Identifying Sovereign Bond Risks*

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Abstract

This paper tries to identify the risks embodied in foreign-currency denominated sovereign bond spreads. It adopts an instrumental variables method, which attributes the explanatory power of fundamentals in a spread equation to their predictive power for observed risk realizations. Using historical data from developing countries, I find that it is possible to describe bond spreads by probabilities consistent with realizations: the reduced form explanatory power of fundamentals can be attributed to their influence on default and illiquidity predictions. There is, however, strong evidence that during currency crises, bond spreads increase more than do risk probabilities.

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1 Introduction

It is a standard notion to view bond yield differentials as the market's assessment of the relative riskiness of the issuers. This immediately raises three important questions: What risks (uncertainties) are involved in such comparisons? Do market participants perceive the probabilities of those risks correctly? Are there certain times when the spread changes more than implied by changes in these risks?

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These issues are necessarily interrelated: without looking at the right risks, one cannot test if their perceived probabilities are close to observed probabilities, or whether spreads deviate from a probability-based pricing equation. On the other hand, it is impossible to identify the risks involved in bond prices and potential deviations unless we have some picture of how such probabilities are formed.

A main determinant of spreads should be default risk: bond price differentials reflect differences in the issuer's ability to pay. Although bonds offer a fixed income, there is a chance of breaking that promise, and its probability is incorporated into the price.

Bonds may also be subject to further risks, for example interest rate (inflation) risk: investors are committing their money long-term to a fixed nominal interest rate, so they are exposed to changes in the short-term rate or inflation. If two bonds are paying their return in different currencies, then investors will also include an exchange rate risk in their calculations.

Reputation, political or strategic elements may also influence borrowing terms of sovereigns (see Obstfeld and Rogoff (1996) as a survey). In contrast to the previous risks, these factors enter the price as a result of some bargaining process, and not as an expected value of some randomness. In the case of bonds, fortunately, with relatively many and small investors buying the bonds, such bargaining factors should have limited effects.

All these risk differences will lead to bond price differentials even with risk-neutral investors, since no arbitrage implies that the expected return, including all sources of randomness, is equalized across bonds, but not necessarily the face value. Market conditions, however, may occasionally deviate from the benchmark setting of no arbitrage: limited participation, financial constraints or informational problems imply that the demand for the bond is not always horizontal. This is usually referred to as the liquidity of the market.

If market conditions are constant in time, which means that the market always operates around the same segment of the demand curve, then this liquidity is a fixed characteristic of the bond, and not a separate source of randomness. Market conditions may, however, fluctuate in time: there are normal times when a sudden transaction means very little loss (horizontal segment of the demand curve), and there are distressed times when almost nobody is willing to buy on the market (upward-sloping segment).[1] So if investors face a chance of early sale, then the expected loss from such a transaction may be incorporated into bond prices (liquidity risk).

[1] This situation is related to the risk factor for "distress" in Fama and French (1998).

In the case of *foreign-currency denominated* sovereign bonds[2], a currency crisis can be the source of such distress (see, for example, Broner and Lorenzoni (2000)). An expected or realized devaluation leads to heavy losses in the *local-currency* denominated bond market. The markets for a country's local- and foreign-currency denominated bonds usually have many common investors, which implies that the liquidity squeeze of the market that was actually hit by a fundamental shock will lead to transactions on the other market as well. If participation is limited and investors face some credit constraints, then potential buyers will lack the necessary funds, so prices on the second market will have to drop *more* than implied by changes, if any, in default risk.

Thus, the paper addresses the following issues. The first is whether bond price differentials can be attributed *entirely* to differences in expected returns, consistent with probabilities predicted from realizations, plus noise, reflecting unobserved or neglected characteristics of bonds and transactions. Second, what risks are involved in the calculation of expected returns; and third, whether market conditions occasionally have an extra impact. This means estimating an arbitrage-based pricing equation for bonds, and testing for a role of imperfections in certain distressed periods.

In order to limit the list of potential risks, I will focus on spreads between sovereign bonds of developing countries and a benchmark. For this benchmark, I choose government bonds of industrial countries (mostly the US, Germany, and Japan), denominated in the same currency (mostly US dollar), and similar in maturity. These benchmark bonds can be assumed to be perfectly safe.

By using developing country bonds denominated in the same currency as the benchmark, these spreads should contain no "pure" exchange rate component. They allow, however, a spillover effect of exchange rate movements, thus enabling a visible role of market conditions. Working with spreads relative to similar maturity government bonds (US Treasuries, etc.), I substantially reduce the interest rate risk: in principle, investors can go short in those nearly riskless bonds and use their proceeds to buy more risky, say, Latin-American bonds. This spread, therefore, should be mostly independent from interest rate movements.

The objective of this paper is to explain foreign-currency denominated bond spreads with default and illiquidity risk – about which much less is known[3]–, to separate the two from

[2]E.g., a dollar-denominated bond issued by the government of Brazil.

[3]There are some theoretical papers, like Grossman and Miller (1988); and empirical contributions, but the latter mostly concentrate on US Treasuries. For example, Redding 1999, Amihud and Mendelson (1991),

each other, and to test whether there are times when spreads change more than implied by changes in those risks.

I will use a moderate-sized sample of historical data on sovereign bonds, exchange rates and default behavior of several developing countries. The approach will use the framework of risk-neutral, rational, but not necessarily unconstrained, investors: I maintain the assumption that the spread depends on the expected value of the uncertain return (losses or gains relative to the face value),[4] but limited participation and borrowing constraints may lead to distressed periods when the spread is higher than implied by expected payoffs.

From a purely forecasting or descriptive viewpoint, it would be sufficient to learn how fundamentals of a borrower (in my case: of a sovereign country) and observable market conditions (e.g. crises) influence the spread it pays on its bond issues. This standard practice, which is adopted in various studies,[5] specifies a relationship between fundamentals and the probability of default, and another between default probabilities and the spread. Substituting one into the other, one can relate spreads directly to fundamentals.

As there are always more fundamentals than what a particular specification contains, and many events or simply words of mouth can play a role, but will not be captured by a researcher, one can never be safe about the reason why that specific fundamental or market indicator has this size of an effect, how much the results will depend on the choice of fundamentals, and whether it is reasonable or rational to have such an effect at all. Even if the specification is correct, its causal interpretation is questionable: it implicitly assumes that there is only once source of risk (default), and all information enters the pricing equation through this risk probability. None of these assumptions can be tested within this framework: in particular, one cannot determine whether a positive effect of a crisis indicator comes from changes in some risks, or reflects overreaction, a role of market conditions, or irrationality.

The main idea of this paper is to attribute these influences by fundamentals to movements in *predicted probabilities of observed risk realizations*. This gives us a structural approach: risk probabilities are predicted by fundamentals, then bond spreads are determined by predicted

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Bradley (1991) and Hirtle (1988). See Benczur (2001) for a more detailed discussion. Pástor and Stambaugh (2001) analyze stock returns, by incorporating a market-level liquidity risk into their analysis.

[4] In principle, the spread shows the difference in the expected values. When compared to developing country bonds, US Treasuries are basically riskless, so practically, the spread reflects the risks associated with the developing country alone.

[5] Among many others: Edwards (1986), Stone (1991), Ozler (1993). A different but still similar article is in Standard and Poor's CreditWeek (1999): it explains how credit ratings, which are often viewed as a measure of credit risk, are responsive to country fundamentals.

probabilities. Spreads will still be influenced by fundamentals, but we will have a clear sense of why: because they predict risk probabilities.

Notice that, in principle, I could introduce risk-aversion into this framework: that would mean including a predicted covariance (or any higher order) term. Since a covariance is also a conditional expectation, it could be treated in a similar way. Precise realizations for such a variable, however, are particularly hard to observe or construct, thus, I do not attempt to incorporate risk-aversion.

This approach should shed light on all the three issues I want to address. First, it tests whether bond spreads can be explained only by risk probabilities predicted from actual realizations, or certain fundamentals influence bond spreads above their effect on conditional probabilities. Second, if default and liquidity risk are sufficient to characterize the expected return, and what is the relative size and importance of these two. Third, whether there are episodes when the spread changes more than implied by predicted probabilities, indicating limited arbitrage.[6]

The method itself is reminiscent of well-known practices for testing rational expectations (e.g. Mishkin (1983), Attfield, Demery and Duck (1985), and in particular, Wickens (1982)). I estimate a structural equation determining sovereign bond spreads, of the form

$$s = \alpha + \beta R + \lambda_{def} E[d|Z] + \lambda_{liq} E[l|Z] + \lambda_{cri} c + \varepsilon_1.$$

Here Z contains information (fundamentals) available at the time of pricing, c is a crisis indicator, R is the benchmark rate; while d and l are future default and illiquidity variables. The conditional expectations (probabilities) are unobserved, but there exists data for realizations of these risk events. Instead of specifying a prediction equation, and using the predicted probability in the pricing equation, I put the realizations directly into the pricing equation. This poses an identification problem: since the actual realizations are correlated with the prediction errors, d and l are not orthogonal to the error terms. The solution is to recognize that any information available at the time of pricing (Z) can serve as valid instruments.

A reinterpretation of this procedure is that it tries to attribute the reduced form fit of

$$s = \alpha' + \beta' R + \Gamma Z + \delta c + \varepsilon_2$$

[6]One can also interpret such episodes as an irrational panic, or a systematic overestimation of default risk. Instead of such behavioral conclusions, I want to work in the framework of constrained rational markets.

to the predictive power of R, c and Z for default and illiquidity risk. Overidentification then receives a central role: it tests whether information only enters through risk probabilities, or there are some additional channels. In the latter case, spread differentials cannot be fully attributed to differences in risk probabilities.

An important ingredient of the approach is sufficiently long data on the actual realizations of the predicted events: then I can observe and predict the realizations of the random variables which the market was only forecasting. The time span of my sample is more than 20 years, and it contains many realizations of the risk events I have chosen. This should reduce, though not fully eliminate, peso-problem type difficulties in empirical predictions.

For default, I will use an indicator of overall repayment difficulties: relief or rescheduling on any form of sovereign borrowing in the next 5 years. My best performing measure for illiquidity (distressed market conditions) will be the 5-year annual sample variance of the spread from any given year on.

Let me briefly summarize the main findings. The influence of fundamentals on bond spreads can be attributed to their effect through predicted risks: When including a repayment trouble indicator, the benchmark interest rate, and country dummies, the overidentification test accepts.

The inclusion of a currency crisis indicator into the instruments leads to a rejection, which indicates that during crises, spreads increase more than the change in default risk. Overidentification is restored either by including the crisis dummy on the right hand side – default risk and market conditions explain the spread–, or the liquidity indicator (future volatility). This latter interprets the extra crisis effect as an increase in liquidity risk.

Although the crisis indicator is not necessary for overidentification in this latter case, its coefficient still stays large and significant when including both a crisis and a liquidity indicator. This full specification yields a strong and robust causal description of the spread: it reflects predicted default and liquidity risk, but market conditions cause deviations during currency crises.

With the specification including repayment problems, price volatility, benchmark interest rates, a currency crisis and country dummies, I find that default risk is on average 27% of the spread. Since country dummies may also reflect default risk considerations, this 27% is likely to understate the role of default risk. A 10 percentage point increase in the probability of future repayment problems adds 6.5 basis points to the spread. This means that spreads are not very responsive to changes in default risk predictions, but there is a sizable default risk component in spread averages. A liquidity-type risk, captured by predicted volatility of pre-maturity bond prices, accounts for the dominant part of the spread, with 60%. Spreads increase by 79 basis points during currency crises (keeping probabilities fixed), which constitutes 6% of the sample average (in the crisis versus non-crisis differential, its effect is more than 50 %). The remaining 7% of the spread is made up of the benchmark rate (which influences the spread itself) and country-specific constants. The benchmark rate has a surprising negative coefficient, which is completely robust to any specifications: a 1 percentage point increase in the benchmark rate leads to a 0.72-0.87 percentage points increase in sovereign bond yields. The confidence interval almost contains one, thus I attribute the further difference to imperfect measures and computation problems of bond yields (adjustments). Country fixed effects, for some reason, almost completely undo the average yield adjustment. I have also checked the robustness of these results with respect to many alternative specifications, and the findings pass these tests.

The paper is organized as follows. The next section describes the basic empirical specification, the estimation strategy, and my data sources. Section 3 presents and discusses the main findings: the first part tries to explain bond spreads only by default risk, while the second part introduces a role for market conditions and illiquidity risk. This approach yields a more successful description of bond spreads, the robustness of which is tested in Section 4. The last section concludes and points to some possible future research directions. Some skipped details are then presented in the Appendix.

2 The setup of the empirical analysis

2.1 Main specification

Each data point j means a bond spread observation, corresponding to some country $i(j)$, in year $t(j)$. For some observations, a more precise date is available, but this information is often missing. Moreover, a full set of country fundamentals is rarely available at a higher-than-annual frequency, so I cannot go beyond the annual level.

Let $p_j = E[d_{i(j)t(j)}|Z_{i(j)t(j)}]$ denote the conditional probability that, as of information available at the time of pricing ($Z_{i(j)t(j)}$), country $i(j)$ does not fully repay its outstanding bonds in the future (neglecting the possibility of a selective default). Then my basic specification for the spread is as follows:

$$s_j = r_j - R_j = \alpha + \beta R_j + \lambda p_j + \varepsilon_{1j}. \tag{1}$$

Here R_j is a similar maturity and currency-denominated "riskless" bond rate at time $t(j)$: a developed-country government bond yield; for example, US Treasuries for dollar bonds.

Since countries often have more than one bond outstanding, it is possible that two different observations belong to the same country and year. Though these multiple bonds may be different in some of their characteristics (zero coupon, amount outstanding), these features are poorly observed in my data. If their currency denomination is different, then the corresponding benchmark yields R_j and $R_{j'}$ differ; otherwise all such differences must go into the error term ε_1. It seems acceptable that these unobserved characteristics are orthogonal to the right hand side variables (benchmark yield, default probability; or, economic indicators in general).

The linear term λp can be derived from risk-neutrality and profit maximization, under the assumption that there is a partial default on the principal but not on the interest:

$$(1 - p)(1 + r) + p(x + r) = 1 + R$$

implies

$$r - R = p(1 - x). \tag{2}$$

Thus, one calculates the spread and tries to explain it with predicted default probabilities.

For a more complicated default case, the relationship between some measure of the spread (the spread itself, or its ratio to the yield) and the probability of default becomes less tractable. The robustness test section considers an alternative left hand side variable, but for the main specification, I will concentrate on this simple, convenient and standard case. It serves to capture a positive relationship between predicted probabilities and spreads.

I will also allow R to enter the right hand side of the specification, which can be rationalized in many ways: the long-term US bond rate may be a proxy for aggregate illiquidity, or investors might be more reluctant to invest in very high return risky bonds once even safe bonds offer a high return. In any case, R will often stay significant in the specification – mostly for problems of bond yield approximations –, which makes it necessary to include in

(1).

The main specification will allow for a second risk term $E[l_{i(j)t(j)}|Z_{i(j)t(j)}]$ (time-varying illiquidity, or market conditions as a second source of randomness), a role for current market conditions (currency crises, $c_j = c_{i(j)t(j)}$), and country-specific fixed effects $h_{i(j)}$:

$$(3) \qquad s_j = \alpha + \beta R_j + \lambda_{def} p[d|Z]_j + \lambda_{liq} E[l|Z]_j + \lambda_{cri} c_j + h_{i(j)} + \varepsilon_{1j}.$$[7]

2.2 The estimation strategy: a structural asset pricing regression

The core problem lies in the fact that the conditional probabilities and expectations are not directly observable. The literature usually assumes that there is only default risk, and its probability is some function of fundamentals, the form of which is known to the market. Then this relationship is substituted into the spread equation, which leads to a reduced-form specification describing the spread itself as some function of fundamentals.

A major shortcoming of this approach is that it necessarily attributes all variation in spreads to changes in the underlying risk (default) probability. Whenever a fundamental changes, it will change the spread entirely through its effect on the unobserved probability.

Such an approach cannot succeed when there is more than one source of risk, or determinant of the spread. More importantly, it is unable to determine whether a certain effect of a fundamental is consistent with the way that fundamental influences actual repayment (or other risk) behavior of the asset. Finally, it hinges on two functional form assumptions: the relation between fundamentals and the risk probability, and also the risk probability and the spread.

One potential solution is to find acceptable proxies for the probabilities themselves: credit rating, for example, might represent default risk. One can then estimate a relation between spreads and credit ratings, and test whether credit ratings are sufficient statistics of available information (Cantor and Packer (1996) follow such an approach). This method, however, still cannot determine what risks are represented by credit ratings, and whether the information is used correctly (i.e., risk probabilities are consistent with realizations).

Cumby and Pastine (2001) use data on different issues of the same borrower to test for

[7] In principle, one could try to explore the panel nature of my data. Time-specific fixed effects are then represented by the $R_{t(j)}$ term: the specifics of a given year should be captured by the bond-specific benchmark rate. However, my data is a very unbalanced and sparse panel. For this reason, I did not attempt to go beyond the simple country dummy treatment.

a common underlying default probability. They find evidence that different issues imply different probabilities. Their approach, however, cannot identify more than one source of risk, or test for a systematic extra effect of fundamentals or events.

As an alternative, I use data on the risk events themselves. Given realizations of the random variables constituting the source of risk, one can estimate their conditional probability. Assume that the conditional expectation (probability) of d_{it} is some function g of available information R_{it} and Z_{it}, then

$$d_{it} = E[d_{it}|R_{it}, Z_{it}] + \varepsilon_{2it} = g(R_{it}, Z_{it}) + \varepsilon_{2it}. \tag{4}$$

Here Z_{it} is a set of country- and world-level economic indicators, available at the beginning of year t. Thus, they usually correspond to data from year $t-1$ and earlier. The particular choice of these variables will be discussed later on.

Though g is unknown in general, the prediction error ε_{2it} is by definition orthogonal to R_{it} and Z_{it}. The interest rate equation becomes

$$s_j = \alpha + \beta R_j + \lambda g(R_{it}, Z_{it})_j + \varepsilon_{1j} = \alpha + \beta R_j + \lambda d_{i(j)t(j)} + \varepsilon_{1j} - \lambda \varepsilon_{2i(j)t(j)}. \tag{5}$$

Here d_{it} is, of course, not orthogonal to the error terms: definitely not to ε_{2it}, and from the simultaneity setup, not even to ε_{1j}. Nevertheless, any subset of $\{Z_{it}, R_{it}\}$ can serve as valid instruments for the problem: by assumption and definition, they are uncorrelated with the error terms, but they are correlated with the event indicator, since they enter the prediction equation.

This even overidentifies the interest rate equation, and eliminates any functional form assumptions or omitted variable problems in the default prediction equation: I do not have to specify or estimate the probability model, it is enough just to know that some fundamental variables are correlated with the risk event, thus they are valid instruments in the interest rate equation. Using only a subset of available information (fundamentals) will not lead to inconsistent estimates, it would only influence efficiency.

Moreover, one can then test this overidentification, and check if there are any variables which have a direct effect on the spread. An indirect effect we should see in any case: more growth, for example, leading to lower repayment trouble prediction, hence a lower spread.

However, there may exist some factor (market conditions, bargaining terms etc.) which has an effect on the spread not only through increased risk, but more directly, too. Then some of the instruments might be proxying for this term, and overidentification would be rejected. Or if the true event the market "fears" is different from the one I am using, then again, some of the instruments might be absorbing the differences of the probability predictions, and overidentification could be rejected.

A rejection might as well be due to the rejection of the rational expectations and risk-neutrality approach used in deriving the interest rate equations: if market participants use a different (non-rational) prediction, then the specification I am estimating will be rejected by the data. As I will show, however, a sufficiently broad description of risks, a role for market conditions (currency crises) and country effects together, offer an acceptable and robust specification, without a need for risk-aversion or market irrationality.

The setup itself is reminiscent of well-known practices for testing rational expectations (e.g. Mishkin (1983), Attfield, Demery and Duck (1985)). Wickens (1982) also proposed using past information as instruments, but under somewhat more restrictive assumptions. The Appendix draws a detailed parallel, and also explains the mechanics of the overidentification test and identification.

As an alternative interpretation of the method described so far, one can start from the reduced form of the asset pricing equation. Certain variables (Z_{it}, R_{it}) have explanatory power in an asset pricing (bond spread) equation:

$$s_j = \alpha + \beta R_j + \Gamma Z_{i(j)t(j)} + \varepsilon_j. \tag{6}$$

This is the standard specification in the literature (though usually with logistic probability models or some other variations). In order to understand where these relationships are coming from, one needs a structural framework. Assume that the spread reflects the expected value of some uncertainty (the "risk" of a certain event, which might be a zero-one, or a continuous variable). Use a rational expectations (linear) prediction of that event:

$$e_{it} = \alpha' + \beta' R_{it} + \Gamma' Z_{it} + \varepsilon_{it}. \tag{4B}$$

If the spread is coming from the risk of this event, then

$$s_j = \alpha'' + \lambda'' E[e_{it}|R_{it}, Z_{it}]_j + \varepsilon''_j \tag{5B}$$

should describe the spread.

To estimate this specification, replace the latent expectation term with its best linear prediction; or, as a more robust interpretation, use the realization itself and do IV. Then one gets

$$s_j = \alpha'' + \lambda'' \left(\alpha' + \beta' R_j + \Gamma' Z_{i(j)t(j)}\right) + \varepsilon_j''' = \alpha'' + \lambda'' e_{i(j)t(j)} + \widetilde{\varepsilon}_j. \tag{5C}$$

This means that one tries to attribute the fit and explanatory power of R and Z to their predictive power for (correlation with) the event e.

The argument shows that the only linearity I need is in the pricing equation (3), but the prediction equation (4) does not have to be linear. This generality makes the method readily applicable in many other asset pricing frameworks: for example, one can estimate an uncovered interest parity condition.[8]

2.3 Data sources

There are three main sources of my data. The IFS, the World Development Indicators and the FED's data site provide all major economic variables for countries and the world, and also world interest rates (long- and short-term government bond yields for the major lending currencies), and exchange rates. Unfortunately, there are many observations missing – though I have all the necessary annual variables whenever I have data on bond yields, the sample size would be fatally reduced with quarterly data.

Arrears, rescheduling and debt relief agreements are from the World Bank's World Debt Tables. A debt relief refers to an event when the debt stock is reduced due to debt forgiveness or such a rescheduling which actually lowers the present discounted value of debt obligations. These relief agreements are restricted to the period starting in 1985. In the appendices of World Debt Tables, all the history of reschedulings and other relief agreements are listed.

Bond price data are from three sources. One is Moody's Bond Record, which gives the yield and the current price of all the sovereign bonds traded in the US. I have entered the data from its January issues, from 1975 to 1997. Unfortunately, it switches to reporting only the current issues, and only the coupon sizes around 1990 – since the coupons are usually

[8] Benczur and Szeidl (2001) apply the method for exactly this scenario: comparing bonds in different denomination. The difference should be due to exchange rate risk, default risk and liquidity (market conditions). Preliminary results suggest that currency crises have an "extra effect" there as well.

chosen right at issue, hence the issue prices are well approximated by 100%.

The other source is Euromoney, which reports each month the currently issued Eurobonds, with their nominal yield and issue price. Again, they stop giving this information around 1987.

The last source is Moody's International Manual, which reports – beside many other information – sovereign bond issues: not for all countries; and sometimes the issue price is given, sometimes not (again, it is usually very close to 100%).

From this less than perfect data, I used the following simple, but also clear and robust, procedure to calculate bond yields and spreads. Given its maturity, coupon and price, the approximate yield on a bond is $r + \frac{100-p}{T}$, and the spread is $r + \frac{100-p}{T} - R_T$. A missing maturity was replaced by the sample average, and a missing issue price was approximated by 100 (full). For the benchmark rate, I used the long-term (10-year) government bond yield of the lending currency, for all observations with at least 3 years to maturity; and the 1-year rate otherwise.

Apart from missing data, this approximation can err in two major points: one is that it basically uses a first-order approximation, which may become imprecise for large interest rates; and the other is that the benchmark yield curve is in general more complicated than the distinction between short and long-term rates. For the second some data might exist, but they are not very accessible. To reduce this problem, I worked only with at least 3-year maturity bonds, where it makes relatively little difference to work with 5- or 7-year rates.

The approximation problem should lead to a systematic downward bias of yields: whenever benchmark rates increase, the approximation error becomes larger, thus the calculated yield increases less than it should. This will lead to a too low benchmark rate coefficient in any such regression – which is exactly what I have found (it is significantly below one). Unfortunately, any more precise attempt to calculate yields is likely to amplify any preexisting data problems: an explicit discounting of future coupon payments, for example, is very sensitive to assumptions about the benchmark yield curve. Moreover, it also reduces the number of observations, since the exact maturity is crucial for such calculations.

Nevertheless, when I tried to calculate the present value of future payments and obtain spreads from those results, the course benchmark rate (1- versus 10-year maturity) coefficient indeed became one. Using the approximated yield curve for the benchmark rate as well (a linear scheme fitted on the 1- and 10-year values), however, produced even smaller interest rate coefficients. This I take as an indication that the too low interest rate coefficient is indeed a result of yield calculation problems, but I still stick to the less precise, but at least more robust, method, and discuss this other alternative only as a robustness test.

These three sources give me approximately 350 observations, from around 100 country-year cells. For the main specification, I keep only the long-term bonds (of at least three years to maturity). This should reduce the problems of yield and spread calculation. I also discard those bonds which were already in default and then were extended. This gives me a sample size of 266, with an average spread of 123 basis points over the benchmark yield.

3 Main results

3.1 Only default risk

First I present the reduced form estimates of (3): it means estimating

$$s_j = \alpha_4 + \beta_4 R_j + \Gamma_4 Z_{i(j)t(j)} + \delta_4 H_{i(j)t(j)} + \varepsilon_{4j},$$

where H_{it} denotes country dummies and a currency crisis indicator (a large depreciation of the currency, abandoning a fixed exchange rate for a float, or a managed float for a free float). Z contains the first lags of the following standard variables (at an annual frequency): reserves to imports, and exports to GDP, external debt to GDP, and current account balance to GDP (positive if in surplus), GDP growth (in percentage), and GDP per capita (in 1000 USD), an indicator of total past repayment troubles (arrears, relief and rescheduling agreements since 1970), and the percentage of countries in the region with arrears (a special form of regional effects, being surprisingly powerful in diagnostic regressions). These regressions simply try to explain the interest surcharge faced by a country. The results are contained in the first four columns of Table 1.

The overall fit is an R^2 of 0.2 (even less without the country dummies). This is not extremely strong, but we see that these variables do have reasonable explanatory power.[9] It also means that though spreads are responsive to fundamentals, their reaction is moderate. On average, fundamentals still explain a reasonable portion of spreads. Given the

[9] One main reason for the low R^2 is that many observations correspond to multiple data in the same country-year cell, and the within-cell variation cannot be captured by the explanatory variables. If one regressed the average values on the same right hand side (which means 71 observations and 11-21 explanatory variables), the fit would improve significantly (to 0.2-0.4). The point estimates would be mostly similar, which supports the initial hypothesis that the within-cell variations are orthogonal to the right hand side variables.

annual frequency of fundamentals, these findings are not surprising: yearly fundamentals have relatively little variation, so they cannot account for all the variation of spreads.

The inclusion of further lags would offer a moderate improvement, but it would also create severe multicollinearity problems. For this reason, I will only work with first lags.

In general, I would not read any strong stories from these descriptive results: first, some multicollinearity might be present even within the first lags of the variables; and second, many further variables can be included on the right hand side (in principle, all information available at the time of price formation), causing a missing variable bias in the reduced form estimates.

I still point out two results: the first is the significant positive effect of the currency crisis dummy. The other is the surprising negative coefficient of the benchmark interest rate. Although it is statistically significant, the confidence intervals "almost" contain zero. My interpretation is that the true coefficient is close to zero, but the approximate yield calculation gives a systematic negative error when long-term rates are high. In the robustness test section, I also used a more precise formula for calculating yields, but it did not resolve the problem.

Mechanically, the future results will be a refinement of these reduced forms: when replacing the right hand side with $\alpha + \beta R + \lambda p$, I impose the parameter restriction

$$\alpha_4 + \beta_4 R + \Gamma_4 Z + \delta_4 H = \alpha + \beta R + \lambda\left(\alpha_2 + \beta_2 R + \Gamma_2 Z + \delta_2 H\right) + \delta H.$$

This means that the structural form fit with *the best linear approximation* of p can be at most as good as the reduced form fit.[10] If p is nonlinear, then the structural relationship can be stronger than what the reduced form fit suggests. To be safe, one should still be careful when interpreting results without the country dummies, since their reduced form fit is modest.

The overidentification test will reject exactly when this interpretation of the reduced form is not acceptable. Such a rejection tells us that the premium cannot be fully attributed to the analyzed source of risk. Maybe the risk itself is the relevant choice, but its indicator is a less than perfect measure (for example, default risk must include arrears, and not only relief and rescheduling agreements). It is also possible that the true risk is completely different, or at least it is more complex (e.g., not only default risk, but liquidity risk as well). Political or

[10] I will not report any R^2 values from the forthcoming two-stage estimations, as the R^2 does not correctly measure the fit of a two-stage procedure. Instead, I will use the value and the p-value of the F test of joint significance.

strategic elements can also influence spreads (for example, past repayment misbehavior may induce punishment surcharges). Such non-probabilistic elements may dominate for certain debt instruments – for bonds, this is unlikely. My objective is, therefore, to see whether I can identify certain risks as the major source of the interest surcharge. As we will see, the answer is reassuringly positive.

Before actually switching to the structural form, I need to discuss briefly the first stages of all structural form estimations: the linear probability equations (columns 5 and 6 of Table 1) – which in fact measure the correlation of the instruments and the right hand side events. For a discussion about the choice and average values of these event variables, see section 3.2.1.

The results suggest that default and variance can be predicted quite well, even without the country dummies, which means that the instruments are highly correlated with this event variable. This would apply much less to crisis indicators: even with country dummies, the R^2 would stay below 0.35. It is hardly surprising, since crises are usually poorly predictable.

The good fit for default, however, conveys an unrealistic picture: in order to interpret the high R^2 as high correlation of the instruments and the events, I kept the same multiple country-year cells. It means that I am using some observations more than once (the only variable in which they are different is the bond yield), which artificially increases the fit. Using country-year averages, however, produces very similar estimates, and an even higher R^2 for both variable. Though the small sample raises different, but equally valid, concerns about the fit, one can still conclude that the selected fundamentals have good predicting power for default, and they are sufficiently correlated with future variance.

Second lags would increase the R^2, but the dominant effect would fall on the point estimates (again, the symptoms of multicollinearity). In general, using more *good* instruments reduces the standard errors, but due to small sample properties of 2SLS, it also produces a higher bias. I chose these particular variables since they are reasonably correlated with the event indicators, and also as a tradeoff between a larger and an even smaller set. I will report some results with different sets of instruments.

The benchmark yield is high and significant for the variance term: higher benchmark rates mean greater price volatility. One explanation is that a benchmark rate increase implies a negative wealth shock for bondholders, thus it can have adverse effects on liquidity and volatility. Much of the interest rate effect, however, is likely to come again from problems with yield calculation. If such problems are more severe with high benchmark rates, then the empirical variance, which is calculated from yields, might also be higher.

Including the square of the benchmark rate, or a dummy for benchmark rates being above certain levels (e.g., 10%, which is the period 1980-1985) would leave all point estimates, but the interest rate coefficient, nearly the same. This supports the miscalculation hypothesis. As a remedy, I will also employ a modified variance term: it is obtained by subtracting a dummy for very high benchmark rates (with the reduced form coefficient of 2.05).

Having checked our instruments in terms of being correlated with d_{it} and l_{it}, we can now turn to estimating (3). Table 2 reports the scenario with a single event, a repayment problems indicator on the right hand side.

In column 1, the choice of the default indicator is the ratio of debt forgiven (in the next 5 years) to current debt stock; in 2, it is an indicator of debt relief, rescheduling or arrears in the next 5 years; finally, 3, 4 and 5 use only relief and rescheduling agreements (again, see section 3.2.1 for further discussion).

The first two choices give insignificant results, and though the overidentification hypothesis is accepted in column 2, it also corresponds to a very weak fit (a p-value of 0.39 for joint significance). The coefficients in columns 3-5, on the other hand, are meaningful, significant and stable: a 10 percent increase in predicted relief or rescheduling adds 8.4-8.8 basis points to the spread. This is not a particularly strong marginal effect, but the average effect is much larger: the sample average of the default indicator is around 0.5, so predicted default risk is approximately 40 basis points from the 123 basis-point average of the spread.[11]

This dual picture of small marginal but large average effect applies to any fundamental or risk term: we have seen it here, in the reduced form, and we will see it for illiquidity as well. The phenomenon is driven by the reduced from results: if probabilities are predicted with fundamentals, but spreads are not very responsive to changes in fundamentals, then spreads will not be very sensitive to changes in predicted probabilities. As argued earlier, the small reduced-form sensitivity can be traced to the inavailability of high frequency fundamentals.

Another feature of the results is the surprisingly stable (-0.1) and significant coefficient of the benchmark interest rate. This coefficient is practically the same as in the reduced form: since the benchmark rate was not significant in the default prediction equation, default probabilities do not change the interest rate coefficient. This reinforces my earlier interpretation

[11]In equation (2), it means $x \approx 0,99$. With the narrow interpretation of default in (2), bondholders do not expect large losses in case of default. For a more general default case, the quantitative meaning of the coefficients is less clear.

of attributing this negative term to approximation and calculation errors in bond yields.

The most important result concerns the overidentification test: with a set of country dummies on the right hand side (thus also as instruments), the structural form is accepted, but it is rejected in all other cases. This finding describes bond spreads by default risk, the benchmark yield and country-specific effects. Note that this also means that one has to be careful when inferring differences in predicted risk by comparing spreads of different countries. As we shall see, however, even the acceptance result is not yet robust; some further elements will also play a role.

3.2 Illiquidity risk and market conditions

3.2.1 Choice of the event indicators

The two major risk choices are a repayment difficulty ("default") variable, and an illiquidity indicator. Once I have both of these probabilities incorporated into the interest rate equation, I can check whether one or the other is enough to explain why fundamentals influence spreads in the way the reduced form shows; and to test if, during crises, spreads increase more than implied by risk movements.

With default observations for bonds, the choice is not evident: hardly any sovereign *bond* defaults have happened since the seventies (which is the beginning of my sample period), and even less in foreign-currency denominated bonds, as documented in Standard and Poor's CreditWeek (1998), for example. An extreme view could be that if there are almost no bond defaults, then the predicted risk is nearly zero, thus there is no default risk in bonds.

Instead, I will use an overall indicator of repayment problems on any form of sovereign borrowing. Such repayment difficulties were quite frequent among developing countries, but they turned out to be systematically restricted to bank lending: arrears, reschedulings or even defaults (usually, in the form of debt relief agreements) on syndicated loans. As the previous subsection shows, the indicator of debt relief or rescheduling in the next 5 years is a successful choice. The sample average of this zero-one variable is 0.5.[12]

To support this choice, I would argue that this privileged repayment discipline on bonds was not foreseen (or even that it could not have been foreseen) by market participants during most of my sample period. Thus, repayment problems on bank loans are also the realiza-

[12] This might look large at first glance. However, it is an indicator of at least one relief or rescheduling event in the next five years, thus, it is reasonable that its value is relatively large in a developing country sample.

tions of the default risk on bonds. Another argument could be that whenever loan defaults become more likely, bond default probabilities also increase, thus predicted loan defaults can proxy predicted bond defaults. The overidentification test shows that this event is useful for describing bond spreads, moreover, its size and significance is robust to many alternative specifications. This confirms the use of this event as a proxy for default.

For the currency crisis indicator, I use a dummy for an at least 50% increase in the exchange rate (devaluation) in the given year, abandoning a pegged exchange rate regime for a float, or moving from managed to free float. Although these episodes might not fully coincide with crises, the results indicate that bond prices indeed behave systematically during these periods. The sample average of this variable is 0.1. Some further choices are discussed in the robustness test section.

Finally, what is the "illiquidity event"? First of all, if illiquid episodes are driven by currency crises, then an indicator of such crises in the future should be a major choice. Unfortunately, this variable is neither significant nor relevant for overidentification: my interpretation is that crises are particularly hard to predict.

In fact, a debt crisis can also trigger illiquidity episodes: the small, but significant, future repayment problem indicator may as well represent future depressed markets (recognizing that default is unlikely to affect bonds). This, however, also implies that a current repayment problem should increase spreads, which is not supported by the data (see section 4.3 for details).

Another, more general candidate for measuring liquidity is the observed behavior of the market itself. Although it would be less clear to see what causes liquidity to fluctuate, it does not restrict depressed periods to currency crises. Moreover, a more general event might be more predictable.

Such measures can be obtained from actual trade quantities, bid-ask spreads, or the prices themselves. For the stock market, Pástor and Stambaugh (2001) used market-level trade intensity to capture liquidity risk. For bonds, however, quantities or bid-ask spreads are hard to get – particularly for a long time horizon and broad cross-section, which would be essential for predicting risks. So the only feasible option is to extract a liquidity measure from the prices, but then this variable will be hard to distinguish from default risk.

One proxy could be the event when the current $\frac{r-R}{r}$ or $r-R$ increases substantially, by more than what could be attributed to changes in default risk (like it is hypothesized during crises). However, that risk can only be estimated, and recycling such an estimation is bound to cause unreliable estimates. One can also assume that large spread movements always have components above default risk (for long-term bonds, even a debt crisis is unlikely to put repayment at immediate danger), so a large spread increase reflects a case when the market for these bonds "dries out". One can define an event indicator for $r - R$ increasing more than certain thresholds in the next (say) 2 years.

I experimented with a number of choices for this indicator: different threshold levels and different time windows. In general, it has the wrong sign, and it is often insignificant (it cannot disentangle illiquidity from default risk). This former finding can be explained by a mechanical link: if spreads will increase substantially in the near future, then they are likely to be below average now, so the probability of a future spread increase might get a negative coefficient in current spreads.

So, instead, I adopted a different liquidity measure: the sample variance of future spreads, taking all bonds of a country into account. The best performing choice is the 5-year variance, which is reasonably significant, moreover, it is very influential in the overidentification test. Such a variance variable also tries to quantify volatile episodes of the market: again, if volatility is not caused exclusively by changes in default risk, then more volatility indicates a bigger role for market conditions.[13] The sample average of this term is 3.08.

In reality (and in a finer version of this approach), it is likely that there is also a bond-, and not just a country-specific liquidity event, l_{itj}. Though this could be managed in the regressions, given the moderate size of my data set, I did not attempt to do so.

3.2.2 Results

This subsection tests whether illiquidity risk and market conditions (in particular: currency crises) also play a role in the determination of bond spreads. The results are reported in Table 3, where specifications include a repayment problem indicator, different liquidity indicators, the benchmark bond rate, a crisis indicator and country dummies (or a subset of these

[13] One can also give a more direct liquidity interpretation to this variable: if bond prices have a large annual variance, then it is more likely that the price is particularly low (distressed) for some months at a random date. So if the investor needs to liquidate her portfolio at a random occasion, there is a chance that the price happens to be low, and it would require too much time for them to recover. It is indeed the long- or medium-frequency variance that matters: with high variance of any frequency, it is more likely that the price is depressed at a random date, but if the medium-term variance is higher than the short-term variance, then it may take several months for prices to return to acceptable levels. In this sense, liquidity is related to the uncertainty of the investment horizon. More generally, the effect of liquidity is that the distribution of terminal payments is no longer sufficient for pricing, dynamic changes in this distribution (the way uncertainty is resolved) also matter. See Benczur (2001) for further discussion.

variables) on the right hand side.

Before interpreting the various liquidity and market condition results, let me point out two common and robust features of all estimates. The coefficient of the benchmark interest rate is always significantly negative, its value is between -0.1 and -0.3. So far, I have attributed this to certain problems with calculating bond yields, which problems are systematically related to the size of interest rates. The remarkable stability of this negative coefficient reaffirms that this mismeasurement is unrelated to fundamentals, default risk and currency crises. As discussed earlier, the variance term is also influenced by these miscalculations, which shows up as a significantly more negative interest rate coefficient in columns 4-6.

The other unchanging result is the significant positive coefficient of default risk, being between 0.65 and 1.29. This small, but significant, number shows that bond spreads indeed reflect predicted default risk, though there are many other factors playing a role as well. As we shall soon see in details, this coefficient is in fact not that small: on average, default risk is responsible for 27% of the non-constant part of bond spreads (after eliminating country-specific fixed effects, and the benchmark rate).

Column 1 repeats the regression from column 3 of Table 2, with using a currency crisis dummy as an extra instrument. The coefficients stay the same, but overidentification is rejected at the 10% level. The positive sign of the crisis indicator in the reduced form thus cannot be fully attributed to higher default risk during such episodes. We see in column 2 that including the crisis dummy on the right hand side re-establishes overidentification; the variable gets a coefficient of 0.75, highly significant.

These results imply that during currency crises, bond spreads increase more than changes in default risk predictions. There are three potential explanations for such an extra effect: one is that there are some other risk factors influencing spreads, and the crisis dummy captures the increase of this other risk. A second is a rational, but constrained, investor story: for example, limited participation and common investors in the local- and foreign-currency denominated bond market of the crisis country. A third explanation, although empirically hardly distinguishable from the second, is that market participants systematically overestimate default risk around crises, at least relative to observed (future) default behavior (a behavioral story). A variant of this argument is that the probability of "true" bond default increases more than the probability of overall repayment problems.

The first explanation implies that the effect of crises should be eliminated by including an appropriate extra risk term; while the other two mean that there is an extra crisis term above any risk probabilities.[14] Columns 3-6 try to confront each explanation with the data.

Column 3 shows that the poor predictability of crises leads to noisy results: the crisis prediction gets a negative, and large, though insignificant, coefficient; the default coefficient increases, and the direct crisis effect becomes insignificant. Most of these results are reversed by the exclusion of country dummies, or by perturbing the set of instruments. Based on this, one should not read strong conclusions from this specification.

I experimented with many further crisis or market condition indicators (future price collapses, spread variance, IMF agreements, various exchange rate regime changes), and all but the variance has led to similar or worse conclusions (even overidentification failed occasionally). The limited success of the variance term (as shown in column 5) indicates that expected future market conditions are incorporated into the spread, in a more general sense than purely crises.

The next step is to look for risks which could replace the direct crisis effect (the first explanation). From the previous list, the spread variance term is again the only successful choice. Column 4 shows that its coefficient is significantly positive, large, and it can take over the crisis effect: overidentification is accepted without a direct crisis term (the same applies in the specification without country dummies).

Accepting overidentification does not mean that the direct crisis effect becomes zero: in column 5, which includes both the variance term and the crisis dummy, the latter stays around 0.7, highly significant (the same holds if one drops the country dummies). The variance coefficient stays the same in magnitude and significance.

A common feature of columns 4 and 5 is the further decrease of the interest rate coefficient. This is due to the variance term: in the first stage regression of variance, the benchmark rate has a large and significant coefficient. This means that a positive structural coefficient of variance must imply a decrease in the structural estimate of the interest rate coefficient. From the effect of interest rates on variance, I attributed a large part to measurement problems with bond yields. This means that a "true variance" would be less responsive to interest rates.

Column 6 tries to make an adjustment into this direction: it uses the modified variance

[14] Explanation two, which assumes rational, but potentially constrained, investors, would also imply that there should be an additional risk factor in spreads: if investors are aware of ill market conditions and implied losses during crises, then a crisis risk should be incorporated into the spreads. Such a term would be missing under explanation three. Crises, however, are usually hard to predict, making the proposed distinction of these two explanations hard to test.

term, which is obtained by subtracting 2.06 from variance in years 1980-1985 (periods with unusually high benchmark interest rates). The interest rate coefficient indeed moves slightly closer to zero, and the variance coefficient increases. One could use further adjusted variance measures (trimmed variance, an indicator of being above certain thresholds, etc.), which would also lead to higher variance, interest rate and, occasionally, even higher default coefficients. In any case, one could not reject that all the interest rate coefficients are equal to each other.

The evidence thus indicates that there is an extra risk included in bond spreads (explanation one), but crisis periods imply an even bigger increase in spreads than the total increase in risks (explanations two and three). This extra risk reflects distressed future market conditions: partly because of future crises, but it appears to be a more general notion of market liquidity.

To get a sense about the relative size of the two risk factors, and the extra effect of crises, I plug in certain sample averages into the specification of column (5). This purely illustrative exercise yields

$$\underbrace{\overline{spread}}_{1.23} = \underbrace{\underbrace{0.65 \cdot \overline{\widehat{def}}}_{\text{default risk}}}_{0.33} + \underbrace{\underbrace{0.24 \cdot \overline{\widehat{variance}}}_{\text{price variation}}}_{0.74} + \underbrace{\underbrace{0.79 \cdot \overline{ccrisis}}_{\text{crisis}}}_{0.079} + \underbrace{\underbrace{2.37}_{\text{country effects}} \quad - \underbrace{0.28 \cdot \overline{benchm}}_{\text{adjustments}}}_{0.08}.$$

The equation suggests that the benchmark rate adjustments and the country effects are sizable determinants of spreads, since both are more than twice the average (measured) spread. The benchmark rate effect is likely to reflect yield calculation problems. It is not clear, however, why country effects are this large: though there can be some country-specific fixed fundamentals, but then those fundamentals must have a large effect above risk probabilities. The fact that the joint effect of the two is nearly zero might mean that the interest rate mismeasurement is largely country-specific, thus it is undone by the country dummies. Section 4.4 offers some further refinements.

The remainder of the spread is a time-and country-varying component above changes in benchmark interest rates and country fixed effects: it can be interpreted as an adjusted spread. From its average value of 1.15, default risk is responsible for 29%, price variance constitutes an additional 64%, and the remaining 7% is the crisis term.[15]

[15] The average value of this adjusted spread is 0.46 in column 2 (with default risk and crisis), and 1.08 in column 4 (default and liquidity risk). From the unreasonably low 0.46 of column 2, 0.38 (83%) is default risk;

How large is this additive crisis effect, relative to increases in risk predictions during crises? Since the crisis dummy is included on the right hand side of the regression, the same average decomposition can be applied to the crisis and the non-crisis sub-samples. Then one can compare the changes in each term during crises:

$$\underbrace{\Delta\overline{spread}}_{0.84} = \underbrace{0.65 \cdot \Delta\overline{\widehat{def}}}_{\text{default risk: } 0.11} + \underbrace{0.24 \cdot \Delta\overline{\widehat{variance}}}_{\text{price variation: } 0.5} + \underbrace{0.79 \cdot \Delta\overline{ccrisis}}_{\text{crisis: } 0.79} + \underbrace{-0.16 - 0.28 \cdot \Delta\overline{benchm}}_{\text{total: } -0.56}.$$

The change in the "adjusted spread" is $0.84 + 0.56 = 1.4$, from which 0.11 (7.8%) can be attributed to increased default risk, 0.5 (35.7%) comes from higher variance (future volatility), but the major effect (56.5%) is the extra additive increase.

Notice that both of the risk predictions increase during crises: the difference between crisis and non-crisis averages is 0.16 for default (compared to the 0.5 unconditional average), and 2.08 (compared to 3.08). So what happens during crises is that default predictions increase, but near-future volatility increases even more. Thus, though the additive crisis effect can also be attributed to a nonlinear relationship between spreads and risk probabilities, default risk is unlikely to be the only source of the crisis effect.

Based on all the results I presented, (3) seems to be a valid specification: the reduced form fit can be attributed to default risk, some form of liquidity risk (future price volatility), the benchmark interest rate and country fixed effects. There is, however, an extra increase during currency crises, above changes in risks and adjustments. With rational, but constrained, investors, this should reintroduce an exchange-rate risk component during normal times: anticipating stressed market conditions during devaluations. Though this relation could not be established in the data, the volatility term (general liquidity) is likely to reflect such investor considerations as well.

4 Robustness checks of the results

In this section, I report estimates from numerous modifications of the specification in column 5 of Table 3. Since this benchmark contains all the relevant variables (benchmark rate, default risk, price volatility, crisis effect, country dummies), these exercises should check the robustness of my previous spread decomposition results.

this number is 0.34 (31%) in column 4. The absolute contribution of default risk is highest in column 3, where the default coefficient is 1.29: there the value is 0.65 (65 basis points). In all cases, default predictions are substantial, but not the only determinants of spreads.

4.1 Different left hand side variable

Instead of the linear formula for yield calculation ($r - R + \frac{100-p}{T}$), I also tried to fit an approximate yield curve to the short- and long-term benchmark rates, and use the implied future rates to accumulate the payoff flow of sovereign bonds (thus assuming that coupon payments are reinvested in benchmark bonds). Using this terminal payoff and the current price level, I can calculate the implied annual rate of return, and then subtract the corresponding benchmark rate (using the approximate yield curve again).

In principle, this version of the spread should depend on the benchmark interest rate in a more reasonable way, since the approximation error from the linear formula is eliminated. Following it literally, in the sense of using the appropriate maturity approximated benchmark rate, the interest rate coefficient moved even further away from zero. When, however, I used the long-term benchmark rate on the right hand side of regressions (and the approximate yield curve only for calculating the left hand side), its coefficient indeed became very close to zero. Altogether, this suggests that there is some systematic calculation error when I use the linear approximation, but in the absence of fine information on the benchmark yield curve, coupon payment frequencies and dates, etc., one cannot eliminate this problem. The estimations show that it is mostly the benchmark rate coefficient that goes wrong and changes with different choices of the spread, so this coefficient seems to capture most of the mismeasurement, and the other results are relatively immune to the problem.

Comparing the estimates using this modified spread (either with the "fine" or the "course" benchmark rate) and the original, one finds the following general features. First of all, the sample becomes substantially smaller (around 180), so the results are much less reliable. Since the overall level of the spread is higher, it translates into somewhat higher default risk, currency crisis and variance coefficients. The presence of the variance term, however, again drives the benchmark rate away from zero. The future crisis term remains insignificant and keeps its wrong sign. For overidentification, it is necessary to include country dummies, the current crisis indicator, default risk and the variance term.

4.2 Different instruments

First I estimated the benchmark specification with OLS, thus neglecting the endogeneity issue. Consistent with characteristics of standard measurement error, the risk coefficients became smaller (closer to zero). Default risk stayed significant, but the variance term became zero. From the exogenous variables, the benchmark rate coefficient has moved towards zero, while the crisis dummy remained nearly the same.

Next, I varied the set of instruments, between the two extremes: a just-identified specification (two instruments), which should be less precise but also less biased, and a large set of instruments, which should improve the precision but it is likely to produce a bias towards OLS in small samples (see Angrist, Imbens and Krueger (1999) for a discussion and further references).

The just-identified results showed some sensitivity to the choice of the two instruments: though the majority of the results showed the same sign and magnitude for the risk coefficients, there were occasional sign switches. The estimates were indeed quite imprecise, but altogether they remained quite similar to my benchmark results.

When using many instruments (further fundamentals, like gross investment growth, credit to private sector etc.; or various time effects), the estimates showed only modest changes. The default and crisis coefficients moved little, the variance parameter has decreased, while the benchmark rate moved closer to zero. The significance level has increased for the crisis effect, and decreased for the rest. Overidentification is accepted in all cases, but with many instruments and a relatively small sample, its power becomes questionable.

On the whole, there seems to be a systematic pattern in these results: the OLS estimates are smaller than with any IV; and the large IV estimates are close to OLS. The first observation is consistent with the standard measurement error specification: the nonorthogonal right hand side variable has a negative covariance with the error term, so OLS produces too small estimates. The second observation matches the pattern that IV estimates are biased towards OLS in small samples (see Angrist, Imbens and Krueger (1999) again). I consider the benchmark set of instruments as a reasonable tradeoff between less bias (just identified) and more precision (large set of instruments).

4.3 Varying the event indicators

Table 3 already contained some variations of the repayment problem indicator. Here, instead of varying the classification itself, I reran the results with different time windows. With a realization within three instead of five years, there are hardly any changes. With ten years, the vast majority of the observations will have an actual default value of one, so the specification is uninformative.

The same applies to the ill-performing "depressed future prices" indicator: even when I changed the cutoff level or the time window, the variable had the wrong sign, it was not influential for the overidentification test, and it was often insignificant.

I also experimented with different choices for the price variance term: I worked with the 3-year variance, the "full forward variance" (up to the most recent observation available), the adjusted versions of these terms, and dummies for the 5-year variance being in the upper 25th or 10th percentile of its sample distribution. None of these changes had any significant impact on other variables, though the coefficients became somewhat smaller in general. The 3-year and full variance had a smaller and less significant estimate than their 5-year counterpart; the adjusted variance terms became completely insignificant. The dummy versions were significant (point estimates of 1.2 for the 75th percentile, 1.7 for the 90th percentile), and equally important for overidentification.

Finally, I considered some alternative measures of current and future crisis. First I added a current default dummy: it corresponded to a completed relief or renegotiation, thus it was exogenous as of time t. This variable was completely insignificant, somewhat defying the interpretation that repayment trouble is also a source of market distress, and its predicted probability is an illiquidity prediction. Then I introduced detailed measures of currency regime changes, e.g. from free float to managed float. These variables did not add anything to the effect of a large devaluation indicator: though some of them were significant (from free to managed float), these variables turned out to be highly correlated with devaluations in the sample. The same applies to their future values: just like future devaluations, future regime changes usually get the wrong sign, and they are also insignificant.

4.4 Refining country effects

I checked whether the effect of country dummies can be described with long-term debtor history of the countries, using data from Lindert and Morton (1989). This history includes bond defaults in the 19th-early 20th century (up to the 1930s), default in the thirties, the number of years in default (in some cases, default episodes spanned many years), and an indicator of a new sovereign (independence or entering the Eastern block after WWII), hence a new debtor.

From these variables, only the indicator of default in the 1930s was significant. It also led to accepting the overidentification with country dummies as instruments, thus replacing the direct influence of country effects. This variable, however, consists only of three country dummies: Argentina, Hungary and Uruguay; and the overidentification result is driven entirely by Argentina. If one checks whether some of the country dummies alone are sufficient for overidentification, this is the case for Argentina and Brazil. This implies that the effect of country dummies above default and liquidity predictions is mostly a treatment differential for Argentina (all other things being equal, a smaller spread) and Brazil (a higher spread). One interpretation of such a difference is that my default observations (or risks in general) are "downgraded" by the market for Argentina, and upgraded for Brazil.

Summarizing the lessons from these robustness checks, I conclude that my benchmark specification passed all the tests reasonably well. The standard errors increased in many cases, but the parameter estimates moved only little.

5 Summary and conclusions

The objective of this paper was to test if we can describe sovereign bond spreads by predicted risk probabilities (default and liquidity risk), and whether there are certain episodes (in particular: currency crises) when spreads increase more than risk probabilities do, indicating limits of arbitrage. I was estimating a structural equation determining sovereign bond spreads, of the form

$$s = \alpha + \beta R + \lambda_{def} d + \lambda_{liq} l + \lambda_{cri} c + \varepsilon_1.$$

Here c is a crisis indicator; while d and l are realizations of a default and an illiquidity variable (the full specification also contained country dummies). Instead of the realizations of the two risk factors, the true specification contains their expectation conditional on information available at the time when prices were formed. A realization is the sum of its conditional expectation and a prediction error. This means that ε_1 contains the prediction errors, so d and l are not orthogonal to the error terms. The key observation is that any information available at the time of pricing can serve as valid instruments.

In principle, R should be excluded and used purely as an instrument: however, it stayed sizeable, significant, and negative in all specifications. I would relate this counter-intuitive finding to potential problems with calculating bond yields (in particular, the discounting of coupons).

This procedure thus tries to attribute the reduced form fit of

$$s_j = \alpha' + \beta' R_j + \Gamma Z_{i(j)t(j)} + \delta c_{i(j)t(j)} + \varepsilon_{2j}$$

to the predictive power of R_{it}, c_{it} and Z_{it} for default and illiquidity risk, plus an extra crisis term. If overidentification passes, this re-interpretation is acceptable; otherwise some further factors are also present in the spread.

I find that the structural form captures the reduced form fit: including a default indicator, benchmark rates, country dummies and a currency crisis indicator, overidentification passes; also with a default indicator, a liquidity term (future price volatility), benchmark rates and country dummies. Even in the second case, the currency crisis dummy stayed large and significant, although not vital for overidentification. These findings depict sovereign bond spreads as being determined by default risk, liquidity risk, an extra increase during currency crises, plus adjustments (the benchmark rate and country effects – the net effect of them is roughly zero). In general, the marginal effect of risk probabilities is relatively small (spreads respond weakly to changes in risk predictions), but on average, risk factors explain a large part of the spread.

My benchmark specification therefore contained a default indicator (debt rescheduling or relief in the next 5 years), a liquidity term (5-year future sample price variance), a currency crisis dummy, the benchmark rate and country dummies.

This specification gave the following results. In terms of sample averages, approximately 27% of the spread can be credited to default risk. For every 10 percentage points increase in predicted default probabilities (the sample average is 50 percentage points), there is a 6.5 basis point increase in bond spreads.

An additional 60% is accounted for by country-specific illiquidity. For an increase of the variance by 0.5 (the average value is 3.09 in the sample), the spread goes up by 12 basis points. The good performance of this variable is a promising finding, it makes this variable a good candidate for representing liquidity (volatile market conditions) in other asset pricing regressions as well.

The currency crisis dummy has a coefficient of 0.79. On average, it contributes only 7% to spreads, but it makes up more than half of the crisis versus non-crisis spread differential. Therefore, bond spreads increase significantly more during crises than changes in predicted risks would imply. This can be attributed to investor overreaction (irrationality), or, within the framework of rational but potentially constrained investors, to a spillover from depressed local currency bond markets.

The leftover (6%) of the spread is made up by the benchmark bond rate and the country-specific constants. These two factors are large in size, but their effects almost completely cancel each other. I attribute the benchmark rate coefficient to problems with bond yield calculation, which are systematically related to the benchmark interest rate. On average, the country terms turn out to balance most of this adjustment, but it is not necessarily a causal finding.

I have checked the robustness of the benchmark results to a couple of alternative specifications. In general, the estimates did not change in any unexpected way, and in most cases, even the size and significance of the changes were minor. Therefore, the results establish a robust decomposition of the spread into liquidity and default risk, and an additional crisis effect (a role of market conditions).

I see a couple of major open agendas here. One is to get a precise picture of these risk events, which would require higher frequency fundamentals, more detailed information on country-specific events, and detailed panel data on individual bonds. Over the time range I have studied, it seems quite a difficult task to get, but I managed to collect monthly price data on many Brazilian, Mexican and Venezuelan dollarbonds for further research.

Another task is to further investigate why the market shrinks so heavily for these bonds at certain times, and why there are no investors coming to arbitrage on this opportunity, thus mollifying the collapse. Potential explanations could also be related to the acceleration of information revelation in these crisis periods, thus an increased volatility of near-future prices; or investor-specific liquidity shocks. This could even yield policy recommendations for developing countries on how to reduce their spreads.

Finally, one could use the same structural framework to study the pricing of other assets. For example, local-currency denominated bonds, where exchange rate fluctuations constitute an additional risk. In that setup, one can handle the otherwise latent expected exchange rate movement by the same instrumental variables method, thus successfully estimate an uncovered interest parity condition. Market conditions, which are closely related to exchange rate behavior, are likely to play a key role there as well.

The method can also be applied to understand the determinants of bank loan spreads. A rejection of the pure risk prediction model is expected there, since political and strategic motivations should have very important effects in loans. Reputation, for example, can be captured by an extra, direct effect of past repayment behavior on spreads, above any effects through predicted risk measures.

6 Appendix

6.0.1 The estimation framework in a general setting

A variable X depends on the predicted value of a (potentially vector) variable Y:

$$X_t = \alpha + \beta E[Y_t|Z_t] + \nu_t, \tag{7}$$

where Z_t is the information available for predicting Y_t. One then specifies a prediction (conditional expectation) equation

$$Y_t = g(Z_t) + \varepsilon_t, \tag{8}$$

and rewrites (7) as

$$X_t = \alpha + \beta g(Z_t) + \nu_t. \tag{9}$$

With some assumptions on the form of g, equations (8) and (9) can be estimated by some full information and in general nonlinear method (GMM).

The reduced form of (7) is

$$X_t = f(Z_t) + \eta_t. \tag{10}$$

It describes how X_t is predicted by past information (Z_t), without implying any causality. Now suppose that some theory suggests that all the influence of Z_t should come through the predicted value of $E[Y_t|Z_t]$ – as given by (7). Then the structural form (9) rewrites the reduced form (10) as

$$f(Z_t) = \alpha + \beta g(Z_t). \tag{11}$$

This gives a straightforward test of whether the structural form is really a good reinterpretation of the reduced from: estimating (8) and (10) simultaneously, and then testing the restriction $f(Z_t) = \alpha + \beta g(Z_t)$.

My approach is similar but importantly different: instead of using any specific functional form for g, then estimating the two equations simultaneously (full information), and testing a nonlinear overidentification hypothesis, I estimate

$$X_t = \alpha + \beta Y_t + \widetilde{\nu}_t \tag{7B}$$

directly. Here the error term is $\widetilde{\nu}_t = \nu_t + \beta\left(g(Z_t) - Y_t\right) = \nu_t + \beta\varepsilon_t$, which is not orthogonal to $Y_t = g(Z_t) + \varepsilon_t$, but orthogonal to Z_t. Moreover, Y_t is correlated with Z_t, so I can estimate (7B) by using Z_t as instruments.

6.0.2 The overidentification test

Here the overidentification test means checking if the residuals $X_t - \widehat{\alpha} - \widehat{\beta}Y_t$ are orthogonal to Z_t: Under the null (all instruments are valid), the estimates are consistent, so the residuals

$$\alpha + \nu_t + \beta E[Y_t|Z_t] - \widehat{\alpha} - \widehat{\beta}Y_t = \alpha - \widehat{\alpha} + \nu_t + \beta\left(E[Y_t|Z_t] - Y_t\right) - \left(\widehat{\beta} - \beta\right)Y_t$$

should be orthogonal to Z_t, since $\widehat{\alpha} - \alpha \longrightarrow 0$, $\widehat{\beta} - \beta \longrightarrow 0$, $\nu_t \perp Z_t$, and $E[Y_t|Z_t] - Y_t \perp Z_t$. The last term suggests that it is crucial that the market uses the right (rational) expectation: without that assumption, the prediction error $E[Y_t|Z_t] - Y_t$ is in general non-orthogonal to the predictors, and overidentification fails. It also fails if the endogenous right hand side variable Y_t is not the true event or not the only event the market was using.

The previous nonlinear test of (11) would become identical to this simple test if one restricts the functions f and g to be linear. Then I would get a linear reduced form:

$$X_t = \alpha' + \Gamma' Z_t + \nu_t \tag{10B}$$

$$Y_t = \alpha'' + \Gamma'' Z_t + \epsilon_t, \tag{8B}$$

and the structural form would impose the restrictions

$$\alpha' = \alpha + \beta\alpha'' \text{ and } \Gamma' = \beta\Gamma''. \tag{11B}$$

However, as the argument shows, testing the orthogonality of the residuals and the instruments is a valid overidentification test even in a nonlinear setup: the only linearity I need is in the pricing equation (7), but the prediction equation (8) does not have to be linear.

6.0.3 Deriving identification for the two event case

The three equations are (skipping the error terms for convenience)

$$
\begin{aligned}
d &= \alpha_2 + \beta_2 R + \Gamma_2 Z + \delta_2 H && (12)\\
l &= \alpha_3 + \beta_3 R + \Gamma_3 Z + \delta_3 H && (13)\\
s &= \alpha + \beta R + \lambda_d d + \lambda_l l + \delta H. && (14)
\end{aligned}
$$

The first two are already in reduced form, and the third becomes

$$
\begin{aligned}
s &= \underbrace{(\alpha + \lambda_d \alpha_2 + \lambda_l \alpha_3)}_{\alpha_1} + \underbrace{(\beta + \lambda_d \alpha_2 + \lambda_l \alpha_3)}_{\beta_1} R \\
&+ \underbrace{(\lambda_d \Gamma_2 + \lambda_l \Gamma_3)}_{\Gamma_1} Z + \underbrace{(\delta + \lambda_d \delta_2 + \lambda_l \delta_3)}_{\delta_1} H. && (15)
\end{aligned}
$$

This means that estimating (12), (13) and (15) immediately gives us α_2, β_2, Γ_2, δ_2, α_3, β_3, Γ_3, δ_3, plus the following conditions:

$$
\begin{aligned}
\alpha_1 &= \alpha + \lambda_d \alpha_2 + \lambda_l \alpha_3 \\
\beta_1 &= \beta + \lambda_d \beta_2 + \lambda_l \beta_3 \\
\Gamma_{1i} &= \lambda_d \Gamma_{2i} + \lambda_l \Gamma_{3i} \\
\delta_1 &= \delta + \lambda_d \delta_2 + \lambda_l \delta_3.
\end{aligned}
$$

If the dimension of Z is at least two (in general: we have at least as many excluded exogenous variables from (14) as endogenous variables, i.e., events), then the Γ equation gives us λ_d and λ_l, even overidentifying those two parameters, and then α, β and δ can be obtained from the appropriate equations. This shows that (14) is identified.

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Table 1: Reduced form results[a]

	LHS variable					
	$r-R$				Default[b]	Variance[c]
	(1)	(2)	(3)	(4)	(5)	(6)
Reserves to imports	-1.19	-1.00	0.35	0.09	-0.61	-4.77
	(4.27)*	(3.26)*	(0.23)	(0.05)	(2.32)*	(2.41)*
Exports to GDP	-0.02	-0.01	0.05	0.04	-0.01	0.00
	(2.68)*	(2.55)*	(2.14)*	(1.82)	(4.36)*	(0.04)
Debt to GDP	0.44	0.46	1.84	1.54	0.93	-2.64
	(1.03)	(1.09)	(1.53)	(1.24)	(5.53)*	(1.31)
Curr. acc. to GDP	-3.24	-2.99	-5.56	-5.35	0.73	-1.65
	(1.64)	(1.59)	(3.94)*	(3.80)*	(1.65)	(0.44)
GDP growth	-2.05	-2.33	-0.73	-0.57	1.28	-5.54
	(0.99)	(1.31)	(0.28)	(0.21)	(1.00)	(1.15)
GDP per capita	0.18	0.17	0.7	0.7	0.1	0.53
($1000)	(1.58)	(1.50)	(2.58)*	(2.49)*	(1.45)	(2.52)*
Past repayment problems	-0.05	-0.03	-0.03	-0.06	0.01	-0.31
	(1.41)	(0.95)	(1.23)	(1.82)	(1.45)	(2.85)*
Arrears in region	1.17	0.76	-1.62	-0.64	0.67	7.37
	(1.59)	(1.08)	(0.79)	(0.31)	(1.37)	(1.75)
Currency crisis		0.55	0.71		-0.10	-0.45
		(2.70)*	(4.40)*		(1.43)	(1.66)
Benchmark yield[d]	-0.13	-0.12	-0.16	-0.17	0.03	0.49
	(2.83)*	(2.78)*	(2.66)*	(2.61)*	(1.26)	(5.17)*
Constant	4.19	4.45			-1.55	4.41
	(1.82)	(2.15)*			(1.02)	(0.82)
Country dummies	no	no	yes	yes	no[e]	no[e]
R^2	0.10	0.11	0.22	0.20	0.56	0.66

a All equations are estimated by OLS. The sample size is 266 in columns 1-5, and 259 in column 6. All variables are annual. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b Default is an indicator of debt relief or rescheduling in the next 5 years (including the current one).

c Variance is the 5-year empirical variance of all bond spreads of the country starting the given year.

d The benchmark yield is the yield on long-term (10-year) government bonds of the appropriate currency.

e Including the country dummies would make the estimates of the economic fundamentals very imprecise, thus insignificant. The R^2 would become 0.75 and 0.83, respectively.

Table 2: Regression results: only default risk considered[a]

	LHS variable: $r-R$				
	Choice of the default indicator[b]				
	rel. size	with arrears	without arrears		
	(1)	(2)	(3)	(4)	(5)
Default indicator	10.89	-7.37	0.86	0.88	0.84
	(1.56)	(0.88)	(5.61)*	(5.25)*	(2.63)*
Benchmark yield[c]	-0.08	-0.09	-0.13	-0.10	-0.10
	(1.50)	(1.51)	(2.94)*	(3.49)*	(2.96)*
Constant				1.60	1.61
				(10.93)*	(12.17)*
Country dummies	included	included	included	instruments	–
F stat. deg. of fr.	F(1,10)	F(1,10)	F(1,10)	F(2,10)	F(2,10)
F stat. value	2.27	0.79	31.56	13.86	4.57
F stat. p value	0.16	0.39	0.00	0.00	0.03
p value of overid test[d]	0.04	0.62	0.28	0.00	0.06

a All estimations are IV, using as instruments the first lag of reserves to imports, exports to GDP, debt to GDP, current account balance to GDP, GDP growth, GDP per capita, past repayment troubles, arrears in region and benchmark bond yields. The sample size is 266. All variables are annual. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b In column 1, the indicator is the sum of the relief to debt stock ratios in the next five years (including the current one). In column 2, it is an indicator of debt relief, rescheduling or arrears in the next 5 years (including the current one). Columns 3-5 is similar to 2, but without arrears.

c The benchmark yield is the yield on long-term (10-year) government bonds of the appropriate currency.

d The overidentification test regresses the residuals on the exogenous right hand side variables and instruments.

Table 3: Main results[a]

		LHS variable: $r - R$					
		(1)	(2)	(3)	(4)	(5)	(6)
Default indicator[b]		0.79	0.77	1.29	0.69	0.65	0.68
		(5.34)*	(4.35)*	(3.68)*	(5.36)*	(7.90)*	(8.54)*
Future crisis[c]				-1.71			
				(1.36)			
Variance[d]					0.24	0.24	0.30
					(2.21)*	(2.20)*	(2.20)*
Current crisis[e]			0.75	0.24		0.79	0.77
			(3.10)*	(0.49)		(3.35)*	(2.97)*
Benchmark yield[f]		-0.13	-0.14	-0.19	-0.27	-0.28	-0.24
		(2.86)*	(2.88)*	(2.82)*	(3.29)*	(3.34)*	(3.79)*
F stat.	deg. of fr.	F(1,10)	F(2,10)	F(3,10)	F(2,10)	F(3,10)	F(3,10)
	value	28.52	11.51	31.06	15.97	33.58	28.30
	p value	0.00	0.08	0.00	0.00	0.00	0.00
p value of overid test[g]		0.09	0.31	0.78	0.63	0.92	0.93
Number of obs.		266	266	259	259	259	259

a All estimations are IV, using as instruments first lags of reserves to imports, exports to GDP, debt to GDP, current account balance to GDP, GDP growth, GDP per capita, past repayment troubles, arrears in region, a current crisis dummy and benchmark bond yields. Country dummies are used as extra right hand side variables. All variables are annual. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b Default is an indicator of debt relief or rescheduling in the next 5 years (including the current one).

c Future crisis is an indicator of a currency crisis next year.

d Variance is the 5-year empirical variance of all bond spreads of the country starting the given year.

e An indicator for a large devaluation or abandoning a fixed or limited float regime.

f The benchmark bond yield is the yield on long-term (10-year) government bonds of the appropriate currency.

g The overidentification test regresses the residuals on the exogenous right hand side variables and instruments.