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Predicting Sovereign Debt Crises

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Predicting Sovereign Debt Crises

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Abstract

We develop an early-warning model of sovereign debt crises. A country is defined to be in a debt crisis if it is classified as being in default by Standard & Poor's, or if it has access to nonconcessional IMF financing in excess of 100 percent of quota. By means of logit and binary recursive tree analysis, we identify macroeconomic variables reflecting solvency and liquidity factors that predict a debt-crisis episode one year in advance. The logit model predicts 74 percent of all crises entries while sending few false alarms, and the recursive tree 89 percent while sending more false alarms.

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I. Predicting Sovereign Debt Crises

As more countries are moving toward flexible exchange rates, currency crises associated with the collapse of a fixed exchange rate regime are becoming less frequent. Sovereign debt-servicing difficulties and, in some cases, outright defaults, by contrast, have become more common in recent years. The macroeconomic misalignments leading to debt crises, however, are still not well understood: the literature has mostly been in the business of attempting to predict currency crises, with some success, and the associated banking crises in some of these episodes. There is a large empirical literature on "twin" currency and banking crises, but little work has lately been done on predicting sovereign debt crises.

In recent years, sovereign debt-servicing difficulties have taken different forms, from outright default on domestic and external debt to rollover/liquidity crises where a solvent, but illiquid, country was on the verge of default on its debt because of investors' unwillingness to roll over short-term debts coming to maturity. We observed outright defaults on domestic and/or external debt in Russia, Ecuador, Argentina; episodes of semi-coercive restructuring (i.e., under the implicit threat of default) of sovereign debt in Ukraine in 2000, Pakistan in 1999, and Uruguay in 2003; and other episodes where the country was most likely solvent but illiquid and a debt-servicing crisis was in part avoided via large amounts of official support by the international financial institutions (IFIs), as well as less coercive forms of private sector involvement in crisis resolution (Mexico in 1994–95, Korea and Thailand in 1997–98, Brazil in 1999 and 2002, Turkey in 2001, and Uruguay in 2002). In many of the latter episodes, one of the sources of debt-servicing difficulties was the short maturities of external or domestic debt obligations of the sovereign or of the private sector (the private banks in Korea, for example), rather than excessive debt associated with a clear insolvency situation. The decision of domestic and international investors not to roll over such short-term liabilities put the country on the verge of outright default, which was avoided, in part, through the financial support of the official sector. In addition to the cases cited above, several other countries have large debt burdens and may be subject to debt-servicing problems in the foreseeable future. Thus, sovereign debt-servicing difficulties (both of the illiquidity and insolvency varieties) that were severe during the 1980s debt crisis, have become relatively frequent phenomena again in the last decade. Thus, assessing and predicting debt sustainability is of great empirical and policy importance.

This paper employs a variety of techniques to assess the role of macroeconomic fundamentals in affecting the risk of sovereign default and a debt crisis, for a large sample of countries loosely defined as having market access and for different definitions of a debt crisis. One innovation in our work is that the crisis definitions include not only cases of outright default or coercive restructuring but those in which such near-default was avoided through the provision of large-scale official financing by the IMF. We ask the following questions: What is the set of economic fundamentals whose misalignment is more likely to result in a debt-servicing crisis? What is the role of such imbalances in getting into a crisis versus getting out of a crisis? Are these effects asymmetric? Can we identify critical thresholds beyond which default risks rise considerably? Can we design an early warning systems (EWS) model of debt crises that can help predict early on the vulnerability to such a crisis? We use a panel dataset for 47 market access countries for the 1970–2002 period. We estimate and use logit models of debt crisis, a binary recursive tree technique and a combination of the two approaches.

Based on our empirical analysis, we reach the following main conclusions.

- The empirical evidence suggests that a number of macroeconomic factors predict a debt crisis and the entry into a debt crisis. Measures of debt "solvency" matter: high levels of foreign debt (relative to a measure of the ability to pay, such as GDP) increase the probability of a default and entry into default. Measures of illiquidity, particularly short-term debt (relative to foreign reserves), and measures of debt-servicing obligations also matter in predicting debt crises, consistent with the view that some recent crises had to do with illiquidity and/or the interaction of illiquidity and insolvency. Other macroeconomic variables suggested from the analytical literature on debt sustainability also significantly matter for predicting debt crises: low GDP growth; current account imbalances; low trade openness; tight liquidity and monetary conditions in the Group of seven countries; monetary mismanagement (in the form of high inflation); policy uncertainty (in the form of high volatility of inflation); and political uncertainty leading to economic uncertainty (years of presidential elections). Among the fiscal variables, only the ratio of public debt to revenue has some predictive power. However, data availability severely limits the ability to appropriately test for the role of such variables. From a number of political economy variables, a dummy for presidential election years, reflecting political uncertainty, and an index of political freedom help crises prediction; crises move fast while institutions change slowly, so that finding significant effects is likely to remain problematic.
- Sovereign debt crises, unlike currency crisis, last long and show persistence. Once a country is in a crisis, it is not easy to get out of one, as these episodes often have long spells. Even when a country wrangles its way out of a default, the macroeconomic picture is often not as positive as for those countries that have successfully avoided default.
- Although we concentrate on understanding the factors that trigger a country's entry into a debt crisis, given the importance of obtaining an early-warning signal of a crisis, we also consider whether these factors affect the likelihood of exit from a crisis. The model predicts much better entry into a crisis than exit from it, since it is hard to determine the exact timing of what leads to the end of a debt-crisis episode. In part, this is due to the fact that even the definition of exit is somewhat ambiguous: do default crises end when the default is cured (as in the case of Brady plans for the 1980s crises) or when economic adjustment and reforms lead to economic recovery?
- Heterogeneity across countries and interdependence of economic variables within countries should not be overlooked when searching for "the" critical thresholds that signal the likelihood of a future crisis. We find that countries with external debt greater than 50 percent of GDP are more likely to experience default episodes.

Default is even more likely, if inflation, public debt, and/or external financing requirements are high. Countries with low external debts may still suffer a high risk of crisis when faced with liquidity problems, political uncertainty, and fiscal mismanagement, or when the exchange rate is overvalued and international capital markets are tight.

- In terms of EWS models, our two models of predicting debt crises outperform the current state-of-the-art literature on early-warning models of currency crises (indicating that it is easier to predict debt crises—and entry into crises—than to predict currency crises). Our logit model predicts 74 percent of entries into a crisis while sending out few false alarms (i.e., predicting a crisis when one does not occur). The recursive tree approach correctly predicts 89 percent of entries into a crisis while sending out more false alarms.

Overall, this paper improves on the empirical literature on debt crises in several respects: data, crisis definition, empirical methodology, and—we think—results. Although a considerable amount of work has been done to analyze the crises of the 1980s, very little has been done on a sample that includes the 1990s. In this respect, our model makes some progress by paying special attention to factors that help predict more recent crisis episodes.

The paper is organized as follows. Section II presents a literature survey. Section III presents the dataset, description of the crisis definition, descriptive statistics, and an event study analysis. Section IV presents and estimates a logit model, and discusses the results obtained with this model and the robustness of these results. Section V presents the results from the binary recursive tree technique. The section also discusses options of combining the logit EWS and the tree EWS to inform policymakers about possible debt-servicing vulnerabilities. Section VI presents some concluding remarks and suggestions for extensions of this work.

II. Related Literature

The literature on debt crisis falls into four broad categories: theoretical models of sovereign default; empirical studies of the determinants of debt crisis; empirical studies of the predictive power of credit ratings; and empirical studies of the determination of spreads. Most studies focus on a particular aspect of debt crisis or particular determinants. Taken together, the literature suggests a number of macroeconomic and other factors that influences the likelihood of sovereign debt-servicing difficulties and default.

The theoretical literature highlights a variety of factors that can trigger sovereign default and debt crises.[2] On the one side, countries can be unwilling to repay their debt, based on an

[2] See Roubini (2001) for a recent overview of debt sustainability and solvency; and Eaton and Fernandez (1995) for a systematic survey of the literature on sovereign debt. Hemming and Petrie (2002) present an extensive and broad discussion of the concept of fiscal vulnerability; the concept includes the failure to avoid excessive deficits and debt. The concept of fiscal sustainability is, for example, discussed in Hemming and Chalk (2000).

intertemporal optimization calculus. On the other side, countries can be unable to repay their debt because they are either insolvent or illiquid. In empirical applications, a host of macroeconomic and institutional variables have thus been used. Whether a sovereign is insolvent or not depends on its stock of debt relative to its ability to pay, measured, for example, by GDP, exports, or government revenues. A sovereign is solvent, if the discounted value of future primary balances is greater or equal to the current public debt stock. Likewise, a country is solvent, if the discounted value of future trade balances exceeds the current stock of external debt. The exchange rate regime and exchange rate misalignment impact these considerations because an overvaluation can cause an external imbalance that leads to debt accumulation. Moreover, a currency crisis triggered by overvaluation can lead to severe balance sheet effects if part of the debt is in foreign currency. Openness can affect the costs of default and thus a country's willingness to default or not. Measures of macroeconomic stability, such as low inflation or low money growth, reflect policy credibility and predictability and thus influence investors' risk attitudes toward a country. A debt crisis can also occur if a country is illiquid rather than insolvent. Hence, liquidity measures, such as short-term debt to reserves or M2 to reserves, are included in some models. Finally, institutional and political factors affect policy credibility, as well as a government's willingness to pursue policies consistent with a sustainable debt path.

Empirical studies use different crisis definition depending on the specific research question and the information available in the data source used. A priori, there is no single empirical definition of what should constitute a sovereign default or a debt crisis. Some studies compile a list of debt crisis or default from case studies and anecdotal evidence (e.g., Beers and Bhatia, 1999; or Beim and Calomiris, 2001). Other studies rely on a more quantitative approach. For example, Detragiache and Spilimbergo (2001) define a country to be in a debt crisis if the country has arrears on external obligations toward commercial creditors in excess of 5 percent of commercial debt outstanding or has a rescheduling or restructuring agreement with commercial creditors. This definition does not differentiate between sovereign or private sector arrears and/or rescheduling due to data limitations. Another problem of this quantitative definition is that it might exclude some incipient debt crises that were only avoided by large-scale financial support from official creditors (IFIs and/or bilateral). Ideally, one could attempt to define a continuous crisis pressure metric similar to the exchange market pressure index underlying some currency crisis studies. A data source that provides uniformly compiled information on sovereign default is Standard & Poor's (2002) who define a country to be in default as long as the sovereign is not current on any of its debt obligation

Studies of the determinants of debt crisis are closest in nature to an early-warning signal model. Factors influencing the probability of a debt crisis occurring are identified by means of probit/logit regressions or signals models. Most studies have focused on the debt crisis of the 1980s, but there are also some recent efforts that look at crisis occurring in the 1990s.[3] Taken together, measures of solvency, such as the debt-to-GDP ratio, and measures of

[3] See for example Detragiache and Spilimbergo (2001) for a study including recent episodes.

liquidity, such as short-term debt to reserves or exports and debt service to reserves or exports, are significant explanatory variables in addition to macroeconomic controls, such as real growth, inflation, exchange rate overvaluation, and the fiscal balance. Reinhart (2002) finds that in 84 percent of the cases in her sample, a debt crisis is preceded by a currency crisis. Hence, variables that are well-suited for predicting currency crisis should also have some explanatory power in models for sovereign default (see also Hemming et al., 2003). Detragiache and Spilimbergo (2001) carry out a number of interesting tests. They find that short-term debt, debt service, and reserves enter their model separately and the null of equal coefficients is rejected. Using ratios such as short-term debt to reserves, therefore, imposes a restriction that is not supported by the data. They also find that short-term debt is endogenous to the model, as countries find it more and more difficult to borrow long term in the run-up to a debt crisis. While most studies use macroeconomic variables only in levels, Catão and Sutton (2002) also include measures of volatility in their model. The in-sample predictive power increases markedly when measures of terms of trade volatility, fiscal policy volatility, monetary policy volatility, and exchange rate policy volatility are added to a model containing real GDP growth, debt service to exports, net international reserves to debt, the fiscal balance, the U.S. interest rate, and the real effective exchange rate.

The predictive power of credit ratings for currency crisis and sovereign default is surprisingly poor. This became evident in the Asian crisis or, more recently, in the Argentinean crisis. Systematic evidence in this regard is presented in Reinhart (2002); Rojas-Suarez (2001); and Larrain, Reisen, and von Maltzan (1997). Related studies have analyzed the determinants of credits ratings. Some studies test whether credit ratings are significantly correlated with a range of economic fundamentals. Measures of external debt, default history, as well as other macroeconomic and political variables are found to be correlated with default/debt-crisis events (e.g., Haque, Nelson, and Mathieson, 1998; Cantor and Packer, 1996; and Lee, 1993).

The determinants of sovereign spreads have been analyzed in several studies. For example, Dell'Ariccia, Schnabel, and Zettelmeyer (2002) find that spreads increased after the nonbailout of Russia in 1998, suggesting that spreads are compressed by moral hazard (see also Lane and Phillips (2001), for other tests of moral hazard that provide mixed results). However, the power of these spreads in predicting debt crisis has not been assessed systematically due to data limitations. Many debt crisis and defaults occurred in the 1980s, while measures of sovereign spread became widely available only in the 1990s, after the commercial bank debt was securitized, converted into Bradies and new Eurobonds and were widely issued and traded. Also, spreads are not available for many poorer developing countries (many of the HIPC countries) that do not borrow on commercial terms but have experienced debt-servicing problems in their obligations to official creditors.

Taken together, the existing literature suggests several regularities that could form the backbone of an empirical model attempting to predict sovereign default:

- Measures of solvency, 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.

- Variables used in models of currency crisis such as the IMF's EWS.
- Measures of external volatility and volatility in economic policies.
- Macroeconomic (control) variables, such as real growth, inflation, exchange rate, etc.
- Political and institutional variables capturing a country's willingness to pay.

III. Data, Descriptive Statistics, and Event Study Analysis

A. The Data

The dataset includes information on 47 economies with market access for the period 1970 to 2002 (Table 1).[4] The debt-crisis indicator is derived from data provided by Standard & Poor's and data on IMF lending. Data on external debt and public debt is taken from the World Bank's Global Development Finance database (GDF) as well as from IMF sources. Data on public finance and other macroeconomic variables are taken from the IMF's World Economic Outlook database as well as the Government Finance Statistics database (GFS). A detailed description of the variables and their source is provided in Appendix IV.

A country is defined to be in a debt crisis if it is classified as being in default by Standard & Poor's or if it receives a large nonconcessional IMF loan defined as access in excess of 100 percent of quota. Standard & Poor's rates sovereign issuers in default, if a government fails to meet principal or interest payment on external obligation on due date (including exchange offers, debt equity swaps, and buy back for cash). A potential problem with this information is that it may not capture quasi defaults that were only prevented through an adjustment program and a large financial package from the IMF. We therefore augment the information obtained from Standard & Poor's with data on IMF nonconcessional lending from the IMF's Finance Department.[5] We use information on the loans approved, approval dates and the actual disbursement of the loans. Based on the information on IMF lending, a country is classified as being in debt crisis if a large nonconcessional loan is approved and a disbursement under this loan is actually made in the first year. The definition of debt crisis thus encompasses actual defaults on debt recorded by Standard & Poor's and "incipient" defaults that were avoided only through a large scale financial support from the IMF. Based on this definition, a country can be in debt crisis for an extended period of time. Initially, we define a large IMF loan as being in excess of 100 percent of quota; this threshold selects the top 10 percent of loans when ranked by the loan to quota ratio. As a sensitivity analysis, we also use a 50 percent and a 150 percent threshold to define the debt-crisis indicator.

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[4] The full dataset includes information on 76 countries. For transition economies, the sample period is 1995 to 2002. Not every variable is available for all countries or for the full time period.

[5] Mainly SBA and EFF lending.

Table 1. Countries and Debt-Crisis Episodes in the Full Sample 1/ 2/

	Number of Crises	Average Length	Years in Crisis	Crisis episodes (entry–exit)
Algeria	1	6.0	6	1991–97
Argentina	3	5.0	15	1982–94, 1995–96, 2001–
Bolivia	2	6.5	13	1980–85, 1986–94
Brazil	3	5.3	16	1983–95, 1998–00, 2001–
Chile	1	8.0	8	1983–91
China	0	…	0	
Colombia	0	…	0	
Costa Rica	1	10.	10	1981–91
Cyprus	0	…	0	
Czech Republic 3/	0	…	0	
Dominican Republic	1	22.	22	1981–
Ecuador	2	8.0	16	1982–96, 1999–2001
Egypt	1	1.0	1	1984–85
El Salvador	1	16.	16	1981–97
Estonia 3/	0	…	0	
Guatemala	1	1.0	1	1986–87
Hungary 3/	0	…	0	
India	0	…	0	
Indonesia	2	2.5	5	1997–2001, 2002–
Israel	0	…	0	
Jamaica	3	4.7	14	1978–80, 1981–86, 1987–94
Jordan	1	5.0	5	1989–94
Kazakhstan 3/	0	…	0	
Korea	2	2.0	4	1980–82, 1997–99
Latvia 3/	0	…	0	
Lithuania 3/	0	…	0	
Malaysia	0	…	0	
Mexico	2	5.0	10	1982–91, 1995–96
Morocco	2	3.0	6	1983–84, 1986–91
Oman	0	…	0	
Pakistan	1	2.0	2	1998–2000
Panama	1	14.	14	1983–97
Paraguay	1	7.0	7	1986–93
Peru	3	6.3	19	1976–77, 1978–81, 1983–98
Philippines	1	10.	10	1983–93
Poland 3/	0	…	0	
Romania 3/	0	…	0	
Russia 3/	1	3.0	3	1998–2001
Slovak Republic 3/	0	…	0	
South Africa	4	1.8	7	1976–78, 1985–88, 1989–90, 1993–94
Thailand	2	1.0	2	1981–82, 1997–98
Trinidad and Tobago	1	2.0	2	1988–90
Tunisia	1	1.0	1	1991–92
Turkey	2	3.5	7	1978–83, 2000–2002
Ukraine 3/	1	3.0	3	1998–2001
Uruguay	3	2.0	6	1983–86, 1987–88, 1990–92
Venezuela	3	3.3	10	1983–89, 1990–91, 1995–98
Total	54	5.5	…	

Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.
1/ A country is defined to be in a debt-crisis if it is classified as being in default by Standard & Poor's or receives a noncossional IMF loan in excess of 100 percent of quota.
2/ Data from 1970–2002.
3/ Transition countries are included only from 1995 onward.

As another robustness check, we use only the Standard & Poor's data excluding debt-crisis episodes that relate only to exceptional IMF lending.

B. Descriptive Statistics

The potential explanatory variables are largely drawn from a list of usual suspects. In particular, we use various measures of external debt and public debt, measures of solvency and liquidity, regressors included in the IMF's currency crisis EWS as there is a possible link between currency crisis and sovereign debt crisis, other macroeconomic variables, as well as fiscal flow variables. Table 2 gives the respective mean of these variables in the full sample, for noncrisis episodes, for years before a country enters a debt crisis, for in-crisis years, and for years before a country exits a crisis.[6] In general, the path of means from noncrisis to entry into crisis and finally exit from crisis is as expected.

- The various measures of external debt (including debt servicing) are relatively low in noncrisis years followed by another noncrisis year. They increase in the year before crisis entry, and most measures increase even further within crisis. The measures drop again in the year before a country exits from crisis, though they are still higher than before the crisis. The measures of public external debt follow the same pattern, suggesting that public external debt is a possible driving force behind external debt developments (as in many countries a large fraction of external debt is public external debt).
- The macroeconomic variables—including those from the IMF's currency crisis EWS—indicate a worsening of the macroeconomic situation in the run-up to a crisis and within a crisis, and an improvement in the situation when exiting from crisis. For example, the current account deficit increases in the year immediately preceding a crisis entry, stabilizes within the crisis, and improves further in the year before exiting a crisis. Real growth falters in the year before crisis entry while inflation spikes. The overall balance as well as primary balance deteriorate in the run-up to crisis. It is interesting to note that both the LIBOR as well as the U.S. treasury bill rate increase in years preceding a crisis, suggesting that tight monetary conditions in the G7 area may reduce capital flows to emerging market economies and thus contribute to debt-servicing difficulties (as it happened in 1982 for example).

Taken together, the descriptive statistics depict a worsening of the debt situation as well as the overall macroeconomic situation in the run-up to a crisis, and an improvement in these indicators before exiting from crisis. Of course, such descriptive statistics are suggestive at best, and the indicated relationships require more rigorous statistical or econometric testing.

[6] Appendix Table 8 reproduces this table for episodes starting in or after 1990.

Table 2. Mean of Variables Used in the Regressions

Current year Next year	All All	Noncrisis Noncrisis	Noncrisis Crisis	Crisis Crisis	Crisis Noncrisis	No. of Obs.
Total external debt in percent of GDP	45.5	37.0	54.7	71.4	63.7	1,05
Total external debt to exports	290.	239.	359.	455.	350.	1,05
Short-term external debt (OM, in percent of GDP)	7.2	6.1	9.5	10.6	8.0	1,01
Short-term external debt (OM, to reserves)	1.1	0.8	1.9	2.1	1.0	1,01
Short-term external debt (RM, in percent of GDP)	10.9	9.4	15.0	15.1	15.7	993
Short-term external debt (RM, to reserves)	1.7	1.2	2.9	2.9	2.2	948
Interest on short-term external debt in percent of	0.5	0.5	0.8	0.6	0.7	754
Interest on short-term external debt to reserves	0.1	0.1	0.2	0.1	0.1	754
Debt service on short-term external debt in percent of GDP	5.3	4.8	6.9	6.4	7.1	1,05 0
Debt service on short-term external debt to reserves	0.8	0.7	1.5	1.2	0.9	1,05
Public external debt in percent of GDP	32.2	25.5	36.4	53.0	46.5	1,05
Public external debt to revenue	1.7	1.3	1.9	3.0	2.3	827
Consolidated central government debt in percent of GDP	47.5	46.4	38.2	57.3	54.0	462
Central government debt in percent of GDP	51.7	50.4	28.4	75.5	51.6	305
Augmented Consolidated central government debt in percent of GDP	50.7	47.8	41.5	67.7	54.8	591
Overvaluation	0.0	0.0	0.0	-0.1	0.0	799
Current account balance in percent of GDP	-2.7	-2.7	-4.3	-2.6	-1.3	1,23
Reserves growth	19.1	20.8	-5.4	17.8	22.9	1,15
Export growth	12.0	13.8	4.9	6.4	7.8	1,27
M2 to reserves	5.6	5.3	7.9	6.2	6.2	1,18
Financing requirement to reserves	1.6	1.3	3.0	2.4	1.4	986
External resource gap in percent of GDP	-0.2	-0.6	-1.5	1.3	2.9	1,11
Trade balance in percent of GDP	-3.7	-4.0	-2.7	-3.4	-1.1	1,27
LIBOR	9.7	9.5	10.5	10.5	9.4	1,22
U.S. treasury bill rate	6.4	6.3	7.8	6.9	6.3	1,22
Inflation (year-on-year, in percent)	54.6	17.5	241.	169.	84.9	1,27
Unemployment rate	9.7	9.0	11.1	10.9	11.6	740
Nominal GDP growth	55.9	22.8	249.	148.	96.0	1,27
Real GDP growth	4.1	4.8	1.8	2.1	2.2	1,27
REER growth	121.	124.	139.	111.	109.	937
Import growth	10.0	12.3	5.3	4.8	6.9	902
FDI in percent of GDP	1.7	1.9	1.1	1.0	1.5	1,02
FDI growth	28.0	26.3	52.6	22.6	53.6	983
Openness	71.2	71.3	64.1	72.1	72.5	903
Overall balance in percent of GDP	-4.3	-4.4	-6.3	-3.8	-4.1	1,01
Primary balance in percent of GDP	0.6	0.3	-0.9	2.0	1.5	616
Primary gap	6.6	5.7	23.1	59.0	-15.0	122
Revenue in percent of GDP	24.3	25.4	22.7	20.1	24.2	1,01
Tax revenue in percent of total	82.5	82.2	85.7	82.7	83.5	819
International trade revenue in percent of total	13.7	13.7	12.1	14.7	11.3	814
Nontax revenue in percent of total	15.0	15.0	13.5	15.4	14.8	822
Grants in percent of total	2.7	3.0	0.7	1.4	2.1	522
Expenditure in percent of GDP	28.6	29.7	29.0	23.9	28.3	1,01
Interest expenditure in percent of total	11.1	9.8	11.0	15.4	15.1	799
Wages in percent of total	23.4	22.8	23.9	25.9	23.3	713
Health expenditure in percent of total	6.5	6.1	5.4	8.5	6.0	628
Social expenditure in percent of total	17.5	17.1	19.4	17.8	22.2	663

Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

C. Event Study Analysis

Event study analysis is a simple graphical approach that can provide some insights as to how variables behave around the time of an event, such as a sovereign debt crisis. The figures show as a broken horizontal line the sample average of a particular variable for all noncrisis episodes (i.e., those episodes that fall outside a window starting three years before crisis entry and ending three years after crisis exit). The solid bold line depicts the average of the particular variable in the three years preceding crisis entry (exit), the crisis entry (exit) year, and the three years following the crisis entry (exit).[7] The two broken lines give the 95 percent confidence interval around the crises observations. If the solid horizontal line depicting the noncrisis episodes is outside the 95 percent confidence interval, the respective variable behaves significantly different during the event.[8] To focus ideas, we discuss only the more interesting variables in our dataset.

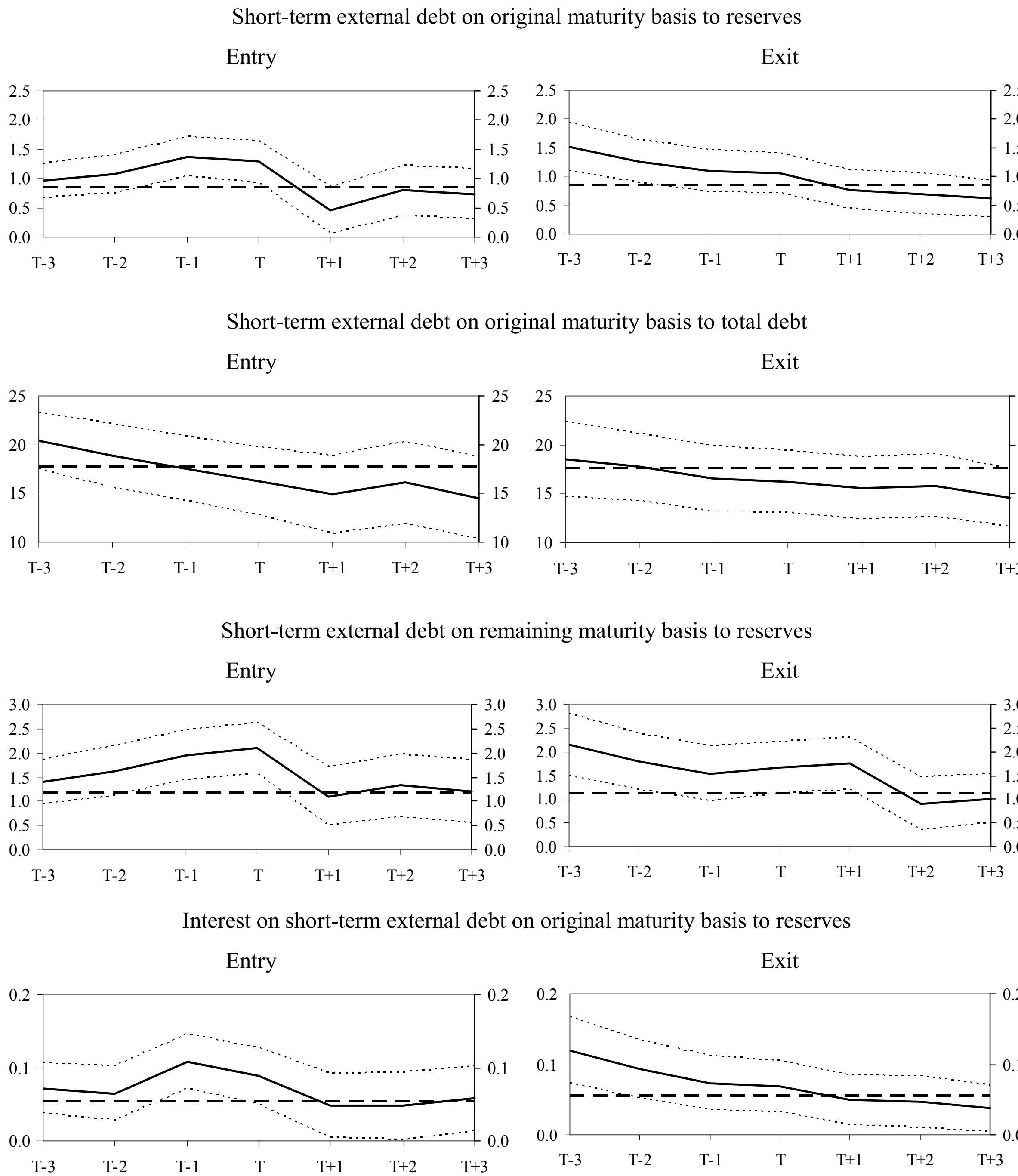
The event study figures show a worsening debt situation and adverse external and domestic developments in the years before entry into crisis (Figures 1 through 4). Developments around exit from crisis are more diverse.[9]

[7] We eliminate overlapping entry (exit) windows by dropping entries (exits) that occur within six years after the preceding entry (exit). Overlapping windows occur, for example, if a country exits from crisis immediately after entering, and then enters another crisis in the following year.

[8] We generate the event study figures through regression of the respective variable on a set of seven dummies for the three years preceding crisis entry (exit), the crisis entry (exit) year itself, and the three years following crisis entry (exit). The estimated constant is the mean of all nondefault episodes, depicted as the broken horizontal line. The estimated coefficients on the dummies give the difference from the nondefault episode mean to the respective event (crisis entry or exit). Hence, the mean for the respective event episode is calculated by adding the estimated constant and the estimated coefficient on the dummy. The confidence interval that indicates whether the means of the event is significantly different from the noncrisis means is calculated from the confidence interval around the estimated event episode dummies, by adding the lower and upper bound of the confidence interval to the estimated constant. This is a simple graphical representation of the test whether the coefficients on the dummies are significantly different from zero and thus whether the means of the event episodes are significantly different from the noncrisis mean.

[9] We show event study charts based on "raw" data because it lends itself to easy interpretation. Alternatively, standardized data can be used which eliminates the effect of outliers or different levels across countries. Charts based on standardized data show the same trends as those presented here and are available upon request.

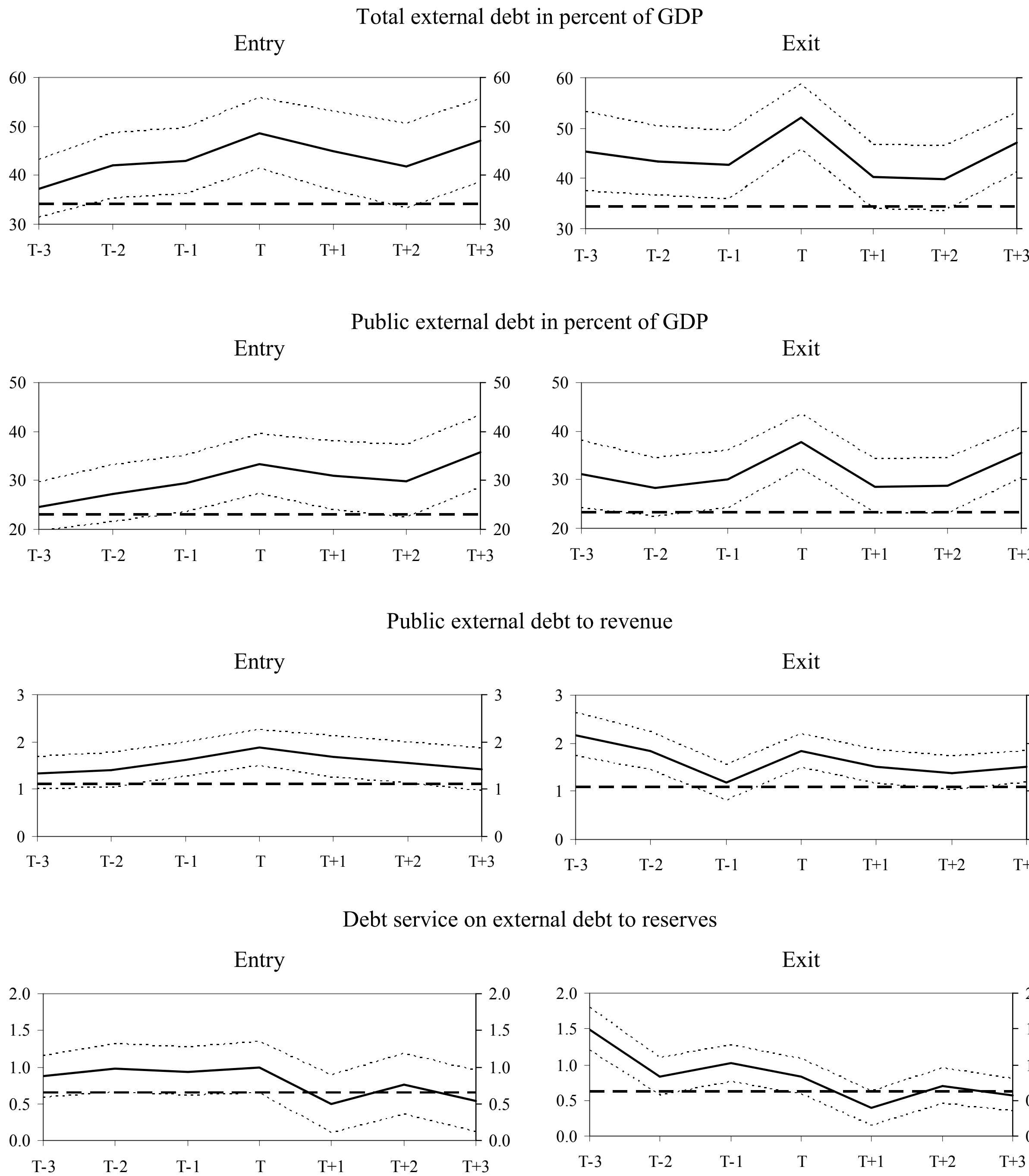
Figure 1. Event Study Analysis: Short-Term Debt Variables 1/



Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

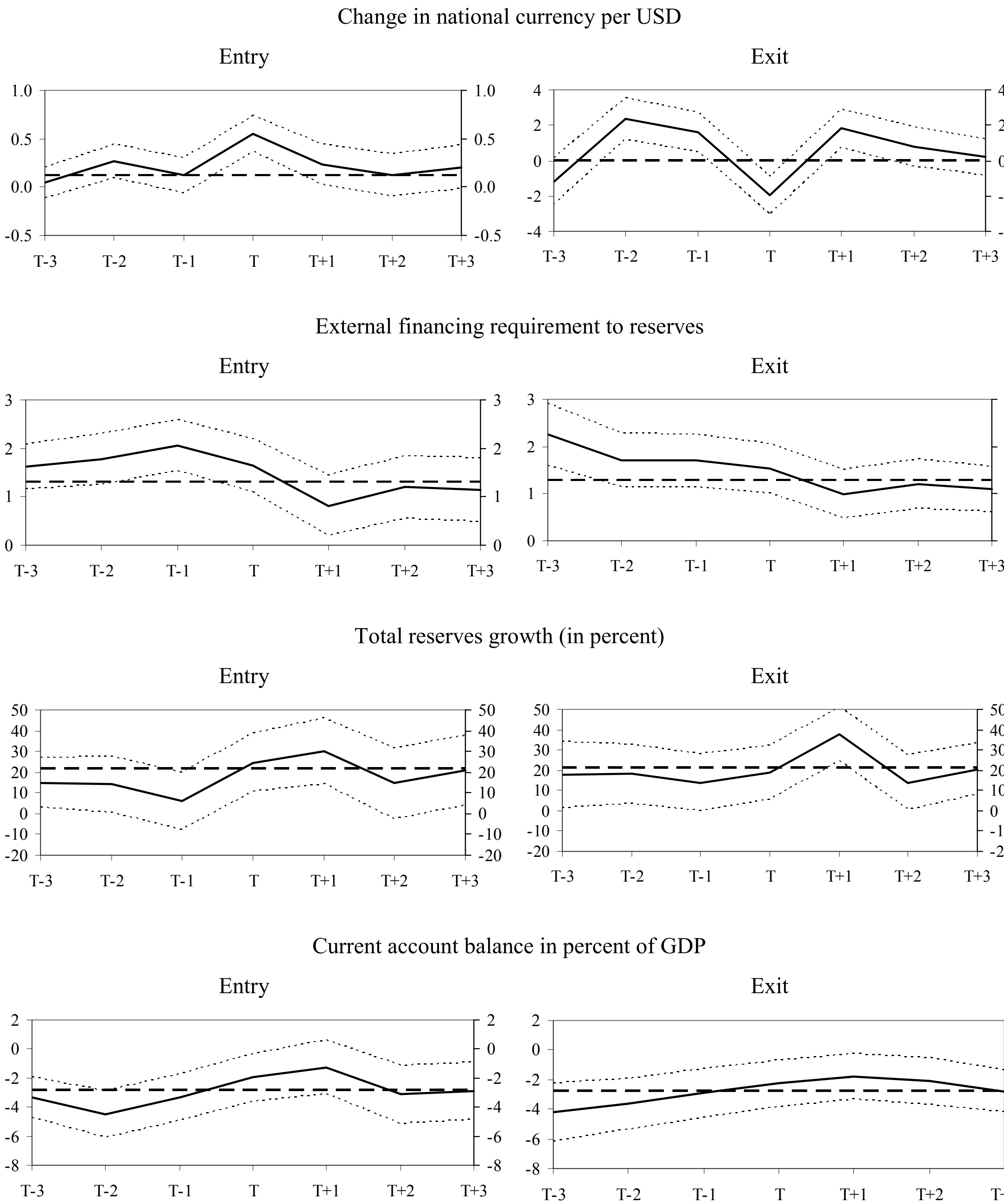
1/ Bold broken line: average of observations outside a +/- 3 year interval around default episodes; bold solid line: average of observations for the years falling in the +/- 3 years interval around default entry (exit); broken lines around bold solid line: 95 percent confidence interval.

Figure 2. Event Study Analysis: Total Debt, Public Debt, and Debt-Service Variables 1/



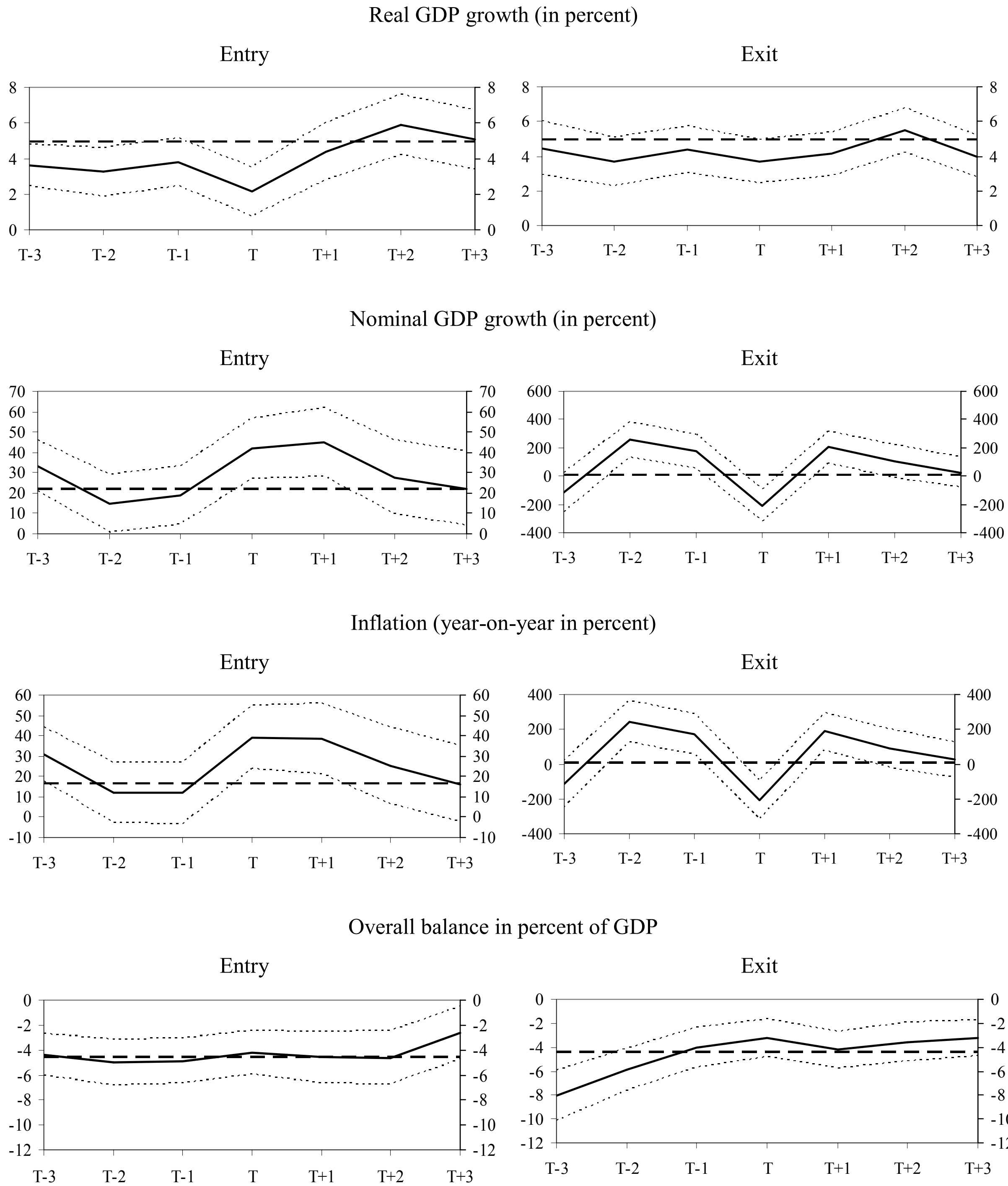
Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.
1/ Bold broken line: average of observations outside a +/- 3 year interval around default episodes; bold solid line: average of observations for the years falling in the +/- 3 years interval around default entry (exit); broken lines around bold solid line: 95 percent confidence interval.

Figure 3. Event Study Analysis: Balance of Payments Variables 1/



Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.
1/ Bold broken line: average of observations outside a +/- 3 year interval around default episodes; bold solid line: average of observations for the years falling in the +/- 3 years interval around default entry (exit); broken lines around bold solid line: 95 percent confidence interval.

Figure 4. Event Study Analysis: Selected Macrovariables 1/



Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

1/ Bold broken line: average of observations outside a +/- 3 year interval around default episodes; bold solid line: average of observations for the years falling in the +/- 3 years interval around default entry (exit); broken lines around bold solid line: 95 percent confidence interval.

- The total external debt as well as the public external debt-to-GDP ratio increase in the run-up to a crisis and are significantly higher than during noncrisis episodes in the year before entry. In the year of exit from crisis, there is a peculiar spike. In general, both total and public external debt remain noticeably higher in crisis countries even after exiting from crisis compared to noncrisis episodes. In terms of dynamics, public external debt appears to be the driving force behind the developments of the total external debt-to-GDP ratio.

- Short-term external debt relative to reserves also increases in the run-up to an entry into debt crisis and is significantly higher than in noncrisis episodes in the year before entry. This holds for short-term debt on an original as well as for short-term debt on a remaining maturity basis. After entering into crisis, short-term debt falls to the level of noncrisis episodes, possibly reflecting difficulties defaulters face in borrowing externally and/or the conversion of short-term debt into longer debt in restructuring episodes. At the time of exit from crisis, short-term debt relative to reserves remains around the level observed in noncrisis episodes.

- Debt service on external debt relative to reserves and interest on short-term external debt relative to reserves are higher than in noncrisis episodes in the year before entry into crisis. Both indicators fall to the level of noncrisis episodes after exit from crisis. Debt service on external debt shows a little spike just before exit from crisis that could reflect resumption of payments close to the time the default episode is resolved.

- On the external side, the current account deficit is larger before entry into crisis than in noncrisis episodes, and reserves growth plummets in the year before entry. As the sum of the current account deficit and short-term debt, the external financing requirement relative to reserves is significantly higher in the year before entry into crisis than in noncrisis episodes. At the time of exit from crisis, these indicators fall back to levels observed during noncrisis episodes, with reserves growth spiking in the first year after exit. The exchange rate shows a large depreciation against the U.S. dollar in the year of entry into crisis (as many debt crises are associated with concomitant currency crises) and a large appreciation against the U.S. dollar in the year of exit from crisis. For entry, this depreciation contributes to the increase in total external debt relative to GDP.

- Domestic developments are adverse before crisis entry and show a return to normal after exit. Real GDP growth is below that observed in noncrisis episodes and plummets in the entry year, pointing to the real costs of debt crisis for the economy. With inflation rising substantially in the entry year, nominal GDP growth also jumps up. The dramatic swings in the inflation rate and the slow stabilization in the three years after exit from a crisis point to the domestic imbalances associated with external debt crises. Interestingly, the overall budget balance in the run-up to crisis does not differ significantly from noncrisis episodes, though there seems to be a modest improvement in the overall balance before exit from crisis.

IV. THE LOGIT EARLY-WARNING SYSTEM

A. Estimation Approach

We employ a modified general-to-specific modeling approach to identify an EWS for sovereign debt crisis. Variables are selected into the final model on the basis of standard specification criteria and, in addition, their ability to predict entry into crisis and being in crisis. In cases of crisis episodes that are longer than one year, entry into crisis relates to the first year of the episode, and being in crisis to the remaining years until exit from crisis. The estimation technique used is the logit approach. We allow the regressors to have a different impact on the probability of entering into crisis and exiting from crisis, as it is a priori not clear that the two should be identical. The remainder of this section discusses the (technical) details of our estimation approach.

The modified general-to-specific approach allows us to test a large number of potential regressors while maintaining a reasonable sample size. The dataset includes information on some 50 variables that differ substantially in availability. While our maximum sample contains 1,276 observations, a joint sample for all potential regressor would muster only around 100 observations. Therefore, we proceed along a three-stage strategy. For this strategy, we divide the variables into six groups: external debt variables; public debt variables; variables from the IMF currency crisis EWS; other macroeconomic variables; fiscal variables; and political economy variables.[10]

- At the first stage, we run individual regressions for each variable to gain some insight as to how well each variable performs with respect to standard criteria and how well it predicts entry into crisis as well as being in crisis. Given that our objective is to build an EWS for sovereign debt crisis, we place particular weight on how well a variable is able to predict entry into crisis. An estimated model is defined to predict entry into crisis or being in crisis, if the estimated probability exceeds the naive, in-sample probability of being in crisis of 20.5 percent.[11]
- At the second stage, we select the "best performers" within each group and run group wise regressions or "horse-races" between similar variables, for example short-term debt in percent of GDP versus in relation to reserves. By "best performers" we mean variables that turn out significant in the individual regressions and/or have a high predictive power for crisis entry as well as for being in crisis. These groupwise regressions help us to further narrow down the variables to be included in the general model with variables from all other groups. As at the first stage, we select and drop variables based on standard tests and their predictive power. This second stage is only employed for groups with several promising variables.

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[10] The classification is somewhat arbitrary but has no impact on the outcome of the specification process.

[11] Other possible cut-off value would, for example, be 50 percent or the in-sample probability of entering into crisis, 5.6 percent.

- At the third stage, we combine the best performers from each group into a "general" model. This general model is tested down by excluding those variables that are either insignificant or do not contribute to the model's predictive power.

The model is estimated using the logit approach. Compared to the probit approach, the logit typically performs better when the dependent variable is not evenly distributed between the two outcomes; in our data, only 20.5 percent of all outcomes are debt crisis and only 5.6 percent are crisis entries. We use a robust variance estimator (Huber White sandwich estimator) with country-specific variances.

The estimation approach allows for different coefficients between entering crisis and exiting from crisis. A priori, it is not clear that a change in, say external debt, that triggers a crisis is necessarily the same as the change that would help a country exit from crisis again. Therefore, we estimate separate coefficients for entering into crisis and for exiting from crisis for each regressor. This is done by multiplying the regressor with the lagged generalized Standard & Poor's crisis indicator, *GSP*. Formally, the probability of being in crisis, *P*, in year *t* is given by

$$P_t = f\left(\left(1 - GSP_{t-1}\right) * X_{t-1}\ ;\quad GSP_{t-1} * X_{t-1}\right) \tag{1}$$

where X_{t-1} denotes the vector of explanatory variables in the previous period, including the constant.[12] The coefficient on the first argument describes the relationship between the explanatory variable and the probability of entering into crisis in *t*, given that the country was not in crisis in *t-1*. The coefficient on the second argument describes the relationship between the explanatory variable and the probability of being in crisis (i.e., not exiting from crisis) in *t*, given that the country was in crisis in *t-1*. This setup is equivalent to estimating separate models for entering into and exiting from crisis. However, it allows to formally test for equal coefficients for entering and exiting.

The specification approach could, in principle, suffer from an omitted variable bias. In the logit model, if a variable that is part of the true model is omitted from the estimated model, the estimated parameter of the included regressor is a linear combination of the parameter of that regressor and the parameter of the omitted variable. Unlike in the least squares case, this bias is present whether the included and the omitted regressor are correlated or not. Hence, the estimated coefficients in our variable by variable regressions are potentially biased (first and second stage). Two cases can arise:

- First, the included variable is not part of the true model, but the estimated coefficient reflects the influence of omitted variables that are part of the true model. In this case, a variable that is not part of the true model could be erroneously retained. However, the erroneously retained variable should drop out of the regression when the general model is estimated which should hopefully include most variables from the true model.

[12] By lagging the regressors one period, we also avoid a possible endogeneity bias.

- Second, and more problematic, the bias could lead to the estimated coefficient of a variable that is part of the true model to be zero. This may lead us to exclude a potentially important variable. To address this problem, and as part of our sensitivity analysis, we include regressors that dropped out in the specification process into our final specification to see whether they improve the model.

B. Specifying the Logit EWS

We specify the logit EWS only for a subsample of episodes starting in or after 1990. Initial estimation results indicated that a model specified for the whole sample starting in the seventies would not be very successful in explaining debt crises of the nineties and beyond, though it is successful at explaining debt crises in the seventies and eighties.[13] Hence, we restrict our sample to the years 1990 and onward for the process of identifying those variables that should be included in the logit EWS. We then estimate this specification for all years with data availability in our sample, allowing for different coefficients for crises occurring as of 1990. This way, we can derive a model that predicts well the more recent episodes (and, thus, hopefully future episodes) while still using as much information from past episodes as possible.

Based on variable-by-variable and groupwise regressions, we include the following variables in a "general" model which is then tested down to arrive at a preferred specification.[14]

- From the list of external debt variables, short-term external debt to reserves on an original maturity, as well as on a remaining maturity basis, interest on short-term debt in percent of GDP and external debt service to reserves appear as best suited to explain crisis episodes in the 1990 onward sample. For the further specification process, we also include total external debt in percent of GDP as a possible explanatory variable because this variable played an important role in related empirical work and is of theoretical interest as a measure of solvency.
- From the list of public debt variables, no indicator is significant at the 5 percent level, nor does any of the indicators have predictive power for crisis entries in the 1990 onward sample. We, therefore, do not include any of these variables in the direct specification process. As a sensitivity test, we included public external debt in the final specification but it did not improve the model consistent with the findings here.
- From the IMF's currency crises EWS, reserves growth helps predicting crisis entries. In addition, we also include the current account balance in the general model.
- From the list of other macroeconomic variables, the U.S. treasury bill rate, real GDP growth, FDI in percent of GDP, trade openness, and the financing requirement calculated as the current account deficit plus short-term debt on an original maturity

[13] A model specified for the whole sample is available from the authors upon request..

[14] The results for the variable-by-variable regressions and the groupwise regressions are available from the authors upon request.

basis[15] help explain and predict sovereign crisis episodes. In addition, inflation volatility measured as a 4-year moving average of the coefficient of variation is included in the "general" model.

- From the list of fiscal variables, no indicator helps predict sovereign crisis episodes. We therefore did not include any fiscal variable in the general model. However, as a sensitivity test, we included the overall balance in the preferred specification without achieving an improvement in performance.
- None of the political economy variables came out well in the variable-by-variable regressions. Suspecting some influence, if marginal, we included the dummy for years with presidential election and an index of freedom status in the general model that appeared promising in initial estimations.

Based on the information from the variable-by-variable and groupwise analysis, we now combine those variables that appear to help predict debt crises in a general model. We estimate this general model for a subsample that includes only the years 1990 and onward because initial experiments have shown that the more recent crisis episodes appear to differ from those of the seventies and eighties. We exclude insignificant variables and variables with a counter-intuitive direction of influence from this general model to arrive at a reduced model (Table 3 and Table 4). This reduced model is reestimated for the full sample including observations from the seventies and eighties. For this, we allow the estimated coefficients to differ for observations starting in or after 1990. Further excluding insignificant variables from the specification and testing whether the coefficient on certain regressors is equal for observations before or after 1990 yields the final specification, which we call the logit EWS (Table 5 and Table 6).

The logit EWS is estimated based on a sample of 594 observations for 37 market access countries from 1976 to 2001. This subsample is determined by data availability for the variables included. The countries covered by this sample are listed in Table 6. Entry into and being in crisis is explained by indicators of external debt, macroeconomic conditions, and political economy factors.

- Solvency problems make entering into crisis more likely. A high total external debt-to-GDP ratio is associated with a high probability of entering into crisis. This effect is even more pronounced in the 1990 onward period. However, the total external debt-to-GDP ratio does not help explain remaining in crisis in the logit EWS.

[15] We also calculated the financing requirement based on short-term debt on a remaining maturity basis and accounting for FDI flows. This definition is available only for a smaller number of observations and did not lead to improved results.

Table 3. Regression Results: Coefficient Estimates, 1990 Onward Sample 1/

(Dependent Variable: Generalized Standard & Poor's Default Indicator)

	General Model			Reduced Model		
	Marginal Effect 2/	Logit Coef.	z-value	Marginal Effect 2/	Logit Coef.	z-value
Total external debt in percent of GDP						
Entry into default	0.002	0.065	2.730	0.002	0.054	3.240
Exit from default	0.000	0.013	1.010			
Short-term debt, original maturity to reserves						
Entry into default	-0.093	-2.700	-1.520			
Exit from default	0.054	1.566	1.590			
Short-term debt, remaining maturity to reserves				0.008	0.268	2.170
Entry into default	0.000	0.003	0.010			
Exit from default	-0.013	-0.388	-1.550			
Interest on short-term debt in percent of GDP						
Entry into default	0.224	6.493	2.390	0.144	4.617	2.270
Exit from default	-0.101	-2.919	-2.190			
External debt service to reserves						
Entry into default	0.051	1.486	1.880	0.032	1.038	1.800
Exit from default	0.019	0.555	0.640			
Current account balance in percent of GDP						
Entry into default	-0.002	-0.047	-0.340	-0.005	-0.156	-1.900
Exit from default	-0.002	-0.067	-0.770			
Reserves growth						
Entry into default	0.000	-0.013	-0.560			
Exit from default	0.000	0.000	0.150			
U.S. treasury bill rate						
Entry into default	0.009	0.270	1.120	0.006	0.185	0.740
Exit from default	0.001	0.043	0.240			
Real GDP growth						
Entry into default	-0.001	-0.032	-0.440	-0.004	-0.142	-2.460
Exit from default	0.000	0.009	0.100			
FDI in percent of GDP						
Entry into default	0.004	0.119	0.550			
Exit from default	0.000	-0.005	-0.030			
Openness						
Entry into default	-0.002	-0.053	-2.090	-0.001	-0.045	-2.200
Exit from default	0.000	0.004	0.540			
Financing requirement to reserves						
Entry into default	0.050	1.444	1.310			
Exit from default	0.012	0.349	0.520			
Inflation volatility	0.000	0.001	1.920	0.000	0.001	1.590
Dummy for high inflation (>50 percent)	0.192	2.290	2.870	0.048	1.027	2.030
Dummy for past default episodes	0.018	0.584	0.720			
Year with presidential election	0.098	1.554	2.700	0.103	1.692	2.530
Index of freedom status				-0.025	-0.790	-2.070
Entry into default	-0.021	-0.620	-0.560			
Exit from default	-0.062	-1.787	-2.480			
Lagged crisis indicator	0.938	8.326	2.520	0.899	7.709	3.220
Constant		-8.440	-3.330		-6.753	-2.710

Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

1/ Logit regression with robust variance estimates, allowing for country-specific variances (Huber White sandwich estimator). z-values are normally distributed.

2/ Marginal effects calculated at sample means. For dummy variables, marginal effects calculated for switch from zero to one.

Table 4. Regression Results: Model Performance, 1990 Onward Sample 1/

(Dependent Variable: Generalized Standard & Poor's Default Indicator)

	General Model	Reduced Model
Observations	353	353
Wald-test for joint significance	Chi(31) = 273,189	Chi(13) = 758
Pseudo-R2	0.66	0.60
Correctly called episodes	89.8	88.1
Correctly called entries into default	69.2	69.2
Incorrectly called entries into default	4.5	5.3
Correctly called exits from default	16.0	0.0
Incorrectly called exits from default	0.0	0.0
Wald test reduced vs. general model		Chi2(18) = 24.5
Debt-crisis entries correctly predicted		
Number	9	10
Debt-crisis entries	Argentina 2001; Brazil 1998, 2001; Ecuador 1999; Mexico 1995; Pakistan 1998; Thailand 1997; Turkey 2000; Venezuela 1990	Argentina 2001; Brazil 1998; Ecuador 1999; Indonesia 1997; Mexico 1995; Pakistan 1998; Thailand 1997; Turkey 2000; Venezuela 1990
Debt-crisis entries not predicted		
Number	4	3
Debt-crisis entries	Argentina 1995; Indonesia 1997; Tunisia 1991; Venezuela 1995	Argentina 1995; Brazil 2001; Tunisia 1991; Venezuela 1995
Countries included in regressions		
Number	37	37
Countries	Algeria, Argentina, Brazil, Chile, China, Colombia, Costa Rica, Dominican Rep, Ecuador, Egypt, El Salvador, Estonia, Hungary, India, Indonesia, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Oman, Pakistan, Panama, Peru, Philippines, Poland, Romania, Slovak Republic, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela	Algeria, Argentina, Brazil, Chile, China, Colombia, Costa Rica, Dominican Rep, Ecuador, Egypt, El Salvador, Estonia, Hungary, India, Indonesia, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Oman, Pakistan, Panama, Peru, Philippines, Poland, Romania, Slovak Republic, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela

Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

1/ Logit regression with robust variance estimates, allowing for country-specific variances (Huber White sandwich estimator).

Table 5. Regression Results: Coefficient Estimates, Full Sample 1/

(Dependent Variable: Generalized Standard & Poor's Default Indicator)

	Reduced Model			Logit EWS		
	Marginal Effect 2/	Logit Coef.	z-value	Marginal Effect 2/	Logit Coef.	z-value
Total external debt in percent of GDP						
Entry into default	0.000	0.003	0.190			
* dummy for 1990 onward	0.004	0.047	2.270	0.004	0.052	3.330
Short-term debt, remaining maturity to reserves	0.033	0.400	1.260	0.035	0.407	3.180
* dummy for 1990 onward	-0.011	-0.133	-0.390			
Interest on short-term debt in percent of GDP						
Entry into default	0.040	0.486	0.930			
* dummy for 1990 onward	0.331	4.054	1.970	0.404	4.710	2.540
External debt service to reserves						
Entry into default	0.042	0.511	0.830	0.048	0.557	1.670
* dummy for 1990 onward	0.038	0.461	0.550			
Current account balance in percent of GDP						
Entry into default	-0.009	-0.106	-1.200	-0.009	-0.100	-1.910
* dummy for 1990 onward	-0.004	-0.043	-0.320			
Openness						
Entry into default	-0.001	-0.010	-0.600			
* dummy for 1990 onward	-0.003	-0.037	-1.370	-0.004	-0.044	-2.410
U.S. treasury bill rate						
Entry into default	0.008	0.099	0.810	0.011	0.130	1.620
* dummy for 1990 onward	0.002	0.022	0.130			
Real GDP growth						
Entry into default	-0.011	-0.133	-1.530	-0.011	-0.124	-2.170
* dummy for 1990 onward	-0.001	-0.010	-0.100			
Inflation volatility	0.001	0.015	0.640	0.000	0.001	1.890
* dummy for 1990 onward	-0.001	-0.014	-0.600			
Dummy for high inflation (>50 percent)	0.034	0.371	0.710	0.089	0.821	1.660
* dummy for 1990 onward	0.063	0.620	1.000			
Year with presidential election	0.383	2.375	2.430	0.273	1.834	3.440
* dummy for 1990 onward	-0.047	-0.740	-0.640			
Index of freedom status	0.089	1.088	2.090	0.089	1.038	2.180
* dummy for 1990 onward	-0.155	-1.899	-3.640	-0.160	-1.862	-3.610
Lagged crisis indicator	0.793	5.469	5.180	0.836	5.817	5.720
* dummy for 1990 onward	0.183	1.484	1.520	0.128	1.100	1.110
Constant		-5.956	-4.280		-6.150	-4.880

Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

1/ Logit regression with robust variance estimates, allowing for country-specific variances (Huber White sandwich estimator). z-values are normally distributed.

2/ Marginal effects calculated at sample means. For dummy variables, marginal effects calculated for switch from zero to one.

Table 6. Regression Results: Model Performance, Full Sample 1/
(Dependent Variable: Generalized Standard & Poor's Default Indicator)

	Reduced Model	Logit EWS
Observations	594	594
Wald-test for joint significance	Chi(26) = 3,350	Chi(15) = 431
Pseudo-R2	0.63	0.63
Correctly called episodes	88.9	89.4
Correctly called entries into default	74.2	74.2
Incorrectly called entries into default	6.9	6.1
Correctly called exits from default	0.0	0.0
Incorrectly called exits from default	0.0	0.0
Wald test logit EWS vs. reduced model		Chi(11) = 3.8
Debt-crisis entries correctly predicted		
Number	23	23
Debt-crisis entries	Argentina 1982, 2001; Brazil 1983, 1998; Chile 1983; Costa Rica 1981; Dominican Republic 1981; Ecuador 1982, 1999; Indonesia 1997; Mexico 1982, 1995; Morocco 1983, 1986; Pakistan 1998; Peru 1983; Philippines 1983; Thailand 1997; Trinidad and Tobago 1988; Turkey 1978, 2000; Venezuela 1983, 1990	Argentina 1982, 2001; Brazil 1983, 1998; Chile 1983; Costa Rica 1981; Dominican Republic 1981; Ecuador 1982, 1999; Indonesia 1997; Mexico 1982, 1995; Morocco 1983, 1986; Pakistan 1998; Peru 1983; Philippines 1983; Thailand 1997; Trinidad and Tobago 1988; Turkey 1978, 2000; Venezuela 1983, 1990
Debt-crisis entries not predicted		
Number	8	8
Debt-crisis entries	Argentina 1995; Brazil 2001; Egypt 1984; El Salvador 1981; Thailand 1981; Tunisia 1991; Uruguay 1987; Venezuela 1995	Argentina 1995; Brazil 2001; Egypt 1984; El Salvador 1981; Thailand 1981; Tunisia 1991; Uruguay 1987; Venezuela 1995
Countries included in regressions		
Number	37	37
Countries	Algeria, Argentina, Brazil, Chile, China, Colombia, Costa Rica, Dominican Rep, Ecuador, Egypt, El Salvador, Estonia, Hungary, India, Indonesia, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Oman, Pakistan, Panama, Peru, Philippines, Poland, Romania, Slovak Republic, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela	Algeria, Argentina, Brazil, Chile, China, Colombia, Costa Rica, Dominican Rep, Ecuador, Egypt, El Salvador, Estonia, Hungary, India, Indonesia, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Oman, Pakistan, Panama, Peru, Philippines, Poland, Romania, Slovak Republic, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela

Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.
1/ Logit regression with robust variance estimates, allowing for country-specific variances (Huber White sandwich estimator).

- Liquidity problems also make entering and remaining in crisis more likely. First, a high short-term debt on remaining maturity basis to reserves ratio is associated with a high probability of entering and remaining in crisis. This relationship is statistically identical for observations before and after 1990. Second, in the 1990 onward period, high interest payments in percent of GDP make entering into crisis more likely. Third, high external debt-service payments in relation to reserves make entering into crisis more likely, with this relationship being statistically identical for observations before and after 1990.
- Positive external developments can reduce the probability of entering into crisis. Countries wither a high current account balance have a reduced probability of entering into crisis. This relationship is identical before and after 1990. From 1990 onward, being open reduces the probability of entering into crisis. Lastly, periods of tight international liquidity as proxied by the U.S. treasury bill rate are associated with an increased probability of entering into crisis. While this relationship was particularly pronounced in the early eighties, it holds over the full sample period.
- Positive domestic developments can also reduce the probability of entering and being in crisis. High real GDP growth is associated with a reduced probability of entering into crisis. However, periods of high inflation volatility (measured as the coefficient of variation of the inflation rate over the last four years) as well as periods of high inflation (exceeding 50 percent) are associated with an increased probability of entering and remaining in crisis. These three links between domestic developments and the probability of crisis are identical before and after 1990.
- Finally, political factors influence the probability of crisis. The probability of entering and remaining in crisis increases in years with presidential elections. In the period before 1990, countries with a better ranking on an index of political freedom appear to suffer from a raised probability of crisis. However, in the 1990 onward period, the effect is reversed and countries that rank higher in terms of political freedom have a reduced probability of crisis.

The logit EWS correctly predicts 74 percent of all crisis entries across the whole sample while sending only 6 percent false alarms that are not followed by a crisis in the next year. For the period starting in 1990, the logit EWS correctly predicts 69 percent of all crisis entries and sends only 5 percent false alarms. It is interesting to look at the false alarms in more detail. In 48 percent of all false alarms, a debt crisis occurs two years after the signal was emitted rather than in the next year. If one were to consider these cases of false alarms as prewarnings, the share of true false alarms when no debt crisis follows in the next two years would drop to 3 percent. For the 1990 onward subsample, the share of false alarms that are followed by a debt crisis within two years is 38 percent. There are also some cases where a crisis that is not predicted in the year immediately preceding the entry is signaled two years in advance (e.g., Argentina, 1995; and Brazil, 2001).

Four crisis entries after 1990 are not anticipated by the logit EWS: Argentina (1995); Brazil (2001); Tunisia (1991); and Venezuela (1995). In the case of Argentina, a very important factor leading to crisis in 1995, was the spillover effect from the Mexican crisis 1994/95 (the Tequila contagion effect). Since we do not include proxies for contagion effects in our model, it might not be surprising that the logit EWS does not anticipate this episode.[16] In Venezuela in 1995, the aftermath of a currency and banking crisis led to a short period of arrears on a small amount of external debt payments; while many economic indicators signaled a worsening of macro conditions in 1994, the models fails to signal an impending crisis but the crisis, at least for what concerns debt payments, was small. In Brazil in 2001, the combination of a domestic energy shock, the U.S. economic slowdown and the worsening of the conditions in Argentina led to the need for a large scale IMF package as a preventive way to avoid more serious debt-servicing problems. But these shocks were largely unpredicted, as of 2000, the year before the crisis.

We probe the robustness of the logit results by running various sensitivity tests, for example with respect to outliers and the definition of the dependent variable, and find that the logit EWS holds up well (see Appendix I). Out of sample predictions are another test of an EWS' performance. Therefore, we reestimate the logit EWS for the years prior to 1995 only and then predict for the years 1995 and onwards. Out of sample, the logit EWS correctly predicts 45 percent of the crisis entries while sending false alarms in 6 percent of the cases. In addition to those crisis entries that were also missed in the in-sample prediction of the logit EWS (Argentina, 1995; Brazil, 2001; and Venezuela, 1995), Indonesia and Thailand in 1997, as well as Argentina in 2001 are missed in the out of sample prediction.

V. The Tree EWS

We use a statistical technique called Classification and Regression Tree (CART) analysis to identify possible (nonlinear) interactions between the potential variables that can help predict the probability of being in crisis. The resulting tree classifies observations into crisis-prone or not crisis-prone based on a few characteristics and their interactions. Information from the tree analysis is then integrated into the reduced logit model to test whether these interactions help improve the predictive power of our model.

A. The Tree-Analysis Methodology

The CART—or tree analysis—methodology produces a sequence of rules for predicting a binary outcome that can be illustrated in the form of a tree.[17] These sorting rules can also be viewed as rules of thumb that can help predict the outcome of a particular observation.

[16] We do not include contagion effects because they are difficult to implement in a forecasting environment.

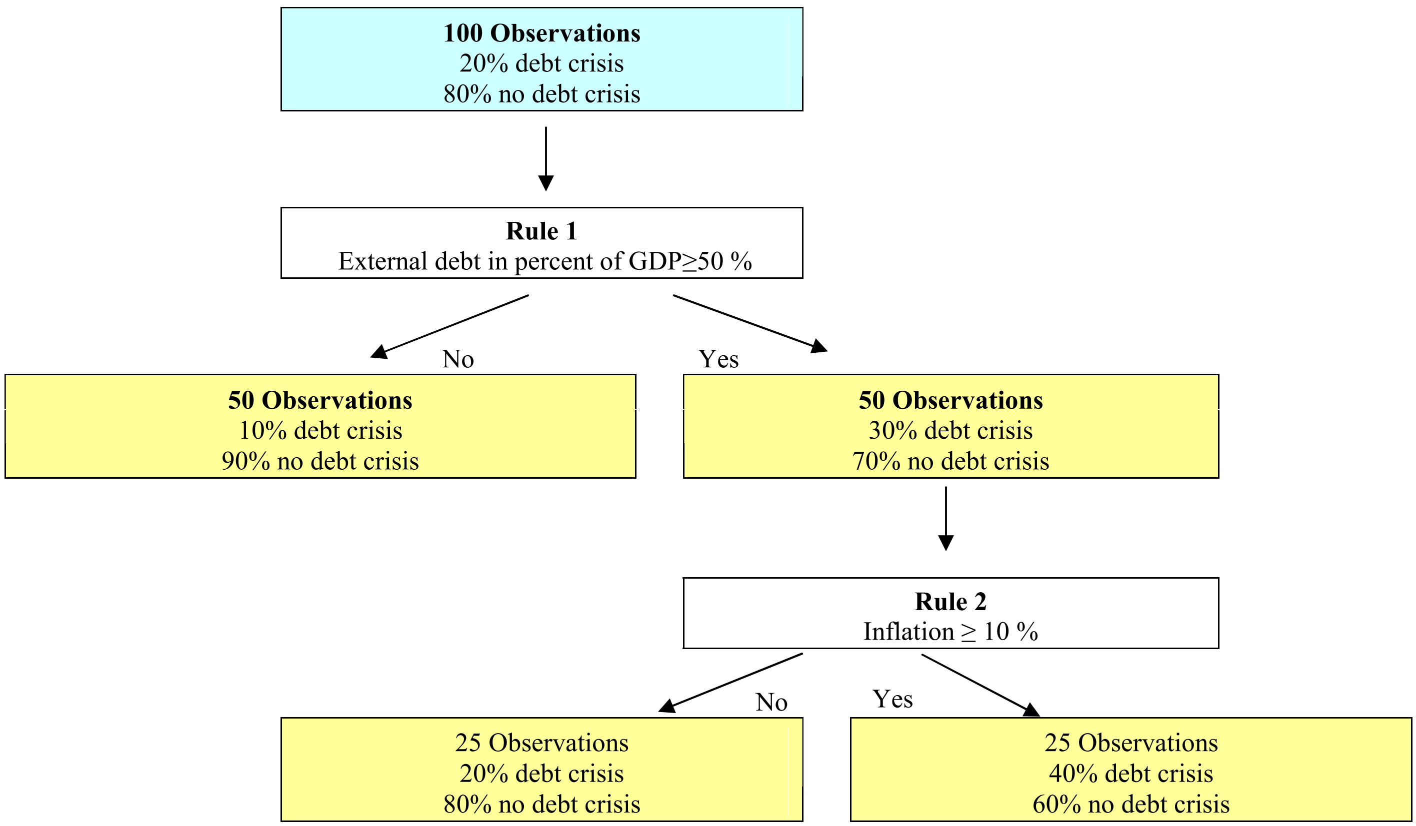
[17] CART was developed by statisticians at Berkeley (Breiman, Stone); Stanford (Friedman); and UCSD (Ohlsen) and has been applied to several fields, including medicine; meteorology; advertising; and evaluation of credit default. See Breiman et al. (1984) for a detailed description of CART;and Ghosh and Ghosh (2002) for an application in the field of economics.

CART is nonparametric and can detect complex relationships between dependent variable and explanatory variables. Therefore, CART is particularly suited for discovering nonlinear structures and variable interactions in datasets with a large number of potential explanatory variables. A rule is chosen to reduce the heterogeneity in the resulting groups compared to the larger group to which the rule is applied. There can be a *n* nested rules that classify the observations into *n+1* disjoint groups of observations. Observations in a particular group share characteristics according to the rules by which they were classified.

The following example in Figure 5 illustrates the procedure. Suppose we have observations on a set explanatory variables that refer to 100 episodes, of which 20 are defaults and 80 nondefaults. The "unconditional" crisis probability in the sample (root node) is 20 percent.[18] By applying rule 1 (for example, debt-GDP above 50 percent) to the sample, we sort half (50) observations to the right node 1 (those which satisfy the rule), and half observations to the left node (those with debt-GDP below 50 percent). In the "low debt" left node, we find 5 crises and 45 noncrises, so that the within node probability of a crisis (e.g., the crisis probability conditional on the debt ratio being below 50 percent) is only 10 percent (= 5/50). Conversely, in the "high debt" right node we find the remaining 15 crises and 35 noncrises. Here the conditional probability of a crisis rises to 30 (=15/50) percent. Nodes 2 and 3 are then determined by applying rule 2 to the observations in their parent node. The rule 2 sorts observations with inflation above 10 percent to the right (node 3, say 25 cases) and those below to the left (node 2, with 25 observations). In the right "high inflation" node now we find 10 crises and 15 noncrisis, so that the default probability conditional on high debt *and* high inflation rises to 40 (=10/25) percent. The remaining five crisis episodes are found in the "low inflation" left node 2, where the conditional crisis probability is 20 (=5/25) percent. We end up partitioning our sample into three terminal nodes: node 1 (low debt) with only 10 percent crisis probability, node 2 (high debt but low inflation) with 20 percent crisis probability, and node 3 (high debt and high inflation) with 40 percent default probability.

[18] In this example we assume that the ex ante (prior) probability of a crisis coincides with the sample frequency.

Figure 5. Example of Tree Methodology

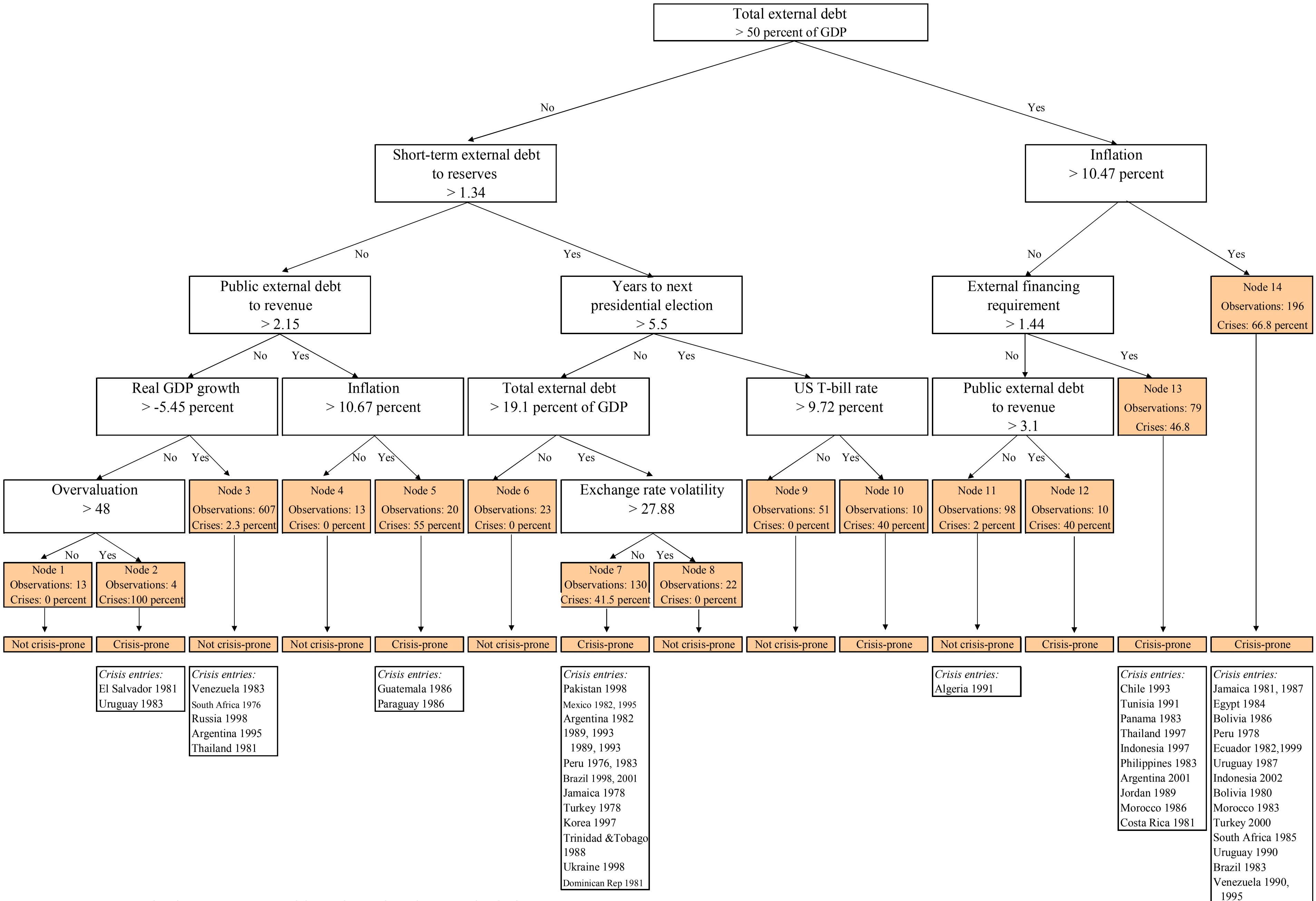


B. Results from the Tree Analysis

The CART methodology selects the following nine variables from our dataset, to partition the sample into crisis episodes and noncrisis episodes (Figure 6 and Table 7):[19] total external debt in percent of GDP ; short-term debt on a remaining maturity basis to reserves; public external debt to revenue; real growth; inflation; the U.S. treasury bill rate; exchange rate overvaluation and exchange rate volatility; external financing requirement to reserves; and the number of years before a presidential election. The first rule splits the sample into two branches: episodes with high external debt (more than 49.7 percent of GDP) go to the right, here the conditional crisis probability rises from 20.5 percent in the entire sample to 45.4 percent; and episodes with low external debt to the left, with default probability of 9.7 percent. A number of interesting features emerge from the analysis:

[19] Details of the tree specification process are available from the authors upon request.

Figure 6. The Empirical Tree



Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

Table 7. The Empirical Tree: Model Performance

	Full sample	1990s onwards
Observations	1276	556
Number of crisis episodes	261	114
Number of crisis entry episodes	54	20
	(In percent)	
Correctly called episodes	82.8	78.8
Correctly called entries into default	88.9	85.0
Incorrectly called entries into default	18.5	15.0
Correctly called exits from default	32.0	35.3
Incorrectly called exits from default	4.8	64.7
Correctly called default episodes	93.9	89.5
Correctly called nondefault episodes	79.9	76.0

Sources: IMF; Standard & Poor's; World Bank; and authors' calculations.

- Episodes of high debt (more than 49.7 percent of GDP) and high inflation (larger than 10.5 percent) incur the largest default risk, 66.8 percent, see terminal node 14. Notice that more than half of all the crisis episodes in the sample satisfy these two simple conditions.
- By contrast, the circumstance that are more favorable for reducing the risk of being in a crisis episode are low external debt, low short-term debt to reserves on a remaining maturity basis (below 1.3) and low public external debt to revenue (below 2.1), coupled with high economic growth, see terminal node 3. Under these circumstances the likelihood of being in a crisis episode is just 2.3 percent. About 58.4 percent of all noncrisis episodes satisfy these conditions.
- Low external debt is not sufficient for eliminating the risk of default, however. Countries characterized by an intermediate ratio of external debt (between 19 percent and 49.7 percent of GDP), but who have potentially serious liquidity problems (short-term debt above 1.3 times reserves), face political uncertainty (presidential elections closer than 5.5 years), and possibly also have a history of pegged exchange rates (low moving average of past coefficient of variation of the exchange rate), also face a large default risk (41.5 percent, see terminal node 7).[20] In particular, a large stock of public

[20] Crises in this node include Argentina; Brazil; Dominican Republic; El Salvador; India; Jamaica; Korea; Mexico; Pakistan; Peru; South Africa; Trinidad and Tobago; Turkey; Ukraine; and Uruguay.

external debt relative to revenue, coupled with high inflation (see terminal node 5), raises the conditional crisis probability considerably (to 55 percent), even when the external debt-to-GDP ratio and short-term debt are low.

- Low external debt is not a necessary condition for averting debt crises. Despite having external debt in excess of 49.7 percent of GDP, countries may not incur a considerable risk of crisis provided that inflation is below 10.5 percent, the external financing requirement to reserves ratio does not exceed 1.5, and the public debt to revenue ratio is below 3 (see terminal node 11).

Based on the set of rules of this tree, observations can be classified as crisis-prone or not crisis-prone. Observations in a particular node are classified as crisis-prone (not crisis-prone), if the within node share of crisis observations is higher (lower) than a threshold. This threshold is a function of the share of crisis observations in the full sample of 20.5 percent and a cost parameter which is set for estimating the tree and determines the relative cost of missing a default episode versus missing a nondefault episode in the objective function underlying the tree algorithm. [21]

The tree correctly predicts 89 percent of all crisis entries in the full sample. However, this comes at the cost of sending 19 percent of false alarms in years that are not followed by a crisis entry. Similarly to the EWS logit model, however, around 14 percent of these "false" alarms are "early" alarms, so that the share of false alarms would fall to 16 percent when counting signals two years in advance as early indications. The tree is also able to correctly predicts 32 percent of crisis exits. The predictive performance is only slightly worse when the focusing only on the 1990 onward period with 85 percent of all crisis entries correctly predicted and 21 percent of false alarms sent. Crisis entries in the 1990 onward period that are not anticipated by the tree are Algeria 1991, Argentina 1995, and Russia 1998.

C. Combining the Logit and the Tree EWS

Combining logit model and tree analysis builds on the different strengths of each approach. The strength of the logit approach is to discover relationships between dependent variable and explanatory variable that hold across the full sample. The tree analysis is weak in this regard because for every rule, it considers only the information available in the subsample upon which that rule is applied. The strength of the tree analysis is to discover nonlinear variable combination that can help predict the outcome of the dependent variable. The logit approach is weak in this regard because it does not include an automatic search mechanism

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[21] The relative performance of correctly predicting default entries while sending as few false alarms as possible can be influenced by a parameter that determines the relative cost of misclassifying a crisis relative to that of a noncrisis episode. We set this cost parameter to 7:1. As a consequence, a node is classified as crisis prone whenever the ratio of crises to noncrises within the node, $N_1(n)/N_0(n)$, exceeds the ratio in the entire sample by at least 55 percent. See also Appendix II.

across all permutations, but relies on the researcher to specify a particular interaction. And, more directly related to our results, the logit EWS has a lower share of correct signals than the tree EWS, but it also has a lower share of false alarms than the tree EWS. A straightforward combination of the two techniques is to define dummy variables for the groups identified in the tree analysis as episodes belonging to a common terminal node and include these dummy variables in a logit model. This approach also allows to formally test whether the groups identified in the tree analysis are statistically significant for predicting crisis.

Including dummies representing the nodes of the tree analysis further improves the performance of the logit EWS.[22] Only a subset of dummies representing the nodes can be included in the logit EWS because the remainder would be perfect predictors of outcomes. Such perfect predictions arise because some nodes contain only crisis or noncrisis episodes and because the sample of the logit EWS is substantially smaller than the sample for which the tree was specified on account of CART's ability to use surrogate data for missing values. When including the feasible subset of dummies representing nodes, the joint model correctly anticipates 81 percent of all crisis entries while sending false alarms in only 6 percent of the cases. Moreover, the joint model correctly predicts 16 percent of all exits from crisis. The dummies representing nodes are jointly significant and all carry a positive sign consistent with their classification as risk-prone except for the dummy denoting node 3 which is classified as not being risk-prone.

An alternative way of combining the logit EWS and the tree EWS is to integrate them into a two-tiered EWS. This EWS would build on the strength of the logit EWS of not sending many false alarms and on the strength of the tree EWS of calling many crisis entries. The two-tiered EWS would indicate that a country is in a situation of stress, if only the tree EWS or only the logit EWS predicts a crisis entry for the next year. In most cases, a single signal is likely to come from the tree EWS which has higher in-sample predictive power at the cost of sending relatively more false alarms. The two-tiered EWS would indicate that a country is at the verge of crisis, if both tree and logit EWS predict a crisis for the next year. Country-specific charts depicting the predicted crisis probability over time as well as the major regressors from the logit EWS can supplement the information from the two-tiered EWS.

VI. SUMMARY AND CONCLUSIONS

In this paper, we have developed two EWS models of sovereign debt crises for a large sample of countries described as having market access. One EWS was based on the estimation of a logit model, the other EWS was based on the classification and regression-tree analysis. We found that variables suggested by economic theory are able to predict crises and, most important for early warnings, provide a good measure of the probability of entering into a debt crisis. These variables include external debt ratios measuring solvency and debt sustainability, measures of illiquidity or refinancing risk, measures of external imbalance and

[22] Results are available from the authors upon request.

debt-servicing pressures, other macrovariables that affect investors' confidence and the country's ability to service debt, macroeconomic (especially monetary) instability, and some political-economy factors leading to policy uncertainty. These results are quite robust.

The predictive power of the models is quite good, but this work would benefit from further extensions. Here are some of them.

- First, we concentrated on the subset of developing countries that have market access. But the history of the last thirty years shows that many poorer developing countries with little access to international capital markets also faced debt-servicing difficulties and outright defaults (see the long list of highly indebted poor countries (HIPCs)). Since our dataset includes such countries, we plan to extend the study to these countries too. Based on our sensitivity analysis, we suspect that the same model may not predict crises in market-access countries and these poorer countries, since the latter have debt burdens that are much larger in relation to their GDPs, but are mostly owed (on partly concessional terms) to official rather than private creditors. So, debt thresholds for crisis may differ for these two groups and parameter estimates may not be similar for the two subsets of countries.
- Second, a large body of previous work has analyzed the crises of the 1980s, but little had been done to predict the debt crises of the 1990s. Our model makes some progress, but there is scope for further improvements in predicting the debt crises of the 1990s and sending fewer false alarms (type-II error). Many, but not all of these more recent crises had to do with illiquidity, rather than near insolvency; but even after controlling for measures of illiquidity, some entries into crises in the 1990s remain unpredicted. Thus, more work needs to be done to try to assess which fundamental vulnerabilities and/or investors' behavior can account for these more recent capital account crises. A sound EWS model should be good at predicting more systematically the more recent genre of crises without sending too many false alarms. It is also possible that the unpredictability of some recent episodes may be consistent with the view that, in a region of fragile fundamentals, multiple equilibria may occur, depending on investors' expectations and behavior.
- Third, many, but not all debt crises episodes have to do with fiscal vulnerabilities of the sovereign. However, there are better data on external debt and trade/external flows than there are about stocks of public debt and fiscal variables, such as real budget deficits and primary gaps. So, although some measures of fiscal imbalance and public debt sustainability signal fragility in the data, lack of data has so far prevented us from testing more systematically for the effects of budget deficits and primary gaps and finding statistically significant effects of these fiscal vulnerability variables. Thus, extending the dataset to have better fiscal flow and debt data may be of great value in testing the role of these fiscal variables in debt crises.
- Fourth, in addition to macrovariables, market indicators of debt sustainability, such as credit ratings and spreads on emerging market debt, may have predictive power in explaining debt crises. Of course, the same macro factors that predict crises are the variables that are used to assess sovereign ratings and to estimate the determinants of

spreads. Still, it would be interesting to test whether, after controlling for our macro determinants of crises, ratings, and spreads have additional predictive power or not. This would be useful in the design of an appropriate EWS system of early debt crises. Some recent work suggests that credit rating agencies have fared poorly in predicting debt-servicing difficulties in recent crises early on ; similarly, spreads are not always very reliable predictors until it is too late and a crisis is incipient. So, doing a "horse race" between our models and ratings and/or spreads or adding such variables to our models may help to assess a country's vulnerability to a debt crisis early on.

- Fifth, sometimes, but not always, debt crises have been associated with currency crises and banking crises (most recently in Argentina, Ecuador, and Russia). Although the precise causal relations among these three type of crises is complex, several ideas are interesting: study the interaction between these crises (i.e., when one or two or three of them occur simultaneously and whether similar variables predict them); and test whether currency and banking crises are leading indicators of debt crises and thus are able to better forecast the latter. An early guess is that these variables may not be leading indicators as debt crises are often concomitant but not lagging currency and banking crises.
- Sixth, it may be worth analyzing in more detail whether crisis episodes where default was avoided because of a large IMF package are different from other episodes in terms of the countries vulnerabilities. In some of these episodes, the IMF's "catalytic approach" of large financial support cum policy adjustment was attempted with mixed success.[23] Ideally, these should be cases of illiquidity with conditional solvency (i.e., solvency conditional on policy adjustment) where exceptional official finance is appropriate. So, studying separately these episodes may be important. However, a major data constraint is that these episodes are relatively rare and recent in our sample dataset.

Given the reemergence of debt crises in the 1990s, after the end of the 1980s debt crisis, the importance of assessing debt sustainability in emerging markets, the recent debates on bail-ins versus bailouts as crisis-resolution tools, the most recent policy debates on the appropriate regimes for orderly debt restructuring (statutory approaches such as the sovereign debt restructuring mechanism versus contractual approaches, such as collective-action clauses), and the need to provide large IMF financial support only when appropriate, the importance of understanding the causes of sovereign debt crises and of predicting them early on cannot be overemphasized. Our study is a contribution to answering some of these important empirical and policy issues.

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[23] For a theoretical model of the IMF's catalytic finance approach, see Corsetti, Guimaraes, and Roubini (2003). For an empirical assessment of this approach, see Cottarelli and Giannini (2002), and Mody and Saravia (2003).

I. Sensitivity Analysis Of The Logit EWS

We carry out a number of sensitivity tests to see how robust the estimated logit EWS is.[24]

- We drop observations with extreme values for the regressors included in the logit EWS.[25] The predictive performance of the logit EWS is not affected by this. The direction of influence of the regressors for which the extreme values are removed remains unchanged, and the coefficient estimates do not exhibit large falls in the z-value.
- Varying the definition of the dependent variable lowers the predictive power of the logit EWS to some extent. All coefficient estimates exhibit the same direction of influence, but a few appear to be no longer relevant and show a large worsening of the z-value (in particular, debt-service-to-reserves ratio and U.S. treasury bill rate). If we use only crisis episodes defined by Standard & Poor's, the model correctly predicts 63 percent of all crisis entries while sending false alarms in 4 percent of the cases. If we lower the threshold beyond which IMF loans are considered a crisis episodes to 50 percent of quota, the model correctly predicts 58 percent of all crisis entries while sending false alarms in 9 percent of all cases. And, if we increase the threshold beyond which IMF loans are considered a crisis episode to 150 percent of quota, the model correctly predicts 66 percent of all crisis entries while sending false alarms in 6 percent of all cases. We would conclude that these results indicate some robustness of our model with regard to variations in the dependent variable, though the results are by no means insensitive.
- We reenter several variables that dropped out of the specification process into the logit EWS to ensure that our specification process was not adversely affected by an omitted variable bias. For example, we reenter the financing requirement, the resource gap, public debt, and the overall balance. In none of these cases do we see the model's predictive power improved.
- We also carried out a specification process based on the full sample (Table 18). While the resulting model fared well in terms of correctly predicting crisis entries in the full sample, it was not very successful at predicting crisis entries from 1990 onward. However, our logit EWS that resulted from a specification process carried out for a sample from 1990 onward was easily generalized to cover the full sample. In fact, this

[24] Results available from the authors upon request.

[25] In separate regressions, we exclude observations with total external debt in excess of 100 percent of GDP, observations with short-term external debt on a remaining maturity basis ratio to reserves in excess of 10, observations with an external debt-service ratio to reserves in excess of 3, observations with a current account balance greater than 10 percent of GDP or smaller than -10 percent of GDP, observations with real GDP growth greater than 10 percent or smaller than -10 percent, openness smaller than 200. In addition, we impose these sample restrictions jointly.

logit EWS did not do any worse at predicting crisis entries before 1990 than the model specified for the full sample. From this we conclude that there has been some structural break in what is driving crises since the beginning of the nineties. However, those indicators that help predict crises from 1990 onward are also useful in predicting crises prior to 1990.

II. Tree Analysis: Prior Probabilities, Misclassification Costs, and Assignment Rules

Any problem of classification of *N* objects into $j=1,\ldots, J$ classes, characterized by a prior distribution $\pi(j), j=1,\ldots,J\ \Sigma j\ \pi(j)=1,$ and a symmetric (unit) misclassification costs $C'(i|j)=C'(j)=1,$ denoting the cost of classifying a type *j* erroneously as class *i*, can be reformulated as a problem with an arbitrary symmetric misclassification costs, $C(j),$ and new priors $\pi'(j),$ provided the following relationships between the two priors holds (see Breiman et al., ch 4.3):

$$\pi'(j) = C(j)\ \pi(j)/[\Sigma j C(j)\ \pi(j)] \text{ all } j=1,\ldots,J \tag{2}$$

In our application C(1)=7,C(0)=1, and the priors are equal to the sample probabilities(data), i.e $\pi(1)=0.205,\ \pi(0)=0.795.$
Hence the new priors are

$$\pi'(1) = C(1)\ \pi(1)/[C(1)\ \pi(1)+ C(0)\ \pi(0)]=7x0.205/[7x0.205+1x0.795]=0.643 \tag{3}$$

$$\pi'(0)=1-\pi'(1)=0.356 \tag{4}$$

Recall that the assignment rule for a problem with unit misclassification costs is to assign node *n* to class 1 when the within node relative probability exceed the sample wide relative probability:

$$[\pi(1)/\ \pi(0)]N_1(n)/N_2(n)> N_1/N_2 \tag{5}$$

Hence for arbitrary symmetric costs $C(j),$ the assignment rule is simply

$$[\pi'(1)/\ \pi'(0)]N_1(n)/N_2(n)> N_1/N_2 \tag{6}$$

In our example $N_1/N_0=0.2571,$ so that from (2) the rule becomes: assign node n to class 1 if

$$N_1(n)/N_2(n)>0.55x\ N_1/N_0 = 0.14 \tag{7}$$

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