Sovereign Risk Premia *

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December 2009

Abstract

Emerging countries tend to default when their economic conditions worsen. If bad times in an emerging country correspond to bad times for the US investor, then these foreign sovereign bonds are particularly risky and should offer high returns. We explore how this mechanism plays out in the data and in a general equilibrium model of optimal borrowing and default. Empirically, we obtain a cross-section of sovereign bond returns: the higher the correlation between past sovereign bond returns and US corporate bond returns, the higher the average sovereign excess returns. A model of risk-averse lenders with external habit preferences qualitatively replicates this feature.

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In this paper, we study sovereign bonds issued by emerging countries in US dollars. The Euler equation for an American investor implies that sovereign bond prices depend on their default probabilities and on covariances between bond payoffs and the investor's marginal utility of wealth. Default probabilities are a well-known driver of emerging bond yields. The worse the Standard & Poor's credit rating, for example, the higher the yield on average. In this paper, we show both theoretically and empirically that covariances between bond returns and risk factors are key determinants of bond prices and debt quantities.

To illustrate the intuition behind this result, assume that an American investor has constant relative risk-aversion and invests in one-period foreign government bonds. Emerging countries tend to default in 'bad times', when foreign consumption is low. If bad times in the foreign economy correspond to bad times in the domestic economy, then foreign countries tend to default in bad times for the US investor. In this case, sovereign bonds are particularly risky, and the US investor expects to be compensated for that risk through a high return. Alternatively, if bad times in the foreign economy correspond to good times for the US investor, then sovereign bonds are less risky and may even hedge domestic consumption. As a result, sovereign bond prices depend on both expected probabilities of repayment and the timing of the bond payoffs.

With this price mechanism in mind, we turn to the data on sovereign debt. We look at bonds issued by emerging market countries that are included in JP Morgan's EMBI Global index. Yields on EMBI bonds increase with the probability of default as measured by Standard and Poor's credit ratings. However, for a given default probability, there is significant cross-sectional variation in yields; at the end of May 2009, for example, spreads were up to 1000 basis points. To disentangle the two price mechanisms, we build portfolios of sovereign bonds by sorting countries along two dimensions: their default probabilities and their covariance with US economic conditions. For the first dimension, we use Standard and Poor's credit ratings to measure the probability of sovereign default. Credit ratings are not investor-specific and do not account for the timing of a potential default. For the second dimension, we compute bond betas, which are defined as the slope coefficients in regressions of one-month sovereign bond returns on one-month US corporate bond returns at daily frequency. In our framework, US corporate bond returns proxy for domestic economic conditions. Our intuition starts off the correlation between macroeconomic conditions in emerging countries and in the US, but most emerging countries lack high frequency macroeconomic data. To address this issue, we thus turn to bonds returns; they offer a high frequency measurement of investor marginal utility of wealth.[1] After sorting countries along these two dimensions, we obtain six portfolios and a large

[1] This is consistent with the literature on corporate bond indices: Krainer (2004) shows that US corporate credit spreads are counter-cyclical; Elton, Gruber, Agrawal, and Mann (2001) find that only a quarter of the spread on US corporate bonds is due to expected default probabilities, and that the remaining portion represents compensation for co-movement with Fama and French (1993) risk factors.

cross-section of holding period excess returns. Our sample starts in January 1995 and ends in May 2009. The average spread between countries with low and high default probabilities is about 500 basis points. The average spread between countries with low and high bond betas is also about 500 basis points. The first spread is well-known, the second is new.

We study this cross-section of excess returns from the perspective of a US investor. We find that a large fraction of the cross-section of average EMBI excess returns can be explained by their covariances with just one risk factor: the return on a US BBB corporate bond. Portfolios with higher exposure to this risk factor are riskier and have higher average excess returns because they offer lower returns when US corporate default risks are higher, e.g in bad times for the US. The market price of risk is in line with the mean of the risk factor, as implied by a no-arbitrage condition. Pricing errors are not statistically significant. Looking at the time-variation in the market price of risk, we find that it increases in bad times, as measured by a high value of the equity option-implied VIX index. We consider several robustness checks, using different sorting variables and risk factors. All our findings point towards a risk-based explanation of sovereign bond returns.

To interpret our findings and uncover their implications in terms of optimal borrowing, we build on the seminal work by Eaton and Gersovitz (1981) and use a dynamic general equilibrium model of sovereign lending with endogenous default choice. In the model, a set of small open economies borrow from a large developed country (the US). We consider endowment economies. The only source of heterogeneity across small open economies is their correlation with the US business cycle. We introduce a key modification to the literature: we assume that investors are risk-averse and have external habit preferences as in Campbell and Cochrane (1999). This feature helps our understanding of the data: without risk-aversion, e.g. when investors are risk-neutral, there is no role for covariances in sovereign bond prices. As a result, a benchmark model with risk neutral investors cannot account for our empirical results. A model with power utility would have counterfactual implications: the large spread in returns due to covariances would imply a very large risk-aversion coefficient and an implausible risk-free rate, as Mehra and Prescott (1985) and Weil (1989) find on equity markets. The high Sharpe ratios on sovereign bonds point to the equity premium literature in order to enrich models of sovereign lending. We focus on Campbell and Cochrane (1999) preferences. They offer a solution to the equity premium puzzle, endogenously delivering a volatile stochastic discount factor that implies high Sharpe ratios. Moreover, their preferences entail time-varying risk aversion, and thus a time-variation in the market price of risk, as in the data.[2]

[2] There are at least two other classes of dynamic asset pricing models that account for several asset pricing puzzles: the long-run risk framework of Bansal and Yaron (2004) and the disaster risk framework of Rietz (1988) and Barro (2006). These two classes of models deliver volatile stochastic discount factors and high risk premia too. They are legitimate candidates to describe the representative investor in models of sovereign lending. We focus on the Campbell and Cochrane (1999) model because it only requires one state variable in order to deliver time-variation in the market

The rest of the model builds on Arellano (2008) and Aguiar and Gopinath (2006). As in the former paper, we assume a nonlinear cost of default. As in the latter, we assume that foreign endowments present a time-varying long-run mean. Unlike these papers, we consider simultaneously shocks to the transitory and permanent components of endowment growth rates. As a result, our model delivers endogenously both high debt levels and large bond spreads. In the model, countries borrow heavily, mostly to smooth out changes in the permanent component of their endowment growth rates. Countries default after receiving negative (often temporary) shocks. The risk of default is compensated by large spreads. When business cycles in emerging countries and in the US are positively correlated, defaults tend to occur when US consumption is low relative to the US habit (or subsistence) level. Bonds issued by emerging countries are riskier and have lower prices because they have low payoffs when the lender's marginal utility of consumption is high. The model matches important features of the emerging markets business cycles. Consumption is more volatile than output; interest rate spreads and trade balances are strongly counter-cyclical. We first focus on the model's implications for bond pricing. In order to analyze the model's results, we build portfolios of bond returns on simulated data, as we did on actual data. In the model, we can precisely measure expected default probabilities and consumption correlation, so we do not need to rely on proxies like Standard and Poor's ratings or corporate spreads. We first rank countries on expected default probabilities and then on consumption growth betas. The model delivers a cross-section excess returns along both dimensions. Higher default probabilities imply higher returns. Countries that are risky from the lenders' perspective offer higher returns.

The model offers a general equilibrium view of debt quantities and prices. Bond issues and defaults are endogenous choices: countries facing high borrowing costs choose to borrow less, thereby lowering their default risk. In the simulations, high beta countries pay higher interest rates even if they borrow less in equilibrium. This result suggests that a nonlinear relationship between debt levels and excess returns. It thus offers a potential explanation to the absence of clear empirical link between these two variables. The riskiest country is not the most indebted one, but the one that might default in bad times.

Three discrepancies between the model and the data are worth mentioning. First, spreads in returns between high and low default probability countries and between high and low beta countries are smaller than in the data. This discrepancy is likely due to the short maturity of simulated bonds: the model only considers one-period bonds, whereas actual bonds have longer maturities. The model could be extended in this direction: Hatchondo and Martinez (2009) and Chatterjee and Eyigungor (2009) offer interesting mechanisms to increase maturities without adding state variables. Second, the model does not take into account interest rate risk. Building macroeconomic models

price of risk.

of the yield curve is still a challenge even for closed economies without default risk. We thus leave the extension to rich yield curve dynamics out for future research. Third, in the model, the cross-country correlation of endowment shocks is fixed, while there is time-variation in the bond betas that we measure. This assumption appears to us as a natural first step. Adding volatility in these correlations would not add much to the model, which already produces some time-variation in consumption betas because of the time-varying means of endowment growth rates. A more fruitful avenue for research would jointly consider stock and bond market returns. Sovereign bond betas on the US stock market would not be constant in the model because of the time-variation in risk aversion.

This paper is related to two strands of existing literature on sovereign debt. First, this paper contributes to the large body of empirical literature on emerging market bond spreads. The paper closest to ours is Longstaff, Pan, Pedersen, and Singleton (2007). They study changes in emerging market credit default swaps spreads and find that global factors, like the return on the U.S. stock market and changes in the VIX index, explain a large fraction of the common variation in swap spreads. They argue convincingly that excess returns are mostly compensation for bearing global risk, with little or no country specific risk premia.[3] Second, our paper contributes to the theoretical literature on sovereign lending with defaults.[4] Here, the papers closest to ours are Aguiar and Gopinath (2006) and Arellano (2008). A limited number of papers introduce risk aversion to bear on this topic. Arellano (2008) mostly focus on risk-neutral investors, but also considers a reduced form of the lenders' stochastic discount factor that is similar to constant relative risk-aversion. Lizarazo (2008) investigates decreasing absolute risk-aversion in the same model. Andrade (2009) specifies an exogenous pricing kernel. Pan and Singleton (2008) study the term structure of CDS sovereign spreads. Broner, Lorenzoni, and Schmukler (2005) propose a three-period model to determine the optimal structure of sovereign debt when investors are risk-averse.

The paper is organized as follows. Section 1 describes the data, how we build EMBI portfolios, and the main characteristics of the EMBI portfolio excess returns. Section 2 shows that one risk factor explains most of the time series variation in portfolio excess returns. In section 3, we interpret these findings in a general equilibrium model of sovereign borrowing. Section 4 considers a calibrated version of the model that qualitatively replicates our empirical findings. Section 5 concludes. A

[3]Other references on the empirical determinants of sovereign spreads include papers by Edwards (1984), Herb, Harvey, and Viskanta (1995), Kamin and von Kleist (1999), Arora and Cerisola (2001), Westphalen (2001), Adler and Qi (2003), McGuire and Schrijvers (2003), Bernoth, von Hagen, and Schuknecht (2004), Favero, Pagano, and von Thadden (2005), Bekaert, Harvey, and Lundblad (2007), Gonzalez-Rozada and Yeyati (2008), Fostel and Geanakoplos (2008), and Hilscher and Nosbusch (2009).

[4]Recent papers in this segment of the literature are Bulow and Rogoff (1989), Atkeson (1991), Kehoe and Levine (1993), Zame (1993), Cole and Kehoe (2000), Alvarez and Jermann (2000), Kocherlakota (1996), Amador (2003), Bi (2006), Yue (2010), Guerrieri and Kondor (2008), Arellano and Ramanarayanan (2009), Benjamin and Wright (2009) and Pouzo (2009).

separate appendix reports additional results.

1 The Cross-Section of EMBI Returns

We focus on sovereign bonds issued in US dollars by emerging countries. To study these bonds, we take the perspective of a US investor who borrows in US dollars to invest in sovereign bonds. We check that these bond returns increase with the probability of default, as measured by Standard and Poor's country ratings. We uncover a second mechanism: the higher the sovereign bond's covariance with US corporate bond returns, the higher the average sovereign excess returns. Using these two results, we build portfolios along two dimensions and obtain a cross-section of sovereign bond excess returns.

We start by describing the raw data and setting up some notation. Then we turn to our portfolio-building methodology, and report the main characteristics of our cross-section of excess returns.

1.1 Data and notations

Data on Emerging Markets We focus on the set of countries included in JP Morgan's EMBI Global index. JP Morgan publishes country-specific and aggregate indices that market participants consider as benchmarks. The EMBI Global index covers low or middle income per capita countries (according to the World Bank classification). It also includes countries that are currently - or have been in the past ten years - restructuring their external or local debts. Our main dataset thus contains 36 countries: Argentina, Belize, Brazil, Bulgaria, Chile, China, Colombia, Cote D'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Hungary, Indonesia, Iraq, Kazakhstan, Lebanon, Malaysia, Mexico, Morocco, Pakistan, Panama, Peru, Philippine, Poland, Russia, Serbia, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela, Vietnam. The sample period runs from January 1995 to May 2009.

The JP Morgan EMBI Global total return index includes accrued dividends and cash payments. In each country, the index is a market capitalization-weighted aggregate of US dollar-denominated Brady Bonds, Eurobonds, traded loans and local market debt instruments issued by sovereign and quasi-sovereign entities. The weight of each instrument in each country-specific index is determined by dividing the issue's market capitalization by the total market capitalization for all instruments in the index. The market capitalization of each issue corresponds to its face value outstanding multiplied by its bid-side settlement price. Weights are updated at the end of each month (see Cavanagh and Long (1999) for details on the construction of EMBI indices). These bonds are liquid debt instruments that are actively traded. Their notional sizes are at least equal to $500 million. Each issue included in the EMBI Global index must have at least 2.5 years until maturity when it enters the index and at least 1 year until maturity to remain in the index. Moreover, JP Morgan sets liquidity criteria such as easily accessible and verifiable daily prices either from an inter-dealer broker or a certified JP Morgan source.

To assess the default probability of each country, we rely on Standard and Poor's credit ratings. They take the form of letter grades ranging from AAA (highest credit worthiness) to SD (selective default). They are available for a large set of countries over a long time period. We collect Standard and Poor's ratings for all the 36 countries in the EMBI index, except Cote d'Ivoire and Iraq. We focus on ratings for long-term debt denominated in foreign currencies and convert ratings into numbers ranging from 1 (highest credit worthiness) to 23 (lowest credit worthiness). Our sample contains several default episodes. Argentina, the Dominican Republic, Ecuador, Russia and Uruguay defaulted on their external debt during our sample period. Argentina was in default status from November, 2001 to May, 2005, the Dominican Republic from February, 2005 to May, 2005, Ecuador in July, 2000 for only one month, Russia from January, 1999 to November, 2000 and Uruguay in May, 2003 for only one month.

Ratings are not traded prices. This obvious fact has two consequences. First, ratings are not tailored to a particular investor. For example, they are the same for a US and a Japanese investor. As a result, ratings do not not take into account the timing of a potential sovereign default: a country that might default in good times for the US has the same rating as a country that might default in bad times. Second, for most countries, credit ratings do not encompass all the information on expected defaults. They are not updated on a regular basis, but rather when new information or events suggest the need for additional Standard and Poor's studies and grade revisions.

To complement the Standard and Poor's ratings, it is now common to rely on credit default swaps (CDS) and debt to GNP ratios. These two measures do not seem appropriate for our study. CDS are insurance contracts against the event that a sovereign defaults on its debt over a given horizon (see Pan and Singleton (2008)). These contracts are traded in US dollars. As a result, their prices should reflect both the magnitude and the timing of expected defaults. This conflicts with our goal to disentangle these two effects. Moreover, CDS data are only available from December 2002 on, and for a subset of the EMBI Global countries. Debt to GNP ratios are available for many countries, but at annual frequency. These ratios do not predict default probabilities and returns as well than Standard and Poor's ratings. To check, however, that high debt levels do not drive our results, we report debt to GNP ratios. Our series come from the World Bank Global Development Finance annual data set. We linearly interpolate the annual debt to GNP ratios to obtain monthly series. Appendix A reports summary statistics on sovereign spreads and debt levels.

As a snapshot of our data set, Figure 1 reports, for each country in JP Morgan's EMBI Global

Index, the annual stripped spread plotted against the Standard and Poor's credit rating at the end of May 2009. The stripped spread is equal to the difference between the average yield to maturity in the emerging country and the corresponding yield to maturity on the US Treasury spot curve, after 'stripping' out the value of any collateralized cash flows. These spreads correspond to the usual representation of sovereign risk premia. They increase on average when credit ratings worsen. But, for any given rating, there exists a lot of heterogeneity in spreads. These two characteristics of sovereign spreads motivate our study. Throughout the rest of the paper though, we use index prices to compute returns.

Notation Before turning to our portfolio-building strategy, we introduce here some useful notation. Let $r^{e,i}$ denote the log excess return, including any accrued dividends, of an American investor who borrows funds in US dollars at the log risk free rate r^f in order to buy country i's EMBI bond, then sells this bond after one month, and pays back his debt. His log excess return is equal to:

$$r^{e,i}_{t+1} = p^i_{t+1} - p^i_t - r^f_t,$$

where p^i_t denotes the log market price of an EMBI bond in country i at date t.

We define the bond beta (β^i_{EMBI}) of each country i as the slope coefficient in a regression of EMBI bond returns on US BBB-rated corporate bond returns:

$$\Delta p^i_t = \alpha^i + \beta^i_{EMBI} r^{BBB}_t + \varepsilon_t,$$

where r^{BBB}_t denotes the log total return on the Merrill Lynch US BBB corporate bond index.

We compute betas on 100-day rolling windows to obtain time-series of $\beta^i_{EMBI,t}$. As a timing convention, we date t the beta estimated with returns up to date t. For each regression, we estimate betas only if at least 50 observations for both the left- and right-hand side variables are available over the previous 100-day rolling window period.

1.2 Portfolios of Excess Returns

EMBI portfolios We build portfolios of EMBI excess returns by sorting countries along two dimensions: their probabilities of defaults and their bond betas. First, at the end of each period t, we sort all countries in the sample in two groups on the basis of their bond betas $\beta_{EMBI,t}$. The first group contains the countries with the lowest $\beta_{EMBI,t}$, the second group contains the countries with the highest $\beta_{EMBI,t}$. Second, we sort all countries within each of the two groups in three portfolios ranked from low to high probabilities of default. We measure default probabilities with Standard and Poor's credit ratings. As a result, we obtain six portfolios. Portfolios 1, 2 and 3 contain countries with the lowest betas, portfolios 4, 5 and 6 contain countries with the highest betas. Portfolios 1 and 4 contain countries with the lowest default probabilities, portfolios 3 and 6 contain countries with the highest default probabilities. Portfolios are re-balanced at the end of every month, using information available at that point. Appendix B reports additional information on our portfolios: Table 7 presents the frequency of reallocation across portfolios and Figure 6 focuses on the portfolio allocation of Argentina and Mexico.

We compute the EMBI excess returns $r^{e,j}_{t+1}$ for portfolio j by taking the average of the EMBI excess returns between t and $t+1$ that are in portfolio j. Daily historical levels of the EMBI indices are available from December 31, 1993 onwards for a limited set of countries. We need at least six countries in the sample to start building our six portfolios and thus start in January 1995. The total number of countries in our portfolios varies over time. We have 6 countries at the beginning of the sample in January 1995 and 32 at the end in May 2009. The maximum number of countries attained during the sample is 32.

Table 1 provides an overview of our six EMBI portfolios. For each portfolio j, we report the average foreign bond beta β^j_{EMBI}, the average Standard and Poor's credit rating, the average total excess return $r^{e,j}$, and the average external debt to GNP ratio. All returns are reported in US dollars and the moments are annualized: we multiply the mean of the monthly return by 12 and the standard deviation by $\sqrt{12}$. The Sharpe ratio is the ratio of the annualized mean to the annualized standard deviation.

Our portfolios highlight two simple empirical facts. First, excess returns increase from low to high betas: portfolio 1, 2 and 3 (low betas) offer lower excess returns than portfolios 4, 5 and 6 (high betas). The average excess return on all the low beta portfolios is 505 basis points per annum. For the high beta portfolios, it is 1020 basis points. As a result, there is on average a 500 basis points difference between high and low beta portfolios. Bilateral comparisons (portfolio 1 versus portfolio 4, 2 versus 5, and 3 versus 6) all show that, for similar credit ratings, high beta bonds always offer higher returns. Second, excess returns also increase with default probabilities: portfolios 1 and 4 (low default probabilities) offer lower excess returns than portfolios 3 and 6 (high default probabilities). For low beta countries, the spread between low and high default probabilities entails a 350 basis point difference in returns. For high beta countries, this difference jumps to 650 basis points. These two empirical facts square well with intuition. An investor receives higher returns to compensate for higher default probabilities. If the investor is risk-averse, then he expects higher returns for assets that co-vary with his return on wealth.

These spreads are economically and statistically significant. As a back-of-the-envelope check to this point, note that the standard error on the mean estimate is approximately equal to the standard deviation of the excess returns divided by the square root of the number of observations (assuming *i.i.d* returns). The average standard deviation is approximately equal to 13 percent. The sample size is 164 quarters (12.8^2). The standard error on the mean is thus around 1 percent, or 100 basis points. A spread of 500 basis points corresponds to five times the standard deviation of the mean.

Patton and Timmermann (2008) propose a more precise test of these cross-sectional properties. We use their non-parametric test to examine whether there exists a monotonic mapping between the observable variables used to sort EMBI countries into portfolios and expected returns. The test rejects at standard significance levels the null of the absence of a monotonic relationship between portfolio ranks and returns against the alternative of an increasing pattern (the p-value is 1.5%).

We check wether our portfolios differ in several dimensions: market capitalization, duration, maturity, higher moments. Table 8 in Appendix B reports these additional statistics for our benchmark portfolios. These returns present large negative skewness and large positive kurtosis. Both characteristics are due to the 1998 and 2008 crises.[5] The high default probability portfolios (e.g portfolios 3 and 6) exhibit the most pronounced deviations from normality. These default probabilities look very much like crash risk. There is, however, no clear pattern in the comparison between low and high beta portfolios. If anything, high beta portfolios have relatively less skewness and kurtosis. We do not pursue in this paper a disaster risk explanation of sovereign spreads, in the vein of Rietz (1988), Barro (2006), Gabaix (2008), and Martin (2008). But we view it as an interesting avenue for future research.

Our benchmark portfolios do not present any clear pattern in terms of market capitalization, duration or maturity. High beta portfolios tend to have lower remaining maturities, lower duration (on average, but not across all rating groups) and lower market capitalization. These differences are rarely statistically significant and their expected impacts on returns point in opposite directions: lower returns for lower maturities because of a positive term premium, but higher returns for lower market capitalizations because of a liquidity premium. We show instead in the next section that our average sovereign bond returns correspond to covariances with a simple risk factor.

Finally, we conduct two robustness checks: different weights and different sorts. We find a similar cross-section of excess returns as before when we build value-weighted (instead of equally-weighted) portfolios using again bond betas and credit ratings (see Table 9 in Appendix B). We also find a similar cross-section when we use stock market betas and credit ratings.[6] The stock market betas correspond to slope coefficients in regressions of sovereign bond returns on the US

[5] These characteristics are also apparent at the country level. Table 5 reports the skewness and kurtosis of our EMBI spreads at monthly frequency. Some countries like Hungary, Malaysia and Thailand exhibit very large kurtosis. The same three countries present the largest positive skewness measures. Clearly, our sample comprises two large crises: the Asian crisis in 1998 and the mortgage crisis in 2008. Both implied first sharp increases in EMBI spreads (e.g lower emerging market bond prices) and thus very low returns.

[6] See Bekaert and Harvey (1995) and Bekaert and Harvey (2000) for the link between emerging and developed equity market returns.

stock market return. We report summary statistics on these additional portfolios in Tables 10 and 11 in Appendix B. Here again, high beta sovereign bonds tend to offer higher returns.

Sorting on sovereign betas and rebalancing portfolios is the key innovation of this section. We run two additional experiments to make this point. First, we sort countries on average bond betas, instead of time-varying betas, maintaining the same sample as for our benchmark portfolios. For each country, we compute the average of all its time-varying betas. We obtain a cross-section of excess returns, albeit smaller than with time-varying betas. The caveat is that such portfolios exhibit forward-looking bias: in order to compute the mean beta, we use information not available to the investor. In order to avoid the forward-looking bias, we consider a second experiment. Assume that, for each country, we fix its beta to its first available value in our sample. As a result, we maintain the same sample as before, but the betas are now constant for each country and known at the time of the investment decision. If we sort portfolios using these fixed betas, we do not obtain a clear cross-section of excess returns. The reason is that there is time-variation in betas. To show this point, Figure 7 in Appendix B plots average rolling betas for each benchmark portfolio. Recall that we regress 100-day actual excess returns on a constant and the return on the US_{BBB} bond index to obtain slope coefficient $\beta^{i,t}$ for each country. We date t the betas estimated with returns up to date t. The end-of-month values of these betas are used to sort countries and build portfolios. We present here the monthly betas of each portfolio, e.g the average of all end-of-month country beta in each portfolio. Betas vary from almost -3 to 5. There is, however, a large common component in the dynamics of these betas. The betas are high at the start of our sample, which corresponds to the end of the Tequila crisis. Betas tend to first dive at the onset of the Asian crisis, then they recover and peak. They are also high during the US recessions in 2001 and particularly in 2008. Overall, betas tend to be high during crises.

To summarize this section, by sorting countries along their Standard and Poor's ratings and bond betas, we have obtained a rich cross-section of average excess returns. We now turn to the dynamic properties of these portfolio returns.

2 Common Risk Factors in EMBI Excess Returns

In this section, we show that covariances with US corporate bond returns account for a large share of our cross-section of average excess returns.

2.1 Asset Pricing Methodology

Linear factor models of asset pricing predict that average returns on a cross-section of assets can be attributed to risk premia associated with their exposure to a small number of risk factors. In the arbitrage pricing theory of Ross (1976) these factors capture common variation in individual asset returns. We test this prediction on sovereign bond returns.

Cross-Sectional Asset Pricing We use $R^{e,j}_{t+1}$ to denote the average excess return on portfolio j in period $t+1$. In the absence of arbitrage opportunities, this excess return has a zero price and satisfies the following Euler equation:

$$E_t[M_{t+1}R^{e,j}_{t+1}] = 0,$$

where M denotes the stochastic discount factor (SDF) of the US investor. We assume that the log stochastic discount factor m is linear in the pricing factors f:

$$m_{t+1} = 1 - b(f_{t+1} - \mu),$$

where b is the vector of factor loadings and μ denotes the factor means. This linear factor model implies a beta pricing model: the log expected excess return is equal to the factor price λ times the beta of each portfolio β^j:

$$E[\widetilde{r^{e,j}}] = \lambda'\beta^j$$

where $\widetilde{r^{e,j}}$ denotes the log excess return on portfolio j corrected for its Jensen term, $\lambda = \Sigma_{ff}b$,$\Sigma_{ff} = E(f_t - \mu_f)'$ is the variance-covariance matrix of the factors, and β^j denotes the regression coefficients of the return $R^{e,j}$ on the factors. To estimate the factor prices λ and the portfolio betas β, we use two different procedures: a Generalized Method of Moments (GMM) applied to linear factor models, following Hansen (1982), and a two-stage OLS estimation following Fama and MacBeth (1973), henceforth FMB. We briefly describe these two techniques.

GMM The moment conditions are the sample analog of the populations pricing errors:

$$g_T(b) = E_T(m_t\widetilde{r^e_t}) = E_T(\widetilde{r^e_t}) - E_T(\widetilde{r^e_t}f'_t)b,$$

where $\widetilde{r^e_t} = [\widetilde{r^{e,1}_t}, \widetilde{r^{e,2}_t}, ..., \widetilde{r^{e,N}_t}]'$ groups all the N EMBI portfolios. In the first stage of the GMM estimation, we use the identity matrix as the weighting matrix, while in the second stage we use the inverse of the spectral density S matrix of the pricing errors in the first stage: $S = \sum E[(m_t\widetilde{r^e_t})(m_{t-j}\widetilde{r^e_{t-j}})']$.[7] We use demeaned factors in both stages. Since we focus on linear factors models, the first stage is equivalent to an OLS cross-sectional regression of average returns on the

[7]We use a Newey and West (1987) approximation of the spectral density matrix The optimal number of lags is determined using Andrews (1991)'s criterion with a maximum of 6 lags.

second moment of returns and factors. The second stage is a GLS cross-sectional regression of average excess returns on the second moment of returns and factors.

FMB In the first stage of the FMB procedure, for each portfolio j, we run a time-series regression of the EMBI excess returns $\widetilde{r}_t^e$ on a constant and the factors f_t, in order to estimate β^j. The only difference with the first stage of the GMM procedure stems from the presence of a constant in the regressions. In the second stage, we run a cross-sectional regression of the average excess returns $E_T(m_t\widetilde{r}_t^e)$ on the betas that were estimated in the first stage, to estimate the factor prices λ. The first stage GMM estimates and the FMB point estimates are identical, because we do not include a constant in the second step of the FMB procedure. Finally, we can back out the factor loadings b from the factor prices and covariance matrix of the factors.

2.2 Results

We first focus on the unconditional version of the Euler equation. We use a single risk factor to account for the returns on our EMBI portfolios. This risk factor is the log total return on the Merrill Lynch US BBB corporate bond index that we used to form portfolios. Table 2 reports our asset pricing results. We focus first on market prices of risk and then turn to the quantities of risk in our portfolios.

Market Prices of Risk The top panel of the table reports estimates of the market price of risk λ and the SDF factor loadings b, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests (in percentage points). The market price of risk is equal to 693 basis points per annum. The FMB standard error is 271 basis points. The risk price is more than two standard errors from zero, and thus highly statistically significant. Overall, asset pricing errors are small. The square root of the mean squared error (RMSE) is 158 basis points and the R^2 is 73 percent. The null that the pricing errors are zero cannot be rejected, regardless of the estimation procedure. Figure 2 plots predicted against realized excess returns for the six EMBI portfolios. Clearly, the model's predicted excess returns are consistent with the average excess returns. Note that predicted excess returns correspond here simply to the OLS estimates of the betas times the sample mean of the factors, not the estimated prices of risk.

Since the factors are returns, the no arbitrage condition implies that risk prices should be equal to the factors' average excess returns. This condition stems from the fact that the Euler equation applies to the risk factor too, which clearly has a regression coefficient β of 1 on itself. In our estimation, this no-arbitrage condition is satisfied. The average of the risk factor is 652 basis points. So the estimated price of risk is 41 basis points removed from the point estimate. The standard error on the mean estimate is equal to 49 basis points. As a consequence, the mean is not statistically different from the market price of risk, and the no-arbitrage condition is satisfied.

Alphas and betas in EMBI returns The bottom panel of Table 2 reports the constants (denoted α^j) and the slope coefficients (denoted $\beta^j_{US_{BBB}}$) obtained by running time-series regressions of each portfolio's excess returns $\widetilde{rx}^{e,j}$ on a constant and the US_{BBB} risk factor.

The first column reports α's estimates. They are generally small and not significantly different from zero. The null that the αs are jointly zero is clearly rejected. The second column reports the βs for our risk factor. These βs increase from 0.91 to 1.05 for the low β_{EMBI} group, while for the second β_{EMBI} group they increase from 0.92 for portfolio 4 to 1.78 for portfolio 6. Betas line up with average excess returns for two reasons: pre-formation betas predict post-formation betas, and bonds with higher default probabilities tend to load more on the risk factor. Comparing portfolios 1 and 4, 2 and 5, and 3 and 6, we note that asset pricing (eg post-formation) betas are always higher in the second group, as they should.

As a robustness check, we run the same asset pricing tests on a different set of returns. We use the EMBI returns sorted on the US stock market betas and credit ratings. We use the same risk factor as before, the US BBB corporate bond return. Results are in Appendix B: Table 11 reports risk prices and quantities, and Figure 8 plots predicted against realized excess returns for these EMBI portfolios. Results are very similar to the previous ones. The market price of risk is positive and significantly different from zero. It is not statistically different from the mean of the factor. Pricing errors are small and not significant.

Conditioning Information We have so far focused on the unconditional Euler equation. We now study the time-variation in the market price of risk, starting from the conditional Euler equation. Hansen and Richard (1987) shows that a simple conditional factor model can be turned into an unconditional factor model using all the variables z_t in the information set of the investor. The conditional Euler equation for portfolio j, $E_t[M_{t+1}R^{e,j}_{t+1}] = 0$, is then equivalent to the following unconditional condition:

$$E_t[M_{t+1}z_tR^{e,j}_{t+1}] = 0.$$

Following Cochrane (2001), we can also interpret this condition as an Euler equation applied to a managed portfolio $z_tR^j_{t+1}$. This managed portfolio corresponds to an investment strategy that goes long portfolio j when z_t is positive and short otherwise. We assume that one scaling variable z_t summarizes all the information set of the investor. Our conditioning variable z is the CBOE volatility index VIX, which is lagged, demeaned and scaled by its standard deviation. We multiply both returns and risk factors by z_t. As a result, we obtain twelve test assets: the original six EMBI portfolios, and the same portfolios multiplied by the scaling variable. For the risk factors, we use the US high yield return r_{t+1}^{BBB} and the same return multiplied by our conditioning variable $r_{t+1}^{BBB} z_t$. Table 12 in Appendix B reports the results. We find that the implied market price of risk associated with the bond risk factor varies significantly through time. The market price of risk tends to increase in bad times, when the implied US stock market volatility is high. Time-varying risk-aversion is a potential interpretation of this finding. But a rise in the VIX index is also often associated with poor market liquidity. We now check if our portfolio returns correspond to liquidity risk.

Liquidity Risk? We consider two additional risk factors: the change in the log VIX index and the TED spread, defined as the difference between Eurodollar yields and Treasury Bills, both at 3-month horizons. These two variables are often used to proxy for liquidity risk, even though they also capture credit risk and/or time-varying risk aversion. To save space, we report our asset pricing results in Tables 13, 14 and 15 in Appendix B.

The change in the VIX index has a negative (as expected) and significant market price of risk. But it explains a small share of the cross-section of returns. The cross-sectional R^2 is less than half the one obtained with the US BBB bond return as risk factor. Moreover, we can reject the null that pricing errors α are jointly 0 (cf panel II in Table 13). In the cross-section, the US BBB bond return drives out the change in VIX index: when both risk factors are used together, the market price of risk of the latter is not longer significant (cf Table 14). In the time-series, portfolio returns load significantly on the change in the VIX index, even after controlling for US BBB returns. But the change in the VIX index affects all portfolios in a similar way (there is no difference in the quantity of risk between portfolios 3 and 6 for example); as result, it helps explains the overall levels of EMBI returns but not their cross-section.

We obtain similar results with the TED spread. Its market price of risk is negative as expected, but it is not significant. Covariances with the TED spread explains a very small share of the cross-section of returns and we can reject the null that the pricing errors are jointly 0, this rejecting the model (cf Table 15). When used in conjunction with the US BBB return, its market price of risk is not significant.

Disentangling liquidity risk from credit risk and time-varying risk aversion is the focus of a large literature and is beyond the scope of this paper. We do not rule out a liquidity-based explanation of EMBI returns, but our asset pricing results point towards a credit risk explanation, with a role for time-varying risk aversion. As a result, we develop a model along this line.

3 A General Equilibrium Model of Sovereign Borrowing

By sorting countries along their Standard and Poor's ratings and bond betas, we have obtained a cross-section of average excess returns which reflects different risk exposures. To study the implications of such risk exposure on debt quantity and prices, we now specify a general equilibrium model of sovereign borrowing. We start off the seminal two-country model of Eaton and Gersovitz (1981) and its recent version in Aguiar and Gopinath (2006) and Arellano (2008). But we depart from the previous literature and assume that lenders are risk averse, instead of being risk-neutral, and that emerging countries' business cycles differ in their correlations to the US business cycle.

This simple departure has key implications on sovereign bond prices. We know that emerging countries tend to default when they experience difficult economic conditions. Again, if bad times in emerging countries correspond to bad times for the investor, then sovereign bonds appear risky: they pay badly in bad times. Risk-averse investors will expect to be compensated for that risk: they will earn on average a premium on these bonds, or equivalently, these bonds will trade at a lower value than their simple, discounted expected payoffs. If bad times in emerging countries correspond to good times for investors, then sovereign bonds appear less risky: they pay badly in good times, and well in bad times. If investors are risk-averse, these bonds trade at a higher value than their discounted expected payoffs.

3.1 Setup

We explore this mechanism and its general equilibrium implications. In the model, there are N-1 small, emerging open economies, and one large developed economy. In each small open economy, there is a representative agent who receives a stochastic endowment stream. In what follows, the superscript i denotes variables corresponding to one of the N-1 small open economies. We do not use any superscript for the large developed economy. Upper case variables denote levels, lower case variables denote logs.

Endowments In the small open economies, endowments are composed of a transitory component z_t^i and a time-varying mean (or permanent component) Γ_t^i as in Aguiar and Gopinath (2006). The countries' log endowments evolve as:

$$Y_t^i = e^{z_t^i}\Gamma_t^i. \tag{3.1}$$

The transitory component, z_t^i follows an AR(1) around a long run mean μ_z:

$$z_t^i = \mu_z(1-\alpha_z) + \alpha_z z_{t-1}^i + \epsilon_t^{z,i}.$$

The time-varying mean is described by:

$$\Gamma_t^i = G_t^i \Gamma_{t-1}^i \tag{3.2}$$

where:

$$g_t^i = log(G_t^i) = \mu_g(1-\alpha_g) + \alpha_g g_{t-1}^i + \epsilon_t^{g,i}.$$

Note that a positive shock $\epsilon^{g,i}$ implies a permanent higher level of output. We assume that $\epsilon^{g,i}$, $\epsilon^{z,i}$ are $i.i.d$ normal and that shocks to the transitory and permanent components are orthogonal ($E(\epsilon^{g,i'}\epsilon^{z,i}) = 0$). All emerging countries have the same endowment persistence and volatility: $E([\epsilon^{z,i}]^2) = \sigma_z^2$ and $E([\epsilon^{g,i}]^2) = \sigma_g^2$.

In the large developed economy, there is a representative agent that receives every period an exogenous consumption endowment. We assume that idiosyncratic shocks to consumption growth are $i.i.d.$ log-normally distributed:

$$\Delta c_t = g + \epsilon_t.$$

We do not introduce a time-varying mean in the consumption growth of the large economy in order to limit the number of state variables and because consumption growth is closer to $i.i.d$in developed economies.

The emerging countries only differ according to their conditional correlation to the developed economy: $E(\epsilon^{z^{i'}}\epsilon^L) = \rho^{z,i}$. This is the key source of heterogeneity across countries in our model. In a separate appendix, we report some evidence that such heterogeneity exists in the data. Correlation coefficients between foreign and US HP-filtered GDP range in our sample from -0.3 to 0.6 on annual data, and from -0.3 to 0.5 on quarterly data. Our model predicts that, everything else equal, countries that are positively correlated with the US, should pay higher spreads to US investors. In our empirical section, we show that countries with high EMBI market betas exhibit higher spreads, once we control for S&P ratings. The intuition for this finding is that market betas offer high frequency measures of the links between emerging countries and the US.

We have shown in the previous section that bond betas in the data are time-varying. In the model, however, we fix the correlation between the lenders and borrowers' endowment shocks. The simulated betas can still vary because they are estimated on rolling window of past consumption growth rates, and borrowing countries have time-varying mean growth rates. We could, of course, extend the model by introducing variable correlation coefficients.

Debt contracts All variables in the model are real, and we abstract from monetary policies. In each emerging economy, a benevolent government maximizes the welfare of its representative citizen. To do so, the government can borrow resources from the developed country. The government, however, can only trade non contingent one-period zero-coupon bonds. These debt contracts are not enforceable: the government can choose to default on its debts at any point in time. In this set-up, if investors are risk neutral, the price of a sovereign bond depends exclusively on the endogenous probability of default, which varies with the amount of funds borrowed and the expected next-period endowment. But if investors are risk-averse, then sovereign bond prices reflect the correlation between the emerging economy' business cycle and the US economy.

3.2 Borrowers

We start with the description of the borrowers. The representative agent in each small open economy maximizes the stream of discounted utilities U_t^i:

$$U^i = E_0 \sum_{t=0}^{\infty} \beta^t U_t^i = E_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t^i)^{-\gamma}}{1-\gamma},$$

where β denotes the time discount factor, and C_t^i denotes consumption at time t. We let the lenders' and borrowers' discount factors differ because developing countries tend to have higher real risk free rates than emerging countries.[8]

The representative household receives a stochastic stream of the tradable good Y_t^i every period. We assume that y_t^i, the log of the borrower's endowment, follows a Markov process. The representative agent also receives a goods transfer from the government in a lump-sum fashion: i.e, any proceeds from international operations are rebated lump-sum from the government to its citizens. The government has access to international capital markets: at the beginning of period t, it can purchase $B_{t,t+1}^i$ one-period zero-coupon bonds at price Q_t. $B_{t,t+1}^i$ denotes the quantity of one-period zero-coupon bonds purchased at date t and coming to maturity at date $t+1$. A positive value for $B_{t,t+1}^i$ represents a saving for the borrowing country, which supplies $Q_t B_{t,t+1}^i$ units of period t goods in order to receive $B_{t,t+1}^i > 0$ units of goods in the following period. On the contrary, a negative value $B_{t,t+1}^i < 0$ implies borrowing $Q_t B_{t,t+1}^i$ units of goods at t and promising to repay, conditional on not defaulting, $B_{t,t+1}^i$ units of $t+1$ good. The representative household's budget constraint conditional on not defaulting at time t is then:

$$C_t^i = Y_t^i - Q_t^i B_{t,t+1}^i + B_{t-1,t}^i. \tag{3.3}$$

In case of default, all current debt disappears. This simplifying assumption implies that the

[8] Political economists argue that politicians tend to have shorter time horizons in small developing countries. In Amador (2003) for example, a low value for the discount factor β^B corresponds to the high short-term discount rate of an incumbent party with low probability of remaining in power in a model where different parties alternate.

sovereign cannot selectively default on parts of its debt.[9] A sovereign that defaults at date t is excluded from international capital markets for a stochastic number of periods and suffers a direct output loss. In this case, consumption is constrained by the value of output during autarky, which is denoted $Y_t^{i,def}$, and the budget constraint is simply:

$$C_t^i = Y_t^{i,def}. \tag{3.4}$$

Following Arellano (2008), we assume an asymmetric direct output cost of default. More precisely, we assume that $Y_t^{i,def} = min\{Y^i, \hat{Y}^i\}$, where $\hat{Y}^i$ is the output upper bound in case of a default and it is defined as $(1-\theta)mean(Y^i)$. This form of direct output cost implies that defaults are more costly in good times. A country that receives a high value of Y^i expects high values of the endowment also in the near future, given the high persistence of the endowment process. If the country defaults when Y^B is high, its consumption is set to be low for the entire time of exclusion from capital markets according to the budget constraint (3.4). When the endowment is high, the utility cost of default (which lasts several periods) is likely to outweigh the utility benefit from not repaying the outstanding debt (which lasts one period). As a result, the country has less incentives to default. In general equilibrium, lenders take that into account, and sovereign countries can borrow more in good times. Take now the opposite case. Consider a country that receives a particularly low value of the endowment. This country would like to borrow to smooth out consumption. Given the high persistence of the endowment process, this country also expects low values of the endowment in the near future. If the endowment is low enough and the country defaults, the direct output cost is likely to be low for the entire exclusion period (because $Y^i < \hat{Y}^i$). At the same time, when the endowment is low, the marginal utility cost of a net capital outflow is very high for a risk averse borrower. Investors anticipate that the borrower is likely to default in this case and they require a high premium to supply any funds. In equilibrium, when Y^i is low enough, there is no borrowing and the sovereign is credit-rationed.

Therefore, this assumption on output cost affects both the size and the timing of debt in equilibrium. It is a convenient way to ensure that countries borrow more when output is above trend, a robust feature of emerging economies' business cycles (see for example Neumeyer and Perri (2005), Aguiar and Gopinath (2007) or Uribe and Yue (2006)). It also implies that countries tend to default when output is below trend, as they do (Tomz (2007)). Note, however, that it is empirically difficult to determine whether the fall in output is the reason for defaulting, or rather the consequence of the default.

A second consequence of a country's default is exclusion from international capital markets. In

[9] Bolton and Jeanne (2008) and Duffie, Pedersen, and Singleton (2003) propose models where the sovereign can selectively default on part of the outstanding debt.

Eaton and Gersovitz (1981) exclusion is permanent, and default is not an equilibrium outcome. We follow Aguiar and Gopinath (2006) and Arellano (2008) and assume that exclusion lasts a stochastic number of periods. Although this assumption implies a degree of coordination by foreign investors that is partially at odds with the assumption that investors behave competitively, it captures the fact that countries in default do not access international capital markets for some time. As Hatchondo, Martinez, and Sapriza (2007) note, in this framework, the equilibrium size of debt is smaller when the exclusion from capital markets is shorter. This is because exclusion works an incentive to repay, thus reassuring lenders, decreasing the risk premium and allowing more borrowing.

3.3 Lenders

We now turn to the description of the lenders. The representative agent receives an exogenous stochastic consumption endowment every period denoted C_t. Lenders are risk-averse and behave competitively. In order to reproduce the large spread between low and high beta countries, we rely on habit preferences similar to Campbell and Cochrane (1999). We assume that lenders maximize the stream of discounted utilities U_t:

$$U = E_t \sum_{t=0}^{\infty} \delta^t U_t = E_t \sum_{t=0}^{\infty} \delta^t \frac{(C_t - H_t)^{1-\gamma} - 1}{1-\gamma},$$

where δ denotes the lenders' discount factor and H_t the external habit level.[10]

Why not power utility? A model where borrowers and lenders share the same constant relative risk-aversion preferences does not produce a large spread in excess returns in this model for low risk-aversion parameters. This result parallels the equity premium puzzle in Mehra and Prescott (1985). To illustrate this point, assume that two countries have the same default probability and the same yield volatility. Then spreads between their bond returns depend on the covariance between the US marginal utility of consumption and return differences. As a result, the maximum spread between these two countries is twice the product of the risk-aversion coefficient times the standard deviation of consumption growth (around 1.5 percent) and the standard deviation of the returns (around 13 percent). A risk-aversion coefficient of 2 would imply a maximum spread of around 80 basis points. This maximum spread is only attained when the correlation coefficients between each sovereign bond return and lenders' pricing kernels is 1 and -1, which is an unlikely extreme event. For an average correlation of 0.3, the maximum spread is 24 basis points. In order to generate a

[10] Some further examples of habit preferences in one-country models are Constantinides (1990), Abel (1990), Jermann (1998), Boldrin, Christiano, and Fisher (2001), Lettau and Uhlig (2000), Wachter (2006), Long Chen and Goldstein (2008), and Verdelhan (2010).

spread of 500 basis points as in the data, the model requires a very high risk-aversion coefficient. But the model would then imply a high and volatile risk free rate. On the contrary, the introduction of habit preferences implies that lenders' risk aversion is time-varying, and higher in 'bad times'. As consumption declines toward the habit in 'bad times', the curvature of the utility function rises, so risky assets prices fall and expected returns rise. Local risk-aversion is sometimes very high, even if the risk-aversion coefficient remains low and the real interest rate is constant and equal to the mean real interest rate in the data.

Following Campbell and Cochrane (1999), we assume that the external habit level depends on the consumption endowment through the following autoregressive process for the surplus consumption ratio, defined as the percentage gap between the endowment and habit ($S_t \equiv [C_t - H_t]/C_t$):

$$s_{t+1} = (1-\phi)\overline{s} + \phi s_t + \lambda(s_t)(\Delta c_{t+1} - g),$$

where g is the average consumption growth. The sensitivity function $\lambda(s_t)$ describes how habits are formed from past aggregate endowments. In this framework, 'bad times' refers to times of low surplus consumption ratios (when consumption is close to the habit level), and 'negative shocks' refers to negative consumption growth shocks ϵ^L. The sensitivity function $\lambda(s_t)$ governs the dynamic of the surplus consumption ratio:

$$\lambda(s_t) = \begin{cases} \frac{1}{\overline{S}}\sqrt{1-2(s_t-\overline{s})} - 1 & \text{if } s_t \leq s_{max} \\ 0 & \text{elsewhere,} \end{cases}$$

where $\overline{S}$ and s_{max} are respectively the steady-state and upper bound of the surplus-consumption ratio. $\overline{S}$ measures the steady-state gap (in percentage) between consumption and habit levels. Note that the non-linearity of the surplus consumption ratio keeps habits always below consumption and marginal utilities always positive and finite. Assuming that $\overline{S} = \sigma\sqrt{\frac{\gamma}{1-\phi}}$ and $s_{max} = \overline{s} + (1-\overline{S})/2$, the sensitivity function leads to a constant risk free rate: $r^f = -\log(\delta) + \gamma g - \frac{\gamma^2\sigma^2}{2\overline{S}^2}$. This model delivers time-varying risk aversion for the lenders. Since the habit level depends on aggregate consumption, the local curvature of the lenders' utility function is $\gamma_t = \gamma/S_t$. When the endowment is close to the habit level, the surplus consumption ratio is low and the lender very risk averse.

Lenders supply any quantity of funds demanded by the small open economy, but they require compensation for the risk they bear. Lenders cannot default. When lenders are risk-neutral, they charge the borrower the interest rate that makes them break-even in expected value. In our model, lenders are risk-averse, and require not only a default premium, but also a *default risk premium*. They expect a higher return on average if defaults are more likely in bad times for them, i.e when their endowment is close to the habit level.

3.4 Recursive equilibrium

In order to describe the economy at time t, we need to keep track of the borrower's endowment stream, his outstanding debt, and the lender's past surplus consumption ratios. Let y^i and s denote the history of events up to t: $y^i = (y^i_0, ..., y^i_t)$ and $s = (s_0, ..., s_t)$. We denote x a column vector that summarizes this information: $x = [y^i, s]'$. Given that the two stochastic endowment processes are Markovian, we denote $f(x', x)$ the conditional density of x', e.g. the value of x at time $t+1$ given the initial value of x at time t. In what follows, the value of a variable in period $t+1$ is denoted with a *prime* superscript.

Given the initial state of the economy, the value of the default option is:

$$v^o(B, x) = max\{v^c(B, B', x), v^d(x)\},$$

where $v^c(B, B', x)$ denotes the contract continuation value, v^d the value of defaulting and v^o the value of function of being in good credit standing at the start of the period. If the government chooses to repay the debt coming to maturity, it can purchase some new debt. As a result, the value of staying in the contract is a function of the exogenous states y^B and s^L, the quantity of debt coming to maturity at time B and future debt B'. In case of default, all outstanding debt is erased, and the small economy is forced into autarky for a stochastic number of periods. Hence, the only state variables that influence the value v^d of defaulting are y^B and s^L. We now define more precisely v^c and v^d.

The value of default depends on the probability of re-accessing financial markets in the future and on the current output loss:

$$v^d(x) = u(y^{def}) + \beta \int_{x'} [\lambda v^o(0, x') + (1-\lambda) v^d(x')] f(x', x) dx',$$

where λ is the exogenous probability of re-entering international capital markets after a default.[11] As we have seen, when a borrower defaults, consumption is equal to the autarky value of output. In the following period, the borrower regains access to international capital markets with no outstanding debt with probability λ, or remains in autarky with probability $1-\lambda$.

The value of staying in the contract and repaying debt coming to maturity is:

$$v^c(B, x) = Max_{B'}\{u(c) + \beta \int_{x'} v^o(B', x') f(x', x) dx'\},$$

subject to the budget constraint (3.3). The borrower chooses B' to maximize utility and anticipates that the equilibrium bond price depends on the exogenous states variable and on the new debt B'.

[11] Kovrijnykh and Szentes (2007) explore the possibility of endogenizing λ.

Figure 3 plots the difference between the value of staying in the contract $v^c(B,x)$ and the value of defaulting $v^d(x)$ as a function of the log trend growth g, for an initial debt level equal to 15 percent of the current endowment and when the investors' surplus consumption ratio is equal to $\overline{s}^L$. When g is low, the borrower prefers to default. The intersection between the red line ($v^c(B,x) - v^d(x)$ and the blue line (0) determines a threshold such that the borrower will default (repay) whenever g is smaller (bigger) than it.

Let Υ denotes the set of possible values for the exogenous states x. For each value of B, the small open economy default policy is the set $D(B)$ of exogenous states such that the value of default is larger than the value of staying in the contract:

$$D(B) = \{x \in \Upsilon : v^d(x) > v^c(B,x)\}.$$

Similarly, $R(B)$ is the set of exogenous states such that the value of default is smaller than the value of staying in the contract. The repayment set $R(B)$ is the complement to $D(B)$:

$$R(B) = \{x \in \Upsilon : v^d(x) \leq v^c(B,x)\}.$$

The default probability dp is endogenous and depends on the amount of outstanding debt and on the endowment realization. In particular, the default probability is related to the default set through:

$$dp(B',x) = \int_{D(B')} f(x',x)dx',$$

where $dp(B',x)$ denotes the expectation at time t of a default at time $t+1$ for a given level B' of outstanding debt due at time $t+1$. Figure 4 plots the default policy set $D(B)$ as a function of the beginning of period asset position B and the trend growth g, when the investors' surplus consumption ratio is equal to $\overline{s}^L$. The grey shaded area denotes combinations of B and g such that the borrower optimally choose to default. Countries tend to default for larger debt levels and when the endowment is low.

3.5 Bond Prices

Bond prices $Q(B',x)$ are a function of the current state vector x and the desired level of borrowing B'. If borrowers do not default at date $t+1$, lenders receive payoffs equal to the face value of the bonds, which is normalized to 1. In case of default at date $t+1$, payoffs are zero. Starting from the investor's Euler equation, the bond price function is:

$$Q(B',x) = E[M' 1_{1-dp(B',x)}] = E[M']E[1_{1-dp(B',x)}] + cov[M', 1_{1-dp(B',x)}], \tag{3.5}$$

where M' is the investors' stochastic discount factor and is equal to:

$$M' = \delta \frac{U_c(C', H')}{U_c(C, H)} = \delta (\frac{S'C'}{SC})^{-\gamma} = \delta e^{-\gamma[g + (\phi - 1)(s_t - \overline{s}) + (1 + \lambda(s_t))(\Delta c_{t+1} - g)]}.$$

A risk free asset pays one unit of consumption good in any state of the world and has a price equal to $Q^{rf} = E[M']$. If investors are risk-neutral, sovereign bond prices depend only on expected default probabilities: $Q(B', x) = E[1_{1-dp(B',x)}] \times Q^{rf}$. Investors' risk aversion introduce a new component to sovereign bond pricing. For a given default probability, bond prices depend on the covariance between investors' stochastic discount factors and default events. If defaults tend to occur in bad times for investors (e.g when their marginal utility of consumption is high), the covariance term in (3.5) is negative, bond prices are low and yields are high. Likewise, if defaults tend to occur in good times for investors, yields are low. Figure 5 plots the bond price (solid line) in 3.5 as a function of the borrowing choice (B') for the lowest (red) and highest (blue) values of the log trend growth g in our grid. The dashed line in the figure represents the bond price function for a model with risk neutral investors. The figure shows two important implications of our model. First, for a given borrowing choice, bond prices are lower in bad times for the borrower. The blue line is always above the red line, but when the two lines are both at 0 or at the risk-free level. Second, bonds issued by countries that tend to default more frequently when the investors' marginal utility is high are riskier and have lower prices. This effect is captured by a model with risk averse investors. In the figure, we plot the bond price functions of a country with a business cycle that is positively related to the investors' consumption growth (in the figure the correlation coefficient ρ_g is equal to 0.5). Bond prices of the model with risk averse investors (solid line) are always below or equal bond prices of the model with risk neutral investors (dashed line) and never above it.

4 Simulation

We simulate the model at quarterly frequency. We start with a brief overview of the calibration.

4.1 Calibration

Table 3 reports all the parameters used in the simulation. Values describing lenders' consumption growth and preferences are from Campbell and Cochrane (1999). They correspond to post-World War II US consumption and real risk-free rates. The value of δ matches an average US real log risk-free rate of 1 percent per annum. Values describing the borrowers' endowments and constraints are mostly from Aguiar and Gopinath (2006). We review them here rapidly. The computational algorithm is described in the appendix.

The direct output cost of default θ is equal to 6 percent per period in line with the evidence of a significant output drop in the aftermath of a default (see, for example, Rose (2005)). This value, however, is higher than in Aguiar and Gopinath (2006). The probability of re-entering capital markets after a default λ is equal to 10 percent per period, implying an average exclusion of 6.6 quarters, as in Aguiar and Gopinath (2006) and consistent with the evidence reported in Benjamin and Wright (2009).[12]

The risk aversion parameter γ in the borrowers' (and lenders') utility function is set equal to 2. Models of this class require low values for β in order to generate large values for the debt to GDP ratio. We assume that borrowers have a low time discount factor of $\beta = 0.80$ as in Aguiar and Gopinath (2006). We also follow Aguiar and Gopinath (2006) for the description of the permanent component of the endowment process. For its temporary component, we pick a lower standard deviation for the shocks, since we consider a simulation with both temporary and permanent shocks. We pick σ_z to match the average volatility of GDP growth in our sample.

4.2 Building Portfolios of Simulated Data

In equilibrium, investors know expected default probabilities and require higher risk premia from borrowers that are more likely to default when investors' consumption is close to their habit levels. We solve our model for a set of 15 uniformly spaced different values of ρ^i, which is the correlation between investors' consumption growth and borrower's endowments. These correlation coefficients vary from $-.5$ to $.5$. Each ρ^i corresponds to a different sovereign borrower. We simulate time series data for countries that differ only with respect to ρ^i and face the same time series for investors' consumption growth. The values for all the other parameters are those in Table 3.

We use the simulated data to build portfolios that mimic the EMBI portfolios described in section 1. What are the equivalents to the Standard and Poor's ratings and EMBI bond betas that we used in section 1 on actual data? In the model, expected default probabilities exist in closed form. We do not need to rely on ratings to proxy them. We denote $E[dp^i]$ the investors' expectation that country i will default next period. In the model, we also have a more direct measure of the business cycle's correlation with the US economy than the bond betas we previously computed. Here, we obtain β^i_{SIM} as the slope coefficient from a regression of the borrower i's past output growth up to time t on a constant and the investor's past endowment growth up to time t. We use a rolling window of 250 periods.

[12] The empirical evidence on the time-length of exclusion is mixed. For example, Gelos, Sahay, and Sandleris (2004) find that in the 1980s the average time of exclusion is 4.7 years, while only 0.3 years in the 1990s. As an example, Argentina defaulted in 2001 and then restructured three quarters of the $95 billion defaulted debt in a 2005 swap. But in September 2008, Argentina still faced legal actions by investors holding out for full repayment. Argentina could not issue new debt on international capital markets for fear it would be embargoed (Financial Times, 25 September, 2008).

The building portfolio strategy runs again in two steps. First, at the end of each period t, we sort all countries in 3 portfolios on the basis of the expected default probability $E[dp^i]$ at that time. Second, at the end of each period t, we sort all countries within each of the previous 3 groups into 2 portfolios on the basis of β^i_{SIM}. The 6 portfolios are re-balanced at the end of every period. For each portfolio j, we compute the excess returns $r^{e,j}_{t+1}$ by taking the average of the excess returns in the portfolio. Excess returns correspond to the returns in emerging countries minus the risk-free rate in the large, developed economy. We have a total of 34 simulated countries, for 5,000 quarters. We compute β^j_{SIM} starting in quarter 500 and use the last 600 quarters for our analysis (150 years). Countries in default in a given quarter are excluded from the sample, given that they do not have access to international capital markets. As a result, the total number of countries in our portfolios varies slightly over time. Table 4 provides an overview of the 6 portfolios.

For each portfolio j, we report the average value for β^j_{SIM}, the excess return $r^{e,j}$, the expected default probability $E[dp^j]$ and the debt to output ratio. All the moments are annualized: we multiply the mean of the quarterly data by 4 and the standard deviation by 2. The Sharpe ratio is the ratio of the annualized mean to the annualized standard deviation.

The first panel reports the average β^j_{SIM} for countries in portfolio j. There is a stark contrast between the first three and the last three portfolios. The business cycle of countries with a low β^j_{SIM} is negatively correlated with the investors' endowment growth. These countries on average default more frequently when investors' consumption is high and above their habit levels. On the contrary, countries with a high β^j_{SIM} default more frequently when investors' consumption is low and close to their habit levels. Figures 9 and 9 in Appendix C make this point clearly; they present average consumption paths in the borrowing and lending countries around default episodes in the case of positively correlated business cycles. The second panel reports average expected default probabilities. Within each $\beta^{low,high}_{SIM}$-group, there is a cross-section of average default probabilities, with a spread up to 0.5 percent. These first two panels correspond to the sorting variables.

Let us turn now to average excess returns. Countries with higher default probabilities offer higher returns. This is the first order effect, with a difference of around 240 basis points between portfolios with low default probabilities (1 and 4) and portfolios with high default probabilities (3 and 6). Countries with larger values of β^j_{SIM} pay higher returns. This is true at all levels of default probabilities. This is the second order effect. The difference in excess returns between low and high beta countries is particularly striking for countries with high default probabilities. It amounts to 40 basis points annually. Comparing these spreads to their actual counterparts, we note that both default probability and beta spreads are much larger in the data than in the model. This is particularly the case for the latter, which is an order of magnitude smaller than in the data. The model also misses the volatility of excess returns by approximately the same proportion, thus delivering significant spreads and high Sharpe ratios. Matching sovereign bond returns calls for longer maturities. Hatchondo and Martinez (2009) show that, even in a model with risk-neutral investors, longer durations increase the mean and volatility of sovereign prices. We do not attempt to match these moments in this one-quarter model.

The model produces reasonable levels of debt to GDP ratios of around 30 percent, slightly lower than the average of 45 percent measured in our sample. The spread in returns due to business cycle betas is not due to higher levels of debt, as the last panel shows. It is actually the opposite: high beta countries tend to pay higher interest rates even if they borrow less in equilibrium. These features echo the characteristics of our EMBI bond portfolios.

5 Conclusion

In this paper, we show that emerging market sovereign bond betas impact sovereign bond spreads and that risk matters on these markets. In the data, countries with higher bond betas pay higher borrowing rates. The difference in spreads between countries with high and low betas is large, as large actually as the difference between low and high default probabilities. Models of optimal borrowing and endogenous defaults with risk neutral investors cannot account for our empirical findings. We study one example of a general equilibrium model of sovereign borrowing and defaults with risk-averse investors. In the model, borrowing countries only differ along one dimension: their endowments are more or less correlated to the lenders' consumption. Lenders' habit preferences lead to spreads in returns between low and high default probability countries, and between high and low beta countries, albeit smaller than in the data.

Our empirical methodology and our model are relevant to address default risk premia in other contexts. The literature on consumer bankruptcy faces endogenous decisions to default that are similar to the ones described in this paper. Notable examples include Chatterjee, Corbae, Nakajima, and Rios-Rull (2007) and Livshits, MacGee, and Tertilt (2007). Likewise, firm dynamics depend on financial market features and endogenous defaults, as shown in Cooley and Quadrini (2001). These papers, however, consider only risk-neutral financial intermediaries. Our work shows that lenders' risk aversion affect both debt quantity and prices.

References

Abel, A. A. (1990): "Asset Prices under Habit Formation and Catching Up with the Joneses," *American Economic Review*, 80(2), 38–42.

Adler, M., and R. Qi (2003): "Long-Duration Bonds and Sovereign Defaults," *Emerging Markets Review*, 4, 91120.

Aguiar, M., and G. Gopinath (2006): "Defaultable debt, interest rates and the current account," *Journal of International Economics*, 69, 64–83.

——— (2007): "Emerging Market Business Cycles: The Cylce is the Trend," *Journal of Political Economy*, 115(1).

Alvarez, F. E., and U. J. Jermann (2000): "Efficiency, Equilibrium, and Asset Pricing with Risk of Default," *Econometrica*, 68(4), 775–798.

Amador, M. (2003): "A Political Model of Sovereign Debt Repayment," Stanford Graduate School of Business Working Paper.

Andrade, S. C. (2009): "A Model of Asset Pricing under Country Risk," *Journal of International Money and Finance*, 28 (4), 671–695.

Andrews, D. W. (1991): "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation," *Econometrica*, 59(1), 817–858.

Arellano, C. (2008): "Default Risk and Income Fluctuations in Emerging Economies," *American Economic Review*, 98.

Arellano, C., and A. Ramanarayanan (2009): "Default and the Term Structure in Sovereign Bonds," Working Paper.

Arora, V., and M. Cerisola (2001): "How Does U.S. Monetary Policy Influence Sovereign Spreads in Emerging Markets," *IMF Staff Papers*, 48.

Atkeson, A. (1991): "International Lending with Moral Hazard and Risk of Repudiation," *Econometrica*, 59(4), 1069–1089.

Bansal, R., and A. Yaron (2004): "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *The Journal of Finance*, 59, 1481–1509.

Barro, R. (2006): "Rare Disasters and Asset Markets in the Twentieth Century," *Quarterly Journal of Economics*, 121, 823.

Bekaert, G., and C. R. Harvey (1995): "Time-Varying World Market Integration," *Journal of Finance*, 50 (2), 403–444.

——— (2000): "Foreign Speculators and Emerging Equity Markets," *Journal of Finance*, 55 (2), 565 – 613.

Bekaert, G., C. R. Harvey, and C. Lundblad (2007): "Liquidity and Expected Returns: Lessons from Emerging Markets," *Review of Financial Studies*, 20(6), 1783–1832.

Benjamin, D., and M. L. J. Wright (2009): "Recovery Before Redemption: A Theory of Delays in Sovereign Debt Renegotiations," Working paper UCLA.

Bernoth, K., J. von Hagen, and L. Schuknecht (2004): "Sovereign Risk Premia in the European Government Bond Market," ECB Working Paper 369.

Bi, R. (2006): "Debt Dilution and the Maturity Structure of Sovereign Bonds," mimeo.

Boldrin, M., L. Christiano, and J. D. Fisher (2001): "Habit Persistence, Asset Returns and the Business Cycle," *American Economic Review*, 91(1), 149–166.

Bolton, P., and O. Jeanne (2008): "Structuring and Restructuring Sovereign Debt: The Role of a Bankruptcy Regime," *American Economic Review*, (forthcoming), forthcoming.

Broner, F. A., G. Lorenzoni, and S. L. Schmukler (2005): "Why Do Emerging Economies Borrow Short Term," mimeo.

Bulow, J., and K. Rogoff (1989): "Sovereign Debt: Is to Forgive to Forget?," *American Economic Review*, 79(1), 43–50.

Campbell, J. Y., and J. H. Cochrane (1999): "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy*, 107(2), 205–251.

Cavanagh, J., and R. Long (1999): "Methodology Brief: Introducing the J.P. Morgan Emerging Markets Bond Index Global," J.P. Morgan Emerging Market Research.

Chatterjee, S., D. Corbae, M. Nakajima, and J. Rios-Rull (2007): "A Quantitative Theory of Unsecured Consumer Credit with Risk of Default," *Econometrica*, 75 (6), 15251589.

Chatterjee, S., and B. Eyigungor (2009): "Maturity, Indebtedness, and Default Risk," Federal Reserve Bank of Philadelphia Working Paper.

Cochrane, J. H. (2001): *Asset Pricing*. Princeton University Press, Princeton, NJ.

Cole, H. L., and T. J. Kehoe (2000): "Self-Fulfilling Debt Crises," *Review of Economic Studies*, 67, 91–216.

Constantinides, G. M. (1990): "Habit Formation: A Resolution of the Equity Premium Puzzle," *Journal of Political Economy*, 98, 519–543.

Cooley, T. F., and V. Quadrini (2001): "Financial Markets and Firm Dynamics Financial Markets and Firm Dynamics," *American Economic Review*, 91 (5), 1286–1310.

Duffie, D., L. H. Pedersen, and K. J. Singleton (2003): "Modeling Sovereign Yield Spreads: A Case Study of Russian Debt," *Journal of Finance*, 83(1).

Eaton, J., and M. Gersovitz (1981): "Debt with Potential Repudiation: Theoretical and Empirical Analys," *Review of Economic Studies*, 48(2), 289–309.

Edwards, S. (1984): "LDC Foreign Borrowing and Default Risk: An Empirical Investigation, 1976-80," *American Economic Review*, 74(4), 726–734.

Elton, E. J., M. J. Gruber, D. Agrawal, and C. Mann (2001): "Explaining the Rate Spread on Corporate Bonds," *Journal of Finance*, 56(1), 247–277.

Fama, E., and J. MacBeth (1973): "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81, 3–56.

Fama, E. F., and K. R. French (1993): "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33, 3–56.

Favero, C., M. Pagano, and E.-L. von Thadden (2005): "Valuation, Liquidity and Risk in Government Bond Markets," IGIER Working Paper.

Fostel, A., and J. Geanakoplos (2008): "Leverage Cycles and the Anxious Economy," *American Economic Review*, 98(4), 1211–1244.

Gabaix, X. (2008): "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro Finance," Working Paper NYU Stern.

Gelos, G. R., R. Sahay, and G. Sandleris (2004): "Sovereign Borrowing by Developing Countries: What Determines Market Access?," IMF Working Paper 221.

Gonzalez-Rozada, M., and E. L. Yeyati (2008): "Global Factors and Emerging Market Spreads," *Economic Journal*, 118.

Guerrieri, V., and P. Kondor (2008): "Fund managers and defaultable debt," University of Chicago, mimeo.

Hansen, L. P. (1982): "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 50, 1029–54.

Hansen, L. P., and S. F. Richard (1987): "The Role of Conditioning Information in Deducing Testable Restrictions Implied by Dynamic Asset Pricing Models," *Econometrica*, 55(3), 587–613.

Hatchondo, J. C., and L. Martinez (2009): "Long-Duration Bonds and Sovereign Defaults," *Journal of International Economics*, 79, 117125.

Hatchondo, J. C., L. Martinez, and H. Sapriza (2007): "Quantitative Models of Sovereign Defaults and the Threat of Financial Exclusion," *Economic Quarterly*, 93(3), 251–286.

Herb, C., C. R. Harvey, and T. Viskanta (1995): "Country Credit Risk and Global Portfolio Selection," *Journal of Portfolio Management*.

Hilscher, J., and Y. Nosbusch (2009): "Determinants of Sovereign Risk: Macroeconomic Fundamentals and the Pricing of Sovereign Debt," *Review of Finance, forthcoming*.

Jermann, U. (1998): "Asset Pricing in Production Economies," *Journal of Monetary Economics*, 41(2), 257–275.

Kamin, S. B., and K. von Kleist (1999): "The Evolution and Determinants of Emerging Market Credit Spreads in the 1990s," International Finance Discussion Papers.

Kehoe, T. J., and D. K. Levine (1993): "Debt-Constrained Asset Markets," *Review of Economic Studies*, 60, 868–888.

Kocherlakota, N. (1996): "Implications of Efficient Risk Sharing without Commitment," *Review of Economic Studies*, 63, 595–610.

Kovrijnykh, N., and B. Szentes (2007): "Equilibrium Default Cycles," *Journal of Political Economy*, 115(3), 403–446.

Krainer, J. (2004): "What Determines the Credit Spread," *FRBSF Economic Letter*, (36).

Lettau, M., and H. Uhlig (2000): "Can Habit Formation Be Reconciled with Business Cycle Facts?," *Review of Economic Dynamics*, 3, 77–79.

Livshits, I., J. MacGee, and M. Tertilt (2007): "Consumer Bankruptcy: A Fresh Start," *American Economic Review*, 97 (1), 402–418.

Lizarazo, S. V. (2008): "Default Risk and Risk Averse International Investors," Working paper ITAM.

Long Chen, P. C.-D., and R. S. Goldstein (2008): "On the Relation Between Credit Spread Puzzles and the Equity Premium Puzzle," *Review of Financial Studies*, 22 (9), 3367–3409.

Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton (2007): "How Sovereign is Sovereign Credit Risk?," Working Paper 13658, National Bureau of Economic Research.

Martin, I. (2008): "Consumption-Based Asset Pricing with Higher Cumulants," Working Paper Stanford University.

McGuire, P., and M. A. Schrijvers (2003): "Common Factors in Emerging Market Spreads," *BIS Quarterly Review*.

Mehra, R., and E. Prescott (1985): "The Equity Premium: A Puzzle," *Journal of Monetary Economics*, 15, 145–161.

Neumeyer, P., and F. Perri (2005): "Business Cycles in Emerging Economies: The Role of Interest Rates," *Journal of Monetary Economics*, 52(2), 345–380.

Newey, W. K., and K. D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55(3), 703–708.

Pan, J., and K. J. Singleton (2008): "Default and Recovery Implicit in the Term Structure of Sovereign CDS Spreads," *Journal of Finance*, 5.

Patton, A. J., and A. Timmermann (2008): "Portfolio Sorts and Tests of Cross-Sectional Patterns," mimeo.

Pouzo, D. (2009): "Optimal Taxation with Endogenous Default Under Incomplete Markets," Working paper.

Rietz, T. A. (1988): "The Equity Risk Premium: A Solution?," *Journal of Monetary Economics*, 22(1), 117–131.

Rose, A. (2005): "One Reason Countries Pay their Debts: Renegotiation and International Trade," *Journal of Development Economics*, 77(1), 189–206.

Ross, S. A. (1976): "The Arbitrage Theory of Capital Asset Pricing," *Journal of Economic Theory*, 13, 341–360.

Shanken, J. (1992): "On the Estimation of Beta-Pricing Models," *The Review of Financial Studies*, 5(2), 1–33.

Tauchen, G., and R. Hussey (1991): "Quadrature-Based Methods for Obtaining Approximate Solutions to Nonlinear Asset Pricing Models," *Econometrica*, 59(2), 371–396.

Tomz, M. (2007): *Reputation and International Cooperation, Sovereign Debt across Three Centuries*. Princeton University Press, Princeton, NJ.

Uribe, M., and V. Yue (2006): "Country Spreads and Emerging Markets: Who Drives Whom?," *Journal of International Economics*, 69, 6–36.

Verdelhan, A. (2010): "A Habit-Based Explanation of the Exchange Rate Risk Premium," *Journal of Finance*, 65 (1), 123–145.

Wachter, J. (2006): "A Consumption-Based Model of the Term Structure of Interest Rates," *Journal of Financial Economics*, 79, 365–399.

Weil, P. (1989): "The Equity Premium Puzzle and the Risk-Free Rate Puzzle," *Journal of Monetary Economics*, 24, 401–424.

Westphalen, M. (2001): "The Determinants of Sovereign Bond Credit Spread Changes," Université de Lausanne, mimeo.

Yue, V. Z. (2010): "Sovereign Default and Debt Renegotiation," *Journal of International Economics, forthcoming*.

Zame, W. R. (1993): "Efficiency and the Role of Default when Security Markets are Incomplete," *American Economic Review*, 83(5), 1142–1164.

Table 1: EMBI Portfolios Sorted on Credit Ratings and Bond Market Betas (Equal Weights)

Portfolios	1	2	3	4	5	6
β^j_{EMBI}		Low			High	
S&P	*Low*	*Medium*	*High*	*Low*	*Medium*	*High*
			EMBI Bond Market Beta: β^j_{EMBI}			
Mean	0.37	0.44	0.26	1.07	1.25	1.56
Std	0.63	0.48	0.61	0.42	0.63	0.68
			S&P Default Rating: dp^j			
Mean	9.05	11.42	14.43	8.69	11.28	14.60
Std	1.55	1.14	1.55	1.32	1.22	1.41
			Excess Return: $r^{e,j}$			
Mean	3.01	5.62	6.54	7.03	10.15	13.50
Std	10.39	11.54	16.63	9.10	12.84	19.26
SR	0.29	0.49	0.39	0.77	0.79	0.70
			Debt/GNP			
Mean	0.44	0.45	0.56	0.41	0.44	0.51
Std	0.16	0.12	0.13	0.10	0.12	0.13

Notes: This table reports, for each portfolio j, the average beta β_{EMBI} from a regression of EMBI returns on the total returns on the Merrill Lynch US BBB corporate bond index, the average EMBI log total excess return, the average Standard and Poor's credit rating, post-formation betasand the average external debt to GNP ratio. Excess returns are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. Panel I reports equally-weighted statistics. Panel II reports value-weighted statistics. The portfolios are constructed by sorting EMBI countries on two dimensions: every month countries are sorted on their probability of default, measured by the S&P credit rating, and on β_{EMBI}. Note that Standard and Poor's uses letter grades to describe a country's credit worthiness. We index Standard and Poor's letter grade classification with numbers going from 1 to 23. Data are monthly, from JP Morgan and Standard and Poor's (Datastream). The sample period is 1/1995 - 5/2009.

Table 2: Asset Pricing: Portfolios Sorted on Credit Ratings and Bond Market Betas

Panel I: Factor Prices and Loadings					
	λ_{US-BBB}	b_{US-BBB}	R^2	$RMSE$	$p-value$
GMM_1	6.93	1.54	77.83	1.58	
	[4.63]	[1.03]			22.02
GMM_2	6.49	1.45	75.50	1.66	
	[2.92]	[0.65]			22.19
FMB	6.93	1.53	73.00	1.58	
	[2.63]	[0.58]			43.79
	(2.71)	(0.60)			49.89
$Mean$	**6.52**				
Std	[0.49]				
Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	β_{US-BBB}^j	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	-2.93	0.91	28.88		
	[2.42]	[0.12]			
2	-0.16	0.88	22.14		
	[2.89]	[0.12]			
3	-0.33	1.05	15.07		
	[5.04]	[0.24]			
4	1.00	0.92	38.89		
	[2.21]	[0.11]			
5	1.81	1.28	37.37		
	[2.63]	[0.16]			
6	1.86	1.78	32.33		
	[5.06]	[0.35]			
All				6.27	0.39

Notes: Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. All excess EMBI returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS regression results. We regress each portfolio return on a constant (α) and the risk factor (the corresponding slope coefficient is denoted β). R^2s are reported in percentage points. The alphas are annualized and in percentage points. The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), page 234). Data are monthly, from JP Morgan in Datastream. The sample period is 1/1995-5/2009.

Table 3: Parameters

Variable	Notation	Value
Lenders		
Risk-aversion	γ	2.00
Mean consumption growth (%)	g	1.89
Standard deviation of consumption growth (%)	σ	1.50
Persistence of the surplus consumption ratio	ϕ	0.87
Mean risk-free rate (%)	r^f	1.00
Borrowers		
Endowment		
Permanent: Persistence	α_g	0.17
Permanent: Standard deviation (%)	σ_g	6.00
Permanent: Mean (%)	μ_g	2.21
Temporary: Persistence	α_z	0.90
Temporary: Standard deviation (%)	σ_z	1.00
Temporary: Mean (%)	μ_z	$-.5\sigma_z^2$
Preferences		
Risk-aversion	γ	2.00
Discount factor	β	0.80
Direct default cost (%)	θ	6.00
Probability of re-entry (%)	λ	10.00

The table reports the parameters used in the simulation. The model is simulated at quarterly frequency. The values for the direct output cost and the probability of re-entering financial markets after a default are per quarter. In the table, the mean and standard deviations of endowments are annualized (e.g. they are reported as $4g^L$, 2σ, $2\sigma_g$, $2\sigma_z$), as well as the persistence of the surplus consumption ratio (ϕ^4) and the risk-free rate ($4r^f$). Values describing lenders' consumption growth and preferences are from Campbell and Cochrane (1999) and correspond to post-World War II US consumption data. These parameters imply a steady-state endowment ratio $\overline{S}$ equal to 5.9 percent and a maximum surplus endowment ratio S_{max} of 9.4 percent. Values describing the borrowers' endowments are from Aguiar and Gopinath (2006).

Table 4: Portfolios of Simulated Data

Portfolios	1	2	3	4	5	6
β^j_{SIM}		Low			High	
$E[dp^j]$	*Low*	*Medium*	*High*	*Low*	*Medium*	*High*
			Consumption beta: β^j_{SIM}			
Mean	−0.38	−0.37	−0.52	0.29	0.33	0.32
Std	0.64	0.59	0.59	0.66	0.56	0.62
			Default probability: $E[dp^j]$			
Mean	0.96	1.92	3.93	0.84	1.81	3.62
Std	0.69	0.95	1.24	0.54	0.91	1.38
			Excess Return: $r^{e,j}$			
Mean	0.82	1.49	3.22	0.92	1.78	3.64
Std	0.57	0.79	1.18	0.58	0.87	1.37
SR	1.44	1.88	2.73	1.61	2.04	2.65
			Debt/GNP: d^j			
Mean	28.90	30.13	31.46	29.04	29.62	30.45
Std	5.00	2.57	3.32	3.97	2.39	3.28

Notes: This table reports, for each portfolio j, the slope coefficient β_{SIM} from a regression of borrowers' output growth on the investors' consumption growth, the average excess return, the average expected probability of default and the debt to output ratio. Excess returns are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. Data comes from simulating our model under the assumption of habit preferences for foreign lenders. The portfolios are constructed by sorting data for different countries obtained by simulating our model in two dimensions: every month, countries are sorted on expected default probabilities and on β_{SIM}. The sample has 600 quarters.

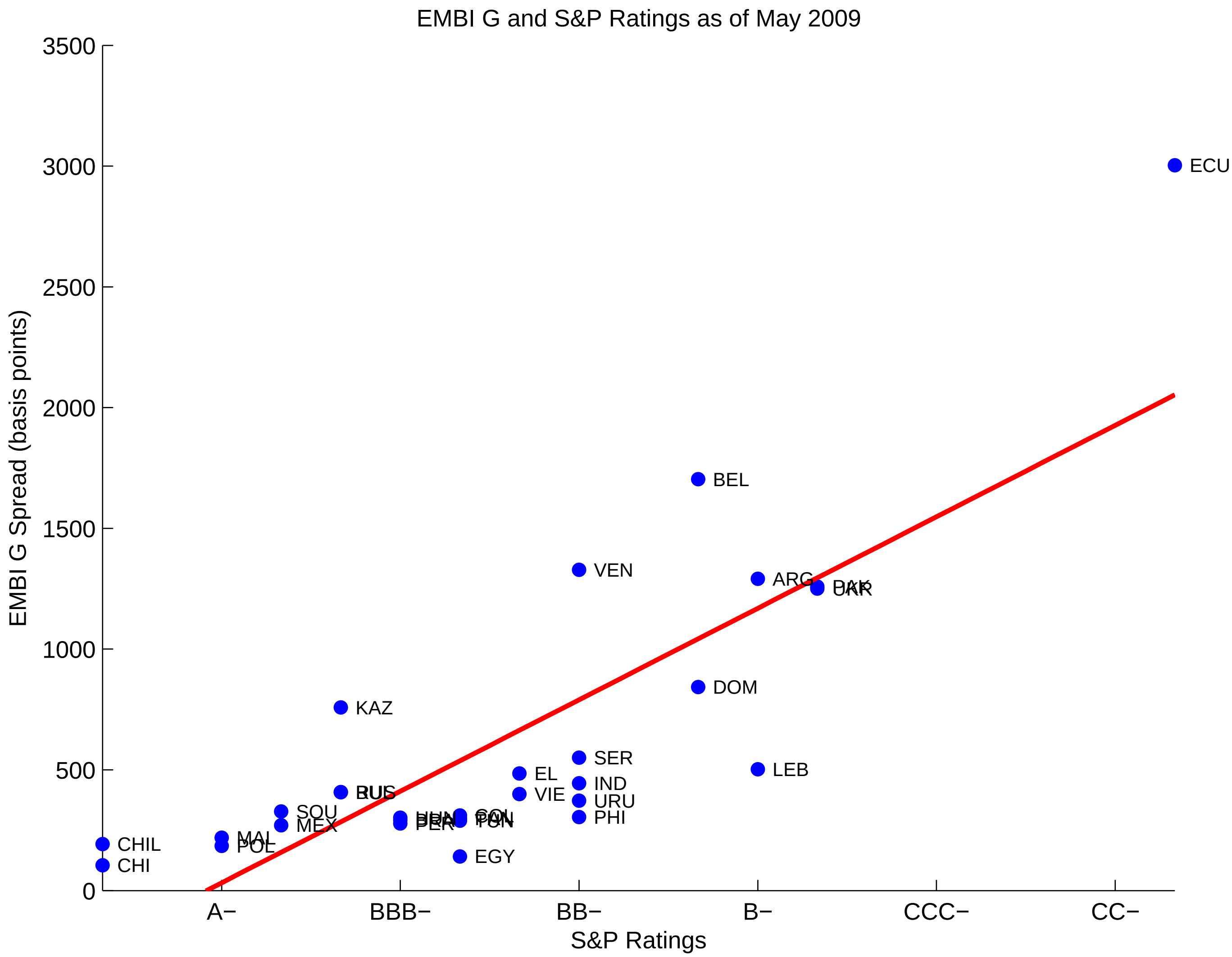

Figure 1: EMBI Global Annual Spreads and Standard and Poor's Ratings

The figure plots, for each country in the EMBI Global Index, the annual stripped spread against the Standard and Poor's credit rating at the end of May 2009. Spreads are in basis points. Standard and Poor's credit ratings are indexed from 1 (AAA) to 23 (SD). A higher number implies a lower credit worthiness. Data are from Datastream.

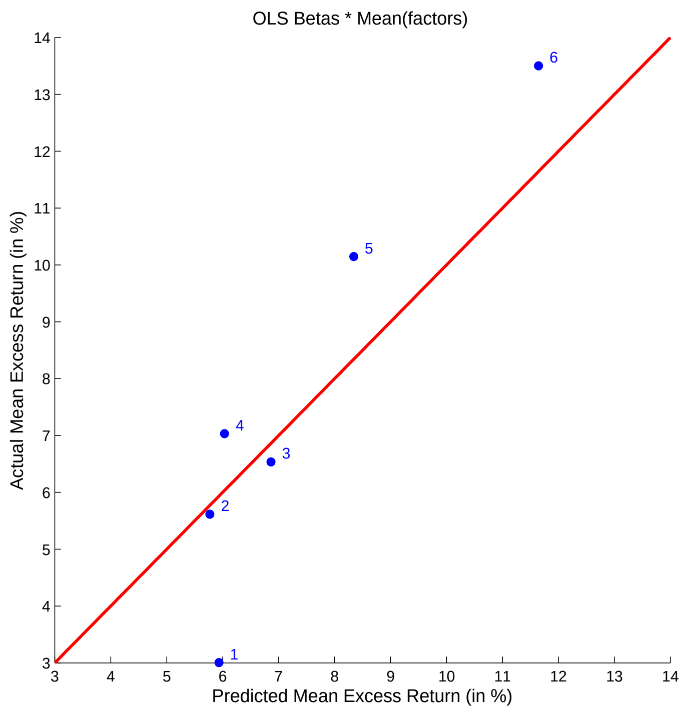

Figure 2: Predicted versus Realized Average Excess Returns

The figure plots realized average EMBI excess returns on the vertical axis against predicted average excess returns on the horizontal axis. We regress each portfolio j's actual excess returns on a constant and our risk factor (e.g, the return on the $US - BBB$ bond index) to obtain the slope coefficient β^j. Each predicted excess return then corresponds to the OLS estimate β^j times the sample mean of the risk factor. All returns are annualized. Data are monthly. The sample period is 1/1995-5/2009.

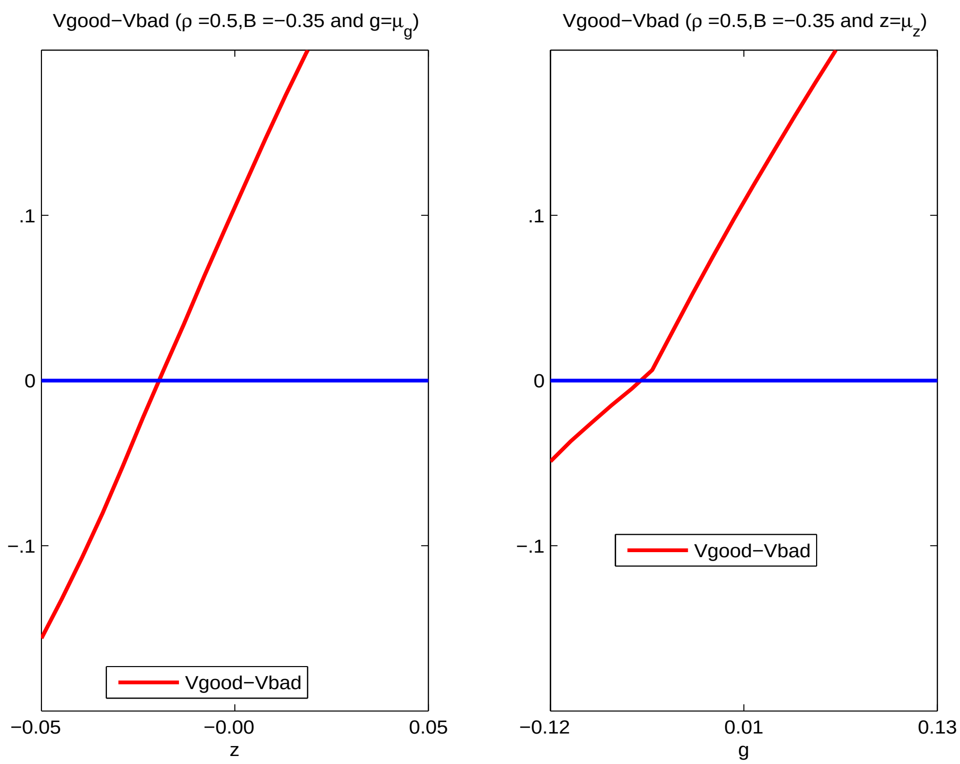

Figure 3: The Value of Repaying vs the Value of Defaulting

This figure plots the difference between the value of staying in the contract ($v^c(B,x)$) and the value of defaulting $v^d(x)$ as a function of the time-varying mean growth rate g (right panel) or temporary shocks z (left panel). The investors' surplus consumption ratio is equal to $\overline{s}$ and the initial asset position is equal to $B = -.35$. The correlation coefficient between shocks to trend growth and shocks to investors' consumption growth ρ_g is equal to 0.5.

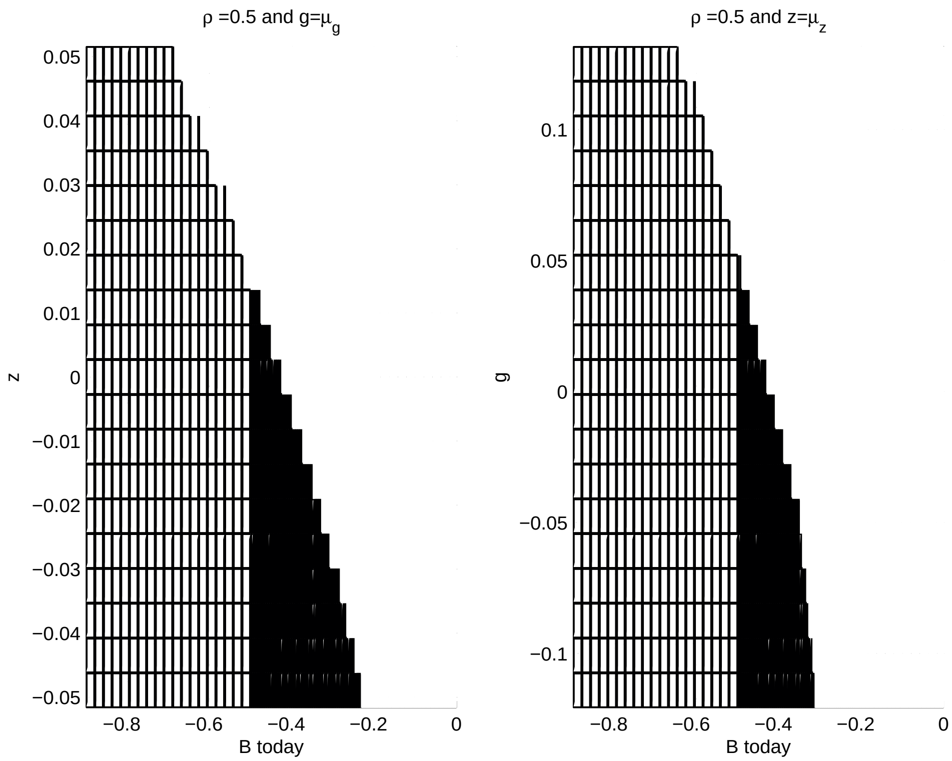

Figure 4: Default Policy Set

This figure plots the default policy set $D(B)$ as a function of the beginning of period asset position and consumption shock. The investor's surplus consumption ratio is equal to $\overline{s}$. In the left panel, we focus on temporary shocks and set the mean growth rate g to its mean value μ_g. In the right panel, we focus on trend shocks and set $\sigma_z = 0$ in the endowment process. The cross-country correlation in consumption growth shocks ρ_g is equal to 0.5.

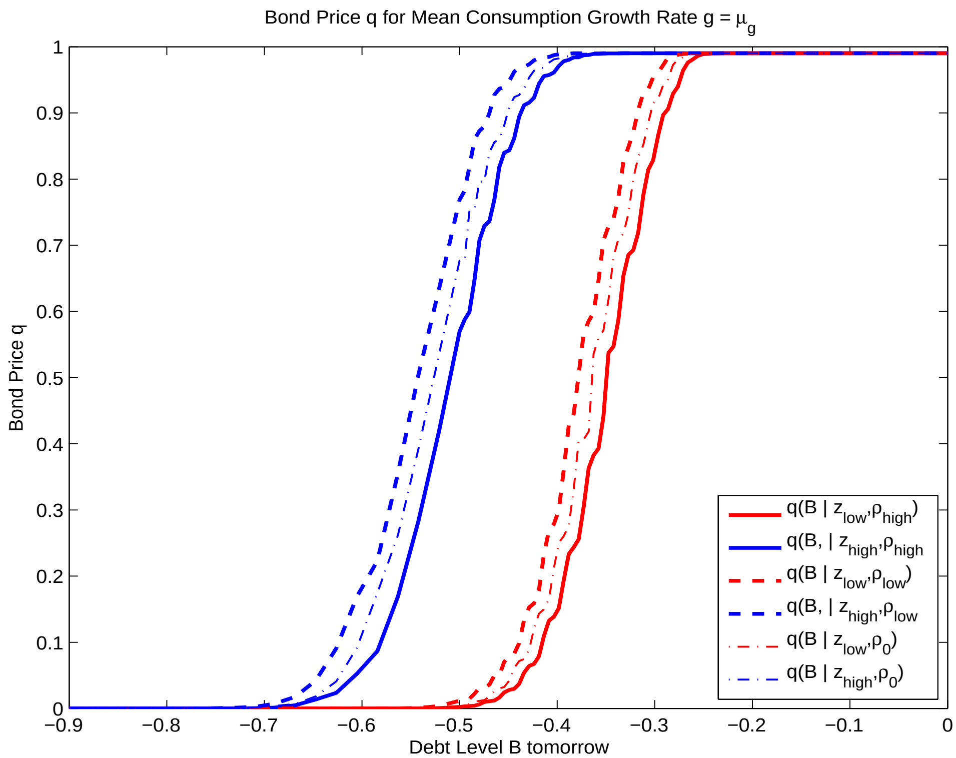

Figure 5: Bond Price Function

This figure plots the bond price $Q(B')$ of a model with risk averse investors. In the figure, the investors' surplus consumption ratio is equal to $\bar{s}$. The correlation coefficient between lenders' and borrowers' consumption growth shocks ρ_g is equal to either -.5 (large dotted line), 0 (dash-dotted line) or 0.5 (large line). For each correlation coefficient, we consider two cases: a negative and a positive shock z to the borrowers' endowment growth rates (-/+ 2%).

Sovereign Risk Premia
- Supplementary Appendix -

Appendix A Data: EMBI Global Sample

Table 5 reports summary statistics on the EMBI stripped spreads for our sample. All spreads are annual. Table 6 reports the ratio of debt to GDP for the countries in our sample, using data from the Global Development Finance.

Appendix B Robustness Checks: Additional Statistics, Different Sorts, Different Risk Factors and Conditional Asset Pricing

- Table 7 reports how frequently countries change portfolios. As an example, Figure 6 plots, for Argentina and Mexico, the monthly S&P credit rating, the bond market beta β_{EMBI} and the portfolio allocation.
- Table 8 reports additional statistics for our benchmark portfolios of countries sorted on credit ratings and bond market betas.
- Figure 7 plots average rolling betas for each benchmark portfolio.
- Table 9 reports summary statistics for portfolios of countries sorted on credit ratings and bond market betas. Statistics are value-weighted.
- Table 10 reports similar information for portfolios of countries sorted on credit ratings and stock market betas. Statistics are equally-weighted.
- Table 11 reports asset pricing results obtained with the equally-weighted portfolios presented in Table 10. The sole risk factor is the return on a US BBB bond index.
- Figure 8 compares expected and realized average excess returns obtained with the equally-weighted portfolios presented in Table 10.
- Table 12 reports the results of our conditional asset pricing tests using VIX as the conditioning variable.
- Table 13 reports asset pricing results obtained with the log change in the VIX index as risk factor.
- Table 14 reports asset pricing results obtained with the log change in the VIX index and the return on a US BBB bond index as risk factors.
- Table 15 reports asset pricing results obtained with the TED spread as risk factor.

Appendix C Model: Assumptions, Calibration, Simulation

GDP correlations Our model assumes that countries differ in one key dimension: the correlation of their output series with the lender's output. We verify here that such an heterogeneity exists in the data. We start off real GDP series for our EMBI countries and the US. We consider either annual or quarterly data. We extract their cyclical components using a HP filter (with the appropriate bandwidth parameter: 100 on annual and 1600 on quarterly data). Table 16 reports the obtained correlation coefficients between each EMBI country and the US. At annual frequency, we use all available data and thus start at different dates for each country. At quarterly frequency, we consider one common sample (1994 - 2008 as in the rest of the paper) and ignore countries with incomplete series over that sample. We obtain correlation coefficients ranging from -0.3 to 0.6 on annual data and from -0.3 to 0.5 on quarterly data. These estimates are inherently imprecise: they rely on less than 60 observations.

Our model predicts that, everything else equal, countries that are positively correlated with the US, should pay higher spreads to US investors. In our empirical section, we show that countries with high EMBI market betas exhibit higher spreads, once we control for S&P ratings. The intuition for this finding is that market betas offer high frequency measures of the links between emerging countries and the US. A natural extension of this finding is thus to directly relate GDP correlations to spreads. We do not, however, attempt to match GDP correlations to spreads because of the very limited number of observations. The results reported in our empirical section rely on time-varying, high frequency betas (estimated on daily observations) and we cannot reproduce this experiment with less than 60 observations for each country. As a consequence, we simply note that heterogeneity in correlation exists and show that it delivers in our model a cross-section of yield spreads that is similar to its empirical counterpart.

US Holdings of Sovereign Long Term Debt Our paper focuses on sovereign bonds issued by emerging countries in US dollars. In table 17, we provide some evidence on US holdings of sovereign debt. We start from World Bank data on US holdings of foreign long term debt in billions of US dollars. In the first column of the table, we consider debt issued by residents in Argentina, Brazil, Mexico, Poland and Turkey. These numbers represent debt issued in local or foreign currency, and by governmental and non-governmental agencies. In order to find estimates of the US holdings of debt issued by governmental agencies (e.g., sovereign debt), we multiply US holdings of foreign long term debt (first column) by the share of public external debt for each of the countries we consider (second column) that we obtain from the IMF World Economic Outlook. We report our estimates in billions of US dollars in the third column of table 17. By these estimates, US investors hold around 20 billions USD of sovereign bonds issued by Argentina, Brazil, Mexico, Poland and Turkey. These numbers are only back of the envelope estimates for at least four reasons. First, the share of sovereign debt bought by US residents might differ from the share of public debt issued by emerging countries. Second, we only look at long term securities and a fraction of sovereign debt is short-term (this bias might, however, be limited since EMBI bonds have an average maturity of several years). Third, US portfolio holdings show large holdings in the Isle of Man, Cayman Islands, etc. Clearly, these are funds domiciliated in these countries and issuing debt from these countries but which might invest somewhere else. Fourth, we do not take into consideration the currency denomination of sovereign debt. Not all debt is issued in US dollars, or more generally in foreign currency. Yet, for the countries for which we have such a currency decomposition, the shares of foreign currency denominated external debt (as a percentage of total external debt) is high: 92 percent for Argentina, 92 percent for Colombia, 77 percent for Thailand, 97 percent for Turkey.

A natural question is how the fact that non-US investors also purchase these sovereign bonds could influence our results. In this section we show that when markets are complete, then if we know how to price EMBI bonds from a US perspective, we know how to price them for any investor.

The Euler equation for the US investor is:

$$E_t(M^{\$}_{t+1}R^{\$}_{t+1}) = 1,$$

where $M^{\$}_{t+1}$ denotes the US real stochastic discount factor and $R^{\$}_{t+1}$ the real return on a sovereign bond issued in US dollars. Foreign investors can also buy the same EMBI bond. In this case, the Euler equation is:

$$E_t(M^{\star}_{t+1}R^{\$}_{t+1}\frac{Q_{t+1}}{Q_t}) = 1,$$

where $M^{\star}_{t+1}$ is the foreign stochastic discount factor, Q_t is the (real) exchange rate in $\star/\$$. If we assume that markets are complete, then the stochastic discount factor is unique and equal to:

$$M^{\star}_{t+1} = M^{\$}_{t+1}\frac{Q_t}{Q_{t+1}}.$$

This paper focuses on determining the US stochastic discount factor that prices sovereign bonds from the US perspective. To take the perspective of other investors, we simply need to add exchange rate risk. In complete markets, the foreign stochastic discount factor that prices sovereign bonds from a foreign investor perspective is the US pricing kernel multiplied by the change in exchange rates.

Computational Algorithm To solve the model numerically we de-trend all the Bellman equations. To de-trend, we normalize all variables by $\mu_g \Gamma_{t-1}$. We discretize the borrower's endowment process in 15 equally spaced grid points between +/- $4\sigma_{\epsilon^B}$. We discretize the investors' surplus consumption ratio in 10 grid points equally spaced between .02 and S_{max}. We build the transition matrix as described in Tauchen and Hussey (1991). The quantity of debt is discretized in 55 grid points between 0 (no debt) and -0.25 and we check in our simulations that this constraint never binds. We start with a guess for the bond price function $Q^0(B', x) = Q^{rf}$ for each B' and x, where Q^{rf} is the price of the risk free bond available to investors and is equal to $Q^{rf} = E[M']$ and $x = [y^L, s]'$ is a vector containing the exogenous state variables. Given the bond price function, we use value function iteration to obtain the optimal consumption, asset holdings and default policy functions. Given the optimal default policy function found in the previous step, we update the bond price function $Q^1(B', x)$ according to 3.5. If a convergence criterion is satisfied, we stop. If not, we use the updated price function to compute new values for the optimal consumption, asset holdings and default policy functions and repeat this routine up to the point that $max\{Q^i(B', x) - Q^{i+1}(B'x)\} < 10^{-6}$. In order to obtain business cycle statistics, we simulate 100,000 quarters and use the last 90,000 to compute relevant moments. Note that the vector of shocks underlying each country simulation is the same.

Table 5: EMBI Global Annual Spreads

The table presents summary statistics on J.P. Morgan EMBI Global stripped spreads. All spreads are annual. We report the mean, standard deviation, min, max, median, skewness, kurtosis and autocorrelation (AC) . The last column reports the total number N of observations for each country in the sample. The stripped spread differs from the more standard 'blended' spread because the values of any collateralized flows are stripped from the bond, when computing the difference between the bond yield to maturity and the yield of a corresponding U.S. Treasury bond. The standard deviation is computed using the monthly series of annual spread. Data are monthly, December 1993 - May 2009 and available on Datastream.

EMBI Global Spread %	Mean	Std	Min	Max	Median	Skewness	Kurtosis	AC	N
Argentina	18.00	20.38	1.93	70.78	7.42	1.29	2.96	0.97	186
Belize	8.60	4.95	3.67	17.90	6.51	0.98	2.35	1.00	27
Brazil	6.91	4.02	1.42	24.12	6.65	1.16	5.26	0.92	182
Bulgaria	6.16	5.19	0.56	21.54	5.30	0.89	2.88	0.95	179
Chile	1.48	0.71	0.55	3.92	1.46	1.01	4.11	0.94	121
China	1.08	0.51	0.44	3.57	1.05	1.47	6.83	0.86	183
Colombia	4.30	2.09	1.17	10.66	4.25	0.42	2.45	0.93	148
Cote D'Ivoire	23.37	7.54	5.86	34.76	24.83	−0.63	2.40	0.92	121
Dominican Republic	6.06	4.08	1.35	17.30	4.74	1.19	3.47	0.93	91
Ecuador	13.53	9.42	4.61	47.64	11.08	1.73	5.46	0.93	172
Egypt	1.91	1.32	0.25	5.43	1.36	0.86	2.59	0.94	95
El Salvador	2.99	1.49	1.20	8.61	2.67	2.13	7.76	0.93	86
Hungary	1.00	1.01	0.07	5.40	0.71	2.84	11.13	0.95	125
Indonesia	3.24	1.77	1.44	9.30	2.75	1.91	5.92	0.93	61
Iraq	6.41	2.29	4.23	12.82	5.46	1.54	4.13	0.91	38
Kazakhstan	6.41	3.80	1.84	13.71	4.70	0.67	1.96	0.89	24
Lebanon	4.29	2.14	1.29	10.52	3.78	1.18	4.06	0.96	134
Malaysia	1.91	1.49	0.40	10.55	1.56	2.81	13.98	0.93	152
Mexico	4.00	2.71	0.93	15.89	3.52	1.64	5.90	0.95	186
Morocco	3.83	2.43	0.54	16.06	3.92	1.36	7.40	0.84	107
Pakistan	6.16	5.65	1.42	21.32	3.36	1.38	3.66	0.96	82
Panama	3.47	1.18	1.17	6.79	3.56	−0.00	2.21	0.90	155
Peru	4.22	2.01	1.00	9.41	4.18	0.33	2.32	0.93	147
Philippine	4.11	1.45	1.38	9.37	4.23	0.51	4.13	0.90	138
Poland	2.04	1.57	0.35	8.71	1.83	1.75	6.64	0.95	176
Russia	9.22	12.83	0.90	57.83	4.15	2.21	6.96	0.96	138
Serbia	3.60	2.62	1.52	12.24	2.45	1.82	5.18	0.94	47
South Africa	2.35	1.37	0.67	6.55	2.18	1.11	4.04	0.95	174
Thailand	1.58	1.27	0.41	9.51	1.30	3.02	16.57	0.80	106
Trinidad and Tobago	3.07	2.41	0.00	9.55	2.68	1.11	3.57	0.64	25
Tunisia	1.73	1.10	0.49	5.35	1.42	1.33	4.05	0.95	85
Turkey	4.63	2.41	1.39	10.73	3.95	0.73	2.52	0.93	156
Ukraine	7.37	7.48	1.34	34.91	3.50	1.47	4.27	0.94	109
Uruguay	5.10	3.37	1.41	16.43	3.76	1.52	4.82	0.93	97
Venezuela	8.88	5.01	1.67	25.26	8.37	0.70	2.82	0.92	186
Vietnam	2.80	2.06	0.95	8.80	1.82	1.48	4.14	0.91	43
All	5.44	3.70	1.38	17.03	4.35	1.30	5.03	0.92	118

Table 6: External Debt EMBI Global countries

The table presents summary statistics on the ratio between total external debt to gross national product (GNP) for the sample of J.P. Morgan EMBI Global countries. We report the mean, standard deviation, min, max, median. Data is from the World Bank Global Development Finance (GDF) database for the period 1993-2007. All moments are computed using monthly series obtained by linear interpolation of the original GDF annual series. No data is available for Hungary, Iraq, Trinidad and Tobago on the GDF database.

External Debt	Mean	Std	Min	Median	Max
Argentina	0.66	0.35	0.28	0.51	1.53
Belize	0.75	0.26	0.35	0.79	1.18
Brazil	0.31	0.09	0.19	0.30	0.47
Bulgaria	0.84	0.17	0.58	0.86	1.14
Chile	0.46	0.09	0.32	0.43	0.64
China	0.14	0.02	0.12	0.14	0.19
Colombia	0.33	0.05	0.22	0.33	0.42
Cote D'Ivoire	−−	−−	−−	−−	−−
Dominican Republic	0.34	0.07	0.25	0.30	0.53
Ecuador	0.70	0.17	0.41	0.70	1.05
Egypt	0.39	0.11	0.23	0.36	0.66
El Salvador	0.38	0.11	0.26	0.35	0.56
Hungary	−−	−−	−−	−−	−−
Indonesia	0.74	0.30	0.34	0.63	1.68
Iraq	−−	−−	−−	−−	−−
Kazakhstan	0.54	0.32	0.08	0.71	1.04
Lebanon	0.64	0.33	0.18	0.58	1.07
Malaysia	0.46	0.07	0.29	0.45	0.62
Mexico	0.32	0.11	0.17	0.27	0.60
Morocco	0.53	0.19	0.27	0.57	0.86
Pakistan	0.44	0.08	0.28	0.46	0.54
Panama	0.70	0.09	0.54	0.69	0.96
Peru	0.51	0.09	0.33	0.53	0.70
Philippine	0.64	0.10	0.42	0.64	0.78
Poland	0.38	0.06	0.27	0.38	0.53
Russia	0.43	0.18	0.26	0.34	0.93
Serbia	0.79	0.21	0.54	0.69	1.28
South Africa	0.17	0.03	0.13	0.18	0.23
Thailand	0.54	0.20	0.27	0.54	0.97
Trinidad and Tobago	−−	−−	−−	−−	−−
Tunisia	0.65	0.06	0.57	0.64	0.77
Turkey	0.41	0.08	0.28	0.39	0.59
Ukraine	0.36	0.14	0.06	0.42	0.55
Uruguay	0.57	0.30	0.29	0.40	1.20
Venezuela	0.42	0.11	0.19	0.42	0.67
Vietnam	0.73	0.43	0.35	0.42	1.88
All	0.51	0.16	0.29	0.48	0.84

Table 7: Portfolio Switching

Portfolios	1	2	3	4	5	6
1	**76.78**	7.37	0.00	7.38	5.15	3.32
2	10.04	**67.51**	11.45	1.74	2.80	6.46
3	0.26	8.39	**79.17**	0.31	0.95	10.92
4	5.66	2.25	0.31	**83.71**	8.07	0.00
5	4.20	3.78	2.40	6.85	**74.66**	8.10
6	1.92	4.86	9.30	0.00	6.28	**77.64**

Average probability that a country is in portfolio j at time $t+1$ conditional on being in portfolio i at time t, where i, j are respectively the rows and columns of the table. Data are monthly.

Table 8: EMBI Portfolios Sorted on Credit Ratings and Bond Market Betas (Additional Statistics)

Portfolios	1	2	3	4	5	6
β^j_{EMBI}		Low			High	
S&P	*Low*	*Medium*	*High*	*Low*	*Medium*	*High*
			Market Capitalization			
Mean	5.22	10.28	8.24	4.99	5.92	6.35
Std	4.46	8.51	5.85	3.63	5.03	5.51
			Higher Moments of Returns			
Skewness	−2.18	−2.21	−3.24	−0.77	−0.74	−1.94
Kurtosis	22.49	17.47	28.00	11.27	10.82	15.40
			Spread Duration			
Mean	5.75	4.19	5.76	5.60	5.14	4.93
Std	0.83	0.85	0.62	1.53	1.35	0.90
			Effective Interest Rate Duration			
Mean	5.55	4.17	5.65	5.72	5.35	4.95
Std	1.04	0.95	0.72	1.62	1.19	0.91
			Life			
Mean	13.08	9.27	9.95	12.07	8.60	8.86
Std	4.12	5.05	1.78	4.44	2.55	1.58
			EMBI Stock Market Beta: β^j_{EMBI} (Post-Formation)			
Mean	0.26	0.32	0.50	0.21	0.39	0.66
Std	0.10	0.09	0.15	0.07	0.09	0.16

Notes: This table reports, for each portfolio j, the market capitalization (in billions of US dollars), higher moments of returns (skewness and kurtosis), spread duration, effective interest rate duration, life of EMBI indices and US stock market betas (post-formation). Post-formation betas correspond to slope coefficients in regressions of monthly EMBI returns on monthly US MSCI stock market returns. The portfolios are constructed by sorting EMBI countries on two dimensions: every month countries are sorted on their probability of default, measured by the S&P credit rating, and on β_{EMBI}. Note that Standard and Poor's uses letter grades to describe a country's credit worthiness. We index Standard and Poor's letter grade classification with numbers going from 1 to 23. Data are monthly, from JP Morgan and Standard and Poor's (Datastream). The sample period is 1/1995-5/2009. Duration measures are available starting in 2/2004.

Table 9: EMBI Portfolios Sorted on Credit Ratings and Bond Market Betas (Value-Weighted)

Portfolios	1	2	3	4	5	6
β^j_{EMBI}		Low			High	
S&P	*Low*	*Medium*	*High*	*Low*	*Medium*	*High*
			EMBI Bond Market Beta: β^j_{EMBI}			
Mean	0.24	0.35	0.31	0.98	1.19	1.41
Std	0.92	0.46	0.64	0.45	0.64	0.68
			S&P Default Rating: dp^j			
Mean	9.01	11.18	13.54	8.52	10.84	14.22
Std	1.43	1.25	1.56	1.26	1.39	1.84
			Excess Return: $r^{e,j}$			
Mean	4.59	1.82	6.84	5.82	10.26	12.38
Std	13.56	10.92	18.00	11.57	13.50	23.35
SR	0.34	0.17	0.38	0.50	0.76	0.53
			EMBI Stock Market Beta: β^j_{EMBI} (Post-Formation)			
Mean	0.32	0.28	0.55	0.22	0.37	0.73
Std	0.14	0.10	0.18	0.09	0.11	0.19

Notes: This table reports, for each portfolio j, the average beta β_{EMBI} from a regression of EMBI returns on the total returns on the Merrill Lynch US BBB corporate bond index, the average EMBI log total excess return, the average Standard and Poor's credit rating, and US stock market post-formation betas. Post-formation betas correspond to slope coefficients in regressions of monthly EMBI returns on monthly USMSCI stock market returns. Excess returns are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. The bond market betas, default ratings and excess returns are value-weighted. The portfolios are constructed by sorting EMBI countries on two dimensions: every month countries are sorted on their probability of default, measured by the S&P credit rating, and on β_{EMBI}. Note that Standard and Poor's uses letter grades to describe a country's credit worthiness. We index Standard and Poor's letter grade classification with numbers going from 1 to 23. Data are monthly, from JP Morgan and Standard and Poor's (Datastream). The sample period is 9/1997-5/2009.

Table 10: EMBI Portfolios Sorted on Credit Ratings and Stock Market Betas

Portfolios	1	2	3	4	5	6
β^j_{EMBI}		Low			High	
$S\&P$	Low	$Medium$	$High$	Low	$Medium$	$High$
			EMBI Stock Market Beta: β^j_{EMBI} (Pre-Formation)			
Mean	0.09	0.14	0.12	0.44	0.47	0.67
Std	0.17	0.20	0.23	0.36	0.33	0.43
			S&P Default Rating: dp^j			
Mean	7.71	9.88	13.44	10.59	12.46	15.28
Std	1.26	1.23	1.11	0.87	0.64	1.45
			Excess Return: $r^{e,j}$			
Mean	3.34	4.24	5.97	8.75	9.80	13.08
Std	7.43	9.03	12.21	13.71	14.78	22.01
SR	0.45	0.47	0.49	0.64	0.66	0.59
			EMBI Stock Market Beta: β^j_{EMBI} (Post-Formation)			
Mean	0.12	0.21	0.31	0.45	0.47	0.78
Std	0.06	0.09	0.10	0.10	0.11	0.20

Notes: This table reports, for each portfolio j, the average beta β_{EMBI} from a regression of one-month EMBI returns on one-month US MSCI stock market returns at daily frequency (pre-formation), the average EMBI log total excess return, the average Standard and Poor's credit rating, post-formation betas, and the average external debt to GNP ratio. Post-formation betas correspond to slope coefficients in regressions of monthly EMBI returns on monthly USMSCI stock market returns. Excess returns are annualized and reported in percentage points. For excess returns, the table also reports Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. The portfolios are constructed by sorting EMBI countries on two dimensions: every month countries are sorted on their probability of default, measured by the S&P credit rating, and on β_{EMBI}. Note that Standard and Poor's uses letter grades to describe a country's credit worthiness. We index Standard and Poor's letter grade classification with numbers going from 1 to 23. Data are monthly, from JP Morgan and Standard and Poor's (Datastream). The sample period is 1/1995 - 5/2009.

Table 11: Asset Pricing: Portfolios Sorted on Credit Ratings and Stock Market Betas

Panel I: Factor Prices and Loadings					
	λ_{US-BBB}	b_{US-BBB}	R^2	$RMSE$	$p-value$
GMM_1	6.80	1.51	84.80	1.32	
	[4.72]	[1.05]			76.45
GMM_2	5.94	1.32	75.51	1.67	
	[2.76]	[0.62]			77.91
FMB	6.80	1.50	81.69	1.32	
	[2.72]	[0.60]			72.50
	(2.81)	(0.62)			76.53
$Mean$	**6.52**				
Std	[0.49]				
Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	β_{US-BBB}^j	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	-1.75	0.78	41.49		
	[1.49]	[0.09]			
2	-1.55	0.89	36.40		
	[2.16]	[0.12]			
3	-0.06	0.92	21.56		
	[3.18]	[0.17]			
4	0.75	1.23	30.15		
	[3.44]	[0.16]			
5	1.99	1.20	24.68		
	[3.72]	[0.14]			
6	1.01	1.85	26.62		
	[6.49]	[0.43]			
All				3.49	0.75

Notes: Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. All excess EMBI returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS estimates of the factor betas. R^2s and p-values are reported in percentage points. The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), page 234). Data are monthly, from JP Morgan in Datastream. The sample period is 1/1995-5/2009. The alphas are annualized and in percentage points.

Table 12: Conditional Asset Pricing: Portfolios Sorted on Credit Ratings and Bond Betas

	$\lambda_{US_{BBB}}$	$\lambda_{US_{BBB}*VIX}$	$b_{US_{BBB}}$	$b_{US_{BBB}*VIX}$	R^2	$RMSE$	χ^2
GMM_1	5.21	19.26	0.44	0.22	88.48	3.42	
	[6.45]	[17.24]	[3.20]	[0.59]			16.51
GMM_2	7.15	25.27	1.01	0.18	58.45	6.50	
	[2.09]	[6.50]	[0.85]	[0.17]			20.70
FMB	5.21	19.26	0.44	0.22	87.37	3.42	
	[3.68]	[8.97]	[2.62]	[0.60]			30.05
	(3.78)	(9.14)	(2.70)	(0.61)			35.28
$Mean$	**6.52**	**17.72**					
Std	[0.50]	[1.67]					

Notes: Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. All excess EMBI returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. In the top panel, the risk factors are the high yield US market return, and the same multiplied by the lagged value of the VIX index scaled by its standard deviation. $b_{US_{BBB}}$ and $b_{US_{BBB}*VIX}$ denote the vector of factor loadings. We use 12 test assets: the original 6 EMBI portfolio excess returns and 6 additional portfolios obtained by multiplying the original set by the conditioning variable VIX (see Cochrane (2001)). Data are monthly, from JP Morgan in Datastream. The sample period is 1/1995-5/2009. We do not include a constant in the second step of the FMB procedure.

Table 13: Asset Pricing: Portfolios Sorted on Credit Ratings and Bond Market Betas: ΔVIX

Panel I: Factor Prices and Loadings					
	$\lambda_{\Delta VIX}$	$b_{\Delta VIX}$	R^2	$RMSE$	$p-value$
GMM_1	−75.94	−0.18	43.51	2.53	
	[49.57]	[0.12]			16.75
GMM_2	−107.49	−0.26	−53.17	4.16	
	[42.07]	[0.10]			20.34
FMB	−75.94	−0.18	29.50	2.53	
	[30.13]	[0.07]			21.07
	(31.62)	(0.08)			28.08
Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	$\beta_{\Delta VIX}^j$	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	0.28	−0.07	15.97		
	[0.19]	[0.03]			
2	0.51	−0.09	20.19		
	[0.23]	[0.02]			
3	0.60	−0.13	22.05		
	[0.31]	[0.04]			
4	0.61	−0.06	13.79		
	[0.19]	[0.02]			
5	0.89	−0.10	19.15		
	[0.21]	[0.02]			
6	1.19	−0.15	21.85		
	[0.36]	[0.04]			
All				17.84	0.01

Notes: Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. All excess EMBI returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS regression results. We regress each portfolio return on a constant (α) and the risk factors (the corresponding slope coefficient is denoted β). R^2s are reported in percentage points. The alphas are annualized and in percentage points. The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), page 234). Data are monthly, from JP Morgan in Datastream. The sample period is 1/1995-5/2009. The risk factor corresponds to the change in the log VIX index.

Table 14: Asset Pricing: Portfolios Sorted on Credit Ratings and Bond Market Betas: ΔVIX and US_{BBB} Bond Return

	Panel I: Factor Prices and Loadings						
	$\lambda_{US_{BBB}}$	$\lambda_{\Delta VIX}$	$b_{US_{BBB}}$	$b_{\Delta VIX}$	R^2	$RMSE$	$p-value$
GMM_1	7.96	-3.65	1.87	0.04	73.72	1.54	
	[4.22]	[59.65]	[1.12]	[0.16]			13.24
GMM_2	5.85	-24.83	1.24	-0.03	67.20	1.72	
	[3.51]	[49.80]	[0.99]	[0.14]			15.55
FMB	7.96	-3.65	1.86	0.04	65.85	1.54	
	[2.92]	[43.72]	[0.87]	[0.12]			32.14
	(3.07)	(46.44)	(0.92)	(0.13)			39.47

	Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	$\beta_{US_{BBB}}^j$	$\beta_{\Delta VIX}^j$	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	-0.16	0.79	-0.05	36.21		
	[0.16]	[0.09]	[0.02]			
2	0.11	0.72	-0.07	33.70		
	[0.20]	[0.10]	[0.02]			
3	0.17	0.78	-0.11	29.73		
	[0.31]	[0.17]	[0.04]			
4	0.15	0.84	-0.03	43.67		
	[0.18]	[0.12]	[0.02]			
5	0.27	1.12	-0.07	45.81		
	[0.20]	[0.14]	[0.02]			
6	0.36	1.51	-0.11	43.40		
	[0.35]	[0.28]	[0.03]			
All					6.38	0.38

Notes: Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. All excess EMBI returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS regression results. We regress each portfolio return on a constant (α) and the risk factors (the corresponding slope coefficient is denoted β). R^2s are reported in percentage points. The alphas are annualized and in percentage points. The χ^2 test statistic $\alpha' V_\alpha^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), page 234). Data are monthly, from JP Morgan in Datastream. The sample period is 1/1995-5/2009. The risk factors correspond to the change in the log VIX index and the return on a US BBB bond index.

Table 15: Asset Pricing: Portfolios Sorted on Credit Ratings and Bond Market Betas: TED Spread

Panel I: Factor Prices and Loadings					
	λ_{TED}	b_{TED}	R^2	$RMSE$	$p-value$
GMM_1	-5.20	-9.48	5.26	3.27	
	[6.09]	[11.09]			20.37
GMM_2	-1.47	-2.67	-263.56	6.41	
	[4.88]	[8.89]			24.81
FMB	-5.20	-9.42	-9.39	3.27	
	[2.10]	[3.80]			4.97
	(2.53)	(4.59)			19.00
Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	β_{TED}^j	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	0.72	-0.81	2.79		
	[0.38]	[0.68]			
2	1.00	-0.91	2.83		
	[0.38]	[0.60]			
3	1.75	-2.07	7.16		
	[0.50]	[0.79]			
4	0.90	-0.55	1.66		
	[0.32]	[0.56]			
5	1.41	-0.97	2.65		
	[0.48]	[0.87]			
6	2.56	-2.46	7.49		
	[0.73]	[1.36]			
All				16.49	0.01

Notes: Panel I reports results from GMM and Fama-McBeth asset pricing procedures. Market prices of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$ and the p-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the vector of factor loadings. All excess EMBI returns are multiplied by 12 (annualized). The standard errors in brackets are Newey and West (1987) standard errors with the optimal number of lags according to Andrews (1991). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. Panel II reports OLS regression results. We regress each portfolio return on a constant (α) and the risk factors (the corresponding slope coefficient is denoted β). R^2s are reported in percentage points. The alphas are annualized and in percentage points. The χ^2 test statistic $\alpha' V_{\alpha}^{-1} \alpha$ tests the null that all intercepts are jointly zero. This statistic is constructed from the Newey-West variance-covariance matrix (1 lag) for the system of equations (see Cochrane (2001), page 234). Data are monthly, from JP Morgan in Datastream. The sample period is 1/1995-5/2009. The risk factor corresponds to TED spread, defined as the difference in yields on 3-month EuroDollar rates minus 3-month Treasury Bills.

Table 16: Cross-Country Correlations

	Annual		Quarterly	
Argentina	(1945/2007)	0.15	(1994:IV/2008:III)	0.51
Brazil	(1991/2007)	−0.01	(1994:IV/2008:III)	0.11
Bulgaria	(1994/2007)	−0.40	(1994:IV/2008:III)	−0.15
Chile	(1945/2007)	0.05		
Colombia	(1945/2007)	0.03	(1994:IV/2008:III)	−0.20
Hungary	(1947/2008)	0.41		
Indonesia	(1958/2008)	−0.35		
Malaysia	(1955/2008)	−0.20	(1994:IV/2008:III)	−0.09
Mexico	(1945/2008)	0.20	(1994:IV/2008:III)	0.52
Peru	(1945/2007)	0.19	(1994:IV/2008:III)	−0.21
Philippines	(1946/2008)	−0.23	(1994:IV/2008:III)	−0.12
Poland	(1980/2008)	0.65		
Russia	(1995/2004)	−0.65		
South Africa	(1945/2007)	0.10	(1994:IV/2008:III)	0.02
Thailand	(1948/2008)	−0.34	(1994:IV/2008:III)	−0.29
Turkey	(1950/2007)	0.50		

Notes: This table reports the correlation coefficients between GDP in the US and in emerging countries. The left panel focuses on annual series. The right panel uses quarterly series. In the left panel, we modify the sample window for each country in order to use all available (annual) data. In the right panel, we impose a common sample (1994:IV - 2008:III) and ignore countries which do not have complete (quarterly) series over the sample. Real GDP series are HP-filtered using a smoothing parameter of 100 on annual and 1600 on quarterly data. Data are from Global Financial Data.

Table 17: US Holdings of Sovereign Long Term Debt

Issuers	US Holdings (*billions*)	Gross External Debt (*% Public*)	Sovereign (*estimates, in billions*)
Argentina	7.9	55	4.3
Brazil	16.2	25	4.0
Mexico	23.9	33	7.9
Poland	4.8	36	1.7
Turkey	5.4	31	1.7

Notes: Sources: World Bank and IMF. The first column reports US holdings of long term debt securities (cf 'Reported portfolio investment assets by economy of nonresident issuer: Long-term debt securities', Table 1.2.A, World Bank). The second column reports the percentage of gross external debt that is public. It corresponds to the following ratio: (General Government + Monetary Authorities)/(Government + Monetary Authorities+ Banks +Other Sectors + Direct Investment: Intercompany Lending) (cf Table C2 - Gross External Debt Position by Sector, World Economic Outlook, 2008Q2, IMF). The third column corresponds to US holdings of foreign long term debt (first column) multiplied by the share of public external debt for each of the countries we consider (second column).

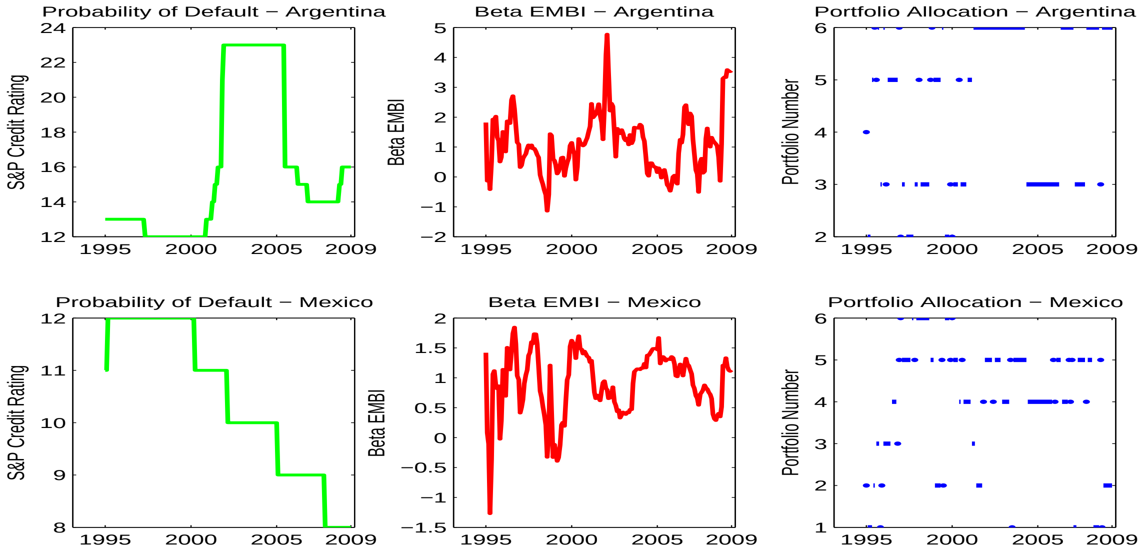

Figure 6: Portfolio Allocation for Argentina and Mexico

This figure plots, for Argentina and Mexico, the monthly S&P credit rating, the bond market beta β_{EMBI} and the portfolio allocation. Data are monthly. The sample is 01/1995 - 05/2009.

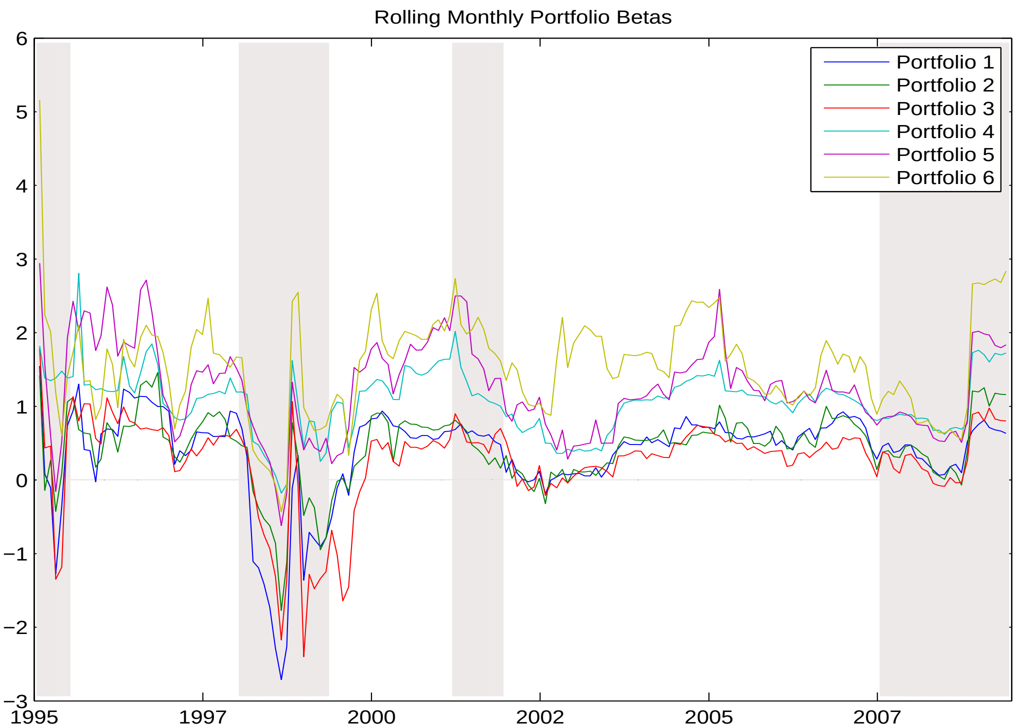

Figure 7: Rolling EMBI Betas

The figure plots average rolling betas β_t^j for each portfolio j. We regress 100-day actual excess returns on a constant and the return on the US_{BBB} bond index to obtain slope coefficient β_t^i for each country. We date t the betas estimated with returns up to date t. The end-of-month values of these betas are used to sort countries and build portfolios. We present here the average betas of each portfolio. The sample period is 1/1995-5/2009. Data are monthly. The shaded areas are the NBER US recessions, the Tequila crisis and the Long Term Capital Management (LTCM) / Asian crisis. The dates for the Tequila crisis and the LTCM crisis were taken from ?.

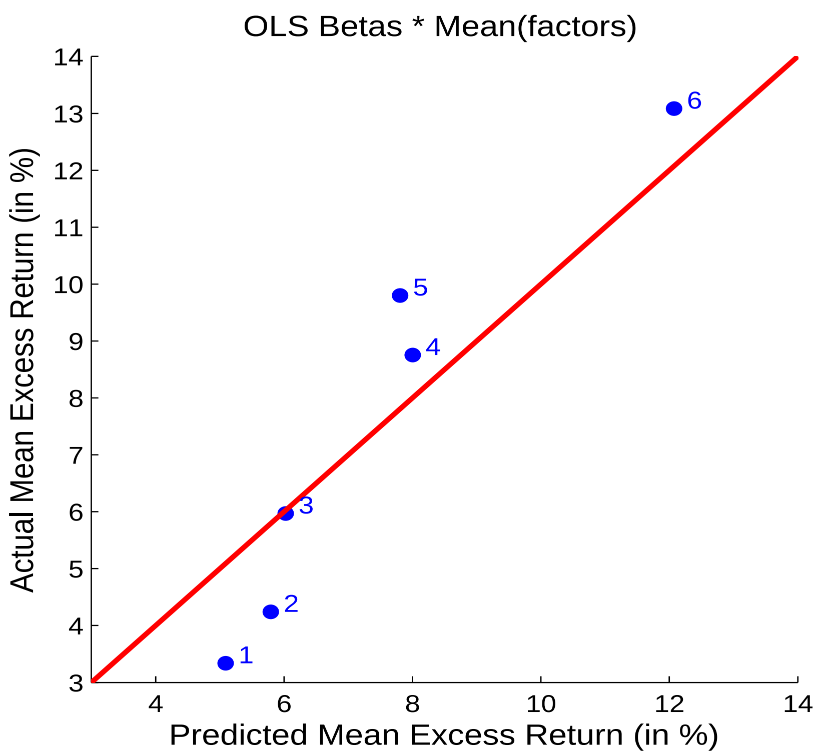

Figure 8: Predicted versus Realized Average Excess Returns

The figure plots realized average EMBI excess returns on the vertical axis against predicted average excess returns on the horizontal axis. We regress actual excess returns on a constant and the return on the US_{BBB} bond index to obtain slope coefficient β^j. Each predicted excess return is obtained using the OLS estimate β^j times the sample mean of the risk factor. Portfolios are built using S&P ratings and US stock market betas. All returns are annualized. Data are monthly. The sample period is 1/1995-5/2009.

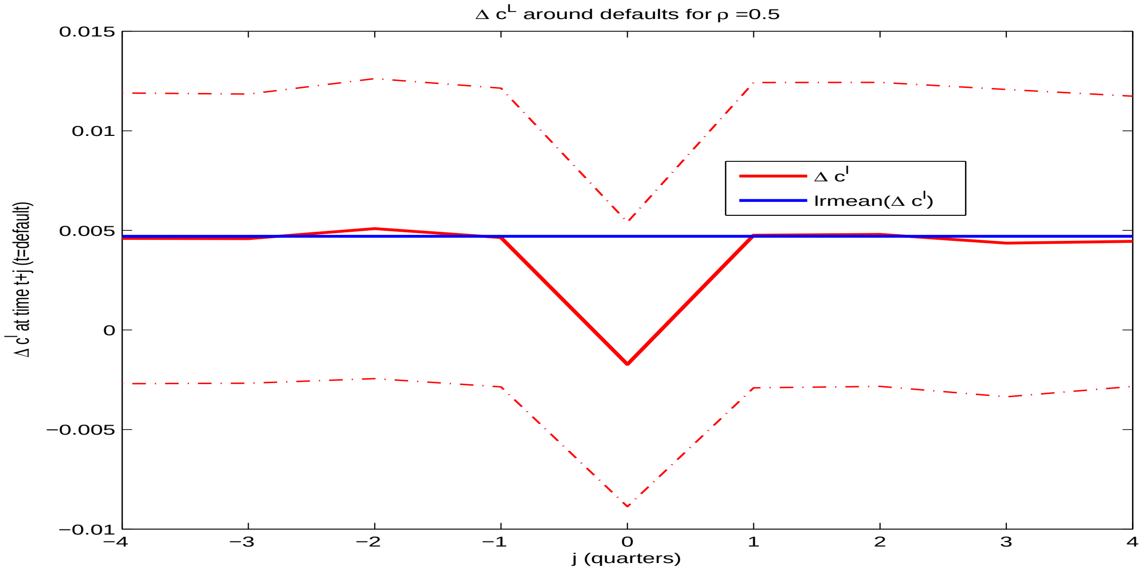

Figure 9: Lenders' Consumption Growth Around Defaults in the Model

This figure plots the average consumption growth of lenders around defaults. The dotted lines represent one standard deviation bands. The correlation between lenders' and borrowers' endowment shocks is 0.5.

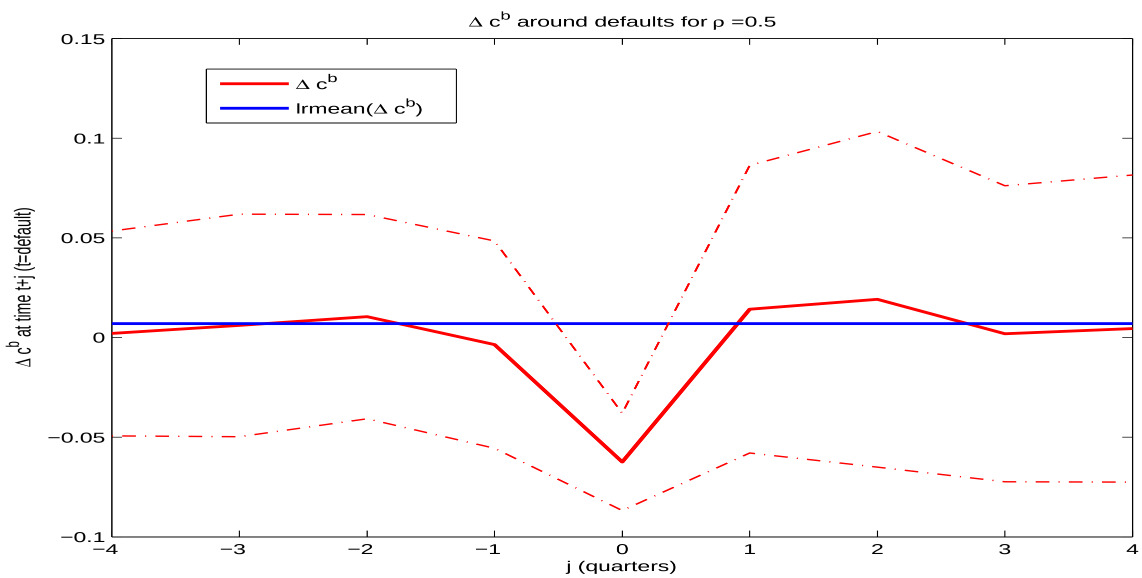

Figure 10: Borrowers' Consumption Growth Around Defaults in the Model

This figure plots the average consumption growth of borrowers around defaults. The dotted lines represent one standard deviation bands. The correlation between lenders' and borrowers' endowment shocks is 0.5.