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Unpleasant Surprises

Sovereign Default Determinants and Prospects

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Abstract

This paper uses model averaging techniques to identify robust predictors of sovereign default episodes on a pooled database for 46 emerging economies over the period 1980–2004. Sovereign default episodes are defined according to Standard & Poor's or by non-concessional International Monetary Fund loans in excess of 100 percent of the country's quota. The authors find that, in addition to the level of indebtedness, the quality of policies and institutions is the best predictor of default episodes in emerging market countries with relatively low levels of external debt. For emerging market countries with a higher level of debt, macroeconomic stability plays a robust role in explaining differences in default probabilities. The paper provides evidence that model averaging can improve out-of-sample prediction of sovereign defaults, and draws policy conclusions for the current crisis based on the results.

This paper—a product of the Economic Policy and Debt Department, Poverty Reduction and Economic Management Network—is part of a larger effort in the department to identify and address developing country vulnerabilities in the face of financial and economic crisis. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org.
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Unpleasant Surprises: Sovereign Default Determinants and Prospects

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1. Introduction

After a period of high growth, macroeconomic stability, and opportunities to accumulate reserves, emerging market countries (EMCs) entered the current global financial crisis in better position compared to past crises. Many emerging economies, especially in East Asia and Latin America, have substantially reduced their debt, consolidated their fiscal position and accumulated a buffer of reserves. Still, many EMCs in Eastern and Central Europe and Central Asia have been severely affected by the crisis due to their exposure to foreign financing and the global growth slowdown in 2009.

From the strength of their initial position, many EMCs implemented countercyclical fiscal policy to counteract the negative effect of stagnating external demand on their economies, and to protect the poor. However, these sizeable fiscal interventions as well as the tight financing conditions have posed threats on their debt sustainability outlooks. Furthermore, deteriorating debt levels and the uncertainty surrounding the exit from discretionary fiscal stimulus have become a major source of concern about a future debt crisis.

The literature on debt crisis has shown that EMCs are more vulnerable to crises than higher income countries. Absent improvement in their fiscal balances, EMCs may face a higher risk of default on their obligations than mature economies, a risk which in the current situation may be further increased through tighter debt markets, flooded by the financing needs of higher income countries.

Given the potential risk of EMCs being awakened by the unpleasant surprise of a wave of debt crisis, it is important to understand which countries are more likely to be affected. Developing econometric models which have good properties in terms of the anticipation of sovereign defaults is also a necessary effort for the policy reaction to be as effective as possible. This paper attempts to unveil those determinants of sovereign default which are robust to model uncertainty using Bayesian model averaging (BMA) techniques.

Using Bayesian model averaging (BMA) techniques, we show that the level of indebtedness with respect to available reserves is the most relevant predictor of default episodes for the entire sample of 46 EMCs. However, countries with a high level of debt (defined as total external debt above 50 percent of GDP, the median of our sample) would lower their probability of default if they maintain a stable macroeconomic environment (proxied by low inflation rates). Countries with low level of debt, on the other hand, have a lower unconditional probability to default than countries with a high level of debt. Low debt countries would further reduce their default probability as their institutional environment and the quality of their policies improve. Model averaged predictions prove also to outperform any other model in predicting sovereign default episodes out of sample. These results are consistent with the recent literature on default episodes, which shows that (i) a limited number of macroeconomic variables are sufficient to predict reasonably well episodes of default; (ii) indebtedness and inflation are the most important predictors of default episodes; and (iii) the recurrence of default episodes could be the symptom of more deeply rooted country characteristics, such as the quality of their policies and institutions. However, BMA results in this paper find that for EMCs which face a statistically significant threshold for total gross external debt, exceeded which macroeconomic stability becomes key to debt sustainability (see also Reinhard and Rogoff, 2010).

The paper is structured as follows. In section 2, we review key findings in the literature of potential determinants of sovereign defaults. In section 3, we present our dataset for 46 EMCs, as well as stylized empirical facts related to debt default. In section 4, we isolate robust determinants of default episodes among variables representing macroeconomic fundamentals, liquidity and solvency risks, as well as quality of policies and institutions. The use of BMA allows us to identify those variables that are most robust to changes in the set of conditioning variables. Finally, in section 5 we draw conclusions and present policy recommendations.

2. On the empirical determinants of sovereign default

Empirical models of sovereign default vary sometimes strongly in the choice of control variables. Most studies start by identifying sovereign defaults based on some definition (which is not necessarily consistent across studies) and build binary dependent variable models, generally logit or probit models, to assess the statistical significance of different potential determinants of debt crises. Table 1 presents a selection of recent empirical contributions of this type, together with the identity of the variables used as explanatory covariates in their respective models. Although there are remarkable differences in the choice of explanatory variables, in general empirical sovereign default models tend to include determinants which can be easily clustered into differentiated groups.

Firstly, country-specific *macroeconomic fundamentals* mirroring the effectiveness of economic policy and developments in the real economy tend to be systematically added as potential determinants of the probability of default. These include GDP growth, current account developments, fiscal and monetary policy variables and measures of real exchange rate misalignment. In addition, measures of the quality of countries' policies and institutions are also widely used to capture the effects of soft-factors, such as institutions, corruption and governance that are not directly considered by macroeconomic variables. Measures of *external solvency and liquidity* proxy the repayment capability of the country and are also systematically included in binary dependent variable models aimed at predicting sovereign default. Among these covariates, the extent and composition of external debt plays a privileged role as an explanatory variable and is usually the object of analysis of most empirical contributions to the determinants of default.

External shocks are also represented in the set of determinants by such variables as the US real interest rate. The effect of external developments on country-specific default probabilities can be thought of as mediated by the degree of external exposure of a given economy, which justifies the inclusion of trade and financial openness measures in debt default models.

In our robustness analysis we use representative variables of each one of these groups in order to evaluate their relative importance in the framework of model uncertainty. In addition, we also add a group of new variables which we label "*debt management variables*" to account for the importance of the structure and characteristics of the existing external debt portfolio and the terms of new borrowing to estimate default probabilities. These include the effective interest rate and the average time to maturity of the portfolio, both defined below.

3. Data and stylized facts

We use a database mirroring an extensive subset of the choice of variables in Manasse et al. (2003) and Fioramanti (2008).[2] The dataset contains information on 16 variables which cover representative regressors from the thematic groups defined above (see Table 2 for a description of the covariates used). In all cases, the frequency is annual. We construct an unbalanced panel of 46 EMCs in the period 1980-2004. Table 3 presents a list with all countries included in the dataset.

The dependent variable is a binary variable taking value one if a given country is defined to be in default at a given year. A country/year 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 non-concessional International Monetary Fund (IMF) loan defined as access in excess of 100 percent of the country's IMF quota. The default episodes are listed in Standard & Poor's (2004), while non-concessional loan are drown from IMF *International Financial Statistics* (IFS) database. This definition corresponds to the criterion used in Manasse et al. (2003) to identify debt crises.

On the regressors' side, we include proxies for the most important determinants of sovereign defaults considered in the literature as cited in Table 1. Explanatory variables are sourced from IMF's *World Economic Outlook* (WEO) and IFS databases, and the World Bank's *Global Development Finance* (GDF) database. The Country policy and Institutional Assessment (CPIA) was obtained from the World Bank. [3]

From GDF, we also obtain two *debt management variables*: effective interest rate and average time to maturity of the portfolio. Each of them represents a different cost and relates to risks which debt managers are expected to minimize. The *effective interest rate* -- calculated as interest rate payments in year *t,* divided by the stock of debt at the end of *t-1,* or the average interest payment per unit of debt -- represents a classical measure of the cost of servicing the existing debt portfolio. An increase in this variable signals higher cost for existing debt and an elevated pressure on the fiscal balance.

On the other hand, the *average time to maturity* measures the average time of rolling over of the existing portfolio. A shortening of this indicator suggests that the portfolio is being rolled over more frequently, and therefore, is more exposed to refinancing shocks. This variable refers to new debt and should thus be considered a concept related to marginal costs of debt accumulation.

Table 4 presents descriptive statistics for the variables in our dataset. We present statistics over the full sample and group countries according to their level of indebtedness over the sample period into two subsamples. A country belongs to the *low debt level group* those

[2] We are very grateful to Marco Fioramanti for kindly sharing his dataset with us.
[3] The CPIA rates countries on a scale from 1 to 6, with higher values indicating better quality of policies and institutions

years when it has a level of total external debt over GNI below 50 percent, which is roughly the median value of this variable over the full dataset. It belongs to the *high debt level group* the years when it has debt ratios above 50 percent of GNI.

Table 4 indicates that countries in the high debt level group are almost twice more likely to default on their external debt than countries less indebted. On average, countries with a low level of debt have an external debt-to-GNI ratio of 31 percent compared to an average ratio of about 84 percent in the group of high debt level. Countries with lower debt on average grow a full 1 percentage point more and have a third of the inflation rates of the countries with debt-to-GNI ratio above 50 percent. This observation is consistent with the recent literature (Reinhart and Rogoff, 2010). Countries with debt below 50 percent of GNI post, on average, a small primary surplus, compared to a primary deficit in countries with a higher debt burden. This result reinforces the empirical finding that in EMCs fiscal surpluses are key to reducing public debt (Gill and Pinto, 2005). We also find that the quality of policies and institutions (measured by the World Bank CPIA Rating) is marginally better in countries with lower level of debt.

Countries with more debt are also more open compared to the group of countries with debt-to-GNI of less than 50 percent. In the former group, on average, the level of openness is twice the value of the less indebted countries. More indebted countries also have larger current account deficits. They also tend to be less covered against (more likely) default episodes, because their reserve coverage is lower with respect to their total external debt, short term liabilities and their current account deficits.

Data in the sample do not highlight significant differences in debt risk indicators. We do not find substantial differences in the interest rate on external debt or in their maturity profile on average, although two outliers in the low-debt group (Paraguay in 1998 and Romania in 2002, with average maturities of 91 and 385.4 years, respectively) are a sizable distortion in this subsample. Countries with lower level of external debt do tend to have a larger share of short-term debt, as an indication that they are on the one hand more exposed to roll-over risk, but on the other hand are also capable of rolling over larger portion of debt, than countries with higher level of external debt. It should be noted that to a certain degree the maturity structure of external debt is endogenous as high debt countries with a higher default probability may find themselves excluded from short-term borrowing markets.

Although the descriptive statistics in Table 4 paint a clearer picture of the differential characteristics of defaulting countries, a full-fledged econometric analysis is needed to assess robust predictors of sovereign default risk. This analysis is carried out in the next section, explicitly considering the role of model uncertainty when specifying limited dependent models for debt crises.

4. Unveiling robust determinants of debt default under model uncertainty

4.1 Assessing model uncertainty

Let us consider the problem of predicting the probability of sovereign default when different models are available. The usual econometric approach used in the literature to assess default determinants is to start by defining a binary variable (y), which takes value one at default periods ($y=1$) and zero in the rest of the sample ($y=0$). Assume that we have a set of variables $\mathbf{X}=\{x_1,\ldots,x_K\}$ composed by K variables which have been proposed as potential explanatory factors for triggering debt default. In principle, any combination of these K variables may be considered as regressors in a model. Let $\mathbf{X}_k$ denote a group of $k \le K$ variables from the set **X**. A typical model explaining default with this group of covariates is given by

$$\mathrm{P}(y=1\,|\,\mathbf{X}_k)=F(\mathbf{X}_k\beta), \tag{1}$$

where $F(z)$ will typically be a logistic function $(1-F(z)=(1+e^{z})^{-1})$ or the Gaussian distribution function ($F(z)=\Phi(z)$), leading to a logit or probit model, respectively.

Once $F(z)$ has been chosen, a model is defined by a list of included variables. Thus, there are 2^K possible models (we will denote each model M_j, for $j=1\ldots 2^K$) which can be considered. Bayesian model averaged estimates of a parameter of interest in this setting can be obtained by weighting each (model-specific) estimate of the parameter with the posterior probability of the model it comes from and summing over the whole model space, which is composed by all 2^K specifications,

$$\mathrm{P}(\beta_s\,|\,y)=\sum_{m=1}^{2^K}\mathrm{P}(\beta_s\,|\,y,M_m)\mathrm{P}(M_m\,|\,y). \tag{2}$$

The posterior model probability is, in turn, a function of the prior probability of the model and its marginal likelihood, so that $\mathrm{P}(M_k\,|\,y)\propto \mathrm{P}(y\,|\,M_k)\mathrm{P}(M_k)$. We need to make a choice on the prior probability over the model space, as well as over the parameters of each specific model. A flat prior probability over models is the preferred choice in the literature, leading to a 0.5 prior probability of inclusion for each one of the K variables considered. However, this choice of model space prior leads to a mean prior model size of $K/2$ and assigns relatively high prior probability to models which may be considered ``too large" for many econometric applications. Recently, Ley and Steel (2009) propose using a hyperprior on model size and show that their approach leads to more robust inference when applying BMA.

Raftery (1995), Kass and Raftery (1995) and Clyde (2000) propose the use of Laplace approximations for determining posterior model probabilities, which simplifies the computational burden for limited dependent variable models considerably. The Bayes factor comparing two models ($B_{jk}=\mathrm{P}(y\,|\,M_j)/\mathrm{P}(y\,|\,M_k)$) can be thus approximated using the

Bayesian information criterion (Schwarz, 1978) as

$$-2\log B_{jk} \approx BIC_k - BIC_j ,$$

where BIC_i is the Bayesian information criterion of model i. Different penalties to the inclusion of new parameters in the model can be achieved by changing the BIC above by the Risk Inflation Criterion (RIC, Foster and George, 1994) or the Akaike Information Criterion (AIC, Akaike, 1973). In these cases, we depart from the purely Bayesian case and average over models using weights which are justified using non-Bayesian approaches to inference, but that have often been used in BMA exercises (see Clyde, 2000 for a theoretical discussion and applications). In our application, we use the RIC approximation to compute weights for the different specifications which form the model space.

The BMA technique allows us to compute statistics such as the *posterior inclusion probability* of the different potential determinants of debt default. This statistic is the sum of the posterior probability of models including a given variable, and can be interpreted as the probability that this variable belongs to the true model determining default. The posterior inclusion probability is routinely interpreted as the robustness of a variable as a determinant of the phenomenon under investigation. Similarly, weighted averages of the parameter estimates and its variance are interpreted as the estimated effect of the covariate and its precision once that model uncertainty has been taken into account. The method is thus able to deliver a full account of the relative importance of the different mechanisms put forward in the literature, as well as estimates of the size of their effect. In particular, the method allows us to create an ordering of explanatory variables in terms of their robustness as predictors of default episodes.

4.2 Robust determinants of sovereign default

We use the BMA setting described above using the Risk Inflation Criterion (RIC) approximation[4] and a Markov Chain Monte Carlo Model Composition (MC^3) method (Madigan and York, 1995) to compute the posterior probability of the different model specifications in our model space.[5] All variables are lagged by one year, so as to impose a causal structure in the models and avoid, to a certain extent, endogeneity problems. The results are presented in Table 5, which presents for each variable the posterior inclusion probability (PIP), the ratio of posterior mean to posterior standard deviation of the parameter associated to each one of the covariates (PM/PSD, a measure of the precision of the estimate) and the model-averaged marginal effect of each variable.

It should be noticed that our dataset includes multi-year periods of debt servicing difficulties, which implies a high degree of persistence in our dependent variable. While estimates based on binary dependent variable models with country-fixed effects are

[4] Alternatively, the BIC approximation was also used, leading to qualitatively similar results to those presented in this section.

[5] The model space in our application contains over 65000 models. Although this is a tractable size, we decide to reduce computing time by using the MC^3 sampler to evaluate the model space, which allows us to estimate less than a third of the models in the full model space (10,000 models after 10,000 runs in the burn-in phase).

theoretically feasible in the setting of BMA, the computational costs are high, so we keep the pooled structure of the data and explain jointly differences across countries and in time. Since many of the potential explanatory variables are also persistent over time, the momentum of debt service problems can be partly assessed by the dynamics of covariates. Alternatively, the dataset may be collapsed as a summary of sustained default and non-default episodes, as in Kraay and Nehru (2006). In our case, the number of observations after compressing the data to such episodes is too small to allow for a reasonable model averaging analysis (defining debt stress periods as lasting more than five years leads to less than 40 usable observations).

The results in Table 5 indicate that, for the entire sample, there is a single variable which at the same time achieves a high posterior inclusion probability and a high degree of precision in the estimation of its effect. Namely, this is the size of external debt as a percentage of reserves. The associated model-averaged parameter is positive, as intuitively expected, implying that access to liquidity decreases the probability of sovereign default. For all other variables, the PIPs are below 0.5 (the benchmark given by the expected value of the prior inclusion probability) and/or the precision of the estimation is too small to consider them robust determinants of sovereign default.

BMA estimates for the two groups of countries with debt below and above 50 percent of GNI indicate possible threshold effects in terms of the robustness of default determinants. For country/years in the group characterized low level of debt, debt defaults episodes are more likely the larger is the external debt in percent of reserves and the poorer their quality of policies and institutions is, measured through the CPIA Index.[6] However, for countries with higher level of debt, the CPIA loses robustness as a predictor of default in terms of posterior inclusion probability while inflation, together with indebtedness, is robustly and positively associated with a higher probability of default.

This result is in line with existing literature (Reinhart et al., 2003), which also singles out indebtedness and macroeconomic stability (proxied by inflation), as the most significant determinants of sovereign defaults. However, our sample selection highlights that indebtedness and inflation are systematically relevant only for the subsample of countries which is characterized by a relatively high level of debt. In countries with lower debt levels, concentrating on improvements in quality of policies and institutions is more relevant to avoid defaults. Low-debt countries have, on average, lower inflation, which also presents a lower level of dispersion. In a group of countries whose macroeconomic variables are more stable, soft factors related to the institutional framework become thus relevant as predictors in episodes of default. The newly introduced debt management variables, which proxy for debt costs and roll over risk of the portfolio, are not robustly associated with the probability of default.

We changed the setting of the BMA exercise in several ways to ensure that our results are

[6] Kray and Nehru (2006) find that the marginal effect of the CPIA on the probability of default is much larger in low-income than in middle-income countries. BMA point estimates of the marginal contribution of the CPIA in EMCs is consistent with the previous finding, but for low debt EMCs, the quality of policies and institutions appears to be a stronger determinant of default than for the whole sample of middle income countries considered by Kray and Nehru (2006), suggesting that for low debt EMCs markets the level of indebtedness is not the only piece of information that markets consider.

consistent when outliers are excluded and reduced sets of covariates are used.[7] In a first round of robustness checks, we exclude the two observations with outlying values for the maturity variable, which leaves our results unchanged. Due to the high correlation between total external debt and short-term debt values, a natural alternative of our setting would be to exclude total external debt over GNI as a potential determinant, while leaving the variables based on short-term debt as part of the variables under study. The results of the BMA analysis then point towards a robust positive effect of the overall level of short term debt over GNI and a robust negative effect of the variable measuring the share of short term debt in total external debt. This implies that the size of the short term debt variable matters, but that in terms of composition, countries with a higher share of long term debt are more prone to defaulting, an effect that is probably related to the exclusion of highly indebted countries from short term debt markets.

4.3 Model averaging and out-of-sample predictive ability for sovereign default

A natural question that arises is whether exploiting model uncertainty can lead to improvements in the out-of-sample predictions of the probability of sovereign default and thus contribute to the anticipation capabilities of economic policy. For this purpose, we carry out a simple out-of-sample forecasting exercise in order to measure the differential predictive abilities of BMA forecasts as compared to single-model forecasts. The prediction exercise is structured as follows. Using data up to 1994, we obtain model averaged predictions of the default probabilities for the countries in our sample for the year 1995, which are computed as weighted averages of single model predictions using posterior model probabilities as weights. In parallel, the predictions of the model with the highest posterior probability is also saved, in order to compare the model averaged results with those which would have been obtained if model selection had been used instead of averaging. We add the observation corresponding to 1995 to the estimation period and obtain predictions for 1996. This is repeated until the end of the sample is reached.

We evaluate the quality of the predictions by transforming the probability forecasts into "alarms" signaling the occurrence of default. For this purpose, we need to delimit the probability threshold that defines alarms for probability predictions above that value. Following the empirical literature on early warning systems (see Berg et al., 2004), we define a simple loss function of the policymaker as the sum of wrongly predicted crises as a share of total crisis periods and wrongly predicted "quiet periods" as a share of total quiet periods. Using this loss function, which implies that the policymaker cares equally about type I and type II errors concerning sovereign default predictions, we estimate the probability threshold defining alarms as the level of probability that minimizes the loss function over the prediction period.[8] This threshold is estimated for both the set of predictions based on BMA and those emanating from the single best specifications (in terms of posterior probability) and statistics concerning the goodness of fit of predictions are computed and presented in Table 4.

[7] The results of the robustness checks are not presented in detail here, but are available from the authors upon request.
[8] The loss function could place more weight on crisis events that are not correctly predicted when true (type II errors), as policymakers may find not acceptable to miss a crisis. However, this could also lead to too many red flags raised when not needed. Hence the choice of equally minimizing types I and II errors.

The results in Table 4 indicate that BMA methods improve on the predictive ability of single models. Model average predictions do particularly well at improving the share of correct alarm signals, at the cost of a small reduction of the share of correctly predicted quiet times. In this sense, our results indicate that methods that make use of quantifications of model uncertainty to aggregate predictions of single models should be added to the instruments used by policymakers to anticipate and measure potential sovereign default risks. It should be noticed that the improvement is relatively modest in quantitative terms with respect to the best model. Partly, this can be explained by the fact that the posterior mass over the model space is very concentrated on very few models, a phenomenon recently dubbed "the supermodel effect" which is related to the priors used in the analysis (see Feldkircher and Zeugner, 2009). The use of a hyperprior structure over parameters should improve mixing among models, but would increase the computational burden of our exercise enormously.

5. Conclusions

Using a database spanning 25 years for 46 EMCs, we use BMA techniques to determine the set of robust determinants of debt default. A first look at the data indicates that countries with different levels of indebtedness have also different characteristics. On average, countries with external debt below 50 percent of GNI (roughly the median of this variable in our sample), grow more, have lower inflation, and achieve primary surpluses compared to countries with a higher level of external debt. They are also less open, and therefore less exposed to shock from external demand, have a lower current account deficit, but have a higher level of reserves than more indebted countries.

For the entire sample, the probability of default is only robustly associated with the level of indebtedness of a country. However, for countries with debt-to-GNI ratio below 50 percent, their quality of policies and institutions become also relevant. In countries with external debt above 50 percent of GNI, the institutional quality is not relevant while inflation, together with indebtedness, is positively associated with a higher probability of debt default. The importance of the institutional settings and quality of policies fades away for countries with higher level of debt.

Variables representing debt costs and rollover risk do not appear robust as predictors of debt default. On the one hand, this result confirms the view in the literature that only few macroeconomic variables and variable of institutional quality are necessary to predict defaults (Kraay and Nehru, 2006). On the other hand, it implies that more analysis is necessary to determine the importance of debt management to decrease the probability of default.

We also show that model averaging improves the out-of-sample predictive ability for debt crises and that such techniques should become part of the set of instruments used by policymakers to assess the degree of sovereign default risk and obtain informational gains on which to base their economic policy measures. Further improvements may be obtained if a fully Bayesian approach is used to obtain model-averaged results, using the results by Albert and Chib (1993) in the framework of BMA. This improvement is straightforward from an analytical point of view, but may be computationally costly.

Table 1. Selection of empirical studies assessing the determinants of sovereign default

Reference	**Variables**		**Sample**
Detragiache and Spilimbergo (2001)	Short term debt	Concessional share	69 countries, yearly data 1971-1998
	Debt coming due	Multilateral share	
	Foreign exchange reserves	Interest rates	
	Total debt to GDP ratio	Overvaluation	
	Commercial share	Openness	
Catao and Sutton (2002)	Terms of trade	Total external debt service to export ratio	25 emerging markets, 1970-2001
	Real interest rate US bond	Foreign exchange reserves to debt	
	Government balance over GDP	Openness	
	REER	Volatility, fiscal policy	
	Short term debt	Volatility, TOT	
	Foreign exchange control index	Volatility, money base coverage	
	Real GDP growth	Volatility, capital control	
Kruger and Messmacher (2004)	Proportion of new financing needs	CA deficit to GDP	42 countries, 1970-2001
	GDP growth	Debt to exports	
	Change in growth rate of TOT	LT debt service to reserves	
	Export growth	LT debt service to GDP	
	US 3 month interest rate	ST debt to reserves	
	Foreign debt to GDP		
Kraay and Nehru (2006)	Present value of debt to exports	Rule of law	LICs, 94 crisis episodes 1970-2001
	Debt service to revenues	Depreciation	
	Debt service to reserves	TOT growth	
	CPIA rating	GDP per capita	
	GDP growth	Inflation	
Pescatori and Sy (2007)	Openness	ST debt over reserves	Several samples, 1975-2002
	Overvaluation	GDP growth	
	Total debt over GDP	Inflation	
Tomz and Wright (2007)	GDP (HP-filtered)		106 countries, yearly data 1820-2004

Table 2. Countries in the sample

Argentina	Latvia
Bolivia	Morocco
Brazil	Mexico
Chile	Malaysia
China	Oman
Colombia	Pakistan
Costa Rica	Panama
Cyprus	Peru
Czech Republic	Philippines
Dominican Republic	Poland
Algeria	Paraguay
Ecuador	Romania
Egypt	Russia
Estonia	El Salvador
Guatemala	Slovak Republic
Hungary	Thailand
Indonesia	Trinidad
India	Tunisia
Israel	Turkey
Jamaica	Ukraine
Jordan	Uruguay
Kazakhstan	Venezuela
Lithuania	South Africa

Table 3. Descriptive Statistics

	Full sample					Below 50% external debt as % of GNI					Above 50% external debt as % of GNI				
	Mean	Median	Maximum	Minimum	Std. Dev.	Mean	Median	Maximum	Minimum	Std. Dev.	Mean	Median	Maximum	Minimum	Std. Dev.
Sovereign default	0.48	0.00	1.00	0.00	0.50	0.36	0.00	1.00	0.00	0.48	0.58	1.00	1.00	0.00	0.49
CPIA	3.80	3.78	6.00	2.05	0.72	3.87	3.80	6.00	2.11	0.71	3.73	3.75	6.00	2.05	0.72
Current account as % of FDI	-366.14	-117.80	31614.29	-34771.29	3299.79	-373.74	-115.40	31614.29	-34588.25	3275.93	-359.04	-119.88	21485.71	-34771.29	3328.24
Current account as % of GNI	-2.19	-2.38	18.52	-17.49	4.71	-1.86	-2.04	9.87	-10.21	3.24	-2.49	-3.18	18.52	-17.49	5.74
Current account as % of reserves	-34.67	-26.47	998.98	-530.20	94.45	-32.37	-24.41	151.62	-460.49	60.75	-36.82	-29.93	998.98	-530.20	117.61
Effective interest rate	5.43	5.04	21.19	0.09	2.34	5.64	5.33	13.44	2.11	1.95	5.24	4.84	21.19	0.09	2.64
Average maturity	16.66	15.50	385.40	0.00	17.73	16.37	13.50	385.40	0.00	25.07	16.93	16.80	34.70	0.00	5.34
External debt as % of GNI	58.44	51.32	253.21	4.13	36.25	31.29	31.86	49.82	4.13	10.97	83.82	71.73	253.21	50.05	33.11
External debt as % of reserves	799.56	513.22	8399.82	44.79	962.08	450.09	322.83	2281.43	44.79	370.25	1126.17	737.59	8399.82	135.48	1201.78
GDP growth	3.48	4.00	16.10	-13.40	4.47	4.06	4.30	15.20	-12.90	4.26	2.95	3.60	16.10	-13.40	4.61
Inflation rate	51.93	9.30	11749.60	-30.30	538.70	39.31	10.90	2075.80	-1.40	183.58	63.72	7.95	11749.60	-30.30	728.48
Openness	77.94	64.38	436.51	15.47	50.70	58.90	52.86	212.08	15.47	31.53	95.73	75.74	436.51	29.16	58.28
Overvaluation	41.21	40.35	95.00	0.00	17.28	41.80	39.68	95.00	15.18	16.49	40.67	40.94	78.45	0.00	18.00
Primary deficit as % of GNI	0.54	0.23	21.70	-20.02	4.46	-0.05	-0.08	7.71	-10.54	2.89	1.10	0.70	21.70	-20.02	5.49
Short term debt as % of reserves	114.40	64.88	2399.83	0.94	199.08	70.47	46.68	610.47	0.94	74.30	155.46	81.25	2399.83	4.81	261.06
Short term debt as % of total external debt	15.02	12.95	65.06	0.83	10.13	16.78	15.40	65.06	1.61	10.63	13.38	10.96	61.14	0.83	9.36
US T-Bill rate	5.37	5.07	14.08	1.61	2.19	5.21	5.02	14.08	1.61	2.16	5.53	5.41	14.08	1.61	2.22
Observations/countries			503/46					261/39					242/35		

Table 4. Model averaging results

	Full sample			Below 50% external debt over GNI			Above 50% external debt over GNI		
	PIP	PM/PSD	MEFF	PIP	PM/PSD	MEFF	PIP	PM/PSD	MEFF
External debt as % of reserves	**1.0000**	**7.7958**	**0.0005**	**1.0000**	**5.0431**	**0.0008**	**1.0000**	**4.6676**	**0.0001**
CPIA	0.2362	-0.5058	-0.0232	**0.9838**	**-2.9691**	**-0.1928**	0.0019	0.0232	0.0000
GDP growth	0.2335	-0.5018	-0.0035	0.0043	-0.0501	0.0000	0.0020	-0.0278	0.0000
Short term debt as % of total external debt	0.0205	-0.1263	-0.0001	0.1642	-0.3970	-0.0015	0.0013	0.0189	0.0000
Openness	0.0071	-0.0714	0.0000	0.0013	0.0076	0.0000	0.0038	-0.0479	0.0000
Overvaluation	0.0051	-0.0602	0.0000	0.0026	0.0049	0.0000	0.2003	-0.4513	-0.0004
External debt as % of GNI	0.0040	0.0457	0.0000	0.0520	-0.2091	-0.0004	0.0043	0.0503	0.0000
Inflation rate	0.0037	0.0455	0.0000	0.0008	0.0087	0.0000	**1.0000**	**3.5289**	**0.0029**
Effective interest rate	0.0036	-0.0500	-0.0071	0.0018	-0.0185	0.0000	0.0009	-0.0134	0.0000
Short term debt as % of reserves	0.0035	-0.0424	0.0000	0.0539	-0.2118	-0.0001	0.0014	0.0133	0.0000
US T-Bill rate	0.0023	0.0280	0.0000	0.0016	-0.0043	0.0000	0.0016	0.0243	0.0000
Current account as % of reserves	0.0013	-0.0163	0.0000	0.0012	-0.0263	0.0000	0.0036	-0.0453	0.0000
Primary deficit	0.0012	0.0183	0.0000	0.0593	-0.2233	-0.0016	0.0041	0.0496	0.0000
Current account as % of FDI	0.0011	-0.0190	0.0000	0.1751	-0.4155	0.0000	0.0006	0.0061	0.0000
Current account as % of GNI	0.0010	0.0197	0.0000	0.0018	0.0299	0.0001	0.0020	-0.0295	0.0000
Effective maturity	0.0006	0.0137	0.0000	0.0009	0.0131	0.0000	0.0130	0.0961	0.0000

Notes: PIP stands for posterior inclusion probability, PM stands for posterior mean (mean of the posterior distribution of the corresponding parameter), PSD stands for posterior standard deviation (standard deviation of the posterior distribution of the corresponding parameter) and MEFF stands for the model-averaged marginal effect. Variables ordered by PIP in the full sample. Results obtained from 10,000 replications of the MC3 procedure after a burn-in phase of 10,000 replications.

Table 5. Prediction results

	BMA predictions	Best model predictions
Value of loss function	0.303	0.329
Cut-off probability threshold	0.362	0.357
Correct alarms as % of total alarms	0.800	0.725
Correct non-alarms as % of quiet moments	0.595	0.617

Results based on out-of-sample predictions for the period 1995-2004 (337 observations).

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