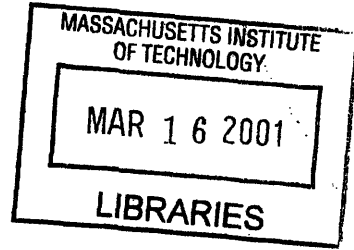


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Sovereign Lending Spreads

by

Peter Benczur

Submitted to the Department of Economics
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

February 2001

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Author.....

Department of Economics
December 18, 2000

Certified by.....

Daron Acemoglu
Professor of Economics
Thesis Supervisor

Certified by.....

Rudiger Dornbusch
Ford International Professor of Economics
Thesis Supervisor

Accepted by.....

Peter Temin
Elisha Gray II Professor of Economics
Chairman, Department Committee on Graduate Students

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Abstract

This thesis studies the determinants of sovereign lending spreads. The objective of the first chapter is to identify and disentangle various risks embodied in foreign currency denominated sovereign bond spreads. Its empirical approach tries to attribute the explanatory power of country fundamentals in a spread equation to their predictive power for default and illiquidity risk. For this, I incorporate rational expectation predictions into the spreads and propose an IV estimation method. The overidentification test offers a test whether the spread can be explained by predicted risk probabilities. Applying this approach to developing country bond data from 1975 to 1995, I find that the non-structural explanatory power of fundamentals can be completely attributed to their influence on predicted risk probabilities.

The second chapter takes a broader view across all public sovereign lending. Data from the World Bank suggests that the *average* spread on all forms of borrowing by developing countries is smaller than for top-rated US corporate bonds. After documenting these facts (with particular care for resolving data problems), the analysis looks behind the averages. Once identifying various sub-types of borrowing, I find that official and other private lending (trade-related) are the main source of the low average spreads. Bond and commercial bank lending shows reasonable spreads. Unlike other and official, bond and bank lending move nearly one in one with world interest rates. All types of private lending significantly differ from each other in the way they incorporate country fundamentals.

The third chapter offers a potential source of liquidity risk in bond markets: in a Diamond-Dybvig type model, where agents face a risk of becoming *more risk-averse* early consumers, changes in the speed of public learning about default risk may increase bond spreads, and decrease investor welfare. This effect operates through a link between future price volatility and current prices: increased expected future price volatility leads to lower prices today.

Thesis Supervisor: Daron Acemoglu
Title: Professor of Economics

Thesis Supervisor: Rudiger Dornbusch
Title: Ford International Professor of Economics

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Contents

Introduction	9
1 Decomposing sovereign bond risks	11
1.1 Introduction	11
1.2 A simple model establishing a link between current and expected future prices	17
1.3 The setup of the empirical analysis	22
1.3.1 Variables, data sources	22
1.3.2 Main specification	23
1.4 Main results	24
1.4.1 First pass: only default risk	24
1.4.2 Identification and generalization of the method	31
1.4.3 Illiquidity risk	36
1.5 Robustness checks of the results	40
1.5.1 Different left hand side variable	40
1.5.2 Different estimation techniques	41
1.5.3 Varying the event indicators	42
1.5.4 Country and time effects	44
1.6 Summary and conclusions	47
1.7 Appendix	50
1.7.1 Multiple equilibria in the model	50
1.7.2 Deriving identification for the two event case	51
References	52
2 The composition of sovereign debt: a description	54
2.1 The behavior of average borrowing rates	54

2.1.1	Borrowing rates are very low	54
2.1.2	Borrowing rates respond too little to world interest rates	58
2.2	Relation to the literature	61
2.3	The data: sources, problems and remedies	62
2.3.1	Economic indicators of countries	62
2.3.2	Debt data	63
2.4	The weighted estimation	66
2.5	Validation of the Data	69
2.6	Main results	72
2.6.1	Differences by lending types	72
2.6.2	Differences by income groups	78
2.7	Robustness checks	83
2.7.1	Using different compositions	83
2.7.2	Different methods, grouping by regions and time periods	84
2.8	Alternative interpretations	84
2.9	Conclusions	89
2.10	Appendix	91
2.10.1	The right hand side variables (factors)	91
2.10.2	The disbursement-commitment correction	93
2.10.3	Regression results	94
	References	96
3	Learning, noise traders, the volatility and the level of bond spreads	97
3.1	Introduction	97
3.2	The model	102
3.2.1	Ingredients	102
3.2.2	Solving the model – slow learning case	103
3.2.3	The fast learning case	105
3.3	Results	107
3.3.1	Comparing slow and fast learning	107
3.3.2	A continuous version of the speed of learning	116
3.4	Conclusions	120

References 121

List of Figures

2-1	Interest rates and spreads	55
2-2	Interest rates and spreads	57
2-3	Currency adjusted spreads, private lending	58
2-4	Data from World Debt Tables vs Borrowing in International Capital Markets	71
2-5	Estimated spreads; using flow and disbursements weights	78
2-6	Lending spreads by income groups	81
2-7	Estimated spreads of private lending types, by income groups	82
2-8	Evolution of the other-official ratio and lagged world interest rates	86
2-9	Private debt of Iran, 1980-1994	89
3-1	Utility comparison for the risk-neutral case	114

List of Tables

1.1	Describing bond yields	26
1.2	The prediction equations	28
1.3	Regression results: only default risk considered	30
1.4	Main results	37
1.5	Different left hand side variable	40
1.6	Different estimation techniques	41
1.7	Country effects	45
1.8	Time effects	46
2.1	Results for total, official and private lending	59
2.2	Comparing the weighted and non-weighted estimates	68
2.3	Bank lending estimates	70
2.4	Baseline costs of lending: decomposition by types	73
2.5	Differences by types of lending	75
2.6	Different types of lending: quantity responses	77
2.7	Reduced form estimates: using "flow" composition	95
3.1	Utility and price comparison	113

Introduction

This thesis studies the determinants of sovereign lending spreads. The first chapter focuses on bonds: its objective is to identify and disentangle various risks (in particular, default and liquidity risk) embodied in foreign currency denominated sovereign bond spreads. First I present a simple model of pure liquidity risk, where risk-neutral investors trade a perfectly safe bond at a positive spread relative to a benchmark interest rate. This effect is driven by a link between current and predicted future, *pre-maturity* price fluctuations.

The main focus is on the empirical approach, which tries to attribute the explanatory power of country fundamentals in a spread equation to their predictive power for default and illiquidity risk. For this, I incorporate rational expectation predictions into the spreads and propose an IV estimation method. The overidentification test then offers a ready test whether the spread can be explained by predicted risk probabilities. Applying this approach to developing country bond data from 1975 to 1995, I find that the non-structural explanatory power of fundamentals can be completely attributed to their influence on predicted risk probabilities.

On average, default risk is 27% of the spread; for a 10 percentage points increase in predicted default probability, the spread rises by 31.5 basis points. Illiquidity, which is captured by future price volatility, gives an additional 27%; for an increase of variance by 10 (the sample average is about 50-60), the spread goes up by 26 basis points. The remaining 46% is attributed to adjustments, country effects and aggregate illiquidity (captured by lagged spreads and US interest rates).

The second chapter takes a broader view across all public and publicly guaranteed sovereign lending. In contrast to all expectations, data from the World Bank suggests that the *average* spread on all forms of borrowing by developing countries is smaller than for top-rated US corporate bonds. Part of this phenomenon is due to official lending, which is

extremely cheap, but even *average* private lending spreads are near or below zero.

The chapter documents these facts (with particular care for resolving various data problems), and then looks behind the averages. Once identifying various sub-types of borrowing, I find that official and other private lending (trade-related, or at least more firm-level lending) are the main source of the surprisingly low average spreads: these two types of lending react very little to movements in international interest rates, which – together with a not sufficiently large constant term – makes these types of loans very cheap. This also gives an "interest rate smoothing" result for official and other private lending.

Bond and commercial bank lending shows reasonable spreads, and both move nearly one in one with world interest rates. All types of private lending significantly differ from each other in the way they incorporate country-specific or worldwide economic conditions. Moreover, low-income countries actively change their disbursement portfolio in response to world interest rates, which leads to "interest rate smoothing" of commercial bank lending rates as well.

The third chapter returns to the issue of liquidity in bond markets. According to the first chapter and various other studies, sovereign bond spreads often deviate from any "sensible" perception of default risk. It is usually attributed to behavioral effects (overreaction) or liquidity. The former explanation imposes some irrationality or bounded rationality on investors; while the latter usually relies on some informational asymmetry or thin markets.

The chapter presents a different source of liquidity risk: in a Diamond-Dybvig type model, where agents face a liquidity risk (becoming *more risk-averse* early consumers), changes in the speed of public learning about default risk may increase bond spreads. This effect will operate through a link between future price volatility and current price levels: increased expected future price volatility (a volatility effect) leads to lower prices today (a level effect). Under reasonable parameter values, accelerated information revelation may increase spreads by 50%.

I also compare the welfare of the issuer and investors under different speeds of learning: revealing information may be good or bad for the issuer (issue prices may increase or decrease), and also for the investors (ex ante utility might be higher or lower).

Chapter 1

Decomposing sovereign bond risks

1.1 Introduction

It is a standard notion to view bond prices as the market's assessment of the riskiness of the issuer. Aside from whether or not market participants are right, it is not clear, however, what this risk is. It might reflect the inability to pay (default risk), or a situation when the investor needs to sell the bond before maturity and the price happens to be low at that point (illiquidity risk). This later event might be restricted to one particular (type) of bond, in which case it is more idiosyncratic (thus it can be diversified), or to the majority of bonds, which is a situation of systemic illiquidity.

Bonds are also subject to interest rate risk: investors are committing their money long-term to a fixed nominal interest rate, and if the short-term rate goes up, they are worse-off than by investing in short-term bonds from period to period. The nominal part can be eliminated by indexed bonds, but a real interest rate risk may still be present. Finally, if the bonds are paying their return in a currency different from the one investors need for consumption (or in which they have to repay what was borrowed), then investors are facing an exchange rate risk as well.

Reputation, political or strategic elements may also influence borrowing terms of sovereigns (see Obstfeld and Rogoff (1986) [1] as a survey): in the case of bonds, fortunately, with relatively many and small investors buying the bonds, such one-to-one relationships are much less present. Therefore, I assume that bond prices reflect non-strategic and predictable risks only.

In order to concentrate on illiquidity risk, about which much less is known,¹ I will focus on spreads of foreign currency (usually US dollar) denominated sovereign bonds. By being foreign currency denominated, these bonds substantially reduce the exchange rate component: the dollar-deutschemark rate might still fluctuate but to a smaller degree, and much better forward markets are available to offset the effect of such fluctuations.

Working with spreads relative to similar maturity and currency-denominated government bonds (US Treasuries, German Government Bonds etc.), I also nullify most of the interest rate risk: in principle, investors can go short in those nearly riskless bonds and use their proceedings to buy, say, Latin-American more risky. This spread, therefore, should be mostly independent from interest rate movements.

The objective of the chapter will be to separate default and illiquidity risk, by using data on sovereign bond issues and default behavior of several developing countries. In doing this, I will basically stay within the framework of risk-neutral investors with rational expectations: I assume that the price (or rather: the spread) depends on the expected value of certain risk events (losses).

From a pure forecasting or descriptive viewpoint, it would be sufficient to learn how fundamentals of a borrower (in my case: of a sovereign country) influence the spread it has to pay on its bond issues, as it is done in various studies.² Then a country can aim at better average terms of borrowing by improving these 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 is having this size of an effect, or whether it is reasonable or rational to have such an effect at all.

It is thus instructive to attribute these influences by fundamentals to movements in perceived probabilities of the risks incorporated into spreads. For that, a structural setup is necessary: risk probabilities are predicted by fundamentals, then bond spreads are determined by predicted probabilities. Spreads will still be influenced by fundamentals, but we will have a clearer sense of why: because they help to predict risk probabilities. Also,

¹There are some theoretical papers, like Grossman and Miller (1988)[2]; and empirical contributions, but the latter mostly concentrate on US Treasuries. For example, Redding 1999 [3], Amihud and Mendelson (1991) [4], Bradley (1991) [5] and Hirtle (1988) [6] See the third chapter for a more detailed discussion.

²Among many others: Edwards (1986) [7], Stone (1991) [8], Ozler (1993) [9]. A different but still similar article is in Standard and Poor's CreditWeek[10]: it explains how credit ratings, which are closely related to predicted but not necessarily to perceived risk, are responsive to country fundamentals.

this approach has the ability of gauging the relative size and importance of different risk factors.

My approach is thus reminiscent of well-known practices for testing rational expectations (e.g. Mishkin (1983) [11], Attfield, Demery and Duck (1985) [12]). There the usual setup is as follows.³ One variable (say X) depends on the predicted value of a (potentially vector) variable Y :

$$X_t = \alpha + \beta E[Y_t|Z_t] + \nu_t \quad (1.1)$$

where Z_t is the information available for predicting Y_t (usually, it has time $t-1$ variables). So one specifies a prediction (conditional expectation) equation

$$Y_t = f(\Gamma, Z_t) + \varepsilon_t \quad (1.2)$$

and rewrites (1.1) as

$$X_t = \alpha + \beta f(\Gamma, Z_t) + \nu_t. \quad (1.3)$$

Then equations (1.2) and (1.3) can be estimated by some full information and in general nonlinear method, mostly by GMM.

The reduced form of (1.3) is

$$X_t = g(Z_t) + \eta_t. \quad (1.4)$$

It describes how X_t is influenced by past information (Z_t). Now suppose that some theory predicts that all the influence of Z_t should come through the predicted value of $E[Y_t|Z_t]$ (specification (1.1)). Then the structural form (1.3) rewrites the reduced form (1.4) as

$$g(Z_t) = \alpha + \beta f(Z_t, \Gamma).$$

This gives a straightforward test whether the structural form is really a good reinterpretation of the reduced form: estimating (1.2) and (1.4) simultaneously, and then testing the

³Since prices should incorporate all the available information, I can drop the otherwise standard unexpected innovation term of the predictors.

restriction $g(Z_t) = \alpha + \beta f(Z_t, \Gamma)$.

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

$$X_t = \alpha + \beta Y_t + \tilde{\nu}_t \quad (1.5)$$

directly. Here the error term is $\tilde{\nu}_t = \nu_t + \beta(f(\Gamma, Z_t) - Y_t) = \nu_t + \beta \varepsilon_t$, which is not orthogonal to $Y_t = f(\Gamma, Z_t) + \varepsilon_t$, but orthogonal to Z_t . Moreover, Y_t is correlated with Z_t , so I can estimate (1.5) by using Z_t as instruments.⁴ I will elaborate this idea in more details in Subsection 1.4.2.

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

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

should be orthogonal to Z_t , since $\hat{\alpha} - \alpha \rightarrow 0$, $\hat{\beta} - \beta \rightarrow 0$, $\nu_t \perp Z_t$, 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) expectations: 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. In general, I will assume rational expectations, and attribute the failure of overidentification to the inappropriate choice (or insufficient number) of events.

The previous nonlinear test 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

$$\begin{aligned} X_t &= \alpha' + \Gamma' Z_t + \nu_t \\ Y_t &= \alpha'' + \Gamma'' Z_t + \varepsilon_t, \end{aligned}$$

⁴This is similar to the approach of Wickens (1982) [13].

and the structural form would impose the restrictions

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

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 that X_t is influenced linearly by the predicted value of Y_t (in (1.1)), but (1.2), the prediction itself does not have to be linear. This makes this method readily applicable in many other asset pricing frameworks (for example, estimating an uncovered interest parity condition).

The major difficulty of the approach in general is that one needs data on Y_t , that is, the actual realizations of the predicted event. If it were a standard economic variable, like future GDP, then we (the econometrician) would indeed observe it a year later – so when I run (1.5) on historical (at least 2-years old) data, then I already have the data which the market only predicted at time t .

With default observations for bonds, the situation is not that simple: hardly any sovereign bond defaults happened since the 70s (which is the beginning of my sample period).⁵ There were, however, much more frequent arrears, reschedulings or even defaults (debt relieves) on bank loans. As a working assumption, I will treat all defaults equally, so even though an actual observation is not a bond default, but that will be used for the bond default prediction equation.⁶

The illiquidity risk is even less clear-cut: actual trade quantity data is rarely available, so there is no other signal for liquidity than the price of the bond itself, but that also captures default risk and many other things. My main measure for illiquidity will be the sample variance of the spread from any given year on (for 3 years, 5 years, or to the end of my sample): the interpretation is that volatile prices indicate that the bond is hard to sell for a secure price, so it is less liquid, there is a potential loss if one is forced to sell at an arbitrary moment. As a whole, this measure will perform its role surprisingly well.

This illiquidity indicator tries to capture an effect of expected pre-maturity prices on current prices. To the degree that price fluctuations are disjoint from predicted default risk, it means that this illiquidity variable should be significant exactly when investors face

⁵See for example [14] as a reference.

⁶An 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.

the chance of having to sell before maturity and they incorporate a potential loss due to low prices into their current pricing decision. Note that this is an effect of "interim" price fluctuations, and it does not come from the variance of the payoffs at maturity. Hence, even with risk-averse investors, this variance is not just a standard risk-aversion component, but it does capture an illiquidity aspect. To make this point even more transparent, I will formulate a model in which risk-neutral investors will trade a perfectly safe bond at a positive spread relative to a benchmark interest rate. In the third chapter, I will pick up the same issue, and develop a still simple but more interesting model, where the speed of information revelation influences future (pre-maturity) price movements, and those fluctuations in general decrease current (issue) prices.

With these less than perfect choices for the realizations of the risk indicators, if the true events are different, then the predicting variables Z_t might be catching up the difference $E[Y_t^{true}|Z_t] - E[Y_t^{chosen}|Z_t]$, and thus the overidentification test of (1.5) fails. A rejection could also be due to non-rational market expectations – and these two possibilities are indistinguishable even theoretically. Therefore, I will attribute any rejection to adjustments for the events (or to the presence of further relevant risks) and not to irrational expectations.⁷ Of course, with the full (vector) Y_t^{true} observed, the overidentification would test the rationality of expectations.

Let me briefly summarize the main findings. In the theoretical part of the chapter, I show that a combination of future price volatility and an exogenous chance of early liquidation leads to a risk premium on bonds with more volatility. In the more important, empirical part, I find that the influence of fundamentals on bond spreads can be completely attributed to their effect through predicted risks. When including at least two risk indicators (default, and arrears or price volatility) and the US interest rate, or any single risk indicator, the US interest rate and an adjustment term (lagged left hand side variable), the overidentification test almost always accepts. Using the default indicator of any kind of repayment troubles, overidentification accepts even without the lagged spread.

With the specification including default, price volatility, US interest rates and the ad-

⁷With the US bond rate and the lagged value of the spread included in the right hand side of (1.5), I will rarely encounter rejections of the overidentification: although it might be due to low power of those test, but I take it as a signal that my events are not so off the truth . For example, bondholders fear any kind of default, even if it is restricted to bank loans, and that fear enters prices as default risk. Price volatility contributes as a second source of risk, related to bond-specific liquidity. I view the US bond rate as some measure of aggregate illiquidity; and the lagged spread as a true adjustment to the choice of events.

justment term, I find that default risk, which is captured by predicted loan and not just bond default risk, is on average 27% of the spread. Illiquidity risk, captured by predicted volatility of bond prices, constitutes an additional 27%. The other 46% of the spread is made up by the lagged value of the spread, the US rate (which influences the spread itself) and the constant. I interpret this 46% partly as an adjustment term reflecting some extra information known to investors (relative to the econometrician), and partly as a notion of aggregate illiquidity. Finally, I check the robustness of the result with respect to many alternative specifications, and my findings pass these tests.

The chapter is organized as follows. The next section sketches a model to access "pure" illiquidity risk. Section 1.3 summarizes my data and the basic empirical specification I am using. Section 1.4 presents and discusses the main findings: The first part tries to explain bond spreads only by default risk. Then the method is generalized to allow for more than one event, non-linear prediction equations and extra information available for the market. This method yields more successful description of bond spreads, the robustness of which is tested in Section 1.5. The last section concludes and points to some possible future research directions. Some skipped details are then presented in the Appendix.

1.2 A simple model establishing a link between current and expected future prices

For a given (sovereign) bond, there is a mass 1 of investors holding that asset. Each of them is having 1 unit. At each point in time, a fraction λ of the investors suffers a liquidity shock and must liquidate her bond. The main assumption is that the potential buyers of the bond have some cost of shifting their investments from other sources to this bond – which gives a slope to demand, plus they also face the same future potential liquidity shock.⁸

A (potentially) random fraction $(1 - \mu_t)\lambda$ investors are to be found without any transfer costs (only the future liquidity shock as threat). They can be thought as big, institutional investors, who do not have to pay transaction costs, while small investors do.⁹ Assume that

⁸Grossman and Miller (1988) [2] also uses an imperfect market structure to capture liquidity. There, however, the cost falls on sellers, in the form of not necessarily finding the right buyer at the right time. In the third chapter, buyers face no cost of portfolio adjustments, but the price will fluctuate due to extra information (learning). With more risk-averse early than late consumers, this will lead to a fall in issue prices.

⁹This distinction is similar to a rationale for having options under perfect capital markets: financial

μ_t is coming from an iid process.¹⁰ The important thing is to have a fluctuating mass of investors with zero cost, thus introducing a variation in the cost level of the marginal buyer.

The bond is paying a per period interest (coupon) of R forever, R being equal to the discount rate. There exists a similar, perfectly safe bond with coupon R , for which $\mu \equiv 0$. Its price is thus identically 1. By this assumption, I exogenously choose one market to be perfectly liquid and the other to be less than perfectly liquid. Thinking about the market for US Treasury Bonds versus developing country sovereign bonds, it looks reasonable to assume such an exogenous difference.

Consider holding one unit of the sovereign bond. Then the discounted value of your flow of returns is the following:

$$X = \frac{R}{1+R} + \frac{\lambda p(\mu_1)}{1+R} + \frac{1-\lambda}{1+R} \left(\frac{R}{1+R} + \frac{\lambda p(\mu_2)}{1+R} + \frac{1-\lambda}{1+R} (\dots) \right)$$

Taking expectations:

$$EX = \frac{R}{1+R} + \frac{\lambda E p(\mu)}{1+R} + \frac{1-\lambda}{1+R} EX$$

$$EX = \frac{R + \lambda E p(\mu)}{\lambda + R}$$

Suppose you are an investor with cost \tilde{c} , which means that you have to pay a fraction \tilde{c} of your transaction as a proportional cost. In this case, you will be ready to buy this bond (instead of holding an equally safe but perfectly liquid bond) if

$$EX \geq p(\mu_0) (1 + \tilde{c}) := \frac{p(\mu_0)}{1 - c},$$

$$1 - \frac{p(\mu_0)}{EX} \geq c.$$

institutions do not have transaction costs, so they can price options using no arbitrage; but small investors do save on transaction costs by having access to this redundant security.

¹⁰Some comments: Even a constant μ_t would give a positive spread. For fluctuations, what matters here is that there is a varying excess supply of these bonds. In this particular choice, supply is fixed but demand shrinks as μ_t decreases. One could also tell a different story for μ_t : it may represent some institutional investors who are ready to buy at full price, but maybe they are not having enough money to buy all the excess supply. In this case, EX has to be modified since there is a chance μ_t of getting 100% for your bond – but this would not alter the results in any significant way.

At each moment in time, there are λ bonds to be sold. Their price hence must be such that there are enough people with low enough costs to find this bond attractive. Since by assumption the marginal investor has a positive cost, so if the CDF of c is F , then the price at time t (given realization μ_0) is determined by

$$F\left(1 - \frac{p(\mu_0)}{EX}\right) = \lambda\mu_0,$$

which yields¹¹

$$p(\mu_0) = EX \left(1 - F^{(-1)}(\lambda\mu_0)\right).$$

Substituting back for EX :

$$(\lambda + R) EX = R + \lambda EX - \lambda EX \cdot E[F^{(-1)}(\lambda\mu)]$$

$$EX = \frac{R}{R + \lambda E[F^{(-1)}(\lambda\mu)]},$$

and finally, this gives us¹²

$$p(\mu_0) = \frac{R - RF^{(-1)}(\lambda\mu_0)}{R + \lambda E[F^{(-1)}(\lambda\mu)]} \leq 1$$

and

$$Ep = \frac{R - RE[F^{(-1)}(\lambda\mu)]}{R + \lambda E[F^{(-1)}(\lambda\mu)]} \leq 1.$$

In order to see how $p(\mu_0)$ and Ep depend on moments of μ , it is convenient to use the Taylor expansion of $F^{(-1)}$: $g_0 + g_1x + g_2x^2 + \dots = g_1x + g_2x^2 + \dots$ ($g_0 = 0$ since $F^{(-1)}(0) = 0$). We must have $g_1 \geq 0$, or rather a strict inequality, because F is increasing. Also assume that investors are more concentrated at lower cost levels, so the pdf of the cost distribution is decreasing. Then F is concave, so $F^{(-1)}$ is convex, hence $g_2 \geq 0$ must be

¹¹With a constant c , we would have $1 - \frac{p(\mu)}{EX} \equiv c$, thus $p(\mu_0) = EX(1 - c)$.

¹²Again, with a constant c and $\lambda > 0$, $EX = \frac{R}{R + \lambda c}$, so $p = \frac{R - Rc}{R + \lambda c}$.

true. Choose $M_1 = E\mu \geq 0$, $M_2 = E\mu^2 \geq 0, \dots$, then

$$p(\mu_0) = \frac{R - R(g_1\lambda\mu_0 + g_2\lambda^2\mu_0^2 + \dots)}{R + \lambda(g_1\lambda M_1 + g_2\lambda^2 M_2 + \dots)} < 1 \quad (1.6)$$

and

$$Ep = \frac{R - R(g_1\lambda M_1 + g_2\lambda^2 M_2 + \dots)}{R + \lambda(g_1\lambda M_1 + g_2\lambda^2 M_2 + \dots)} < 1$$

unless (in general) $\mu \equiv 0$ or $\lambda = 0$. In these cases, $p_t \equiv 1$.

Both p and Ep are decreasing in M_1 and M_2 : with less zero cost investors available, the expected loss from liquidation increases, which is reflected in lower prices already at the purchase. If there is more variation in the number of zero cost investors, then $p(\mu_0)$ goes down for any value of μ_0 : there is a larger chance of very few zero cost investors around, and then you need to attract very high cost small investors (concavity of F), so again, the expected loss increases. For higher moments M_i , since the sign of g_i is unclear, one cannot easily get similar results.

It would be nice to establish a negative relationship between Ep and Vp , the expected value and the variance of the price level: more volatile prices go hand in hand with higher spreads. However, Vp depends on higher moments of μ as well, which makes this relationship unclear and intractable.

The mechanism that gives a positive spread on this perfectly safe bond (at least in terms of no default risk) is clear: there is a probability λ that you have to sell the bond, and then you have to find investors ready to buy. As they have a cost, you have to offer a lower price for them. Furthermore, as they are subject to the same future liquidity shock, and they know that they will not necessarily get the same price at sale, they will require an extra discount. Expecting this in the future, you will offer a lower price for the bond already today.

If buyers do not face the same potential liquidity shock, or they do not realize it for some reason (so they do not incorporate it into their reservation price), then the price would be

$$p^*(\mu_0) = 1 - F^{(-1)}(\lambda\mu_0) = 1 - g_1\lambda\mu_0 - g_2\lambda^2\mu_0^2 - \dots,$$

so

$$Ep^* = 1 - g_1\lambda M_1 - g_2\lambda^2 M_2 - \dots$$

It is straightforward to check that $Ep < Ep^*$, so with less than fully rational agents (who do not anticipate the liquidity shock) we get a higher average price of the bond than with perfectly rational agents.

Another interesting feature of the model is that p^* gives a spread independent of R , while p does depend on R :

$$Ep = Ep^* \cdot \frac{R}{R + \lambda(g_1\lambda M_1 + g_2\lambda^2 M_2 + \dots)}$$

This is increasing in R : as the size of the coupon goes up, the interest payment becomes more and more important, and the liquidity risk affects only the principal. So the spread is "countercyclical" here: as the benchmark interest rate goes up, the spread goes down, which is the opposite of what I usually find in my empirical results (the coefficient of R is positive in the spread equation, although often insignificant; it is never larger than 1 though). Although one can also argue for "procyclical" spreads – the model still clearly points to the importance of the coupon size; and if, for example, λ is positively correlated with R , or if a default might occur on interest payments as well, that might act in the opposite direction: with larger coupon, a higher stake is at default risk.¹³

The model is in fact not yet closed – so far, nothing has determined the behavior of μ , the distribution of zero-cost investors. I simply assumed that there is an exogenous variation in μ , without specifying any explicit entry condition or borrowing constraint. There is also a multiple equilibrium flavor of the setup: if you expect that it will be hard to sell the bond in the future, then you will require a lower buying price now, but then, if the future people make their buying decision based on past prices, they will indeed demand a lower price. The Appendix shows a somewhat more formal exposition of the same idea – still without a rigorous closing of the model: However, already this partial form is sufficient to illustrate how future price volatility may be the source of a liquidity premium, which will be one of the main empirical findings of the coming sections.

¹³Kim, Ramaswamy and Sundaresan (1999) [15] also argues for an interaction between dividend size and default risk.

1.3 The setup of the empirical analysis

1.3.1 Variables, data sources

There are three main sources of my data. The IFS [16] and the World Development Indicators [17] 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). Unfortunately, there are quite many observations missing – but I do have all the necessary variables whenever I have data on bond yields.

Arrears, reschedulings and debt relieves are from the World Bank’s World Debt Tables [19], the latter variable from 85 only. 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. In the appendices of World Debt Tables, all the history of reschedulings and other relief agreements are listed, country by country, with quantities and dates also available.

The actual bond price data is from three sources. One is Moody’s Bond Record [20], which gives the yield and the current price of all the sovereign bonds traded in the US (which is a much smaller set than all the sovereign bonds). 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 chosen right at issue, hence the issue prices are well approximated by 100%.

The other source is Euromoney [21], 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 [22], which gives a description of most country’s biggest corporate entities, plus a general economic picture of the country. There it reports sovereign bond issues as well: not for all countries; sometimes the issue price is given, sometimes not (again, it is usually very close to 100%).

These three sources give me approximately 350 observations, from around 100 country-year cells. I then reduce this sample to 272 observations: I discard those bonds which were already in default and then they were extended (these are usually traded at 30-70% of their face value), and to make my data more panel-like, I also delete those country-year cells which do have no information in at least one of the preceding two years. Finally, my main

illiquidity proxy will be the future (empirical) variance of spreads,¹⁴ so I keep only those observations for which this can be calculated.

1.3.2 Main specification

Let p_{it} denote the probability that the country defaults in some way on its outstanding bonds.¹⁵ Then my main specification for the spread of a bond is the following:

$$r_{itj} - R_t = \alpha + \beta R_t + \lambda p_{it} + \varepsilon_{1itj} \quad (1.7)$$

Here i refers to a country, t to a specific year, and the index j refers to the possibility that some countries might have more than one bond issued or traded at any given year. Though those bonds may be different in some of their characteristics (like being a bond already in default and rescheduled – these I have already eliminated from the sample), but these features are unobserved (in my data at least), so all such differences go into the error term ε_{1itj} . The assumption that these unobserved characteristics are orthogonal to economic indicators seems acceptable.

The linear term λp_{it} 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

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

In this case, 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

¹⁴The average sum of squares minus the square of the average, starting from any point in time and going either to the end of the sample, or the following 3-5 years. Thus I cannot have this variable for the last year of my data, for example.

¹⁵In reality, default might be limited to one bond and not affecting the other: I will not make this distinction

less tractable. I will therefore concentrate on this simple, convenient and standard case, but I will also allow R to enter the right hand side of the specification. This can be rationalized in many ways: R 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 say significant in the specification, which makes it reasonable to include in (1.7).

As p_{it} is not observable, one needs to make assumptions on how it is predicted. As a starting point, I assume that there is a linear probability equation determining actual future defaults d_{it} :

$$d_{it} = \alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it} + \varepsilon_{2it} \quad (1.8)$$

Here Z_{it} is a set of country- and world-level economic indicators, available at the beginning of year t . So in fact they correspond to data from year $t-1$ and earlier. The particular choice of these variables will be discussed later on. The seemingly strong assumption about the linear probability equation will be relaxed in Subsection 1.4.2.

Finally, p_{it} is replaced by $E[d_{it}|R_t, Z_{it}] = \alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it}$. This is in fact the rational expectations (linear) prediction of future default probability. I will assume that the market knows the true coefficients, thus (1.7) becomes

$$r_{itj} - R_t = \alpha + \beta R_t + \lambda (\alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it}) + \varepsilon_{1itj}. \quad (1.7A)$$

1.4 Main results

1.4.1 First pass: only default risk

First I present the reduced form estimates of the system (1.7) and (1.8): it means estimating

$$r_{itj} - R_t = \alpha_4 + \beta_4 R_t + \Gamma_4 Z_{it} + \delta_4 H_{it} + \varepsilon_{4itj},$$

where H_{it} denotes the past average of the right hand side variable.¹⁶ The choice of Z is the following: reserves to imports ratio, external debt to GDP ratio, current account balance

¹⁶This serves to control for fixed effects. Later on, I will give this term a more convincing interpretation in terms of an adjustment for the imperfect choice of the risk events.

to GDP ratio (positive if in a surplus), GDP growth (in percentage), GDP per capita (in 1000 USD), an indicator of total past repayment troubles (arrears, relieves and reschedulings since 1970), 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 (in fact: they capture quite a large part of) the interest surcharge (the risk premium) faced by a country. The results are contained in Table 1.1.

The overall fit of the $\frac{r-R}{r}$ specification is around an R^2 of 0.1, it goes up to 0.2 for the more linear $r - R$ case. These are not extremely good fits, but we see that these variables do have reasonable explanatory power. One main reason for the low R^2 is that many observations correspond to multiple bond spreads in the same country-year cell, and none of the within-cell variation can be captured by the explanatory variables. If one regressed the average values on the same right hand side,¹⁷ the point estimates would be very similar and the fit would improve significantly (to .22 in the $\frac{r-R}{r}$ case and .52 in the $r - R$ case). This first fact also supports the initial hypothesis that the within-cell variations are orthogonal to the right hand side variables.

We see that the lagged dependent variable is not significant in the $\frac{r-R}{r}$ specification, but it is in the $r - R$ case. This means that there is some effect of past private information on the current spread, but not with the other functional form choice. It is even possible, however, to have a variable (say v) insignificant in the reduced form and still cause a rejection of the overidentification test: if the event at hand is such that v is highly correlated with it, then this variable has an indirect effect $\lambda\gamma_2v \neq 0$ on the spread, so the residual will contain $(\gamma_4 - \lambda\gamma_2)v \neq 0$, and it might be not offset by the other variables. And as we will see, this lagged value will play an important role in forthcoming estimations.

The inclusion of further lags helps in both cases, but does not improve the fit meaningfully. Nevertheless, it shakes the point estimates (and the standard errors) substantially: as most of the variables are highly correlated with past values, this symptom of multicollinearity is not surprising. It also legitimates the choice of not using both lags as instruments, but only the first one.

Apart from these, I do not want to read any strong stories from these descriptive results: first, some multicollinearity might be present even within the first lags of the variables; and

¹⁷74 observations and 10 explanatory variables: US bond rate, lagged dependent variable, constant and the first lags of the 7 economic indicators.

Table 1.1: Describing bond yields^a

	LHS variable							
	$\frac{r-R}{r}$				$r - R$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
reserves to imports	-0.50	-0.50	-0.49	-0.50	-5.36	-6.59	-5.05	-8.35
(first lag)	(5.99)*	(6.07)*	(3.57)*	(3.33)*	(5.19)*	(3.49)*	(1.68)	(1.74)
debt to GDP	-0.43	-0.44	0.82	0.81	-3.64	-6.58	5.05	6.78
(first lag)	(2.56)*	(2.92)*	(2.67)*	(2.54)*	(1.92)	(2.44)*	(1.09)	(2.25)*
curr. acc. to GDP	-0.05	-0.06	-0.66	-0.63	-6.40	-4.76	-10.03	-8.26
(first lag)	(0.27)	(0.31)	(2.05)	(1.94)	(1.40)	(0.75)	(1.67)	(0.98)
GDP growth	-2.11	-2.15	-3.47	-3.43	-17.73	-29.03	-22.60	-37.56
(first lag)	(2.68)*	(2.99)*	(3.68)*	(3.72)*	(1.53)	(2.39)*	(1.77)	(3.91)*
GDP per capita	-0.01	-0.01	0.32	0.31	0.58	0.13	2.5	2.9
(\$1000, 1. lag)	(0.86)	(0.87)	(3.51)*	(3.67)*	(2.48)*	(0.38)	(1.89)	(2.31)*
past trouble	0.006	0.007	-0.11	-0.12	-0.34	-0.29	-1.34	-0.37
(first lag)	(0.60)	(0.82)	(1.02)	(0.98)	(2.06)	(1.43)	(1.23)	(0.40)
arrears in region	0.05	0.03	0.21	0.31	9.94	14.32	31.63	17.57
(first lag)	(0.14)	(0.09)	(0.36)	(0.69)	(2.10)	(2.17)	(5.00)*	(1.92)
reserves to imports			-0.12	-0.11			-0.63	0.00
(second lag)			(1.27)	(0.98)			(0.14)	(0.00)
debt to GDP			-1.07	-1.05			-6.67	-11.70
(second lag)			(2.64)*	(2.60)*			(1.20)	(2.92)*
curr. acc. to GDP			0.74	0.73			7.03	12.08
(second lag)			(1.91)	(1.87)			(0.46)	(0.66)
GDP growth			-1.76	-1.71			-9.67	-7.90
(second lag)			(1.24)	(1.30)			(0.47)	(0.29)
GDP per capita			-0.48	-0.47			-3.2	-3.8
(\$1000, 2. lag)			(3.31)*	(3.39)*			(1.93)	(2.60)*
past trouble			0.13	0.14			1.15	0.06
(second lag)			(0.99)	(0.96)			(0.88)	(0.06)
arrears in region			0.38	0.31			-18.14	-0.51
(second lag)			(0.65)	(0.63)			(3.46)*	(0.08)
US bond yield ^b	0.008	0.01	0.004	0.002	0.50	0.96	0.33	0.94
	(0.57)	(0.78)	(0.56)	(0.48)	(2.20)*	(2.17)*	(2.38)*	(5.08)*
lagged LHS variable ^c	0.02		-0.02		0.35		0.39	
	(0.38)		(0.43)		(5.29)*		(7.19)*	
constant	2.74	2.78	6.09	5.99	16.55	27.56	33.17	45.27
	(3.05)*	(3.42)*	(2.46)*	(2.58)*	(1.25)	(2.07)*	(0.93)	(1.23)
R ²	0.10	0.10	0.17	0.17	0.23	0.20	0.25	0.22
No. of obs.	272	272	272	272	272	272	272	272

a All equations are estimated by OLS. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b US bond yield is the yield on long-term (10 years) US government bonds.

c Lagged LHS variable is calculated as the average of all bonds of the same country one year ago; or two years ago if no data for previous year.

second, many further variables can be included on the right hand side (in a very extreme rational expectations approach: all information available at the time of price formation), causing a missing variable bias in the reduced form estimates.

I still point out some counter-intuitive signs among the estimates: for example, a higher debt to GDP ratio seems to decrease spreads, and a higher GDP per capita tends to increase spreads. Though it may be due to some data problems (sample, multicollinearity, missing variables), but we will get some further interpretation from the prediction equations later on.

As all the future results will be a refinement of these reduced forms, their overall fit can be at most as good as these fits.¹⁸ The refinements are obtained in the following manner: when replacing the right hand side with $\alpha + \beta d_{it}$, I force α_4 , β_4 , Γ_4 and δ_4 to be such that

$$\alpha_4 + \beta_4 R_t + \Gamma_4 Z_{it} + \delta_4 H_{it} = \alpha + \lambda(\alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it} + \delta_2 H_{it}) + \delta H_{it}$$

holds. The overidentification will reject exactly when this interpretation of the reduced form is not acceptable. Such a rejection tells us that the premium is coming from a different source of risk: maybe only the choice of my event indicator is off from the right one, or maybe the "true" event is completely different.¹⁹

Before actually switching to the structural form, I need to discuss briefly the first stages of all structural form estimations: the linear probability equations (Table 1.2) – which are in fact measuring how correlated the instruments are with the right hand side events.

One feature of the results is the surprisingly high R^2 : 0.6-0.7 for the different default indicators, and around 0.5 for price volatility. This means that the set of instruments I am working with is highly correlated with the variables for which they are instrumenting.

There is a saddle issue here: 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 (the number of observations stayed 272). However, this means that I am simply using some observations more than once (the only variable in which they are different is the bond yield). To check

¹⁸I will not, in general, 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.

¹⁹One can also say that maybe the spread has components completely unrelated to any particular risky events – my goal is, however, to see how far I can get in identifying certain risks as being the main source of the premium.

Table 1.2: The prediction equations^a

LHS variable	trfut5 ^b		drfut5 ^c		variance ^d	
	(1)	(2)	(3)	(4)	(5)	(6)
	reserves to imports (first lag)	0.07 (0.541)	-0.43 (1.69)	-0.75 (2.60)*	-0.74 (2.43)*	-58.32 (0.91)
debt to GDP (first lag)	-1.1 (5.70)*	-1.14 (3.47)*	0.01 (0.05)	-1.28 (2.59)*	-114.01 (3.79)*	113.42 (1.33)
curr. acc. to GDP (first lag)	0.7 (0.57)	0.66 (1.35)	0.51 (0.99)	-0.59 (0.91)	20.47 (0.16)	-27.56 (0.21)
GDP growth (first lag)	-1.16 (1.3)	-1.56 (1.51)	0.50 (0.31)	2.61 (2.10)	85.47 (0.55)	67.74 (0.56)
GDP per capita (\$1000, 1. lag)	0.06 (2.22)*	0.06 (0.75)	0.08 (1.56)	-0.33 (2.76)*	-5.16 (0.48)	26.07 (1.54)
past trouble (first lag)	-0.01 (1.10)	-0.09 (1.60)	0.00 (0.40)	0.05 (0.96)	-7.25 (2.25)*	-8.73 (0.58)
arrears in region (first lag)	1.68 (4.70)*	2.97 (4.03)*	1.76 (3.11)*	6.23 (6.33)*	109.11 (1.44)	48.12 (0.27)
reserves to imports (second lag)		0.58 (3.45)*		-0.02 (0.14)		-17.44 (0.25)
debt to GDP (second lag)		0.00 (0.00)		1.35 (2.50)*		-237.89 (2.76)*
curr. acc. to GDP (second lag)		-0.05 (0.09)		2.38 (3.37)*		170.43 (1.13)
GDP growth (second lag)		0.03 (0.10)		0.50 (0.33)		-290.71 (2.66)
GDP per capita (\$1000, 2. lag)		-0.03 (0.23)		0.42 (2.25)*		-37.04 (1.54)
past trouble (second lag)		0.09 (1.88)		-0.02 (0.32)		1.68 (0.10)
arrears in region (second lag)		-1.26 (2.30)*		-5.25 (4.88)*		77.04 (0.43)
US bond yield ^e	-0.01 (0.40)	-0.01 (0.73)	0.04 (0.86)	0.03 (1.21)	8.85 (1.70)	10.24 (2.22)*
past spread ^f	0.00 (0.14)	0.00 (0.74)	-0.01 (1.71)	0.00 (0.05)	0.29 (0.17)	-0.39 (0.26)
constant	2.33 (2.23)*	2.76 (2.02)	-0.88 (0.45)	-3.42 (1.28)	-54.28 (0.32)	277.10 (1.57)
R ²	0.73	0.78	0.58	0.75	0.45	0.53
No. of obs.	272	272	272	272	272	272

a All equations are estimated by OLS. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level. The results for "relpdf5" – the sum of the relief to debt stock ratios in the next five years (including the current one) – are not reported, but quite similar.

b The variable "trfut5" is an indicator of debt relief, rescheduling or arrears in the next 5 years (including the current one).

c "drfut5" is similar to "trfut5" but does not include arrears.

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

e The lagged spread is calculated as the average of all spreads one or two years ago.

f US bond yield is the yield on long-term (10 years) US government bonds.

how much difference it makes, I reran the same linear probability models with country-year averages. The results are quite similar, there are no large and significant changes in the estimates.²⁰ The R^2 changes to around 0.6 for the default indicators, and reduces to 0.4 in the variance case (using single lags for all three).

The second lags increase the R^2 by 0.05-0.18, so they do improve the fit, but the fit is already acceptable with only the first lags. We see the multicollinearity of the lags again, which shows that using the second lags as additional instruments might even cause imprecise 2SLS estimates.²¹

Returning to the counter-intuitive signs from the reduced form, we can see that a higher debt to GDP ratio decreases the predicted variance of the spread, and it has a negative sign in general whenever it is significant (at least the first lag). Past repayment trouble does not influence risk predictions, but it lowers the variance significantly. So if these risk predictions have a positive effect on the spread (and this is the case, as we will see soon), then a higher debt to GDP ratio can in fact *lower* spreads, by making bond markets more liquid, prices less volatile and hence decreasing the illiquidity risk by more than increasing the default risk (if increasing at all).

The yield on US bonds is marginally significant for the variance term. The past value of $r - R$ is insignificant in all cases (all conclusions remain true for the country-year average estimation). Since the lagged value was significant in the spread specifications of Table 1.1, these two findings together suggest that there is extra information incorporated to the spreads, but it is not related directly to repayment troubles or liquidity shocks of the bonds.

Having checked our instruments in terms of being or not correlated with d_{it} and l_{it} , we can turn to estimating (1.7) now. The question is whether we can attribute the fit of the reduced form entirely to $\lambda(\alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it})$ or not. Since the $\frac{r-R}{r}$ specification seems much less appropriate, I will focus on $r - R$, and report some $\frac{r-R}{r}$ results only as robustness checks.

Table 1.3 reports the results for only with default risk included on the right hand side. In columns 1 and 2, the choice of the default indicator is the ratio of debt forgiven (in the

²⁰The only major change is that the sign of GDP per capita changes in the "trfut5" specification, it stays small but significant.

²¹In general, using more *good* instruments reduces the standard errors, but due to small sample properties of 2SLS, it might also produce 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.

next 5 years) to current debt stock; in 3 and 4, debt relief, rescheduling or arrears in the next 5 years; finally, 5 and 6 uses only relieves and reschedulings. The coefficient on the default risk indicator is always at least marginally significant and large: a 1 percent relief increases the spread by 26-27 basis points; a 10 percent increase in all predicted repayment troubles adds 35-74 basis points, and 27-36 if it is only predicted relief or rescheduling.

Table 1.3: Regression results: only default risk considered^a

		LHS variable: $r - R$					
		Choice of the main default indicator					
		relpdf5 ^b		trfut5 ^b		drfut5 ^b	
		(1)	(2)	(3)	(4)	(5)	(6)
default indicator		27.33 (0.42)	26.51 (0.65)	7.49 (2.51)*	3.58 (2.42)*	3.69 (1.84)	2.78 (1.92)
lagged spread ^c			0.49 (5.84)*		0.38 (6.80)*		0.46 (7.15)*
US bond yield ^d		1.18 (5.52)*	0.75 (3.29)*	1.18 (7.90)*	0.86 (6.34)*	0.94 (2.51)*	0.59 (2.70)*
constant		-5.23 (3.51)*	-4.43 (3.38)*	-11.12 (4.31)*	-7.63 (4.34)*	-4.63 (1.50)	-3.97 (3.21)*
F stat.	deg. of fr.	F(2,14)	F(3,10)	F(2,14)	F(3,10)	F(2,14)	F(2,17)
	value	18.05	714.91	42.07	280.61	85.59	487.78
	p value	0.000	0.000	0.000	0.000	0.000	0.000
p value of overid test ^e		0.00	0.21	0.36	0.51	0.00	0.54
Number of obs.		299	272	299	272	299	299

a All estimations are IV, using lagged values of reserves to imports, debt to GDP, current account balance to GDP, GDP growth, GDP per capita, past repayment troubles, arrears in region and US government bond yields as instruments. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b "relpdf5" is the sum of the relief to debt stock ratios in the next five years (including the current one). "trfut5" is an indicator of debt relief, rescheduling or arrears in the next 5 years (including the current one). "drfut5" is similar to "trfut5" but does not include arrears.

c The lagged spread is calculated as the average of all spreads one or two years ago.

d US bond yield is the yield on long-term (10 years) US government bonds.

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

The fit always increases when the lagged spread is included, its coefficient is stable around 0.4-0.5, highly significant. This may indicate country-specific fixed effects, or, as I will argue later, some adjustments to the risk events (the difference between my choice and the "true" choice). For overidentification to pass, we almost always need to include the lagged value (with the exception of column 3). Column 3 indicates that the chance of any kind of financial trouble is very influential in determining the spreads: in other words, bond spreads do reflect the overall chance of repayment problems, but those problems, for some reasons, ended up not leading to bond defaults. Once including more than one event at the same time, the more restrictive default indicator and the price volatility term will

yield a more substantive risk decomposition (into default and liquidity risk), so I will use that as the main specification later on.

The last important feature of the results is the surprisingly stable (0.6-1.18) and significant coefficient of the US interest rates. This implies that *spreads* increase nearly one in one with the US interest rate, above any potential effect through increased default risk. This can indicate important aggregate liquidity effects, or investors may be less eager to hold risky bonds when even safe bonds offer high returns. Once I include the price volatility term, most of the effect of US rates will go through that term; so US interest rates will have a much smaller effect above their influence over default and liquidity risk.

1.4.2 Identification and generalization of the method

There is a very important and general interpretation of the entire approach I am using. Certain variables Z_{it} and some others have explanatory power in an asset pricing (bond spread) equation:

$$r_{itj} - R_t = \alpha + \beta R_t + \Gamma Z_{it} + \varepsilon_{itj}$$

This is the standard approach in the literature (though usually with logistic probability models or some other variations). However, to understand where these relationships are coming from, one needs a structural approach. Assume that the spread reflects some measure of the risk of a certain event (this might be a zero-one, or a continuous variable). Use a rational expectations (linear) prediction of that event of the form

$$e_{it} = \alpha' + \beta' R_t + \Gamma' Z_{it} + \varepsilon_{it}.$$

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

$$r_{itj} - R_t = \alpha'' + \lambda'' E[e_{it}|R_t, Z_{it}] + \varepsilon''_{itj}$$

should describe the spread. Using the best linear prediction of the conditional expectation (or, in a more robust sense, doing the IV process mentioned in the introduction and discussed

in more details later in the subsection), one gets

$$r_{itj} - R_t = \alpha'' + \lambda'' (\alpha' + \beta' R_t + \Gamma' Z_{it}) + \varepsilon'''_{itj} = \alpha'' + \lambda'' e_{it} + \widetilde{\varepsilon}_{itj}.$$

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 . Then a rejection of the overidentification means that either the choice of the event is not perfectly right (or at least, there is something else also playing a role), or that expectations are not fully rational.

Unless one has a very strong case for a particular choice of a (default or any other) event, it is impossible to distinguish the rejection of rational expectations from the rejection of the choice of the event. I will maintain rational expectations, and at the same time, introduce different choices of the event e – maybe even more than one event at a time.

For foreign-currency denominated sovereign bonds, the two major choices will be a repayment difficulty ("default") variable, and an illiquid markets indicator.²² 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 the country-time variation of bond spreads.

The treatment of the illiquidity event is the same as earlier: one specifies a linear prediction model for actual future illiquidity shocks

$$l_{it} = \alpha_3 + \beta_3 R_t + \Gamma_3 Z_{it} + \varepsilon_{3it}, \quad (1.9)$$

and then add $E[l_{it}|R_t, Z_{it}] = \alpha_3 + \beta_3 R_t + \Gamma_3 Z_{it}$ to (1.7A):

$$r_{it} - R_t = \alpha + \beta R_t + \lambda_1 (\alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it}) + \lambda_2 (\alpha_3 + \beta_3 R_t + \Gamma_3 Z_{it}) + \varepsilon_{1itj} \quad (1.7B)$$

What is this event l_{it} ? One proxy could be the following: whenever the current $\frac{r-R}{r}$ or $r - R$ is high, it means that the current price is much lower than what a safe and liquid bond would have. If I assume that this movement does not *entirely* reflect a sudden increase in the default risk of the bond, then it is a time when the market for these bonds "dries out". So one can define an event indicator for $\frac{r-R}{r}$ or $r - R$ being above certain thresholds at least once in the next (say) 2 years.

²²With local-currency denominated bonds, a devaluation risk event could and should be introduced in a similar way.

I experimented with many choices of this indicator: different threshold levels and different time windows. In general, it turns out not to be a very successful choice for disentangling illiquidity from default risk: if low future prices are mostly reflecting higher perceived default risk, then this illiquidity variable might not be distinguishable enough from default risk – and this is what the results show. So instead, the (sample) variance of future prices can play the role of an illiquidity indicator: if an investor faces a chance of having to sell her bonds before maturity, then the variance of the interim prices (spreads) capture the potential loss from that transaction. With high variance, there is a larger chance of getting a low price when forced to liquidate the portfolio. This can be interpreted as investors caring not only for expected returns but also trying to ensure a good return with high probability,²³ or being more risk-averse when forced to liquidate, therefore pre-maturity price volatility is an additional source of risk.

Note that I am restricting the illiquidity event to be the same across bonds of a given country. In reality (and in a finer version of this approach), it is possible to have l_{itj} , a different event indicator for different bonds. With the moderate size of my data set, I am neglecting this issue.²⁴

Turning to identification, both of the linear prediction models are identified: there are no endogenous variables on the right hand side. One can try to include total disbursements, which then introduces a simultaneity bias. Then identification becomes again possible if one excludes R_t . As we will see soon, however, I never need the complete specification of the probability equation to still estimate the spread equation (in other words, the reduced form will always be enough).

The interest rate equation is more problematic: the parameters satisfy certain restrictions, but these restrictions are nonlinear and cross-equation. One can still show that the reduced form of the three equation system²⁵ is invertible, so the restrictions imposed are sufficient for structural form estimation.²⁶ However, estimation and inference would require nonlinear (hence not particularly robust and precise) techniques.

²³Formally: $\max EX$ s.t. budget constraints plus $P(\bar{X} \geq \underline{X}) \geq p$. For distributions with fixed means and varying variance, this probability is a decreasing function of the variance; so the objective function can be rewritten as the expected value plus a penalty term for price fluctuations (like a Lagrangian).

²⁴One could distinguish between bonds close to maturity and far away from maturity: the closer maturity is, the less likely it is that you cannot hold on to the bond until you get its full value (assuming no default).

²⁵Meaning the d_{it} , the l_{it} and the interest rate equations.

²⁶Even if we have more than one event and all being predicted with the same variables: if we have more predictors than total events, we have identification. See the Appendix for a simple derivation showing this.

The remedy is to rewrite (1.8) as

$$\alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it} = d_{it} - \varepsilon_{2it},$$

so the interest rate equation (1.7A) can be rewritten as

$$r_{itj} - R_t = \alpha + \gamma R_t + \lambda d_{it} + \varepsilon_{1itj} - \lambda \varepsilon_{2it}. \quad (1.7C)$$

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_{1itj} . However, any subset of $\{Z_{it}, R_t\}$ can serve as valid instruments for the problem: by assumption, 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 concerns about using the linear probability model: I do not have to specify or estimate the probability model, it is enough just to know that those variables are correlated with the event, so they can be my instruments in the interest rate equation.

To make this point more transparent, suppose that the true determination of default is driven by

$$d_{it} = 1 \text{ if } f(R_t, Z_{it}) + \varepsilon_{2it} > 0$$

for some unknown function f and error term ε_{2it} with some distribution. Then $d_{it} = E[d_{it}|R_t, Z_{it}] + \varepsilon'_{2it} = g(R_t, Z_{it}) + \varepsilon'_{2it}$, where the prediction error ε'_{2it} is by definition orthogonal to R_t and Z_{it} . The interest rate equation becomes

$$r_{it} - R_t = \alpha + \beta R_t + \lambda g(R_t, Z_{it}) + \varepsilon_{1itj} = \alpha + \beta R_t + \lambda d_{it} + \varepsilon_{1itj} - \lambda \varepsilon'_{2it},$$

and again, any subset of $\{Z_{it}, R_t\}$ gives valid instruments.

Moreover, one can then test this overidentification, and check if there is a set of 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. But there is no big reason to think that there should be any further, more direct effect.

However, if there is any other component considered relevant by market participants

(thus having an effect on the spread not only through increased risk but more directly, too), then some of the instruments might be proxying for those, and hence the 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 as well be catching up the differences of the probability predictions, and overidentification could be rejected.²⁷

A rejection might as well be due to the rejection of the rational expectation approach used in deriving the interest rate equations: if market participants are using a different (non-rational) prediction, then the specification I am estimating will be rejected by the data. Notice that if market participants have extra private information relative to the economic indicators I use in my estimation (which is definitely the case), but they still have rational expectations, my specification remains valid.

To see this point, assume that the extra information is captured by a (potentially vector) variable X_{it} , and the true specification of the interest rate equation is given by

$$r_{itj} - R_t = \alpha + \beta R_t + \lambda E[d_{it}|R_t, Z_{it}, X_{it}] + \varepsilon_{1itj}.$$

Instead of this, I have

$$r_{itj} - R_t = \alpha + \beta R_t + \lambda E[d_{it}|R_t, Z_{it}] + \widetilde{\varepsilon}_{1itj}.$$

So when I turn to estimation, my specification becomes

$$r_{itj} - R_t = \alpha + \beta R_t + \lambda d_{it} + \varepsilon_{1itj} + \lambda (E[d_{it}|R_t, Z_{it}, X_{it}] - d_{it})$$

Here d_{it} is not orthogonal to the error terms, but by assumption, R_t and Z_{it} are correlated with d_{it} and orthogonal to ε_{1itj} ; and by definition, orthogonal to $E[d_{it}|R_t, Z_{it}, X_{it}] - d_{it}$ as well. So they are still valid as instruments.

To test whether significant private (or excess) information is present in bond prices, I consider the following specification. If I had this variable X_{it} , I could use it as an extra instrument, and estimate directly the finer model. However, even in this case, X_{it} might be

²⁷One major reason why this is likely to be the case: we are pricing bonds, but the actual realizations of default are mostly for loans. It is natural to suspect that these two events are not fully compatible. However, as there are hardly any bond defaults in this time period, one must use default on other forms of debt. It still remains a valid question how bond spreads reflect predicted overall default probabilities, without realizing that those defaults were to be systematically restricted to bank loans.

reflecting an adjustment term for the fact that my event indicators are different from the true ones. So one would then use X_{it} as an additional right hand side variable (and not just an extra instrument).

One can include various country or time effects as this adjustment term, without risking the consistency of the estimates: the sample has a cross-section and a time series dimension as well, and both dimensions are acceptably large. Or, assuming that this extra information (adjustment term) is relatively stable through time, then past values of $r_{itj} - R_t$, or more conveniently, its average across j (different bonds of the same country, at the same time) can proxy for X_{it} . Thus I will use both certain country and time effects, and the past (average) value of $r_{itj} - R_t$ as a right hand side variable in (1.7C). Note that the lagged left hand side variable also deals with potential fixed effects to some degree.

This reinterprets the results from Table 1.3: including the lagged left hand side value seems to be quite important in terms of accepting overidentification. So far, I interpreted that as a sign of country fixed effects – now a second interpretation is a persistent adjustment term coming from the imperfect choice of the default indicators. In Table 1.2, I have found that the lagged value is not directly related to defaults or to illiquidity shocks, so it is really an extra component relative to the risk measures.

To see better whether the event indicators are good enough, I will use many different choices for the default events: a dummy for debt relief, rescheduling or arrears in the next 5 years, a similar variable but without arrears, finally, the relative size of debt relief to total debt stock.

1.4.3 Illiquidity risk

Table 1.4 reports the main results, when (potentially a subset of) different default indicators, the future variance of bond prices, the US bond rate and the lagged (country-average) spread is included on the right hand side.

Looking first at the full specification (default, volatility, lagged spread, US interest rate) but varying the choice of the default indicator (columns 1-3), we find that the signs and orders of magnitude of the results are reasonable: a 10 percentage points increase in the predicted probability of relief, rescheduling or arrears in the next 5 years leads to a 34.8 basis points increase of the spread. Excluding arrears changes the effect to 31.57 basis points. A 1 percent debt relief (0.01 of the total debt stock) gives a 45 basis points spread

Table 1.4: Main results^a

	LHS variable: $r - R$								
	relpdf5 ^b			trfut5 ^b			drfut5 ^b		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
main default indicator	45.17 (0.87)	3.48 (1.79)	3.17 (2.67)*	4.48 (2.85)*	1.24 (1.10)	3.69 (1.84)		2.78 (1.92)	
second default indicator (trfut5)					6.74 (2.52)*				
variance ^c	0.02 (4.09)*	0.001 (0.90)	0.02 (5.35)*	0.06 (6.99)*			0.04 (1.94)		0.01 (2.78)*
lagged spread ^d	0.44 (4.09)*	0.39 (6.87)*	0.40 (7.95)*					0.46 (7.15)*	0.45 (7.95)*
US bond yield ^e	0.49 (2.14)	0.84 (4.58)*	0.31 (1.09)	0.13 (0.26)	1.10 (4.55)*	0.94 (2.51)*	0.17 (0.38)	0.59 (2.70)*	0.51 (2.08)
constant	-3.54 (1.98)	-7.47 (3.15)*	-2.78 (1.55)	-1.22 (0.31)	-10.46 (3.74)*	-4.63 (1.50)	3.06 (0.62)	-3.97 (3.21)*	-2.99 (1.97)
	F(4,10)	F(4,10)	F(4,10)	F(3,14)	F(3,14)	F(2,14)	F(2,17)	F(3,10)	F(3,10)
F stat. value	105.25	215.75	250.99	41.94	63.11	85.59	2.48	487.78	361.55
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.113	0.000	0.000
p value of overid test ^f	0.45	0.51	0.86	0.87	0.43	0.00	0.00	0.54	0.27
Number of obs.	272	272	272	299	299	299	315	272	272

a All estimations are IV, using lagged values of reserves to imports, debt to GDP, current account balance to GDP, GDP growth, GDP per capita, past repayment troubles, arrears in region and US government bond yields as instruments. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b "relpdf5" is the sum of the relief to debt stock ratios in the next five years (including the current one). "trfut5" is an indicator of debt relief, rescheduling or arrears in the next 5 years (including the current one). "drfut5" is similar to "trfut5" but does not include arrears.

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

d The lagged spread is calculated as the average of all spreads one or two years ago.

e US bond yield is the yield on long-term (10 years) US government bonds.

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

increase. These estimates are only marginally significant.

The variance variable is insignificant when arrears are included, but significant in the other two cases, and has a fairly constant estimate. If the predicted variance goes up by 10, that leads to an extra 20 basis points in the spread.²⁸

There are three further common features of these three estimates. The coefficient of the lagged spread is highly significant and is around 0.4. This means that there is important extra information in past spreads which also influences current spreads. The second feature is that the US bond rate has a positive coefficient, although not always significant. In column 3, the coefficient is 0.31, so for every percentage point rise in the US bond rate, foreign bond rates increase by 1.3 percentage points *above* any changes in the predicted values of default and illiquidity risks. It might capture a systemic illiquidity component: whenever bond rates are up, the value of portfolios are down, so investors start downsizing their portfolios, and the more risky sovereign bonds are first to sell. Finally, the overidentification test passes highly in all three cases.

To get a sense of how important each factor is in determining the spread, I plug in all the sample-averages of the right hand side of the specification in column 3 – the endogenous variables being replaced by their predicted values. This yields

$$\overbrace{\text{spread}}^{6.03} = \underbrace{3.15 \cdot \overbrace{drfut5}^{1.64}}_{\text{default risk: 27\%}} + \underbrace{0.026 \cdot \overbrace{bondvar}^{1.62}}_{\text{price variation: 27\%}} + \underbrace{0.40 * \overbrace{sprav1}^{2.67}}_{\text{systemic illiquidity, adjustments, etc.: 46\%}} + \underbrace{0.31 \cdot \overbrace{USbond}^{2.92}}_{\text{systemic illiquidity, adjustments, etc.: 46\%}} - 2.84$$

Though the grouping of the variables is somewhat arbitrary, but on average, predicted default risk contributes 164 basis points to the spread (27%), price fluctuations additional 162 basis points (27%), and the rest is attributed to lagged information and the US bond rate (46%).

Columns 4-5 report results with only two of the right hand side risk variables kept. The exclusion of the lagged spread changes the point estimates: the default risk indicators are getting a higher share together, but the variance term also increases. This is not surprising: Suppose that lagged spreads contain excess information relative to the current risk predictions. Then some of that will be proxied by the current predictions, once lagged

²⁸This variable is in fact the square of variance. Its average value (mean or median) is around 60 counting multiple country-year cells.

spreads are excluded.

The fit, however, seems weaker than in most other columns, but the overidentification passing level stays satisfactorily high. All these indicate that the lagged spreads are an important determinant of current spreads, but a detailed enough description of default risk, or default risk and illiquidity risk is sufficient to explain the reduced form fit of bond spreads.

Columns 6-7 includes one event indicator: default or variance, and the lagged spread is also excluded (column 6 is in fact the same as column 5 of Table 1.3). We get a clear rejection of the overidentification test: the spread cannot be attributed to a single risk factor. In Table 1.3, there was a case when already one event was enough for accepting overidentification (default and arrears). The further inclusion of the lagged spread, however, is always enough to make the overidentification test pass, so the spreads can also be described as reflecting one source of risk and some adjustment terms.

We see that overidentification was accepted in 7 of the 9 cases. As we also see, however, overidentification passes very frequently, which puts some doubts on the power of the test. Hence, I will also use the F value of the regressions to compare the relative fit and explanatory power of different specifications.

Based on these results, (1.7) seems to be a valid specification: the reduced form fit can be attributed to either two predicted risk probabilities plus US rates; one risk indicator, the US rates and an adjustment term (lagged spreads); or even to one particular default indicator and the US rates. Having such an adjustment term, however, does not have a particularly clear interpretation: is that term capturing an extra source of risk, or a difference between my event indicator and the true one? For this reason, I will choose the specification with a default indicator, price volatility and the US bond rate as the benchmark, For the default indicator, I will use debt relief or rescheduling event ("drfut5"), since it offers a more reasonable decomposition into default and liquidity risk (column 4).

Before moving on to check how robust the estimates are, with respect to certain alternative specifications, I repeat the average decomposition of bond spreads for column 4:

$$\underbrace{\overline{spread}}_{6.04} = \underbrace{4.48 \cdot \overline{drfut5}}_{2.19} + \underbrace{0.064 \cdot \overline{bondvar}}_{3.76} + \underbrace{0.13 \cdot \overline{USbond} - 1.22}_{1.21}$$

default risk: 36%
price variation: 62%
systemic illiquidity, adjustments, etc.: 2%

We see that most of the adjustment terms is captured by the volatility term, making it the dominant factor of the spread. Though the 62% number is likely to be an overstatement of the importance of liquidity, but all specifications clearly suggest an important and sizable role for expected price volatility.

1.5 Robustness checks of the results

1.5.1 Different left hand side variable

Table 1.5: Different left hand side variable

	LHS variable: $\frac{r-R}{r}$ ^a		
	(1)	(2)	(3)
default indicator	0.06	0.05	
(drfut5) ^b	(0.77)	(0.77)	
variance ^c	0.00		0.001
	(1.76)		(1.63)
lagged ^e $\frac{r-R}{r}$	0.09	0.10	0.12
	(0.84)	(0.82)	(1.20)
US bond yield ^f	-0.00	0.01	-0.004
	(0.12)	(0.70)	(0.26)
constant	0.20	0.12	0.25
	(1.07)	(0.75)	(1.63)
F stat.			
{ deg. of fr.	F(4,12)	F(3,12)	F(3,16)
{ value	6.85	68.34	1.64
{ p value	0.004	0.000	0.21
p value of overid test ^g	0.07	0.02	0.09
Number of obs.	285	285	297

a All estimations are IV, using lagged values of reserves to imports, debt to GDP, current account balance to GDP, GDP growth, GDP per capita, past repayment troubles, arrears in region and US government bond yields as instruments. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b The variable "drfut5" is an indicator of debt relief or rescheduling in the next 5 years (including the current one).

c The illiquidity indicator "nomf52" is a dummy for $\frac{r-R}{r}$ being above 0.35 or no bond data at least once in the next two years.

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

e The lagged LHS value is calculated as the average of all LHS variables one or two years ago.

f US bond yield is the yield on long-term (10 years) US government bonds.

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

Table 1.5 reports a few results for the choice of $\frac{r-R}{r}$ as the left hand side variable. The

overall fit is much weaker, overidentification fails at the 10 % level, and hardly any variable is significant (even marginally). It might be, however, due to an imperfect choice of the functional form: maybe for the $\frac{r-R}{r}$ case, a logarithmic specification would be more appropriate. Then, however, the IV procedure becomes problematic: we cannot replace the log of a predicted probability by the log of the actual event (log of zero-one) and then use the same instruments. Since I do not find any particular functional form necessarily more relevant or reasonable than a linear, I will stick to that one; and in the linear right hand side case, the spread seems to be the appropriate left hand side variable to consider.

1.5.2 Different estimation techniques

Table 1.6: Different estimation techniques^a

		LHS variable: $r - R$			
		Benchmark IV	OLS	Large IV	Small IV
		(1)	(2)	(3)	(4)
default indicator		4.48	1.91	3.36	3.94
(drfut5) ^b		(2.85)*	(1.38)	(1.64)	(1.23)
variance ^c		0.06	0.02	0.02	0.05
		(6.99)*	(2.15)*	(2.61)*	(3.19)*
US bond yield ^d		0.13	0.75	0.77	0.27
		(0.26)	(2.46)*	(2.31)*	(1.00)
constant		-1.22	-3.37	-4.80	-1.72
		(0.31)	(1.46)	(1.85)	(0.63)
F stat.	deg. of fr.	F(3,14)	F(3,14)	F(3,12)	F(3,14)
	value	41.94	30.31	48.33	7.11
	p value	0.000	0.000	0.000	0.003
p value of overid test ^e		0.87	-	0.10	-
Number of obs.		299	299	261	299

a See the text for a description of the instruments used in columns 3 and 4. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b The variable "drfut5" is an indicator of debt relief or rescheduling in the next 5 years (including the current one).

c Variance is the empirical variance of all bond spreads of the country starting from next year.

d US bond yield is the yield on long-term (10 years) US government bonds.

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

Table 1.6 reports estimates of the benchmark specification, using the benchmark set of

instruments, OLS, a just-identified²⁹ and a large set of instruments.³⁰ I made some experiments with further choices of instruments, and the results were similar.

There are no striking differences among the coefficients and their significance levels. This can be attributed to the very good predictability of the events: if they are very close to being a linear combination of exogenous variables, then the non-orthogonality is relatively weak and so OLS will not produce a large inconsistency or bias.³¹ For the default indicator, the difference is notable: the OLS estimates are smaller than with any IV; and at least for the large versus small IV cases, the smaller the set of instruments, the further away the estimates are from OLS (this pattern is reversed in the benchmark IV though). 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 of IV estimates being biased (towards OLS) in small samples (see Angrist, Imbens and Krueger (1999) [23] for a discussion and further references). I consider the benchmark set of instruments as a reasonable tradeoff between less bias (just identified) and more precision (large set of instruments).

1.5.3 Varying the event indicators

Table 1.4 already contained some variations in terms of the default indicator: whether arrears are included, or if the size of default (or relief) is considered. Here, instead of varying the classification of default itself (debt relief or rescheduling), I reran the results with different time windows: default in the next 3, 5 (this is the benchmark) and 10 years.

The results are not particularly instructive, so I just briefly discuss them. With three years, the default indicator gets a smaller coefficient, while the estimates for the variance and the US bond rate increase; but none of these effects are particularly large. The sig-

²⁹The two instruments used are reserves to imports and debt to GDP.

³⁰The instruments are: reserves to imports, exports to GDP, debt to GDP, current account balance per GDP, gross investment growth, GDP per capita, GDP growth, M2 growth, credit to private sector, savings to GDP, current large devaluation, a count variable of the former, dummies for exchange rate regimes (free or managed float), current regime changes, a count variable of the former, current large terms of trade change, a count variable, regions (IFS classification), arrears, total number of reschedulings, that of debt relieves, regional arrears, oil price changes, world production changes, dummies for pre- and post-debt-crisis, dummy for pre-1989 (economic transition in the East), an indicator of US recessions.

³¹The differences are much bigger once I estimate the same specification for country averages: the IV estimates are quite close to the reported results, but the OLS coefficients are notably smaller. Unfortunately, that sample has only 75 observations, so I stick to my larger but noisier sample.

nificance of the estimates stays unchanged. With ten years, however, the event indicators become insignificant, the default coefficient goes up, the variance coefficient down (but stays positive). The other estimates also move a bit but they stay similar. This is hardly surprising: with the ten year window, the vast majority of the observations will have an actual default value of one, so this indicator becomes almost useless and the entire specification highly multicollinear.

Although the particular choice of the low future price indicator was not significant and sizable in Table 1.4, I also experimented with different cutoff levels and time window sizes for this variable. The cutoff levels were 0.25, 0.35 (the benchmark), 0.45 and 0.55. The first corresponds to the 30 percentile of all levels of $\frac{r-R}{r}$, the second is the median, the third is the 60 and the last is the 75 percentile. Comparing to BAA rated US corporate bond averages (obtained from [18]), 0.25 is around the 75 percentile, 0.35 is the 90 percentile, and there are no observations with at least 0.45.³² In terms of the time window, I checked the values 1, 2, 3 and 5 years.

The results can be best summarized as follows. The 0.25 and 0.35 cutoffs with 1 and 2 years as the time window, lead to no important changes in sign, size or significance of the estimates. For all cutoffs, the 3- and 5-year window results are very imprecise and change relatively more: again, the issue is that most observations get a 1 for these large window sizes. Finally, the 0.45 and 0.55 cutoffs with 1 and 2 years lead to negative but mostly insignificant coefficients of the low price indicator. The variance term also becomes less significant, and once even negative. The default indicator usually gets a higher coefficient. These are, however, not significant changes.

I also experimented with different choices of the price variance term: instead of calculating the 5-year forward empirical variance, I worked with the 3-year variance, and with the "full forward variance (from any year on, up to the most recent observation available). Using the 3 or the 5 year variance made no significant difference; using the full forward variance kept most estimates roughly the same, but notably increased the significance of the US bond rate term. This later result is due to the fact that US interest rates have a much bigger coefficient in the 5-year variance first stage than in the full variance first stage, so they should be more significant in the structural form estimation in the full variance

³²This is for averages though: many individual bonds may have comparably large levels than my sample. Also, the corresponding spread levels of the sovereign sample are much higher than the BAA averages.

case.

1.5.4 Country and time effects

Table 1.7 reports different estimates that incorporate country-specific but time-invariant effects.³³ This either means country dummies (as instruments, or as right hand side variables, hence also instruments) or the long-term debtor history of the country.³⁴ This history includes bond defaults in the 19th-early 20th century (up to the 1930s), the number of years in default (in some cases, default episodes spanned through many years), and an indicator of a new sovereign (independence or entering the Eastern block after WWII, hence a new debtor).

The estimates in column 1 are the benchmark numbers, without the necessary modification of standard errors.³⁵ Once we include default history as extra instruments (column 2) or right hand side variables and instruments (column 3), the estimate for the US bond rate increases but all the others decrease. The changes are occasionally statistically significant, but never really substantial. The overidentification passes even with having the history variables only as instruments. So there is no evidence for a very long memory of the bond markets.

With country dummies as instruments (column 4), we gain a bit in significance (except for the variance term), but the only other major change is the slight drop in the default and variance estimates. This is the same phenomenon as in section 1.5.2: the estimate of an endogenous variable moves closer to the OLS coefficient with more instruments, and the OLS estimate is closer to zero. Notice that the overidentification test passes here as well.

When the country dummies are included also in the right hand side (column 5), all the results move further towards OLS, but the estimates become very imprecise. The dummies are jointly significant in the regression, which again raises the issue of how powerful the overidentification was in column 4 and in general.

Next I consider time effects instead of country effects: year dummies, or a dummy for years 1980, 1982, 1986 and 1993, years with an unusually large jump in $\frac{r-R}{r}$ of the US BAA

³³Once we have country effects, or at least something closely related, it should eliminate the within-country correlation of the error terms. However, since there are many multiple country-year observations, error terms still have to be adjusted for clustering at the country-year level.

³⁴The source is [24]

³⁵See footnote 33.

Table 1.7: Country effects

		LHS variable: $r - R$				
		Country effects incorporated				
		Old default none	Old default history	Old default history	country dummies	country dum. in RHS
			as instr.	in RHS and instr.	as instr.	and instr.
		(1)	(2)	(3)	(4)	(5)
default indicator		4.48	3.39	2.09	3.76	1.39
(drfut5)		(2.85)*	(2.56)*	(1.44)	(3.94)*	(0.69)
variance		0.06	0.05	0.01	0.04	-0.00
		(6.99)*	(11.45)*	(0.43)	(3.89)*	(0.20)
US bond yield		0.13	0.36	0.67	0.43	1.00
		(0.26)	(1.03)	(2.79)*	(1.44)	(2.24)*
constant		-1.22	-1.99	-1.88	-2.40	-
		(0.31)	(0.65)	(0.36)	(0.83)	-
F stat.	deg. of fr.	F(3,14)	F(3,14)	F(7,14)	F(3,86)	F(12,86)
	value	41.94	65.85	266.93	12.75	3.71
	p value	0.000	0.000	0.000	0.000	0.000
p value of overid test		0.87	0.60	0.75	0.81	0.99
Number of obs.		299	299	299	299	299

Notes. All estimations are IV, using lagged values of reserves to imports, debt to GDP, current account balance to GDP, GDP growth, GDP per capita, past repayment troubles, arrears in region and US government bond yields as instruments. Old default history is captured by the following variables: number of bond defaults prior to WWII, total years with some bonds in default prior to WWII, default in the 30s and a dummy for sovereignty established or entering the Eastern block after WWII. The variable "drfut5" is an indicator of debt relief or rescheduling in the next 5 years (including the current one). Variance is the 5-year empirical variance of all bond spreads of the country starting from next year. US bond yield is the yield on long-term (10 years) US government bonds. The overidentification test regresses the residuals on the right hand side variables and instruments. T statistics are in parentheses. They are robust to clustering at the country-year level. * denotes significance at the 95% level.

bond average. The results are in Table 1.8.

Column 2 corresponds to the inclusion of the single time dummy as an instrument. It hardly changes the estimates, but the overidentification is rejected at the 18% level. When this dummy is included also on the right hand side (column 3), it increases the default estimate, decreases the variance coefficient, and its own coefficient is high, positive but insignificant: one interpretation is that defaults have large peaks in the early 80s and also in the early 90s, so the time dummy is capturing some of these waves. It also produces a high value of the joint significance F-test: though just like in most cases, the corresponding F-levels are practically zero, so the comparisons are being made very far on the tail of the F distribution, where the difference in the F values might not be very informative.

Year dummies as instruments (column 4) produce a very different picture: both default

Table 1.8: Time effects^a

		LHS variable: $r - R$					
		Time effects incorporated:					
	none	bad BAA year ^b as instrument	bad BAA year as instr. and RHS	year dummies as instruments	year dummies as instr. and RHS	year dummies instr., bad BAA as RHS	
	(1)	(2)	(3)	(4)	(5)	(6)	
default indicator	4.48	5.12	4.62	2.37	2.46	2.40	
(drfut5) ^c	(2.85)*	(2.78)*	(2.44)*	(1.65)	(0.60)	(1.61)	
variance ^d	0.06	0.05	0.04	0.02	0.05	0.02	
	(6.99)*	(8.63)*	(3.68)*	(1.86)	(1.19)	(1.97)	
US bond yield ^e	0.13	0.39	0.40	0.66	-	0.70	
	(0.26)	(0.84)	(0.93)	(2.28)*	-	(2.58)*	
bad BAA year ^b			2.20		3.15		
			(0.99)		(1.78)		
constant	-1.22	-3.49	-3.26	-3.11	-	-4.01	
	(0.31)	(1.01)	(1.04)	(1.36)	-	(2.02)	
F stat.	deg. of fr.	F(3,10)	F(4,10)	F(3,14)	F(14,14)	F(4,10)	
value		41.94	192.12	30.24	49453	146.86	
p value		0.000	0.000	0.000	0.000	0.000	
p value of overid test ^f		0.87	0.18	0.00	0.99	0.28	
Number of obs.		299	272	299	299	272	

a All estimations are IV, using lagged values of reserves to imports, debt to GDP, current account balance to GDP, GDP growth, GDP per capita, past repayment troubles, arrears in region and US government bond yields and the indicated set of time effects as instruments. T statistics are in parentheses. They are robust to clustering at the country level. * denotes significance at the 95% level.

b Bad BAA years are selected based on the behavior of average US BAA-rated bond spreads: there was a large increase in $\frac{r-R}{r}$ in 1980, 82, 86 and 93.

c The variable "drfut5" is an indicator of debt relief or rescheduling in the next 5 years (including the current one).

d Variance is the empirical variance of all bond spreads of the country starting from next year.

e US bond yield is the yield on long-term (10 years) US government bonds.

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

and volatility get smaller and less significant coefficients, moreover, overidentification is rejected. It again passes, but the year dummies are jointly significant once they are also included on the right hand side (column 5). This specification drops the constant and the US bond rate, since these are linear combinations of the year dummies. The risk indicators become a bit larger than in column 4, but completely insignificant. These effects are mostly maintained when only the single time dummy is put on the right hand side (column 6), and though the overidentification passes, but that single variable is not likely to capture all the time dummies.

Summarizing the lessons from these robustness checks, I conclude that my benchmark specification passed all the tests reasonably. The standard errors did increase in many cases, but the parameter estimates moved relatively little. The risk indicators sometimes went up or down, but mostly for statistical reasons: inconsistent (too small) OLS estimates, IV estimates with many instruments biased towards OLS, and systematic patterns of defaults through time.

1.6 Summary and conclusions

In the theoretical part of the chapter, I sketched a simple model that establishes a link between expecting a bad (volatile) market tomorrow and therefore requiring a lower buying price today, in the presence of investors with different costs of reallocating their portfolios and also being subject to a liquidity shock (which forces early liquidation of their portfolio).

The main focus of the chapter was to attribute the influence of country fundamentals on bond spreads to their predictive power for certain risk measures (in particular: default and illiquidity). I was estimating a structural equation determining sovereign bond spreads, of the form

$$r_{itj} - R_t = \alpha + \beta R_t + \lambda_{def} d_{it} + \lambda_{liq} l_{it} + \varepsilon_{litj}.$$

Here d_{it} and l_{it} are realizations of a default and an illiquidity variable. Since the true specification should contain their expectation conditional on information available at the time when prices were formed, and the actual realizations are correlated with the prediction errors, so d_{it} and l_{it} are not orthogonal to the error terms. However, any information available at the time of pricing can serve as valid instruments.

In principle, R_t should also be excluded and used purely as an instrument: however, it stayed sizeable and significant in many specifications. Besides, it can capture illiquidity or any other events at the aggregate level; so I kept it on the right hand side. Another variable which often proved to be important is the lagged value of the spread itself: it might capture country fixed effects, or adjustments to the imperfect choice of the realizations of the risk events.

This procedure thus tries to attribute the reduced form fit of

$$r_{itj} - R_t = \alpha' + \beta' R_t + \Gamma Z_{itj} + \varepsilon_{2itj}$$

to the predictive power of R_t and Z_{itj} for the default and the illiquidity variables. Generally speaking, the structural form captures most of the reduced form fit, although the overidentification test, which is one way to see if the reduced form is explained well enough, seems to have low power. In particular, including two event indicators (from default, arrears and price volatility) and the US interest rates, overidentification passes; also with one event, the US rate and lagged spreads; or with the broadest repayment trouble indicator and US rates.

The full specification gave the following results. In terms of sample averages, approximately 27% of the spread can be credited to default risk. This refers to the choice of default being debt reschedulings and relieves in the next 5 years. For every 10 percentage points increase in predicted default probabilities, there is a 31.5 basis points increase in bond spreads.

With arrears also included, or when the size of relief is also taken into account, I got much less precise and clear results. I also experimented with choosing a different time window for the default choice: 3 or 10 years instead of 5. For 3, it hardly made any difference; for 10, the estimates became completely blurred, since most countries in the sample had this variable as identically one.

An additional 27% was the contribution of country-specific illiquidity, captured by predicted future variance of the country's bonds. For an increase of the variance by 10 (the average value is about 50-60 in the sample), the spread goes up by 26 basis points. The alternative indicator (depressed future prices) proved hardly distinguishable from default, so it had a negligible effect in general. These results were not altered by varying the cutoff

level or the time window for "depressed prices"; neither by adopting a longer or shorter horizon empirical variance of future prices.

The leftover is made up by the lagged left hand side variable, the US bond rate and the constant. Past spreads seem to add 40% of their value to current spreads, which I view as potential country effects and adjustments for the imperfect event indicators. For every percentage point increase of the US rate, sovereign spreads go up by 0.3 percentage points, keeping predicted probabilities fixed. The total effect from the reduced form is 0.5 (thus incorporating the effect of higher interest rates on risk predictions).

I have checked the robustness of the main results (having the two event indicators but not the lagged spread) to a couple of alternative specifications. Apart from those already cited, these were the following. First, I used $\frac{r-R}{r}$ as the left hand side variable, which led to much weaker fits and less precision, but the signs of the effects were not changed. I then checked if the results are modified by using different instruments or none at all: OLS, IV with a set of just identifying instruments, then using almost all the instruments I had. Again, there was little change, only the risk coefficients were moving up and down slightly, mostly in accordance with the bias in OLS and large IV relative to just identified or small IV. Finally, I have incorporated different versions of country and time effects. The former had little impact. Time effects do make some difference for overidentification and the risk probabilities: using time effects as instruments leads to a rejection of overidentification, which is restored by including one particular time effect (a dummy for a large increase in US BAA-rated spreads). Once year dummies are included as instruments and right hand side variables, the risk coefficients drop and become insignificant. As for the default coefficient, I attribute this to a noticeable time pattern of defaults: peaking around the early 80s and early 90s, thus the year dummies taking away much of the default effect. In general though, the estimates do not change in any unexpected way, and in most cases, even the size and significance of the changes are very minor. Therefore, my results really establish a decomposition of the spread into liquidity and default risk.

I see a couple of major open questions here. One is to get an even more precise picture of these risk events, which would require more detailed information on country-specific events, bonds (maturity, actual repayment, some other bond-specific characteristics) and more individual bond-based panel data. In the time range which I was studying, it seems quite hard to get, but I managed to collect monthly price data on many Brazilian, Mexican

and Venezuelan dollarbonds for further research.

Another is to try to explain why the market actually shrinks so heavily for these bonds in some times, and why there are no investors coming to arbitrage on this opportunity. One potential explanation could be related to the acceleration of learning in these periods, thus an increased volatility of near-future prices. This could even yield concrete policy recommendations for developing countries on how to decrease their spreads. Of course, a similar question can be asked for developed countries as well – there the default risk is even smaller, but still, there are differences in spreads and also credit ratings among them.

Finally, one could use the same structural framework to study the pricing behavior of other types of assets. For example, local-currency denominated bonds, where exchange rate fluctuations constitute an additional source of risk. It can also be applied to understand the determinants of bank loan spreads to developing countries. A rejection of the pure risk prediction model would be much more natural there (political and strategic motivations may have very important effects). As there is also less secondary market for bank loans, the relevant risk is narrower, it should be some form of less than full repayment.

1.7 Appendix

1.7.1 Multiple equilibria in the model

The expression

$$p(\mu_0) = \frac{R - R(g_1\lambda\mu_0 + g_2\lambda^2\mu_0^2)}{R + \lambda(g_1\lambda M_1 + g_2\lambda^2 M_2)} \quad (1.6)$$

establishes a link between the distribution of μ and of p . Assume that a similar one exists in the opposite direction as well: a lower value of, say, Ep , translates into a "worse" distribution of μ , either by a higher M_1 or M_2 . In terms of an $Ep-M_1$ or $Ep-M_2$ schedule, (1.6) gives a downward-sloping curve. The other mechanism also implies a downward-sloping schedule – which gives the potential for more than one intersection. Suppose that the "reaction function" of the zero cost investors is such that they are not willing to buy any of this bond if its price was ever below 100%, but ready to buy anything offered in all other cases. It means that μ is identically zero if $Ep = 1$ (which means that the price is always one, and there are always enough zero cost investors), and μ is identically 1 if

$Ep < 1$ (thus $M_1 = 1$ and $M_2 = 1$, never any zero cost investors). Then both ($p = 1, \mu = 0$) and ($p = \frac{R - Rg_1\lambda - Rg_2\lambda^2}{R + g_1\lambda^2 + g_2\lambda^3}, \mu = 1$) represent an equilibrium.

1.7.2 Deriving identification for the two event case

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

$$d_{it} = \alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it} + \delta_2 H_{it} \quad (1.10)$$

$$l_{it} = \alpha_3 + \beta_3 R_t + \Gamma_3 Z_{it} + \delta_3 H_{it} \quad (1.11)$$

$$r_{it} - R_t = \alpha + \beta R_t + \lambda_d (\alpha_2 + \beta_2 R_t + \Gamma_2 Z_{it}) + \lambda_l (\alpha_3 + \beta_3 R_t + \Gamma_3 Z_{it}) + \delta H_{it}. \quad (1.12)$$

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

$$\begin{aligned} r_{it} - R_t = & \underbrace{(\alpha + \lambda_d \alpha_2 + \lambda_l \alpha_3)}_{\alpha_1} + \underbrace{(\beta + \lambda_d \beta_2 + \lambda_l \beta_3)}_{\beta_1} R_t \\ & + \underbrace{(\lambda_d \Gamma_2 + \lambda_l \Gamma_3)}_{\Gamma_1} Z_{it} + \underbrace{(\delta + \lambda_d \delta_2 + \lambda_l \delta_3)}_{\delta_1} H_{it}. \end{aligned} \quad (1.13)$$

This means that estimating (1.10), (1.11) and (1.13) gives us $\alpha_2, \beta_2, \Gamma_2, \delta_2, \alpha_3, \beta_3, \Gamma_3, \delta_3$ immediately, plus the following conditions:

$$\alpha_1 = \alpha + \lambda_d \alpha_2 + \lambda_l \alpha_3$$

$$\beta_1 = \beta + \lambda_d \beta_2 + \lambda_l \beta_3$$

$$\Gamma_{1i} = \lambda_d \Gamma_{2i} + \lambda_l \Gamma_{3i}$$

$$\delta_1 = \delta + \lambda_d \delta_2 + \lambda_l \delta_3$$

If the dimension of Z_{it} is at least two (we have at least as many excluded exogenous variables from (1.12) as events, i.e., as how many problematic variables are included), then the Γ equation gives us λ_d and λ_l , it even overidentifies those two parameters, and then α, β and δ can be obtained from the appropriate equations. This shows that (1.12) is identified.

However, instead of estimating this reduced form and obtaining nonlinear overidentification constraints and structural form estimates, one can use the IV (limited information) method described in the main text.

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Chapter 2

The composition of sovereign debt: a description

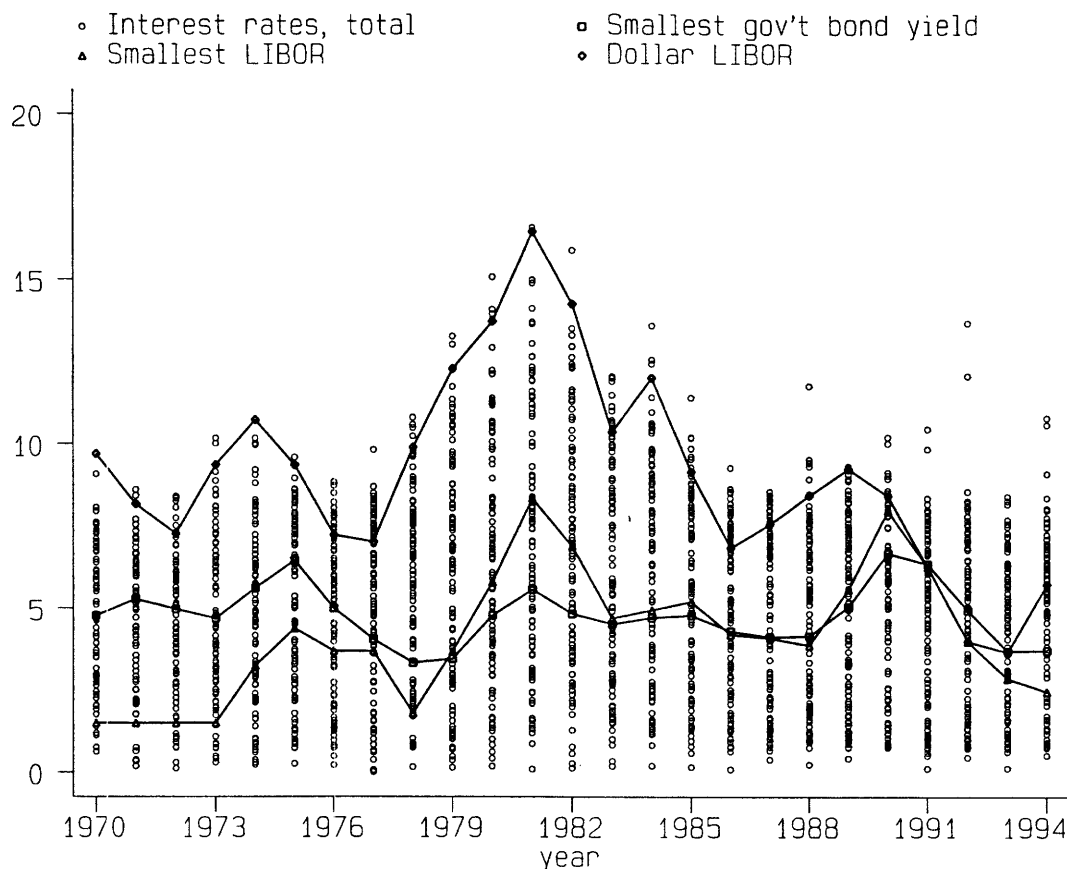
2.1 The behavior of average borrowing rates

2.1.1 Borrowing rates are very low

How do sovereign lending rates respond to changes in the world interest rate and the country's characteristics? If loans are supplied by a competitive market, then there should be a positive spread relative to a benchmark interest rate, which then reflects some (mostly default) risk premium. If, however, some of the loans are offered as parts of larger packages (e.g., a trade opening or other cooperation), it is possible that lending rates are not meaningful just in themselves.

A closer look at actual developing country data (from the World Bank's main sovereign debt publication, World Debt Tables [1]) gives a shocking view about these spreads. Figure 2-1 depicts the interest rates on total lending against various world interest rates. Lending rates are almost always below the dollar LIBOR – they are below even the annual *minimum* of all major currency LIBOR or government bond rates! Panel A of Figure 2-2 shows the same information in terms of average interest rates and currency-composition weighted world interest rates: average interest rates are almost always below the benchmark world interest rate. Furthermore, Panels B and C make it clear that it is not simply official lending that leads to very low average interest rates (being often below the minimum of government bond rates), but private lending rates are also very close to the benchmark world rates.

Figure 2-1: Interest rates and spreads



Since there is large variation in the currency composition of new disbursements, and also in the different currency LIBORS, one needs to adjust the spreads for that¹. Panel D of Figure 2-2 shows that private spreads² are again very low: though they are usually positive, but also smaller than the average spread on BAA-, and in many cases even the AAA-rated US company bonds³.

Such striking numbers raise concerns about the reliability of the data. Though I have not found any other publication using the same interest rate data, but there are many papers using another World Bank publication⁴ – and bank lending rates behave really similarly in that data source than in mine (see Section 2.5 for further details). So instead of concluding that the data is wrong or lending rates are meaningless, I want to investigate what drives

¹See Sections 2.3 and 2.7 for a discussion of currency composition.

²Adjusted spreads mean adding an extra 10% for all bond issues (multiplied by the weight of bond borrowing), in order to compensate for missing issue price data. See section 2.3 for further discussion.

³Data is the Federal Reserve's historical interest rates site. AAA refers to firms with exceptional financial security, BAA firms offer adequate financial security.

⁴Borrowing in International Capital Markets [2]; see for example, Ozler 1992 [3], more particularly, Edwards 1986 [4].

private lending rates this low.

One explanation could be that these results are artifacts coming from imperfect currency composition data. However, private spreads would be low even with the *lowest* LIBOR currency: there are many observations where private lending rates are below the minimal LIBOR. Another possible explanation is that neither of these world interest rates are the true opportunity costs of the lenders – but it would be surprising to see such a large deviation between LIBOR and the cost of private lenders (in particular, for bank or bond lending). A fraction of private lending is coming from firms, but then those firms should be big enough to have access to near-LIBOR lending opportunities. For official, it is not that surprising that lending rates are not closely related to the cost of the lending government; but for private lending, having a benchmark cost substantially different from LIBOR or government bond rates would be surprising.

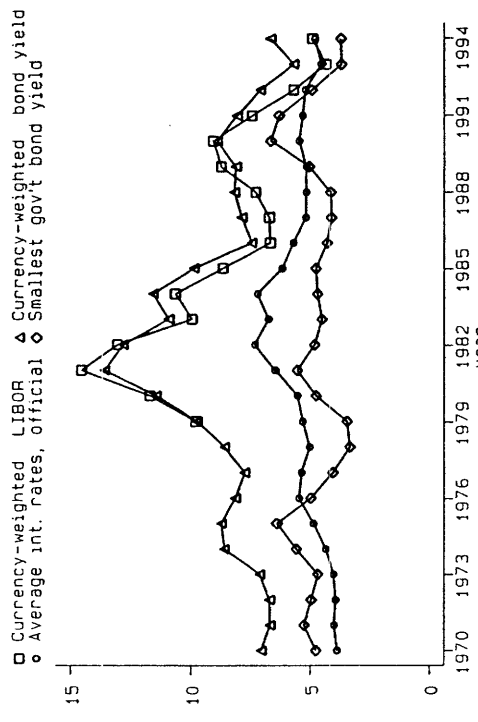
Instead of immediately accepting any of these interpretations, I want to explore the finer composition of private lending. These categories are bond, bank and "other" lending⁵, and they might substantially differ in their sensitivity to world interest rates or country characteristics. In other words, average private rates display the mix of the behavior of various sub-types. Bond and bank lending behave consistently with conventional wisdom, their interest rates are indeed above world rates. Low average private spreads are driven by this "mysterious" other category. It has a larger constant than bank or bond lending, but does not respond much to LIBOR. It also behaves differently with respect to certain country risk characteristics.

So why do not I just present the same pictures for these three categories as before? The problem is that the disaggregation of interest rates stops at the private-official lending level. Other data sources do offer bond-level or loan-level price data for many countries, but I found no possibility of obtaining the interest rates on other lending (which is key to my analysis). Though it might be possible to recover them from bond, bank and average rates, but that would require a near-complete knowledge of bond and bank rates, which is rarely the case⁶. So I have to look for an answer without these more detailed series (in particular,

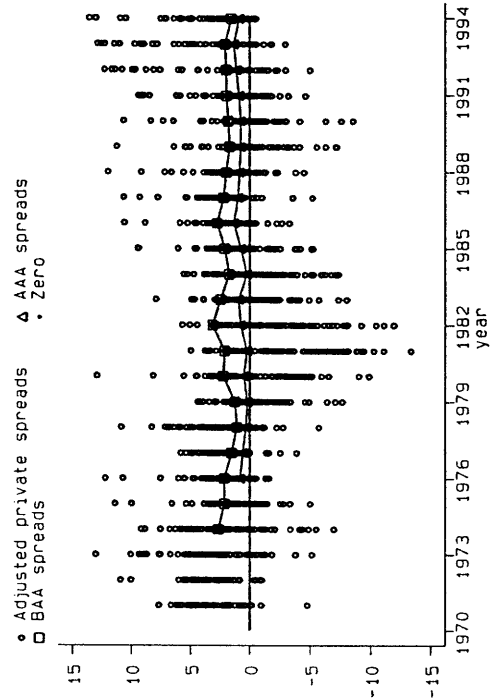
⁵"Public and publicly guaranteed other private credit from manufacturers, exporters, and other suppliers of goods, and bank credits covered by a guarantee of an export credit agency." The maturity is still 3-10 years in general, and there are quite many countries for which this other lending is all their private disbursement, and also sizable. See Section 2.8 for a more detailed discussion.

⁶See Section 2.5 for more discussion.

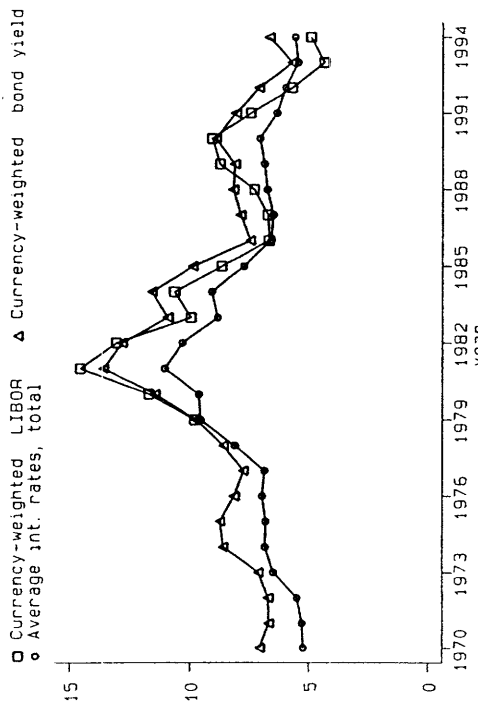
Figure 2-2: Interest rates and spreads



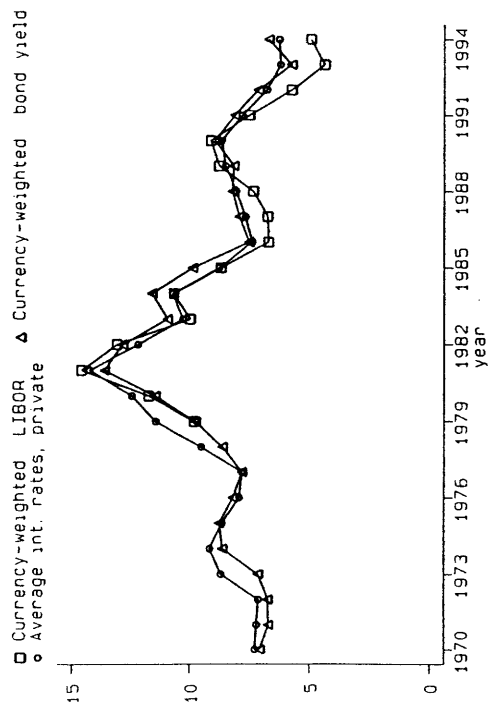
Panel B: Average interest rates, official lending



Panel D: Adjusted private spreads

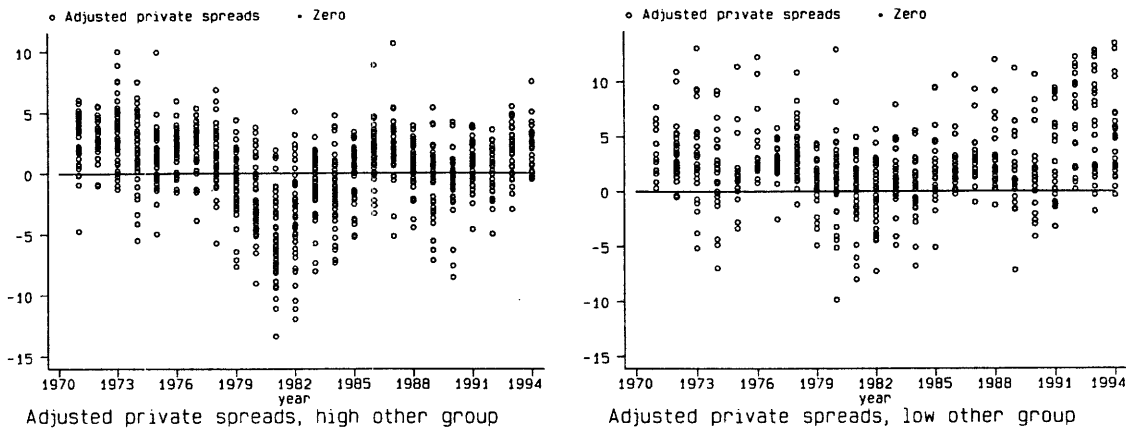


Panel A: Average interest rates, total lending



Panel C: Average interest rates, private lending

Figure 2-3: Currency adjusted spreads, private lending



I will be able to show estimated versions of the spread pictures, for bond, bank and other lending – in Figure 2-5) .

The only graph I can show here is Figure 2-3: when I cut the sample based on the fraction of this other lending in private, the lower half produces significantly higher spreads than the upper half. The effect is most notable at the early eighties (debt crisis), but not entirely limited to that period. I view this as an indication that other lending is a main contributor to low spreads.

A final concern could be that these low spreads correspond to small debt disbursements – but this is not the case: all types of lending were and still are of substantial size, no matter whether we look at all or just a subset of developing countries. Furthermore, if I calculate world or regional (weighted) average interest rates, those rates are again surprisingly low (Figure 2-2 showed world averages; Figures 2-6-2-7 on pages 81 and 82 display averages by income groups.). So it is not the case that cheap loans are small; rather, loans on average are cheap.

2.1.2 Borrowing rates respond too little to world interest rates

The second pattern will in fact help us understanding what "goes wrong" with average lending rates. Table 2.1 presents simple OLS regressions of total, official and private lending rates on the appropriate (currency-weighted) world rate, various country-specific and worldwide economic indicators (for an explanation of the variables, see Section 2.3 and the Appendix; Table 2.2 of the Appendix also gives more detailed results of the same regres-

sions), fractions of different sub-types and regional dummies.

Table 2.1: Results for total, official and private lending

	LHS variable: interest rates, using flow data for currency composition					
	total lending		official lending		private lending	
	(1)	(2)	(3)	(4)	(5)	(6)
world rate ^a	0.18 (6.62)*	0.28 (7.17)*	0.08 (4.12)*	0.12 (3.83)*	0.40 (10.46)*	0.55 (10.98)*
fraction of official lending	3.04 (7.43)*	2.21 (4.81)*				
fraction of bond lending	4.97 (6.45)*	4.20 (5.30)*			4.94 (10.10)*	3.51 (6.30)*
fraction of bank lending	8.01 (12.49)*	7.39 (10.89)*			5.93 (11.60)*	4.69 (7.67)*
fraction of other lending	5.78 (8.32)*	4.91 (6.71)*			4.35 (10.02)*	2.97 (5.53)*
constant			3.98 (9.54)*	3.61 (7.34)*		
Number of observations	1113	1113	1322	1322	983	983
Number of regressors ^b	22	22	19	19	21	21
R ²	0.62	0.62	0.54	0.54	0.42	0.42

a Government bond rate for (2), (4) and (6); LIBOR in all other cases.

b Not reported: first factor of the liquidity, development, credit, currency, trade, repay and the world variable groups, unexpected default, managed float regime, free float, pre-debt crisis, during-debt crisis, pre-transition and four regional dummies.

* Denotes significance at the 5% level. T-stats are corrected for clustering at the country level.

The most striking feature of the table is that the estimates of the world interest rate coefficient are surprisingly low: between 0.18 and 0.28 for total (columns 1 and 2); 0.08 and 0.12 for official (columns 3 and 4); 0.40 and 0.55 for private lending rates (columns 5 and 6). Note that if the spread were independent of the world rate, that would imply a coefficient of 1. So it means that sovereign lending rates are hugely underreacting to movements in world interest rates.

I will propose a framework that enables me to estimate how these unobserved lending rates are influenced by world interest rates and country fundamentals. This will give the following finding: bond and bank lending move approximately one to one with world rates, other lending rates with a coefficient of 0.1 (marginally significant). Also, the constant terms, and coefficients on country fundamentals in general, will be different across types, with important sign switches as well.

I relate these differences to the completely different nature of these types of lending. Bond prices reflect a spread above world rates, and the spread is determined mostly by default risk: bonds are held by many and relatively small investors, whose only objective is to earn a good return, and the only way to get compensation for the risk they bear is in terms of higher spreads. For bank lending, it is not just the price that can incorporate the

risk but also the availability (restricting access to future borrowing; using credit ceilings); and also, the lender and the borrower is in a one-to-one relation, where the price will be influenced by some bargaining process. Hence the world interest rate and fundamentals have different effects on bank lending rates than on bond yields. Banks also have access to better monitoring, which may reduce their risk premium; though the one-to-one nature of a bank loan arrangement gives more renegotiating power to distressed borrowers. Moreover, many bank loans may represent refinancing of ill-performing old loans, which serve as an investment to protect previous outlays.

Other lending is likely to have good self-enforcement: it is more like discounted credit between long-term production partners⁷, and this long-term relationship makes enforcement more efficient (or enables better monitoring), via involvement in joint projects, or allowing the lender to hold shares from the borrower's project. Establishing (or maintaining) such a relationship also creates (or protects) a surplus: it generates future cash-flows for both parties. Other lending thus can also be interpreted as a way of sharing this surplus (it may also involve trade at distorted prices, like transfer pricing), or that the borrower was selling the right to establish such a relation with itself (for example, opening its market to a foreign firm or country), and the cheap loan was in fact the sale price of this asset. Lastly, such a loan may have additional benefits: it can be subsidized by one of the governments (thus the loss from the negative spread is recovered through some subsidy), it can serve as a hidden form of direct investment, overcome legal restrictions to lending, or enable tax evasion. In analyzing the case of Iran in the 1990s, I find "anecdotal evidence" supporting most of these aspects of other lending.⁸

The chapter is organized as follows. The next section relates my findings and approach to the existing literature. Section 2.3 explains the economic data I am using: its sources, the main weaknesses, and the approaches I took to resolve these problems. Section 2.4 explains the weighted estimation which enables estimating the spread equations of different subtypes without having the corresponding interest rates. Using all the methodology developed in

⁷See Section 2.8 for further discussion on other lending.

⁸Official lending is likely to share quite many of these characteristics. In some sense, sovereign borrowing can be divided into two main parts: one is supplied directly by financial markets (bank and bond), it is mostly "pure" lending, and the prices are determined by maximizing financial profits. The other is linked to larger packages or various side-deals (other and official), and it is much less of "pure lending". The prices are possibly set by profit maximization, but the profits are not restricted to the financial investment aspect of the loans.

these parts, Section 2.5 explores the reliability of my data, mostly by comparing it to other data sources. Section 2.6 shows and discusses the main results, then the next section explores how robust the findings are. Section 2.8 focuses on interpreting the results: can the results be explained by missing fees; what is this other lending; and is it related to firms, trade or production? Finally, Section 2.9 concludes.

2.2 Relation to the literature

Though the theme of the chapter is "documenting facts", there are a number of related topics and articles in the literature. The closest area is the empirical analysis of sovereign lending, quantities and prices. One general approach⁹ is to specify a loan demand by countries, and then a ceiling set by banks. The other focus of the literature was to analyze the pricing of sovereign lending. Among others, Edwards 1986 [4] and Ozler 1992 [3] follow an approach that is close to mine: they specify an equation determining the spread by default probabilities. Then they assume that default probabilities are a logistic function of certain country characteristics, which leads to a tractable regression of the logarithm of spreads on economic indicators.

Compared to these papers, my approach has two major differences: first, instead of regressing the logarithm of the spread on country characteristics, I regress the interest rate itself. Since I want to get a description of the data, and explore how different types of lending are different, choosing a simple but robust specification should be the right choice. The other big difference is that I do not constrain the benchmark interest rate coefficient to be one. Since the data suggests that this coefficient is indeed different from one, it is a necessary assumption.

Edwards 1986 [4] has a particular finding that is quite related to my results: he documents that there are substantial differences between bank and bond lending, namely, most of the economic indicators get different coefficients. Though my bond estimates will be noisy, but I also get similar differences, and I get a significantly different behavior of bank and other lending.

My findings about particularly cheap and "privileged" forms of lending can also be

⁹Though it was used mostly by the early literature, e.g. Eaton and Gersovitz 1981 [6], and McFadden et al 1985 [7].

related to various other articles. Mohr et al 1998 [8] argue that one can manage sovereign risks better by bundling different contracts together. Their example is sovereign lending and environmental contracts: by linking these two together with a cross-default contract, the risks of both can be reduced. A similar interpretation can be given to my finding about cheap official and other (trade-related) credit: if they are linked to such side-arrangements, then both might become less risky, moreover, the benefit of the linkage might make it possible to offer the credit itself below its price.

Petersen and Rajan 1997 [10] and Biais and Gollier 1997 [11] explicitly argue about numerous cost advantages trade credit might have relative to bank lending: cheap monitoring, smaller information asymmetries, advantage in controlling the borrower, price discrimination, transaction costs. For all these reasons, they find that firms are using trade credit extensively; moreover, the mix of their financing responds to changes affecting the ease of getting bank credit (monetary contraction, or a credit shrunk in general). This is quite parallel to my finding that poor countries will actively vary the proportion of other lending as a response to increases in world interest rates.

Gooptu and Brun 1992 [5] analyze alternative financing resources available for developing (mostly African) countries. They find that short-term trade credit is an important extra source, and they also mention medium-term trade credit as a possibility. In contrast to my findings (and in accordance with the common view), short term trade credit is not cheap: its interest rate is between 0.8 and 4 percentage points over LIBOR.

2.3 The data: sources, problems and remedies

2.3.1 Economic indicators of countries

There are two main sources of my data for economic variables: IFS [12] and World Development Indicators [13]. These sources, although not immune from data problems, are used quite frequently¹⁰. In general, it is hard to decide which variables to include in a regression: theoretically, the risk characteristics of a country are related to any socio-economic or political indicators (and all of their history). However, it is not possible to include all such measures: on the one hand, the list is endless and not all pieces are available; on the other hand, most of these variables are highly correlated. The issue of multicollinearity might

¹⁰For example, Edwards 1986 [4] and Ozler 1992 [3] also use the IFS for economic indicators.

make any individual coefficient and significance level meaningless, and the results would be very sensitive to the particular choice of the right hand side variables.

To get around both of these issues, I adopted the next approach. I started with a large list of variables, which I divided into certain groups: for example, liquidity variables, domestic credit markets, currency regime and its stability. Then I estimated the first principal component¹¹ of each group, and used that factor as a representative of that particular variable group. This reduced the number of variables in any regression, resolved most of the multicollinearity problem, but still kept the regression coefficients meaningful. The variable groups I use are the following: liquidity (a positive measure), economic development (wealth), domestic credit markets (developed), currency regimes (volatile), international trade (openness), repayment problems, global economy (unclear sign). The rest of the variables are used individually (if at all): constant, regional dummies, pre-debt crisis dummy, debt crisis dummy, free float regime, managed float regime¹² and an unexpected default variable¹³. See the Appendix for a more detailed description.

In general, I am using the first lag (and maybe some further) of all these variables. The main reason is timing and endogeneity: When the debt contract is signed, it is usually the previous year's data which is known, so the contract should be based solely on that information. Also, since the consecutive lags are highly correlated, it should not make a big difference. Though current values of indicators may proxy for some information that was already known at the time of the contract but not included in my economic data – but then the endogeneity of these proxies may arise. In order to cut it short, I never work with current values, only lags.

2.3.2 Debt data

Debt data is from the World Bank's World Debt Tables CD ROM, 1996. It has detailed stock, flow and composition data on all sovereign borrowing of nearly all the developing countries. Also, it has the average interest rate and maturity of total borrowing and some sub-categories.

¹¹The linear combination of all the variables within that group that explains the most of the within-group variation.

¹²Hence the float regime coefficients capture the difference relative to the fixed exchange rate regime.

¹³A debt relief or rescheduling is unexpected if its (linear) prediction equation suggested a fitted probability less than half. The dummy is one for such events in the past two years.

Unfortunately, there are many data problems here: disbursements versus commitments, the currency composition of debt, and interest rates in general. Starting with the first one: It is disbursements for which the composition is given¹⁴, but commitments that have their average interest rates¹⁵. Some of current disbursements are from previous years' commitments, and some of current commitments are to be disbursed only in future years, or maybe never. The data on undisbursed debt is also not fine enough to recover the actual origin of each disbursement. Fortunately, just for the quantity of new debt, using disbursements or commitments in some diagnostic regressions did not make a difference, so I will use disbursements, and treat the interest rates as their price. For the detailed composition, it does make some difference; so for private lending, I obtained estimates and figures using both the disbursement composition data and a correction for the commitment-disbursement difference (see the appendix for a description of this correction). The differences, if any, are discussed in Section 2.7.

The next problem is about the currency composition of sovereign debt: there is some currency composition data available, but it is the currency composition (into major lending currencies) of sovereign debt *stocks*, and it is reported at the aggregate level only. What I would need is the composition of debt *flows*, and at the official, private, and preferably at the bond-bank-other private lending level.

As for the latter issue, I assume that all types have the same (or at least similar) currency composition. Though it is not likely to be completely true (bond issues and bank loans are more concentrated in dollars), I see no safe way of adjusting the currency composition within types. Moreover, when using only the dollar rate for bank lending (see Section 2.5), the overall picture stayed similar. So I will mostly stick to the assumption of homogeneity across types.

To "recover" the composition of flows, I apply a similar approximation to what I did for the commitments adjustment. The only assumption that I make is that repayment in each year has the same composition as the *old* debt stock, and this already enables me to infer the composition of new disbursements easily¹⁶. Of course, this assumption is definitely

¹⁴Within private lending, the fractions of bank, bond and other lending; within official, the fractions of multilateral concessional and non-concessional, bilateral concessional and non-concessional.

¹⁵And no finer composition than official and private is available.

¹⁶Knowing last year's debt stock and composition, I know the debt stock for each currency. Then I subtract the repayment (assuming that the composition of repayment is proportional to the entire stock). Using next year's debt stock and composition, I can calculate the currency-specific new disbursements necessary to

not fully valid. To be as safe as I can be, I work both with the stock- and the flow-based compositions to see how much difference the two makes. As we will see, the results will depend slightly on which composition I am using, but not much. For example, using flow compositions for obtaining the total, official and private spread pictures makes almost no visible difference, and definitely no difference in terms of the low, usually negative spreads. This I will interpret as a signal that my results would be quite similar even with "the true" currency composition.

There are two basic problems with the interest rate data as reported by the World Bank. The first is that it does not necessarily reflect the total cost of a disbursement. For example, it gives only the coupon size for bonds, but not the issue price differential; loan contracts might have important extra costs, which significantly increase the total cost the borrower is facing. Occasionally, these costs are even confidential. For bank lending, there is some fee data available, from *Borrowing in International Capital Markets* [2]. Though fees might add an extra 3-4 percentage point in some cases (occasionally, much more), but they rarely change overall borrowing terms: at least in the late 70s-early 80s, they were relatively small. See Section 2.5 for further discussion on bank costs.

To get around the bond price problem, I looked at several bond issues of developing countries: the issue price is usually (though not always) quite close to 100%. Moreover, the deviation of the issue price from full did not seem to be correlated with world interest rates. So if the deviation is nearly constant, or at least, orthogonal to the right hand side variables (most importantly: the world interest rates), then the regression coefficients should represent the "true" coefficients, and the issue price effect should be absorbed by the bond-specific constant or the error term¹⁷.

The really troublesome weakness of the interest rates data is its coarseness: it is available for total, private and public (all publicly guaranteed) lending, but not in finer classification. So one cannot easily estimate the effect of a change in world interest rates or any economic indicators on, for example, bond-specific interest rates. Of course, if those effects were the same through all types of lending, this would not be a problem. But it is plausible that

reach the new stock.

¹⁷Though in the previous chapter, I obtained slightly higher interest rate coefficients from bond data – but it is unlikely that the extra appr. 0.1 was driven by the inclusion of issue prices, since most of the issue prices were full there. As an extra correction, I have added 10% to bond interest rates in panel D of Figure 2-2 (this would mean that the bond-specific constant contains 10% issue price differential), and still, as the figure shows, spreads stayed low.

these effects are significantly different: just like in Table 2.1, where the aggregate regression of total lending rates was hiding a totally different behavior of private and official lending, those two broad categories might also camouflage diverse patterns of their sub-types (and we will see that they actually do).

In section 2.4, I explain a simple framework that enables me to estimate those coefficient differentials. Under somewhat (but not unreasonably) restrictive assumptions, those estimates will be consistent; and in general, they will be good enough at least to tell apart the coefficients of the different lending types. Later, I will also report some descriptive results using only bank rates, mostly for comparison.

2.4 The weighted estimation

Assume that there is a separate spread equation for each type j :

$$r_{it}^j = \alpha^j + \beta^j r_t^j + \lambda^j X_{it} + \varepsilon_{it}^j$$

Multiply it with the proportion of type j disbursements, $\frac{q_{it}^j}{q_{it}}$, and add them up:

$$r_{it} = \sum \alpha^j \frac{q_{it}^j}{q_{it}} + \sum_j \beta^j r_t^j \frac{q_{it}^j}{q_{it}} + \lambda^j X_{it} \frac{q_{it}^j}{q_{it}} + \widetilde{\varepsilon}_{2it}. \quad (2.1)$$

When the different types correspond to different currencies, it is plausible to assume that only r_t was different across types, no other parameters or variables. So $\alpha^j = \alpha^i$, $\beta^j = \beta^i$, $\lambda^j = \lambda^i$. Using the fact that the sum of the fractions is one, (2.1) becomes

$$r_{it} = \alpha + \beta \left(\sum_j r_t^j \frac{q_{it}^j}{q_{it}} \right) + \lambda X_{it} + \widetilde{\varepsilon}_{it} = \alpha + \beta \sum_j r_t^j \frac{q_{it}^j}{q_{it}} + \lambda X_{it} + \widetilde{\varepsilon}_{it}$$

This means that one can regress average interest rates (which are reported) on economic variables and the currency-weighted world interest rate $\sum_j r_t^j \frac{q_{it}^j}{q_{it}}$.

For the adjustment by lending types, I do not want to make the assumption that the coefficients are the same across different types – because I am interested exactly in those differentials. Since the weights $\frac{q_{it}^j}{q_{it}}$ are reported, I can construct the interaction terms of the fractions with the relevant world rates, country fundamentals etc., and regress the

interest rate on all these. As the composition does vary over time and across countries, the coefficients of the different type spread equations are identified, even though the detailed interest rates are missing. Moreover, if some of the RHS variables are endogenous, but I have instruments Z_{it} for them, then $Z_{it} \frac{q_{it}^j}{q_{it}}$ can be used as instruments for the weighted equation.

This is like a Chow test of coefficient stability, with a non-binary and stochastic classification. Both the OLS and the IV method works there nicely. Here, however, $\frac{q_{it}^j}{q_{it}}$ might be correlated with X_{it} , thus $\varepsilon_{it}^j \frac{q_{it}^j}{q_{it}}$ might be correlated with X_{it} . Suppose that there are only two types, and classification is driven by $\frac{q_{it}^1}{q_{it}} = c + dX_{it} + \eta_{it}$. Then the weighted equation is

$$r_{it} = \alpha^1 + (\alpha^2 - \alpha^1) \frac{q_{it}^1}{q_{it}} + \beta^1 X_{it} + (\beta^2 - \beta^1) X_{it} \frac{q_{it}^1}{q_{it}} + \zeta_{it}.$$

For OLS to be consistent, we need that the constant, $\frac{q_{it}^1}{q_{it}}$, X and $X \cdot \frac{q_{it}^1}{q_{it}}$ be orthogonal to ζ . This is equivalent to $X, X^2, X\eta \perp \varepsilon X, \varepsilon\eta$. We know that $X \perp (\varepsilon, \eta)$, so $\sum \frac{X_{it}^k \varepsilon_{it}}{N} \rightarrow 0$. For $\sum \frac{X_{it}^k \varepsilon_{it}^a \eta_{it}^b}{N} \rightarrow 0$, it is enough that $\sum \frac{\varepsilon_{it}^a \eta_{it}^b}{N} \rightarrow 0$ from the independence of X_{it} , so if ε and η are uncorrelated, then the specification is valid. This argument can be extended to more than two types and endogenous right hand side (IV).

Is this strong independence assumption acceptable as a working hypothesis, or at least, are the estimates not too bad? For some evaluation, I apply this method to total lending and the official-private distinction, where I have the detailed interest rates data. The comparison of the true and the weighted results are given in Table 2.2. Looking at these numbers, the weighted method gets the coefficients, in sign, magnitude and often even in significance, right.

Finally, let me emphasize that I do not "invent" data here: I start from correct specifications, aggregate them to the level of my data, then I estimate the parameters which can be estimated. In fact, any supply-demand estimation is subject to this "aggregation bias". The only question is whether the distribution among the different types is "random enough" to make the procedure work, or if the coefficients are similar enough across types to eliminate this problem.

Table 2.2: Comparing the weighted and non-weighted estimates

	lending type					
	total		official		private	
	(1)	(2)	(3)	(4)	(5)	(6)
		weighted	separated	weighted	separated	
world rate ^b	0.18 (6.62)*	0.28 (7.17)*	0.10 (1.69)	0.12 (3.83)*	0.43 (5.77)*	0.40 (10.46)*
liquidity	0.003 (0.04)	-0.00 (0.06)	0.08 (0.70)	-0.13 (1.69)	-0.16 (0.94)	-0.14 (1.32)
development	0.31 (3.02)*	0.32 (3.14)*	0.69 (3.68)*	0.65 (5.50)*	-0.03 (0.31)	0.03 (0.47)
credit	0.35 (3.06)*	0.36 (3.20)*	0.56 (1.87)	0.66 (5.29)*	0.04 (0.25)	0.08 (1.17)
currency	0.01 (0.23)	0.00 (0.14)	-0.04 (0.51)	-0.007 (0.11)	0.20 (2.02)*	0.05 (0.86)
trade	0.16 (1.72)	0.14 (1.49)	0.09 (0.60)	-0.12 (1.31)	0.08 (0.68)	0.13 (1.26)
repayment	-0.10 (0.95)	-0.11 (1.02)	-0.15 (0.99)	-0.27 (2.54)*	-0.003 (0.01)	-0.12 (1.10)
world	0.00 (0.00)	0.04 (1.68)	0.01 (0.22)	-0.06 (2.88)*	0.002 (0.05)	0.06 (1.99)*
unexpected default	0.29 (1.40)	0.27 (1.29)	0.10 (0.23)	0.06 (0.33)	0.42 (0.98)	0.38 (1.53)
managed float	0.88 (3.21)*	0.84 (3.09)*	0.33 (0.77)	1.04 (3.38)*	1.14 (2.57)*	0.40 (1.72)
free float	1.04 (3.72)*	1.04 (3.63)*	0.74 (1.77)	0.97 (2.73)*	0.63 (1.69)	0.62 (2.13)*
pre-debt	0.36 (2.42)*	0.28 (1.95)	0.29 (1.40)	0.42 (3.01)*	0.25 (0.79)	0.18 (1.14)
during-debt	0.32 (2.90)*	0.24 (2.22)*	0.34 (1.99)*	0.36 (3.65)*	0.28 (1.20)	0.06 (0.56)
pre-transition	-0.19 (0.74)	-0.27 (1.08)	-0.58 (1.25)	-0.36 (1.65)	0.99 (1.63)	0.46 (1.62)
Africa ^c	-0.77 (2.65)*	-0.76 (2.65)	-0.83 (1.96)	-0.66 (2.06)*	-0.25 (0.53)	-0.47 (2.04)*
Asia ^c	-1.24 (2.81)*	-1.22 (2.84)*	-1.58 (2.16)*	-1.42 (2.97)*	-0.16 (0.23)	-0.50 (1.62)
Europe ^c	-0.20 (0.50)	-0.17 (0.43)	0.75 (1.47)	-0.34 (0.36)	-0.07 (0.15)	-0.56 (2.06)*
Middle East ^c	-1.51 (1.74)	-1.39 (1.57)	-1.35 (0.94)	-1.08 (1.39)	-1.93 (0.70)	-2.49 (2.13)*
fraction of bond	4.97 (6.45)*	4.20 (5.30)*			3.99 (4.73)*	4.94 (10.10)*
fraction of bank	8.01 (12.49)*	7.39 (10.89)*			4.92 (5.35)*	5.93 (11.60)*
fraction of other	5.78 (8.32)*	4.91 (6.71)*			2.76 (3.34)*	4.35 (10.02)*
constant or fraction of official	3.04 (7.43)*	2.21 (4.81)*	4.31 (5.45)*	3.61 (7.34)*		
Number of obs.	1113	1113	1113	1322	1113	983
R ²	0.62	0.62	0.66	0.54	0.66	0.42

a OLS with the interest rate on the left hand side, and the reported regressors on the right hand side.

b Government bond yield for official, LIBOR for private lending.

c The Latin America dummy is excluded, hence all regional dummies are relative to Latin America.

* Denotes significance at the 5% level. T-stats are corrected for clustering at the country level.

2.5 Validation of the Data

The main concern is my interest rate data: I have not found any papers using WDT interest rates, although a very similar publication of the World Bank (Borrowing in International Capital Markets, for bank and bond lending) is used by Edwards 1986 [4] and Ozler 1991 [3]. For all these reasons, now I try to relate my data and my findings to this better-known interest rate data and to some other results, in order to check that my numbers are not very far.

The result that bond rates respond nearly or a bit more than one in one to world rates is both reasonable, and I find similar interest rate coefficients in the previous chapter as well. A similar argument applies to the different behavior of bond and bank lending: among others, Edwards 1986 [4] also documents similar differences.

For bank lending¹⁸, I can directly compare my results to estimates based on data from Borrowing in International Capital Markets (see Table 2.3). First of all, the interest rate coefficient I keep getting has a reasonable magnitude, it shows that bank rates do respond to world interest rates. Using WDT data but the dollar LIBOR (column 2) pushes this estimate even closer to one – it is indistinguishable from the pure bank lending results, but still less than one. Comparing the other coefficients of columns 1-4, the only visible but still not very significant deviation is for the effect of currency regimes. Columns 3 and 4 are nearly identical, which shows that the effect of fees is negligible. In general, bank lending shows an impressively similar behavior in both data sources.

I also compared the bank lending interest rates of the two sources: this is displayed in Figure 2-4. Panel A shows bank lending rates (from Borrowing in International Capital Markets) and private rates (from WDT) of all applicable observations. Though the two are not identical and they should not be identical (private lending is not only bank lending), but they move together more or less. Panel B shows only those observations where private lending was mostly bank lending – the numbers still do not coincide, but they are mostly close. Panels C and D plot an approximate private lending rate (bank rates plus a flat 5% for other lending) against the WDT data, which moves the observations even closer¹⁹. I

¹⁸I also tried to "back up" other lending rates (for many no-bond observations, I have the composition, the weighted average interest rate, and bank interest rates, then I can solve for the missing other rate), but I got very noisy data and thus insignificant results. Since the bank contract data cannot be fully matched with WDT commitments or disbursements, it is not surprising that these "other" rates were uninformative.

¹⁹From the 84 observations with both types of interest rates and at least 80% of bank lending within

Table 2.3: Bank lending estimates

	LHS variable:			
	private lending rates		bank rates no fees	bank rates plus fees ^a
	weighted		separate	
	(1)	(2)	(3)	(4)
interest rate ^b	0.77 (3.76)*	0.92 (5.17)*	0.93 (83.20)*	0.94 (66.35)*
liquidity	0.44 (0.53)	-0.04 (0.06)	-0.28 (3.55)*	-0.26 (2.44)*
development	-0.02 (0.02)	0.08 (0.10)	0.03 (0.37)	0.25 (1.69)
credit	-0.67 (1.13)	-0.62 (1.26)	-0.17 (2.81)*	-0.26 (2.98)*
currency	0.31 (1.14)	0.27 (1.20)	-0.09 (1.88)	-0.10 (1.63)
trade	0.48 (1.33)	0.31 (1.26)	0.08 (1.49)	0.13 (1.47)
repayment	-0.27 (0.12)	-0.64 (0.35)	-0.37 (2.20)*	-0.31 (1.27)
world	0.08 (0.55)	-0.08 (0.77)	-0.02 (1.06)	-0.05 (1.59)
unexpected default	0.42 (0.36)	0.29 (0.29)	-0.04 (0.32)	-0.04 (0.23)
managed float	0.27 (0.28)	0.42 (0.58)	0.22 (1.07)	0.33 (1.31)
free float	-1.49 (1.44)	-1.33 (1.34)	-0.05 (0.48)	0.05 (0.48)
constant ^c	1.75 (0.69)	0.30 (0.13)	0.90 (6.65)*	1.07 (5.66)*
Number of obs.	137	137	138	138
R ²	0.73	0.72	0.98	0.97

a Main interest rate plus management, other and (average) participation fees, whenever available.

b The RHS interest rate is the currency-weighted average for column 1, dollar LIBOR for column 2, and the appropriately weighted (mostly dollar) LIBOR for columns 3 and 4.

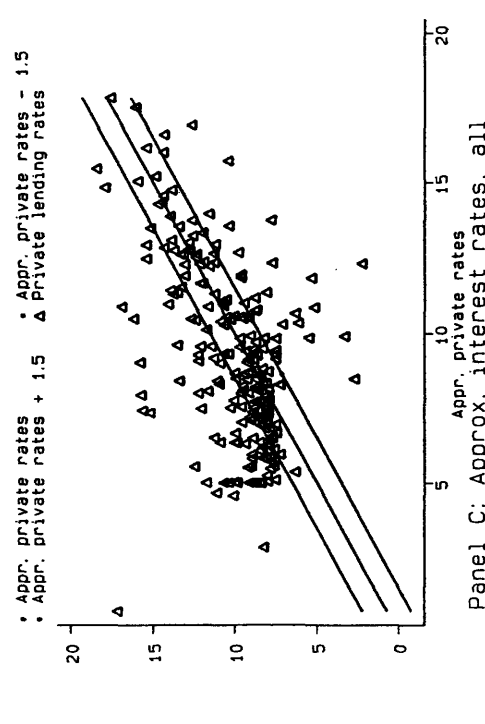
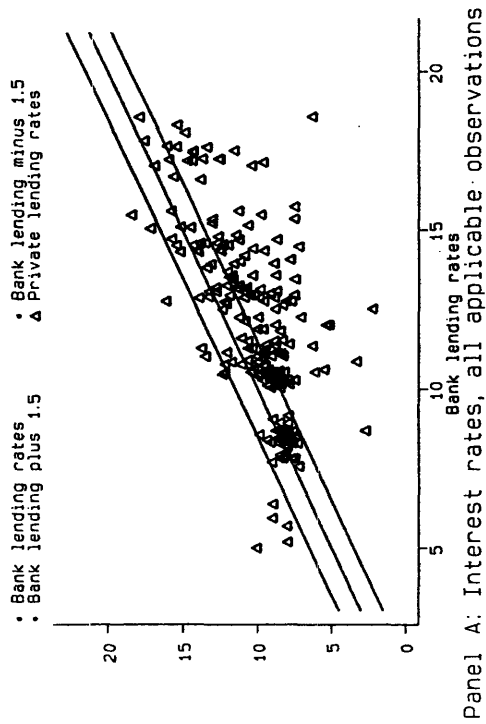
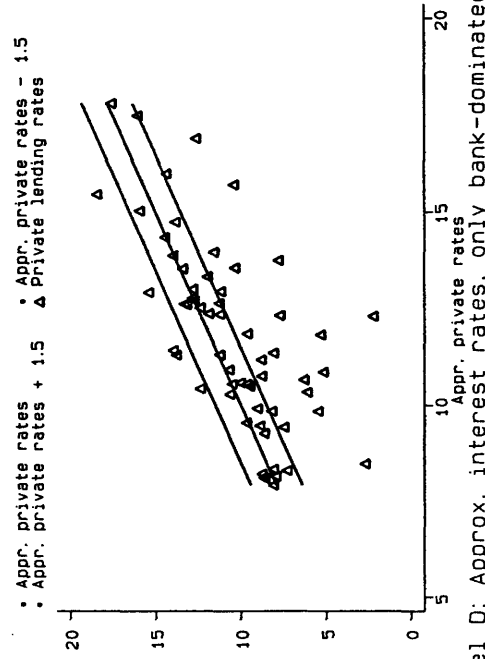
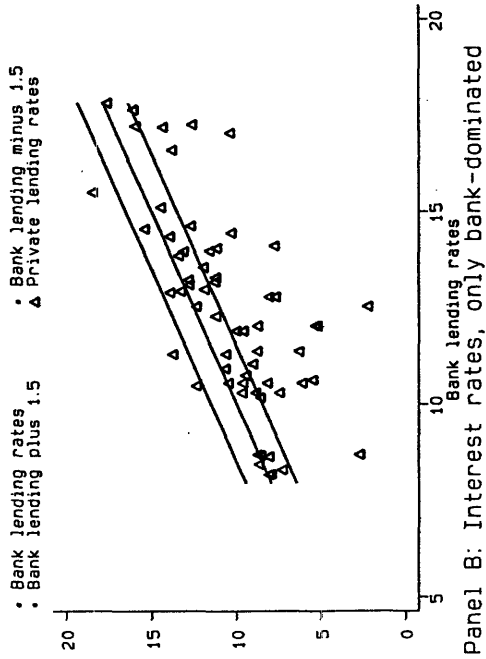
c Regional dummies are not reported, but they are insignificant and there are no differences among them.

* Denotes significance at the 5% level.

find this comparison remarkably good: There are potential timing differences (a loan this year might enter as commitment this year but not as a disbursement), currency composition issues (only eurocurrency loans, mostly dollars – all the rest should be cheaper). Moreover, the total amount of bank loans I have found in the alternative source was much smaller than either commitments or disbursements in the given year, so a large fraction of further lending might have had different interest rates. Based on these, one cannot hope for a lot more; but all the comparisons suggest that the WDT data is in fact similar to other sources, and my results are not just an artifact of noisy data.

private, 44 was within 150 basis points distance from each other in panel B; 49 in panel D.

Figure 2-4: Data from World Debt Tables vs Borrowing in International Capital Markets



2.6 Main results

2.6.1 Differences by lending types

The main puzzle is the surprisingly low borrowing spread that developing countries are paying on their new debt disbursements (on average). Table 2.1 suggested that these low spreads are largely driven by a too low coefficient on world interest rates. This was true for official lending, and more surprisingly, for private lending as well. I want to show that these low private spreads and world interest rate coefficients are again caused by different components within private lending. Giving some relief, the estimates on bond and bank rates will be much closer to one. So it will be the third category, other lending, which will have a low coefficient, and since this lending is sizable, that will pull the aggregate private responsiveness down.

To see how the interest rate coefficient and the constant term depend on the different type of lending, Table 2.4 presents the different estimates of these terms. First it reports the estimates using the existing lending rate for total lending, then for official and private; then the results from the weighted estimates for further refinements. Private is broken down into bond, bank and other lending; official is divided into bilateral and multilateral, then both is split by concessional and non-concessional²⁰

The most important feature of the table is how the decomposition changes the point estimates (notice also that the stock vs. flow composition makes no difference). For total, the interest rate coefficient is 0.17-0.18, which splits into 0.12-0.14 for official and 0.40-0.41 for private. So the average coefficient of 0.18 was hiding different behavior of the two major components.

Splitting official, there is no big difference between bilateral and multilateral lending.

²⁰The World Debt Tables terminology for concessional is the following: a loan is concessional if it has an original grant element of at least 25%. The grant element of a loan is the ratio of its grant equivalent to the total amount committed. The grant element of a loan is defined as the difference between the commitment present value and the discounted present value of contractual debt service (conventionally, discounted at 10%). What this means is that a concessional loan has an interest rate substantially below 10%: then, when adding up its interest and principal repayments, the present value will be smaller than the loan value. So when world interest rates are high (like in the 1980s), most loans even with negative spreads will *not* be concessional; and a Yen-loan with a positive spread (relative to the very low Yen interest rates, usually around 5%) will be classified as concessional. Still, there is some information in the distinction of concessional vs non-concessional: one can view those as quantiles of the entire distribution of official lending rates. It is not surprising that concessional will have a lower coefficient than non-concessional; but if multilateral concessional has a different coefficient than bilateral concessional, it means that the overall distribution of bilateral and multilateral is different.

Table 2.4: Baseline costs of lending: decomposition by types

Panel A: using stock data for currency composition			
total			
		0.18 · r_{libor} + 3.78 (5.34) (6.87)	
official		private	
0.14 · r_{bond} + 3.54 (4.31) (7.28)		0.41 · r_{libor} + 5.14 (9.58) (10.32)	
bilateral	multilateral	bond	other
0.12 · r_{bond} + 3.89 (1.78) (5.40)	0.16 · r_{bond} + 2.62 (2.25) (3.02)	1.13 · r_{bond} + 0.83 (5.00) (0.33)	0.11 · r_{libor} + 7.35 (2.63) (10.56)
non-concess.	non-concess.		
0.15 · r_{bond} + 4.55 (1.39) (4.02)	0.37 · r_{bond} + 4.13 (6.58) (6.07)	0.83 · r_{libor} + 1.54 (13.03) (1.98)	0.11 · r_{libor} + 7.35 (2.63) (10.56)
concess.			
		0.03 · r_{bond} + 2.04 (0.46) (2.64)	
Panel B: using approximated flow data for currency composition			
total			
		0.17 · r_{libor} + 3.80 (5.25) (7.04)	
official		private	
0.12 · r_{bond} + 3.61 (3.89) (7.34)		0.40 · r_{libor} + 5.22 (10.07) (11.36)	
bilateral	multilateral	bond	other
0.13 · r_{bond} + 4.12 (1.98) (5.56)	0.11 · r_{bond} + 2.66 (1.72) (3.02)	0.97 · r_{bond} + 2.68 (7.08) (1.54)	0.12 · r_{libor} + 7.17 (3.17) (11.10)
non-concess.	non-concess.		
0.14 · r_{bond} + 4.51 (1.69) (4.03)	0.34 · r_{bond} + 4.21 (6.03) (5.98)	0.75 · r_{libor} + 2.24 (12.83) (3.05)	0.12 · r_{libor} + 7.17 (3.17) (11.10)
concess.			
		0.06 · r_{bond} + 1.72 (1.00) (2.29)	

However, while bilateral does not produce any significant difference between concessional and non-concessional; multilateral does: 0.37 vs nearly zero. So multilateral and bilateral have the same average responsiveness to world interest rates, but the expensive part of multilateral is more expensive not only because of a higher constant term, but also because of a higher interest rate effect.

Within private, bond lending gets a coefficient of 0.97-1.13 – as most people would expect. Bank rates are also closer to one: 0.75-0.83, but they are still significantly below one²¹; and other rates have a very low but still significant responsiveness, 0.11-0.12.

The evolution of the constant term ("flat fee") is also interesting: first it is larger for private than for official. It seems to be somewhat larger for bilateral than for multilateral. Within bilateral, there is no further difference; within multilateral, non-concessional means a higher interest rate coefficient *and* a higher constant term. Within private, once we allow the types to differ in *both* the constant and the interest rate coefficient, we see a clear pattern: bond and bank has a high interest rate coefficient and a *low* constant term, while it is just the opposite for other. Referring back to Table 2.1, there the type-specific constants were very similar to each other – but with the interest rate coefficient constrained to be the same across types! Once that restriction is dropped, we get a separation into two kinds of lending: one with "no basic fee" but interest rates closely following the world rates (bond and bank), and another with a large flat fee but not much responsiveness to world interest rates (other lending). In this sense, other lending smoothes the big swings of the world interest rates: it is relatively more expensive when world rates are low (though it is cheap even then), but it stays cheap when world rates shoot up. Official rates also show this smoothing aspect, but they are always very low.

Table 2.5 reports all the benchmark cost estimates type by type, plus several test results: equality of the interest rate terms, constant terms, economic variables and regional dummies (across types). First of all, a disclaimer about all bond coefficient estimates. From all the appr. 1000 observations, less than 300 has bond disbursements at all. That would still constitute a large enough number for estimating a separate bond equation – but with the

²¹This is not inconsistent with having a positive spread: if the spread depends negatively on the interest rate, that would still imply an overall coefficient below one – this is what I found in Section 2.5. In the weighted regressions, the bank estimate has another reason to be too low: other lending has a much smaller coefficient, and this might pull down the bank and bond coefficients. A third reason for bank estimates being too low is that they might have different currency composition; see Section 2.5.

weighted method, the no-bond observations also have bond specific (zero) right hand side variables. This makes all the bond estimates imprecise – I find the interest rate coefficients still sensible, but I would not draw too many conclusions from any other bond variables. The

Table 2.5: Differences by types of lending

	lending type								
	private			official					
	bond	bank	other	bil.	mul.	bil.	bil.	mul.	mul.
						nc ^a	conc. ^a	nc ^a	conc. ^a
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
world rate ^b	0.97	0.75	0.12	0.13	0.11	0.14	-0.02	0.34	0.06
	(7.08)*	(10.99)*	(3.17)*	(1.98)	(1.72)	(1.69)	(0.31)	(6.03)*	(1.00)
constant	2.68	2.24	7.17	4.12	2.66	4.51	4.42	4.21	1.72
	(1.54)	(3.05)*	(11.1)*	(5.56)*	(3.02)*	(4.03)*	(5.44)*	(5.98)*	(2.29)*
world rate differentials ^c	b=c: 0.17; c=o: 0.00; b=o: 0.00			0.86		mc=mnc: 0.00; bc=bnc: 0.17; mnc=bnc: 0.09; mc=bc: 0.48			
constant differentials ^c	b=c: 0.82; c=o: 0.00; b=o: 0.01			0.27		mc=mnc: 0.01; bc=bnc: 0.95; mnc=bnc: 0.84; mc=bc: 0.04			
economic indicators differentials ^c	b=c: 0.00; c=o: 0.01; b=o: 0.00			0.01		mc=mnc: 0.02; bc=bnc: 0.01; mnc=bnc: 0.04; mc=bc: 0.63			
regional dummies differentials ^c	b=c: 0.05; c=o: 0.30; b=o: 0.07			0.00		mc=mnc: 0.03; bc=bnc: 0.00; mnc=bnc: 0.07; mc=bc: 0.00			
Number of obs.	983			1322		1322			
# of regressors ^d	57			38		76			
R ²	0.53			0.56		0.76			

a See footnote 20 on page 72 for a description of concessional loans.

b LIBOR for bank and other, government bond yield for all the rest.

c All are p-values of (joint) equality tests.

d The regressors are: world interest rate, type-specific constants, all the factors and regional dummies; all interacted with the fraction of each type of lending.

* Denotes significance at the 5% level. T-statistics are robust to clustering at the country level.

world rate and constant term test results merely support the comparisons we saw in Table 2.4: in particular, for private lending, bank and bond have equal constants and interest rate coefficients, while other is significantly different. The economic indicator estimates differ across types in all but one case (bilateral concessional and multilateral concessional), and the same applies for regional effects (here bank and other lending is the exception). So in general, these lending rates differ in the way they reflect economic and regional differences²², and there are also systematic differences in their responsiveness to world interest rates. Notice that any bias of my estimation method is working against these findings: weighting is likely to push the different coefficients closer to each other, so actual differences should

²²Edwards 1986 [4] cites and documents a similar difference of bond and bank behavior.

even be bigger than my findings.

As for the bank-other lending differential, I would attribute these deviations to completely different motifs of the lenders. There can be a difference in the enforcement mechanism²³: with bank lending, the lenders can punish mostly financially (by restricting future lending) or legally (which is not very effective in the case of sovereigns), and though monitoring is possible, but it is not easy. For other lending, the two parties have a close-range relationship²⁴, with some involvement in joint production or trade. This makes both monitoring and punishment easier than for bank loans²⁵, moreover, the overall condition of the borrower country's economy is less relevant to determine the terms of the loan.

For bank loans, the cost of the borrower and the benefit of the lender is almost entirely the interest payment. Therefore, it should be large enough to cover the cost of the funds to the lender (LIBOR), management costs and the compensation for risk. For other lending, the lender might be able to get various extra benefits. The loan can be a part of a trade agreement, where either the prices are distorted to compensate for the cheap loan (like transfer pricing), or the existence of the agreement, even at "market prices", establishes a surplus, thus means a benefit to the lender in the form of manufacturing orders (finding a market for its products). This in some sense means that the borrower country had an asset, the opening of its market to foreign producers, and asking for a cheap loan is a special way to sell this asset. The loss of the asset then can be interpreted as a cost to the borrower – but if the asset had been kept unused otherwise, this cost might not be substantial at all.

Table 2.6 briefly summarizes the behavior of the quantities of different lending types. It is the reduced form of a quantity equation, without any particular causal interpretation (it is neither a supply nor a demand relation). Surprisingly, almost all quantities increase when the world interest rates go up – the only significant exception is bond lending. Apart from bonds, there is no clear sign of high world interest rates depressing sovereign borrowing markets. When world interest rates go up, bonds become both expensive and scarce in quantities. Bank lending does not contract much, but its price increases almost as much as for bonds. Other private and official lending show very little price and quantity response.

Using the weighted method, I can now present estimates of the figures that were "miss-

²³See Eaton et al 1986 [9] for a discussion of enforcement problems in sovereign lending.

²⁴See Section 2.8 arguing that other lending is indeed more focused on firms.

²⁵There is a related literature on the cost advantage of trade credit, for example, Petersen and Rajan 1997 [10], Biais and Gollier 1997 [11].

Table 2.6: Different types of lending: quantity responses

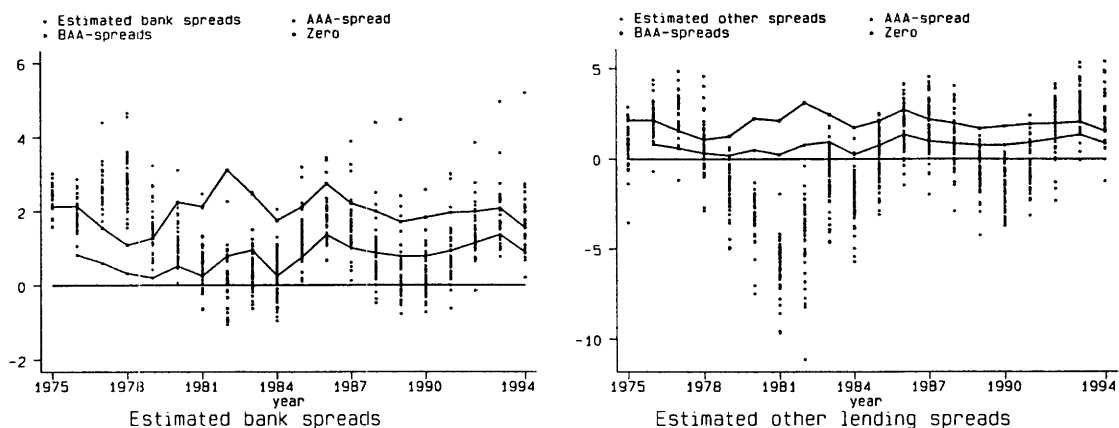
	Lending type					
	total	private				official
		aggr.	bond	bank	other	aggr.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: disbursements (only when positive)						
world rate ^b	0.02	0.01	-0.043	0.03	-0.003	0.006
	(1.00)	(1.00)	(1.67)	(1.98)	(0.47)	(1.06)
constant	0.49	0.19	0.51	-0.13	0.17	0.23
	(1.54)	(0.64)	(1.60)	(0.63)	(1.17)	(2.34)*
# of obs.	1327	1113	207	846	1055	1326
R ²	0.41	0.35	0.23	0.28	0.31	0.46
Panel B: net flows (all observations) ^c						
world rate ^b	0.03	0.02	-0.005	0.02	0.003	0.01
	(2.07)*	(1.51)	(1.36)	(1.81)	(0.91)	(2.15)*
constant	-0.19	-0.25	0.09	-0.28	-0.05	0.03
	(1.15)	(1.66)	(1.46)	(2.20)*	(1.47)	(0.49)
# of obs.	1045	1045	1045	1045	1045	1045
R ²	0.26	0.16	0.20	0.13	0.12	0.35

a All regressions are OLS, using all factors and regional effects as regressors.
b LIBOR for total, private, bank and other, government bond yield for bond and official (all currency-weighted).
c When running the same regressions only for observations with positive disbursements, apart from the larger R^2 values (due to smaller sample size), the only difference would be for bonds: the interest rate coefficient becomes -0.03 and significant, the constant becomes 2.04 and significant.
* Denotes significance at the 5% level. T-statistics are robust to clustering at the country level.

ing” from the introduction: bond, bank and other lending spreads (from now on, I will focus only on private lending). In order to do this, one just needs to use the predicted values, type by type. These estimates are not substitutes for the real data (in particular: the residuals might be quite large), but they still offer some further insight about the puzzling lending spreads. Since my bond results are particularly noisy, I do not report estimated bond spreads (they are quite dispersed, still often negative, though their overall pattern is more reasonable than private lending as a whole).

Figure 2-5 suggests a close pattern of bank lending spreads: there is relatively little dispersion within each year, so there cannot be much room for differentiating among countries. The spreads are mostly positive or near zero, but they are still below the BAA-spread line, and in many cases, below the AAA-spread line as well. Note that the weighted estimation method might pull down predicted bond and bank spreads and push up other lending spreads – so it is likely that bond and bank spreads are actually positive and of reasonable

Figure 2-5: Estimated spreads; using flow and disbursements weights



size, but other lending spreads are even more negative.

So the main source of the very low overall private lending spreads is other lending, which is on the right panel of Figure 2-5. Compared to bank lending, the spreads are much lower, and there is more dispersion within each year. So there is much more differentiation in this type of lending than in bank lending. Both features fit well into my interpretation of other lending: these loans are linked to more general economic packages or cooperation, so depending on the other conditions of the entire deal, the actual interest rate on the loan part might differ a lot across countries and contracts, and it might show a net financial loss of the lender, which is then offset by some (non-financial) benefits.

2.6.2 Differences by income groups

The data suggests a systematic difference in the borrowing rates and behavior of low- versus middle-income countries: low-income countries have lower total, official and private spreads than middle-income countries (see Figure 2-6). The difference is clear and stable for total and official lending; for private, the gap occasionally widens or narrows, or even slightly reverses, but for most of the time range, low-income countries have lower spreads than middle-income countries.

Figure 2-6 answers another question as well: so far, each observation was treated equally, so the low interest rate coefficients might hide a large number of cheap but small loans, and a small number of large and reasonably-priced loans²⁶. What we see, however, is that the

²⁶I also run a “double-weighted” reduced form regression: the weighted method, and then weighting each

average of the spreads stays low as well – so even large disbursements must have low spreads.

Do low-income countries get cheaper loans within all private types, or do they face the same overall price but use (or have access to) more of the cheap forms? Panels A and B of Figure 2-7 report the estimated income-group average spread for each type²⁷. For bond spreads, since the estimates are particularly noisy, I do not present them. They would show no evidence for low-income countries having cheaper bond-financing than middle-income countries – if anything, then the contrary. Moreover, as panel A shows, this conclusion strongly applies for bank lending: with one early exception, middle-income countries are getting *cheaper* bank loans than low-income countries²⁸. Turning to other lending (panel B), low-income countries still face very similar, in some cases even higher spreads than middle-income countries.

So how is it possible that private lending spreads are still lower for low-income countries than for middle-income countries? The answer cannot be in more favorable spreads per lending types – if anything, bond and bank lending seems to be more expensive for low-income countries, other lending nearly equally cheap – rather, it must be the *different composition* of disbursements. Other lending is not less expensive for low-income countries, but they have access to relatively more loans of this sort.

Actual compositions are displayed in panels C and D of Figure 2-7: it gives the relative importance of the three types of private lending, plus a measure for world rates (the minimum of all major lending currency government bond rates, lagged and scaled). For low-income countries, the fraction of other lending and the world rate shows a striking co-movement up to 1989; while there is no clear pattern for middle-income countries in the same period²⁹. So low-income countries shifted their disbursements towards this very cheap other lending when loans became more expensive³⁰. Whether it was a demand- or a supply

observation by the size of private disbursements; and the results stayed similar.

²⁷Most of the estimated spreads will be highly negative. This is again related to averaging here: though residuals are centered around zero, but here the residuals would also be weighted by disbursement quantities, so if the estimates produce systematically positive residuals for large debtors and negative residuals for small debtors, then the average estimated series will tend to have low spreads. So the level of these spreads does not necessarily reflect the truth, but the group differential and the time profile still conveys important information.

²⁸If other rates pull down bank coefficients more for middle-income economies than for low-income economies, then bank spreads might actually be similar for the two income groups. But it is still improbable that the order would be reversed.

²⁹After 1989, the situation seems to be reversed, but also, other lending becomes much less cheap as well.

³⁰This is in parallel with the results of Petersen and Rajan 1997 [10], Biais and Gollier 1997 [11], who find that firms change their financing composition in response to monetary contractions, or loan shortages

driven shift, one cannot tell from this figure.

This may also correspond to a sale of certain "assets" of the country: giving the right to enter its market to firms or other countries, in exchange for cheap financing. Whenever regular sources of funding are particularly scarce, poor countries, who are likely to still have most of this type of assets unsold, can get extra funding by selling them. In this sense, cheap other loans could represent a major part of the sale price of these assets.

It would be interesting to get similar data for developed countries: do the same types of (private) loans have similar interest rates, thus borrowing cost differences are driven by different debt portfolios, or are there some types of lending where there is some special treatment for certain countries?

There is another notable feature of all the figures: the landscape is surprisingly similar. There is a large drop around 1981-82, then a steady increase until 1988; a second large decrease and then spreads climb back to near zero levels. In both valleys, there is a significant increase in world interest rate, and once world rates are low again, spreads become positive in many cases. It is reminiscent of consumption smoothing: whenever world rates are high, lending rates are relatively low, but when world rates decrease, lending rates stay relatively high. For official and other private lending, the low interest rate coefficient is the main explanation of this smoothing result. For bank, the coefficient is around 0.8, which would not produce this much smoothing – so it should be the case that country characteristics provide the additional effect. It might reflect a varying pool of borrowing countries: when interest rates are high, poor and non-healthy economies shift away from bank lending, so the average risk component decreases.

As for total quantities, most of these spikes do not witness large setbacks of sovereign lending. The spike of the early eighties led to a decrease in the growth rate of new disbursements, but the trend stayed increasing until 1982. Lending resumed its positive growth between 1984 and 1988 – together with the gradual increase in world interest rates. At the peak of 1989, lending again contracted, but then further increased.

Other and official lending shows even less decline in these episodes. Bond lending was quite stable throughout the entire period, with two spikes in 1982 and 1985, and a steady increasing trend. Most of the declines are thus restricted to bank lending, which showed big drops in 1980, 1983 and 1984, and a steady decline after 1988. Overall, it seems that

in general.

Figure 2-6: Lending spreads by income groups

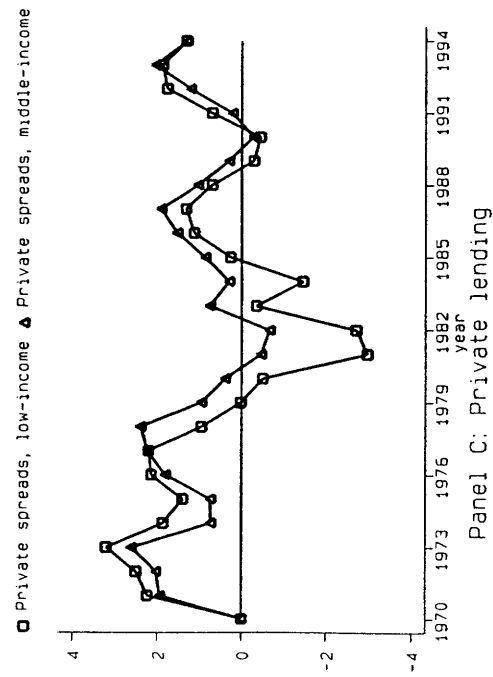
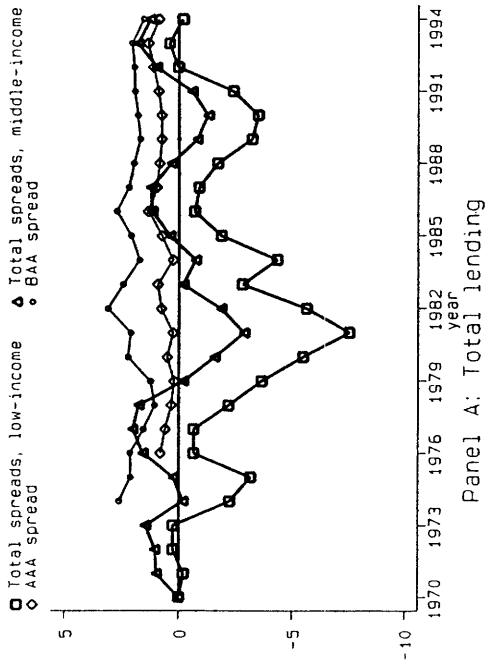
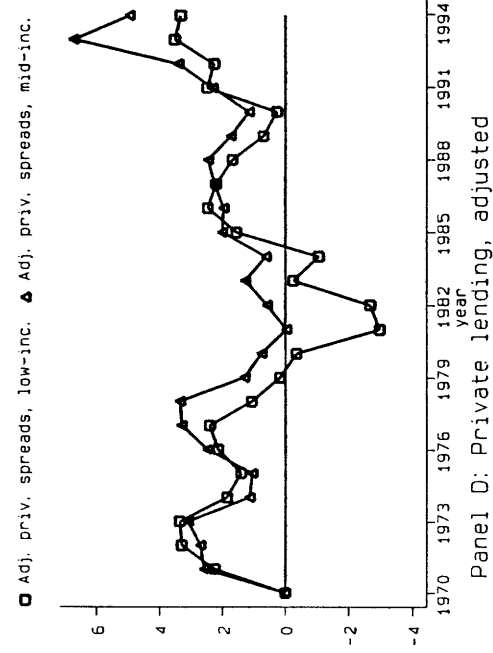
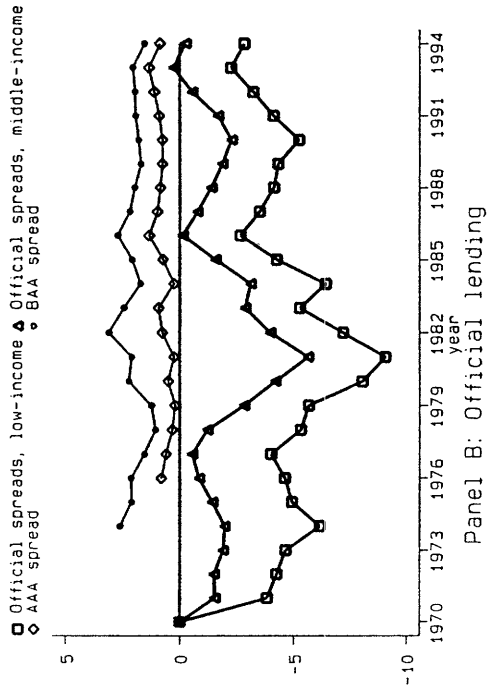
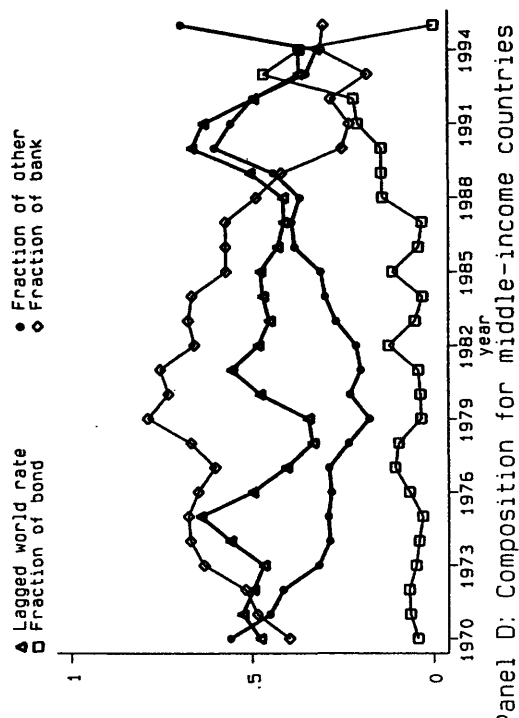
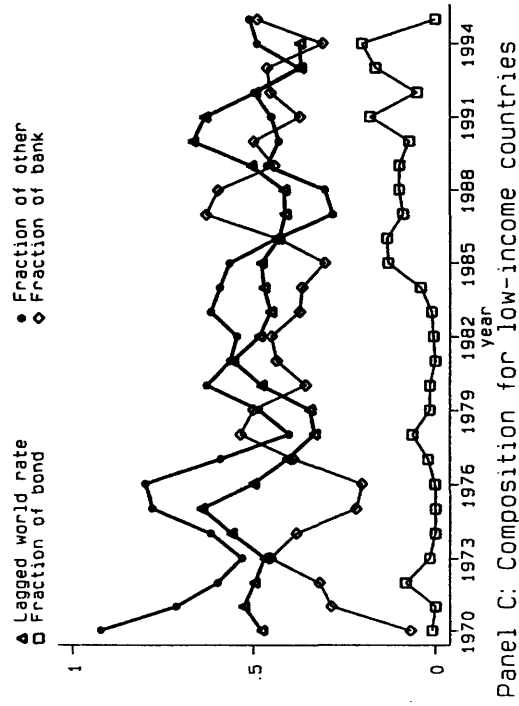
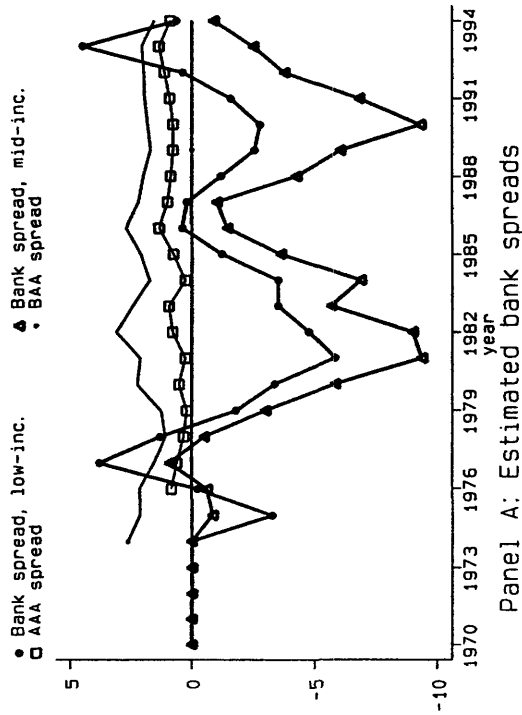
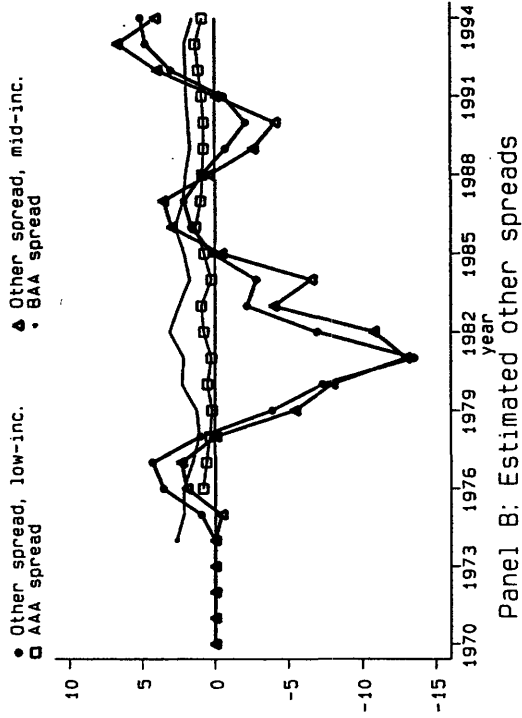


Figure 2-7: Estimated spreads of private lending types, by income groups



high world interest rates imply a notable decline in the average spread, but much less of a drop in disbursements. This is also in line with the regression results of Table 2.6.

2.7 Robustness checks

2.7.1 Using different compositions

In this subsection, I briefly discuss how my main results (for private lending) would change if I used different currency or within-type compositions. In most cases, my earlier tables and figures (e.g. Figure 2-2) used the flow composition numbers, so I comment on potential deviations from those results.

I reran my benchmark regression for stock vs. flow currency compositions, and also, for disbursements- or commitments-based within-type breakdown. For official lending, all the baseline cost coefficients stay almost the same when using stock or flow compositions.

For private lending, there is more variation of the estimates, but the baseline lending cost coefficients (the interest rate coefficient and the constant) are remarkably stable. For bond, the interest rate estimate is in the range of 0.96-1.31, always significant. This is basically a coefficient of one, slightly above. Flow estimates tend to be lower than stock estimates; and commitment numbers are larger than disbursement numbers.

The interest rate coefficient for bank lending is between 0.61 and 0.83, significantly positive and less than one. Commitment results are smaller than disbursement numbers, and the estimates decrease slightly as we move from stock to flow. For other lending, the interest rate coefficient is between 0.09 and 0.19, almost always significant. There is no real difference between the flow and the disbursement approach; and just like for bonds, commitment numbers are higher than disbursement numbers.

The constants are also quite stable: for bond, it is around zero (with one exception); for bank, it is around 2-4, significant and at least marginally larger than for bonds; for other, the range is 6.3-7.8, always significant and (at least marginally) larger than the other two. Most coefficient differential tests also show impressive stability.

For total, official or private spread figures, the two set of composition numbers makes no difference: spreads do not change, they stay low, mostly negative. It makes some difference for estimated (predicted) bond, bank and other interest rates: the dispersion occasionally increases, but the overall pattern stays the same.

2.7.2 Different methods, grouping by regions and time periods

Including country dummies has no effect on the interest rate coefficients or the difference tests. For year dummies, I can no longer have interest rates on the right hand side, as they are collinear with the year dummies. The economic indicators (factors) remained different from each other in both cases; and the comparison of the type-specific constants was also unaltered.

In the regional split, as the number of observations is smaller, I get noisier estimates, but no changes in the order of the interest rate coefficients: the bond estimate is close to the bank estimate, and other lending is different from the other two. Neither do the differential of the constants or the economic indicators change in any major way.

Estimation by 5-year subperiods gives particularly imprecise interest rate coefficients – which is natural, since the world interest rates do not vary much in five years. Still, the relative order of these coefficients stays the same (one exception of a negative but insignificant bond coefficient). The economic indicators are jointly different for other and bond, but this is a bit less true for the other two comparisons. The constants for the sub-types vary much more, there is no clear comparison pattern for them.

Though different methods and sub-samples might decrease the precision of certain estimates, what I find in general is that the economic indicator coefficients stay different across types, and the interest rate coefficients obey the same rule we saw many times by now: with some exceptions, the bond and bank estimates are similar, close to one, and the other lending estimate is close to zero. The comparison of type-specific constants is less robust, but it is still usually true that the bond and bank coefficients are similar, and they are different from other lending. So most of the key results pass the robustness checks.

2.8 Alternative interpretations

Here I want to explore some alternative explanations or interpretations of the results I have obtained. First I will discuss how much missing fees might matter. Then I evaluate the hypothesis of other lending being hidden (or misclassified) official lending. Finally, I try to find some support for other lending being related to trade, production, or at least being firm-oriented.

How much can we attribute to missing fees (or other costs) from the very low spreads,

and the small interest rate coefficients for other (and official) lending? For official and other, it is quite hard to imagine so huge and so procyclical fees that would make total (or private) spreads positive, or that would make official and other lending costs to move one-in-one together with world interest rates. Some non-financial costs are also possible (foreign influence, allowing imports or exports, etc.) – one interpretation of the results is exactly that they have to be very large. Part of those cost might be rather a benefit for the lender (economic cooperation, having access to a market, political influence etc.), which would then stand against the pure financial loss of the loan.

For bank lending, the low interest rate coefficient estimates (and the correspondingly somewhat negative spread predictions) are likely to go away with the elimination of estimation bias and missing fees. Indeed, all bank contracts reported in [2] specify a positive spread over LIBOR, plus even some fees. The slightly less than one interest rate coefficient, however, remains true even in the pure bank estimation (see Table 2.3). The estimates are really close to one, but still below it (the 95% confidence interval does not include 1)³¹.

Based on the similarity of official and other lending rates, it is a natural suspicion that other lending might correspond to misreported official lending. As it is mentioned in the book *Debt Survey of Developing Countries* [14], some misclassification (or double reporting) is possible here³². Rather than just double-counting, it is possible that some of this other lending is actually guaranteed in the lending country, so it is closer to an official than a private loan. And if these loans constitute the cheap part of other lending, then "regular" other lending rates might look much more reasonable.

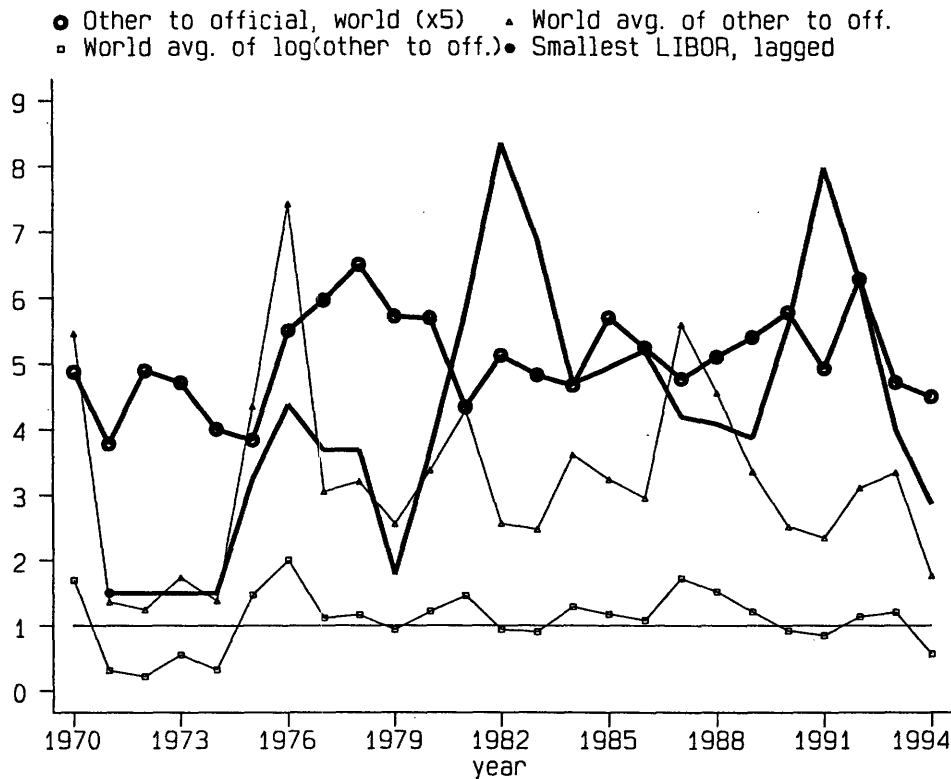
There is a straightforward test whether much of other loans is de facto official. If the misclassification is random (does not depend on world interest rates), then the ratio of other to official lending should not respond systematically to world interest rates. If, however, there is a substantial amount of "true" other lending, also being cheap and therefore its proportion increasing with world interest rates, then the other-official ratio should follow world interest rates.

Figure 2-8 reports the evolution of average other-official ratios and world interest rates.

³¹For those observations where I have both bank interest rates and fees, the total cost can be estimated as $0.34+1.005*\text{interest}$ (an R^2 of 0.98). This would not change any of the spread graphs or the regression results.

³²"Occasionally, loans being guaranteed in the borrowing country are also guaranteed in the lending country. Therefore a certain degree of double-counting cannot be excluded."

Figure 2-8: Evolution of the other-official ratio and lagged world interest rates



Though not for all episodes, but a hike in world interest rates usually comes with higher other-official ratios: the world ratio, the average ratio and the average log ratio all go up with interest rates near 1976, then come back together; and similarly (though more sluggishly) for the early 80s and early 90s. As a whole, the ratio of other to official lending goes up whenever world interest rates go up, which rejects the hypothesis of other lending being mostly disguised official lending. There is some systematic difference between these two types of lending. So what is this other lending – is it coming mainly from suppliers? Is it really trade-, or at least firm-related credit? As for the first question, it is not evident who the lenders are. In old issues, the World Debt Tables used the distinction of financial markets versus suppliers within private lending. Later it was changed to bond, bank and other. Unfortunately, there is no clear correspondence of the old supplier credit and the new other lending categories: neither in principle, nor in practice³³. All we are left with is

³³Other lending might also come through banks, but still "intermediated" by firms (suppliers, or production partners). When inspecting the detailed data, I found it hard to argue that other credit is closely

the data definition of other lending, which refers to trade, or at least production relations.

When trying to connect other lending to trade, I did not manage to establish any clear relationship: the regression of the fraction of other lending on country characteristics has produced a positive but insignificant exports ratio coefficient. Countries with less liquidity, being less developed, having less developed credit markets, with more repayment problems and with fixed exchange rate regimes tend to have higher fractions of other lending.

Should there be a tight relationship between other lending and trade flows? I would argue that it is not necessarily the case: a country might not export heavily and still receive much producer or supplier loans. Maybe it is the domestic market that the two cooperating firms (foreign and domestic) are supplying; or exports of the loan recipient are not large compared to the country's GDP, but the loan received is large relative to all long-term debt disbursements.

I do have some evidence, however, that other lending is closely related to lending to firms. One issue of the World Debt Tables reports the sectoral breakdown of debt stocks, for the years 1970, 1980, 1983-1990. The sectors are central government, local government, central bank, official development banks, public corporations, private corporations. I find a sizable correlation between the debt stock of firms (public and private) and the stock of other loans³⁴, so there is some evidence that other lending is targeted to firms. The plots of firm stock versus other stock would confirm the correlation results: within small stock observations, there is a tight relationship, with a slope of nearly one, and a plausible fit. When including large stock observations, they increase the slope but the "visual" fit decreases³⁵.

The last type of evidence which I have for supporting my interpretation of other lending is a brief case study on the borrowing behavior of Iran (using articles from the Financial Times, 1991³⁶). Before 1990, there was very little long-term borrowing in Iran: none from

related to supplier credit.

³⁴I regressed the stock of firm debt on the stock of other lending. The result is $2.23 \cdot \text{other stock} + 392M$ (t-statistics: 27.88, 2.69, R^2 of 0.42, 1049 observations) for standard OLS with robust standard errors. Since this result might be driven by a small number of very large observations, I also used robust regression methods. The result then becomes $1.39 \cdot \text{other stock} + 61M$ (t statistics: 289.16, 7.25, $F(1, 1045)=83612$). Though the coefficient became much smaller with this method, but the overall strong positive relationship remained there.

³⁵This also explains the difference of the two regressions: robust regression "downweights" outliers (the large observations), thus gets the smaller slope coefficient.

³⁶Among others: February 1 - "Payment in kind"; February 26 - "The Gulf War: Iranians are uneasy bystanders..."; March 7 - "Neutral Iran beckons..."; March 19 - The Middle East: Smiles are the best

official sources, and negligible flows from private creditors. This latter took the form of other lending, which was mostly due to the strict Islam regulation against interest payments (or borrowing as a whole).

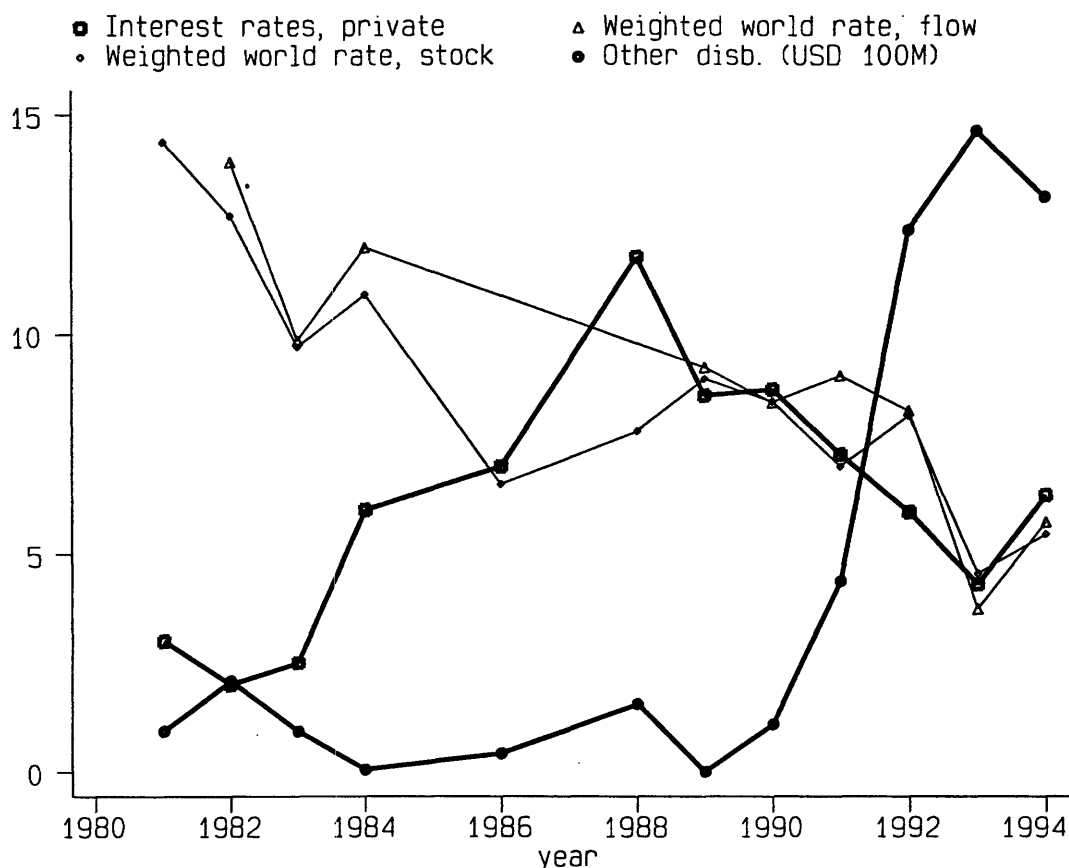
Though the regulation stayed mostly similar, the overall picture of borrowing has changed around 1991. Iran was getting large and cheap other loans: as Figure 2-9 documents, disbursements were around one billion dollars annually, and the interest rates were near, often below the benchmark world rates (both for the flow and the stock composition series). The cause for the increased role of borrowing was twofold: after the Gulf War, there was a definite shift in Iran towards opening its markets, matched with a less strict interpretation of prohibiting loans and interest payments – which led to higher possible supply of loans to Iran, and a competition for its market; and also, there was a huge demand in Iran for resources, to start the reconstruction after the Gulf War, to put all the idle manufacturing capacities to work.

Other lending stayed the nearly exclusive source of medium- and long-term lending to Iran: for most of the period, its share was 100%. The motivations and the strategies of different lenders were mostly common: they tried to get manufacturing orders by offering trade credit (Italy, for example); they linked loans to joint industrial projects or temporary shares in domestic projects, thus getting over the constraint of interest payments, decreasing the risk and also securing manufacturing orders. Germany, Iran's leading trade partner, was the leader in lending as well; but many Japanese and Brazilian firms also started cooperation with Iran, boosted by loan commitments.

We can see many important features of other lending from this example. It is potentially connected to major market openings, reconstructions, with countries or firms competing for a market share, and offering cheap loans during this process. In this case, the borrower is basically selling an asset, the right to enter its market, and the low cost of the loan reflects the sale price of this asset. Other lending is also more firm-, or project-oriented, it comes together with establishing production relations, obtaining shares in projects, or securing orders from the firm or the country. This latter is reminiscent of transfer pricing, when the price of the loan itself is not the only part of the deal, but it is bundled with a trade

measure of Iran's economy"; June 25 – "Iran turns to west for critical financing"; August 14 – "German banks set to lend Iran DM510m"; December 4 – "West scrambles for share of Iranian market"; December 9 – "The price of aggression – Export credits".

Figure 2-9: Private debt of Iran, 1980-1994



transaction (at a price different from standard market prices) as well. Finally, other lending might be a good opportunity to get around various restrictions on lending, or to evade taxes.

2.9 Conclusions

The chapter analyzed the spreads on all sovereign borrowing by developing countries. The main finding was that these spreads are surprisingly low, often well below any relevant world interest rate – for total, official and private lending as well. This finding has proven to be quite robust: no matter what currency composition, world interest rate or extra cost adjustment I was using, spreads stayed very low. Moreover, the result is not driven by cheap but small loans: loans are cheap on average. I have also checked whether the interest rate data I have was reliable enough – when compared to another World Bank data source, which reports bank lending rates at a contract level, I have found that the two sources are quite similar, and they produce similar results.

I traced these very low spreads to different types of sovereign lending. Two components were the most responsible for the strange aggregate behavior: other private (which is some medium-term trade related lending) and official lending. Though these two types are quite similar, and private loans guaranteed by the lending country might cause double-counting or misclassification, but I have checked that other lending is different from (disguised) official lending.

Apart from displaying this information graphically, I estimated many specifications, describing the spread by world interest rates, certain country and world economic indicators. Since the detailed interest rate series are unavailable, I relied on a less precise weighted estimation. Under certain assumptions, this method produces consistent estimates for the sub-type equations as well, without having their interest rates. Though those assumptions might not be fully met, but as a general assessment, this method of "weighted" OLS performs acceptably well. It is not precise enough to produce reliable estimates type by type, but it showed the difference among those types very robustly³⁷. Types differ in their sensitivity to world interest rates and the constant term, and also in the way they incorporate economic indicators.

By far, the most important and robust finding was an "interest rate smoothing" result: – other private lending and official lending are barely responding to world rates. Bank lending also has slightly "countercyclical" spreads. However, I attributed it to the effect of country characteristics (thus a changing pool of bank borrowers), and not to a low world interest rate coefficient (since it is close to one).

The composition of disbursements varied in such a way that the very high interest rates around the debt crisis and the early 90s did not leave developing countries without affordable resources. Low income countries were using, or were having more access to cheap official and other lending, which made their total cost of borrowing less responsive to world interest rates. Middle income countries did not use these cheap forms of borrowing that intensively, though other lending is nearly as cheap for them as for low-income countries. So middle-income countries do not pay a significantly higher price for other lending, they simply use less of it.

The fact that overall lending seems to have been cheap does not mean that developing

³⁷Though it is possible that the weighted method pushes the coefficients towards each other – but then the true differential must be even bigger than my findings.

countries received cheap bank loans or issued bonds at favorable conditions. On the contrary, they were paying high rates on these standard forms of borrowing. And since other lending is most likely to be channeled directly to firms, the debt service of low-income country governments may still represent a heavy burden.

There are many issues that are connected to this project and deserve future attention and research. One major topic is the quality of debt data: price, quantity and composition. Using average interest rates disguises the true behavior of the different types, and may yield misleading conclusions. Having access to reliable and detailed data on sovereign bonds, loans and other lending could further clarify the puzzling aggregate behavior I presented here. One could also compare how different types of lending incorporate sovereign risk into the pricing decision. With the bank loans data I have, I should be able to answer these questions for bank lending at least.

Are there any other – non-financial – costs of these cheap loans? This could explain why firms (and governments) are willing to offer these cheap ways of borrowing, and that middle-income countries are more reluctant (or less able) to use them. Maybe this financing corresponds to opening up new markets, establishing trade relationships – and more developed countries have less such new opportunities, or they are less eager to sell these “assets” in return for cheap loans. Other private lending might also correspond to hidden foreign investment, or may reflect tax considerations. A detailed look at such contracts (their costs, true maturity, context of the deal) should explain many of these issues.

Let me add just one concluding remark. In the introduction to Chapter 39 (Sovereign Debt), Handbook of International Economics [15], Eaton and Fernandez cite three main “facts” about sovereign lending: it is usually substantial in size, it is eventually repaid, but this repayment is often complicated. My project then adds a fourth fact: when considering all types of sovereign borrowing, it is also cheap *on average*, but that average hides a very polarized behavior of different types.

2.10 Appendix

2.10.1 The right hand side variables (factors)

1. International liquidity variables: first (and second) lag of reserves to imports, exports to GDP, (external) debt to GDP, current account balance per GDP, being in

arrears (from WDT). The first principal component estimate is $0.32 \cdot \text{reserves}_1 + 0.31 \cdot \text{reserves}_2 - 0.03 \cdot \text{exports to GDP}_1 - 0.03 \cdot \text{exports to GDP}_2 - 0.45 \cdot \text{debt to GDP}_1 - 0.44 \cdot \text{debt to GDP}_2 + 0.39 \cdot \text{current account balance}_1 + 0.40 \cdot \text{current account balance}_2 - 0.23 \cdot \text{arrears}_1$. It explains 34% of variation of the group, and indicates a positive notion of liquidity. We should expect this variable to have a negative relationship with interest rates paid by the country: with more liquidity, there is a smaller default risk per se.

2. Economic development indicators: investment growth, GDP per capita, GDP growth, growth of M2. The first principal component is $0.01 \cdot \text{investment growth}_1 + 0.02 \cdot \text{investment growth}_2 + 0.7 \cdot \text{GDP per capita}_1 + 0.7 \cdot \text{GDP per capita}_2 - 0.06 \cdot \text{GDP growth}_1 - 0.04 \cdot \text{GDP growth}_2 + 0.03 \cdot \text{growth of M2}_1 + 0.02 \cdot \text{growth of M2}_2$. It explains 24% of all variation, and captures wealth. By its effect on repayment capacities, it should have a negative effect on interest rates; but if interest rates are having a subsidy component, or if there is any price discrimination, then it might also have a positive effect.
3. Domestic credit markets: credit to private sector per GDP, national savings to GDP. The first principal component is $0.5 \cdot \text{credit to private sector per GDP}_1 + 0.5 \cdot \text{credit to private sector per GDP}_2 + 0.49 \cdot \text{savings to GDP}_1 + 0.49 \cdot \text{savings to GDP}_2$. It explains 59% of all variation, and captures the size and maybe the development of the domestic credit market. With respect to its effect on interest rates, the same discussion applies as for development indicators.
4. Currency regimes: current large devaluation, a count variable of such an event, current currency regime, current change, number of regime changes. The corresponding group variable is $0.43 \cdot \text{very large devaluation last year} + 0.46 \cdot \text{number of large devaluations in the past}_1 + 0.51 \cdot \text{currency regime change in last year} + 0.56 \cdot \text{number of past regime changes}_1$. It explains 45% of the variation, and captures exchange rate (level and regime) volatility. Hence, it should increase the risk of crises in the country.
5. Trade variables: current change in terms of trade (large import or export price movement) and a count variable for such events, exports to GDP³⁸. The group variable is

³⁸Notice that the export share was also included in the liquidity group – but it is related both liquidity and trade.

0.08· number of large terms of trade movements₁ + 0.06· large terms of trade change last year + 0.7· exports to GDP₁ + 0.7· exports to GDP₂. It explains 48% of the variation, and measures mostly the exposure to international trade, and partly trade volatility. As to the latter, that should increase borrowing rates, but it is not clear for trade openness in general.

6. Repayment variables (all from WDT): being in arrears (private and public), total number of reschedulings so far, total number of relieves ("default") so far, total number of reschedulings and relieves so far, fraction of countries in arrears within region, fraction of countries in "default" within region, debt to GDP, current account balance. The representative variable is 0.24· arrears₁ + 0.33· number of past relieves₁ + 0.34· number of any past repayment problems₁ + 0.33· fraction of countries with arrears within region₁ + 0.40· fraction of countries with any repayment trouble in last two years₁ + 0.35· debt to GDP₁ + 0.36· debt to GDP₂ - 0.18· current account balance per GDP₁ - 0.32· current account balance per GDP₂ - 0.32· pre-transition dummy. It explains 42% of all variation, and suggests a measure of actual and potential repayment problems,³⁹; hence it is expected to have a positive effect on interest rates.
7. Global economy indicators: change in oil prices, change of OECD production, US recessions. The group variable is 0.23· change of oil prices₁ - 0.51· change of oil prices₂ - 0.14· change of oil prices₃ + 0.61· change of OECD output₁ + 0.23· change of OECD output₂ - 0.39· change of OECD production₃ + 0.25· US recession indicator. This component explains 27% of all variation. It is not fully clear, however, whether it measures a positive or negative "world business cycle effect", but it is not very significant in the regressions.

2.10.2 The disbursement-commitment correction

I have the data for new disbursements in each detailed type of private lending, and the quantity of private commitments in each year. The key assumption I make is that bank lending is the most likely to cause the difference in disbursements and commitments, and

³⁹The pre-transition dummy is included here in order to capture the emergence of many new regimes, with a higher risk of defaulting on their predecessor's external debt. Though transition might also lead to better enforcement, hence a decrease in risk.

bond lending is the least. So I treat all bond disbursements as being from new commitments. Therefore the quantity of new bond commitments is the same as the quantity of new bond disbursements. The next part of commitments goes to other lending: if there are enough total commitments, then the quantity of other commitments is again the same as the quantity of other disbursements, the rest of commitments is bank lending. Otherwise, there are no bank commitments that year, and all the missing disbursements are from previously undisbursed contracts.

Though this is far from an exact and absolutely reliable correction, but it does perturb the composition notably, and, as we saw, the main findings stayed quite unchanged – so it is reasonable to believe that the true data would also give nearly the same conclusions.

2.10.3 Regression results

Table 2.7: Reduced form estimates: using "flow" composition

	private				official				
	bond	comm. bank	other	multi-lateral	bi-lateral	multilateral		bilateral	
	(1)	(2)	(3)	(4)	(5)	non-conc. ^a	conc. ^a	non-conc. ^a	conc. ^a
world rate ^b	0.97 (7.08)*	0.75 (12.83)*	0.12 (3.17)*	0.11 (1.72)	0.13 (1.98)	0.34 (6.03)*	0.06 (1.00)	0.14 (1.69)	-0.02 (-0.31)
liquidity	-0.24 (-0.53)	0.41 (1.90)	-0.48 (-3.31)*	-0.11 (-1.03)	-0.02 (-0.20)	-0.18 (-1.76)*	-0.04 (-0.48)	0.19 (0.95)	-0.08 (-0.52)
development	0.32 (0.92)	-0.08 (-0.43)	-0.06 (-0.37)	1.14 (4.83)*	0.25 (2.18)*	0.38 (2.74)*	0.32 (0.82)	0.08 (0.51)	0.53 (3.34)*
credit	0.02 (0.08)	-0.25 (-1.22)	0.27 (3.00)*	0.43 (1.89)	0.91 (5.48)*	0.00 (-0.06)	0.05 (0.46)	0.26 (1.45)	0.42 (2.56)*
currency	-0.06 (-0.31)	0.06 (0.61)	0.05 (0.60)	-0.01 (-0.14)	-0.04 (-0.42)	-0.07 (-0.90)	-0.04 (-0.51)	-0.08 (-0.59)	0.09 (0.67)
trade	-0.45 (-1.50)	0.26 (1.33)	0.09 (0.54)	-0.06 (-0.45)	-0.19 (-1.39)	-0.23 (-1.75)*	0.11 (0.91)	0.13 (0.64)	-0.15 (-0.95)
repayment	-0.12 (-0.47)	0.34 (1.87)	-0.56 (-3.05)*	-0.32 (-2.00)*	0.12 (0.55)	-0.15 (-1.01)	-0.16 (-1.37)	0.25 (0.90)	-0.09 (-0.45)
world	-0.02 (-0.12)	0.13 (1.85)	0.00 (-0.07)	-0.01 (-0.22)	-0.11 (-1.94)	-0.10 (-1.72)	0.06 (0.52)	0.00 (-0.07)	-0.09 (-1.30)
unexp. default	-0.40 (-0.51)	0.38 (1.04)	0.58 (1.57)	0.37 (1.12)	-0.11 (-0.28)	-0.53 (-1.70)	0.06 (0.27)	0.19 (0.37)	-0.15 (-0.40)
man. float	-2.16 (-2.42)*	0.15 (0.35)	0.79 (2.32)*	1.35 (2.56)*	0.75 (1.29)	0.24 (0.77)	-0.43 (-1.13)	1.27 (2.15)*	0.00 (0.02)
free float	-0.74 (-0.86)	-0.28 (-0.61)	0.91 (1.94)	1.62 (2.26)*	0.21 (0.30)	0.29 (0.80)	-0.01 (-0.04)	0.98 (1.38)	-0.28 (-0.61)
pre-debt. cr.	0.4 (0.63)	0.87 (2.91)*	-0.38 (-1.70)	0.92 (3.75)*	0.27 (0.83)	0.56 (1.82)*	0.00 (-0.04)	-0.34 (-0.40)	0.30 (1.27)
during-debt. cr.	-0.09 (-0.26)	0.30 (1.14)	-0.06 (-0.38)	0.48 (2.10)*	0.37 (1.21)	0.71 (2.96)*	0.10 (0.55)	-0.43 (-0.57)	0.33 (1.53)
pre-transition	-0.04 (-0.05)	0.38 (0.61)	0.24 (0.51)	-0.22 (-0.50)	-0.14 (-0.25)	-0.50 (-1.03)	-0.36 (-0.91)	2.35 (1.56)	-0.87 (-1.46)
constant ^c	2.68 (1.54)	2.24 (3.05)*	7.17 (11.10)*	2.66 (3.02)*	4.12 (5.56)*	4.21 (5.98)*	1.72 (2.29)*	4.51 (4.03)*	4.42 (5.44)*
Africa ^c	-6.21 (-3.15)*	-0.15 (-0.31)	-0.34 (-0.86)	0.12 (0.17)	-1.56 (-3.89)*	0.42 (1.07)	-0.32 (-0.74)	-0.44 (-0.78)	-0.64 (-1.54)
Asia ^c	-0.94 (-1.06)	0.28 (0.54)	-0.86 (-1.36)	-0.29 (-0.33)	-2.30 (-3.40)*	1.02 (2.00)*	-0.64 (-1.19)	-0.95 (-1.04)	-0.88 (-2.21)*
Europe ^c	-0.42 (-0.41)	-0.02 (-0.04)	-0.34 (-0.27)	1.32 (1.67)	-2.74 (-4.07)*	0.66 (1.74)*	-4.61 (-5.21)*	-1.03 (-1.30)	-0.54 (-0.78)
Middle-East ^c	-0.62 (-0.22)	2.37 (1.43)	-2.98 (-2.45)*	0.30 (0.16)	-1.57 (-1.16)	-1.18 (-0.52)	3.32 (4.76)*	3.64 (3.14)*	-2.17 (-3.63)*
No. of obs.	983			1322		1322			
R ²	0.531			0.566		0.766			

a Concessional is a loan with an interest rate much lower than 10%. See the text for further discussion.

b Government bond yield for all official and private bond; LIBOR for bank and other private.

c The Latin America dummy is excluded, hence all regional dummies are relative to Latin America.

* Denotes significance at the 5% level. T-stats are corrected for clustering at the country level.

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Chapter 3

Learning, noise traders, the volatility and the level of bond spreads

3.1 Introduction

What determines the price of a sovereign bond? It should reflect various risks investors face: default risk (you do not get the payment which was expected), exchange rate risk (the value of your payment decreases because of exchange rate fluctuations), interest rate risk (the short-term interest rates move so the discount rate changes) and liquidity risk (when you sell, prices are low – either for exogenous reasons, or because your sale has a big price effects; or there might be some pure transaction costs). Looking at foreign currency denominated sovereign bond spreads, the exchange rate risk and the interest rate risk should be mostly eliminated: you get the payments in the "right" currency, and the payment is appropriately in excess of the benchmark (dollar) interest rate. Then all is left is default and liquidity risk.

Sovereign bond spreads often deviate too much from what one would think as reasonable default probability perceptions. Based only on default risk considerations, for example, crisis times should have much less effect on long-term than on short-term bond spreads – Broner and Lorenzoni 2000 [1] documents the opposite. The empirical results in the first chapter also suggests that bond spreads reflect many other factors besides pure default

risk, illiquidity risk being a major extra risk component (in the form of expected future price volatility). This effect is in some sense also reminiscent of the excess volatility puzzle (Leroy and Porter 1981 [13], Shiller 1981 [14]): here changes in default probability lead to too large movements in spreads (a level and a volatility effect), while there stock prices move much relative to movements in dividends (a volatility effect) .

One can attribute this to some form of bounded rationality of investors – instead, I want to maintain full rationality and look for a potential explanation within that framework. Then the natural candidate for the extra spread increase is the liquidity of the bond, which may come from many different sources. Maybe all potential buyers are without sufficient resources to buy the bond, so the price will have to drop a lot to attract a buyer. Or the market size is small, therefore each transaction will substantially reduce the price. A nearly mechanical though also canonical form of illiquidity is the presence of transaction costs (brokerage fees, bid-ask spread differentials). Another traditional source of illiquidity is asymmetric information: if you have any private information, then your sale might give a bad signal to the market, thus depress the prices even more than the true increase in default risk.

These considerations are not new in the literature. For example, Bradley (1991) [6] studies price differences among comparable Eurobond issues: after controlling for maturity, coupon size and default risk (proxied by credit rating, which is not necessarily a perfect measure), bonds from different issuer groups still have different prices, which can be attributed to liquidity. The approach, however, lacks a clear identification of a channel through which liquidity would operate.

Hirtle 1988 [7] finds little *aggregate* liquidity effect in the junk bond markets: following certain aggregate shocks to market-specific liquidity, junk bond returns decrease only for a very short-term. These results are likely to be specific to the particular market and episode though: they are unlikely to hold after the East Asian and Russian crises; also, Broner and Lorenzoni 2000 [1] show that the behavior of Latin American sovereign bonds can be explained by market-specific liquidity shocks.

Amihud and Mendelson 1991 [5] show that T-notes are substantially less liquid than T-bills, which is attributable to a smaller number of potential buyers, and it also leads to higher fees and bid-ask spread differentials for T-notes than for T-bills. These differentials then clearly translate into price differentials, driven by liquidity. Redding 1999 [4] picks

up a related point: the paper analyzes the difference between currently issued thus heavily traded, and already existing but similar maturity US Treasury Bonds, and finds evidence for a liquidity premium. In both cases, the source of liquidity is the depth of the market: with many sellers, it is easier to do transactions, which forces fees to be smaller, and increases liquidity in general. However, unless one explicitly models systematic fluctuations in this depth, liquidity will be nearly constant, so spreads should move fully together with changes in default risk.

Instead of any of these particular explanations, I want to use a more general form of illiquidity: investors have a chance that they need to sell the bond before they initially were planning to, and for *any* reason, the price may be particularly low at that time. The price may be low because the lack of aggregate resources, informational problems, thin markets or any other explanation – that does not change the overall interpretation that they are selling the bond at the wrong time. The general feature is that investors care not only for the terminal payoff (repayment probability, maybe even its variance), but the way uncertainty is resolved also matters. With many interim steps of the terminal payoff lottery, pre-maturity prices will fluctuate a lot, and with a chance of early sale (liquidation), investors will value such a bond less.

This approach is somewhat similar to Grossman and Miller 1988 [3]: in their model, investors occasionally need to adjust their portfolios. Then they face the choice between selling immediately but maybe not for the most eager buyer, or searching longer but risking a price drop. Some intermediate liquidity providers may then take away some of this risk. It is not fully clear, however, how this framework relates to price volatility: with more volatility, waiting increases the chance of a price drop, but also of a recovery. Still, liquidity is also modeled in terms of potential price movements near times when investors may want to rebalance (or downsize) their portfolios.

In my framework, the reason why investors care for volatile pre-maturity prices is the following: they usually have uncertain investment horizons, so there is a less than one probability that they can hold on to the particular asset as long as planned, desired or in some sense optimal. Thus there is also a possibility that they have to liquidate some or all of the investment at earlier stages, so fluctuating pre-maturity prices impose some risk. Therefore, I will try to link higher future (expected) volatility to lower current prices: thus a future volatility effect would lead to a current level effect.

If the source of future price fluctuations is different from a change in the *current* default risk, then this effect should be particularly clear: if something happens today that increases future volatility *without* increasing the current (expected) default probability, then one would see a drop in prices without an increase in perceived risk. The effect would also be present if a change in current default probabilities implies higher future price volatility: current prices would drop more than implied by the change in default risk.

This naturally leads to the conclusion that learning, or more precisely, changes in the speed of information revelation can give us the desired effect. Since sovereign bond defaults are rare, and they are usually driven by the unwillingness, and not just the inability of the country to pay, there is an adherent uncertainty about default. Investors can, however, observe the behavior of countries through time – which might change their beliefs about how bad fundamentals must be to have a default. This also means that investors would get much more new information about the country around crises – then they do see whether the country resisted a storm of a given size or had to bend.

Faster learning, the revelation of more precise information will in general lead to more volatile prices. This is documented in various empirical papers: for example, Ederington and Lee 1993 [9], and Harvey and Huang 1991 [10] show that announcements lead to increased price volatility of US Treasuries and also in foreign exchange futures markets. Jones, Kaul and Lipson 1994 [11] also find that public information is the major source of short-term volatility in the stock market. Krebs 1999 [8] provides a theoretical model supporting the same argument.

Expecting an increase in the speed of learning, thus anticipating more volatile prices in the near the future may cause large expected wealth fluctuations – and if there is a chance that an investor has to liquidate her portfolio exactly in those volatile weeks, that increases the risk of the bond. Even for the same levels of volatility and risk further away in the future, the bond becomes more risky, which then drives the price down, potentially much more than what the increase or uncertainty about default probabilities would imply. This effect might dominate for long-term bonds: with any new twist of a crisis, their default risk changes slightly, leading to higher current and expected price volatility. Increased expected volatility then amplifies the initial level effect of higher risk, leading to a much larger price drop.

The aim of the chapter is to establish this channel in a model with rational agents

who face a Diamond-Dybvig 1983 [2] type taste shock. Under certain assumptions, I will establish that getting more information before maturity may decrease issue prices, together with (or intuitively: driven by) increased pre-maturity price volatility. This effect can be quite important quantitatively: under reasonable parameter assumptions, the spread may increase by 50% in response to accelerated learning. In this sense, releasing information may hurt the issuer of the bond (getting a lower issue price), but it may also hurt investors (decreasing their welfare). This latter result is similar to Hirshleifer 1971 [15], where a release of some information eliminates the possibility of self-insurance, thus decreases total welfare. My result is driven by the following mechanism. Suppose agents are subject to the same wealth constraints (hence, the same bond price, and they must buy 1 unit per head) but they can self-insure among themselves. For a common price level p , early information revelation is unambiguously good: it enables fully contingent consumption plans. If, however, the price levels are different for the two learning scenarios, the wealth effect (through the budget constraints) and this contingency effect might have opposite signs and the comparison is ambiguous. Moving to the no self-insurance setup, there is a welfare loss: the joint budget constraint of early and late consumers might be sub-optimally split into two separate constraints. Whether this loss is bigger for early revelation than for late revelation is again ambiguous – so the comparison of no self-insurance welfare levels is ambiguous, fast learning can increase or decrease investor welfare.

In order to have learning at all, I need to have a positive default probability – otherwise no interesting information could be ever released. Let me emphasize that learning is completely mechanical here, it simply refers to the revelation of some information, getting or not some (perfect) public information – there are no noisy signals, or a need to estimate probabilities based on past realizations of events. That kind of a more sophisticated learning also has very important effects on pricing behavior, as explored and surveyed in Cassano 1999 [12] (among others).

The key ingredient for my results is that early consumers are more risk-averse than late consumers: if late consumers are risk-neutral while early consumers show any small degree of risk-aversion, the result applies. For risk-averse late consumers, there must be a sufficient difference in the risk aversion of the two types of consumers, but for any concave utility function u of late consumers, it is possible to find appropriate utility functions v for early consumers in a way that the results hold.

In reality, this entire learning process is obscured by the very important fact that default is ultimately a deliberate action of the country. This means that countries might try to strategically alter their behavior in order to decrease the market's risk perception. And it is indeed the case that developing countries have mostly refrained from bond defaults ever since the debt crises. In my simple framework, I will not be able to address this issue – I assume that there is a reduced form of the country's behavior, so these strategic elements are already taken into account.

The chapter is organized as follows. The next section describes the model, and derives the first order conditions of investor maximization. Section 3.3 contains the results: first the price and welfare comparison of slow and fast learning, then a more continuous mixture of these two extremes. Finally, Section 3.4 concludes.

3.2 The model

3.2.1 Ingredients

I want to model learning as getting a more precise signal about the default realization before maturity. In one extreme, you do not get any signal, so you do not learn anything new before maturity – late, or slow learning case; the other extreme is a perfect signal, or complete information revelation: you learn before maturity whether repayment will be made – early, or fast learning case.

There is a continuum of agents, who face a potential (unobservable and idiosyncratic) taste shock: with some probability, they become early consumers, who value consumption (or in general: asset returns) at an early period. The model thus must have three periods: an issue period with a fixed (inelastic) supply of the bond (period zero), a pre-maturity period 1, when some investors are hit by idiosyncratic and unobservable taste shocks, plus the uncertainty is potentially resolved; finally, a maturity period, when repayment is realized, and all investors get their returns.

In period 0, investors buy the risky bond at p_0 , and store the rest of their initial wealth (one to one technology). There is a fixed (inelastic) supply of the bond, which gives 1 in period 2 with probability α , and zero with probability $1 - \alpha$. In period 1, they learn whether they are early consumers (in which case they cash all their assets and eat only in period 1) or not (consume only in period 2). In the case of slow learning, they trade after this

was realized. There is a chance λ of becoming an early consumer, but there is no aggregate uncertainty about it (idiosyncratic risk, continuum of agents) – so there will be one price level.

In the case of early learning, agents also learn whether the bond will be paid back or not (same probabilities as ex ante: α and $1 - \alpha$), and then they can trade based on both pieces of information – so there will be two price levels: $p = 1$ if there is repayment, $p = 0$ if no repayment. Finally, in period 2, repayment is realized, and late consumers consume all of their wealth.

The utility of consumers is given by $E[u_1(c_1) + u_2(c_2)]$. For late consumers, $u_1 = 0$, $u_2 = u$; for early consumers (hit by liquidity shock), $u_1 = v$, $u_2 = 0$. I assume that agents are not risk-lovers (either risk-neutral or risk-averse), and that early consumers are at least as risk-averse as late consumers. A special case is when late consumers are risk-neutral, but early consumers are risk-averse.

3.2.2 Solving the model – slow learning case

In period zero, all agents are identical, and have a wealth of 2. There is some fixed (positive) quantity of the risky bond offered by the issuer – it must be less than 2, otherwise there would not be enough aggregate resources to buy all the bonds. For simplicity, I assume that the supply of bond is 1. Each agent maximizes her expected utility by buying some amount b_0 of bonds and keeping x_0 in cash. There is an equilibrium price p_0 at the bond market.

In period 1, early consumers sell all their bonds at the equilibrium price p_1 and eat all of their wealth, thus $c_1 = x_0 + p_1 b_0$. Late consumers buy b_1 bonds and keep $x_1 = x_0 + p_1 b_0 - p_1 b_1$ in cash.

In period 2, late consumers eat $c_{2G} = x_1 + b_1$ if bond is repaid (probability α), or only $c_{2B} = x_1$ if no repayment (probability $1 - \alpha$).

The expected utility at period zero is:

$$\begin{aligned}
 U &= \lambda v(c_1) + (1 - \lambda) [\alpha u(c_{2G}) + (1 - \alpha) u(c_{2B})] = \lambda v(x_0 + p_1 b_0) \\
 &\quad + (1 - \lambda) [\alpha u(x_0 + p_1 b_0 - p_1 b_1 + b_1) + (1 - \alpha) u(x_0 + p_1 b_0 - p_1 b_1)]
 \end{aligned}$$

Agents want to maximize this with respect to x_0 , b_0 and b_1 , subject to the initial budget

constraint $x_0 + p_0 b_0 = 2$ (the period 1 constraint is already substituted in). Denote the Lagrange multiplier of the budget constraint by μ , then the first order conditions for x_0 and b_0 are:

$$\begin{aligned} \frac{\partial}{\partial x_0} : \\ \mu &= \lambda v'(x_0 + p_1 b_0) + (1 - \lambda) \alpha u'(x_0 + p_1 b_0 - x_1 - p_1 b_1) \\ &\quad + (1 - \lambda)(1 - \alpha) u'(x_0 + p_1 b_0 - p_1 b_1) \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial b_0} : \\ p_0 \mu &= \lambda p_1 v'(x_0 + p_1 b_0) + (1 - \lambda) \alpha p_1 u'(x_0 + p_1 b_0 - x_1 - p_1 b_1) \\ &\quad + (1 - \lambda)(1 - \alpha) p_1 u'(x_0 + p_1 b_0 - p_1 b_1) \end{aligned}$$

Since the marginal utilities are strictly positive, these two first order conditions imply that in equilibrium, we must have $p_0 = p_1 = p$. The intuition and interpretation of this result is clear: since there is no uncertainty about the period 1 price, it cannot be different from the period 0 price, because then everyone would want to buy infinite amounts of the bond or nobody would be ready to buy at all. For this constant price level, individuals are indifferent between bonds and cash in period 0, since the period 1 returns of the two are equal. So $b_0 = 1$ can be achieved (market clearing condition for bonds at period zero).

Using this, the objective function can be rewritten as

$$U = \lambda v(2) + (1 - \lambda) [\alpha u(2 - p b_1 + b_1) + (1 - \alpha) u(2 - p b_1)].$$

This is an unconstrained maximization, and the first order condition becomes

$$\frac{\partial}{\partial b_1} : \alpha u'(2 - p b_1 + b_1)(1 - p) = (1 - \alpha) p u'(2 - p b_1)$$

In equilibrium, we must have $b_1 = \frac{1}{1 - \lambda}$, since there are $1 - \lambda$ agents buying bonds, and the total holding must be equal to the amount of bonds, which is 1. This gives us an

equation for $p_{late}(\lambda)$:

$$\alpha u' \left(2 + \frac{1-p}{1-\lambda} \right) (1-p) = (1-\alpha) u' \left(2 - \frac{p}{1-\lambda} \right) p$$

$$\frac{\alpha}{1-\alpha} \frac{1-p}{p} = \frac{u' \left(2 - \frac{p}{1-\lambda} \right)}{u' \left(2 + \frac{1-p}{1-\lambda} \right)} \quad (3.1)$$

Compared to the "no taste shock, no learning" benchmark ($\lambda = 0$), one can see an "excess supply" effect in this equation: the price level is determined through market equilibrium in period 1, when there are only $1 - \lambda$ agents as buyers. If they are risk-averse, the price must fall in order to make them willing to hold that much of the risky asset.

3.2.3 The fast learning case

At period 0, the equilibrium price is p_0 , and agents choose to hold x_0 in cash and b_0 in bonds. In period 1, if the news were good, then $p_1 = 1$ (the bond becomes a perfect substitute for money, since it is perfectly safe), the wealth of consumers is $x_0 + b_0$. Early consumers thus eat $x_0 + b_0$, late consumers then eat $x_0 + b_0$ in the second period. In period 1, if the news were bad, then the bond becomes worthless, $p_1 = 0$, early consumers eat x_0 , late consumers choose $c_2 = x_0$. So the objective function of investors is:

$$U = \alpha(1-\lambda)u(x_0 + b_0) + \alpha\lambda v(x_0 + b_0) + (1-\alpha)(1-\lambda)u(x_0) + (1-\alpha)\lambda v(x_0).$$

Using the budget constraint, I can eliminate x_0 from the objective function: $x_0 = 2 - p_0 b_0$, thus

$$U = \alpha(1-\lambda)u(2 - p_0 b_0 + b_0) + \alpha\lambda v(2 - p_0 b_0 + b_0) \\ + (1-\alpha)(1-\lambda)u(2 - p_0 b_0) + (1-\alpha)\lambda v(2 - p_0 b_0).$$

First order condition:

$$\alpha(1-\lambda)(1-p_0)u'(2 - p_0 b_0 + b_0) + \alpha\lambda(1-p_0)v'(2 - p_0 b_0 + b_0) \\ = (1-\alpha)(1-\lambda)p_0 u'(2 - p_0 b_0) + (1-\alpha)\lambda p_0 v'(2 - p_0 b_0)$$

In equilibrium, we must have $b_0 = 1$, which gives us a single equation defining $p_{early}(\lambda)$:

$$\begin{aligned} & \alpha(1-\lambda)(1-p)u'(3-p) + \alpha\lambda(1-p)v'(3-p) \\ = & (1-\alpha)(1-\lambda)pu'(2-p) + (1-\alpha)\lambda pv'(2-p) \\ \\ & \frac{\alpha}{1-\alpha} \frac{1-p}{p} = \frac{(1-\lambda)u'(2-p) + \lambda v'(2-p)}{(1-\lambda)u'(3-p) + \lambda v'(3-p)} \end{aligned} \quad (3.2)$$

Assume that $v(x) = f(u(x))$. Later I will specify what assumptions are necessary about this function f – in general, it should be concave, which makes v more concave than u , so early consumers are more risk-averse than late consumers. Then $v'(x) = f'(u(x))u'(x)$. Substituting this into (3.2):

$$\frac{\alpha}{1-\alpha} \frac{1-p}{p} = \frac{u'(2-p)}{u'(3-p)} \underbrace{\frac{(1-\lambda) + \lambda f'(u(2-p))}{(1-\lambda) + \lambda f'(u(3-p))}}_{\text{Adjustment term } K} \quad (3.3)$$

Here there is no "excess supply" effect: the argument of the marginal utilities corresponds to period zero, where each agent must end up holding one unit of the bond. There is, however, the wealth fluctuation term K . This reflects the fact that the uncertainty is resolved already at period one, and some of the period one investors (the early consumers) are different from the period two investors (late consumers): if f' is not constant, i.e., early consumers have a different risk-aversion from late consumers, then period zero prices will reflect this difference. With $\lambda > 0$ and f' decreasing, K is greater than one, which decreases the price, compared to the "no taste shock, no learning" benchmark ($\lambda = 0$).

Intuitively, fast learning makes the risky asset riskless before maturity, so its issue price will be determined by equilibrium at the time of issue – when demand is high (all investors are buyers). However, fast learning also leads to pre-maturity wealth fluctuations, while slow learning keeps wealth constant. At the time of issue, since all investors have a chance to get the taste shock, this makes bonds more risky, which works to lower issue prices for fast learning. Depending on the balance of these two effects, accelerated future learning may increase or decrease current bond prices.

3.3 Results

3.3.1 Comparing slow and fast learning

My object of interest is the price and welfare difference between slow and fast learning. If it is possible to have $p_{late} > p_{early}$, then an increase in the speed of information revelation may decrease bond prices, thus increase bond spreads – even without those news being bad in expectations. Similarly, I am interested in welfare: is more information (faster learning) always good for investors or for the issuer?

The first result is about the "no taste shock" benchmark: it is easy to see that the speed of learning will have no effect on prices or welfare. If agents care only about their terminal payoffs, it does not matter how uncertainty is resolved; thus the "no taste shock" case is identical to the "no taste shock, no learning" benchmark.

Proposition 1 *If $\lambda = 0$, then $p_{early} = p_{late}$.*

Proof. In this case, the two first order conditions (3.1) and (3.3) become identical, so period zero prices are the same. In period one, there are no trades no matter whether new information is released or not, since everyone is identical. Therefore, the level of utility is also the same in the two cases. ■

This means that without the chance of some investors becoming early consumers ("noise traders"), a bond with earlier information revelation will always sell at the same price than a bond with late information, and investors are unaffected by way uncertainty is resolved. The reason is that both effects ("excess supply" and "wealth fluctuations") are reduced to zero: without early consumers, no investor cares for period one wealth fluctuations, and there is no difference between period zero and period one demand for the bond.

In order to establish conditions under which it is possible to have $p_{early} < p_{late}$, I will use the monotonicity of certain terms from the first order conditions. These properties are established in the following lemmas.

Lemma 2 *For any concave function u , $\frac{u'(2-px)}{u'(2+(1-p)x)}$ is increasing in x .*

Proof. If $x > x'$, then $2 - px < 2 - px'$, so $u'(2 - px) > u'(2 - px')$. Similarly,

$u'(2 + (1 - p)x) < u'(2 + (1 - p)x')$. This means

$$\frac{u'(2 - px)}{u'(2 + (1 - p)x)} > \frac{u'(2 - px')}{u'(2 + (1 - p)x')}.$$

■

Lemma 3 *For any concave u with nonincreasing coefficient of absolute risk aversion, $\frac{p}{1-p} \frac{u'(2-p)}{u'(3-p)}$ is increasing in p .*

Proof. The term $\frac{p}{1-p}$ is increasing in p : when p increases, the numerator goes up and the denominator goes down. So all I need is that $\frac{u'(2-p)}{u'(3-p)}$ is increasing. Its derivative is

$$\frac{-u''(2-p)u'(3-p) + u''(3-p)u'(2-p)}{(u'(3-p))^2} = \frac{u'(2-p)}{u'(3-p)} \left(\frac{-u''(2-p)}{u'(2-p)} - \frac{-u''(3-p)}{u'(3-p)} \right),$$

which is positive if u has nonincreasing coefficient of absolute risk aversion. Note that this term will be decreasing if the coefficient of absolute risk aversion is increasing – but the $\frac{p}{1-p}$ might be still increasing enough to make the product also increasing. So the statement is true for a moderately increasing absolute risk aversion case as well. ■

Proposition 4 *It is possible to have $p_{early}(\lambda) < p_{late}(\lambda)$. In particular, if late consumers are risk-neutral ($u(x) = x$) and $\lambda > 0$, then accelerated learning decreases period zero bond prices. Moreover, for any concave u , v has to be "sufficiently more concave" than u in order to have $p_{early} < p_{late}$. Having $u = \beta v$ (standard Diamond-Dybvig) is not sufficient to generate this effect.*

As the probability of a liquidity shock becomes positive, early information revelation (fast learning) might cause the period 0 price to drop – the effect of period 1 wealth fluctuations on early consumers becomes dominant and makes the bond less desirable. In the risk-neutral late consumer case, the "excess supply" channel is simply reduced to zero: with risk-neutral buyers at period one, demand for the bond is flat.

In general, the wealth fluctuations effect is large if early consumers are sufficiently hurt by wealth fluctuations, so if v is concave enough. The "excess supply" effect depends on how much risky asset each late consumer must end up buying ($\frac{1}{\lambda}$) and how much premium they require to compensate for the riskiness of the bond (the concavity of the u). Thus, in order to have the wealth fluctuations effect dominate the excess supply effect, the adjustment

term K in (3.3) has to be large, so f' must be sufficiently decreasing, which means that v must be sufficiently more concave than u .

Proof. When $u(x) = x$, the argument is straightforward: in the late revelation case, the period 1 price is determined by risk neutral traders, so it is equal to the expected value α ; and period 0 prices must be equal to period 1 prices. In the early revelation case, period 0 trade involves risk-averse traders (the component λv of their utility function), so the bond must be traded below its expected value. More formally: when u' is constant, (3.1) implies $\frac{\alpha}{1-\alpha} = \frac{p_{late}}{1-p_{late}}$. As long as f' is decreasing (so f is concave, so v is more concave than u) and $\lambda > 0$, K is larger than one, so (3.3) means that $\frac{\alpha}{1-\alpha} > \frac{p_{early}}{1-p_{early}}$, thus $p_{late} > p_{early}$.

If $u = \beta v$ (so f is basically linear), then the adjustment term in (3.3) is 1. So

$$\begin{aligned}\frac{\alpha}{1-\alpha} &= \frac{p_{late}}{1-p_{late}} \frac{u' \left(2 - \frac{p_{late}}{1-\lambda}\right)}{u' \left(2 - \frac{1-p_{late}}{1-\lambda}\right)} \\ \frac{\alpha}{1-\alpha} &= \frac{p_{early}}{1-p_{early}} \frac{u' (2 - p_{early})}{u' (3 - p_{early})}\end{aligned}$$

According to Lemma 2, since $\lambda > 0$,

$$\frac{u' (2 - p)}{u' (3 - p)} < \frac{u' \left(2 - \frac{p}{1-\lambda}\right)}{u' \left(2 + \frac{1-p}{1-\lambda}\right)},$$

so

$$\frac{u' (2 - p_{late})}{u' (3 - p_{late})} \frac{p_{late}}{1 - p_{late}} < \frac{u' (2 - p_{early})}{u' (3 - p_{early})} \frac{p_{early}}{1 - p_{early}}.$$

From Lemma 3, $g(p) = \frac{u'(2-p)}{u'(3-p)} \frac{p}{1-p}$ is increasing, which shows that $p_{early} > p_{late}$ holds.

Consider the case when f is concave, then the adjustment term of (3.3) is greater than 1. The same argument as for $u = \beta v$ gives us that $g(p_{late}) < g(p_{early})K$ for some $K > 1$. If $p_{late} > p_{early}$ holds, then we also have $g(p_{late}) > g(p_{early})$, using Lemma 3 again. So the adjustment term $K = \frac{(1-\lambda)+\lambda f'(u(2-p))}{(1-\lambda)+\lambda f'(u(3-p))}$ must be large enough to enable $p_{late} > p_{early}$. ■

Notice that the variance of period 1 prices is zero in the slow learning case, and it is positive in the fast learning case – so a bond with the same default probability but higher interim price volatility will have a lower price than with the same default probability but smaller interim price volatility. However, this is not always the case – for other parameter

values, the higher volatility bond would have a higher price. Still, this is a potential explanation of my empirical findings from the first chapter – without any correlation with the rest of the market, under certain conditions, a bond with more volatile future prices is less attractive today.

The next example shows that the risk-neutrality of late consumers is not necessary for the previous result. Moreover, for any u , one can find an appropriate v which leads to $p_{late} > p_{early}$ (by choosing an appropriately decreasing function f').

Example 5 *For some concave u , it is possible to have $p_{late} > p_{early}$.*

Choose $u = \frac{1}{\sigma}x^\sigma$, $v = \frac{1}{\beta}x^\beta$. For $\alpha = 0.5$, $\lambda = 0.1$, $\sigma = 0.9$, $\beta = 0.1$, solving numerically the first order conditions (3.1) and (3.2), one gets $p_{late} = 0.4858\dots$, $p_{early} = 0.4811\dots$, so $p_{early} < p_{late}$. For $\sigma = 0.95$, $\beta = -3$, $\lambda = 0.5$, $\alpha = 0.95$, we have an even bigger difference: $p_{early} = 0.9180\dots < p_{late} = 0.9426\dots$ In this second example, the spread has increased by near 3 percentage points in response to faster learning – in other words, it has increased by nearly 50%, and faster learning is "responsible" for almost one third of the total spread.

Proposition 6 *For any concave u and $\bar{\lambda} > 0$, it is possible to have v such that for any $1 > \lambda > \bar{\lambda}$, $p_{late}(\lambda) > p_{early}(\lambda)$ holds.*

Proof. First I show that $p_{late}(\lambda)$ is decreasing. When λ increases, the right hand side of the first order condition (3.1) increases (using lemma 2). In order to restore equality, $\frac{p}{1-p} \frac{u'(2-\frac{p}{1-\lambda})}{u'(2+\frac{1-p}{1-\lambda})}$ must decrease. A straightforward modification of lemma 3 shows that this implies a decrease in p , so p_{late} is really decreasing.

So there is some declining function $p_{late}(\lambda)$. Now specify an arbitrary but also declining "target" path for p_{early} , always being below p_{late} (with the exception of 0 and 1 – in 0, the two functions must coincide; in 1, p_{late} is undefined since nobody is willing to hold any bonds if there is nobody to buy them in period one). This implies a target path for the adjustment term K in (3.3). Since p_{early} is decreasing, then $\frac{p_{early}}{1-p_{early}} \frac{u'(2-p_{early})}{u'(3-p_{early})}$ is also decreasing, so K must be increasing.

Now I will construct a concave function f ($f' > 0$ but decreasing) that will achieve the target path of K – so $v = f \circ u$ will implement the target path of p_{early} . I need to define f consistently in the intervals $[u(2 - p_{early}(0)), u(2)]$ and $[u(3 - p_{early}(0)), u(3)]$: for any λ , I have a condition on f' at $2 - p_{early}(\lambda)$ and $3 - p_{early}(\lambda)$, plus f' has to be

decreasing. Choose a value for $\lambda = 0$, and then a decreasing path in the first interval – from the monotonicity of p_{early} , this can be done in an arbitrary fashion. All I need to ensure is that $f'((2)) > f'(u(3 - p_{early}(0)))$ holds. Later I will restrict the choice of f' in the first interval to imply monotonicity in the second interval.

Let $f'(u(2 - p(\lambda))) = g(\lambda)$ and $h(\lambda) = f'(u(3 - p(\lambda)))$, as implied by the target path of K . It is already ensured that f' is decreasing in $[u(2 - p_{early}(0)), u(2)]$, and its value in $3 - p_{early}(0)$ is even smaller. So if I show that $h(\lambda)$ is decreasing, then f' is decreasing, and the proof is done. Recall the definition of K :

$$K(\lambda) = \frac{1 - \lambda + \lambda g(\lambda)}{1 - \lambda + \lambda h(\lambda)},$$

so

$$h(\lambda) = \frac{(1 - \lambda)(1 - K(\lambda)) + \lambda g(\lambda)}{\lambda K(\lambda)}$$

and its derivative is

$$A^2 [(-1 + K - (1 - \lambda)K' + g + \lambda g')\lambda K - ((1 - \lambda)(1 - K) + \lambda g)(K + \lambda K')]$$

for some constant A . Expanding the bracket term:

$$h'(\lambda) = A^2 (\lambda^2 K g' - K - \lambda K' + K^2 + \lambda^2 K' - \lambda^2 g K').$$

Here $\lambda^2 K g' < 0$, $(\lambda^2 - \lambda) K' < 0$, so I need to ensure that $K^2 - K - \lambda^2 g K'$ is not too positive. But I can multiply g with any positive constant, which will still maintain the monotonicity of f' in the first interval and the starting point of the second interval. Given that $K^2 - K$ has a maximum in $[\bar{\lambda}, 1]$, and $\lambda^2 K'$ has a (strictly positive) minimum, I can choose g in a way that $h' < 0$ holds. ■

So far, I have shown that if agents face a chance of future taste shocks (becoming early consumers, or "noise traders") and they are aware of this possibility, then an increase in the speed of information revelation decrease the current price of a bond. Its mechanism was through an increase in period one (pre-maturity) wealth fluctuations, which, if agents might have to consume in that period due to the taste shock, makes the bond less attractive

ex ante. In a more general interpretation, it means that the way uncertainty is resolved will affect the price of a risky asset.

Notice that the issue price is negatively related to the welfare of the *issuer*: for the same expected repayment, the issuer gets smaller funds. So it might be in the interest of the issuer to try to restrict information about its future repayment behavior. Let me now turn to the welfare of investors: are they better-off with faster learning? I will show that the welfare loss from period one wealth fluctuations might cause their period one expected utility level to decrease; but it is not necessarily the case.

Proposition 7 $U_{late}(\lambda) < U_{early}(\lambda)$ and $U_{late}(\lambda) > U_{early}(\lambda)$ are both possible. Further, it is possible to have any combinations of utility and price rankings; but in the risk-neutral case ($u(x) = x$), we always have $U_{late}(\lambda) < U_{early}(\lambda)$.

So fast learning might increase or decrease the welfare of consumers. Further, it is possible that fast learning increases the price and decreases utility (the issuer is happy to give the information, but the market would prefer not to listen); it might increase both the price and utility (everyone is happy with the information); $p_{early} < p_{late}$ and $u_{early} > u_{late}$: in this case, investors would be willing to incur some cost for fast learning, but that would decrease the price. Which means that the issuer of the bond would lose – it gets a smaller amount for the same expected repayment. In this case, the issuer may even try to limit the speed of revealing information – a current piece of news describes a similar event, though the explanation is not necessarily restricted to the effect I am exploring: China restricted posting news to websites without government approval (Financial Times, November 7 and 8, 2000). Finally, faster learning might decrease the price and the level of utility, making it undesirable for both parties.

Proof. Again, choose $u(x) = \frac{1}{\sigma}x^\sigma$, $v(x) = \frac{1}{\beta}x^\beta$, $\alpha = 0.5$. Table 3.1 gives four different combinations of λ , β and σ , for which the relative ranking of utilities and prices shows all possible variations.

For the risk-neutral late consumers case, it is clear that $p_{late} = \alpha > p_{early}$. As for the utility levels,

$$u_{late} = \lambda v(2) + (1 - \lambda) \cdot 2$$

Table 3.1: Utility and price comparison

λ	σ	β	p_{early}		p_{late}	u_{early}		u_{late}
0.1	0.9	0.1	0.4811..	<	0.4858..	2.9463..	>	2.9445..
0.1	0.7	0.1	0.4574..	<	0.4583..	3.1711..	<	3.1774..
0.1	0.4	0.1	0.4238..	>	0.4190..	4.0650..	<	4.0671..
0.9	-1	-1.01	0.2844..	>	0.0222..	-0.468..	>	-0.474..

and

$$\begin{aligned}
 u_{early} &= \alpha(1-\lambda)(2-p) + \alpha\lambda v(3-p) + (1-\alpha)(1-\lambda)(2-p) + (1-\alpha)\lambda v(2-p) \\
 &= (1-\lambda) \cdot 2 + (1-\lambda)(\alpha-p) + \alpha\lambda v(3-p) + (1-\alpha)\lambda v(2-p).
 \end{aligned}$$

The difference of these two is

$$u_{late} - u_{early} = -(1-\lambda)(\alpha-p) + \lambda[v(2) - \alpha v(3-p) - (1-\alpha)v(2-p)]. \quad (3.4)$$

The first order condition for p_{early} is

$$\frac{\alpha}{1-\alpha} \frac{1-p}{p} = \frac{(1-\lambda) + \lambda v'(2-p)}{(1-\lambda) + \lambda v'(3-p)} = \frac{(1-\lambda) + \lambda const_1}{(1-\lambda) + \lambda const_2},$$

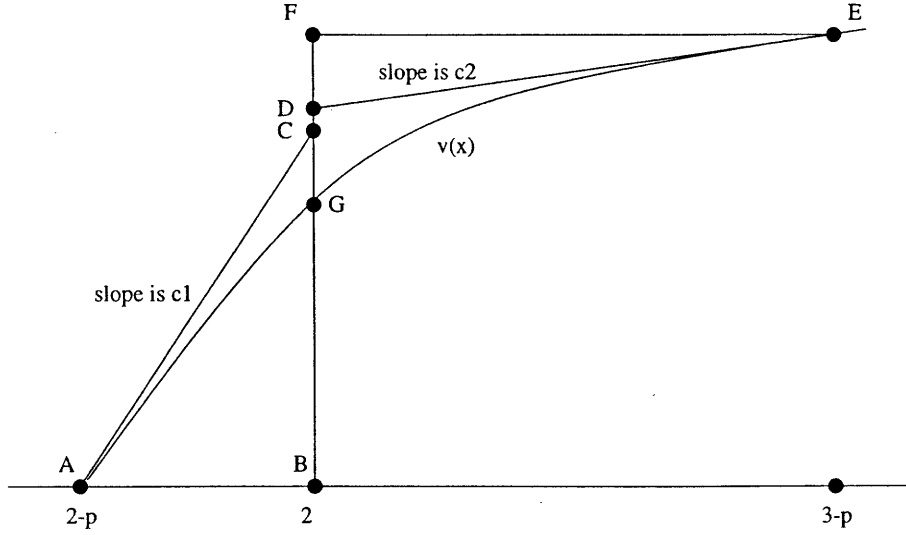
which yields

$$p = \frac{\alpha - \alpha\lambda + \alpha\lambda const_2}{1 - \lambda + const_1\lambda - const_1\alpha\lambda + const_2\alpha\lambda}. \quad (3.5)$$

Note that this is not a "real" closed form of the solution, since $const_1$ and $const_2$ also depend on p , but this will be sufficient. Using the notations from Figure 3-1, $v(2) = v(2-p) + \overrightarrow{BC} + \overrightarrow{CF} = v(2-p) + pc_1 + \overrightarrow{CG}$, $v(3-p) = v(2-p) + \overrightarrow{BC} + \overrightarrow{CD} + \overrightarrow{DF} = v(2-p) + pc_1 + \overrightarrow{CD} + (1-p)c_2$, since the slope of AC is $const_1 =: c_1$, and the slope of DE is $const_2 =: c_2$. Substituting these into (3.4), one gets

$$\begin{aligned}
 u_{late} - u_{early} &= -\alpha + \alpha\lambda + p - p\lambda + \lambda \left(pc_1 + \overrightarrow{CG} - \alpha pc_1 - \alpha \overrightarrow{CD} - \alpha c_2 + \alpha pc_2 \right) \\
 &= \underbrace{p(\lambda c_1 - \alpha \lambda c_1 + \alpha \lambda c_2 + 1 - \lambda) + \alpha\lambda - \alpha - \lambda \alpha c_2}_{\text{}} + \lambda(\overrightarrow{CG} - \alpha \overrightarrow{CD}).
 \end{aligned}$$

Figure 3-1: Utility comparison for the risk-neutral case



Plugging in the expression for p from (3.5), the underbracketed term cancels, so

$$\begin{aligned} u_{late} - u_{early} &= \lambda (\overrightarrow{CG} - \alpha \overrightarrow{CD}) \\ &= \lambda (\overrightarrow{CG} - \alpha \overrightarrow{CG} - \alpha \overrightarrow{GD}) = \lambda ((1 - \alpha) \overrightarrow{CG} - \alpha \overrightarrow{GD}). \end{aligned}$$

Now I need to use the concavity of u : since G is $v(2)$, so it must be below the tangent from $2 - p$. It implies that $\overrightarrow{CG} < 0$. Moreover, G is also below the tangent from $3 - p$, which means $\overrightarrow{GD} > 0$. Putting these two together shows that $u_{late} - u_{early} < 0$. ■

Let me give some interpretation to this result. Given a certain price level p_0 , I define a constrained efficient allocation: it corresponds to the case when agents can write contracts based on the taste shock, but they are still subject to the same bond prices and the same uncertainty about terminal repayment. This can be thought as a coalition of agents investing their total wealth, and agreeing on an allocation rule between late and early consumers (self-insurance). I am imposing the same investment decision on this coalition (buying one unit of the bond, at the same price p_0) – I want to focus only on the allocation of consumption within the coalition, without any changes in its total wealth. Let c_{ED} be the level of consumption of early consumers if the bond issuer defaults, c_{ER} under repayment; c_{LD} and c_{LR} are the consumption levels for late consumers. The optimal arrangement for early

information revelation then maximizes

$$\lambda\alpha v(c_{ER}) + \lambda(1 - \alpha)v(c_{ED}) + (1 - \lambda)(\alpha u(c_{LR}) + (1 - \alpha)u(c_{LD}))$$

subject to the budget constraints:

$$\lambda c_{ER} + (1 - \lambda)c_{LR} = 3 - p_0$$

$$\lambda c_{ED} + (1 - \lambda)c_{LD} = 2 - p_0$$

Under slow information revelation, we have a similar optimization problem, but with a potentially different price level p_0 and the extra constraint of $c_{ED} = c_{ER}$, since the repayment uncertainty is not yet resolved when early consumers need to get their consumption.

Moving from this second best allocation to the one without self-insurance (which is the market outcome), the investor choice problem in fact means maximizing the same objective function, subject to separated budget constraints: the total endowment $3 - p_0$ is forced to be split evenly in the fast learning case ($c_{ER} = c_{LR}$, $c_{ED} = c_{LD}$); and in another fixed way in the slow learning case ($c_{ED} = c_{ER} = 2$, $c_{LR} = \frac{3-p_0-2\lambda}{1-\lambda} = 2 + \frac{1-p_0}{1-\lambda}$, $c_{LD} = 2 - \frac{p_0}{1-\lambda}$).

When one compares the second best welfare levels of the different information revelation scenarios, we have two effects in general: a "wealth" effect, coming from a potentially different p_0 , and the additional constraint $c_{ED} = c_{ER}$ (not allowing fully contingent consumption plans). If $p_{early} < p_{late}$, this comparison is unambiguous: with fast learning, you have higher wealth and less constraints. If $p_{early} > p_{late}$, the two effects work against each other, so the comparison is ambiguous.

Moving to the market outcomes, one cannot determine which scenario implies a larger welfare loss relative to second best – so we can have any combinations of price and welfare comparisons. Note that if $p_{early} < p_{late}$, the second best level is higher for the fast revelation case, so to have this order reversed in the market outcome, the distortion due to the lack of self-insurance must be large. With risk-neutral late consumers, we always have $p_{early} < p_{late}$, so in a second best world, it is always desirable to get new information, and the distortion can never be large enough to reverse this conclusion. As the examples show, with risk-averse late consumers, it is possible that fast learning is desirable under the second best allocation of consumption ($p_{early} < p_{late}$), but without self-insurance, $u_{early} < u_{late}$. This is also the

case when both the issuer and the investors are worse-off.

3.3.2 A continuous version of the speed of learning

In the previous subsection, I have compared two extremes: one case when there was no new information revealed at period one, the other when there was full revelation in period one. This comparison also gave me a two-point relationship between issue (period zero) prices and interim (period one) price volatility. Now I want to do a more continuous version of the same comparison. One potential way would be to assume that even slow learning involves getting some new information, and fast learning implies much more but not perfect revelation. Under this modification, the same two effects would be present as before: the "excess supply" channel and the "wealth fluctuations" channel, yielding similar, though maybe less clear results (one may need stronger assumptions on parameters, utility functions etc.).

In some sense, fast learning would be a mean-preserving spread relative to slow learning – in the risk-neutral late consumer case, it is definitely true for period one prices: Slow learning means that the ex ante binary outcome (repayment or default) is refined into some interim positions, each with a binary outcome but different probabilities. Period one prices are then equal to these probabilities. Under fast learning, we get the same refinement as with slow learning, and some extra: each node is further decomposed into binary nodes. So at each node, period one prices become a lottery with the same expected value as the slow learning period one price at that node, which is a mean-preserving spread.

I will instead mix the fast and the slow learning cases in a probabilistic sense: assume that there is a chance μ that in period 1, investors learn the repayment behavior (fast learning case), and $1 - \mu$ that there is no news revelation. This in general defines $p_0(\mu)$ and $V_0[p_1](\mu)$. I will give conditions under which $V'(\mu) > 0$ and $p'(\mu) < 0$ – so with a bigger chance of getting new information, prices actually go down, together with increased future price volatility.

This can be an explanation for crisis periods giving much bigger movements in long-term bond prices than any "sensible" estimates of changes in default probability: in crises, you expect to learn quite much about the country's ability and willingness to repay, so this mechanism would increase near-future price volatility and decrease current prices, even without any change in α (default risk) or λ ("noise trader" risk). We would see, however, no

extra effect on trade volumes – noise traders sell inelastically, so the quantity traded must stay the same if λ stayed the same. Once λ also fluctuates, one can get quantity effects as well.

Proposition 8 $V'(0) > 0$, so for small values of μ , the variance term is increasing. If $u(x) = x$, then $V' > 0$ for all μ . If $u(x) = -\frac{1}{\theta}e^{-\theta x}$ (CARA), then under some conditions on α , λ and θ , V is increasing.

Proof. The period one price level is 1 with probability $\mu\alpha$, 0 with probability $\mu(1-\alpha)$, and p_1 with probability $(1-\mu)$. So its variance is

$$\begin{aligned}
V(\mu) &= \mu\alpha + (1-\mu)p_1^2 - (\mu\alpha + (1-\mu)p_1)^2 \\
&= \mu\alpha + p_1^2 - \mu p_1^2 - \mu^2\alpha^2 - (1-\mu)^2 p_1^2 - 2\mu\alpha(1-\mu)p_1 \\
&= \mu\alpha + p_1^2 - \mu p_1^2 - \mu^2\alpha^2 - p_1^2 - \mu^2 p_1^2 + 2\mu p_1^2 - 2\mu\alpha p_1 + 2\mu^2\alpha p_1 \\
&= -\mu^2(\alpha - p_1)^2 + \mu(\alpha - p_1)^2 + \mu(\alpha - \alpha^2) \\
&= \mu(\alpha - \alpha^2) + (\mu - \mu^2)(\alpha - p_1)^2.
\end{aligned}$$

In general, p_1 is coming from the period-one, slow learning case maximization problem and market clearing. The objective function is

$$\alpha u(x_1 + b_1) + (1-\alpha)u(x_1) = \alpha u(3 - p_0 + b - p_1 b) + (1-\alpha)u(3 - p_0 - p_1 b),$$

and the first order condition is

$$\alpha u'(3 - p_0 + b(1 - p_1))(1 - p_1) = (1 - \alpha)p_1 u'(3 - p_0 - bp_1).$$

Market clearing implies that $b = \frac{1}{1-\lambda}$, so p_1 is the solution of

$$\alpha u' \left(3 - p_0 + \frac{1 - p_1}{1 - \lambda} \right) (1 - p_1) = (1 - \alpha)p_1 u' \left(3 - p_0 - \frac{p_1}{1 - \lambda} \right). \quad (3.6)$$

It is clear that p_1 in general also depends on μ : though μ itself does not appear in the

equation, but p_0 depends on μ . So there is some function $p_1(\mu)$. Then

$$V'(\mu) = \alpha - \alpha^2 + (1 - 2\mu)(\alpha - p_1)^2 - 2(\mu - \mu^2)(\alpha - p_1)p_1'.$$

For $\mu = 0$, this value is $\alpha - \alpha^2 + (\alpha - p_1)^2 > 0$, so V is increasing for small values of μ .

If $u(x) = x$, then $p_1 = \alpha$, and $V(\mu) = \mu(\alpha - \alpha^2) > 0$. Finally, if $u(x) = -\frac{1}{\theta}e^{-\theta x}$, then the solution of the first order condition (3.6) is $p_1 = \frac{\frac{\alpha}{1-\alpha}e^{-\frac{\theta}{1-\lambda}}}{1 - \frac{\alpha}{1-\alpha}e^{-\frac{\theta}{1-\lambda}}}$, which is a constant. Then $V'(\mu) = \alpha - \alpha^2 + (1 - 2\mu)(\alpha - p_1)^2$ is decreasing in μ . In order to have $V'(\mu) > 0$ for all μ , it is enough that $V'(1) > 0$ holds. That requires $p_1 > \alpha - \sqrt{\alpha - \alpha^2}$, which is equivalent to

$$1 < \sqrt{\frac{1-\alpha}{\alpha}} + e^{-\frac{\theta}{1-\lambda}} + \sqrt{\frac{\alpha}{1-\alpha}}e^{-\frac{\theta}{1-\lambda}}. \quad (3.7)$$

So if α, θ and λ are such that this condition is satisfied, then $V'(\mu) > 0$. ■

Intuitively, one would expect the variance to be increasing in μ : with a higher chance of fast learning, there is higher chance of a random price next period, which means more variance. This effect clearly dominates initially. Later, however, as μ becomes even larger, $p_1(\mu)$ might be significantly different from α , which is the expected price in the fast learning realization, so the slow learning realization may end up contributing more to the total variance than the fast learning case. If this is the case, an increase in μ might decrease the variance. With constant absolute risk aversion, $p_1(\mu)$ is constant – but it still may be too far from α . Condition (3.7) ensures that $p_1(\mu)$ is close enough to α .

Next I turn to the behavior of prices. I will show that prices are always monotonic in μ (the chance of fast learning, or more generally, the speed of learning) – so if $p(0) > p(1)$, then $p(\mu)$ is decreasing. For this I first establish a relationship between p_0 and p_1 (slow-learning period one prices).

Lemma 9 *If u has nonincreasing absolute risk aversion and $p_0 > p_0'$, then $p_1 < p_1'$.*

Proof. With the slow learning realization, wealth in period 1 is $W = x_0 + p_1 b_0 = 2 - p_0 b_0 + p_1 b_0 = 2 - p_0 + p_1$. Suppose $p_0' < p_0$. Then at the same period one price level p_1 , $W < W'$. Given that u has nonincreasing absolute risk aversion, lower wealth implies

lower demand for the risky asset (the bond). So with W' , there would be excess demand for bonds at period 1 (since the market clears with wealth W), which implies $p'_1 > p_1$. ■

Proposition 10 *The period zero price is always a monotonic function of μ . In particular, if $p(0) = p_{late} > p_{early} = p(1)$, then $p(\mu)$ is decreasing.*

Proof. Consider the period zero objective function:

$$U = \underbrace{\mu [\alpha (\lambda v(x+b) + (1-\lambda) u(x+b)) + (1-\alpha) (\lambda v(x) + (1-\lambda) u(x))]}_{\text{fast learning}} + \underbrace{(1-\mu) [(1-\lambda) v(x+p_1b) + \lambda \max\{\alpha u(x_2+b_2) + (1-\alpha) u(x_2)\}]}_{\text{slow learning}}$$

The indirect utility of the slow learning realization depends only on wealth at period 1 (since the price level is fixed at the equilibrium level), so it can be rewritten as $g(x+p_1b) = g(2-pb+p_1b)$. It is clear that $g' > 0$. For the early learning realization, utility is a function of both x and b , but $x = 2-pb$, so the utility can be written as $h(b)$. So the first order condition is

$$g'(2-pb+p_1b)(p_1-p) = \mu [g'(2-pb+p_1b)(p_1-p) - h'(b)].$$

From market clearing, $b = 1$, so p satisfies

$$g'(2-p+p_1)(p_1-p) = \mu [g'(2-p+p_1)(p_1-p) - h'(b)].$$

Suppose that $\mu' > \mu$. If $p(\mu) < p(0)$, then from lemma 9, $p_1(\mu) > p_1(0) = p(0)$. Look at the first order condition for $p = p(\mu)$ and μ . Since $g' > 0$ and $p_1 > p$, the right hand side must also be positive. So if one replaces μ with μ' , at the same price levels p and p_1 , the first order condition becomes negative. So with μ' , at the same p (thus p_1), investors would want to hold less bonds than 1 – so the equilibrium price, $p(\mu')$, must be smaller.

Similarly, if $p(\mu) > p(0)$, then p is increasing at μ . So if p is increasing at zero, then it goes above $p(0)$, and it has to stay above and further increase; if p is decreasing at zero, then it is decreasing everywhere. ■

This is quite an intuitive result (though the argument was a bit complicated): as μ goes

from zero to one, there is an increasing chance to get the realization with fast information revelation. Therefore, the importance of the wealth fluctuation effect is increasing, and the role of the excess supply effect is decreasing. At any point, the infinitesimal change in $p(\mu)$ is determined by whether we are "subtracting more" from the supply effect or "adding more" from the fluctuations effect. If the full fluctuation effect is bigger than the full supply effect ($p(0) > p(1)$), then this infinitesimal change is negative, and $p(\mu)$ is decreasing; and vice versa.

3.4 Conclusions

The chapter presented a Diamond-Dybvig type model in which agents face a liquidity risk (becoming *more risk-averse* early consumers), and the speed of learning about default risk may also change. The two extremes of learning were no information revelation between issue and maturity, versus full information revelation at some point before maturity. Later I also considered a more continuous form of the speed of learning: learning is either fast or slow, with some probability μ and $1 - \mu$.

In general, there are two effects at work when one compares price and welfare levels of the two extremes: one is an "excess supply", the other is a "wealth fluctuation" effect. The excess supply effect applies to the slow learning case: without new information, period zero and period one prices must be the same, so the issue price will be determined by asset market equilibrium in period one, when demand is low and supply is high (only the late consumers are ready to hold the asset, and all the early consumers want to sell). When compared to the "no learning, no taste shock" benchmark, this decreases issue prices: in order to make risk-averse investors hold more of the risky bond, the price must fall.

The wealth fluctuation channel operates under fast learning: with new information in period one, the period one price level becomes a random variable. This generates wealth fluctuations, which hurts early consumers: they consume from their period one wealth, and if they are more risk-averse when hit by the taste shock, these fluctuations make them worse-off. Incorporating the chance of a taste shock in the period zero maximization problem then makes issue prices go down in equilibrium.

So the price comparison of fast and slow learning depends on the relative strength of these two effects: if wealth fluctuations matter more, then fast learning will lead to lower

issue prices. Under certain conditions (for example, risk-neutral late consumers but risk-averse early consumers), it is true that the wealth effect dominates the excess supply effect. This result carries through to the continuous case: under the same conditions, the period zero price level was decreasing in the probability of the fast learning realization.

I also compared the welfare of the issuer and investors under different speeds of learning: revealing information may be good or bad for the issuer (issue prices may increase or decrease), and also for the investors (period zero utility might be higher or lower). The potential decrease in investor welfare was driven by a very high loss due to the lack of self-insurance.

I view my model as an example of a general notion of illiquidity: investors face a risk that they need to sell the bond before they initially were planning to, and for *any* reason, the price may be particularly low at that time. The price may be low because the lack of aggregate resources, informational problems, thin markets or any other explanation – that does not change the overall interpretation that investors are selling the bond at the wrong time. The crucial feature is that they care not only for the terminal payoff, but also the way uncertainty is resolved. With many interim steps of the terminal payoff lottery, pre-maturity prices will fluctuate a lot, and with a chance of early sale (liquidation), investors value such a bond less.

Faster learning, more precise information will in general lead to more volatile prices. Expecting such an event in the future may lead to important price changes already today: if there is a chance that an investor has to liquidate her portfolio exactly in those volatile weeks, that increases the risk of the bond, driving its price down, potentially much more than what the increase in or the uncertainty about default probabilities would imply. Moreover, this effect should be more profound for long-term bonds: their default risk might change only slightly, but price volatility still increases during a crisis, which leads to a larger than expected overall drop in prices.

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