Sovereign Risk Premia *

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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 foreign sovereign bonds are particularly risky. We explore how this mechanism plays out in the data and in a general equilibrium model of optimal borrowing and default. Empirically, the higher the correlation between past foreign and US bond returns, the higher the average sovereign excess returns. In the model, sovereign defaults and bond prices depend not only on the borrowers' economic conditions, but also on the lenders' time-varying risk-aversion.

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In this paper, we study sovereign bonds issued by emerging countries in US dollars and take the perspective of US investors. We show both empirically and theoretically that covariances between bond returns and risk factors are key determinants of sovereign bond prices and debt quantities. In the data, average sovereign bond excess returns line up with their quantities of risk, as implied by a simple no-arbitrage condition. Building on this finding, we develop a general equilibrium model of optimal borrowing and lending with endogenous default choices and risk-averse investors. Our model replicates our asset pricing results. Sovereign risk premia imply a novel link across countries: lenders' time-varying risk-aversion influences borrowers' default decisions, and thus sovereign bond prices. Opening up capital markets thus exposes emerging countries to US business cycle risk.

The intuition behind our results is simple. US investors are risk-averse and invest in foreign government bonds. Emerging countries tend to default in 'bad times', when, for example, their 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 US investors. In this case, sovereign bonds are particularly risky, and US investors expect to be compensated for that risk through a high return. Alternatively, if bad times in the foreign economy correspond to good times for US investors, then sovereign bonds are less risky and may even hedge US aggregate risk. As a result, sovereign bond prices depend on both expected probabilities of default and the timing of the bond payoffs.

Risk-aversion implies that optimal borrowing and default decisions depend not only on the borrowers' but also on the lenders' economic conditions. Let us assume that business cycles are positively correlated across countries. In this case, sovereign bonds command positive risk premia. If lenders are very risk-averse, risk premia are high and interest rates too. In this case, borrowing is not very attractive and emerging countries might not fear much the exclusion from financial markets that sovereign defaults entail. As a result, emerging countries choose to default when they experience bad shocks. The same economic conditions in the borrowing countries, however, would not trigger defaults if lenders were less risk averse and risk premia lower.

With this price mechanism in mind, we turn to the data on sovereign debt. We look at bonds issued by emerging countries that are included in JP Morgan's EMBI Global index. 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 excess returns on one-month US corporate bond excess returns at daily frequency. 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. After sorting countries along these two dimensions, we obtain six portfolios and a large cross-section of holding period excess returns. Our sample starts in January 1995 and ends in May 2009. If investors were risk-neutral, all average excess returns should be zero. They are clearly not. The spread in average excess returns between low and high default probability countries is about 5 percent per year. The spread in average excess returns between low and high bond beta countries is also about 5 percent per year.

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 higher than but not statistically different from the mean of the risk factor's excess return, 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 volatility (VIX) index. We consider several robustness checks, using different sorting variables and risk factors. Notably, we obtain similar results when sorting countries on their stock market betas (obtained as slope coefficients of daily emerging bond excess returns on US stock market returns). Again, our sorting procedure delivers a clear cross-section of average excess returns and a positive and significant market price of risk. We also check our results in panel regressions of country-level EMBI returns. They load significantly on the US BBB corporate returns, and the loadings increase for countries with poor ratings. Country-level asset pricing tests also imply a positive market price of risk. All our findings point towards a risk-based explanation of sovereign bond returns.

To uncover the implications of our findings 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 and borrowing with endogenous default choice in incomplete markets. 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).

The rest of the model builds on Aguiar and Gopinath (2006) and Arellano (2008). As in the latter paper, we assume a nonlinear cost of default. As in the former, 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. Every period, foreign countries decide to either default and face exclusion from financial markets, or repay their debt and consider borrowing again.

The key novelty of the model appears in the link between lenders' risk premia and borrowers' optimal default decisions. In our model, defaults depend partly on lenders' risk aversion. To illustrate this point, let us again assume that business cycles are positively correlated. In this case, sovereign bonds are risky. When lenders experience a series of bad consumption growth shocks, their consumption becomes closer to their subsistence level and their risk-aversion increase. If lenders are very risk averse, risk premia are high and interest rates too. Since it is very costly to borrow, emerging countries tend to default as soon as they experience adverse conditions. As a result, when shocks across countries are positively correlated, defaults in emerging countries are more likely when lenders' risk aversion is high. In times of extreme risk-aversion, it looks as if lenders are pushing borrowers to default.

As lenders' risk aversion influences borrowers' default decisions, it also impacts optimal debt quantities and prices. Let us again assume that shocks across countries are positively correlated. Sovereign bonds are then risky investments since borrowers are more likely to default in bad times for investors. Higher probabilities of default imply higher yields and lower bond prices. Those lower prices occur in bad times for investors. In equilibrium, these bonds thus offer higher expected returns than bonds issued by countries whose shocks are not correlated to the lenders' business cycle. The larger the risk-aversion, the larger the sovereign risk premium, and the higher the spreads in average excess returns across countries. As a result, the model offers a general equilibrium view of debt quantities and prices in which risk premia link lenders' and borrowers' economies.

Our model delivers endogenously both high debt levels – as in Aguiar and Gopinath (2006) – and large bond yields – as in Arellano (2008). In the model, countries borrow heavily, mostly to smooth out changes in the permanent component of their endowment growth rates. Default probabilities increase when the permanent components of endowment growth decrease – i.e in bad times. Countries default after receiving negative (often temporary) shocks. This risk of default is thus compensated by large spreads, which increase when the emerging country experiences a long period of low growth. As a result, bond prices reflect the interaction between transitory and permanent shocks. The model, as its predecessors, matches important features of the emerging markets business cycles.

In order to analyze the model's results and compare them with actual data, we replicate on simulated series our previous experiment. The model delivers time-varying equity excess returns in the US, so we rank countries on stock market betas as we did on actual data and we build portfolios of simulated sovereign bonds. The model delivers a cross-section of average excess returns. Countries that are risky from the lenders' perspective offer higher returns. But bond issuances and defaults are endogenous choices: countries facing high borrowing costs choose to borrow less, thereby lowering their default probabilities. In the simulations, high beta countries pay higher interest rates even if they borrow less in equilibrium. From the perspective of the US investor, the riskiest country is not the most indebted one, but the one that might default in bad times. We run on simulated data the same asset pricing tests as on actual data. Since we do not have long term corporate bonds in our model, we use the simulated US stock market return as our risk factor. As expected, it accounts for the cross-section of sovereign bond returns. High sovereign excess returns correspond to high beta portfolios.

The model suggests new approaches to some old puzzling questions. We do not attempt to solve these puzzles here but simply mention the model's implications. First, the model implies that there is no linear relation between interest rates and debt levels, or between interest rates and output. Second, the model offers an interpretation to the large increase in yields in the fall of 2008, based on an endogenously higher risk-aversion and thus higher market prices of risk. Finally, the model implies that currency unions might lead to higher borrowing costs since they imply higher business cycles' synchronizations.

Three discrepancies between the model and the data are worth mentioning. First, average excess returns and spreads 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: we only consider one-period (i.e three-month) bonds, whereas the average maturity is close to 10 years in the data. Such a maturity difference matters: term structures of credit default swaps (CDS) rates are strongly upward-sloping on average, with 10-year rates being on average 5 times higher than short-term rates. As a result, we do not attempt to match actual returns with our one-period bonds. The model could be extended in this direction: Hatchondo and Martinez (2009) and Chatterjee and Eyigungor (2010) offer potential mechanisms to increase maturities without adding state variables. Second, the model does not take into account interest rate risk. Building macroeconomic models of the yield curve is still a challenge even for closed economies without default risk. This challenge is particularly obvious for emerging economies because their counter-cyclical real interest rates lead to downward sloping real yield curves in existing macroeconomic models. 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 the sole source of heterogeneity across countries. It is constant, 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 economics of the model, which already produces some time-variation in betas because of the time-varying means of endowment growth rates and time-varying risk-aversion. Likewise, adding heterogeneity in the endowment volatilities would offer a second source of cross-sectional variation in excess returns – and thus justify sorting countries along two dimensions – but it would not change the mechanism of the model.

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 (2011). They study changes in emerging market CDS 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 CDS spreads. They argue convincingly that CDS are mostly compensation for bearing global risk, with little country-specific risk premia.[1] Second, our paper contributes to the theoretical literature on sovereign lending with

[1]Other references on the empirical determinants of sovereign spreads include papers by Edwards (1984), Boehmer and Megginson (1990), Adler and Qi (2003), Bekaert, Harvey and Lundblad (2007), Favero, Pagano and von Thadden (2010), and Hilscher and Nosbusch (2010). See Almeida and Philippon (2007) for related evidence on corporate bond

defaults.[2] Here, the papers closest to ours are Aguiar and Gopinath (2006) and Arellano (2008). But these papers, as many others in the literature, focus on risk-neutral investors. As a result, expected excess returns are there equal to zero, whereas we uncover large excess returns in the data. 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 (2010) 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 (2008) propose a three-period model to determine the optimal term structure of sovereign debt when investors are risk-averse.

This paper also builds on the macro-finance literature. Without risk-aversion, i.e when investors are risk-neutral, there is no role for covariances in sovereign bond prices, and expected excess returns are zero. With constant risk-aversion, 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. Campbell and Cochrane (1999) preferences offer a solution to the equity premium puzzle, endogenously delivering a volatile stochastic discount factor that implies high Sharpe ratios. Moreover, these preferences entail time-varying risk aversion, and thus a time-variation in the market price of risk, as in the data.[3]

The paper is organized as follows. Section 1 describes the data, our empirical methodology, and our portfolios of sovereign bonds. Section 2 shows that one risk factor explains most of the cross-sectional variation in average excess returns across our portfolios. In section 3, we interpret these findings in a general equilibrium model of sovereign borrowing. Section 4 presents a calibrated version of the model that qualitatively replicates our empirical findings. Section 5 concludes. A separate appendix reports additional results. Our portfolios of sovereign bond excess returns are available on our websites, along with the Matlab code to simulate our model.

spreads and its implications on corporate capital structure, and see Coval, Jurek and Stafford (2009) for related evidence in structured finance.

[2]Recent papers in this segment of the literature include Bulow and Rogoff (1989), Atkeson (1991), Kehoe and Levine (1993), Zame (1993), Cole and Kehoe (2000), Alvarez and Jermann (2000), Duffie, Pedersen and Singleton (2003), Bolton and Jeanne (2007), Amador (2008), Fostel and Geanakoplos (2008), Arellano and Ramanarayanan (2009), Benjamin and Wright (2009), Pouzo (2009), Chien and Lustig (2010), Yue (2010), and Broner, Martin and Ventura (2010).

[3]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.

1 The Cross-Section of EMBI Returns

We take the perspective of a US investor who borrows in US dollars to invest in sovereign bonds issued in US dollars by emerging countries. 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 sovereign excess returns.

1.1 Data and notation

Data on Emerging Markets JP Morgan publishes country-specific indices that market participants consider as benchmarks. The JP Morgan EMBI Global indices cover low or middle income per capita countries and 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, Philippines, Poland, Russia, Serbia, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela, Vietnam. The sample period runs from December 1993 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. 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 optimal for our study. CDS are insurance contracts against the event that a sovereign defaults on its debt over a given horizon. These contracts are traded in US dollars. As a result, their prices reflect both the magnitude and the timing of expected defaults. More crucially, CDS data are only available from December 2002 on, and for a small subset of the EMBI Global countries (see Pan and Singleton (2008) for a study of three countries over the 2001-2006 period). 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.

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

$$r^{e,i}_{t+1} = \alpha^i + \beta^i_{EMBI} r^{e,BBB}_t + \varepsilon_t,$$

where $r^{e,BBB}_t$ denotes the log total excess return on the Merrill Lynch US BBB corporate bond index.[4] We obtain similar results when we use EMBI and US BBB returns instead of excess returns. We compute betas on 200-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 100 observations for both the left- and right-hand side variables are available over the previous 200-day rolling window period.

[4]We do not attempt here to summarize the large literature on corporate spreads. See Giesecke, Longstaff, Schaefer and Strebulaev (2010) for a survey and long historical time-series, see Gilchrist, Yankov and Zakrajsek (2009) for recent evidence, and see Bhamra, Kuehn and Strebulaev (2010) for a recent model with counter-cyclical corporate spreads.

1.2 Portfolios of Excess Returns

EMBI portfolio returns 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, while portfolios 4, 5 and 6 contain countries with the highest betas. Portfolios 1 and 4 contain countries with the lowest default probabilities, while 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. To give an example, Mexico turns out to be a high beta country on average, while Thailand is a rather low beta country. This is not very surprising considering the strong connection between the US and Mexican economies. Note, however, that the composition of portfolios changes every month: Table 12 in Appendix B 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 size of our sample varies over time, reaching a maximum of 32 countries.

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 means of monthly returns by 12 and standard deviations 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 (i.e 5%) 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.

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
s.e	[2.55]	[3.09]	[4.29]	[2.43]	[3.22]	[5.04]
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 excess returns on the Merrill Lynch US BBB corporate bond excess returns (first panel), the average Standard and Poor's credit rating (second panel), the average EMBI log total excess return (third panel), and the average external debt to GNP ratio (fourth panel). Excess returns are annualized and reported in percentage points. For excess returns, the table also reports standard errors on the averages, as well ass standard deviations and Sharpe ratios, computed as ratios of annualized means to annualized standard deviations. Standard errors are obtained by bootstrapping, assuming that returns are *i.i.d*. 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.

These spreads are economically significant, although standard errors on the averages are large. We compute those standard errors by bootstrapping, assuming that returns are *i.i.d*, in order to take into account the small sample size. Standard errors range from 240 to 500 basis points per year. The excess returns of high beta portfolios are more than two standard errors away from zero, while the excess returns of the low beta portfolios are not. Focusing on the differences between high and low beta portfolios, once we control for ratings, we obtain an average spread of 400 basis points between portfolios 1 and 4, 450 basis points between portfolios 2 and 5, and 700 basis points between portfolios 3 and 6. The small sample standard errors on these spreads are respectively 220, 260, and 360 basis points. As a result, spreads across portfolios are close to two standard errors away from zero.

Patton and Timmermann (2010) propose a 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%).

Other moments We check whether our portfolios differ in several other dimensions: market capitalization, duration, maturity, and higher moments. Table 13 in Appendix B reports these additional statistics. Sovereign bond returns present large negative skewness and large positive kurtosis. Both characteristics are due to the 1998 and 2008 crises.[5] The low beta portfolios exhibit the most pronounced deviations from normality. The low skewness and high kurtosis of these returns is reminiscent of crash risk. We do not, however, pursue in this paper a disaster risk explanation of sovereign spreads, in the vein of Rietz (1988), Barro (2006), Gabaix (2008), and Martin (2008) because the differences in skewness and kurtosis between the high and low beta portfolios are not significant. But we view crash risk as an interesting avenue for future research on sovereign bonds.

Our benchmark portfolios tend to differ in terms of market capitalization, duration and maturity. These differences may account for part of the cross-section of excess returns across portfolios, but they are unlikely to explain the whole cross-section of excess returns.

High beta portfolios tend to have lower market capitalization. Their higher returns may thus correspond to potential liquidity risk premia. Yet, inside each beta group, there is no monotonic variation in market capitalization even though returns increase with default probabilities (as measured by low ratings). Mapping market capitalizations into returns is thus not obvious, but liquidity remains anyway a valid concern and we explore it further below and in the next section.

We also note that our portfolios differ in terms of duration and maturities. Portfolios with high betas and high default probabilities (low ratings) tend to exhibit longer durations and maturities. These higher durations may also explain part of the cross-section of returns. The difference in duration is, however, limited (from 5 years for the first portfolio to 7 years for the last portfolio). A pure term premium, as measured for example from the US government bond yield curve, is unlikely to account for the large spread in returns that we observe on emerging markets sovereign bonds. The spread in returns between 5- and 7- year US government bonds (0.4%) is an order of magnitude smaller than the spread we obtain between our first and last portfolios (10%). Term premia certainly matter, but they must interact with sovereign risk premia in order to account for the cross-section of EMBI returns.

Unfortunately, we do not have bid-ask spreads on EMBI indices and thus cannot correct our excess returns for transaction costs. Such costs are certainly important, and would reduce the Sharpe ratios on these portfolios. We attempt to obtain orders of magnitudes for these transaction costs using emerging market sovereign bonds available in Bloomberg. We report detailed results in the appendix.

[5]These characteristics are also apparent at the country level. Table 6 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 crises implied first sharp increases in EMBI spreads (i.e lower emerging market bond prices) and thus very low returns.

Building portfolios of equally-weighted individual bonds (using the same sort as for EMBIs), we obtain median bid-ask spreads ranging from 43 to 65 basis points. These transaction costs impact the overall level as well as the spread in returns. We use here a simple back-of-the-envelop approach to make these points. The composition of our portfolios changes by an average of 0.8 country each period, implying an average of 10 changes per year. Assuming an average bid-ask spread of 50 basis points, transaction costs would amount to 500 basis points per year and per portfolio. They would reduce our cross-section of excess returns from the 3 to 13.5% range to the -2 to 8.5% range. Transaction costs would also reduce the spread in returns between the first and last portfolio by 200 bp (i.e 2%), from 10 to 8%. Note, however, that these numbers are guesstimates: we cannot rule out a larger or smaller impact of transaction costs on our EMBI returns since we do not have the exact same individual bonds and weights that JP Morgan used to build EMBI series.

To sum up, we acknowledge that liquidity and term premia may differ systematically across our portfolios and that these risk premia may account for at least part of the cross-section of excess returns. We do not disentangle sovereign risk from liquidity and term risk premia. Estimating the latter risk premia is the object of large literatures and is beyond the scope of this paper. We also note that the lower skewness and higher kurtosis of the low beta portfolios may be indicative of "peso" explanations of excess returns: in this logic, high average returns in sample simply correspond to luck, with large and negative returns waiting to happen, such that all excess returns would be zero in a very long sample. This is a valid concern a priori, but we show in the next section that our average sovereign bond returns correspond to covariances with a simple risk factor. As a result, our EMBI returns correspond to risk premia, not peso events.

Other sorts Finally, we conduct two robustness checks: we consider 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 14 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 US stock market returns. We report summary statistics on these additional portfolios in Tables 15 and 16 in Appendix B. Here again, high beta sovereign bonds tend to offer higher excess 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

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

to avoid the forward-looking bias, we consider a second experiment. For each country, we fix its beta to the 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. 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 Systematic Risk 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 excess 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 for a US investor on portfolio j in period $t+1$. In the absence of arbitrage opportunities, there exists a strictly positive discount factor such that 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.

As already noted, we focus in this paper on US investors. It is a natural first step since these bonds are issued in US dollars and US investors indeed own a significant amount of sovereign bonds. According to the 2008 survey of US Portfolio Holdings of Foreign Securities published by the US Treasury, US investors own $42 billions of long-term government debt issued in US dollars by the emerging countries in our sample. Table 7 in the separate appendix details the US holdings of sovereign long term debt for each country in our sample.[7]

We further 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, $\lambda = \Sigma_{ff} b$, Σ_{ff} is the variance-covariance matrix of the factors, and β^j denotes the regression coefficients of the returns $R^{e,j}$ 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 in Appendix B.

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. The Euler equation thus implies that expected excess returns are fully explained by the covariances between bond returns and the risk factor. We naturally interpret past ratings and past betas as signals on those key covariances and we show that, even if we formed portfolios on two dimensions, we can account for the cross-section of excess returns with an unique risk factor. This is also true in the model presented in Section 3.

2.2 Results

Starting from the unconditional version of the Euler equation, we focus first on market prices of risk and then turn to the quantities of risk in our portfolios. Table 2 reports our asset pricing results.

[7]Note that we only need to assume free-portfolio formation and the law of one price to postulate the existence of a SDF that prices these returns (see Cochrane (2001), chapter 4). We do not assume that US investors are the only buyers of sovereign bonds. They only own a fraction of all EMBI bonds, whose total market capitalization is $243 billions at the end of 2008. Our results, however, can be easily extended to non-US investors who also buy emerging market sovereign bonds. Their Euler equation is: $E_t(M^{\star}_{t+1} R^{e,j}_{t+1} \frac{Q_{t+1}}{Q_t}) = 0$, where $M^{\star}_{t+1}$ is the foreign stochastic discount factor, Q_t is the (real) exchange rate expressed in foreign good per unit of domestic good. If we assume that markets are complete, then the stochastic discount factor is unique and equal to: $M^{\star}_{t+1} = M_{t+1} Q_t / Q_{t+1}$. In complete markets, the foreign stochastic discount factor that prices sovereign bonds from a foreign investor's perspective is the US pricing kernel multiplied by the change in exchange rates. As a result, in order to take the perspective of other investors, we then simply need to add exchange rate risk. The case of incomplete markets is more difficult and we leave it out for future research. Instead, we show that the Euler equation for a US investor offers new insights on emerging market's sovereign debt.

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).[8] 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 away 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 cross-sectional R^2 is 73 percent. The null that the pricing errors are zero cannot be rejected, regardless of the estimation procedure.

Since the risk factor is a return, the no arbitrage condition implies that the risk price should be equal to the factor average excess return. 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, the market price of risk is higher but not statistically different from the mean excess return of the factor, so the no-arbitrage condition is not rejected. The average of the excess return on the US BBB corporate index is 290 points. So the estimated price of risk is 400 basis points removed from the point estimate. The standard error on the mean estimate is equal to 169 basis points and the standard error on the risk price is, again, 271 points. As a consequence, the mean is not statistically different from the market price of risk. Moreover, our EMBI portfolios do not take into account transaction costs, which would likely reduce EMBI returns more than US corporate returns. Figure 1 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, even though the first portfolio exhibit a large pricing error.

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 estimates. They are generally small and not significantly different from zero. The null that the αs are jointly zero cannot be 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

[8]Our asset pricing tables report two p-values: in Panel I, the null hypothesis is that all the cross-sectional pricing errors are zero. These cross-sectional pricing errors correspond to the distance between expected excess returns and the 45-degree line in the classic asset pricing graph (expected excess returns as a function of realized excess returns). In Panel II, the null hypothesis is that all intercepts in the time-series regressions of returns on risk factors are jointly zero. We report p-values computed as 1 minus the value of the chi-square cumulative distribution function (for a given chi-square statistic and a given degree of freedom). As a result, large pricing errors or large constants in the time-series imply large chi-square statistics and low p-values. A p-value below 5% means that we can reject the null hypothesis that all pricing errors or constants in the time-series are jointly zero.

5, and 3 and 6, we note that asset pricing (i.e post-formation) betas are always higher in the second group, as they should.

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
$Mean$	2.90				
	[1.68]				
Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	β^j_{US-BBB}	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
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	39.31

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. We also report the mean of the excess return on the US-BBB risk factor and the corresponding standard error obtained by bootstrapping. 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_{US-BBB}). 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 V_α (with one 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.

As a robustness check, we run the same asset pricing tests on a different set of returns. We use the EMBI returns sorted on US stock market betas and credit ratings. We use the same risk factor as

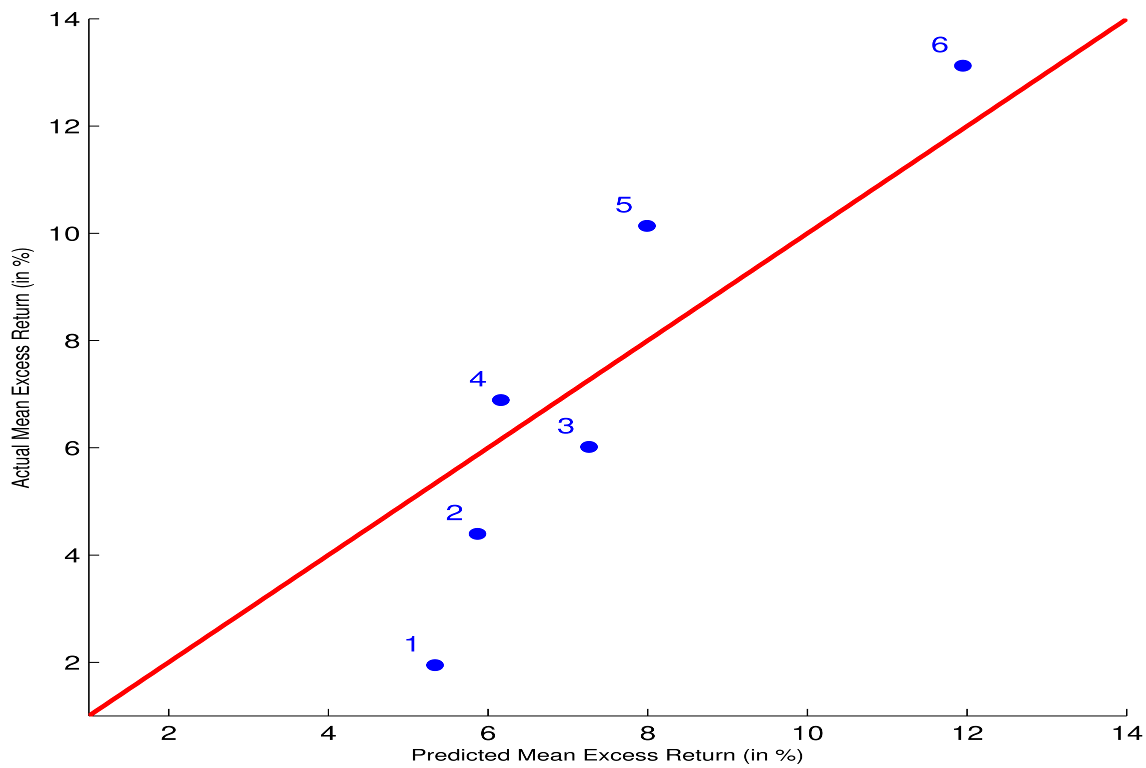

Figure 1: Predicted versus Realized Average Excess Returns

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 multiplied by the estimated market price of risk. All returns are annualized. Data are monthly. The sample period is 1/1995-5/2009.

before, the US BBB corporate bond return. Results are in Appendix B: Table 16 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 risk factor. Pricing errors are small and not significant.

Country-level Results We also check that our results are not driven by our portfolio building exercise. To do so, we run panel regressions and asset pricing tests at the country level. Results are described in detail in Appendix B and presented in Table 21. We implement the original Fama and MacBeth (1973) procedure on country excess returns. This procedure does not correspond to implementable trading strategies (unlike our portfolios) but it confirms our previous results: the market price of risk is positive and significant, and is higher but not statistically different from the mean excess return on the US BBB risk factor. In panel tests, we check that country-level EMBI excess return load significantly on the risk factor. The worse the rating, the higher the loading on the US BBB risk factor. Country-level results are thus fully consistent with our portfolio results.

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) show 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:

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

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_t 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^{BBB}_{t+1} and the same return multiplied by our conditioning variable $r^{BBB}_{t+1}z_t$. Table 17 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 18, 19, and 20 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 18). In the cross-section, the US BBB bond return drives out the change in the VIX index: when both risk factors are used together, the market price of risk of the latter is no longer significant (cf Table 19). 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, thus rejecting the model (cf Table 20). 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 General Equilibrium Impact of Sovereign Risk Premia

By sorting countries along their Standard and Poor's ratings and bond betas, we have obtained a cross-section of average excess returns that reflects different risk exposures. We have shown that countries with high EMBI market betas offer higher excess returns. The intuition for this finding is that market betas offer high frequency measures of the links between emerging countries and the US: everything else equal, countries whose business cycles are positively correlated with the US are riskier because their bond prices tend to fall in bad times for US investors.

To study the implications of systematic risk on debt quantity and prices, we now specify a general equilibrium model of sovereign borrowing and default. 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 and quantities. We first describe our setup and then turn to our calibration.

3.1 Setup

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 $Y_t^i = e^{z_t^i}\Gamma_t^i$. 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: $\Gamma_t^i = G_t^i \Gamma_{t-1}^i$, 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 $\epsilon^{g,i}$ and $\epsilon^{z,i}$ 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 endowment. We assume that consumption in the large developed economy is not affected by the small emerging countries. There is, for example, no feedback effect of defaults on lenders' consumption. We assume that idiosyncratic shocks to the lenders' consumption growth are *i.i.d.* log-normally distributed with mean g and volatility σ:

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

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.

Emerging countries only differ according to their conditional correlation to the developed economy: $E(\epsilon^{z^{i'}}\epsilon) = \rho^i$. This is the key source of heterogeneity across countries in our model. In a separate appendix, we report evidence that such heterogeneity exists in the data. Correlation coefficients between foreign and US HP-filtered GDP series range in our sample from -0.3 to 0.6 on annual data, and from -0.3 to 0.5 on quarterly data. This source of heterogeneity allows us to study the impact of default risk premia on optimal quantities and prices.

We have shown in the previous section that bond betas in the data are time-varying. In the model, however, we keep the correlation between the lenders and borrowers' endowment shocks constant. The simulated betas can still vary slightly because they are estimated on rolling windows of past equity and bond returns. Time-varying mean growth rates of borrowers and time-varying risk-aversion of lenders introduce time-variation in the betas. We could, of course, extend the model by introducing variable correlation coefficients without changing its message.

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 citizens. 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: governments can choose to default on sovereign debt at any point in time. In this setup, if investors are risk neutral, prices of sovereign bonds depend exclusively on the endogenous probabilities of default, which vary with the amount of funds borrowed and the expected value of 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 now describe lenders and borrowers, starting with the latter. The representative agent in each small open economy maximizes the stream of discounted utilities U_t^i:

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

where β denotes the time discount factor, and C_t^i denotes consumption at time t. We let lenders' and borrowers' discount factors differ because developing countries tend to have higher real risk free rates than emerging countries.[9]

The representative household receives a stochastic stream of the tradable good Y_t^i every period. 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:

$$C_t^i = Y_t^i - Q_t^i B_{t,t+1}^i + B_{t-1,t}^i. \tag{3.1}$$

In case of default, all current debt disappears. This simplifying assumption implies that the sovereign cannot selectively default on parts of its debt. 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

[9] Political economists argue that politicians tend to have shorter time horizons in small developing countries. In Amador (2008) for example, a low value for the discount factor β 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.

denoted $Y_t^{i,default}$, and the budget constraint is simply:

$$C_t^i = Y_t^{i,default}. \tag{3.2}$$

Following Arellano (2008), we assume an asymmetric direct output cost of default. More precisely, we assume that $Y_t^{i,default} = min\{Y_t^i, (1-\theta)\overline{Y^i}\}$, where $\overline{Y^i}$ is the mean output level and θ a measure of the default cost. This assumption implies that defaults are more costly in good times. A country with a large endowment Y^i today expects a large endowment in the near future, given the high persistence of the endowment process. If the country defaults, its consumption is set to be low for the entire time of exclusion from capital markets according to the budget constraint (3.2). 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 cost into account, and sovereign countries can borrow more in good times.

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), Uribe and Yue (2006), and Aguiar and Gopinath (2007)). 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. Mendoza and Yue (2008) propose a model where sovereign defaults endogenously produce output costs that are an increasing, strictly convex function of productivity shocks. As in their work, our assumption also implies that costs are increasing with output, but we keep the function linear for simplicity.

A second consequence of a country's default is its exclusion from international capital markets. In 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.[10] 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 the threat of exclusion works as an incentive to repay, thus reassuring lenders, decreasing the risk premium and allowing more borrowing.

[10]We assume an exogenous probability of regaining access to financial markets as in Aguiar and Gopinath (2006) and Arellano (2008). Kovrijnykh and Szentes (2007) endogeneize this probability in a model of strategic lending.

3.3 Lenders

We now turn to the description of the lenders. The representative agent receives an exogenous stochastic endowment every period denoted C_t. Lenders are risk-averse. In order to reproduce the large spread in returns between low and high beta countries, we rely on Campbell and Cochrane (1999) external habit preferences.[11] 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 or subsistence level, which depends on past consumption.

Why not power utility? A model where borrowers and lenders share the same constant relative risk-aversion preferences does not produce a large enough spread in excess returns for reasonable 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 multiplied by 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 spread of 500 basis points as in the data, the model requires a very high risk-aversion coefficient. But it would then imply a very high and volatile risk-free rate. On the contrary, the introduction of habit preferences implies that lenders' risk-aversion is endogenously 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. The real interest rate is constant and equal to the mean real interest rate in the data.

Habit preferences Following Campbell and Cochrane (1999), we assume that the external habit level depends on consumption growth through the following autoregressive process for the surplus

[11] A large literature in finance study the role of habit preferences in the resolution of the equity premium puzzle. We do not attempt to summarize it here. We focus on examples of Campbell and Cochrane (1999) habit preferences. Recently, Wachter (2006) considers their implications for the term structure; Chen, Colin-Dufresne and Goldstein (2008) focus on credit spreads, and Verdelhan (2010) on exchange rates. Garleanu and Panageas (2008) propose a model that is observationally similar to Campbell and Cochrane (1999) but based on heterogenous agents with finite lives.

consumption ratio, defined as the percentage gap between the endowment and habit levels ($S_t \equiv [C_t - H_t]/C_t$):

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

The sensitivity function $\lambda(s_t)$ describes how habits are formed from past aggregate consumption. In this framework, 'bad times' refers to times of low surplus consumption ratios s (when consumption is close to the habit level or subsistence level), and 'negative shocks' refers to negative consumption growth shocks ϵ. 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 s_{max} is the upper bound of the log 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 implies 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 subsistence 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 this case, emerging market yields can be high but expected excess returns are zero by definition. 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 their subsistence level.

Time-varying market price of risk In this model, the maximal value of the conditional Sharpe ratio is equal to:

$$SR_t = \frac{\sigma_t(M_{t+1})}{E_t(M_{t+1})} = \frac{\gamma\sigma}{\overline{S}}\sqrt{1-2(s_t-\overline{s})}.$$

In bad times, consumption is close to the subsistence level, surplus consumption ratios are low, and Sharpe ratios are high, i.e the compensation for bearing risk is high. As a result, the model implies a counter-cyclical market price of risk.[12] It is thus consistent with our asset pricing results: in the data,

[12]To be precise, the market price of risk corresponds to $Var(M)/E(M)$, whereas the Sharpe ratio is $\sigma(M)/E(M)$. In the model, however, the two series have similar dynamics.

market prices of risk also increase in bad times, as measured by a high value of the VIX index, which is often referred to as the "fear index" of investors. We can formalize this link between the model and the data. If we log-linearize the sensitivity function around the steady-state habit level, we obtain a log SDF that depends on consumption growth and consumption growth multiplied by $(s_t - \overline{s})$, the deviation of the surplus-consumption ratio from its steady-state. The last term mirrors the role of our conditioning variable in the empirical exercise. We interpret a high value of the VIX index as an index of high risk-aversion (i.e a low value of the surplus consumption ratio). Note, however, that this model does not produce enough variation in the conditional Sharpe ratio to match its empirical counterpart on stock markets (see Lettau and Ludvigson (2009) and Lustig and Verdelhan (2010) for additional evidence).

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: $y^i = (y_0^i, ..., y_t^i)$ 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', i.e. 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 being in good credit standing at the start of the period. If the government chooses to repay the debt coming to maturity, it can issue new debt. As a result, the value of staying in the contract is a function of the exogenous state vector x, 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 value v^d of defaulting depends only on the state vector x. 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:

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

where π is the exogenous probability of re-entering international capital markets after a default. 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 π, or remains in autarky with probability $1 - \pi$.

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 (3.1). 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'.

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:

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

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 2 plots default policy sets $D(B)$ as a function of the beginning-of-period asset position B and the endowment shock z. We consider different levels of the mean growth rate g. Each frontier defines a default region, and countries default for values of debt and endowments that are below the frontier: for a given mean growth rate g (i.e a particular frontier on this graph) and a given debt level, countries tend to default when they experience bad endowment shocks z. The higher the debt levels, the more likely the defaults. In other words, a country with little debt can sustain without defaulting larger negative shocks than a highly indebted country. But default policies also depend on overall economic conditions: in good times, when the mean growth rate is high, it takes a much larger negative shock for a country to default than in bad times, when the mean growth rate is low. Now that we have default sets, we turn to bond prices. We come back to this figure in the next section to study the impact of the lenders' risk-aversion.

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.[13] Starting from

[13] This simplifying assumption can be relaxed: see Arellano and Ramanarayanan (2009) for an example of a convex recovery rate.

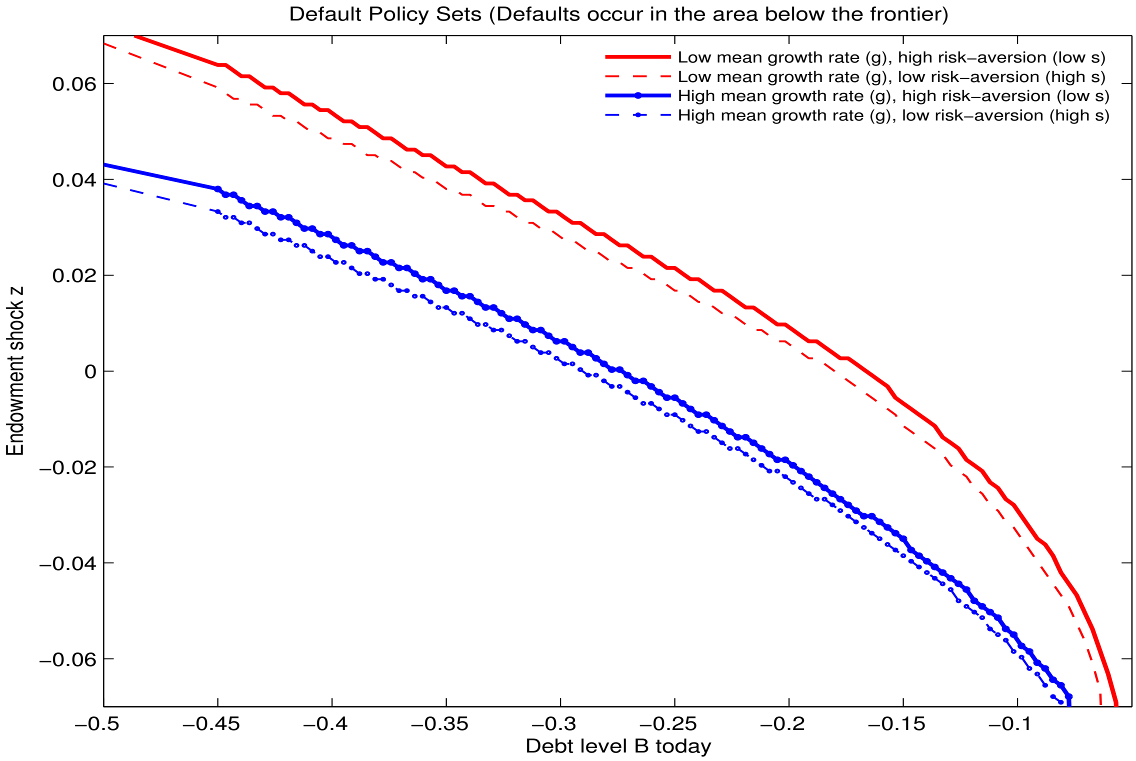

Figure 2: Default Policy Set

This figure plots the default policy set $D(B)$ as a function of the beginning-of-period asset positions B and consumption shocks z for different values of the mean endowment growth rate g and local risk-aversion of the lender. A low surplus-consumption ratio s is equivalent to a high risk-aversion coefficient of the lender. The cross-country correlation in consumption growth shocks ρ is equal to 0.5. For a given adverse endowment shock, countries are more likely to default if they are more indebted, if the mean growth rate is low and if lenders are more risk-averse.

the investor's Euler equation, the bond price function is:

$$Q(B', x) = E[M' 1_{1-dp(B',x)}] = E[M']E[1_{1-dp(B',x)}] + cov[M', 1_{1-dp(B',x)}], \tag{3.3}$$

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

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

A risk free asset pays one unit of the consumption good in any state of nature 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 (i.e when their marginal utility of consumption is high), the covariance term in (3.3) is negative, bond prices are low and yields are high. Likewise, if defaults tend to occur in good times for investors, yields are low.

4 Simulation

We simulate the model at quarterly frequency. We start with a brief overview of the calibration. To describe our results, we first focus on the impact of risk-aversion on equilibrium debt characteristics in a given country and then turn to portfolios of countries, as we do in section 1. We show that the model reproduces the results of our previous asset pricing experiments. We end this section with a succinct description of the model's implications regarding some puzzles in international economics.

4.1 Calibration

Table 3 reports all the parameters used in the simulation. Given our interest in time-varying risk premia, we cannot log-linearize the model, and we resort to a fairly standard discrete dynamic programming approach with four state variables. We use parallel computing to solve the model. The computational algorithm is described in Appendix C. Parameters describing lenders' consumption growth and preferences are from Campbell and Cochrane (1999). They correspond to post-World War II US consumption, real risk-free rates and equity returns.[14] Parameters describing the borrowers' endowments and constraints are from Aguiar and Gopinath (2006, 2007), except for the direct output cost of default. We review these parameters here rapidly.

As already noted, the output cost of default is difficult to measure precisely because defaults are endogenous: in the data, expectations of bad economic conditions in the future might trigger current defaults. In the model, a large cost ensures that emerging countries do not default too often and thus can borrow at low interest rates. We pick a value that appears in lower range of the literature. We assume that the output cost of default θ is equal to 4% per period in the model. This value is higher than in Aguiar and Gopinath (2006) (2%) but lower than in Hatchondo and Martinez (2009) (10% minimum) and in line with the evidence of a significant output drop in the aftermath of a default (see, for example, Rose (2005)).

The probability π of re-entering capital markets after a default is equal to 10 percent per period, implying an average exclusion of 2.5 years, as in Aguiar and Gopinath (2006) and consistent with the evidence reported in Gelos, Sahay and Sandleris (2004). This value, again, appears conservative. Benjamin and Wright (2009), for example, report a longer average time of exclusion of 6 years.

The risk aversion parameter γ in the borrowers' (and lenders') utility functions is set equal to 2. Our model, as its predecessors, requires a low discount factor β in order to generate large debt to GDP ratios: it is equal to 0.80 as in Aguiar and Gopinath (2006).

We follow Aguiar and Gopinath (2007) for the description of the permanent and transitory components of the endowment process. We pick σ_g and σ_z equal to 2% and 1% respectively at quarterly

[14] The value of δ matches an average US real log risk-free rate of 1% per annum as in Aguiar and Gopinath (2006). The value of ϕ corresponds to the persistence of the price-dividend ratio in the data. The model implies an equity risk premium of 6.5%.

frequency. The persistence of the transitory component is 0.9 as in many business cycle models. The persistence of the permanent component is 0.2. These values imply that 45% of the total variance comes from the permanent component.

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	0.20
Permanent: Standard deviation (%)	σ_g	4.00
Permanent: Mean (%)	μ_g	2.31
Temporary: Persistence	α_z	0.90
Temporary: Standard deviation (%)	σ_z	2.00
Temporary: Mean (%)	μ_z	$-Var(z)/2$
Preferences		
Risk-aversion	γ	2.00
Discount factor	β	0.80
Direct default cost (%)	θ	4.00
Probability of re-entry (%)	π	10.00

Notes: This 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 $4g$, 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).

4.2 Risk-aversion and optimal debt price, quantity and default

We turn now to the simulation results. We first focus on the key innovation of the model: the impact of risk premia on sovereign default decisions, debt prices and quantities.

We go back to Figure 2 to present the intuition. Recall that default decisions depend on overall economic conditions, i.e high or low mean growth rates and endowment shocks. This is the first order effect. But a second mechanism is at play. In order to describe it, we first focus on low mean endowment growth rates (the upper frontiers in Figure 2). The solid line corresponds to a low value of the investors' log surplus consumption ratio, i.e a high curvature of the investor's utility function, akin to a high coefficient of risk-aversion. The dotted line corresponds to low risk-aversion.

The novelty is that the borrower's decision to default depends on the lenders' risk aversion. Graphically, the default frontier is higher when risk-aversion is high. What is the intuition for this result? If lenders are very risk averse, risk premia are high and interest rates too. Each period, borrowers decide to repay or to default. Repaying past debt offers the foreign country the option to borrow again. Since it is now very costly to borrow, this option is less attractive. As a result, the emerging country tends to default even for mildly adverse shocks. On the contrary, when lenders are not risk-averse, risk premia are low and interest rates too. It is less costly to borrow and the emerging country can withstand larger adverse shocks without defaulting. The same logic applies when mean growth rates are higher, as shown in the lower two frontiers. In good times, defaults occur only when the country experiences a very negative temporary shock. But again, the impact of this shock depends on the lenders' risk aversion. A given shock might trigger a default when investors are very risk-averse but not otherwise.

We obtain naturally the opposite results when the correlation between borrowers and lenders business cycles is negative ($\rho = -0.5$). In this case, with high risk-aversion, insurance premia are high and interest rates are low (since bad times in the emerging country are good times in the US).

The model thus illustrates the link between lenders' risk aversion and borrowers' default decisions. When business cycles are positively correlated, default sets are larger the higher the lenders' risk aversion. For a given negative shock in the emerging country, defaults become more likely the higher the lenders' risk aversion. In equilibrium, it looks as if very risk averse lenders push emerging countries towards defaults.

We turn now to bond prices. Default decisions depend on the interaction between temporary and permanent shocks and on lenders' risk-aversion. These variables naturally affect bond prices. Figure 3 plots those bond prices as a function of borrowing levels (B'). The left panel focuses on the impact of the borrower's economic conditions, for a given low level of the lender's risk-aversion. The right panel focuses on the impact of risk aversion, for a given low mean growth rate of the borrower's endowment. We start with the left panel.

For a given debt level, bond prices are higher and interest rates lower when the emerging country experiences positive rather than negative temporary shocks. This first effect is large; in the figure it corresponds to the difference between the two lines with round markers (upper part) and the two lines without markers (lower part). This effect is amplified by permanent shocks. Bad shocks during low average growth periods imply lower prices and higher yields than the same shocks during high average growth times. The impact of permanent shocks on bond prices corresponds to the difference between the solid and dotted lines. To sum up, sovereign yields are high in bad times for the borrower because default probabilities are high. This would be the case if investors were risk-neutral too.

Let us focus now on the right-hand side panel. We compare here the price of a bond with and without the risk premium component (i.e the covariance term in equation 3.3). We consider an emerging country with a business cycle that is positively related to the investors' consumption growth (the correlation coefficient ρ is equal to 0.5). In the figure, the solid lines describe the full bond price. The dotted line corresponds to bond prices without their risk premium components. In a first approximation, these bond prices correspond to risk-neutral pricing.[15] As we expect, the risk premium lowers bond prices and increase yields: bonds issued by countries that tend to default more frequently when the investors' marginal utility is high are riskier and command higher yields. This cross-country link would not exist with risk-neutral investors. It is sizable only when risk-aversion is high and vanishes as risk aversion decreases.

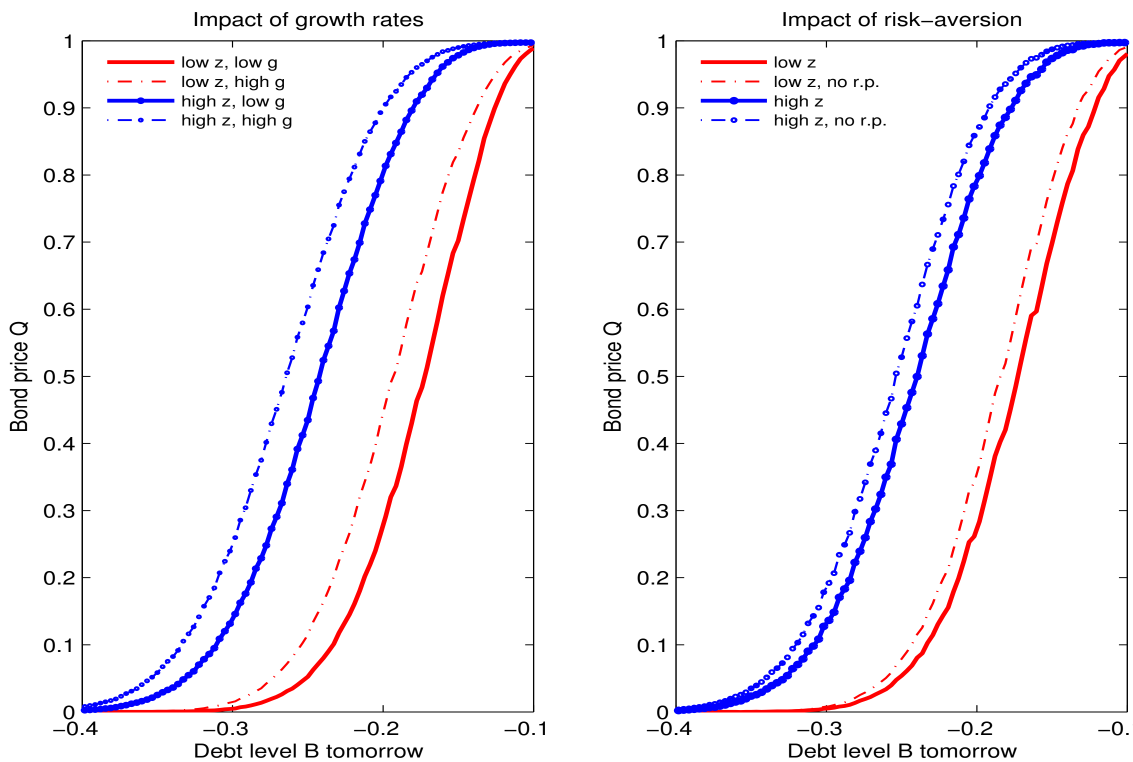

Figure 3: Bond Price Function

This figure present bond prices Q as a function of the amount of debt issued B. The cross-country correlation in endowment growth shocks ρ is equal to 0.5. In the left panel, we focus on the impact of the borrowers' economic conditions. Lines with circular markers correspond to high values of the transitory component of endowment z. Lines without markers correspond to low values of z. In each case, dotted lines correspond to high values of the permanent component of endowment growth g. In bad times, bond prices are low and yields are high, particularly so during periods of low average growth. In the right panel, we focus on the impact of the lenders' risk aversion. Solid lines correspond to bond prices. Dotted lines correspond to bond prices without their risk premium components. Lines with (without) markers correspond to high (low) values of z. Countries that tend to default more frequently in bad times for investors pay higher yields than other countries.

To sum up, in equilibrium, borrowers tend to default when they experience adverse economic shocks. Investors know expected default probabilities and require higher risk premia from borrowers that are more likely to default in bad times and whose default probability increase in bad times, from

[15]Note, however, that emerging countries dealing with risk-neutral investors would choose slightly different debt quantities. In this figure, in order to highlight the impact of risk aversion for a given indebtness, we simply compute artificial prices without the covariance term in equation 3.3 but for the same debt dynamics.

the investors' perspective. We now turn to the quantitative implications of the model.

4.3 Country-level results

We solve our model for a set of 36 countries. Again, these countries differ only along one dimension: the correlation between investors' consumption growth and borrowers' endowments. These correlation coefficients are uniformly spaced between $-.5$ and $.5$. Each ρ^i corresponds to a different sovereign borrower. All borrowing countries face the same investors' consumption growth, and thus the same time-varying risk-aversion. The values for all the other parameters are those in Table 3. Table 4 reports simulation results at the country level, for three different values of the cross-country correlation: $\rho =$ -0.5, 0, and 0.5. We compare simulation results to averages obtained over the same set of countries as in the sample of Section 1. Emerging market moments are computed by combining JP Morgan EMBI and Standard and Poor's data with the IMF-IFS (National Accounts) macroeconomic time series for the countries in our sample. As a result, macro moments are based on a sample of 26 emerging market economies (we drop Iraq, Philippines, Serbia, Uruguay and Ukraine for lack of data). Debt to income ratios come from the World Bank Global Development Finance database.

Panel A focuses on real business cycle moments. We consider HP-filtered variables and first log differences. We report the annualized volatility of HP-filtered output, output growth, consumption, and trade balance as a fraction of GDP, along with their first-order quarterly autocorrelation coefficients. The model broadly matches these moments. The volatility of GDP is 6.6% in the model and 5.4% on average in the data, while the first-order autocorrelation is 0.8 in both. The volatility of output growth and the trade balance are a bit too high in the model (4.6% vs 3.6% for output growth; 7.6% vs 5.0% for the trade balance). The autocorrelation of output growth is too low (0.15 vs 0.45). The model implies that consumption is more volatile than output, as is the case in emerging countries. The ratio of these two volatilities is on average 1.6 in the model and 1.3 in the data. But the model misses three macroeconomic moments. First, it underestimates the counter-cyclicality of the trade balance as a fraction of GDP (the correlation of the trade balance with GDP is -0.13 in the model versus -0.3 in the data). Second, it underestimates debt levels as a fraction of GDP. The average debt level is equal to 49% on average in the data, but only around 29% on average in the model. Note, however, that the model produces large maximum debt levels, with values up to 60%. Third, the model overestimates default probabilities. They are around 2% in the data. For countries whose business cycles are positively correlated to the US ($\rho = 0.5$), default probabilities are 3%, thus reasonably close. But they jump to 6% for countries whose business cycle are negatively correlated to the US ($\rho = -0.5$): in the model, defaults are not too costly for those countries; they do not have to pay high interest rates and thus optimally choose to default often.

Panel B focuses on asset pricing moments. The model produces excess returns that increase with the business cycle correlation. As expected, countries whose business cycles are positively (negatively) correlated with the US offer positive (negative) excess returns to US investors. The difference in excess returns across these two polar cases is 3.4%, thus sizable but lower than in the data. Excess returns appear very volatile, but this is only an artefact of the strong assumption we made on the recovery rate. We assume that, in times of defaults, US investors lose 100% of their investment. In samples without defaults, simulated excess returns are actually much lower than in the data. The correlation of excess returns and trade balances is close to zero in the simulations and to 0.1 on average in the data. Likewise, the correlation of excess returns and output is on average equal to -0.1 in the simulations; it is equal to -0.2 on average in the data. The model delivers yield spreads, defined as differences between yields on foreign bonds and yields on US bonds of similar maturities, that are in line with the data.

Overall, the main achievement of the model is to produce sizable average excess returns. To study them further and average out their idiosyncratic components, we turn now to portfolios of sovereign bonds.

4.4 Building Portfolios of Simulated Data

We use the simulated data to build portfolios that mimic the actual EMBI portfolios described in Section 1. In the model, expected default probabilities exist in closed form. We do not need to rely on ratings to proxy them. In the model, cross-country correlation coefficients on endowment shocks are constant and we could use them to sort countries. Yet, to be closer to our empirical procedure, we use stock market betas computed on rolling windows. We obtain these betas by regressing realized excess returns on a constant and US stock market excess returns. Note that the model, as in Campbell and Cochrane (1999), reproduces the characteristics of US equity markets: time-varying equity excess returns thus introduce some time-variation in stock market betas.

Unlike on actual EMBI portfolios, here we sort bonds along only one dimension. The reason is simple: there is only one source of risk that is priced in the model: it is the correlation between consumption growth in the US and bond returns. In order to interpret the two-dimensional sort we used in the data, we would need to introduce a second source of heterogeneity across countries. If countries differ in terms of their endowment volatility (and the correlation is not zero), then expected default probabilities reflect risk premia: for a given beta, higher endowment volatilities entail higher default probabilities and higher expected excess returns. For example, if the volatility of temporary shocks (σ_z) doubles, the equilibrium default probability is multiplied by four and the average excess return more than doubles. As a result, introducing heterogeneity in endowment volatilities and sorting countries on default probabilities would also produce a cross-section of excess returns, similar to the one we obtain in the data by sorting on ratings. This additional cross-section would naturally be priced by the same risk factor. As previously noted, we keep the model simple and only introduce one key source of heterogeneity, the cross-country correlation of endowment shocks.

At the end of each period t, we thus sort all countries into 6 portfolios on the basis of market betas (β_{Mkt}). The 6 portfolios are re-balanced at the end of every period. For each portfolio j, we

Table 4: Country-Level Simulation Results

Macro Moments				
		Model		Data
Cross-country correlation:	Low	Zero	High	
$\sigma(Y)$	6.61	6.61	6.61	5.39
$\sigma(\Delta Y/Y)$	4.60	4.60	4.60	3.60
$\rho(Y)$	0.78	0.78	0.78	0.81
$\rho(\Delta Y/Y)$	0.15	0.15	0.15	0.45
$\sigma(C)/\sigma(Y)$	1.66	1.61	1.56	1.30
$\sigma(TB/Y)$	8.12	7.59	7.03	5.00
$\rho(TB/Y,Y)$	-0.11	-0.13	-0.15	-0.33
$\rho(C,Y)$	0.69	0.71	0.74	0.59
E(Default)	6.67	4.97	3.27	1.91
E(Debt/Y)	-30.30	-28.96	-27.50	-49.68
Asset Pricing Moments				
		Model		Data
Cross-country correlation:	Low	Zero	High	
$E(R^e)$	-2.20	$--$	1.15	7.00
$\sigma(R^e)$	26.21	$--$	18.36	18.07
$\rho(Y,R^e)$	-0.07	$--$	-0.06	-0.19
$\rho(TB/Y,R^e)$	-0.02	$--$	-0.01	0.14
$E(spread)$	4.69	4.92	4.50	5.44
$\sigma(spread)$	1.15	1.22	1.07	3.77

Notes: This table reports macro (first panel) and asset pricing (second panel) moments from simulated and actual data. The first three columns present moments from simulated data for three countries with different cross-country correlations in endowment growth shocks ρ: low $(-.5)$, zero (0) and high (.5). The last column report their empirical counterparts. Macroeconomic variables in levels are HP-filtered. Before filtering the series, we remove the seasonal components with the X-12-ARIMA algorithm from the US Census Bureau. The first panel reports the volatility and autocorrelation of output and output growth; the volatility of consumption and the volatility of the ratio of net exports to GDP; the correlation of consumption and net exports with output; the mean default rate and the average debt as a percentage of output. The second panel reports the mean and volatility of EMBI bonds' yield spreads and excess returns, along with the correlation of bond excess returns with income and net exports (as a fraction of GDP). Yield spreads correspond to the difference between yields on foreign bonds and yields on US bonds of similar maturities. Yields are obtained as the inverse of bond prices. Note that the debt levels and correlation measures pertaining to excess returns correspond to samples without defaults. Emerging market moments are computed by combining JP Morgan EMBI and Standard and Poor's data with IMF-IFS (National Accounts) macroeconomic time series for the countries in our sample. As a result, macro moments are based on a sample of 26 emerging market economies (we drop Iraq, Philippines, Serbia, Uruguay and Ukraine for lack of data). Debt to income ratios come from the World Bank Global Development Finance database. The mean probability of default is the mean frequency, in the sample, of episodes defined as "selective default" by Standard and Poor's. The sample period is 1/1995 - 5/2009 (for some countries the sample is shorter, depending on data availability). All moments are at quarterly frequency. Averages and standard deviations are annualized and in percentages.

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. Table 5 provides an overview of the 6 portfolios.

The first panel reports the average β^j_{Mkt} for countries in portfolio j. Business cycles of countries with low β_{Mkt} are negatively correlated with the investors' consumption growth. These countries on

Table 5: Portfolios of Simulated Data

Portfolios	1	2	3	4	5	6
			Stock market beta: β_{Mkt} (Pre-Formation)			
Mean	−0.25	−0.12	−0.05	0.00	0.05	0.13
Std	0.20	0.15	0.11	0.10	0.10	0.13
			Default probability			
Mean	5.85	5.41	4.89	4.50	4.17	3.84
Std	1.33	1.21	1.09	1.02	0.96	0.91
			Excess return: r^e			
Mean	−1.24	−0.66	−0.14	0.29	0.52	0.65
Std	21.06	19.73	18.64	17.88	17.28	16.68
Std*	1.02	1.01	1.01	1.02	1.03	1.04
			Debt/Output			
Mean	30.14	29.71	29.29	29.01	28.67	28.52
Std	7.09	6.92	6.78	6.73	6.73	6.67
			Stock market beta: β_{Mkt} (Post-Formation)			
Mean	−0.14	−0.08	−0.04	0.00	0.03	0.05
Std	0.01	0.01	0.01	0.01	0.01	0.01

Notes: This table reports, for each portfolio j, the average slope coefficient β_{Mkt} (pre-formation) from a regression of one-quarter sovereign bonds' excess returns on the investors' stock market excess returns (first panel), the average expected probability of default (second panel), the average excess return (third panel), the debt to output ratio (fourth panel) and the post-formation betas (fifth panel). Post-formation betas correspond to slope coefficients in regressions of quarterly portfolios' excess returns on quarterly investor's stock market excess returns. Probabilities of default, excess returns and debt ratios are reported in percentage points. Excess returns and default probabilities are annualized. For each variable, the table reports its mean and its standard deviation. For excess returns, the table also reports standard deviations (denoted $Std*$) in samples without defaults.

average default more frequently when investors' consumption is high and above their habit levels. On the contrary, countries with high β_{Mkt} default more frequently when investors' consumption is low and close to their habit levels.[16] The second panel reports average expected default probabilities. Sorting on β_{Mkt} implies a cross-section of average default probabilities, with a spread of 2 percent. Note that high beta countries have lower default probabilities than low beta countries.

Let us turn now to average excess returns. The larger the market β^j_{Mkt}, the higher the excess returns. This is exactly what we expect. Higher beta countries are riskier because their bonds pay badly in bad times for investors, and thus they should offer higher excess returns on average. The model produces average excess returns that range from -1.2 percent to 0.7 percent per annum. In the model, some countries are good hedges to US consumption growth risk, and thus the negative average excess returns. We do not find so perfect hedges in the data. This discrepancy is due to our distribution of correlation coefficients, which is for simplicity symmetric around 0. More importantly,

[16] Figures 10 and 11 in Appendix C illustrate this point; they present average consumption paths in the borrowing and lending countries around default episodes in the case of positively correlated business cycles.

the difference in excess returns between low and high beta countries in the model is large and amounts to 190 basis points annually. Those excess returns, however, are lower than in the data. They also appear much more volatile than in the data. Again, this volatility reflects our assumption that recovery rates are zero in case of defaults. In samples without defaults, standard deviations are much lower and close to 1 percent.

Matching means and variances of sovereign bond excess returns would certainly necessitate to look at longer maturities. To show that maturities matter, we report in Table 9 of Appendix A the mean senior CDS rates at different horizons for countries in our sample. Our dataset comprises series for 1, 2, .. 10-year horizons over a short sample. We obtain the fitted CDS curves by spline interpolation of existing CDS contracts. We impose the boundary condition that the CDS rates tend to 0 when the horizon tends to 0 (i.e, there is no instantaneous risk of default). We compute fitted values only when at least the 1-year, 5-year and 10-year CDS rates are available. We find that, on average, 10-year rates are more than 5 times higher than 3-month rates. As a result, we do not attempt to match EMBI returns with our one-period model.

The model produces reasonable levels of debt to GDP ratios of around 30 percent, but lower than the average of 50 percent measured in our sample. The spread in returns due to market betas is not due to higher levels of debt. 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 and illustrate the role of risk premia.

Finally, we run on simulated data the same asset pricing experiment as on actual data. Using the simulated US stock market return as a risk factor, we obtain a clear cross-section of portfolio betas, as reported in the last panel of Table 5. Table 22 in Appendix C reports additional asset pricing results. The cross-sectional R^2 is equal to 95% and the market price of risk is in line with the average US stock market return. Our model offers a natural interpretation of our empirical facts.

4.5 Implications

We end this paper by succinctly presenting some additional implications of the model regarding the interest rate elasticity of debt levels, the correlations between output and interest rates, and the large increase in yields in the fall of 2008. More broadly, the model implies that monetary unions might lead to higher borrowing costs for some members because of higher business cycles' synchronizations. We simply highlight here the connections to our findings, as potential avenues for future research. But we do not claim to solve any of these puzzles and acknowledge that each of these topics connects to a large literature and deserves further study.

Interest rate elasticity of debt The link between interest rates and debt levels seems obvious: interest rates are expected to rise when debt levels increase, because default probabilities increase. Yet, this link is empirically elusive. Edwards (1984) finds that the external debt to GDP ratio plays a significant role in explaining country spreads. More recently, however, Uribe and Yue (2006) do not find any significant role for debt to GDP ratios. We can offer an explanation that reconciles these findings. Looking back at our portfolios, we see that an increase in debt to GDP ratios goes along with a worsening of S&P ratings and an increase in returns for either low or high beta bonds. But across beta groups, there is no clear pattern. The highest returns do not correspond to the highest debt levels. In other words, for a given beta, there might be a link between interest rates and debt levels but there is no unconditional relation between the two.

Output-interest rate correlations Interest rates in emerging markets are in general counter-cyclical with respect to their own GDP. But there exist large variations in the correlation coefficients between output and interest rates.[17] Our model offers an interpretation of this heterogeneity.

Recall that interest rates reflect default probabilities and covariances. On the one hand, if the borrowers' output is positively correlated with the US output, then we should expect high interest rates in bad times: both the default probability and the risk premium (due to investors' time varying risk aversion) should be high in bad times. This mechanism leads to a very negative correlation between interest rates and output in the emerging country. On the other hand, if the borrowers' output is negatively correlated with the US output, then the risk premium should now be lower, leading to a higher correlation between interest rates and output. It is, however, difficult to test this prediction since emerging countries do not offer long and high frequency measures of GDP growth rates.[18]

Fall 2008 Eichengreen and Mody (2000) attribute past variations in emerging market spreads to investor sentiment. We offer a different perspective. We show in this paper that average returns on EMBI bonds satisfy a no-arbitrage condition. Variations in spreads are thus at least partly rational, and not only behavioral, responses to economic conditions. We apply this reasoning to the large increase in sovereign bond spreads in the fall of 2008.

Our conditional asset pricing results show that the market price of risk increases in bad times, e.g when the option-implied VIX index is high. The fall of 2008 indeed corresponds to a five-standard deviation shock to this index. A higher market price of risk implies higher expected excess returns in the future and thus lower prices now. During this period, we also observe an increase in the quantity of risk. This increase in betas also implies higher expected returns and lower prices, but the model does not capture this second effect, as the quantity of risk is fixed. The model, however, implies

[17]Uribe and Yue (2006) for example estimate the following correlations between 1994 and 2001: −0.67 in Argentina, −0.51 in Brazil, −0.80 in Ecuador, −0.58 in Mexico, −0.37 in Peru, −0.02 in the Philippines, and −0.07 in South Africa. The first four are significantly different from zero; the others are not.

[18]At least, our data do not seem to reject this reasoning. Looking at the correlation between the HP-filtered US and foreign GDP series, we obtain a high and positive correlation for Argentina (0.51) and Mexico (0.52) and a somehow lower but still positive correlation for Brazil (0.11) – see Table 10 in the separate appendix. These countries are characterized by highly counter-cyclical interest rates. The Philippines, Peru and South Africa have both a-cyclical interest rates and low correlation with the US (-0.12, -0.21 and 0.02).

large variations in the market price of risk. Feeding the model with the actual US consumption growth series, we obtain a doubling of the market price of risk during the mortgage crisis.[19] This time-variation in risk-aversion implied by the model accounts for large changes in bond prices, but it is not enough to replicate the sudden drop and rapid rebound experienced on emerging bond markets. Additional factors, either behavioral or due to additional sources of risk, are needed to fully account for this episode.

Monetary unions Finally, we note that our results offer a new perspective on monetary unions. At the time of this writing, several European countries face high borrowing costs compared to Germany for example. Our paper focuses on US investors buying emerging market debt issued in US dollars. A similar reasoning, however, applies to German investors buying the debt of other members of the euro area. Insofar as monetary unions entail convergence across business cycles (and thus higher correlations and betas), they may imply higher borrowing difficulties, particularly acute in bad times, because of sovereign risk premia. By removing currency risk premia, however, currency unions also affect interest rates. We leave the study of the interaction between sovereign and currency risk premia out for future research.

5 Conclusion

In this paper, we show that emerging market betas impact sovereign bond prices 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. The leading structural models of sovereign debt assume that investors are risk-neutral and thus cannot account for our empirical findings.

We propose one example of a general equilibrium model of sovereign borrowing and default 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. The model illustrates the impact of lenders' time-varying risk aversion on borrowers' default decisions.

Our empirical methodology and our general equilibrium 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

[19] Figure 12 in the appendix reports the time-series of the maximal Sharpe ratio in the model during the period from 1995:I to 2009:II.

Quadrini (2001). These papers, however, consider only risk-neutral financial intermediaries. Our work shows that lenders' risk aversion affect both debt quantities and prices.

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Sovereign Risk Premia
- Supplementary Online Appendix -
NOT FOR PUBLICATION

This separate Appendix contains three sections. Appendix A reports additional statistics on our data set. Appendix B describes our asset pricing methodology and reports additional asset pricing results. Appendix C details our computational algorithm and reports additional simulation results.

Appendix A Data

Cavanagh and Long (1999) offer a detailed description of the construction of EMBI indices. As a snapshot of our data set, Figure 4 reports, for each country in the 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 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.

We report below additional descriptive statistics on our data.

- Table 6 reports summary statistics on the EMBI stripped spreads for our sample. All spreads are annual.
- Table 7 presents the market value of US holdings of long term foreign government debt.
- Table 8 reports the ratio of debt to GDP for the countries in our sample, using data from the Global Development Finance dataset of the World Bank.
- Table 9 reports mean senior CDS rates at different horizons for countries in our sample.
- Table 10 reports the cross-country correlation coefficients between each EMBI country's real GDP and the US real GDP. 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). 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) 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.

EMBI series do not account nor report bid-ask spreads. In order to obtain an order of magnitude of transaction costs, we build a database of individual sovereign bonds in emerging markets. We collect in Datastream all the ISIN codes corresponding to these bonds and retrieve their end-of day bid and ask prices from Bloomberg.[20] We obtain a very unbalanced panel: from 5 bonds at the start of the sample in 1995 to 350 bonds at the end

[20]We thank James Hebden for his help in assembling this large database.

in 2009. Figure 5 plots the number of active, emerging markets sovereign bonds in our data set through time. Our dataset comprises many outliers, with bid-ask spreads that are either negative, zero, or extremely large.

We delete all observations that correspond to negative or zero bid-ask spreads. We also delete bid-ask spreads that are above 20% if the spread was below this cutoff the day before or the day after the spread is recorded. We keep, however, spreads above 20% if they do not appear as single observations. We then proceed in two steps. First, for each country, we compute the median bid-ask spreads at the end of each month (using the same dates as for our EMBI series). Second, we form 6 portfolios of those spreads using the same sorts as for our benchmark EMBI portfolios. In each portfolio, spreads are equally-weighted. Note that our data set does not correspond to the one used by JP Morgan in order to build EMBI indices. We do not have the list of bonds included in those indices or their weights.

Table 11 shows that, in our sample, median bid-ask spreads vary between 41 basis points on the second portfolio to 65 basis point on the last portfolio.

Appendix B Asset Pricing Tests

We briefly describe here the asset pricing tests used in the text. See Cochrane (2001) for a comprehensive presentation and discussion. We then report additional asset pricing results, first using portfolios of countries and then using individual countries.

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

$$g_T(b) = E_T(m_t \widetilde{r_t^e}) = E_T(\widetilde{r_t^e}) - E_T(\widetilde{r_t^e} f_t')b,$$

where $\widetilde{r_t^e} = [\widetilde{r_t^{e,1}}, \widetilde{r_t^{e,2}}, ..., \widetilde{r_t^{e,N}}]'$ 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: $S = \sum E[(m_t \widetilde{r_t^e})(m_{t-j} \widetilde{r_{t-j}^e})']$.[21] 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 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.

[21]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.

Robustness Checks on EMBI Portfolios This section reports robustness checks: additional statistics, different sorts, different risk factors and conditional asset pricing results.

- Table 12 reports how frequently countries change portfolios.
- Figure 6 plots for Argentina and Mexico – as an example – the monthly S&P credit rating, the bond market beta β_{EMBI} and the portfolio allocation.
- Table 13 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 along with NBER recessions and financial crisis dates. Theses dates are from Kho, Bong-Chan, Dong Lee and Rene M. Stulz, (2000), *American Economic Review*, 90 (2), p28-31.
- Table 14 reports summary statistics for portfolios of countries sorted on credit ratings and bond market betas. Statistics are value-weighted.
- Table 15 reports similar information for portfolios of countries sorted on credit ratings and stock market betas. Statistics are equally-weighted.
- Table 16 reports asset pricing results obtained with the equally-weighted portfolios presented in Table 15. 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 15.
- Table 17 reports the results of our conditional asset pricing tests using VIX as the conditioning variable.
- Table 18 reports asset pricing results obtained with the log change in the VIX index as risk factor.
- Table 19 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 20 reports asset pricing results obtained with the TED spread as risk factor.

Country-Level Asset Pricing Results We have shown that our results are robust to the choice of past betas and to different portfolio weights. We now consider an additional robustness check: we run country-level Fama and MacBeth (1973) tests.

We first describe the procedure and then reports our results. The Fama and MacBeth (1973) procedure has two steps. In the first step, we run time series regressions of each country's i bond excess return on a constant and our risk factor $r^{US_{BBB}}$:

$$r_{t+1}^{e,i} = c^i + \beta_i r_{t+1}^{US_{BBB}} + \epsilon_{i,t+1}, \text{for a given } i, \forall t.$$

In a second step, we run cross-sectional regressions of all bond excess returns on betas:

$$r_t^{e,i} = \lambda_t \beta_i + \xi_t, \text{for a given } t, \forall i.$$

We compute the market price of risk as the mean of all these slope coefficients: $\lambda = \frac{1}{T}\sum_{t=1}^{T}\lambda_t$.

This procedure is the original Fama and MacBeth (1973) experiment. Its first step is similar to the procedure described above and used on portfolios. Its second step differs: we run here T cross-sectional regressions (one for each date in the sample) instead of running one single cross-sectional regression on the average excess returns. We implement this modification because the number of countries varies along the sample period. Note that this procedure does not require forming portfolios. But it has one main drawback: it does not correspond to an implementable trading strategy since we use the whole sample to estimate the betas.

The first panel of Table 21 reports our asset pricing results. The market price of risk is positive and significant. It is higher than but not statistically different from the mean of the risk factor's excess return. The square root of the mean squared errors and the mean absolute pricing error are larger than on portfolios, but we cannot reject the null hypothesis that all pricing errors are jointly zero.

A simple figure illustrates our results clearly. Figure 9 plots realized average excess returns on the vertical axis against predicted average excess returns on the horizontal axis. As described above, we regress each actual country-level excess return on a constant and the risk factor to obtain the slope coefficients β. Each predicted excess returns is then obtained using the OLS estimate of β times the market price of risk. All returns are annualized. As Figure 9 shows, a single risk factor explains a large share of the variation across countries and pricing errors are concentrated on a few countries like Argentina, Russia, and Trinidad and Tobago. High beta countries tend to offer high unconditional currency excess returns.

The second panel of Table 21 checks that EMBI country returns load significantly on the US BBB corporate returns. We report six sets of panel regression results. We regress all the country-level excess returns on the US BBB corporate returns, the country ratings, as well as the product of ratings and BBB returns. The first three columns correspond to panels without fixed effects, while the last three columns include fixed effects. In the former case, standard errors are clustered by country and time. EMBI country returns load very significantly on the US corporate returns: the slope coefficient is 1.2 with a standard error of 0.2. The introduction of ratings and/or fixed effects does not alter this result. Adding the interaction of ratings and BBB returns does affect the initial slope coefficient: the worse the ratings, the larger the loading of EMBI country returns on the US BBB returns. The slope coefficient of this interaction is equal to 2.2 with a standard error of 0.7. This result is consistent with our portfolios: when we sort countries on along the ratings and beta dimensions, we obtain a double cross-section of portfolio excess returns. The higher the betas, the higher the average excess returns, especially for countries with poor ratings.

Appendix C Simulations

Computational Algorithm To solve the model numerically we de-trend all the Bellman equations. To do so, we normalize all variables by $\mu_g \Gamma_{t-1}$.

Hatchondo, Martinez, and Sapriza (2010) show that evenly spaced and coarse grids imply biases in the mean debt levels and volatility of spreads. To alleviate the biases, we discretize the borrower's endowment process using non evenly spaced grid points that span -5 to +5 standard deviations around the mean of each process. Most of the grid points are between one and three standard deviations around the means. We discretize the investors' surplus consumption ratio in 6 grid points equally spaced between .0072 and S_{max}. We build the transition matrix as described in Tauchen and Hussey (1991). The quantity of debt is discretized between 0 (no debt) and -0.95 and we check in our simulations that this constraint never binds. Most grid points are between -20% and +20% around the mean debt level. The exact definition of our grids and our programs are available on our websites.

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 $x = [y, s]'$ 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 equation 3.3. 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 $max\{Q^i(B', x) - Q^{i+1}(B'x)\} < 10^{-6}$.

We also compute the price of a claim on total consumption and its return. To obtain the equilibrium price-dividend ratio in the Campbell and Cochrane (2009) model, we follow Wachter (2005). In our simulation, the price-dividend ratio has a mean of 17.85 and a standard deviation of 13.13 (both annualized), and a quarterly autocorrelation of 0.97.

Due to the large number of state variables and the large number of countries, we run our code in parallel mode on 32 processors. We start with small grids and interpolate the obtained value functions to use them as initial guesses for larger grids. We have a total of 36 simulated countries, for 90,000 quarters; we use the second half of the sample for our analysis.

We reproduce on simulated data the same experiment that we run on actual data. Table 22 reports asset pricing results on portfolios of simulated data. We use the US stock market return as our risk factor. We obtain a positive and significant market price of risk that is in line with the mean of the risk factor. This unique risk factor explains 95% of the cross-section of average sovereign bond excess returns. The alphas are overall small and not statistically significant at the 1% level. For the high beta portfolios, however, the alphas are individually significant. This result is in line with the model: the investors' preferences imply that the market price of risk is time-varying and cannot be perfectly summarized by a unique risk factor. We also obtain a clear cross-section of betas. High beta countries offer high sovereign risk premia. This is in line with the data: as shown in the last panel of Tables 13, 14, and 15, high (pre-formation) beta portfolios exhibit high (post-formation) stock market betas. Note that the time-series R^2 are small because of missing risk factors (higher order terms in the log linearization of the stochastic discount factor), idiosyncratic variations and our assumption of zero recovery rates in case of defaults.

Time Series Figures 10 and 11 present the average consumption growth of lenders and borrowers before and after defaults.

Figure 12 reports the time-series of the Sharpe ratio in the model, using actual consumption growth shocks in the US.

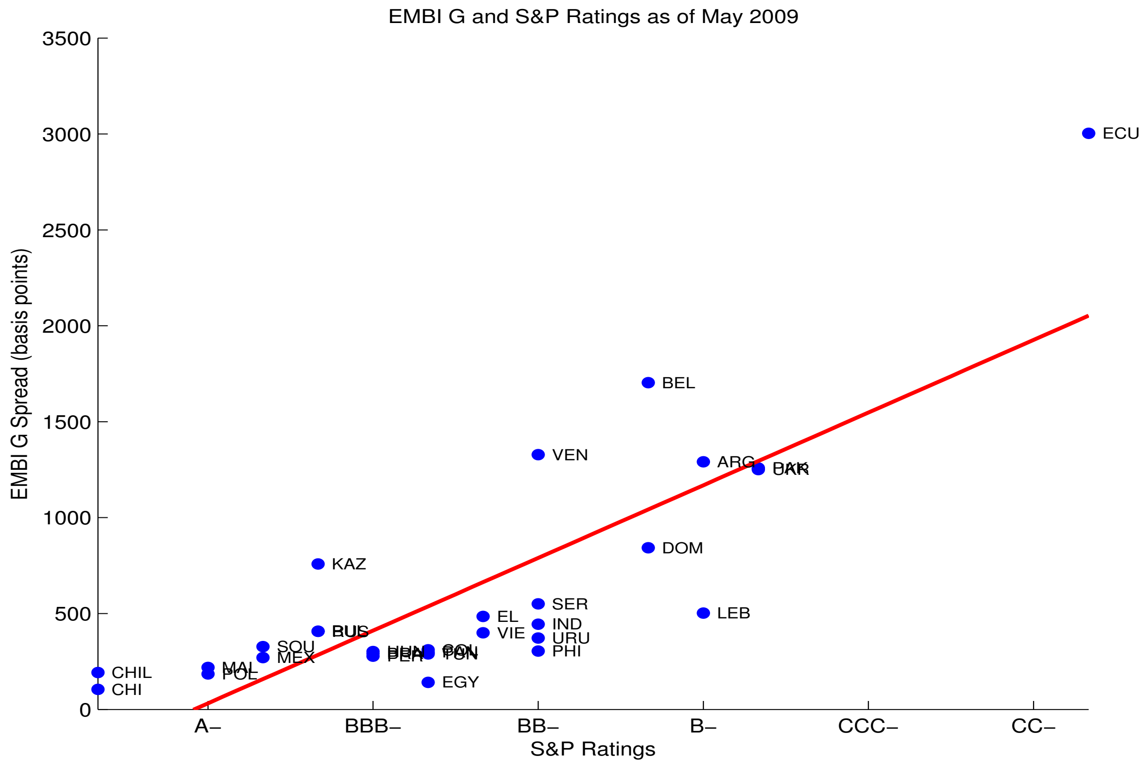

Figure 4: EMBI Global Annual Spreads and Standard and Poor's Ratings

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.

Table 6: 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 7: US Holdings of Foreign Long Term Government Debt

The table presents the market value of US holdings of long term foreign government debt. Data are available in different pdf documents at *http://www.treas.gov/tic/fpis.shtml#usclaims*. The information comes from the surveys of Foreign Portfolio Holdings of US Securities. We report here all the available years. For 2008, the table also reports the market value US holdings of long term foreign government debt *issued in US dollars* (in the last column). Amounts in millions of US dollars.

Countries	1997	2001	2003	2004	2005	2006	2007	2008	2008 (USD)
Argentina	14112	1339	1341	1923	4058	7281	6079	2579	1794
Belize	0	0	32	14	9	25	27	49	49
Brazil	8189	8768	15234	16611	17822	14820	12580	15671	7476
Bulgaria	1041	1663	1437	1167	350	184	169	86	83
Chile	202	248	1891	1821	1501	1103	827	576	576
China	1534	171	579	481	406	464	332	363	361
Colombia	1337	2071	2903	3338	3464	4724	5059	4585	2340
Cote D'Ivoire	26	43	38	83	75	92	153	60	30
Dominican Republic	25	113	496	428	622	513	562	303	303
Ecuador	1366	672	853	1023	900	506	663	343	343
Egypt	0	248	48	46	981	1134	1632	1461	1258
El Salvador	1	15	506	626	791	897	788	474	474
Hungary	1152	267	564	575	491	422	1370	1009	87
Indonesia	259	61	362	594	1440	2107	2876	3725	2083
Iraq	−−	−−	−−	−−	−−	−−	−−	−−	−−
Kazakhstan	63	110	5	11	9	11	0	0	0
Lebanon	438	31	97	155	285	265	272	179	179
Malaysia	161	557	1185	1394	1618	1650	2981	2604	390
Mexico	10916	11355	17947	18791	16751	12465	11949	10294	6946
Morocco	163	177	80	136	114	28	46	21	16
Pakistan	219	78	48	20	15	187	313	20	176
Panama	1848	1723	2808	2839	2898	2348	2211	1626	1626
Peru	673	1071	2878	3196	3688	2695	2926	270	1607
Philippines	1217	1646	2452	2638	3180	3541	3404	2166	2100
Poland	2448	1725	1536	2466	2750	4377	4737	2827	460
Russia	1843	5025	7466	9739	9215	7360	5729	4124	4124
Serbia	1	1	0	0	101	93	59	96	96
South Africa	1982	797	2451	2759	2260	2691	2998	1899	917
Thailand	801	212	341	503	644	757	65	397	0
Trinidad and Tobago	143	254	569	437	462	329	405	297	297
Tunisia	27	155	405	245	384	340	265	389	244
Turkey	640	1003	1813	2269	2898	3934	5107	3961	2216
Ukraine	2	189	585	1413	1079	1130	1337	748	559
Uruguay	301	512	520	717	925	1659	1711	1202	898
Venezuela	3758	2325	4101	5084	4556	4421	3946	2868	2693
Vietnam	24	20	81	113	306	231	233	192	192
All	56912	44645	73652	83655	87048	84784	83180	69118	42993

Table 8: 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, median, and max. 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 9: CDS Curves for EMBI Global countries

The table presents mean senior CDS rates (in basis points) for the sample of J.P. Morgan EMBI Global countries at different horizons. The last column reports the ratio of the 10-year (observed) to the 3-month (fitted) CDS rates. Our dataset comprises series for 1, 2, .. 10-year horizons. We obtain the fitted CDS curves by spline interpolation of the rates from existing CDS contracts. We impose the boundary condition that the CDS rates tend to 0 when the horizon tends to 0. We compute fitted values only when at least the 1-year, 5-year and 10-year CDS rates are available. We do not have data for Belize, Cote d'Ivoire, Dominican Republic, Trinidad and Tobago and Uruguay. The sample period is 1/2003-5/2009, but most series start later than January 2003.

	3-month	1-year	5-year	10-year	Slope 10-yr / 3-month
Argentina	350.01	848.96	896.83	953.09	2.72
Belize	–	–	–	–	–
Brazil	24.17	80.27	237.18	289.55	11.98
Bulgaria	–	–	–	–	–
Chile	11.11	29.92	52.85	69.57	6.26
China	9.81	25.87	47.66	58.45	5.96
Colombia	25.84	78.25	222.63	280.70	10.86
Cote d'Ivoire	–	–	–	–	–
Dominican Republic	–	–	–	–	–
Ecuador	382.23	945.81	1033.78	1032.09	2.70
Egypt	65.08	165.88	243.05	267.94	4.12
El Salvador	35.73	95.58	164.19	194.44	5.44
Hungary	26.00	65.65	90.66	102.01	3.92
Indonesia	50.43	134.75	255.50	312.60	6.20
Iraq	48.87	177.39	662.87	1178.04	24.11
Kazakhstan	78.58	202.31	246.10	250.00	3.18
Lebanon	94.15	282.33	441.11	522.37	5.55
Malaysia	14.44	37.68	64.58	75.76	5.25
Mexico	20.01	55.04	112.34	146.81	7.34
Morocco	28.61	82.31	150.38	182.35	6.37
Pakistan	251.74	609.76	643.95	676.69	2.69
Panama	23.67	70.71	186.64	242.28	10.24
Peru	26.81	76.48	199.55	252.93	9.43
Philippine	49.17	136.46	294.55	359.74	7.32
Poland	12.61	32.63	51.39	61.72	4.90
Russia	56.66	140.30	164.47	186.34	3.29
Serbia	28.39	78.86	179.09	296.99	10.46
South Africa	23.52	63.13	116.25	144.55	6.15
Thailand	15.15	39.57	73.31	88.50	5.84
Trinidad and Tobago	–	–	–	–	–
Tunisia	19.45	54.14	94.31	115.18	5.92
Turkey	38.89	110.57	244.88	304.44	7.83
Ukraine	226.92	553.66	603.72	628.36	2.77
Uruguay	–	–	–	–	–
Venezuela	171.64	439.21	590.32	634.56	3.70
Vietnam	48.55	126.67	209.75	239.93	4.94

Table 10: Cross-Country Correlations

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.

	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		

Table 11: Bid-Ask Spreads on Individual Bonds

The table presents summary statistics on individual bonds' bid-ask spreads for each portfolio. Our data set corresponds to all available bonds in Bloomberg with ISIN numbers that match those of sovereign bonds in Datastream (for the emerging countries in our sample). We delete all observations that correspond to negative or zero bid-ask spreads. We also delete bid-ask spreads that are above 20% if the spread was below this cutoff the day before or the day after the spread is recorded. We then obtain our portfolio series in two steps. First, for each country, we compute the median bid-ask spreads at the end of each month. Second, we form 6 portfolios of those spreads using the same sorts as for our benchmark EMBI portfolios. In each portfolio, spreads are equally-weighted. All spreads are in basis points. We report the median, mean, max, min, and standard deviation of those spreads. Data are monthly. The sample is 01/1995 - 05/2009.

Portfolio	1	2	3	4	5	6
Median	43.63	41.91	51.96	48.23	49.25	65.52
Mean	73.81	44.19	57.85	43.98	52.37	68.83
Max	906.63	119.74	219.65	100.20	262.57	220.16
Min	9.80	15.76	11.49	9.80	10.57	32.98
Std	123.27	18.88	27.80	23.22	36.16	24.08

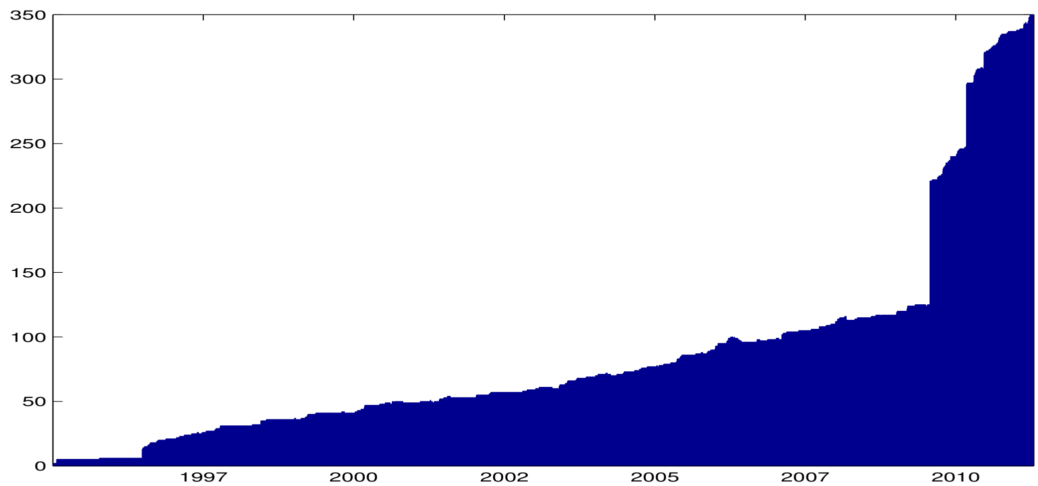

Figure 5: Number of Active Bonds

This figure plots the number of active, emerging markets sovereign bonds in our data set. It corresponds to all available bonds in Bloomberg with ISIN numbers that match those of sovereign bonds in Datastream (for the emerging countries in our sample). Data are monthly. The sample is 01/1995 - 05/2009.

Table 12: 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.

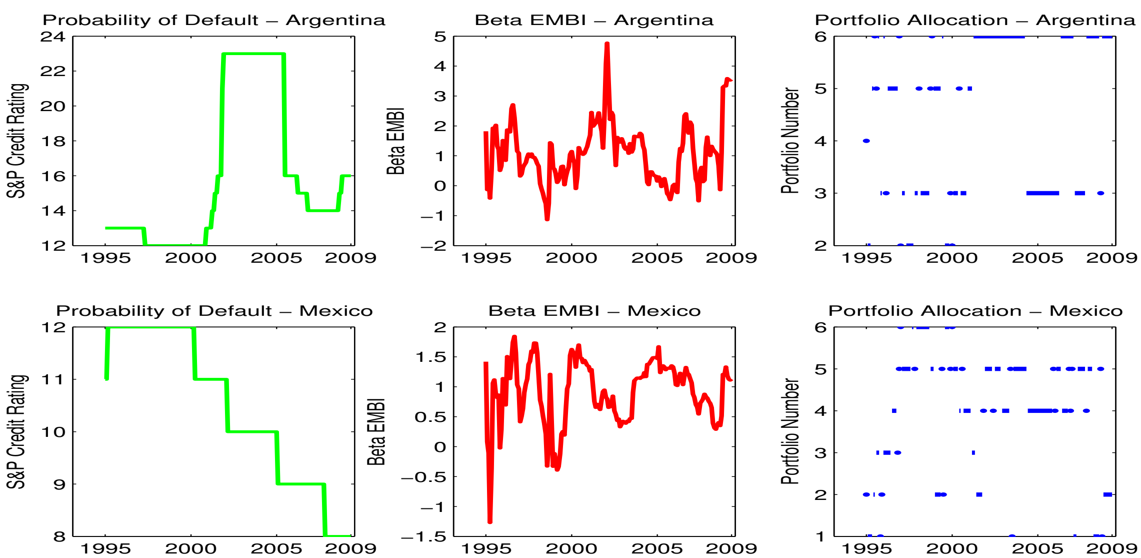

Figure 6: Portfolio Allocation for Argentina and Mexico

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.

Table 13: 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	−2.23	−3.24	−0.77	−0.74	−1.94
Kurtosis	22.37	17.59	27.99	11.27	10.82	15.40
			Spread Duration			
Mean	4.95	5.75	5.55	5.90	6.54	7.00
Std	1.03	0.92	1.26	0.52	0.48	1.41
			Effective Interest Rate Duration			
Mean	4.91	5.57	5.73	6.10	6.56	7.22
Std	1.17	1.13	1.07	0.63	0.49	1.34
			Life			
Mean	8.44	10.13	10.28	10.26	12.77	14.19
Std	3.87	4.01	2.78	3.57	3.22	2.06
			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). The average life L of a bond index at time t is calculated by: $L_t = \frac{\sum L_{i,t} * N_{i,t}}{\sum N_{i,t}}$, where the summations are over the bonds currently in the index, L is the life to assumed maturity, and N is the nominal value of amount outstanding. 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.

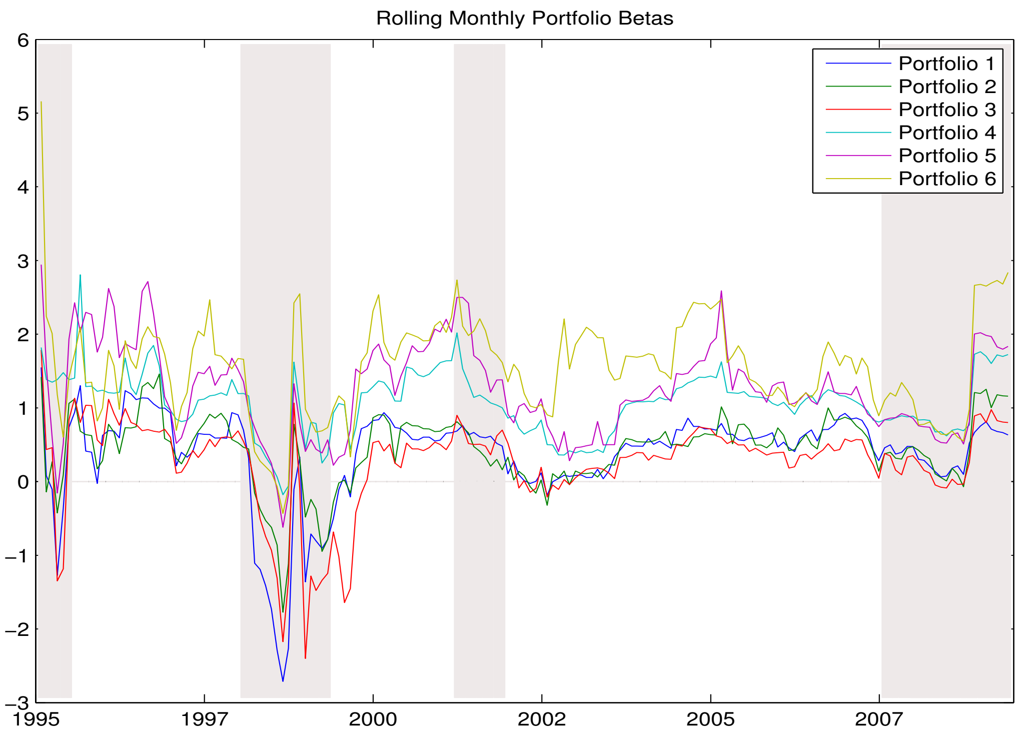

Figure 7: Rolling EMBI Betas

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 Kho, Lee and Stulz, (2000).

Table 14: 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 15: 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 16: 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
$Mean$	2.90				
	[1.67]				
Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	β^j_{US-BBB}	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
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	74.57

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.

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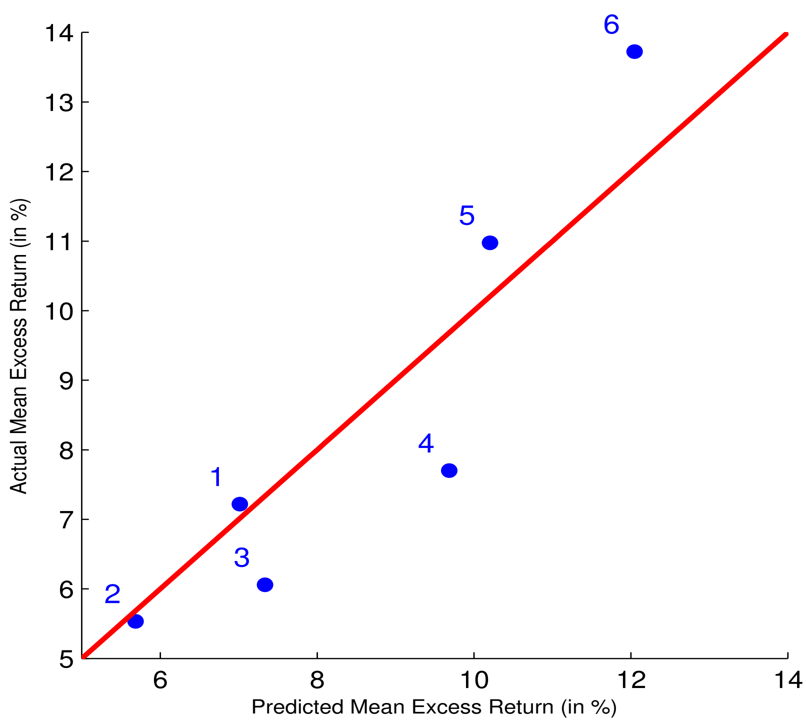

Figure 8: Predicted versus Realized Average Excess Returns

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 market price of risk. 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.

Table 17: Conditional Asset Pricing: Portfolios Sorted on Credit Ratings and Bond Betas

Panel I: Factor Prices and Loadings							
	$\lambda_{US_{BBB}}$	$\lambda_{US_{BBB}*VIX}$	$b_{US_{BBB}}$	$b_{US_{BBB}*VIX}$	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
$Mean$	2.90	14.10					
	[1.67]	[5.66]					

Panel II: Factor Betas									
$\alpha_0^j(\%)$	β^j_{US-BBB}	$\beta^j_{US-BBB*VIX}$	$R^2(\%)$	$\alpha_0^j(\%)$	β^j_{US-BBB}	$\beta^j_{US-BBB*VIX}$	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
	Portfolios 1 to 6				Portfolios 7 to 12				
−3.04	0.53	0.09	26.82	−6.25	−1.32	1.26	38.93		
[2.26]	[0.30]	[0.09]		[7.25]	[1.22]	[0.45]			
−1.12	0.61	0.09	23.99	−0.31	−1.27	1.32	38.87		
[2.80]	[0.32]	[0.07]		[8.27]	[0.73]	[0.22]			
−0.91	0.84	0.08	16.78	−1.72	−0.49	1.30	26.18		
[5.09]	[0.42]	[0.10]		[14.86]	[1.00]	[0.35]			
1.27	0.49	0.14	40.12	9.30	−2.27	1.69	46.66		
[2.18]	[0.24]	[0.08]		[8.05]	[1.15]	[0.42]			
3.13	0.39	0.25	44.84	12.73	−3.04	2.28	59.61		
[2.26]	[0.20]	[0.06]		[8.11]	[0.67]	[0.23]			
2.60	0.63	0.36	36.02	3.89	−2.29	2.74	43.33		
[4.57]	[0.70]	[0.25]		[17.42]	[3.36]	[1.26]			
								15.87	19.70

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 18: 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	0.66

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 19: 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	$\alpha_0^j(\%)$	$\beta^j_{US_{BBB}}$	$\beta^j_{\Delta VIX}$	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
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	38.22

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 20: 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	1.14

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 21: Country-Level Asset Pricing

Panel I: FMB Asset Pricing						
	λ_{US-BBB}	b_{US-BBB}	R^2	$RMSE$	$MAPE$	χ^2
FMB	7.75	20.58	-5.44	4.55	3.25	
	[2.68]	[7.11]				40.96
	[2.79]	[7.42]				61.33
$Mean$	4.40					
	[1.90]					

Panel II: Panel Regressions						
	(1)	(2)	(3)	(4)	(5)	(6)
US_{BBB}	1.18	1.18	0.08	1.18	1.18	0.08
	[0.18]	[0.18]	[0.19]	[0.16]	[0.16]	[0.23]
$Ratings$		0.02	0.01		0.04	0.03
		[0.01]	[0.01]		[0.02]	[0.02]
$US_{BBB} * Ratings$			2.22			2.21
			[0.65]			[0.69]
R^2	20.54	21.00	22.60	20.93	21.32	22.91
N	4722	4722	4722	4722	4722	4722
$F.E$	No	No	No	Yes	Yes	Yes

Notes: The first panel of this table reports results from the Fama-McBeth asset pricing procedure on country-level data. The market price of risk λ, the adjusted R^2, the square-root of mean-squared errors $RMSE$, the mean absolute pricing error $MAPE$, and the *p*-values of χ^2 tests on pricing errors are reported in percentage points. b denotes the factor loading. The first panel also reports the mean excess return of the risk factor and its standard error. All excess returns are multiplied by 12 (annualized). Shanken (1992)-corrected standard errors are reported in parentheses. We do not include a constant in the second step of the FMB procedure. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). The second panel of this table reports six sets of panel regression results. We regress all the country-level excess returns on the US BBB corporate returns, the country ratings, as well as the product of ratings and BBB returns. The first three columns correspond to panels without fixed effects, while the last three columns include fixed effects. In the former case, standard errors are clustered by country and time. In the latter case, they are clustered by time. The panel reports the slope coefficients and their standard errors, the R^2 in percentages, the number of observations N, as well the presence of absence of fixed effects ($F.E$). Data are monthly. The sample period is 1/1995 – 10/2010.

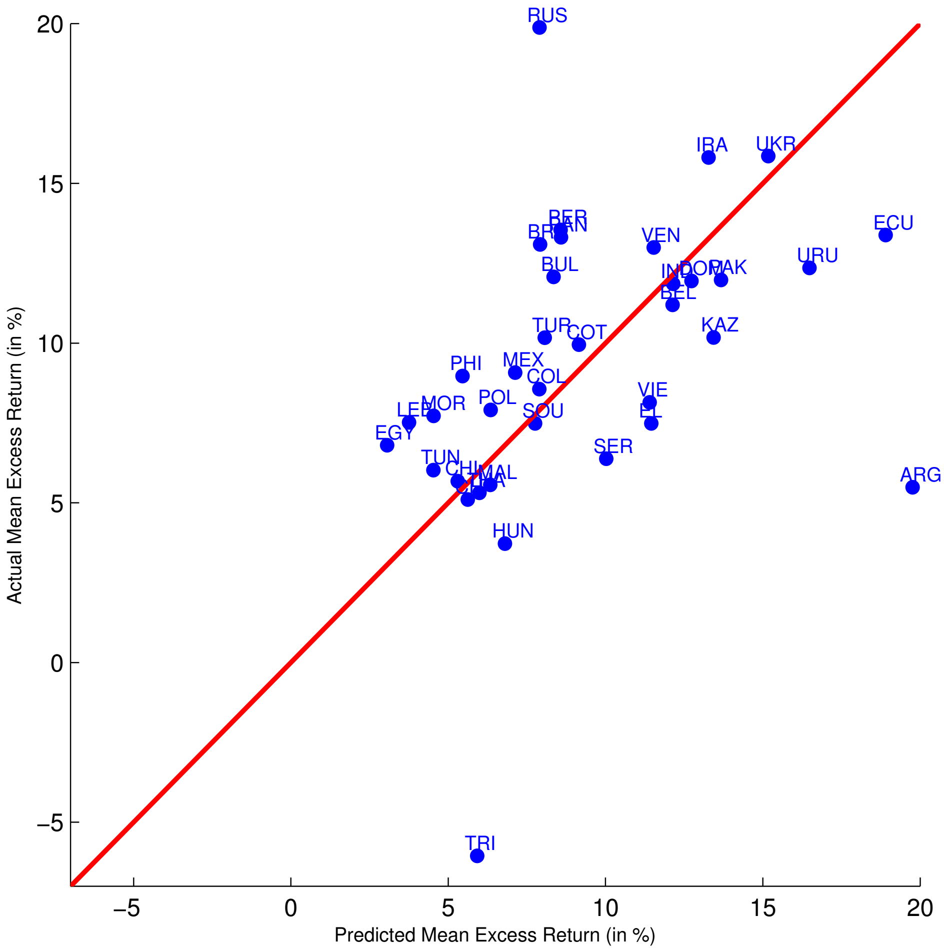

Figure 9: Predicted Against Unconditional Actual Country-Level Excess Returns.

This figure plots realized average excess returns on the vertical axis against predicted average excess returns on the horizontal axis. We regress each actual country-level excess return on a constant and the risk factor (the return on the US BBB corporate bond index $r^{US_{BBB}}$) to obtain the slope coefficients β^j. Each predicted excess returns is obtained using the OLS estimates of β^j times the market prices of risk. All returns are annualized. The data are monthly. The sample is 1/1995 – 10/2010.

Table 22: Asset Pricing: Simulated Portfolios Sorted on Stock Market Betas

Panel I: Factor Prices and Loadings					
	λ_{Mkt}	b_{Mkt}	R^2	$RMSE$	$p-value$
GMM_1	8.72	1.59	85.52	0.26	
	[1.23]	[0.22]			18.45
GMM_2	10.14	1.85	83.22	0.28	
	[0.89]	[0.16]			41.84
FMB	8.72	1.59	95.10	0.26	
	[1.40]	[0.25]			36.38
	(1.49)	(0.27)			44.28
$Mean$	6.48				
	[0.06]				
Panel II: Factor Betas					
Portfolio	$\alpha_0^j(\%)$	β_{Mkt}^j	$R^2(\%)$	$\chi^2(\alpha)$	$p-value$
1	-0.04	-0.14	0.62		
	[0.04]	[0.01]			
2	-0.01	-0.08	0.25		
	[0.04]	[0.01]			
3	0.05	-0.05	0.09		
	[0.04]	[0.01]			
4	0.08	-0.00	0.00		
	[0.04]	[0.01]			
5	0.09	0.02	0.02		
	[0.04]	[0.01]			
6	0.09	0.04	0.08		
	[0.04]	[0.01]			
All				14.01	2.95

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 simulated excess returns are multiplied by 4 (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 quarterly. Details on the simulation are in section 4 of the paper. The alphas are annualized and in percentage points.

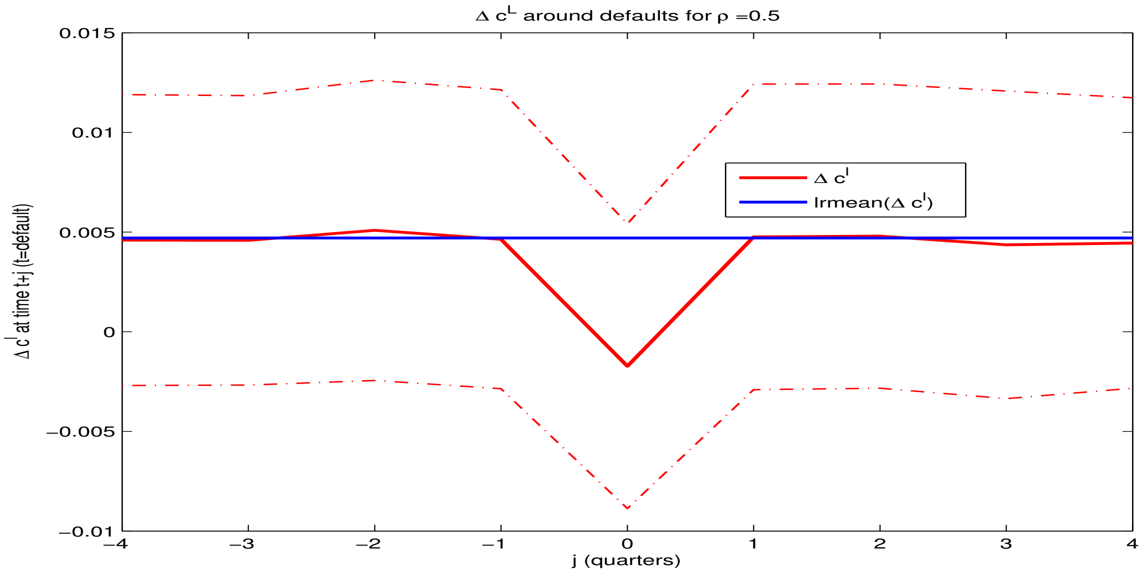

Figure 10: Lenders' Consumption Growth Around Defaults in the Model

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.

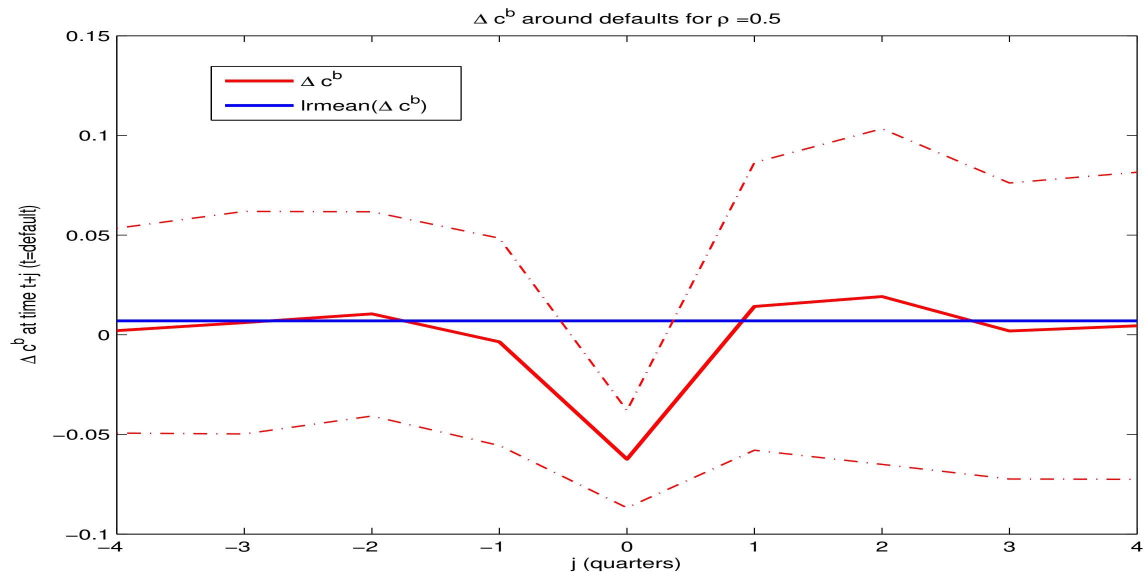

Figure 11: Borrowers' Consumption Growth Around Defaults in the Model

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.

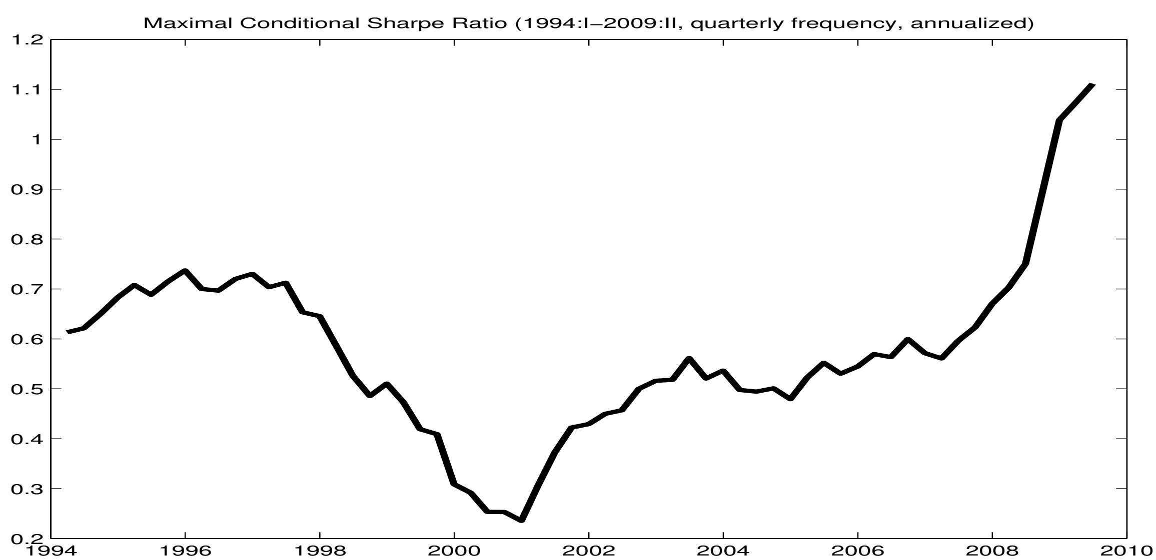

Figure 12: Lenders' Maximal Sharpe Ratio in the Model

This figure plots the maximal conditional Sharpe ratio in the model. We use actual real US consumption growth per capita to compute the dynamics of the surplus consumption ratio and the maximal conditional Sharpe ratio. Data are quarterly and start in 1952:I. The graph corresponds to our sample period, 1994:I–2009:II.