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Are Debt Crises Adequately Defined?

ANDREA PESCATORI and AMADOU N.R. SY*

Crises on external sovereign debt are typically defined as defaults. Such a definition adequately captures debt-servicing difficulties in the 1980s, a period of numerous defaults on bank loans. However, defining defaults as debt crises is problematic for the 1990s, when sovereign bond markets emerged. Not only were there very few defaults in the 1990s, but liquidity indicators do not play any role in explaining defaults in this period. In order to overcome the resulting dearth of data on defaults and capture the evolution of debt markets in the 1990s, we define debt crises as events occurring when either a country defaults or its bond spreads are above a critical threshold. We find that, when information from bond markets is included, standard indicators—solvency and liquidity measures, as well as macroeconomic control variables—are significant.
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A large body of economic literature has focused on the determinants and prediction of debt crises in the aftermath of the severe global turbulence in debt markets in the 1980s. Most studies focus on sovereign defaults and pay little attention to the more basic question, "What is a debt crisis?" This is not surprising given the high frequency of sovereign defaults in this period.

*Andrea Pescatori is at the Federal Reserve Bank of Cleveland and Pompeu Fabra University. Amadou N.R. Sy is a senior economist at the IMF. We wish to thank the editors, an anonymous referee, Giancarlo Corsetti, Arnaud Jobert, and Enrica Detragiache as well as seminar participants at the IMF and Pompeu Fabra University for their comments. We also thank Axel Schimmelpfennig for making available the macroeconomic data set, Peter Tran for research assistance, and Graham Colin-Jones for editorial suggestions.

Sovereign defaults are not, however, the only possible outcome of serious foreign debt servicing difficulties. For instance, the period starting with the Mexican "crisis" in 1994–95 has been characterized by turbulent sovereign debt markets and substantial IMF assistance to a number of countries. Yet, according to Moody's Investors Service (2003), only seven rated sovereign bond issuers have defaulted on their foreign currency-denominated bonds since 1985 and all those defaults happened between 1998 and 2002. The surprisingly low number of sovereign bond defaults by emerging market sovereign borrowers contrasts with the numerous defaults on bank loans in the 1980s.

We argue that defining debt crises solely as sovereign defaults does not take into account the development of international capital markets and, notably, the advent of the bond market for emerging market sovereign issuers. We show how sovereign defaults have become a less reliable indicator of debt-servicing difficulties and suggest a broader indicator of debt-servicing difficulties (debt crisis) that takes into account turbulence in emerging bond markets.

More precisely, we consider events where either there is a sovereign default or secondary market bond spreads are higher than a critical threshold. Using extreme value theory as well as kernel density estimation, we find that the 1,000 basis point (bp) (10 percentage point) threshold corresponds to significant tail events. In practice, market participants often view sovereign bond spreads above the 1,000 bp mark as a signal of turbulence in bond markets.

Formally, we assume that foreign debt–servicing difficulties can be represented by an unobservable latent variable. The standard empirical approach typically uses sovereign defaults as an indicator of debt-servicing difficulties. We argue, however, that sovereign defaults are no longer the appropriate indicator for foreign debt–servicing difficulties, given their rarity since the advent of emerging market bonds. As an alternative, we propose an indicator that complements sovereign defaults with available information from the sovereign bond market. This alternative framework enables us to take into account the development of the bond market for emerging economies in the 1990s and overcome the data limitations owing to the dearth of defaults in the 1990s.

We find that typical theoretical determinants of debt-servicing difficulties—solvency and liquidity measures, as well as macroeconomic control variables—better explain our broader definition of debt crises. In contrast, typical empirical models of debt-servicing problems fail to explain debt crises when they are defined solely as defaults, especially in the period after 1994. In particular, liquidity indicators are significant in explaining our definition of debt crises although they do not play any role in explaining defaults after 1994.

I. Review of the Literature

Episodes of serious foreign debt–servicing difficulties in the 1980s in Latin America and Africa have led to a large body of literature on the determinants of debt crises.[1] These studies typically define debt crises as defaults and study the factors that lead to the nonpayment of pre-agreed debt service (Sachs, 1984).[2]

A related body of literature focuses on the risk of default and uses spreads between the interest rate charged to a particular country and a benchmark as a proxy for the probability of sovereign default (see Edwards, 1984, for instance). As an alternative, it is possible to determine the probability of default from spreads (see Edwards, 1984; and Duffie and Singleton, 2003) or credit default swaps (Chan-Lau, 2003). Another method uses credit ratings to measure the risk of default (Kaminsky and Schumkler, 2001). Rating downgrades are therefore perceived as an increase in the probability of default, and it is useful to focus on the intensity of rating actions or "rating crises," as in Jüttner and McCarthy (1998). The probability of sovereign default can also be derived from an estimated transition matrix of the default, as in Hu, Kiesel, and Perraudin (2001).

Sovereign defaults are often associated with other types of financial crises. As a result, some researchers have studied the relevance of sovereign debt variables in explaining financial crises other than debt crises. In Radelet and Sachs (1998) and Rodrik and Velasco (2000), large reversals of capital flows are seen as significant events, whereas in Frankel and Rose (1996); Milesi-Ferretti and Razin (1998); Berg and Pattillo (1999); and Bussière and Mulder (1999) currency crises are considered to be important. In addition, Reinhart (2002) and Sy (2004) study the relationship between defaults and currency crises. Debt-servicing difficulties can, however, manifest themselves in different forms, and a number of recent studies have taken a closer look at the definition of debt crises.

What Is a Debt Crisis?

Debt crises as sovereign defaults

Rating agencies typically focus on default events. For instance, Moody's Investors Service (2003) defines a sovereign issuer as in default when one or more of the following conditions are met:

- There is a *missed or delayed disbursement of interest and/or principal*, even if the delayed payment is made within the grace period, if any.
- A distressed exchange occurs, where
    - the issuer offers bondholders a new security or package of securities that amounts to a diminished financial obligation, such as new debt instruments with lower coupon or par value; or

[1] See McDonald (1982); Edwards (1984); and Eichengreen and Mody (1998 and 1999); among others.

[2] For nominal domestic debt, episodes of surprise inflation have also been studied (Calvo, 1988; and Alesina, Prati, and Tabellini, 1990).

  - the exchange had the apparent purpose of helping the borrower avoid a "stronger" event of default (such as missed interest or payment).

Similarly, Standard & Poor's (S&P) (Chambers and Alexeeva, 2003) defines default as "the failure of an obligor to meet a principal or interest payment on the due date (or within the specified grace period) contained in the original terms of the debt issue." The agency notes that:

- For local and foreign currency bonds, notes, and bills, each issuer's debt is considered in default either when a *scheduled debt-service payment is not made* on the due date or when an *exchange offer of new debt contains less favorable terms* than the original issue.
- For bank loans, when either a scheduled debt-service payment is not made on the due date or a rescheduling of principal and/or interest is agreed to by creditors at less favorable terms than those of the original loan. Such rescheduling agreements covering short- and long-term bank debt are considered defaults even where, for legal or regulatory reasons, creditors deem forced rollover of principal to be voluntary.[3]

In addition, many rescheduled sovereign bank loans are ultimately extinguished at a discount from their original face value. Typical deals have included exchange offers (such as those linked to the issuance of Brady bonds), debt-equity swaps related to government privatization programs, and/or buybacks for cash. S&P considers such transactions defaults because they contain terms less favorable than the original obligation.

Beim and Calomiris (2001) use a variety of sources to compile a list of major periods of sovereign debt–servicing incapacity from 1800 to 1992. They examine bonds, suppliers' credit, and bank loans to sovereign nations, but exclude intergovernmental loans, and focus on extended periods (six months or more) during which all or part of interest and/or principal payments due were reduced or rescheduled. Some of the defaults and rescheduling involved outright repudiation (a legislative or executive act of government denying liability); others were minor and announced ahead of time in a conciliatory fashion by debtor nations.

The end of each period of default or rescheduling was recorded when full payments resumed or a restructuring was agreed to. Periods of default or rescheduling within five years of each other were combined. In the case of a formal repudiation, its date served as the end of the period of default, and the repudiation is noted in the notes (for example, in Cuba in 1963). Where no clear repudiation was announced, the default was listed as persisting through 1992 (for example, in Bulgaria). Finally, voluntary refinancing (Colombia in 1985 and Algeria in 1992) was not included.

[3]For central bank currency, a default occurs when notes are converted into new currency of less-than-equivalent face value.

Debt crises as large arrears

Detragiache and Spilimbergo (2001) classify an observation as a debt crisis if either or both of the following conditions occur:

- There are *arrears of principal or interest* on external obligations toward commercial creditors (banks or bondholders) of more than 5 percent of total commercial debt outstanding.
- There is a *rescheduling or debt restructuring* agreement with commercial creditors listed in the World Bank's *Global Development Finance*.

Detragiache and Spilimbergo (2001) argue that the 5 percent minimum threshold serves to rule out cases in which the share of debt in default is negligible; the second criterion makes it possible to include countries that are not technically in arrears because they reschedule or restructure their obligations before defaulting.

As a sensitivity test they also set the minimum threshold on arrears at 15 percent of commercial debt service due. Also, because they are interested in defaults with respect to commercial creditors, arrears or rescheduling of official debt do not count as crisis events. Finally, observations for which commercial debt is zero are excluded from the sample because they cannot be crisis observations based on their definition.

A second issue is how to distinguish the beginning of a new crisis from the continuation of the preceding one: an episode is considered concluded when arrears fall below the 5 percent threshold; however, crises beginning within four years of the end of a previous episode are treated as a continuation of the earlier event. In a sensitivity test, Detragiache and Spilimbergo (2001) exclude all episodes that follow the initial crisis, so that each country has at most one crisis. Finally, because the authors seek to identify the conditions that prompt a crisis rather than the impact of the crisis on macroeconomic developments, all observations while the crisis is ongoing are excluded from the sample.

These criteria identify 54 debt crises in the baseline sample. Although events tend to cluster in the early 1980s, when most Latin American countries and several African countries defaulted on their syndicated bank debt following the borrowing boom of the 1970s, there are crises throughout the sample period. Episodes on external payment difficulties that do not result in arrears or rescheduling, such as the Mexican crisis of 1995, are not captured by their definition of crisis. Notably, they identify only four crises in the 1994–98 period.

Debt crises as large IMF loans

Manasse, Roubini, and Schimmelpfennig (2003), hereinafter referred to as MRS, argue that there are different types of sovereign debt–servicing difficulties, which range from an outright default on domestic and external debt (Russia in 1998, Ecuador in 1999, and Argentina in 2001) to semicoercive restructuring; that is, under the implicit threat of default (Pakistan in 1999, Ukraine in 2000, and Uruguay in 2003) and rollover/liquidity crises (Mexico in 1994–95, Korea and Thailand in 1997–98, Brazil in 1999–2002, Turkey in 2001, and Uruguay in 2002) where a solvent but illiquid country is on the verge of default on its debt because of investors' unwillingness to roll over short-term debt coming to maturity, and a crisis was in part avoided via large amounts of official support by international financial institutions as well as less coercive forms of private sector involvement.

MRS argue that sovereign debt–servicing difficulties (of both the illiquidity and insolvency varieties), which were severe during the 1980s debt crisis, have become relatively frequent phenomena again in the past decade. As a result, the authors argue that the data in Detragiache and Spilimbergo (2001) may exclude some incipient debt crises that were avoided only as a result of large-scale financial support from official creditors. They therefore consider a country to be experiencing a debt crisis if:

- it is classified as being in *default* by S&P as previously defined, or
- it has access to a *large nonconcessional IMF loan* in excess of 100 percent of quota.

S&P rates sovereign issuers in default if a government fails to meet a principal or interest payment on an external obligation on the due date (including exchange offers, debt-equity swaps, and buyback for cash). For MRS, debt crises include not only cases of outright default or semicoercive restructuring, but also situations where such near-default was avoided through the provision of large-scale official financing by the IMF.

Debt crises as distress events

Given the limited number of sovereign bond defaults, even under a very broad definition such as Moody's, Sy (2004) suggests a parallel with the distressed-debt literature in corporate finance and defines debt crises as sovereign bond distress events. The author assumes that sovereign bonds are distressed securities when *bond spreads are trading 1,000 bps or more* above U.S. Treasury securities.

Sy (2004) argues that in practice, the 1,000 bps mark for spreads is often considered a psychological barrier by market participants. Under the above definition of sovereign distress, the author finds 140 distressed-debt events (about 14 percent of observations) from 1994 to 2002 that were associated with reduced access to the sovereign bond market.

II. The 2002 Brazilian "Debt Crisis"

Events in Brazil, in 2002, illustrate the case of a sovereign that experiences serious debt-servicing difficulties that are not captured by sovereign defaults.[4] That year, spreads on Brazil's external bonds rose sharply along with a 40 percent depreciation of the domestic currency, the *real*. These developments led investors to focus on the impact of the weakness of the *real* on local debt dynamics, because Brazil's domestic government debt remained largely indexed to the U.S. dollar and domestic short-term interest rates. The heavily indexed structure of domestic government debt amplified the impact of external shocks, as reflected in rising debt-service costs. With almost one-third of the domestic debt linked to the exchange rate, Brazil's debt-to-GDP ratio risked rising significantly, potentially leading to a sovereign default.

Against this background, Brazil reached an agreement with the IMF on August 7 that would commit $30 billion in additional financing by the IMF, 80 percent of which would be disbursed during 2003. The program relaxed the previous net international reserve floor. In addition, it ensured fiscal sustainability over the medium term through the maintenance of a primary surplus target of no less than 3.75 percent of GDP during 2003. The fall in Brazilian spreads triggered by the IMF program announcement quickly reversed, however, whereas the *real* weakened once more to 3.15 per dollar, not far from its all-time low of 3.60 per dollar.

The Brazilian authorities did not default on their large obligation in the bond markets, an option that may have been very costly. Instead, they reached an agreement with the IMF. However, Brazilian bond spreads were consistently above 1,000 bps during this period, indicating the country's debt-servicing difficulties.

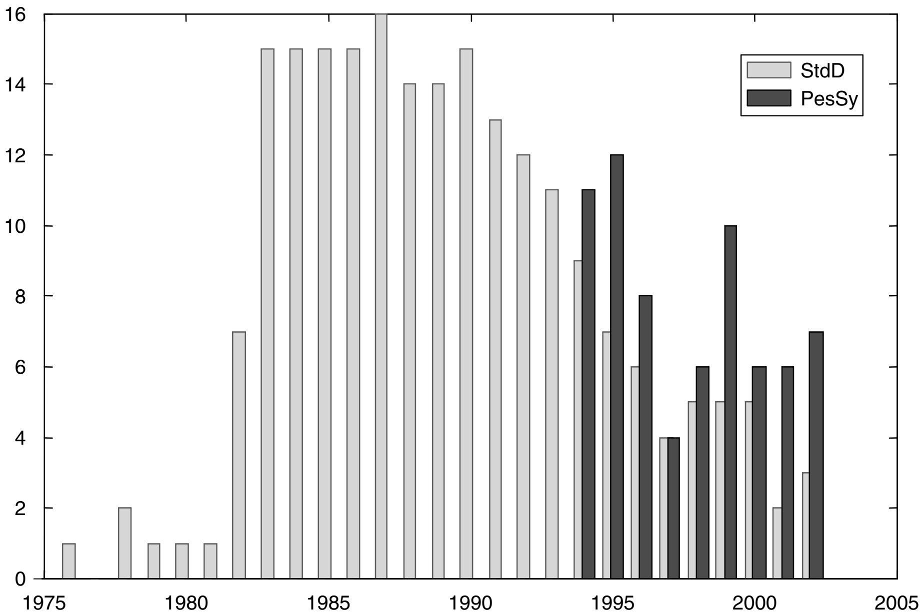
III. A Broader Definition of a Sovereign Debt Crisis

One problem with using sovereign defaults data to proxy for foreign debt–servicing difficulties relates to the dearth of observed post-1994 defaults. In fact, this period is often associated with a number of sovereign credit events in emerging market economies, starting with the Mexican and the Asian "crises" (see Figure 1 and Table 1).

Our concern that defaults are not a measure subtle enough to capture changes in the nature of debt-servicing difficulties and the evolution of international capital markets is shared by other authors. For instance, MRS propose that defaults be complemented with events during which a sovereign receives substantial IMF assistance.

[4]Other cases of major turbulence in debt markets that did not result in sovereign defaults (as defined by S&P) include Algeria (1999), Argentina (1995), Brazil (1995 and 1999), Côte d'Ivoire (1999), Ecuador (1996 and 1998), Malaysia (1995), Nigeria (1994–96 and 1999–2002), Pakistan (2001), Turkey (2000), Ukraine (2001), and Venezuela (1994 and 1999).

Figure 1. Comparison Between PesSy and Standard & Poor's Defaults (Number of Crises)



Source: Authors' calculations.

Note: "StdD" stands for defaults as defined by Standard & Poor's defaults. "PesSy" refers to events when there is either a default as defined by Standard & Poor's or sovereign bond spreads are above 1,000 bps (10 percentage points).

IMF bailouts, however, do not show a structural change between the two periods before and after 1994. In fact, the percentage of countries receiving IMF assistance of more than 100 percent of quota has barely increased, to 4.8 percent post-1994 from 4.5 percent in the previous period. Moreover, the percentage of countries receiving IMF bailouts without defaulting has barely increased, to 36 percent post-1994 from 32 percent in the previous period.[5] In other words, although the MRS methodology of complementing default events with IMF bailouts increases the total number of crisis events, it does not change the relative number of crises per period—that is, the ratio of the number of crisis events in the 1980s to the number of crisis events in the 1990s. So we are still left with the puzzle of a drastic drop in debt crises post-1994.

A possible explanation for the rarity of post-1994 default events could be that the determinants of defaults improved in the 1990s relative to their

[5]For a broad sample of 76 countries, most of them not members of the Organization for Economic Cooperation and Development (OECD).

Table 1. Number of Crises, by Definition

	Total Observations	Percentage	Number of Crises
Defaults (1975–2002)	886	24	214
PesSy (1975–2002)	886	27	238
Defaults (1994–2002)	287	16	46
PesSy (1994–2002)	287	24	70
Defaults (1975–93)	599	28	168

Source: Authors' calculations.

Note: Defaults refer to default events as defined by Standard & Poor's. PesSy refers to events when there is either a default as defined by Standard and Poor's or when secondary market sovereign bond spreads are higher than 1,000 bps (10 percentage points).

earlier levels. If so, the factors that successfully explained defaults in the 1970s and 1980s should have no problem predicting the reduced number of defaults in the 1990s. Our regression results show, however, that this may not be the case. Empirical models of debt crises that worked well until the 1980s cannot explain the few default events in the 1990s and instead predict a greater number of such events.

It is also possible that there was a structural break between the regressors and the dependent debt crisis variables. Such a break could be attributed to the development of international financial markets in the 1990s. In this case, we should expect that models estimated for the 1970s and 1980s would no longer work for the 1990s. We will, however, show that this may not be the case, although we believe that financial development deserves closer examination. In particular, we will attempt to show that the rapid development of the sovereign bond market for emerging economies can be used to obtain a relevant definition of debt crises.

We start from the following simple consideration. The more emerging countries have gained access to sovereign bond markets, the more they have reduced the share of bank loan debt to total debt. This means that defaulting could be associated with both forms of debt contracts but also with only one of them. So as a first step it seems sensible to proxy for foreign debt–servicing difficulties using bank loans, bonds, or both types of debt instruments.

A second consideration is that very few countries have defaulted on their foreign bonds in the post-1994 period. As a result, the usual definition of bond default must be one that is not subtle enough to capture the wide range of debt-servicing difficulties. The anonymous structure of bond markets makes renegotiation more difficult for bond contracts than bank loans. Renegotiation, however, is one of the most common credit events for other types of debt contracts such as bank loans and is a clear sign of debt-servicing difficulties. In contrast, we are likely to miss important periods of debt-servicing difficulties when we restrict ourselves to the usual definition of default, because of the difficulty of renegotiating bond contracts.

In order to overcome this problem, we add a market-oriented measure of debt-servicing difficulties based on sovereign bond spreads: a debt crisis happens when there is either a default as defined by rating agencies (in this case S&P) or when the secondary market sovereign bond spreads are higher than a critical threshold. For simplicity we will refer to debt crises defined as above as the PesSy indicator of foreign debt–servicing difficulties.

Presumably, spreads on foreign currency–denominated sovereign bonds may be part of a broader set of measures of macroeconomic or financial conditions that characterize the ability and willingness of a sovereign borrower to repay its debt. However, there are advantages in using sovereign bond spreads, given the high frequency and quality of the data as well as the simplicity in distinguishing among entry, continuation, and exit from a crisis.

Because they provide market information, however, sovereign bond spreads are not immune from possible overreaction from market participants. Hence, bond spreads could be, at times, misaligned with economic fundamentals and rather reflect market participants' overreactions to new information about the borrower. Our crisis indicator would therefore capture a credit event, whether it is due to economic imbalances or market overreactions. From a policy perspective, however, both types of events are important and have to be managed to avoid negative spillover effects in the economy. For instance, Dailami, Masson, and Padou (2005) model the probability of sovereign default so that it (1) depends on stock of debt as well as lagged income, (2) is highly nonlinear, and (3) can have multiple solutions. Their intuition is that by expecting a default, investors can make a default more likely. However, this is true in only certain ranges for the variables and the parameters. In particular, debt has to be large enough that increases in interest costs can make debt service painful for the emerging market borrower. Because of the existence of multiple equilibria, the effect of explanatory variables on spreads is different, depending on which equilibrium is chosen.[6]

High interest rate increases also may not be attributed solely to debt-servicing problems. For instance, Garcia and Rigobon (2004) compute events during which the probability of the simulated debt-to-GDP ratio exceeds a threshold deemed risky. These authors find that such "risk probabilities" are closely correlated to sovereign spreads. In this type of framework, the relevant variables do not have independent paths, and high interest rates can occur because of the co-movement observed in the variables of interest and debt dynamics. For instance, the authors find that, as is typically the case for emerging markets, a recession can cause the fiscal accounts to deteriorate, the

[6]For instance, the existence of multiple equilibria gives a natural role to contagion effects in international capital markets. The authors suggest, therefore, dividing their sample into two subsamples: "normal" times and "crisis" periods when a particular country faces sharply higher spreads as a result of a debt default or currency attack, which is consistent with our paper. Because of the difficulty in dating crises, the authors used periods when a currency crisis occurs.

real interest rate and inflation to rise, and the exchange rate to fall. Such debt dynamics worsen when the sovereign debt is dollar denominated.

Figure 1 shows the number of crises signaled by defaults—as defined by S&P—and by our crisis indicator.[7] In Table 1, we divide the overall sample—which goes from 1975 to 2002—into two subsamples ranging from 1975 to 1993 and from 1994 to 2002. The data show a dramatic drop in the number of defaults to 16 percent of total observations in the 1994–2002 period, from 28 percent in the 1975–93 period. In contrast, our proxy for sovereign debt–servicing difficulties indicates more stable behavior with a proportion of 24 percent of debt crises in the 1994–2002 period.

In order to formalize the previous argument and compare the two definitions of debt crises—namely, sovereign defaults and the indicator of debt-servicing difficulties (PesSy), we assume that there is an unobservable state of nature that corresponds to a country experiencing foreign debt–servicing difficulties. These foreign debt–servicing difficulties are not observable per se by creditors,[8] but the observation of some indicators, such as the inability of a sovereign to repay its debt, may be used to infer the true state of affairs.

We assume the existence of a latent variable, y^*, that represents foreign debt–servicing difficulties for a particular country. The underlying response variable is then defined by a regression relationship:

$$y_t^* = \beta' x_t + u_t. \tag{1}$$

The next step is to link the latent variable to some observable variables. The standard approach is to use sovereign defaults as an indicator of debt-servicing difficulties. Thus, the default indicator I is defined as

$$I_t = \begin{cases} 1 & \text{if } y_t^* > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

In contrast, it is possible to use the information from the bond market and assume that a sovereign credit event is also signaled when a country's bond spreads, s, cross a threshold, τ. We define the spreads in excess of the threshold as

$$s_t - \tau_t = h(y_t^*),$$

where h is any strictly increasing Borel function defined on the y^* probability space, such that $h(0) = 0$. We then construct a binary indicator related to the

[7]The data for spreads start from 1994 so that the two variables overlap in the period before.

[8]It is private information for the sovereign debtor.

latent variable, S, such as

$$S_t = \begin{cases} 1 & \text{if } s_t - \tau_t > 0, \\ 0 & \text{otherwise,} \end{cases} \quad \text{or} \quad \begin{cases} 1 & \text{if } Y_t^* > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

We propose a more general model combining the default indicator with the spreads-based indicator, so that a debt crisis occurs when either a default exists or bond spreads are above a threshold. In this case, the latent variable is linked to a bivariate observable variable, $\tilde{y}_t \equiv (I_t, S_t)$, such that

$$\tilde{y}_t = \begin{cases} (1,1) & \\ (1,0) & \text{if } y_t^* > 0, \\ (0,1) & \\ (0,0) & \text{otherwise,} \end{cases} \tag{4a}$$

which can be reduced to the following univariate variable:

$$y_t = \begin{cases} 0 & \text{if } \tilde{y} = (0,0), \\ 1 & \text{otherwise.} \end{cases} \tag{4b}$$

If specification (4a)–(4b) is the ''true'' model, then models (2) and (3) are misspecified. Furthermore, using model (2) implies assuming that the conditional probability is unconditional. From model (2) we get

$$P(I_t = 1) = P(y_t^* > 0) = 1 - F(-\beta' x_t).$$

From model (4) we have

$$1 - F(-\beta' x_t) = P(y_t^* > 0) = P(I_t = 1/S_t = 0).$$

Until the beginning of the 1990s, conditioning on $S = 0$ was consistent with the fact that most emerging economies did not have access to international bond markets. In contrast, it seems reasonable to assume that such a specification may miss the information given by bond markets, because emerging markets are gradually using sovereign bonds as a major source of funding. We therefore complement the typical default indicator with an indicator that uses the information from international bond markets.

As an alternative, our proposed indicator assumes that there has been historically no structural break between the latent variable and the covariates. Rather, there have been difficulties in choosing a proper indicator of an unobservable dependent variable. In the next section, we use statistical methods to estimate the critical threshold for bond spreads, τ.

Estimating the Threshold for Bond Spreads Using Extreme Value Theory

Sovereign bond spreads, like most financial series, are not typically distributed. Instead, bond spreads are characterized by extreme observations or fat tails and volatility clustering. We can use extremal analysis to capture extreme events, which we define as debt crises. Extremal analysis has in addition the advantage of using nonparametric methods rather than assuming a particular distribution for bond spreads.

Our approach is similar to that in a number of studies that attempt to capture extreme events in the foreign exchange markets, such as Hols and de Vries (1991); Koedijk, Stork, and de Vries (1992); and Pozo and Amuedo-Dorantes (2003). Typically, studies using extreme value theory focus on the estimation of a tail parameter α or alternatively on the inverse of the tail parameter, $\gamma = 1/\alpha$, by use of the nonparametric Hill estimator. This requires stationary and serially uncorrelated data. Our bond spread series are clearly stationary, at all frequencies, but are not serially uncorrelated at high frequency (daily and monthly). As a result, we focus on annual data (see the Appendix).

We pool the data and rank-order the observations from the lowest to the highest, $S_1 \ldots S_n$, in order to compute the following measure of the tail parameter:

$$1/\hat{\alpha} = \hat{\gamma} = \frac{1}{m}\sum_{i=0}^{m} \ln(S_{n-1}/S_{n-m}).$$

The key point in the estimation of the critical bond spread threshold is the choice of the variable m, where $\hat{\gamma}$ is stable. We therefore use Hill plots to estimate the values of $\hat{\gamma}$ against possible values of m. To verify that we have identified stabilization in the behavior of $\hat{\gamma}$ we also use recursive least squares to regress $\hat{\gamma}$ on a time trend and a constant, successively adding observations and obtaining a one-step-ahead forecast with the respective 90 percent confidence interval (see the Appendix).

For the yearly sample we find that a value of m between 42 and 50 makes the parameter $1/\hat{\alpha}$ relatively stable. Using the above relationship, $m = 42$ leads to a value of 1,072 bps and $m = 50$ to 969 bps. Because the relationship between m and the extreme value threshold is clearly monotonic, we conclude that our threshold reasonably lies between 969 and 1,072 bps (see Table A2).

We also assess the extent to which the threshold for bond spreads estimated using extreme value theory would affect the construction of the binary crisis dependent variable. Table 2, which uses the 1,000 bps mark, shows that the use of a critical threshold from extreme value estimation does not significantly change the classification of the data in crisis periods. Using the upper estimation, we add 2.3 percent crisis periods and using the lower estimation we ignore 1.4 percent crisis events with respect to the total number of crises (Table 2).

We find that the estimated values for the critical bond spread threshold are consistent with anecdotal evidence (the 1,000 bps mark is between the

Table 2. Extreme Value Theory (EVT) vs. 1,000 bps Thresholds
(Sample: 1994–2002)

	Matching	EVT Adding	EVT Crossing Out	Total
Total number	[211, 213]	[5, 0]	[0, 3]	216
As percentage	[0.98, 0.99]	[0, 0.023]	[0, 0.014]	1

Source: Authors' calculations.
Note: The abbreviation bps denotes basis points (hundredths of a percentage).

lower and upper estimate) and do not significantly affect our dependent binary variable. In the next section, we take a second look at the data using kernel density estimation.

Estimating the Threshold for Bond Spreads Using a Kernel Density Estimation

As discussed above, sovereign bond spread series do not follow a typical distribution. In this section, we use kernel density estimation as an alternative to extremal analysis to estimate the key features of our sovereign bond spread series. We are particularly interested in the possible existence of modes around high spread values. If bond spreads tend to cluster around some low and large observations, then we can use these values to define "tranquil" and "crisis" periods.

Intuitively, whenever spreads are close to a limit that cannot be passed smoothly, the observations will concentrate around it until the limit is finally passed or the surging pressure reduced. Because the body of the distribution lies to the left of our threshold we also should expect that the mode is slightly on the left (see Section II of the Appendix for an illustration).

We analyze both yearly and daily data. In this case, the presence of autocorrelation, which is very strong for daily data, does not spoil the results. In a univariate sample that is not identically and independently distributed but autocorrelated, we expect its histogram to show a mode for each relevant turning point, and in this case around tranquil and crisis periods. In addition, there may be smaller modes for very high spreads that have been peaks or turning points for some countries.

The kernel density estimation confirms the assumption that there is a mode for tranquil and crisis periods. In particular, we find a mode around 1,000 bps for both daily and yearly data. Because the yearly data are not correlated, we also fit a gamma and a Weibul distribution (an extreme value distribution) to estimate the 90th percentile.[9] We choose the 90th percentile as a proxy for extreme events. Our results indicate that the 1,000 bp threshold

[9] We do not estimate the 90th percentile for daily data because of the presence of strong multimodality.

Table 3. Thresholds for Bond Spreads from Kernel Density Estimations

	Estimated 90th Percentile—95 Percent Confidence Interval	
Gamma distribution	1,036.52	[980.55, 1,093.85]
Weibul distribution	978.82	[795.10, 1,248.05]
	Percentile Corresponding to 1,000 bps	
Gamma distribution	0.88	
Weibul distribution	0.91	

Source: Authors' calculations.
Note: bps = basis points.

is inside the 95 percent confidence bands for the 90th percentile of the fitted distribution (Table 3).

Psychological/Market Threshold

Sovereign bond market participants typically consider the 1,000 bps mark for spreads a critical psychological threshold. Indeed, discussions with market participants suggest that price quotes are increasingly based on expected recovery values in case of a default, when bond spreads cross the 1,000 bps mark.

For instance, Altman (1998) defines distressed securities as those publicly held and traded debt and equity securities of firms that have defaulted on their debt obligations and/or have filed for protection under Chapter 11 of the U.S. Bankruptcy Code. Under a more comprehensive definition, Altman (1998) considers that distressed securities would include those publicly held debt securities selling at sufficiently discounted prices so as to be yielding, should they not default, a significant premium of a minimum of 1,000 bps (or 10 percent) over comparable U.S. Treasury securities. Similarly, some market participants consider securities to have reached distressed levels when they have lost one-third of their value.

The sections above corroborate the existence of a 1,000 bps market threshold. Table 4 presents the debt crisis dates for both the standard default definition (S&P) and our broader indicator (PesSy) in the period 1994–2002. Prior to 1994, both indicators coincide, because the bond market for emerging economies was not developed. In the next sections, we use the framework developed above to estimate econometric models of debt crises.

IV. Defaults vs. Market-Based Definition of Debt Crises (PesSy)

In this section, we investigate whether the typical determinants of debt crises found in the literature are significant when we broaden the definition of debt crises to include information from the bond markets. We also study how well

Table 4. Debt Crises Dates, 1994–2002

Country	PesSy[1]	Default (S&P)
Algeria	1994–96, 1999	1994–96
Argentina	1995, 2001–02	2001–02
Brazil	1994–95, 1999, 2002	1994
Côte d'Ivoire	1994–2002	1994–98, 2000–02
Chile	No crisis	No crisis
China	No crisis	No crisis
Colombia	No crisis	No crisis
Dominican Rep.	1994	1994
Ecuador	1994–96, 1998–2002	1994–95, 1999–2000
Egypt	No crisis	No crisis
El Salvador	No crisis	No crisis
Hungary	No crisis	No crisis
Indonesia	1998–2000, 2002	1998–2000, 2002
Korea	No crisis	No crisis
Lebanon	No crisis	No crisis
Malaysia	1995	No crisis
Mexico	1995	No crisis
Morocco	No crisis	No crisis
Nigeria	1994–96, 1999–2002	No crisis
Pakistan	1998–99, 2001	1998–99
Panama	1994–96	1994–96
Peru	1994–97	1994–97
Philippines	No crisis	No crisis
Poland	1994	1994
Russia	1994–2000	1994–2000
South Africa	No crisis	No crisis
Thailand	No crisis	No crisis
Tunisia	No crisis	No crisis
Turkey	No crisis	No crisis
Ukraine	1998–2001	1998–2000
Uruguay	No crisis	No crisis
Venezuela	1994–97,1999, 2002	1995–97

Source: Standard & Poor's and authors' calculations.
Note: S&P = Standard & Poor's.
[1]Default or bond spreads above 1,000 bps.

these explanatory variables forecast our proposed broader definition of debt crises. As an illustration, we also repeat the same exercise for sovereign defaults.

Baseline Regressions, 1975–2002

The theoretical and empirical literature has highlighted a number of variables that help predict sovereign defaults. The explanatory variables usually include (1) liquidity indicators (short-term debt over reserves; or short-term debt, debt service due, and reserves separately); (2) variables that measure the magnitude and structure of external debt; and (3) macroeconomic control variables, such as measures of openness and real exchange rate over-valuation.

For instance, MRS, after reviewing the empirical and theoretical literature on debt crises, emphasize the following determinants of debt crises:

- solvency measures, such as public and external debt relative to capacity to pay;
- liquidity measures, such as short-term external debt and external debt service, possibly in relation to reserves or exports;
- currency crisis (early-warning systems) variables;
- external volatility and volatility in economic policy measures;
- macroeconomic control variables, such as growth, inflation, and exchange rate; and
- political and institutional variables that capture a country's willingness to pay.

We follow the literature and use the typical determinants of debt crises as explanatory variables. In fact, we assume that standard explanatory variables are the correct ones in predicting debt crises but that indicators of debt crises may be inaccurate.

As a first descriptive step we use the whole sample from 1975 to 2002. In Table 5, we show the estimation results for the standard framework—where the sovereign default variable is the indicator variable for debt crises. In Table 6, we present the results for the alternative market-based indicator (PesSy).[10]

We find that, for the 1975–2002 period, solvency measures (total debt over GDP) and liquidity indicators (short-term debt over reserves) are statistically significant in explaining debt crises, independently of how they are defined. However, the liquidity indicator (short-term debt over reserves) plays a more important role; inflation is not significant when the market-based indicator is used. Other macroeconomic control variables—in particular, real growth rate, inflation, and real exchange rate overvaluation—are also important in explaining crises, as is a measure of openness (imports plus exports over GDP). All regressors are significant at 5 percent in both specifications (with or without inflation) and enter with the right sign.

Finally, a comparison of the Wald statistics suggests that standard macro variables, except for inflation, provide a better explanation of debt crises as defined by the market-based indicator (PesSy).

[10]Our logit methodology is quite standard but suits our purpose well. Recent research illustrates how the relationship between the explanatory variables used to predict debt crises can be dynamic and nonlinear. For instance, in Garcia and Rigobon (2004), episodes where the debt-to-GDP ratio is higher than a critical threshold are the relevant events. However, their model exploits the covariance of stochastic debt and other macro variables by using a vector autoregressions (VAR) methodology. Similarly, in Dailami, Masson, and Padou (2005), spreads in normal and (currency) crisis periods are used but in a highly nonlinear model with multiple equilibria, which necessitates the use of a pooled mean group estimator.

Out-of-Sample Comparisons

Typically, model estimation attempts to find the explanatory variables that better explain a particular dependent variable. In this section, we take the explanatory variables as given and focus instead on finding the better proxy for the *unobservable* dependent variable, *debt-servicing difficulties*. We show that debt-servicing difficulties are better captured when we use information from both sovereign defaults and bond markets.

The two indicators of debt-servicing difficulties coincide in the period before 1994—that is, before the advent of the emerging bond market—and differ only afterward. We therefore estimate the model for the period 1975–93 to forecast debt crises in 1994–2002 (out-of-sample). We then compare our forecasts with actual proxies of the dependent variable in 1994–2002. We find that forecasted debt crises are statistically closer to the *actual* observations of our market-based indicator than sovereign defaults.

Estimation results for the subsample 1975–93 are shown in Table 7.[11] All variables are significant except for inflation, and the Wald statistic is comparable to the values obtained earlier. The solvency (total debt over GDP) and liquidity (short-term debt over reserves) variables play a bigger role compared with the results obtained using the whole sample with the default indicator. The opposite is true for inflation, which is now insignificant. In other words, the estimation results for the 1975–93 period seem to be comparable to the results obtained with the market-based indicator for the whole sample period (1975–2002) (compare Table 7 to Table 6 and Table 5).

Given that we estimate a binary variable model, we follow the early-warning indicator literature for currency crises and estimate the number of matched crises (A), false alarms (B), missing crises (C), and matched tranquil periods (D).[12]

In this framework, a signal is sent whenever the estimated probability of a crisis crosses a given threshold, T. Typically, the threshold is set to be equal to the unconditional probability of a crisis occurring. Because we are trying to match the crisis events, there is no clear reason for setting T to the unconditional probability, and we instead leave the variables A, B, C, and D as a function of the threshold T, which is optimally determined. In order to calculate the optimal threshold value for issuing a warning, T^*, we minimize the following noise-to-signal ratio: $L(T) = B(T)/A(T) + C(T)/D(T)$. Because the standard error for the forecasts is quite high, we estimate the values for T^* using a bootstrapping method, and hence for $A(T^*)$, $B(T^*)$, $C(T^*)$, $D(T^*)$, and $L(T^*)$. Table 8 shows the ratios for "Matched Crises over Total Crises," $A(T^*)/[A(T^*) + C(T^*)]$, and "False Alarms over Tranquil Periods," $B(T^*)/[B(T^*) + D(T^*)]$.

[11] In order not to give an advantage or penalize the PesSy indicator, we use the baseline model with inflation among regressors.

[12] For a review of the method used here, we refer the reader to Berg and Pattillo (1999).

Table 5. Regression Results Using Default Definition, 1975–2002

S&P Default Definition	Coeff.	Z	$P > \lvert z \rvert$	95 Percent CI		Coeff.	Z	$P > \lvert z \rvert$	95 Percent CI	
Openness	−0.05	−3.14	0.00	−0.08	−0.02	−0.05	−3.08	0.00	−0.07	−0.02
Overvaluation	0.01	3.40	0.00	0.01	0.02	0.01	3.37	0.00	0.00	0.02
Total debt over GDP	0.06	3.57	0.00	0.03	0.09	0.06	3.56	0.00	0.03	0.09
Short-term debt over reserves	0.19	2.07	0.04	0.01	0.36	0.19	2.05	0.04	0.01	0.37
Real growth rate	−0.08	−2.49	0.01	−0.15	−0.02	−0.08	−2.35	0.02	−0.15	−0.01
Inflation						0.00	2.67	0.01	0.00	0.00
Constant	−1.94	−2.43	0.02	−3.51	−0.37	−2.09	−2.48	0.01	−3.74	−0.44
Wald χ^2 (5) and (6)	44.0					46.1				

Source: Authors' calculations.

Note: GEE logit population-averaged model, correlation exchangeable, Huber-White estimator. 567 observations. CI refers to the confidence intervals.

Table 6. Regression Results Using PesSy Indicator, 1975–2002

PesSy Indicator	Coeff.	Z	$P > \lvert z \rvert$	95 Percent CI		Coeff.	Z	$P > \lvert z \rvert$	95 Percent CI	
Openness	−0.03	−2.06	0.04	−0.07	0.00	−0.03	−2.15	0.03	−0.06	0.00
Overvaluation	0.01	2.75	0.01	0.00	0.02	0.01	2.41	0.02	0.00	0.01
Total debt over GDP	0.06	4.26	0.00	0.03	0.09	0.06	4.46	0.00	0.03	0.09
Short-term debt over reserves	0.30	2.50	0.01	0.06	0.53	0.30	2.47	0.01	0.06	0.53
Real growth rate	−0.09	−2.61	0.01	−0.17	−0.02	−0.08	−2.29	0.02	−0.15	−0.01
Inflation						0.00	1.25	0.21	0.00	0.01
Constant	−2.80	−4.01	0.00	−4.18	−1.43	−3.08	−4.99	0.00	−4.29	−1.87
Wald χ^2 (5) and (6)	48.0					45.4				

Source: Authors' calculations.

Note: GEE logit population-averaged model, correlation exchangeable, Huber-White estimation. 567 observations. CI refers to confidence intervals.

The results, shown in Table 8, indicate that, in terms of matched crises, the typical determinants of debt crises forecast better the market-based indicator (PesSy) than sovereign defaults. This is not really surprising given that there are more debt crises under the market-based definition than defaults. Hence, for a more conclusive answer and to aggregate the previous results, we introduce a

Table 7. Regression Results, Subsample for 1975–93 (Common Framework)

S&P Default Definition = PesSy Indicator	Coeff.	Z	$P > \|z\|$	95 Percent CI	
Openness	−0.04	−2.92	0.00	−0.07	−0.01
Overvaluation	0.01	2.27	0.02	0.00	0.02
Total debt over GDP	0.07	4.05	0.00	0.03	0.10
Short-term debt over reserves	0.23	1.97	0.05	0.00	0.46
Real growth rate	−0.09	−1.93	0.05	−0.17	0.00
Inflation	0.00	0.88	0.38	0.00	0.01
Constant	−2.37	−4.29	0.00	−3.45	−1.29
Wald χ^2 (6)	39.20				

Source: Authors' calculations.

Notes: GEE logit population-averaged model, correlation exchangeable, Huber-White estimation. 360 observations. CI refers to confidence intervals.

loss function—also in this case taken from the early-warning-indicator literature. The loss function equals the weighted sum of false alarms (as a share of total tranquil periods) and missed crises (as a share of total crisis periods).[13]

Results are shown in Table 9. The S&P defaults–associated "loss" is, with a 90 percent confidence, within 1.13 and 2.14, whereas the loss associated with the market-based indicator is between 0.75 and 1.07.[14]

These results support the idea that defining debt crises solely as defaults is too strict to capture debt-servicing difficulties in the 1990s. In addition, we do not find evidence of a structural break for the usual macro determinants in 1994 stemming from the advent of the bond market for emerging economies. Instead, we find that the model estimated in the 1975–93 period still predicts debt crises quite well in the 1994–2002 period, provided debt crises are broadly defined to include both defaults and events when bond spreads are above 1,000 bps. In contrast, the model does not predict sovereign defaults well in the 1994–2002 period.

1994–2002: A New Decade

Finally, we illustrate the robustness of the model in the period after 1994, rather than for the whole sample, because this period is characterized by the growth of the emerging bond markets.

We estimate the model for the 1994–2002 subsample and find that, without inflation, the Wald statistic is 29.4 when debt crises include

[13]This paper places equal weight on the share of alarms that are false and the share of crises that are missed. (The former might be thought of as Type 1 errors and the latter as Type 2 errors, if the null hypothesis is no crisis.)

[14]In the same table are also shown the optimal threshold T^*, endogenously obtained. For completeness we have also calculated the in-sample loss and the associated threshold T^*. (We recall that for the in-sample period the two indicators coincide.)

Table 8. Matched Crises over Total Crises, and False Alarms over Tranquil Periods

	Matched Crises over Total Crises	False Alarms over Tranquil Periods
S&P defaults	0.43 [0.33, 0.50]	[0.12, 0.13]
PesSy	0.61 [0.55, 0.67]	[0.19, 0.20]
In sample (point estimate)	0.86	0.14
In sample	0.69 [0.52, 0.91]	[0.02, 0.20]

Source: Authors' calculations.

Note: The in-sample point estimation refers to the estimated parameters without bootstrapping; 90 percent confidence intervals are in brackets; S&P = Standard & Poor's.

Table 9. Bootstrapped Results for Standard and PesSy Distress Definition Loss Function (10th percentile, mean value, 90th percentile for the loss function)

	Mean and CI
Default definition loss (*out of sample*)	1.50 [1.13–2.14]
Associated optimal threshold	0.34 [0.23 and 0.28]
PesSy definition loss (*out of sample*)	0.89 [0.75, 1.07]
Associated optimal threshold	0.32 [0.38 and 0.36]
In-sample result loss	0.39
In-sample result optimal threshold:	0.57

Source: Authors' calculations.

information from the bond market, and 8.4 when sovereign defaults are used. When inflation is considered as a regressor, the Wald statistics are 59.5 and 41.6, respectively. Real growth and openness variables are not as significant as before, whereas inflation is strongly significant in both setups.

More interesting, the liquidity variable (short-term debt over reserves) does not play any role in the 1994–2002 period when debt crises are defined as defaults. In contrast, it is significant and has the right sign when debt crises are defined to include turbulence in bond markets. Results are shown in Tables 10 and 11.

V. Conclusion

In this paper, we propose a definition of debt crises that complements the usual default definition. Because there were very few defaults on emerging market bonds in the 1990s in spite of a succession of turbulent foreign debt–servicing episodes, we conclude that defining debt crises as defaults is too strict as an indicator of foreign debt incapacity. We therefore propose a measure that attempts to capture the evolution of capital markets from an environment dominated by bank loans to one in which bond markets have become increasingly important.

Table 10. Regression Results Using Default Definition, Subsample for 1994–2002

Defaults	Coeff.	Z	$P>\|z\|$	95 Percent CI		Coeff.	Z	$P>\|z\|$	95 Percent CI	
Openness	−0.03	−1.47	0.14	−0.07	0.01	−0.03	−1.39	0.17	−0.06	0.01
Overvaluation	0.02	2.03	0.04	0.00	0.03	0.01	1.87	0.06	0.00	0.03
Total debt over GDP	0.04	1.84	0.07	0.00	0.09	0.04	1.80	0.07	0.00	0.09
Short-term debt over reserves	0.12	0.49	0.63	−0.35	0.58	0.13	0.53	0.60	−0.35	0.60
Real growth rate	−0.04	−0.91	0.37	−0.13	0.05	−0.04	−0.93	0.35	−0.14	0.05
Inflation						0.00	2.40	0.02	0.00	0.00
Constant	−2.16	−1.74	0.08	−4.59	0.27	−2.26	−1.75	0.08	−4.80	0.28
Wald χ^2 (5) and (6)	8.4					41.6				

Source: Authors' calculations.
Note: GEE logit population-averaged model, correlation exchangeable, Huber-White estimation. 207 observations.
CI refers to confidence intervals.

Table 11. Regression Results Using PesSy Indicator, Subsample for 1994–2002

PesSy indicator	Coeff.	Z	$P>\|z\|$	95 Percent CI		Coeff.	Z	$P>\|z\|$	95 Percent CI	
Openness	−0.02	−1.23	0.22	−0.05	0.01	−0.02	−1.09	0.28	−0.05	0.01
Overvaluation	0.02	1.83	0.07	0.00	0.04	0.01	1.50	0.13	0.00	0.03
Total debt over GDP	0.06	3.31	0.00	0.02	0.09	0.06	3.32	0.00	0.02	0.09
Short-term debt over reserves	0.34	1.89	0.06	−0.01	0.70	0.39	2.00	0.05	0.01	0.76
Real growth rate	0.01	0.17	0.87	−0.09	0.10	0.00	0.08	0.94	−0.10	0.10
Inflation						0.00	3.87	0.00	0.00	0.00
Constant	−3.53	−3.29	0.00	−5.64	−1.43	−3.84	−3.40	0.00	−6.05	−1.62
Wald χ^2 (6) and (7)	29.4					59.5				

Source: Authors' calculations.
Note: GEE logit population-averaged model, correlation exchangeable, Huber-White estimation. 207 observations.
CI refers to confidence intervals.

We define debt crises as events either when there is a default or when secondary-market bond spreads are higher than a critical threshold. We show, using extreme value theory and kernel density estimation, that a threshold of 1,000 bps does represent a statistically significant critical threshold. In practice, this threshold is often used by market participants.

We find that our definition accurately captures debt-servicing difficulties in the period from 1975 to 2002 and captures such difficulties better than the usual default definition, especially in the period after 1994. More precisely, we find that when our definition is used, the typical determinants of bank loan defaults in the 1980s still have predictive power for debt-servicing difficulties—on both bank loans and bonds—in the period from 1994 to 2002.[15] In contrast, the standard definition of default implies much worse out-of-sample performance. In addition, we find that liquidity indicators are significant in explaining our definition of debt crises, although they do not play any role in explaining defaults in the period from 1994 to 2002.

APPENDIX

Extreme-Value-Theory Approach

Like most financial data, emerging market bond spread series are not typically distributed but rather characterized by higher skewness, volatility clustering, and kurtosis (fat tails) than a typical distribution (see Mauro, Sussman, and Yafeh, 2002). Such fat tails indicate that extreme observations are more frequent than under a normal distribution.

Rather than assuming a particular distributional model, which would capture these fat tails, we use extremal analysis to characterize the distribution of bond spreads and identify extreme observations (see Koedijk, Schafgans, and de Vries, 1990; Hols and de Vries, 1991; Koedijk, Stork, and de Vries, 1992; and Pozo and Amuedo-Dorantes, 2003). Using extremal analysis, we can estimate the value of the tail parameter (α) or alternately its inverse ($\gamma = 1/\alpha$) to make inferences about the distribution of bond spreads. The tail parameter takes on values between 0 and 2 when the distribution of bond spreads is in the domain of attraction of a stable law; it takes on values of 2 and above for the Student-t and specific ARCH cases.

Following Pozo and Amuedo-Dorantes (2003) and Koedijk, Stork, and de Vries (1992), we use the nonparametric Hill estimator to estimate the value of the tail parameter á for our bond spread series. The Hill estimator requires that the bond spread series be stationary and serially uncorrelated.

We use the Hill estimator because our bond spreads series are stationary (Dickey-Fuller and Phillips-Perron tests results not shown) and serially uncorrelated except for a few cases. To test for serial correlation we use the Ljung-Box Q-statistics for up to eight-order serial correlation. For annual data, the null hypothesis of no serial correlation is rejected for only four out of 31 countries (Table A.1). The countries are those for which our bond spread sample is very small.

[15]By pooling the data, we obtain more precise estimates for the tail parameter α but at the cost of constraining its value to be the same for all countries (see Pozo and Amuedo-Dorantes, 2003).

We pool the data and rank-order the observations from the lowest to the highest, $S_1 \ldots S_n$, in order to compute the following measure of the tail parameter:

$$1/\hat{\alpha} = \hat{\gamma} = \frac{1}{m}\sum_{i=0}^{m} \ln(S_{n-1}/S_{n-m}).$$

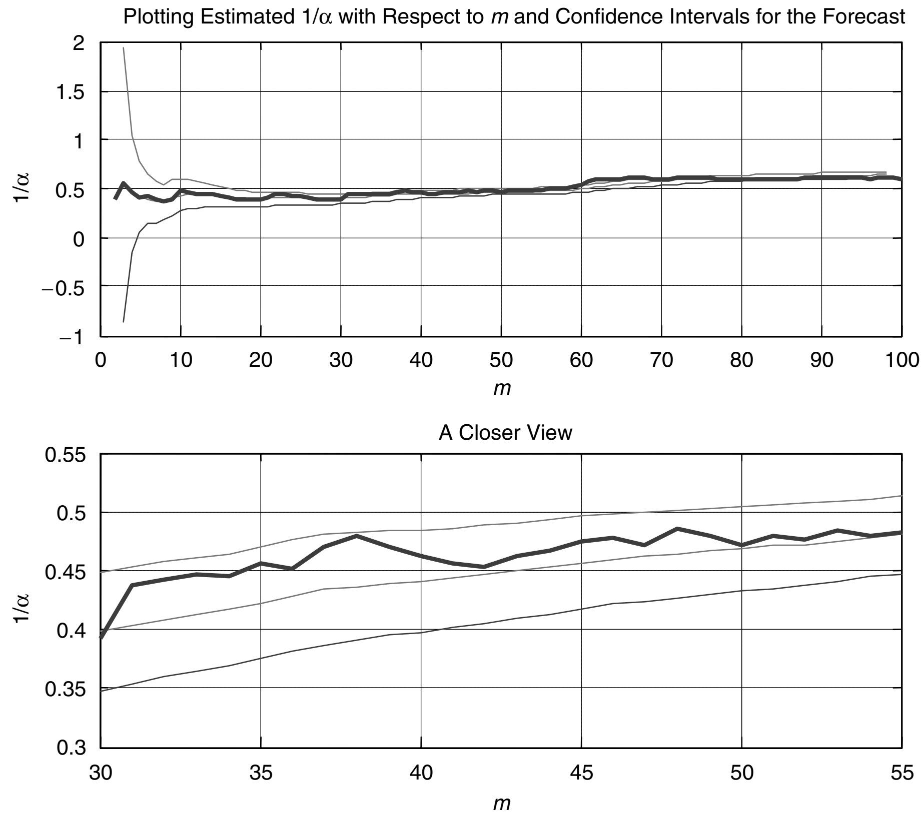
The key point in the estimation of the critical bond spreads threshold, τ, is the choice of the variable m where $\hat{\gamma}$ is stable. The Hill plots for our bond series show the estimated values of $\hat{\gamma}$ against possible values of m. To verify that we have identified stabilization in the behavior of $\hat{\gamma}$ and its associated m for our sample, we also use recursive least squares to regress $\hat{\gamma}$ on a time trend and a constant, successively adding observations and obtaining a one-step-ahead forecast with the respective 90 percent confidence interval (Figures A.1 and A.2).

Table A.1. Ljung-Box Q-Test Results

Country	Null	*p*-Value	*Q*-Statistic	Critical Value
Algeria	0	0.11	7.47	9.49
Argentina	0	0.27	11.07	16.92
Brazil	0	0.33	10.20	16.92
Côte d'Ivoire	1	0.04	11.54	11.07
Chile	0	0.37	4.28	9.49
China	1	0.02	12.93	11.07
Colombia	0	0.44	4.81	11.07
Dominican Rep.	0	0.52	1.30	5.99
Ecuador	0	0.33	9.10	15.51
Egypt	0	0.22	3.01	5.99
El Salvador	0	0.16	2.00	3.84
Hungary	0	0.08	8.29	9.49
Korea	0	0.23	6.93	11.07
Lebanon	0	0.24	6.70	11.07
Malaysia	1	0.01	22.60	16.92
Mexico	0	0.54	7.99	16.92
Morocco	0	0.06	10.44	11.07
Nigeria	0	0.48	8.53	16.92
Pakistan	0	0.20	3.27	5.99
Panama	0	0.89	2.90	14.07
Peru	0	0.19	8.73	12.59
Philippines	0	0.83	5.05	16.92
Poland	0	0.08	15.34	16.92
Russia	0	0.48	5.55	12.59
South Africa	1	0.04	11.71	11.07
Thailand	0	0.24	6.74	11.07
Tunisia	0	0.16	2.00	3.84
Turkey	0	0.48	4.51	11.07
Ukraine	0	0.11	6.00	7.81
Uruguay	0	0.28	2.51	5.99
Venezuela	0	0.71	6.33	16.92

Source: Author's calculations.

Figure A.1. Yearly Data



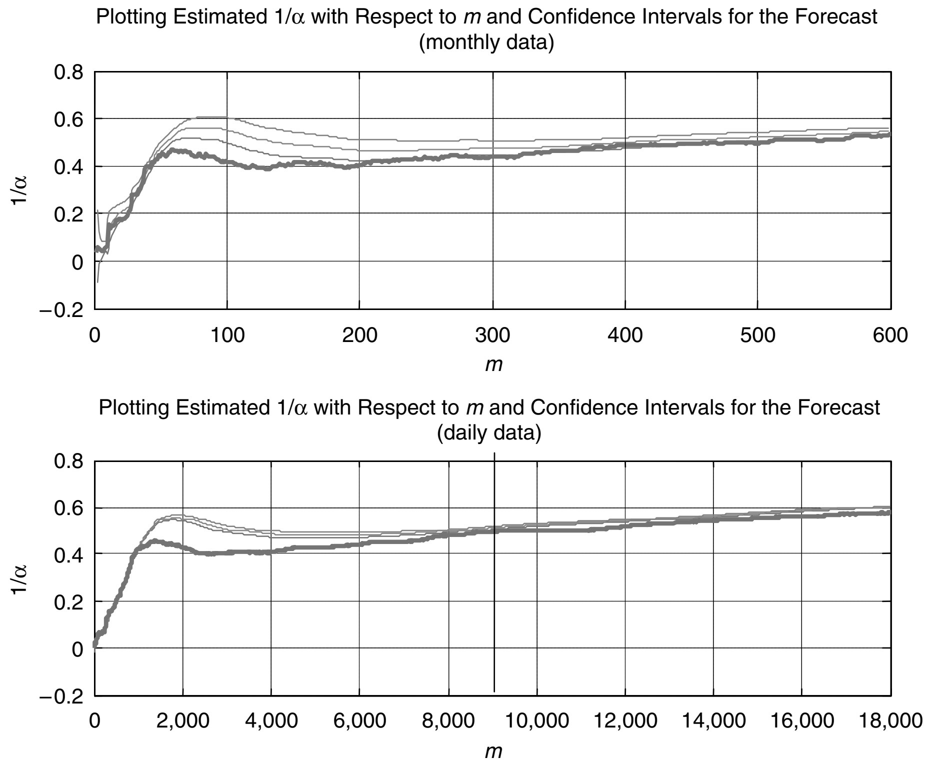
Source: Authors' calculations.

For our yearly sample we conclude that a value of m between 42 and 50 makes $1/\hat{\alpha}$ relatively stable. Using the above relationship, $m = 42$ leads to a value of 1,073 bps and $m = 50$ to 969 bps. Because the relationship between m and the extreme value threshold is clearly monotonic, we conclude that our threshold reasonably lies between 969 and 1,072 bps (see Table A.2).

We also assess to what extent the threshold for bond spreads estimated using extreme value theory would affect the construction of our binary crisis-dependent variable. Table 2, which uses the 1,000 bps mark, shows that the use of a critical threshold from extreme value estimation does not significantly change the classification of the data in crisis periods. Using the upper estimation, we add 2.3 percent crisis periods and using the lower estimation we ignore 1.4 percent crisis events with respect to the total number of crises.

We repeat our extreme-value-theory analysis also for monthly and daily data as a robustness check. The interpretation of the estimation results is more difficult probably because of the presence of serial autocorrelation. For the monthly case, it seems more plausible that there is stabilization around a value of $m = 400$ (that is, a

Figure A.2. Monthly and Daily Data



Source: Authors' calculations.

Table A.2. Extreme Value Theory: Estimated *m* and Implied Threshold τ

Yearly data	$m \in [42, 50]$	$\tau \in [969, 1{,}072]$
Monthly data	$m = 400$	$\tau = 1{,}117$
Daily data	$m = 9{,}000$	$\tau = 1{,}084$

Source: Author's calculations.
Note: *m* represents the number of tail observations used to estimate the tail parameter and ô is the critical threshold for bond spreads.

bond spread value of 1,118 bps). For daily data, the critical threshold is $m = 9{,}000$ (that is, a bond spread value of 1,084 bps) (Table A.3).

Kernel-Density-Estimation Approach

Estimating the distribution of sovereign bond spreads can be useful in the identification of debt crises. In particular, the existence of modes around certain

Table A.3. Comparison: Extreme Value Theory (EVT) and 1,000 bps Thresholds, Sample for 1994–2002

	Matching	EVT Adding	EVT Crossing Out	Total
Yearly				
Total number	[211, 213]	[0, 5]	[0, 3]	216
As percentage	[98, 99]	[0, 2.3]	[0, 1.4]	100
Monthly				
Total number	2,252	92	0	2,344
As percentage	96	3.9	0	100
Daily				
Total number	48,863	1,466	0	50,329
As percentage	97	2.9	0	100

Source: Author's calculations.
Note: bps = basis points.

values can be interpreted as evidence of "tranquil" and "crisis" periods. In this section, we illustrate how kernel density estimation can be used to estimate such modes.

To have a better idea of why a particular threshold, τ, should imply a mode around it we present the following example. Suppose we have a stochastic process, $\{y_t\}$, of the following form:

$$\text{for } y_{t-1} < \tau$$

$$y = \begin{cases} y_{t-1} & \text{if } \varepsilon_t \leq \tau - y_{t-1} \\ \begin{cases} x_t & \text{with } p \\ y_{t-1} + \varepsilon_t & \text{with } 1 - p \end{cases} & \text{otherwise} \end{cases}$$

$$x_t \mapsto D(\theta_t) \quad \text{and} \quad F_x(x \leq y_{t-1}) = 0,\, F_x(x \geq \tau) = 1$$

$$\varepsilon_t \mapsto U(-a, a)$$

$D(\theta_t)$ is a generic distribution with the interval $[y_{t-1}, \tau]$ as support (over which it takes strictly positive values). For simplicity of exposition the errors are uniformly distributed between $-a$ and a.

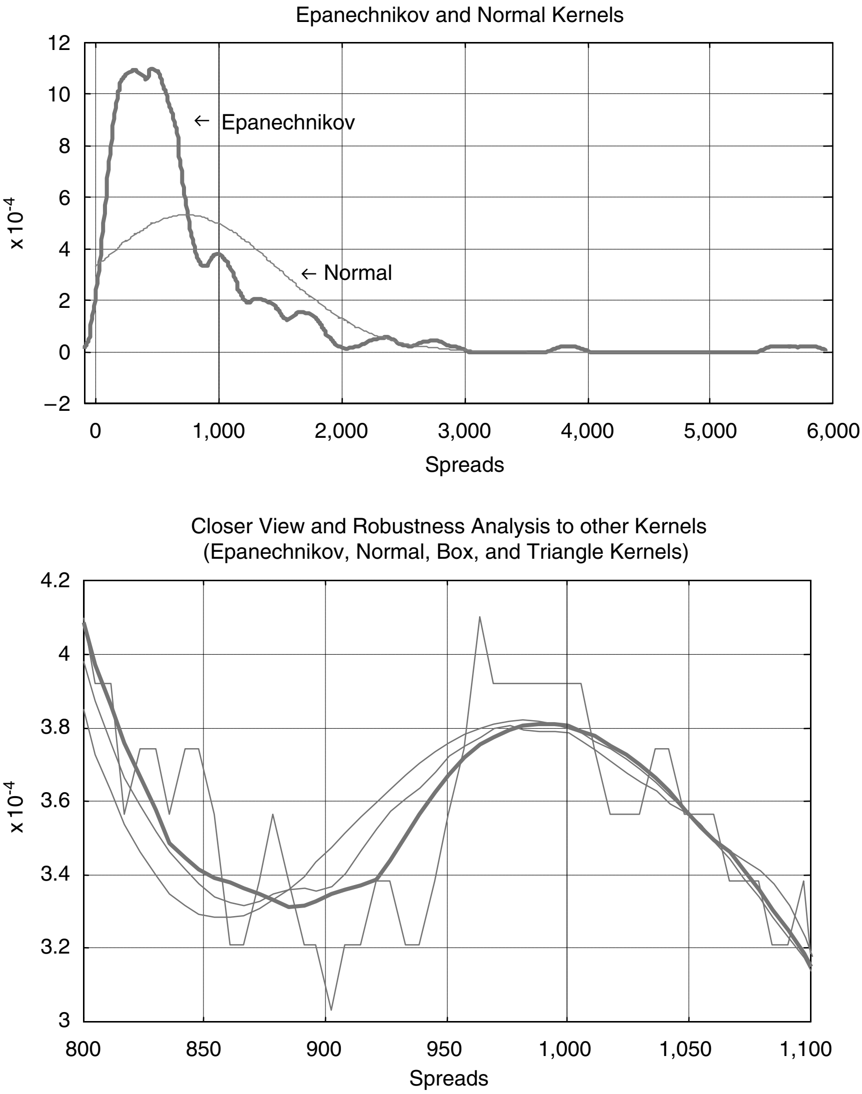
In particular, the "inner" random walk crosses the threshold τ with probability $(1-p)$. With a probability p instead it will be a number between its previous state, y_{t-1}, and the threshold (this is the job of the generic distribution D).

Given a $\delta < a$, whenever $a \leq \tau - y_{t-1}$ we have

$$P(y_t \in I(y_{t-1}, \delta)/y_{t-1}) = \delta/a.$$

With y_{t-1} far away from τ, the conditional probability of being in the neighborhood of y_{t-1} is proportional to δ.

Figure A.3. Pooled Yearly Spreads Kernel Density



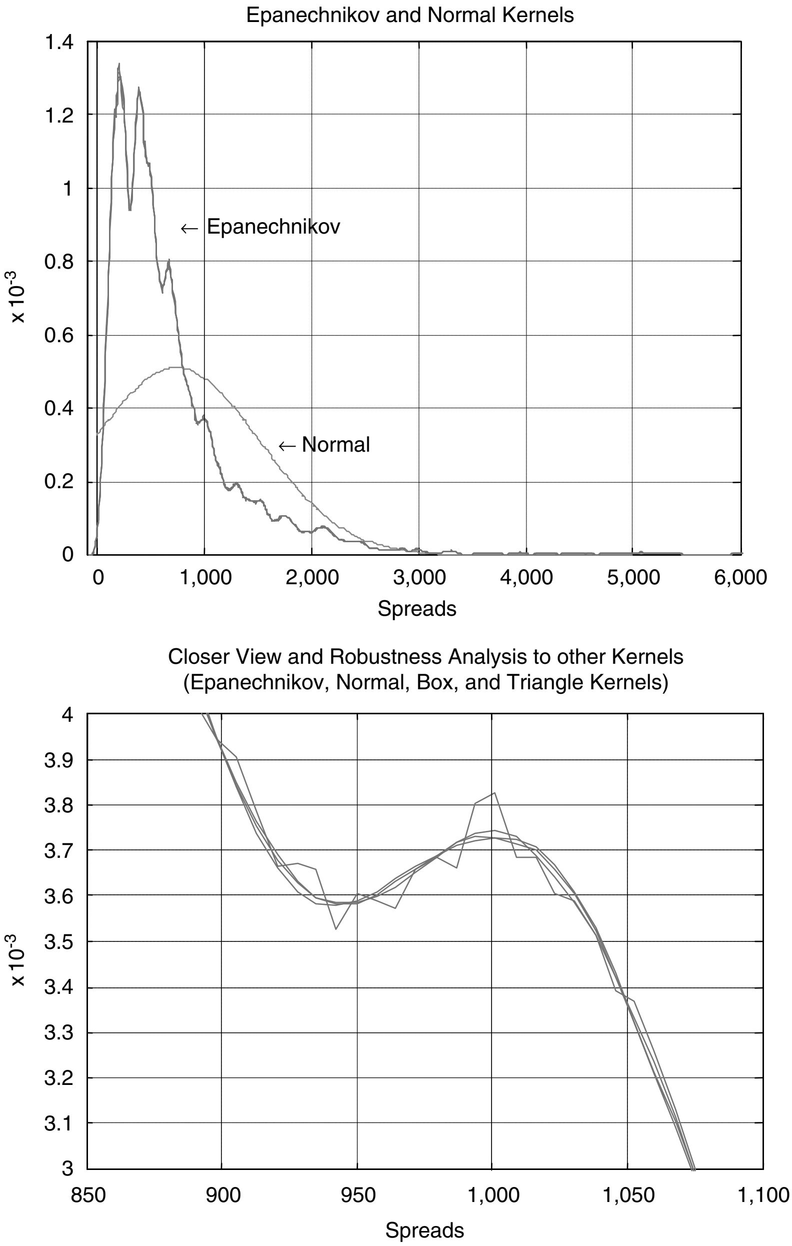
Source: Authors' calculations.

On the other hand, whenever $a > \tau - y_{t-1}$ we have

$$P(y_t \in I(y_{t-1}, \delta)/y_{t-1}) = \delta/a + pP(\varepsilon_t > \tau - y_{t-1}) \\ \times P(x_t \in [y_{t-1}, y_{t-1} + \delta]) > \delta/a.$$

Therefore, because by recurrence we should hit the threshold with a probability of 1, sampling from the previous model will give a mode around the threshold.

Figure A.4. Daily Spreads Kernel Density



Source: Authors' calculations.

The kernel density estimation confirms the assumption that there is a mode for "crisis" periods (see Figures A.3 and A.4). We find a mode around 1,000 bps for both daily and yearly data.

REFERENCES

Alesina, Alberto, Alessandro Prati, and Guido Tabellini, 1990, "Public Confidence and Debt Management: A Model and a Case Study of Italy," in *Public Debt Management: Theory and History*, ed. by Rudiger Dornbusch and Mario Draghi (Cambridge, Cambridge University Press).

Altman, Edward I., 1998, "Market Dynamics and Investment Performance of Distressed and Defaulted Debt Securities," Working Paper (New York, New York University).

Beim, David O., and Charles W. Calomiris, 2001, *Emerging Financial Markets* (New York, McGraw-Hill/Irwin).

Berg, Andrew, and Catherine Pattillo, 1999, "Are Currency Crises Predictable? A Test," *Staff Papers*, International Monetary Fund, Vol. 46 (June), pp. 107–138.

Bussière, Matthieu, and Christian Mulder, 1999, "External Vulnerability in Emerging Market Economies: How High Liquidity Can Offset Weak Fundamentals and the Effects of Contagion," IMF Working Paper 99/88 (Washington, International Monetary Fund).

Calvo, Guillermo A., 1988, "Servicing the Public Debt: The Role of Expectations," *American Economic Review*, Vol. 78 (September), pp. 647–661.

Chambers, John, and Daria Alexeeva, 2003, "2002 Defaults and Rating Transition Data Update for Rated Sovereigns," in *Ratings Performance 2002, Default, Transition, Recovery, and Spreads* (New York, Standard & Poor's), pp. 75–86. Available via the Internet: http://www.standardandpoors.co.jp/spf/pdf/products/RatingsPerformance.pdf.

Chan-Lau, Jorge, 2003, "Anticipating Credit Events Using Credit Default Swaps, with an Application to Sovereign Debt Crises," IMF Working Paper 03/106 (Washington, International Monetary Fund).

Dailami, Mansoor, Paul R. Masson, and Jean Jose Padou, 2005, "Global Monetary Conditions vs. Country-Specific Factors in the Determination of Emerging Market Debt Spreads," Policy Research Working Paper No. 3626 (Washington, World Bank).

Detragiache, Enrica, and Antonio Spilimbergo, 2001, "Crises and Liquidity: Evidence and Interpretation," IMF Working Paper 01/2 (Washington, International Monetary Fund).

Duffie, Darrell, and Kenneth J. Singleton, 2003, *Credit Risk: Pricing, Measurement, and Management* (Princeton, New Jersey, Princeton University Press).

Edwards, Sebastian, 1984, "LDC Foreign Borrowing and Default Risk: An Empirical Investigation, 1976–80," *American Economic Review*, Vol. 74 (September), pp. 726–734.

Eichengreen, Barry, and Ashoka Mody, 1998, "What Explains Changing Spreads on Emerging-Market Debt: Fundamentals or Market Sentiment?" NBER Working Paper No. 6408 (Cambridge, Massachusetts, National Bureau of Economic Research).

———, 1999, "Lending Booms, Reserves, and the Sustainability of Short-Term Debt: Inferences from the Pricing of Syndicated Bank Loans," NBER Working Paper No. 7113 (Cambridge, Massachusetts, National Bureau of Economic Research).

Frankel, Jeffrey A., and Andrew K. Rose, 1996, "Currency Crashes in Emerging Markets: An Empirical Treatment," *Journal of International Economics*, Vol. 41 (November), pp. 351–366.

Garcia, Márcio, and Roberto Rigobon, 2004, "A Risk Management Approach to Emerging Market's Sovereign Debt Sustainability with an Application to Brazilian Data," NBER Working Paper No. 10336 (Cambridge, Massachusetts, National Bureau of Economic Research).

Hols, M.C.A.B., and C.G. de Vries, 1991, "The Limiting Distribution of Extremal Exchange Rate Returns," *Journal of Applied Econometrics*, Vol. 6 (June–September), pp. 287–302.

Hu, Yen-Ting, Rudiger Kiesel, and William Perraudin, 2001, "The Estimation of Transition Matrices for Sovereign Credit Ratings," (unpublished; London, Bank of England). Available via the Internet: http://www3.imperial.ac.uk/portal/pls/portallive/docs/1/43673.PDF.

Jüttner, Johannes D., and Justin McCarthy, 1998, "Modelling a Ratings Crisis," (unpublished; Sydney, Australia, Macquarie University).

Kaminsky, Graciela, and Sergio Schumkler, 2001, "Emerging Markets Instability: Do Sovereign Ratings Affect Country Risk and Stock Returns?" Policy Research Working Paper No. 2678 (Washington, World Bank).

Koedijk, K.G., M.M.A. Schafgans, and C.G. de Vries, 1990, "The Tail Index of Exchange Rate Returns," *Journal of International Economics*, Vol. 29 (August), pp. 93–108.

Koedijk, K.G., P.A. Stork, and C.G. de Vries, 1992, "Differences Between Foreign Exchange Rate Regimes: The View from the Tails," *Journal of International Money and Finance*, Vol. 11 (October), pp. 462–473.

Manasse, Paolo, Nouriel Roubini, and Axel Schimmelpfennig, 2003, "Predicting Soveregin Debt Crises," IMF Working Paper 03/221 (Washington: International Monetary Fund).

Mauro, Paolo, Nathan Sussman, and Yishay Yafeh, 2002, "Emerging Market Spreads: Then vs. Now," *Quarterly Journal of Economics*, Vol. 117 (May), pp. 695–733.

McDonald, D., 1982, "Debt Capacity and Developing Country Borrowing: A Survey of the Literature," *Staff Papers*, International Monetary Fund, Vol. 29, pp. 603–646.

Milesi-Ferretti, Gian Maria, and Assaf Razin, 1998, "Current Account Reversals and Currency Crises: Empirical Regularities," IMF Working Paper 98/89 (Washington, International Monetary Fund).

Moody's Investors Service, 2003, "Sovereign Bond Defaults, Rating Transitions, and Recoveries (1985–2002)" Special comments (February), pp. 2–52.

Pozo, Susan, and Catalina Amuedo-Dorantes, 2003, "Statistical Distributions and the Identification of Currency Crises," *Journal of International Money and Finance*, Vol. 22 (August), pp. 591–609.

Radelet, Steven, and Jeffrey Sachs, 1998, "The East Asian Financial Crisis: Diagnosis, Remedies, Prospects," *Brookings Papers on Economic Activity: 1* (Brookings Institution), pp. 1–90 (Washington D.C., Brookings Institution).

Reinhart, Carmen M., 2002, "Default, Currency Crises and Sovereign Credit Ratings," NBER Working Paper No. 8738 (Cambridge, Massachusetts, National Bureau of Economic Research). Also in *World Bank Economic Review*, Vol. 16, No. 2, pp. 151–70.

Rodrik, Dani, and Andrés Velasco, 2000, "Short-Term Capital Flows," in *Proceedings of the 1999 Annual Bank Conference on Development Economics*, ed. by Boris Pleskovic and Joseph E. Stiglitz (Washington, World Bank).

Sachs, Jeffrey D., 1984, *Theoretical Issues in International Borrowing*, Princeton Studies in International Finance No. 54 (Princeton, New Jersey, Princeton University Press).

Standard and Poor's, 2002, "Sovereign Defaults: Moving Higher Again in 2003?" September 24, 2002. Reprinted for *Ratings Direct*.

Sy, Amadou N.R, 2004, "Rating the Rating Agencies: Anticipating Currency Crises or Debt Crises?," *Journal of Banking and Finance*, Vol. 28 (November), pp. 2845–2867.