it+1} = \gamma W_{it+1},$$

where δ_{it+1} denotes recovery rates. In logs, recovery value moves one for one with the index:

$$\log(\delta_{it+1}) = \log(\gamma) + w_{it+1}.$$

We use spread observations in default to calculate a measure of the market expected recovery rate. In particular, we assume that the recovery rate is close to the current market price of the debt, i.e. $\delta_{it+1} = \frac{1}{1+\left(s_{it+1}+r_f\right)}$.

We then calculate $\widehat{w}_{it+1} = \hat{\beta}' x_{it+1}$ using the probit estimates. Regressing $\log(\delta_{it+1})$ on $\widehat{w}_{it+1}$ and a constant, we choose κ such that the coefficient on $\widehat{w}_{it+1}$ is equal to one and rescale the weights and the threshold accordingly. We also get an estimate of the recovery parameter $\hat{\gamma}$ from the constant in the recovery rates regression. This gives us unique estimates $\widehat{\beta}, \widehat{\sigma}_w, \widehat{w}_0$, and $\hat{\gamma}$.

6.2 Model implied default probabilities and spreads

We first consider the implications of our model for default probabilities. Since we are using fewer explanatory variables, the fit for default prediction of the probit estimates is not as good as our best logit specification in Table 5. This leads to less accurate spread estimates.[28] In order to address this problem, we scale each country's volatility to match the country's average model implied default probability to the one implied by the logit specification (4) in Table 5. In Table 6, Panel B we report summary statistics for the entire distribution of model implied and logit probabilities for the EMBI spread estimation sample and find that they are closely in line.

Another way to interpret the large and significant coefficient on the default dummy is to assume that there are two default thresholds: one for going into default and one for coming out of default. Instead of requiring $w_{it} - \eta$ to lie above w^* for the country to emerge from default, we could equivalently require w_{it} to lie above a threshold $w^{**} = w^* + \eta$.

The reason for these different thresholds is related to the fact that country wealth does not directly determine default. Once a country is in default, fundamentals may improve substantially during the restructuring process without immediately triggering an emergence from default. The situation is somewhat akin to a firm filing for Chapter

[28] This point is related to Huang and Huang (2003) who find that there is substantial variation in model implied spreads due to variation in implied default probabilities.

11 bankruptcy protection. In this case it is possible that the firm's asset value may be higher than liabilities during the restructuring process.

In Figure 3 we plot a histogram for the distance to default implied by our estimated parameters. In interpreting the graph, it is useful to recall that the probability of being in default next period is equal to the cumulative normal distribution function of distance to default. We notice several things. There are two distinct groups of observations: distance to default for country year observations in and out of default. The separation of the distributions reflects the large and significant coefficient on the default dummy, which implies a significant difference between the thresholds w^* and w^{**}. Overall, the values for distance to default are reasonable: they range from 0.7 to 2.8, implying default probabilities between 0.3% and 24.1% for countries that are not currently in default.

Since creditors receive less than face value in default, we choose to scale the index by W^{**} in order to calculate recovery value. In particular, we assume that in default the payoff is equal to $\gamma W_{t+1} = \lambda \frac{W_{t+1}}{W^{**}}$, i.e. that $\gamma = \frac{\lambda}{W^{**}}$. Since we already have an estimate of $\hat{\gamma}$, this reinterpretation has no impact on the spread calculation. Rather, it is purely for intuition: $\frac{W_{t+1}}{W^{**}}$ empirically lies below 1 in default. From our estimate of the coefficient on the default dummy, we get an estimate of $\hat{\lambda} = 1.03$.

We now have estimates of all the relevant parameters for the calculation of model implied spreads:

$$\widehat{s}_{it} = g\left(\exp\left(\hat{\beta}' x_{it}\right); \hat{W}^*, \frac{\hat{\lambda}}{\hat{W}^{**}}, \widehat{\sigma}_{wi}\right) \equiv -\log\left(\begin{array}{c} \widehat{\lambda}\exp\left(-\hat{w}^{**} + \widehat{\beta}' x_{it} + \frac{1}{2}\widehat{\sigma}_{wi}^2\right) \\ *\Phi\left(\frac{\widehat{w}_0 - \widehat{\beta}' x_{it}}{\widehat{\sigma}_{wi}} - \widehat{\sigma}_{wi}\right) \\ +\Phi\left(\frac{-\widehat{w}_0 + \widehat{\beta}' x_{it}}{\widehat{\sigma}_{wi}}\right) \end{array}\right).$$

A priori we would expect this type of model to have some difficulties matching observed spreads closely for several reasons. First, we are only estimating the component of the spread that is due to default risk. This means that to the extent that there are other spread components related to liquidity, risk aversion, and taxes, we expect the observed spread to be higher on average than the model implied spread. Second, fitting structural form models to the data generally produces estimates that range from less than a fraction of a basis point all the way up to unreasonably large numbers. The reason is often that the implied default probabilities are extreme as well.[29] Our empirical implementation alleviates this problem since we constrain default probabilities to independently estimated values. Third, unlike reduced form models (including our analysis in Section 4), our model estimation does not use observed spreads as an input. This means that there is no constraint that forces model implied and observed spreads to be broadly in line.

[29] Eom, Helwege and Huang (2004), Huang and Huang (2003).

6.3 Comparison of realized and model implied spreads

We calculate model implied spreads for the EMBI regression sample. Results are reported in Table 6, Panel B. Overall, we find that our model implied spreads match observed spreads surprisingly well: fitted spreads vary from 19 to 1247 bps, compared to actual spreads varying from 58 to 1679 bps. Our model implies a mean spread of 271 bps compared to a mean observed spread of 524 bps.

We now consider the ability of our model to explain the variation in observed spreads. This exercise is more specific than our reduced form exploration in Section 4 since we now ask how much of the variation in spreads is explained by variation in default risk. Table 6, Panel C reports results from regressions of realized on predicted spreads. We find that our model explains 30% of the variation in observed spreads and that a 1% increase in model implied spreads is associated with a 0.73% increase in observed spreads. This means that most of the variation in spreads seems to be due to changes in default risk.[30] With regards to the average spread level, we estimate a constant of 327 bps, reflecting other spread components.

In Figure 4 we plot observed spreads against model implied spreads; we also include the 45 degree line in order to see if observed spreads tend to be higher or lower than predicted spreads. We find that most observations lie above the 45 degree line; consistent with the fact that we only model default risk, we underestimate spreads.

A simple alternative approach to calculating predicted spreads is to assume that recovery rates are fixed so that creditors receive a constant fraction of face value in default, independently of the level of the state variable. We set this fraction equal to 0.6 in our calculations, which is broadly in line with average historical experience. We use the fitted probabilities from the logit specification (4) in Table 5 to calculate spreads. This means that when we compare spreads from the fixed recovery rate model to those from our model, implied default probabilities will be broadly in line. Table 6, Panel B reports summary statistics for the fixed recovery case. Spreads vary from 21 bps to 3025 bps. When regressing observed on fitted spreads in Table 6, Panel C, we find that we can explain 23% of the variation. The coefficient on spreads is 0.44 and the constant is 419 bps. Compared to our model, fixed recovery spreads explain a smaller share of the variation, observed spreads move less with fitted spreads, and a larger share of spreads is explained by the constant.

Comparing means of observed and model implied spreads, we already know that a large component of the spread is not explained by our model. In order to explore if there is variation in the explained fraction for different credit risk, we group spreads by their

[30] The spread also moves with other factors such as risk and liquidity. Correlation of the predicted spread from our model with these components will introduce bias in our estimate.

estimated default probability and compare average observed and fitted spreads across groups. We choose break points using the distribution of fitted probabilities from the entire estimation sample (1970-2002). Table 6, Panel D reports frequencies of spread observations in the different bins as well as average default probabilities implied by the logit and structural models.

Figure 5 plots average realized and implied spreads by bins. We find that fitted spreads on good credit are much smaller than observed spreads, while spreads on poor credit are almost as high as observed spreads. Given that there are other spread components, it is likely that poor credit is overpriced; in other words its spread levels are too small. We find similar results when we calculate spreads assuming a fixed recovery rate.

These findings are consistent with patterns in the corporate bond market. Huang and Huang (2003) show that the fraction of observed spreads accounted for by structural form models decreases with credit quality. In other words, model implied spreads are far too low on companies of good credit quality but they are closer to realized spreads for companies of poor credit quality. The fact that credit risk only accounts for a small fraction of the average spread in the sovereign debt market is consistent with what Huang and Huang find for corporate bonds. In order to more accurately price sovereign debt, it will be important to increase our understanding of the other spread components.

7 Conclusion

In this paper we present a model of sovereign debt prices and implement it empirically for a set of emerging market countries. A country defaults once its debt burden becomes too high and it can no longer generate enough revenue for repayment. We capture this idea by assuming that default occurs when an index of macroeconomic fundamentals falls below a certain threshold. This implies that both the level and the volatility of fundamentals affect spreads, consistent with standard option theory. We identify the components of the index and their relative weights from historical data on defaults and recovery values.

Our empirical analysis of sovereign yield spreads has two main parts. First, we use macroeconomic fundamentals to explain spreads for a sample of 32 emerging market countries from 1994-2002 in a reduced form framework. We find several interesting results. As predicted by our model, the volatility of terms of trade has a statistically and economically significant effect on spreads. In our main specification, a one standard deviation increase in terms of trade volatility is associated with an increase of 124 basis points in spreads. The debt to GDP ratio does not explain cross country variation in spreads. Instead it adds substantial explanatory power in the time series. In other words, what matters is whether a country's debt to GDP is high relative to its own mean, not whether it is high relative to other countries. In addition, even after controlling for fundamentals, a country's default history has a significant impact on spreads. Overall, we obtain a good fit, both across countries and over time, with just a few variables.

Second, we fit our structural model to the data and find that it can explain a substantial share of the variation in spreads. This is surprising given that our estimation only uses data on defaults and recovery values to calculate predicted spreads. We also find that our model accounts for a higher fraction of observed spread levels for borrowers of lower credit quality. This is similar to documented patterns for corporate bond prices.

A Derivation of the yield spread in the model

The price of the bond in period t depends on the expected payoff to the bond and the appropriate risk adjusted discount rate r_t:

$$\begin{aligned} B_t &= \exp(-r_t) E_t [B_{t+1}] \\ &= \exp(-r_t) D \left[P_t (W_{t+1} > W^*) + P_t (W_{t+1} < W^*) E_t \left[\frac{W_{t+1}}{W^{**}} \lambda | W_{t+1} < W^* \right] \right]. \end{aligned}$$

We assume that W_{t+1} is conditionally lognormally distributed:

$$\begin{aligned} w_{t+1} &= w_t + \phi_{t+1} \\ \phi_{t+1} &\sim N(0, \sigma_w^2). \end{aligned}$$

The conditional probability of the country defaulting next period is given by $P_t (W_{t+1} < W^*) = P_t (w_{t+1} < w^*)$, where $w^* = \log(W^*)$. Given our distributional assumption, the probability of default is equal to:

$$P_t (w_{t+1} < w^*) = \Phi \left(\frac{w^* - w_t}{\sigma_w} \right),$$

where $\Phi(.)$ denotes the c.d.f. of the normal distribution.

If investors are risk neutral and the riskfree rate is constant, the price of the bond is given by:

$$\begin{aligned} B_t &= \exp(-r_f) D \left[P_t (W_{t+1} > W^*) + P_t (W_{t+1} < W^*) E_t \left[\frac{W_{t+1}}{W^{**}} \lambda | W_{t+1} < W^* \right] \right] \\ &= \exp(-r_f) D \left[\lambda \exp(-w^{**}) \int_{-\infty}^{w^*} \exp(w) f(w) dw + \int_{w^*}^{\infty} f(w) dw \right] \\ &= \exp(-r_f) D \left[\lambda \exp \left(-w^{**} + w_t + \frac{1}{2} \sigma_w^2 \right) \Phi \left(\frac{w^* - w_t}{\sigma_w} - \sigma_w \right) + \Phi \left(\frac{-w^* + w_t}{\sigma_w} \right) \right]. \end{aligned}$$

Bond prices are commonly quoted in yields and yield spreads. With a constant interest rate, the bond's yield and yield spread are given by

$$\theta_t = -\log \left(\frac{B_t}{D} \right), s_t = -\log \left(\frac{B_t}{D} \right) - r_f,$$

where θ_t is the yield on the bond, and s_t is the spread.

With risk neutral investors, the spread is thus given by:

$$\begin{aligned} s_t &= -\log \left(\lambda \exp \left(-w^{**} + w_t + \frac{1}{2} \sigma_w^2 \right) \Phi \left(\frac{w^* - w_t}{\sigma_w} - \sigma_w \right) + \Phi \left(\frac{-w^* + w_t}{\sigma_w} \right) \right) \\ s_t &= g \left(W_t; W^*, \frac{\lambda}{W^{**}}, \sigma_w \right). \end{aligned}$$

If investors are risk averse, we can rewrite the bond price as:

$$B_t = E_t \left[M_{t+1} \left\{ P_t \left(W_{t+1} > W^* \right) D + P_t \left(W_{t+1} < W^* \right) E_t \left[\frac{W_{t+1}}{W^{**}} \lambda D | W_{t+1} < W^* \right] \right\} \right],$$

where M_{t+1} is the stochastic discount factor. Then we can risk neutralize to find the price:

$$\begin{aligned} B_t &= DE_t \left[\exp \left(m_{t+1} \right) \min \left(\exp \left(0 \right), \exp \left(w_{t+1} - w^* \right) \lambda \right) \right] \\ B_t &= \exp \left(-r_f \right) E_t^Q \left[\min \left(\exp \left(0 \right), \exp \left(w_{t+1} - w^* \right) \lambda \right) \right] \\ w_{t+1} &\sim N \left(w_t + \sigma_{wm}, \sigma_w^2 \right), \text{ under } Q. \end{aligned}$$

With risk averse investors, the spread is given by:

$$\begin{aligned} s_t &= -\log \left(\begin{array}{r} \lambda \exp \left(-w^{**} + w_t + \sigma_{wm} + \frac{1}{2} \sigma_w^2 \right) \Phi \left(\frac{w^* - w_t - \sigma_{wm}}{\sigma_w} - \sigma_w \right) \\ + \Phi \left(\frac{-w^* + w_t + \sigma_{wm}}{\sigma_w} \right) \end{array} \right) \\ s_t &= g \left(\exp \left(w_t + \sigma_{wm} \right); W^*, \frac{\lambda}{W^{**}}, \sigma_w \right). \end{aligned}$$

where σ_{wm} denotes the covariance of the willingness to pay index with the stochastic discount factor.

B Data appendix

J. P. Morgan's EMBI index includes U.S. dollar denominated debt instruments issued by emerging market governments. It includes Brady bonds, loans, and Eurobonds. In order for a country to be eligible for inclusion in the index, it needs to be classified as low or middle income by the World Bank for the last two years, or have restructured external or local debt in the past 10 years, or have restructured external or local debt outstanding. For a debt instrument to be eligible, it needs to be issued by a sovereign or quasi-sovereign entity (100% owned/guaranteed by the government), its issue size needs to be greater than or equal to U.S.$500 million, its remaining maturity needs to be greater than 2.5 years, it needs to have verifiable daily prices and cash flows, and it has to fall under G7 legal jurisdiction.[31]

We use annual terms of trade data provided by the Development Data Group at the World Bank. Terms of trade indices are constructed as the ratio of an export price index to an import price index. The underlying price and volume indices were compiled by the United Nations Conference on Trade and Development (UNCTAD). We normalize the series so that each country's sample mean over the period 1970-2003 is equal to 100.

Our measure of government external debt is the Total Debt series from the World Bank Global Development Finance (GDF) dataset.

GDP data comes from the International Monetary Fund World Economic Outlook (WEO). Per capita GDP series are from Summers Heston Penn World Tables (2002).

The 10-year U.S. Treasury yield, 6-month Treasury rate, and 3-month Eurodollar rate are from the Federal Reserve Bank of St. Louis. Yields on Baa U.S. corporate bonds are from Amit Goyal's website. The VIX measure of volatility of the S&P500 index is provided by the Chicago Board Options Exchange.

From these primary series we construct the macroeconomic variables used in our analysis:

Debt to GDP is the level of total government external debt scaled by GDP.

Change of terms of trade over the last five years is the percentage change of the terms of trade over the previous five years, i.e. a positive number means that a country's exports have become more expensive relative to its imports.

Terms of trade volatility is the standard deviation of the terms of trade. It is calculated using annual data over a backward looking ten year window.

[31] Source: *Emerging Markets External Debt Handbook for 2002-2003*, J.P. Morgan.

C Maximum likelihood estimation

In this appendix we outline how to estimate the weights on the index as well as the threshold by maximum likelihood.

Recall the process for willingness to pay:

$$w_{it+1} = w_{it} + \phi_{it+1} \text{ where } \phi_{it+1} \sim N\left(0, \sigma_{wi}^2\right).$$

We can use observable variables to get an estimate of volatility which will also depend on the relative weights of the index:

$$\phi_{it+1} = \beta' \left(x_{it+1} - x_{it}\right).$$

Then:

$$\begin{aligned} \sigma_{wi}^2 &= \beta' \Sigma_{\Delta xi} \beta, \\ \text{where } \Sigma_{\Delta xi} &= E[\left(x_{it+1} - x_{it}\right)\left(x_{it+1} - x_{it}\right)']. \end{aligned}$$

In principle, we could estimate the parameter vector using maximum likelihood. Note that $\Sigma_{\Delta xi}$ can be estimated from the data.

The likelihood function is given by:

$$\begin{aligned} L(Y, x; \beta, w^*) &= \prod_{i=1}^{n} \prod_{t=1}^{T-1} \Phi\left(\frac{w^* - \beta' x_{it}}{\left(\beta' \Sigma_{\Delta xi} \beta\right)^{\frac{1}{2}}}\right)^{Y_{it+1}} \\ &\quad * \left[1 - \Phi\left(\frac{w^* - \beta' x_{it}}{\left(\beta' \Sigma_{\Delta xi} \beta\right)^{\frac{1}{2}}}\right)\right]^{1 - Y_{it+1}}. \end{aligned}$$

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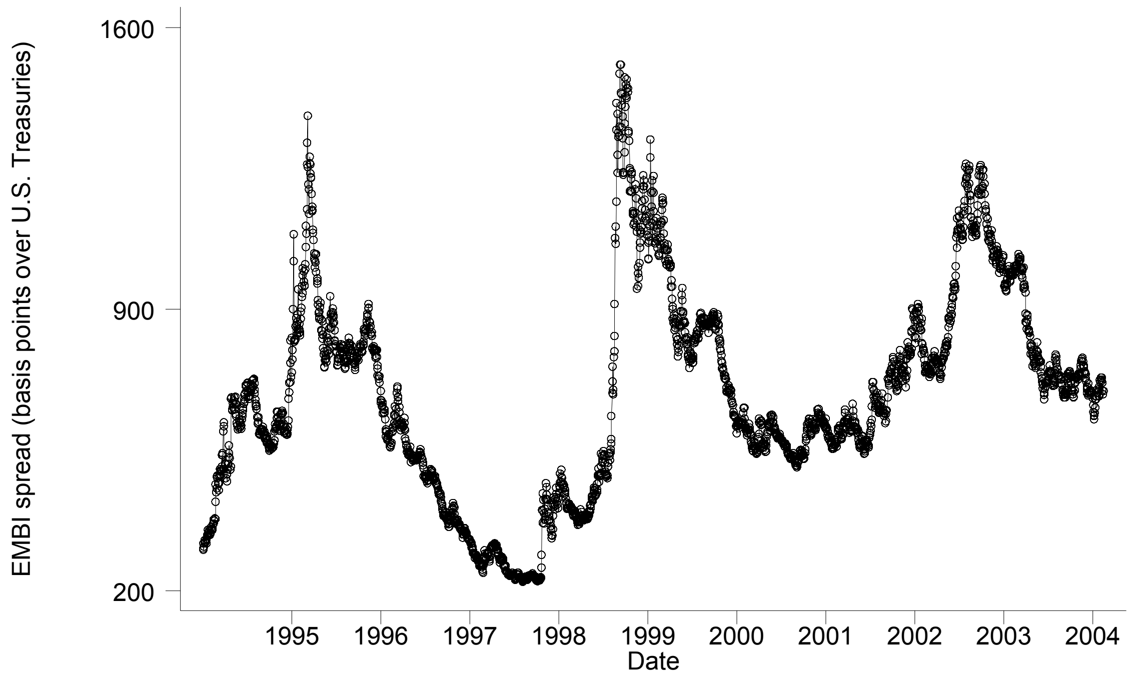

Figure 1: EMBI (weighted by external debt)

EMBI spreads over the period 1994-2004. Series is calculated by weighting individual countries' EMBI spread by their relative level of external debt. Spreads are from J.P. Morgan's Emerging Market Bond Index.

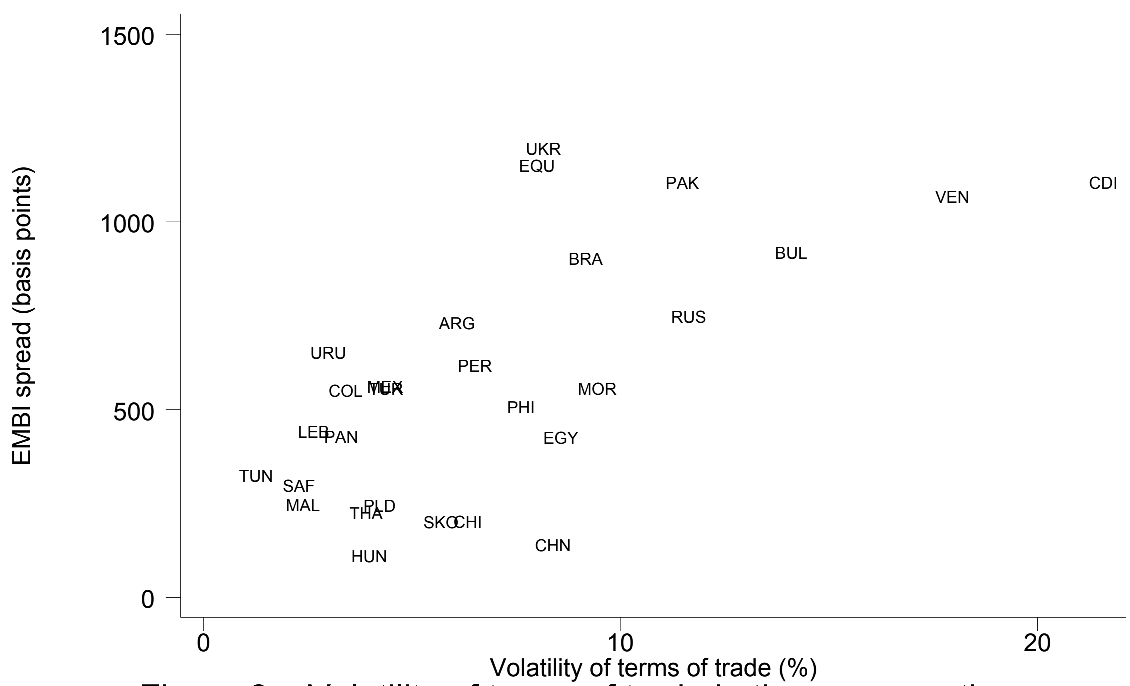

Figure 2a: Volatility of terms of trade in the cross section

Country average of volatility of terms of trade for the EMBI regression sample from 1994-2002. Terms of trade data are from the World Bank.

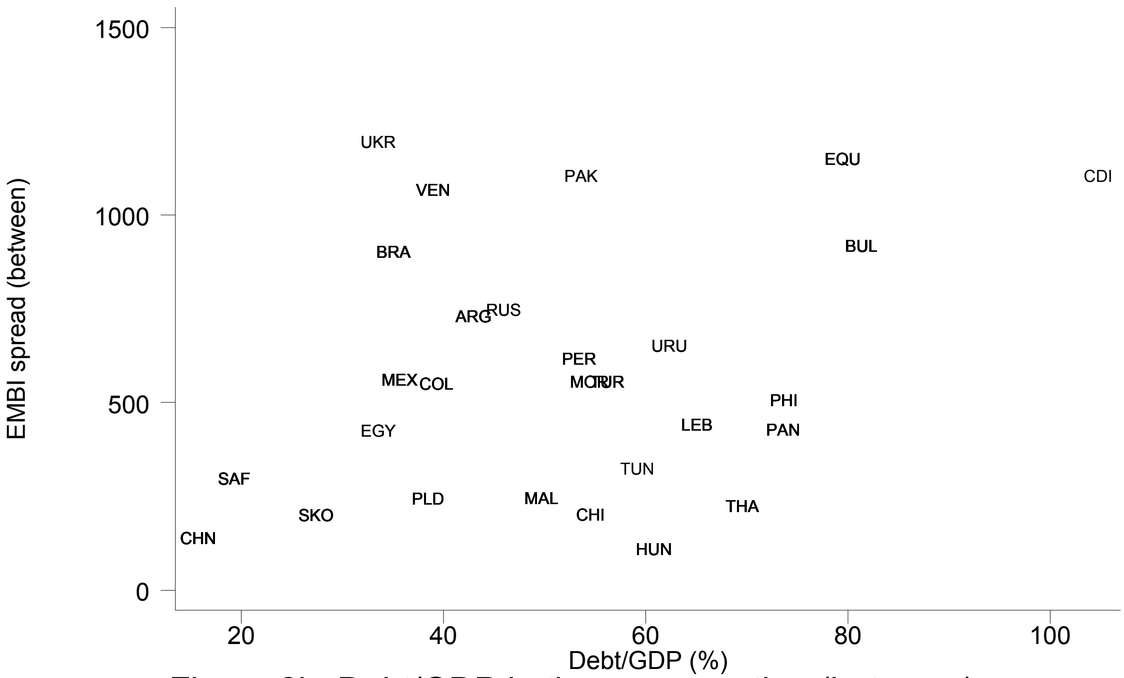

Figure 2b: Debt/GDP in the cross section (between)

Country average of total external debt to GDP calculated for the EMBI sample 1994-2002. Total external debt is from World Bank Global Development Finance (GDF), GDP is from the IMF World Economic Outlook (WEO).

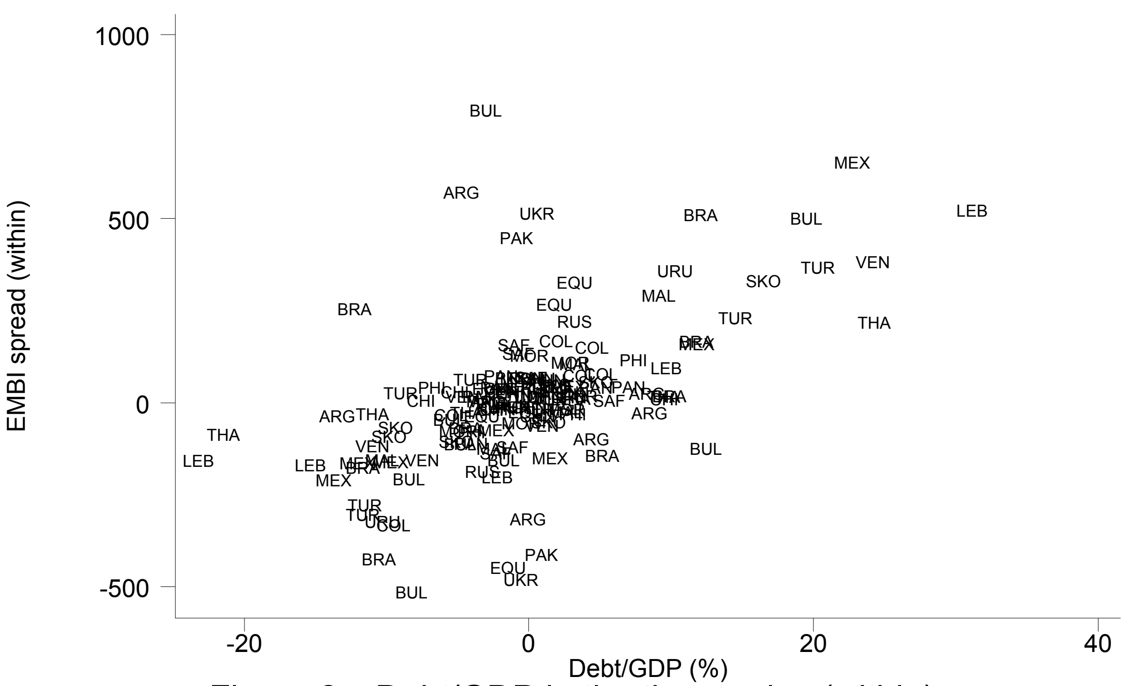

Figure 2c: Debt/GDP in the time series (within)

Debt to GDP minus country specific mean debt to GDP, calculated for the EMBI sample 1994-2002. Series are from GDF and WEO.

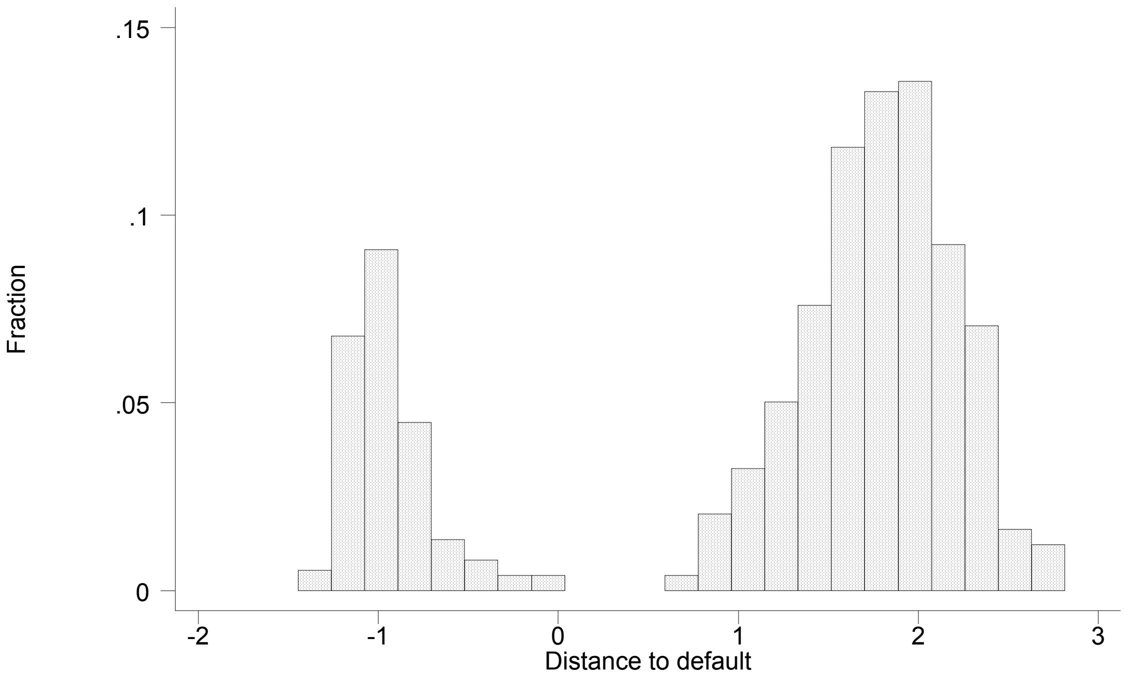

Figure 3: Normalized distance to default

Distance to default, calculated as the volatility scaled difference between the level of the index and the threshold. Histogram includes observations from 1970-2002, corresponding to Table 6, Panel A.

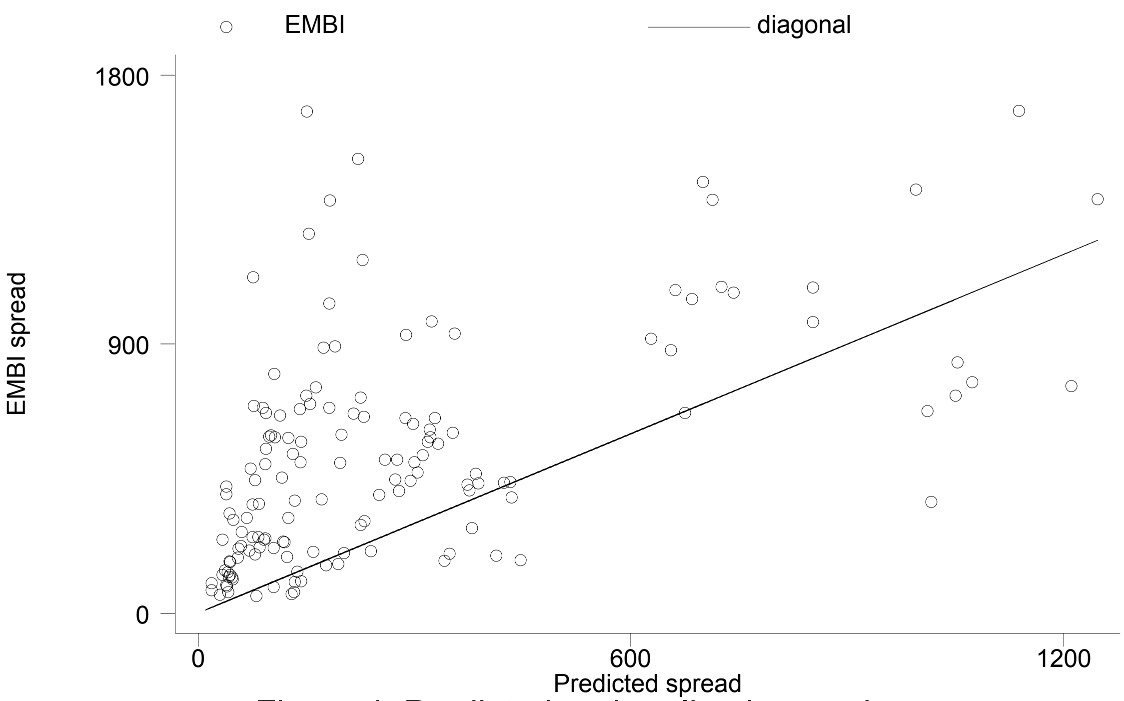

Figure 4: Predicted and realized spreads

Plot of observed EMBI spread against model implied spread for EMBI sample as well as the 45 degree line. Sample is from 1994-2002. Data correspond to Table 6, Panel C.

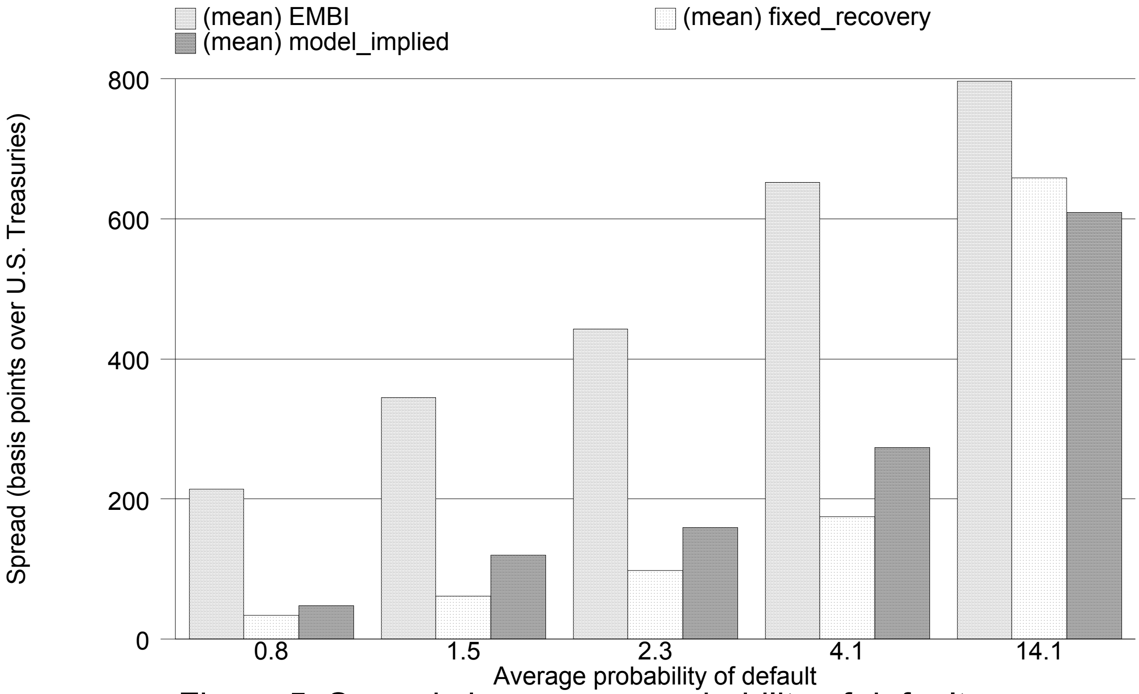

Figure 5: Spreads by average probability of default

Average observed, model implied, and fixed recovery spreads for default probability sorted bins. Breakpoints are chosen using default prediction sample from 1970-2002, average spreads are calculated using the EMBI sample from 1994-2002. Average probability of default using the fitted probabilities from specification (4) in Table 5 are reported.

Table1: Summary statistics by country

EMBI refers to median daily spreads in 2003 on J.P. Morgan's Emerging Market Bond Index, measured in basis points over U.S. Treasuries. Start is the first year for which EMBI data is available. Debt/GDP is the level of external debt divided by GDP. Volatility of terms of trade is calculated using annual data from a ten year backward-looking rolling window. Number of defaults is the number of times the country has gone into default since 1970. Statistics for macroeconomic explanatory variables are calculated for the sample starting in 1970, and are reported as medians. Export groups are for 2000-2001 (UNCTAD).

	Country	Code	Start	EMBI	Debt/ GDP	Volatility of terms of trade	Number of defaults	Top two exports (SITC group) and their percentage of total exports
Latin America	Argentina	ARG	1994	5359	38.2	9.9	2	Crude petroleum (10%), Feeding stuff for animals (10%)
	Ecuador	EQU	1995	1130	76.1	20.1	2	Crude petroleum (41%), Fruit, nuts, fresh, dried (18%)
	Venezuela	VEN	1994	974	41.0	27.4	3	Crude petroleum (59%), Petroleum products, refined (25%)
	Brazil	BRA	1994	775	33.9	13.7	1	Aircraft (6%), Iron ore and concentrates (5%)
	Uruguay	URU	2001	742	30.9	8.2	4	Meat, fresh, chilled, frozen (16%), Leather (10%)
	Dominican Rep.	DMR	2001	632	29.6		1	Men's outwear non-knit (17%), Under garments knitted (13%)
	Colombia	COL	1997	471	33.9	9.2	0	Crude petroleum (26%), Coffee and substitutes (8%)
	Peru	PER	1997	429	54.0	12.9	4	Gold, non-monetary (17%), Feeding stuff for animals (13%)
	Panama	PAN	1996	366	78.3	3.3	1	Fish, fresh, chilled, frozen (20%), Fruit, nuts, fresh, dried (20%)
	El Salvador	ESD	2002	331	29.1	9.4	0	Coffee and substitutes (16%), Paper and paperboard, cut (6%)
	Mexico	MEX	1994	231	33.3	13.4	1	Passenger motor vehicles, exc. bus (10%), Crude petroleum (8%)
	Chile	CHI	1999	126	42.2	9.2	1	Copper (27%), Base metals ores (13%)
Africa	Côte d'Ivoire	CDI	1998	2725	116.2	18.7	2	Cocoa (28%), Petroleum products, refined (18%)
	Nigeria	NIG	1994	957	73.6	55.0	1	Crude petroleum (99.6%)
	Morocco	MOR	1998	250	59.7	6.0	2	Women's outwear non-knit (11%), Men's outwear non-knit (8%)
	Tunisia	TUN	2002	180	54.5	9.1	0	Men's outwear non-knit (17%), Women's outwear non-knit (10%)
	South Africa	SAF	1995	173	18.2	7.8	3	Pearl, prec., semi-prec. stones (13%), Special transactions (12%)
Eastern Europe	Ukraine	UKR	2000	323	27.7	14.2	1	Iron, steel primary forms (13%), Iron, steel shapes etc. (8%)
	Russia	RUS	1998	296	19.1	12.9	1	Crude petroleum (24%), Gas, natural and manufactured (17%)
	Bulgaria	BUL	1994	235	73.0	15.7	1	Petroleum products, refined (11%), Copper (7%)
	Croatia	CRO	1996	117	45.3		1	Ships, boats etc. (15%), Petroleum products, refined (8%)
	Poland	PLD	1994	81	39.7	4.4	1	Furniture and parts thereof (7%), Ships, boats etc. (4%)
	Hungary	HUN	1999	32	58.5	4.7	0	Int. combust. piston engines (9%), Automatic data proc. eq. (7%)
Southeast Asia	Philippines	PHI	1998	441	62.3	8.8	1	Transistors, valves etc. (42%), Automatic data proc. eq. (13%)
	Malaysia	MAL	1996	141	39.1	6.5	0	Transistors, valves etc. (19%), Office, adp. mach. parts (12%)
	South Korea	SKO	1994	101	34.6	5.1	0	Transistors, valves etc. (12%), Passgr. motor vehicl. exc. bus (7%)
	Thailand	THA	1997	99	35.2	9.5	0	Office, adp. mach. parts (9%), Transistors, valves etc. (8%)
	China	CHN	1994	56	14.1	9.3	0	Telecom equip., parts, acces. (5%), Automatic data proc. eq. (5%)
Middle East & South Asia	Turkey	TUR	1996	688	33.8	4.5	2	Outer garments knit non-elastic (6%), Under garments knitted (6%)
	Lebanon	LEB	1998	486	25.1	2.4	0	Gold, silver ware, jewelry (9%), Gold, non-monetary (7%)
	Pakistan	PAK	2001	301	44.4	18.3	1	Textile articles (16%), Textile yarn (12%)
	Egypt	EGY	2001	208	51.4	13.6	1	Petroleum products, refined (39%), Crude petroleum (10%)

Table 2: Summary statistics for spread regression and default prediction samples

EMBI refers to spreads on J.P. Morgan's Emerging Market Bond Index, debt/GDP denotes US dollar denominated debt to GDP, change in terms of trade is calculated over the previous five years. Volatility of terms of trade is calculated using annual data from a ten year rolling window. Years since last default measures the number of years since the last year in which the country was in default, capped at 10. It is equal to zero if the country is in default and is equal to 11 if the country has never defaulted. Default is an indicator variable that takes the value 1 in years where a country is in default according to Reinhart, Rogoff, and Savastano (2003). The sample in Panel A corresponds to the regression sample, default observations are excluded. The sample in Panel B is the default prediction sample: it starts in 1970. For Panel B, data is winsorized at the 5 percent level.

Panel A: Spread regression sample

	EMBI	Debt/GDP	Change in terms of trade	Volatility of terms of trade	Years since last default	10-year U.S. Treasury	Default yield spread
mean	524	48.8	0.0	6.7	7.2	5.9	2.1
median	445	47.3	-1.6	5.2	8.0	6.0	2.0
sd	372	21.3	11.8	4.8	3.6	0.8	0.6
min	58	13.6	-30.1	1.1	1.0	4.6	1.5
max	1679	104.7	55.3	22.6	11.0	7.1	3.2
N=143						*(N=9)*	*(N=9)*

Correlations	EMBI	Debt/GDP	Change in terms of trade	Volatility of terms of trade	Years since last default
Debt/GDP	0.36	1.00			
Change in tot	-0.11	-0.10	1.00		
Volatility of tot	0.54	0.13	0.18	1.00	
Years since def.	-0.62	-0.14	-0.07	-0.48	1.00
N=143					

Panel B: Default prediction sample

non-default observations (not in default next period):

	Debt/ GDP	Change in terms of trade	Volatility of terms of trade	Years since last default	10-year U.S. Treasury	Default yield spread
mean	40.6	-0.7	11.7	9.3	8.0	2.0
median	39.0	-1.1	8.7	11.0	7.6	2.0
sd	18.9	15.5	9.3	3.1	2.3	0.5
min	9.9	-33.8	2.8	1.0	4.6	1.1
max	103.6	33.7	41.1	11.0	13.9	3.2
N=535					*(N=33)*	*(N=33)*

default observations (in default next period):

	Debt/ GDP	Change in terms of trade	Volatility of terms of trade	Years since last default
mean	60.5	-2.7	18.7	7.1
median	62.5	-3.6	18.8	10.0
sd	24.4	19.6	11.4	4.5
min	11.9	-33.8	3.1	1.0
max	103.6	33.7	40.1	11.0
N=25				

Table 3: Spread Regressions

This table reports results from regressions of mean annual EMBI spreads on explanatory variables. We drop country-year observations when the country is in default.

Panel A: Regression specifications and robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Debt/GDP	6.369	5.220	4.612	4.239	4.140	3.717	3.782
	(4.65)**	(4.45)**	(4.47)**	(4.19)**	(4.20)**	(3.62)**	(3.73)**
Volatility of terms of trade		38.707	23.020	25.659	29.536	26.392	25.821
		(7.49)**	(4.49)**	(5.06)**	(6.05)**	(5.27)**	(5.18)**
Years since last default			-45.611	-45.410	-33.888	-47.486	-48.392
			(6.56)**	(6.71)**	(4.34)**	(7.04)**	(7.14)**
Change in terms of trade				-5.423	-4.622	-5.137	-5.035
				(2.95)**	(2.63)**	(2.82)**	(2.77)**
10-year Treasury						-68.441	
						(2.21)*	
Default spread							85.980
							(2.36)*
Africa					-117.527		
					(1.67)		
Eastern Europe					-182.743		
					(2.90)**		
Southeast Asia					-227.348		
					(3.68)**		
Middle East & South Asia					10.006		
					(0.14)		
Constant	213.134	9.838	474.089	473.314	459.749	890.695	315.168
	(2.92)**	(0.15)	(5.14)**	(5.27)**	(5.23)**	(4.26)**	(2.84)**
Observations	143	143	143	143	143	143	143
R-squared	0.1329	0.3810	0.5273	0.5553	0.6190	0.5705	0.5726

Absolute value of t-statistics in parentheses

* significant at 5%; ** significant at 1%

Panel B: Economic significance of coefficients in specification (4)

	Regression coefficient	sd	Predicted change
Debt/GDP	4.2	21.3	90
Volatility of terms of trade	25.7	4.8	124
Years since last default	-45.4	3.6	-162
Change in terms of trade	-5.4	11.8	-64

Table 4: Spreads in Cross Section and Time Series

This table reports results from regressions of mean annual EMBI spreads on explanatory variables. Columns (1) to (3) calculate between estimates. Columns (4) to (8) calculate within estimates. We drop country-year observations when the country is in default.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Debt/GDP	4.822	1.813	1.462	13.964	13.665	12.272	12.064	12.124
	(1.54)	(0.71)	(0.71)	(7.23)**	(7.45)**	(6.55)**	(6.50)**	(6.66)**
Volatility of terms of trade		44.445	21.501		22.039	16.202	17.252	16.354
		(4.13)**	(1.96)		(3.67)**	(2.57)*	(2.76)**	(2.67)**
Years since last default			-52.979			-25.385	-37.530	-49.720
			(3.90)**			(2.15)*	(2.80)**	(3.44)**
Change in terms of trade			-3.641			-4.828	-4.291	-3.816
			(0.74)			(2.73)**	(2.42)*	(2.17)*
10-year Treasury							-52.728	
							(1.84)	
Default spread								101.970
								(2.76)**
Constant	311.295	150.588	697.088	-157.364	-290.450	0.198	385.156	-56.112
	(1.79)	(1.06)	(3.82)**	(1.65)	(2.97)**	(0.00)	(1.55)	(0.42)
Observations	143	143	143	143	143	143	143	143
Number of countries	28	28	28	28	28	28	28	28
R-squared (between)	0.0836	0.4552	0.6809					
R-squared (within)				0.3145	0.3874	0.4472	0.4638	0.4831

Absolute value of t-statistics in parentheses
* significant at 5%; ** significant at 1%

Table 5: Default prediction regressions

This table reports results from logit regressions of the default indicator on explanatory variables. The default indicator is equal to one if the country is in default during the next year, but is not currently in default. Data for the explanatory variables corresponds to the sample in Panel B in Table 2.

Regression specifications and robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Debt/GDP	0.045	0.047	0.040	0.041	0.065	0.034	0.037
	(4.64)**	(4.78)**	(3.82)**	(3.92)**	(4.71)**	(3.16)**	(3.50)**
Volatility of terms of trade		0.065	0.068	0.073	0.063	0.051	0.083
		(3.66)**	(3.74)**	(3.82)**	(3.17)**	(2.38)*	(4.18)**
Years since last default			-0.105	-0.106	-0.024	-0.199	-0.132
			(1.82)	(1.85)	(0.38)	(3.15)**	(2.27)*
Change in terms of trade				0.011	0.010	0.012	0.013
				(0.85)	(0.79)	(0.97)	(1.00)
10-year Treasury						0.354	
						(3.96)**	
Default spread							1.146
							(2.82)**
Latin America					2.010		
					(3.42)**		
Constant	-5.306	-6.383	-5.217	-5.316	-8.181	-6.917	-7.590
	(8.80)**	(8.79)**	(5.55)**	(5.67)**	(5.89)**	(6.62)**	(5.86)**
Observations	560	560	560	560	560	560	560
# of defaults	25	25	25	25	25	25	25
Pseudo R-squared	0.1072	0.1669	0.1824	0.1859	0.2543	0.2646	0.2250

Absolute value of z-statistics in parentheses
* significant at 5%; ** significant at 1%

Table 6: Estimation of the model

Panel A reports results from the first stage probit regression. Panel B summarizes realized and model predicted spreads, fixed recovery spreads, logit probability (specification for Table 5), model implied probability (using scaled volatility), and distance to default. The sample corresponds to the EMBI sample used in Table 3. Panel C reports estimates from regressions of realized on model predicted spreads and realized on fixed recovery spreads. Panel D reports average probabilities for the bins in Figure 5, both logit and model implied.

Panel A: Probit

Log terms of trade	-0.349
Log debt/GDP	0.475
	(3.14)**
Default dummy	2.534
	(16.19)**
Constant	-3.462
	(6.02)**
Observations	737
Pseudo R-squared	0.5737

Absolute value of t-statistics in parentheses * significant at 5%; ** significant at 1%

Panel B: Spreads and default probabilities

stats	EMBI	Model implied spread	Fixed recovery spread	Logit probability	Model implied probability	Distance to default
mean	523.80	270.85	236.52	0.052	0.059	1.72
p50	445.38	163.75	116.62	0.027	0.039	1.76
sd	372.00	280.57	400.48	0.078	0.055	0.44
min	57.51	18.62	21.40	0.005	0.005	0.70
max	1679.06	1246.98	3024.51	0.559	0.241	2.61
N=143						

Panel C: Regression of realized on predicted spreads

	(1)	(2)
Model implied spread	0.726	
	(7.77)**	
Fixed recovery spread		0.443
		(6.45)**
Constant	327.111	418.954
	(8.99)**	(13.14)**
Observations	143	143
R-squared	0.3000	0.2277

Panel D: Average probability of default for the bins in Figure 5

bin	P_logit	P_model	N
1	0.008	0.011	25
2	0.015	0.028	24
3	0.023	0.037	24
4	0.041	0.061	35
5	0.141	0.127	35