Sovereign Rescheduling Probabilities in Emerging Markets: A Comparison with Credit Rating Agencies' Ratings

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ABSTRACT

This study estimates default probabilities of 124 emerging countries from 1981-2002 as a function of a set of macroeconomic and political variables. The estimated probabilities are then compared with the default rates implied by sovereign credit ratings of three major international credit rating agencies - Moody's Investor's Service, Standard & Poor's and Fitch Ratings. Sovereign debt default probabilities are used by investors in pricing sovereign bonds and loans as well as in determining country risk exposure. The study finds that credit rating agencies usually underestimate the risk of sovereign debt as the sovereign credit ratings from rating agencies are usually too optimistic.

JEL Classification: F33, F34

Key words: sovereign debt, default probabilities, credit rating agencies, credit ratings

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1. INTRODUCTION

Major international banks and international investors use risk neutral default probabilities in pricing models for bonds and loans as well as real world default probabilities as an input to their credit risk management models to determine country risk exposure limits. According to the new version of the Basel Capital Accord – Basel II (Basel Committee on Banking Supervision, 2004), banks are allowed to use their internal ratings, credit ratings from rating agencies and their associated default rates in determining their required regulatory capital against credit risk. Thus, the ratings from rating agencies are important for international capital allocation. However, as examined in this study, default probabilities from rating agencies may not be adequate proxies for sovereign default probabilities.

This study utilizes models specifically developed for assessing sovereign default risk based on a sample of 124 emerging countries over the period 1981-2002. This study therefore covers recent period for an extended group of countries, as majority of the studies in the area focus on more limited samples. The models that we use for assessing probabilities of default are typical for these types of studies, however, they are further enhanced by use of Principal Component Analysis in identifying the main forecasting variables. The models are explained and tested in detail in Georgievska et al. (2005).

The purpose of this study is to examine whether sovereign default/rescheduling probabilities derived from our models, which are specifically designed for sovereigns, are more appropriate measures of probability of sovereign default than credit agencies' default rates. The study, therefore, compares the estimated probabilities from our models with the assigned credit rating probabilities of three major international rating agencies, namely, Moody's, Standard & Poor's (S&P) and Fitch. The main incremental contribution of this paper is therefore to compare the accuracy of determining default rate probabilities using our best forecasting models versus the ones provided by credit rating agencies[1].

2. ANALYTICAL FRAMEWORK

The literature on sovereign debt suggest that a number of macroeconomic, political and capital markets factors influence the probability of a country's sovereign debt repayment difficulties. Sovereign default may either be triggered by countries' 'unwillingness' to repay their external debts or by countries 'inability' to repay their external debts due to insolvency or illiquidity. Thus, a country's solvency or the country's stock of debt in relation to the country's ability to pay can be measured by the GDP, government revenues or exports. If the discounted value of future trade balances exceeds the current external debt stock we can say that the country is solvent (e.g., Roubini, 2001). Subsequently, the exchange rate regime plays a role in the country's solvency since an overvaluation may lead to external imbalances that lead to debt accumulation. Moreover, theory suggests that the openness[2] can affect the country's willingness to default since the costs of default are affected (e.g., Eaton and Fernandez, 1995). Macroeconomic stability affects the risk attitudes of investors; e.g. high inflation and high money growth deter investors from a country. Illiquidity can also cause sovereign default, which is usually measured by the short-term debt to reserves or M2 to reserves. Finally, political and institutional factors can cause sovereign default since they affect the credibility of a country's policies and government willingness to adopt a sustainable debt strategy (e.g., Hemming and Petrie, 2002 and Hemming and Chalk, 2000).

[1] For the purpose of this study we have selected two out of four forecasting models developed in our previous study based on their superior level of forecasting ability. In addition, we have adjusted the data sample to match the country coverage with credit rating agencies for comparison purposes – reducing the sample from 127 to 124 emerging economies.

[2] The higher the imports in relation to the size of the economy the more open is the country, thus more vulnerable to foreign shocks, and more likely to external debt rescheduling (e.g., Frenkel, 1983)

A number of econometric studies, which mainly used panel logit and probit analysis, developed models that predict rescheduling/default events with a high degree of accuracy. In such models, the dependent variable is transformed into the probability of an event, which in our case, is the event of rescheduling; see also Rivoli and Brewer (1997). The period analysed by key studies in the area mainly covers early 1970s to 1990s, except for Detragiache and Spilimbergo (2000) which covered the period from 1971-1998.

All empirical studies specify the dependent variable as a binary outcome that can take the value of 1 in the case of defaulting (rescheduling) and 0 in the case of non-defaulting (non-rescheduling) event. The empirical studies differ in defining what constitutes a default or rescheduling event[3].

A small number of explanatory variables are found to be systematically significant in most of the studies performed. Three financial ratios have been most often tested and found most consistently significant: reserves to imports (e.g., Aylward and Thorne, 1998); total external debt to GDP (e.g., Balkan, 1992, Detragiache and Spilmbergo, 2000 etc.); and total debt service payment to exports (e.g., Solberg, 1988 and Rivoli and Brewer, 1997). Some macroeconomic and policy variables such as GDP growth, inflation and indicators of exchange rate overvaluation, are found to have a significant effect on country's ability to repay its debts in some studies, but are insignificant in others. A number of studies have tested the significance of the past repayment records and lagged rescheduling events, as an explanatory variable for a country's current repayment behaviour. All those studies, such as Hajivasiliou (1987, 1989 and 1994), Solberg (1988) and McFadden et al. (1985) found that a country's historical debt servicing performance has a significant impact on its current repayment performance. Finally, political factors even though

[3] Some studies define a country as in default if there is a debt rescheduling agreement or negotiations. Other studies consider sovereign default if there are arrears on principal or interest payments, or a country concludes an upper-tranche IMF agreement.

found important (e.g., Citron and Nickelsburg, 1987) have been included in only a few studies mainly due to scarcity of data[4]. Some studies such as Schwartz and Zurita (1992), and Lee (1991) tried to differentiate between a country's 'ability' to service its debts and its 'willingness' to do so by using macroeconomic and political proxies, but due to limitations in political variables data, most of the results obtained are insignificant.

Other variables suggested to be used in modelling sovereign debt re-scheduling are: loan demand and supply measured through international reserves, current account and debt service due as in McFadden et al. (1985) and Hajivassiliou (1989) which have not been found consistently significant; credit ratings for sovereign defaults and currency crises as in Reinhart (2002) and Rojaz-Suarez (2001) which exhibit poor predictive power; and debt ratios as in Berg and Sachs (1998) which yield more consistent results in explaining the differences in the repayment performance by countries.

Data limitations have prevented the close examination of predictive power of sovereign spreads for sovereign defaults. The data for sovereign spreads became available during the 1990s when the debts of commercial banks were securitized and converted into Bradies and Eurobonds that were easily traded. However, most of the debt defaults occurred in the 1980s when spreads data were not available. A study performed by Dell'Ariccia et al. (2002) suggested that spreads are affected by moral hazard, since the spreads increased after the Russian non-bailout in 1998.

From the existing empirical studies on sovereign defaults reviewed in greater detail in Georgievska et al. (2005), the variables that explain sovereign defaults can be classified into five groups: (1) Solvency

[4] Examples of political variables used in some studies are: democracy index, political instability index, long- and short-term armed conflict, changes of the finance minister and/or the minister of the economy

variables[5]; (2) Liquidity Variables[6]; (3) Variables used in currency crises models[7]; (4) Macroeconomic control variables[8]; and (5) Political variables[9].

3. EMPIRICAL MODEL SPECIFICATION

3.1 Dependent Variable – Rescheduling Event

In common with most of the previous studies we define a rescheduling 'event' as occurring in the year a rescheduling agreement is finalized. Our dependent variable is a dichotomous variable that is binary-valued in the sample i.e.

$$\boldsymbol{Rescheduling}_{it} = \begin{cases} 1 & \text{if country } i \text{ reschedules its external debt in year } t \\ 0 & \text{if country } i \text{ does not reschedule its external debt in year } t \end{cases}$$

The value 1 or 0 in the above formulation is determined by using the 'total amounts of debt rescheduled' (TADR) figure in US dollars obtained from the World Bank *Global Development Finance* 2004. This does not distinguish between multilateral, bilateral or private creditors in different years, but our main interest is in the event of rescheduling, regardless of the type of debt involved. If a country *i* has a TADR bigger than zero in time period *t*, we consider that as rescheduling event, i.e. assign a value of '1' to this observation in time period *t*.

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[5] Private or official debt in relation to the capacity of repayment.

[6] External debt service/reserves or External debt service/exports.

[7] E.g. Money/Gross International reserves, Exchange rate devaluation, as per IMF research.

[8] Real growth, exchange rate, inflation etc.

[9] Variables that explain the country's 'willingness to pay', e.g. government stability, socioeconomic conditions, external conflict, internal conflict, corruption, military in politics, religion in politics, democratic accountability etc.

3.2 Explanatory Variables

We originally started our analysis with 35 potential independent variables, as identified in the literature. However, since such a large volume of the data can cause over-fitting in the model and multicolinearity, we performed a principal component analysis (as described in section 3.5.) in order to reduce the dimension of our data. We selected the most important variables that fulfil the following criteria: (1) the variables are individually and jointly significant in the econometric model; (2) the coefficients on the variables included in the model show their expected sign; and (3) the variables included optimize the fit of the model. The following eight variables generated the best fit for our models (Appendix 1 provides a table of the variables used):

(1) Solvency Variables: Total Debt/GNP; Arrears/Exports; Exports/GDP

(2) Liquidity Variable: International Reserves/GDP

(3) Macroeconomic Variables: Current Account Balance/GDP; Imports/GDP*;*

(4) Political Variable: ICRG Composite Index Rating. ICRG composite index is produced by PRS Group. It is comprised of the following indicators: 50% political risk, 25% financial risk, and 25% economic risk[10].

We also included the lagged dependent variable (rescheduling event) as an explanatory variable to reflect the past repayment performance of a country.

3.3 Sample and Data

The study focuses on 124 emerging countries over the period 1981-2002. Appendix 2 lists the countries included in our analysis, the period examined for each country, and the rescheduling observations for each country. Data on external debt and amounts rescheduled are from *Global Development Finance*

[10] The cost of obtaining and processing this information is marginal providing the analytical set up in a financial institution is already in place. For lower net worth individual investors there may be a cost advantage of utilizing the existing credit rating agencies' default probabilities.

2004 CD-ROM. Data on economic variables used in the study are from various sources: *World Development Indicators 1999 and 2004* CD-ROMs, World Bank *Global Development Finance Country Tables from 1998-2004*, IMF (*IFS) International Financial Statistics*, and various *OECD* publications. Data on political risk indicators are obtained from various issues of *International Country Risk Guide* published by PRS (Political Risk Services) Group. Our final sample contains 1380 observations. All explanatory variables used in the econometric model are lagged by 1 year to reduce the problem of endogeneity. While economic and political variables exert pressure on debt rescheduling probabilities at the same time they may also be a consequence of it.

3.5 Principal Component Analysis – PCA

The reason for performing the PCA is to find the most parsimonious set of variables to include in our analysis, as well as to identify the interrelationships among the variables. For example, variables discovered to be highly correlated and members of the same factor (component) will be expected to have similar profiles. Our objective is to reduce most of the original information into a small number of factors for prediction purposes. PCA takes into account the total variance and derives factors that contain small proportions of unique variance and error variance. The primary reason for choosing a PCA analysis rather than other factor analysis is because PCA is more appropriate when the primary concern is about prediction or finding the minimum number of factors needed to account for the maximum portion of the variance represented in the original set of variables (e.g., Hair et al., 2003). PCA results suggest that we can identify ten dimensions (components) in our data, and we have selected no more than two to three variables from each of those dimensions to include in the model. We believe those are sufficient for explaining the whole dimension.[11]

[11] The PCA analysis is presented and discussed in detail in Georgievska et al. 2005.

3.6 The Model

We are using panel logit models developed in Georgievska et al. (2005) in order to estimate the sovereign rescheduling probabilities of 124 emerging market countries as a function of a number of variables. The panel logit model is a binary choice model that can be explained in the following manner:

Consider a sovereign country *i* observed over T periods of time, where $t = 1,\ldots,T$ and $i = 1,\ldots,N$. For this sovereign country there exists an unobservable random variable y^*_{it} indicating whether a country reschedules its sovereign debt in a year *t*. y^*_{it} is a function of lagged explanatory variables $\mathbf{X}_{it}$, constant unobserved individual **country** effects α and random error term $\boldsymbol{u}_{it}$. The use of only lagged explanatory variables is for the purpose of avoiding simultaneity effects and to reflect direct causation. The following equation represents the above

$$y^*_{it} = \alpha + \mathbf{b'}\,\mathbf{X}_{it} + \boldsymbol{u}_{it} \qquad (1)$$

y^*_i is a dummy variable defined by

$$\boldsymbol{y^*_i} = \begin{cases} 1 & \text{if } y^*_i > 0 \\ 0 & \text{otherwise} \end{cases}$$

b is a (k x 1) vector of parameters, and the error terms $\{u_{it}\}$ are independent and identically distributed (i.i.d.) with zero mean and unit variance, and follows a logistic distribution. α_i represents the unobserved country specific characteristics.

The core equation or the probability that a sovereign *i* will reschedule its debt at time *t* can be represented as follows:

$$\text{Prob}(\boldsymbol{Rescheduling}_{it} = 1) = \frac{\exp(\alpha + \boldsymbol{\beta'}\,\mathbf{X}_{it})}{1 + \exp(\alpha + \boldsymbol{\beta'}\,\mathbf{X}_{it})} \qquad (2)$$

where $\alpha = \frac{\pi}{\sqrt{3}}\alpha$ and $\boldsymbol{\beta} = \frac{\pi}{\sqrt{3}}\mathbf{b}$, which can be estimated through the maximization of the likelihood function and through iteration solving for the parameters (e.g. Greene, 2003).

4. RESULTS

In this study we utilise two models for our analysis because Model A maximises percent correct classifications and Model B minimises type I error. Model A attempts to use variables identified as significant in various component dimensions from PCA, which should provide us with a model of sovereign debt that has a large percentage of correct classifications, i.e. a well-fitted model. Model B considers the most relevant and significant variables obtained from Model A, and a model which uses at least one variable from each component identified by PCA. Model B also assesses the importance of a political variable in determining the probability of sovereign rescheduling. Table 1 shows the results of Model A and Model B.

Both Model A and Model B give us estimates of rescheduling probabilities that are going to be used for our further comparisons with the probabilities assigned by international rating agencies, i.e., Moody's, Standard and Poor's and Fitch, as described in section 5.

In Model A, the most significant variables are the lagged dependent variable (rescheduling event) and the total debt/GNP. However, the coefficients obtained by the model are not the marginal effects since the logit model is non-linear and these coefficients do not assign any economic meaning to the variable. Marginal effects are calculated at the sample means of the independent variables except for the dummy lagged rescheduling variable where the marginal effect is calculated for discrete change from 0 to 1. Marginal effects measure the change in the expected value of y as one independent variable increases by unity while all other variables are kept constant. For continuous variables, marginal effects at mean (MEM) are calculated as:

$MEM = \beta_i f(\beta\bar{x})$

Where βx denotes the linear combination of parameters and variables, $f(\beta\bar{x})$ is the derivative of $F(\beta x)$[12] with respect to βx.

When assessing marginal effects, we can observe that the current account balance/GDP ratio has the greatest economic importance. A one unit increase in current account balance/GDP will result in a 4.44% increase in the probability of rescheduling/default. Therefore, in economic terms, if a country experiences a large current account deficit this will induce the problem of servicing maturing debt if there is a shock that will disturb the country from accessing the international lending market. Two other variables with economic relevance are lagged dependent variable and international reserves/GDP with 2.14% and -2.68% marginal effects respectively. The remaining variables have considerably lower economic importance.

In Model B, the ICRG composite index, which is the proxy political risk factor included in this model, is significant at 5% level. According to the marginal effects, however, this is the most significant variable in economic terms. A one unit increment in the country's risk (one unit increase in ICRG) will result in a 3.78% decrease in the country's probability of rescheduling[13].

Comparing Model A and Model B presented in Table 1, one can observe that Model A has a higher percentage of correct classifications. However, taking into consideration type I and II errors neither of the two models outperforms since Model A outperforms in terms of type II error and under-performs in terms

[12] $F(\beta x)$ is the cumulative distribution function

[13] Similarly, Balkan (1992) finds the political factors and proxies of political factors very significant variables in explaining a country's rescheduling/default and the country's risk exposure faced by international lenders.

of type I error or vice versa. Thus, we can not simply choose a model by comparing the type I and II errors. However, since type I error and percent correct predictions are important mostly for international lenders, the model that maximizes the percentage correct predictions and minimizes the type I error would be preferred. Table 1 suggests that Model A maximizes the percent correct classifications but Model B minimizes the type I error better than Model A. Thus, estimated rescheduling probabilities from both Model A and Model B are going to be used for our further comparisons with the probabilities assigned by international rating agencies.

-- Insert Table 1 here --

5. ESTIMATED MODELS' RESCHEDULING PROBABILITIES VS RATING AGENCIES' DEFAULT RATES

5.1 Sovereign Credit Ratings and Default Probabilities

The one year default/rescheduling probabilities estimated from Model A and Model B can be indirectly compared to the one year long-term foreign currency sovereign credit ratings from three leading credit rating agencies (CRAs) - Moody's, Standard and Poor's, and Fitch Ratings. Moody's sovereign rating system is mainly based on the default risk for medium and long term foreign currency debt obligations issued by a national government (Moody's Investor Service, 1995). Standard and Poor's uses a similar rating system mainly based on each government's capacity and willingness to repay its foreign currency debt according to its terms (Standard and Poor's, 1997). Fitch's ratings specifically track sovereign defaults (Fitch Ratings, 2002). Default/rescheduling probabilities obtained in Model A and Model B can not be directly compared to the letter ratings ranging from AAA (Aaa for Moody's, AAA for S&P's) to C by these rating agencies. Thus, a way to overcome this is to transform the letter ratings with their associated one-year cumulative default probabilities or ranges of default probabilities when appropriate.

Appendix 3 presents Moody's, S&P's, and Fitch's rating scales together with their most recent (2002) associated 1-year default probabilities. All three rating agencies compile 1-year cumulative default rates' data associated with their letter ratings tracking periods of up to 20 years. For instance, the average 1-year cumulative default rate associated with a rating grade of B2 (Moody's) is 6.81%, which is the historical number of obligors that defaulted within one year of being assigned a B2 rating grade expressed as a percentage of total number of countries and companies with B2 rating over the same one year period.

Moreover, most major banks use credit ratings and their associated default probabilities to feed their credit risk management models, to price bonds and loans, and to determine their country exposure limits. According to the current version of the new international capital adequacy framework, commonly known as Basel II, banks are allowed to use internal rating models and associated default rates (mainly based on credit ratings by CRAs) to determine their required regulatory capital needed against credit risk exposure (Basel Committee, 2004). Thus, credit ratings play an important role in the international capital allocation. However, the central issue is that the sovereign credit ratings of emerging markets are mainly based on corporate defaults since rating agencies have very little data on sovereign defaults. The reason is that very few sovereigns have defaulted since World War II when many rating agencies started collecting relevant data (e.g., Haque et al., 1998). Therefore, rating agencies are faced with population problem for sovereigns.

Nevertheless, a most common practice by banks is to use corporate default rates as representatives for sovereign default rates. However, these are fundamentally different borrowers in terms of legal status as well as in terms of "solvency". Thus, such an assumption seems doubtful. Therefore, the purpose of this section is to examine whether sovereign default/rescheduling probabilities derived from models specifically designed for sovereigns, such as Model A and Model B in this study, are more appropriate measures of likelihood of sovereign default than rating agencies' corporate default rates.

5.2 Comparison of default/rescheduling probabilities in year 2002

Table 2 summarizes default/rescheduling probabilities derived from Model A and Model B along with default probabilities obtained from Moody's, S&P's, and Fitch's ratings for 42 countries that were rated at the beginning of 2002. From the 37 countries rated by Moody's, 35 (95.59%) had lower 1-year cumulative default rates than the estimated country 1-year default probabilities from Model A and 36 (97.30%) had lower 1-year cumulative default rates than those estimated from Model B. From the 35 countries rated by Standard and Poor's, 30 (85.71%) of them had generally lower 1-year cumulative default rates than Model A estimated default probabilities while 31 (88.57%) had lower 1-year default rates than Model B estimated 1-year default probabilities. Additionally, from the 27 countries rated by Fitch, 26 (96.3%) had lower 1-year cumulative default rates than Model A predicted ones and 25 (92.59%) had lower 1-year cumulative default rates than Model B estimated default probabilities.

Of particular interest are the results obtained for Bolivia, Honduras, Indonesia, Jordan, Mexico, Nicaragua, Pakistan, and Russia as those countries actually rescheduled/defaulted in 2002. For all these countries, the implied default rates from their ratings at the beginning of 2002 seem too optimistic. Indeed, the Model A and Model B estimated default probabilities were all high (most of them above 50%), indicating rescheduling, but their default probabilities assigned by the agencies were very low, mainly below 10% (with exception to Indonesia's and Pakistan's Fitch rating of up to 100% default rate where Indonesia actually defaulted). This indicates that rating agencies largely lagged or were not effective in predicting rescheduling/default in 2002. In particular, for Russia, Model A and Model B predict high default probabilities of 61.73% and 55.17% respectively when Russia actually defaulted, while Moody's, S&P's, and Fitch, predicted only 1.58%, 2.63-3.33%, and 1.55-1.68% default rates respectively.

An interesting exceptional case to our general result is Argentina, where both Model A and Model B as well as the Moody's and S&P's default rates indicate a high possibility of default (mainly above 50%) but

Argentina actually did not default in 2002. Only Fitch's low default probability of 1.55 – 1.68% was actually correct in assessing Argentina's non-default in 2002. This is because our models' and the Moody's and S&P's default rates were largely influenced by Argentina's previous year's (November 2001) default.

-- Insert Table 2 here --

These results overall indicate that rating agencies' default rates largely underestimate sovereign default risk over one year horizon. This is because rating agencies' default rates are mainly based on historical corporate default rates (with the exception of Fitch's rating specially tracking sovereign defaults). This finding is consistent with the common observation that emerging market sovereign bonds usually trade at much higher yield spreads than similarly rated US corporate bonds[14]. One interpretation is that emerging market sovereigns usually exhibit higher default probabilities than US corporates. Another interpretation is simply that rating agencies' sovereign ratings are generally too optimistic. This implies that corporate rating grades and their associated default probabilities generally do not appear to be good proxies for sovereign default probabilities.

A systematic underestimation of sovereign default risk might lead to underestimation of credit risk for banks, hence under-pricing of sovereign bonds and loans and excessive capital inflows to underestimated countries. Subsequently, unexpected global or country specific shocks such as unexpected policy shift (default) might trigger reassessment of the effective market and credit risks involved and ratings may quickly be downgraded. At that point, international investors (banks) will struggle to decrease their exposure in these, now more risky, countries. Consequently, following this process, a vicious circle may develop as capital outflows incur deteriorating country fundamentals, thus leading to more rating

[14] International Monetary Fund, 2000

downgrading, resulting in a self-fulfilling crisis (see e.g. Hutchison and Neubetger (2001), Goldstein et al. (2000) for further details).

5. CONCLUSIONS

A comparison of the estimated sovereign default/rescheduling probabilities as per our models with the default rates associated to the sovereign credit ratings of three leading rating agencies, namely, Moody's, Standard & Poor’s and Fitch, provide insights into the adequacy and the applicability of sovereign credit ratings for international investors.

The results from the comparison between our modelled rescheduling/default probabilities and the Moody's, S&P's, and Fitch's associated default rates, yield conclusions in two main areas. Firstly, on an empirical level, it appears that rating agencies' default rates considerably underestimate sovereign default probabilities. Thus, rating agencies' sovereign default rankings usually lag in predicting defaults/rescheduling. Secondly, on a theoretical level, consistent underestimation of default rates by rating agencies might lead banks and other international investor to put excessive capital inflows in risky countries and to underestimate their risk exposure. So when a debt default occurs, this might lead to excessive capital outflows from those countries resulting in acceleration and deepening of the crisis.

One recommendation for further research is an analysis of whether rating agencies consistently underestimate emerging countries' default risk and if so whether such systematic underestimation leads to self-fulfilling debt crises.

APPENDIX 1 –Codes of Variables Used in the Study

Variables Codes and Their Description:

Variable	Code	Variable	Code
Lagged Rescheduling	L_rsch	Inflation rate (consumer prices)	L_inflcons
Total Debt/GNP	L_tdgnp	Inflation rate (GDP deflator)	L_infldefl
ICRG Rating Assigned	L_icrgrating	Devaluation of Exchange rate	L_exchdev
Total Debt/Exports	L_tdexp	Interest arrears on LDOD/Exports	L_iaexp
Short-term Debt/Total Debt	L_sdtd	Principal arrears on LDOD/Exports	L_paexp
Interest Service due/Exports	L_isexp	Interest arrears on LDOD/Debt	L_iad
PNG, total private nonguaranteed/Exports	L_pngexp	Principal arrears on LDOD/Debt	L_pad
PPG, official creditors/Exports	L_ppgoexp	Domestic Saving Rate	L_dsr
PPG, total public and publicly guaranteed/Exports	L_ppgexp	Government Expenditure/GDP	L_gegdp
Debt Service due/Exports	L_dsexp	US 1-YEAR US DEP. LONDON OFFER	L_uslibor
Reserves/Imports	L_resexp	UK 3-MONTH LIBOR:OFFER PARIS	L_uklibor
Exports/GDP	L_expgdp	IMF RATE 0F REMUNERATION	L_imfremr
Imports/GDP	L_impgdp	IMF SDR INTEREST RATE	L_imfsdrr
Current Account Balance/GDP	L_cargdp	IC CHANGES IN CONSUMER PRICES	L_icppi
International Reserves/GDP	L_iresgdp	OECD CHANGES IN CONSUMER PRICES	L_oecdcpi
Credit to private sector/GDP	L_cpsgdp		
Log GDP per capita (constant 1995 $US)	L_logGDPPC		
GDP per capita growth(constant 1995 $US)	L_gdppcg95		
GDP growth rate	L_gdpgr		
Exports growth rate	L_expgr		

APPENDIX 2 – Sample and Data

Table 3: Sample and Data

Country	Period Examined	Reschedulings during the period	Country	Period Examined	Reschedulings during the period	Country	Period Examined	Reschedulings during the period
Albania	1993-2002	5	Georgia	1998-2002	2	Paraguay	1990-2002	1
Algeria	1990-2002	6	Ghana	1990-2002	3	Peru	1990-2002	10
Angola	1990-2002	7	Grenada	1990-2002	0	Philippines	1981-2002	10
Argentina	1990-2002	9	Guatemala	1990-2002	3	Poland	1991-2002	5
Armenia	1994-2002	4	Guinea	1990-2002	9	Romania	1991-2002	0
Azerbaijan	1994-2002	1	Guinea-Bissau	1990-1997	8	Russian Federati	1995-2002	8
Bangladesh	1990-2002	0	Guyana	1993-2002	6	Rwanda	1990-2002	5
Belarus	1994-2002	3	Haiti	1990-2002	2	Samoa	1990-2002	0
Belize	1990-2002	1	Honduras	1990-2002	12	Sao Tome and Pri	1990-2002	7
Benin	1990-2002	10	Hungary	1990-2002	0	Senegal	1990-2002	11
Bhutan	1990-2002	0	India	1990-2002	0	Seychelles	1990-2002	0
Bolivia	1990-2002	9	Indonesia	1990-2002	4	Sierra Leone	1990-2002	8
Botswana	1990-2002	0	Iran, Islamic Re	1990-2002	4	Slovak Republic	1994-2002	0
Brazil	1990-2002	9	Jamaica	1990-2002	7	Solomon Islands	1990-2002	1
Bulgaria	1992-2002	6	Jordan	1990-2002	12	South Africa	1995-2002	1
Burkina Faso	1990-2002	8	Kazakhstan	1996-2002	2	Sri Lanka	1990-2002	0
Burundi	1990-2002	1	Kenya	1990-2002	4	St. Kitts and Ne	1990-2002	0
Cambodia	1994-2002	3	Kyrgyz Republic	1994-2002	6	St. Lucia	1990-2002	0
Cameroon	1990-2002	11	Lao PDR	1990-2002	1	St. Vincent and	1990-2002	0
Cape Verde	1990-2002	3	Latvia	1994-2002	0	Sudan	1990-2002	0
Central African	1990-2002	8	Lebanon	1990-2002	0	Swaziland	1990-2002	0
Chad	1990-2002	9	Lesotho	1990-2002	0	Syrian Arab Repu	1990-2002	1
Chile	1990-2002	4	Lithuania	1994-2002	0	Tajikistan	1998-2002	4
China	1990-2002	0	Macedonia, FYR	1997-2002	3	Tanzania	1990-2002	12
Colombia	1990-2002	1	Madagascar	1990-2002	7	Thailand	1990-2002	0
Comoros	1990-2002	5	Malawi	1990-2002	2	Togo	1990-2002	11
Congo, Rep.	1990-2002	11	Malaysia	1990-2002	0	Tonga	1990-2002	0
Costa Rica	1990-2002	5	Maldives	1990-2002	0	Trinidad and Tob	1990-2002	4
Cote d'Ivoire	1990-2002	12	Mali	1990-2002	7	Tunisia	1990-2002	0
Croatia	1994-2002	4	Mauritius	1990-2002	0	Turkey	1990-2002	0
Czech Republic	1994-2002	0	Mexico	1990-2002	5	Turkmenistan	1994-1998	0
Dominica	1990-2002	0	Moldova	1995-2002	3	Uganda	1990-2002	9
Dominican Republ	1990-2002	10	Mongolia	1994-2002	0	Ukraine	1995-2002	6
Ecuador	1990-2002	10	Morocco	1990-2002	5	Uruguay	1990-2002	2
Egypt, Arab Rep.	1990-2002	10	Mozambique	1990-2002	11	Uzbekistan	1996-2002	1
El Salvador	1990-2002	4	Nepal	1990-2002	0	Vanuatu	1990-2002	0
Equatorial Guine	1990-2002	1	Nicaragua	1990-2002	13	Venezuela, RB	1990-2002	1
Eritrea	1999-2002	0	Niger	1990-2002	12	Vietnam	1997-2002	4
Estonia	1994-2002	0	Nigeria	1990-2002	6	Yemen, Rep.	1991-2002	7
Ethiopia	1990-2002	8	Oman	1990-2002	0	Zambia	1990-2002	12
Fiji	1990-2002	0	Pakistan	1990-2002	3	Zimbabwe	1990-2002	0
Gabon	1990-2002	12	Panama	1990-2002	6			
Gambia, The	1990-2002	0	Papua New Guinea	1990-2002	0	**Total**	**1981-2002**	**519**

APPENDIX 3

Table 4: Average 1-Year Cumulative Default Rates by Letter Rating
Moody's Investor Services, Standard and Poor's, and Fitch Ratings

Moody's Ratings	Moody's Average 1-Year Cumulative Default Rates (%) *	Standard and Poor's Ratings	Standard and Poor's Average 1-Year Cummulative Default Rates (%) **	Fitch Ratings	Fitch's Average 1-Year Cumulative Default Rates (%) ***
Aaa	0.00%	**AAA**	0.00%	**AAA**	0.00%
A1	0.00%	**AA+**	0.00%	**AA+**	0.00%
A3	0.43%	**AA**	0.00%	**AA**	0.00%
Baa1	1.26%	**AA-**	0.00%	**AA-**	0.00 - 0.05%
Baa2	0.73%	**A+**	0.00%	**A+**	0.00 - 0.05%
Baa3	1.78%	**A**	0.00%	**A**	0.05%
Ba1	1.58%	**A-**	0.00%	**A-**	0.05 - 0.36%
Ba2	1.41%	**BBB+**	0.00%	**BBB+**	0.05 - 0.36%
Ba3	1.58%	**BBB**	0.00%	**BBB**	0.36%
B1	2.00%	**BBB-**	0.00 - 2.63%	**BBB-**	0.36 - 1.94%
B2	6.81%	**BB+**	0.00 - 2.63%	**BB+**	0.36 - 1.94%
B3	6.86%	**BB**	2.63%	**BB**	1.94%
Caa1	13.95%	**BB-**	2.63 - 3.33%	**BB-**	1.94 - 2.54%
Caa2	33.93%	**B+**	2.63 - 3.33%	**B+**	1.94 - 2.54%
Caa3	30.59%	**B**	3.33%	**B**	2.54%
Ca	50.00%	**B-**	3.33 - 100%	**B-**	2.54 - 26.53%
C	40.00%	**CCC-C**	100.00%	**CCC-C**	26.53%

* Moody's Investors Service, 2003, "Default & Recovery Rates of Corporate Bond Issuers: A Statistical Review of Moody's Ratings Performance, 1920-2002", Special Comment, February (New York, Moody's Investor Service)

** Standard and Poor's , 2002, "Sovereign Ratings 2001:The Best of Times, The Worst of Times", Sovereigns, April (New York, Standard and Poor's)

*** Fitch Ratings, 2002, "Fitch Corporate Finance 2002 Rating Migration and Default Study", Corporate Finance, (New York, Fitch Ratings)

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TABLES

Table 1: Estimation Results

Dependent variable - Rescheduling	Model A			Model B		
	(5)		(6)	(7)		(8)
	Coef		Marginal Effects %	Coef		Marginal Effects %
Variable	(z-stat)		(dy/dx)	(z-stat)		(dy/dx)
l_rsch	8.4674	***	2.1362	10.1028	***	2.3128
	(10.21)			(10.07)		
l_tdgnp	5.9149	***	1.7775	4.5033	***	1.5048
	(6.62)			(4.88)		
l_icrgrating				0.0228	**	-3.7790
				(-3.16)		
l_iaexp				0.5933	*	-0.5220
				(-1.98)		
l_impgdp				0.1745	**	-1.7459
				(-2.65)		
l_expgdp	0.1815	**	-1.7065			
	(-2.74)					
l_cargdp	84.4973	**	4.4367			
	(3.15)					
l_gdpgr						
l_iresgdp	0.0689	*	-2.6750			
	(-2.1)					
Constant	-2.0439	***		0.3026		
Sigma_u	1.0222			0.7966		
σ^2_u cons	0.0438			-0.4547		
Log-Likelihood		-526.31			-418.79	
LR Statistic (degrees of freedom)		(5) 222.79			(5) 215.75	
P-value of LR stat		0.0000			0.0000	
Model Chi-Squared		231.12			207.8	
Cut off point		0.45			0.475	
Correct Classifications (%)		82.68			82.54	
Type I Error (%)		9.13			8.33	
Type II Error (%)		8.19			9.13	
No. of Observations		1380			1008	
No. of Countries Analysed		124			91	
Period Analysed		1981-2002			1981-2002	

*significant at 10% level of significance
**significant at 5% level of significance
***significant at 1% level of significance

Table 2: Model A and Model B 1-Year Default/Reschediling Probabilities vs. Rating Agencies' 1-Year Default Rate in 2002

(42 Emerging Countries rated by Moody's, S&P's, and Fitch)

NO.	Country	Actual Rescheduling	Model A Predicted Default Probabilities	Model B Predicted Default Probabilities	Moody's associated 1-Year Default Probability (%) beginning 2002	S&P's associated 1-Year Default Probability (%) end 2001	Fitch's associated 1-Year Default Probability (%) end 2001	Moody's Rating	S&P Rating	Fitch Rating
1	**Argentina**	**NO**	**63.88%**	**66.31%**	**50.00%**	**100.00%**	**1.55 – 1.68%**	**Ca**	**SD**	**BB-**
2	Azerbaijan	NO	5.14%	5.86%	---	---	1.55 - 1.68%	---	---	BB-
3	Belize	NO	4.78%	---	1.41%	2.63 - 3.33%	---	Ba2	BB-	---
4	Benin	NO	52.53%	---	---	2.63 - 3.33%	---	---	B+	---
5	**Bolivia**	**YES**	**12.90%**	**14.09%**	**2.00%**	**2.63 - 3.33%**	**---**	**B1**	**B+**	**---**
6	Botswana	NO	0.38%	2.93%	0.00%	0.00%	---	A2	A	
7	Brazil	NO	13.25%	15.14%	2.00%	---	1.55 - 1.68%	B1	BB-	B+
8	Bulgaria	NO	5.82%	7.31%	2.00%	---	1.55 - 1.68%	B1	BB-	B+
9	Chile	NO	9.14%	8.61%	1.26%	0.00%	0.00 - 0.04%	Baa1	A-	AA-
10	China	NO	6.41%	6.15%	0.43%	0.00%	0.04 - 0.27%	A3	BBB	A-
11	Colombia	NO	11.72%	16.02%	1.41%	2.63%	0.27%	Ba2	BB	BBB
12	Costa Rica	NO	6.08%	5.06%	1.58%	2.63%	0.27 - 1.55%	Ba1	BB	BB+
13	Croatia	NO	5.92%	6.22%	1.78%	0.00 - 2.63%	0.27 - 1.55%	Baa3	BBB-	BBB-
14	Czech Republic	NO	2.62%	3.12%	1.26%	0.00%	0.04 - 0.27%	Baa1	A-	BBB+
15	Dominican Republic	NO	5.85%	5.01%	1.41%	2.63 - 3.33%	---	Ba2	BB-	---
16	Ecuador	NO	60.95%	66.63%	33.93%	3.33 - 100%	---	Caa2	CCC+	---
17	Egypt, Arab Rep.	NO	9.51%	9.57%	1.58%	0.00 - 2.63%	0.27 - 1.55%	Ba1	BB+	BBB-
18	El Salvador	NO	7.07%	5.85%	---	0.00 - 2.63%	0.27 - 1.55%	---	BB+	BB+
19	Estonia	NO	3.08%	2.70%	---	0.00%	0.04 - 0.27%	---	A-	A-
20	Fiji	NO	---	---	1.41%	---	---	Ba2	---	---
21	Guatemala	NO	6.79%	7.13%	1.41%	2.63%	---	Ba2	BB	---
22	**Honduras**	**YES**	**46.33%**	**58.62%**	**6.81%**	**---**	**---**	**B2**	**---**	**---**
23	Hungary	NO	4.51%	4.23%	0.43%	0.00%	0.04 - 0.27%	A3	A-	A-
24	India	NO	9.84%	10.54%	1.41%	2.63%	1.55%	Ba2	BB	BB
25	**Indonesia**	**YES**	**66.63%**	**76.43%**	**6.86%**	**100.00%**	**1.68 - 21.97%**	**B3**	**CCC**	**B-**
26	Jamaica	NO	4.88%	7.51%	1.58%	2.63 - 3.33%	---	Ba3	B+	
27	**Jordan**	**YES**	**36.29%**	**48.18%**	**1.58%**	**2.63 - 3.33%**	**---**	**Ba3**	**BB-**	
28	Kazakhstan	NO	47.48%	48.58%	1.41%	2.63%	1.55%	Ba2	BB	BB
29	Latvia	NO	8.26%	7.78%	0.73%	0.00%	0.27%	Baa2	BBB	BBB
30	Lebanon	NO	2.98%	---	1.41%	3.33%	1.55 - 1.68%	B2	B	B+
31	Lithuania	NO	5.97%	5.34%	1.58%	0.00 - 2.63%	0.27 - 1.55%	Ba1	BBB-	BBB-
32	Malaysia	NO	2.04%	2.23%	0.73%	0.00%	0.27%	Baa2	BBB	BBB
33	**Mexico**	**YES**	**7.83%**	**6.89%**	**1.78%**	**0.00 - 2.63%**	**0.27 – 1.55%**	**Baa3**	**BB+**	**BB+**
34	Moldova	YES	8.65%	9.12%	13.95%	---	21.97%	Caa1	---	CC
35	Mongolia	NO	7.10%	9.45%	---	3.33%	---	---	B	---
36	**Nicaragua**	**YES**	**76.25%**	**85.31%**	**6.81%**	**---**	**---**	**B2**	**---**	**---**
37	**Pakistan**	**YES**	**65.88%**	**70.98%**	**13.95%**	**3.33 - 100%**	**---**	**Caa1**	**B-**	**---**
38	Philippines	NO	10.90%	10.61%	1.58%	0.00 - 2.63%	0.27 - 1.55%	Ba1	BB+	BB+
39	Poland	NO	7.85%	6.88%	1.26%	0.00%	0.04 - 0.27%	Baa1	BBB+	BBB+
40	Romania	NO	5.74%	8.04%	6.81%	3.33%	1.68%	B2	B	B
41	**Russian Federation**	**YES**	**61.73%**	**55.17%**	**1.58%**	**2.63 - 3.33%**	**1.55 – 1.68%**	**Ba3**	**B+**	**B+**
42	Trinidad and Tobago	NO	5.45%	4.97%	1.78%	0.00%	---	Baa3	BBB-	---

--- data not available/countries not rated

Annex 1: Full Model Derivation (not to be published)

Consider a sovereign country i observed over T periods of time, where $t = 1,\ldots,T$ and $i = 1,\ldots,N$. For this sovereign country there exists an unobservable random variable y^*_{it} indicating whether a country reschedules its sovereign debt in a year t. y^*_{it} is a function of lagged explanatory variables $\mathbf{X}_{it}$, constant unobserved individual county effects α and random error term $\boldsymbol{u}_{it}$. The use of only lagged explanatory variables is for the purpose of avoiding simultaneity effects and to reflect direct causation. The following equation represents the above

$$y^*_{it} = \alpha + \mathbf{b}'\,\mathbf{X}_{it} + \boldsymbol{u}_{it}$$

y^*_i is a dummy variable defined by

$$y^*_i = \begin{cases} 1 & \text{if } y^*_i > 0 \\ 0 & \text{otherwise} \end{cases}$$

b is a (k x 1) vector of parameters, and the error term $\boldsymbol{u}_{it}$ is independent and identically distributed (i.i.d.) with zero mean and unit variance, and follow a logistic distribution. α_i represents the unobserved country specific characteristics. Moreover, the following equation represents the logistic cumulative distribution function

$$\Lambda(X) = \frac{\exp(\frac{\pi}{\sqrt{3}}\frac{X-\mu}{\sigma})}{1+\exp(\frac{\pi}{\sqrt{3}}\frac{X-\mu}{\sigma})}$$

where the mean is represented by **μ** and the variance by $\boldsymbol{\sigma}^2$.

From the above distribution it is implied that the probability density function (PDF) of X is the following

$$\lambda(X) = \frac{\exp(\frac{\pi}{\sqrt{3}}\frac{X-\mu}{\sigma})}{\frac{\pi}{\sqrt{3}}\sigma(1+\exp(\frac{\pi}{\sqrt{3}}\frac{X-\mu}{\sigma}))^2}$$

And the CDF of the standardized error term $\boldsymbol{u}_{it}$ is therefore

$$\Lambda(\boldsymbol{u}_{it}) = \frac{\exp(\frac{\pi}{\sqrt{3}}\boldsymbol{u}_{it})}{1+\exp(\frac{\pi}{\sqrt{3}}\boldsymbol{u}_{it})}$$

Thus, taking our binary dependent variable (*Rescheduling*$_{it}$) into the model, the probability of observing a rescheduling event in year t can be represented

$$\text{Prob}(\textbf{\textit{Rescheduling}}_{it} = 1) = \text{Prob}(y^*_{it} > 0) = \text{Prob}(\alpha + \mathbf{b}'\,\mathbf{X}_{it} + \boldsymbol{u}_{it} > 0) = \text{Prob}(\boldsymbol{u}_{it} > -\,\alpha - \mathbf{b}'\,\mathbf{X}_{it})$$

Constructing the CDF of the standard error term symmetric with the property of the logistic distribution function, we obtain the probability of a sovereign rescheduling in the following form

$$\text{Prob}(\boldsymbol{Rescheduling}_{\iota\tau} = 1) = \text{Prob}(\boldsymbol{u}_{it} < \alpha + \mathbf{b'}\,\mathbf{X}_{it}) = \frac{\exp(\alpha + \boldsymbol{\beta}'\,\mathbf{X}_{it})}{1 + \exp(\alpha + \boldsymbol{\beta}'\,\mathbf{X}_{it})}$$

and the probability that there will be no sovereign rescheduling

$$\text{Prob}(\boldsymbol{Rescheduling}_{\iota\tau} = 0) = 1 - \text{Prob}(\boldsymbol{Rescheduling}_{\iota\tau} = 1) = \frac{1}{1 + \exp(\alpha + \boldsymbol{\beta}'\,\mathbf{X}_{it})}$$

where $\boldsymbol{\alpha} = \frac{\pi}{\sqrt{3}}\alpha$ and $\beta = \frac{\pi}{\sqrt{3}}\mathbf{b}$

Taking into consideration the assumption about the i.i.d. of the error term across all *i* and for all *t* and the probability of rescheduling and no rescheduling equations, one can derive the joint probability function for all[15] observations used in the panel as

$$L = \frac{\prod_{\boldsymbol{i}=1}^{\boldsymbol{N}}\prod_{\boldsymbol{t}=1}^{\boldsymbol{T}} \exp[(\alpha + \boldsymbol{\beta}'\,\mathbf{X}_{it})\boldsymbol{Rescheduling}_{\boldsymbol{it}}]}{\prod_{\boldsymbol{i}=1}^{\boldsymbol{N}}\prod_{\boldsymbol{t}=1}^{\boldsymbol{T}} [1 + \exp(\alpha + \boldsymbol{\beta}'\,\mathbf{X}_{it})\boldsymbol{Rescheduling}_{\boldsymbol{it}}]}$$

where α and **β** can be estimated through the maximization of the likelihood function and through iteration solving for the parameters. (e.g., Greene, 2003)

Even though we are interested in obtaining the above parameters in order to analyse the significance of the determinants of sovereign rescheduling probabilities, we also have to consider the fact that the logit model is a binary choice-model that is non-linear in terms of the parameters obtained as well as the independent variables. In this manner through the logit model we can obtain closed-form solution for the marginal effects of the determinants. Taking the partial derivative of the sovereign rescheduling probability solves for the marginal impact of the determinant on the probability of rescheduling

$$\frac{\partial}{\partial \text{X}_{it,k}}\text{Prob}(\boldsymbol{Rescheduling}_{it} = 1) = \frac{\exp(\alpha + \boldsymbol{\beta}'\,\mathbf{X}_{it})}{[1 + \exp(\alpha + \boldsymbol{\beta}'\,\mathbf{X}_{it})]^2}\beta_k$$

where $\text{X}_{it,k}$ is the k^{th} element of the $\mathbf{X}_{\boldsymbol{it}}$ determinant vector, and β_k is the k^{th} element of vector **β**.

[15] All *N*x*T* observations

As we can observe by comparing the above equation with the probability density function (PDF) there is linear function of the logistic PDF and the coefficient of the determinant β_k that defines the marginal effect of the k^{th} determinant on the probability of sovereign rescheduling[16]. Thus, the marginal impact of all determinants of sovereign rescheduling not only depends on the size of the determinant itself but also on the size of all other determinants at that observation. The slopes of the linear function represent the marginal impact of the determinants and thus in order to evaluate them we will have to evaluate each slope with its respective determinant sample mean. (e.g., Greene, 2003)

Therefore the core equation or the probability that a sovereign *i* will reschedule its debt at time t can be represented as follows

$$\text{Prob}(\boldsymbol{Rescheduling}_{it} = 1) = \frac{\exp(\alpha + \boldsymbol{\beta}'\mathbf{X}_{it})}{1 + \exp(\alpha + \boldsymbol{\beta}'\mathbf{X}_{it})}$$

The determinants $\mathbf{X}_{it}$ that a country *i* will reschedule its sovereign debt can be stretched over time *t* or *t+1*, *t+2*, and the above expressions can be rewritten accordingly. The next section presents the results obtained through the panel logit model.

[16] $\alpha + \boldsymbol{\beta}'X_{it}$

Annex 2 – Principal Component Analysis (PCA) (may or may not be published)

Table 5 reports the unrotated factor matrix that is computed in order to assist us in obtaining a preliminary indication for the number of factors to be extracted. The matrix contains factor loadings for each variable and each factor. Higher loadings make the variable more representative of the factor. This will assist us in reducing the data and adequately interpreting the variables. In determining which factor loadings are significant we have used a cut-off point of ± 0.20 simply due to our sample size (e.g., Hair et al., 2003). Moreover, we have also rotated[17] the factor matrix (table 6) in order to obtain a more meaningful factor structure and improve the interpretation of the factors. From the identification of the most significant factor loadings for each variable on each factor, we have determined the dimension of each of the 10 factors (components) which were previously indicated by latent root criterion and scree test. The columns in tables 5 and 6 represent the 10 dimensions and the rows represent the variables contributing in each dimension (factor loadings). The extracted 10 dimensions are separate factors that explain the variability of the total set of variables, namely: 1. solvency or debt, 2. interest rates, 3. trade activity, 4. inflation, 5. credit to private sector, 6. economic growth, 7. liquidity related to reserves, 8. 'immediacy' dimension or simply the country's ability to service its debt and interest due by exports, 9. short term debt and finally, 10. the last component includes the current account balance/GDP and the domestic savings rate.

The above analysis is beneficial for determining which variables should be included in our econometric model as to avoid multicollinearity and over-fitting the model. Thus, from each dimension (component), we have selected no more than two to three variables to include in the model, which are sufficient in explaining the whole dimension.

[17] We have used orthogonal rotations in which the axes are maintained at 90 degrees.

Table 5: Unrotated Component Analysis Factor Matrix

(Unrotated Factor Loadings)

Variables	***Factors*** 1 *Debt Related (Solvency) Dimension*	2 *Interest Rates*	3 *Trade Activity (exports-imports) Dimension*	4 *Inflation*	5 *Credit to Private Sector Dimension*	6 *GDP*	7 *Liquidity Dimension related to Reserves*	8 *Dimension Not Identified*	9 *Short-Term Debt Dimension*	10 *Dimension Not Identified*	Uniqueness
l_rsch	**0.38872****	0.01992	0.03309	-0.05905	0.15491	-0.06267	-0.04821	0.33495*	0.05955	0.0394	0.69638
l_icrgrating	**-0.70117****	-0.24142*	0.01406	0.07724	0.05203	0.25835*	-0.01635	0.22077*	0.10126	0.19213	0.27828
l_tdgnp	**0.70184****	-0.30939*	0.24206*	-0.12608	0.37771*	0.03483	0.02777	0.17518	0.06192	-0.10126	0.1478
l_tdexp	**0.9009****	-0.20428*	-0.14676	-0.00859	0.01244	0.20491*	0.1473	0.02282	0.08967	-0.00549	0.0526
l_sdtd	-0.11261	-0.00232	0.30707*	0.1697	0.0532	0.32546*	-0.3664*	-0.26366*	**-0.56652****	0.13386	0.21284
l_isexp	0.3669*	0.31797*	**-0.52359****	-0.00284	0.34276*	0.21329*	-0.06548	0.32804*	-0.17805	0.24856*	0.12177
l_pngexp	-0.06065	-0.04333	-0.46391*	0.16052	**0.4705****	0.40141*	-0.17628	-0.32794*	0.05868	-0.32983*	0.12011
l_ppgoexp	**0.86001****	-0.22527*	-0.126	-0.07989	-0.0634	0.13445	0.22048	0.05803	0.1372	-0.06116	0.09074
l_ppgexp	**0.88748****	-0.19602	-0.12908	-0.04363	-0.03134	0.154	0.1992	0.07261	0.11317	-0.00621	0.07289
l_dsexp	0.31746*	0.25198*	**-0.58813****	0.01284	0.35508*	0.17733	-0.02872	0.30904*	-0.15624	0.17123	0.18207
l_resexp	-0.34826*	0.02023	-0.00969	0.11568	-0.1942	0.5531*	**0.59143****	-0.12446	0.02553	0.18296	0.12179
l_expgdp	-0.36823*	-0.2155*	**0.6755****	-0.17576	0.46255*	-0.03369	0.00021	0.11658	0.1523	-0.0487	0.07652
l_impgdp	-0.1281	-0.3144*	**0.6886****	-0.23408*	0.46809*	-0.03018	0.03309	0.20252*	-0.01157	-0.1774	0.06205
l_cargdp	-0.4787*	0.29729*	-0.11277	0.10295	-0.15855	-0.03239	0.03445	-0.211	**0.50438****	0.24362*	0.2735
l_iresgdp	-0.35984*	-0.0863	0.32852*	-0.04757	-0.03089	0.50164*	**0.62354****	-0.10387	-0.03895	0.02471	0.09856
l_cpsgdp	-0.19169	-0.07469	-0.3191*	0.09982	**0.57688****	0.32847*	-0.18959	-0.36186*	0.16581	-0.35148*	0.08728
l_gdppcg95	-0.22226*	-0.08651	0.11835	-0.10324	-0.33374*	**0.52046****	-0.20201*	0.15453	0.02139	-0.22555*	0.42017
l_gdpgr	-0.04135	0.12337	0.18575	0.03247	-0.42449*	**0.4573****	-0.32602*	0.30774*	0.01451	-0.14151	0.33696
l_expgr	-0.04549	0.08128	0.18615	-0.0779	-0.33685*	**0.38407****	-0.31102*	0.2357*	0.18558	-0.14626	0.48151
l_inflcons	0.11088	0.2862*	0.19665	**0.87118****	0.00057	-0.04132	0.07519	0.15541	0.03295	-0.18321	0.042
l_infldefl	0.10979	0.28311*	0.19177	**0.87677****	-0.00166	-0.03747	0.07467	0.15909	0.03144	-0.18272	0.03563
l_exchdev	0.168	0.24393*	0.08712	**0.78645****	0.09685	-0.15056	0.16816	0.03477	-0.00831	-0.02556	0.22393
l_iaexp	**0.74597****	-0.29026*	0.17163	0.12031	-0.01235	0.25643*	-0.09303	-0.15642	0.05421	0.21442*	0.16741
l_paexp	**0.83009****	-0.32276*	0.1092	0.06869	-0.01899	0.24875*	0.03819	-0.09132	0.12058	0.13362	0.0857
l_iad	**0.53222****	-0.17649	0.46952*	0.20617	0.03049	0.01706	-0.30619*	-0.23038*	-0.01627	0.28635*	0.19233
l_pad	**0.60993****	-0.2614*	0.44308*	0.14214	-0.01256	-0.03604	-0.1907	-0.21652*	0.0424	0.16452	0.22956
l_dsr	-0.40826*	0.07578	0.05928	0.07821	0.41374*	0.03316	-0.16159	0.10822	**0.51127****	0.36389*	0.21404
l_gegdp	-0.21063*	-0.06283	0.25394*	-0.08134	0.36841*	0.02817	**0.44385****	0.08961	-0.23881*	-0.07654	0.47615
l_uslibor	0.08733	**0.58273****	0.14215	-0.13468	0.07367	0.10944	-0.06549	-0.02285	0.21348*	-0.17289	0.51678
l_uklibor	0.27*	**0.85986****	0.20073*	-0.21018*	0.08417	0.04445	0.03154	-0.08896	0.008	-0.02904	0.0844
l_imfremr	0.30084*	**0.86631****	0.20712*	-0.20787*	0.05998	0.04743	0.03618	-0.06086	-0.02031	0.00858	0.06155
l_imfsdrr	0.30122*	**0.86804****	0.2053*	-0.20815*	0.0623	0.04702	0.03451	-0.0619	-0.02133	0.00936	0.05864
l_iccpi	0.27771*	**0.7545****	0.20999*	-0.15746	-0.0127	0.09594	-0.01598	0.04343	0.01218	0.01377	0.27287
l_oecdcpi	-0.14721	**-0.51127****	-0.09096	0.09155	-0.06673	-0.00427	-0.07133	0.2231*	0.02091	-0.07086	0.63549
l_logGDPPC	**-0.59036****	0.12194	0.05844	0.21025*	0.28452*	0.30777*	-0.13841	0.12248	-0.14023	0.37542*	0.21854

*significant factor loadings ≥ ± 0.20

**highest significant factor loading for each variable

Table 6: Rotated Component Analysis Factor Matrix

(Rotated Factor Loadings)

	Factors										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
Variables	***Debt Related (Solvency) Dimension***	***Interest Rates***	***Trade Activity (exports-imports) Dimension***	***Inflation***	***Credit to Private Sector Dimension***	***GDP***	***Liquidity Dimension related to Reserves***	***Immediacy Dimension***	***Short-Term Debt Dimension***	***Current Account Related to Savings Rate***	Uniqueness
l_rsch	**0.31494****	0.10207	0.1733	0.04961	-0.13964	0.03532	-0.22315*	0.27405*	0.12461	0.0187	0.69638
l_icrgrating	**-0.46589****	-0.425*	0.18421	-0.05665	0.02298	0.2312*	0.32278*	0.09642	-0.04827	0.3422*	0.27828
l_tdgnp	**0.74692****	0.01799	0.46793*	-0.01245	0.03449	-0.06312	-0.1926	0.13734	0.05081	-0.10564	0.1478
l_tdexp	**0.92701****	0.03977	-0.12876	0.0067	0.04107	-0.01905	-0.0287	0.18717	0.111	-0.14007	0.0526
l_sdtd	-0.11684	0.02396	0.07475	0.04549	0.10646	0.13537	0.06722	-0.01105	**-0.84212****	-0.1477	0.21284
l_isexp	0.18729	0.22391*	-0.2014*	0.00029	0.12402	-0.0486	-0.10071	**0.85038****	-0.00311	0.03751	0.12177
l_pngexp	0.00742	-0.08991	-0.10477	0.01698	**0.90911****	-0.00379	0.0214	0.17829	-0.04176	-0.00151	0.12011
l_ppgoexp	**0.89242****	0.02581	-0.1096	-0.03363	-0.03078	-0.01265	-0.01419	0.11305	0.23229*	-0.17604	0.09074
l_ppgexp	**0.9084****	0.04599	-0.11643	-0.00338	-0.03657	-0.02199	-0.01991	0.17151	0.18154	-0.14712	0.07289
l_dsexp	0.15469	0.13985	-0.20854*	0.00316	0.18582	-0.0818	-0.09958	**0.8214****	0.07153	0.00144	0.18207
l_resexp	-0.10408	-0.05518	-0.15806	0.03508	0.01623	0.06809	**0.90727****	-0.01742	0.00776	0.09859	0.12179
l_expgdp	-0.18651	-0.04743	**0.87966****	-0.06372	0.00731	-0.00665	0.06942	-0.21951*	-0.06252	0.22708*	0.07652
l_impgdp	0.01629	-0.0633	**0.94951****	-0.07782	-0.02639	0.01016	0.01119	-0.14394	-0.05929	-0.02973	0.06205
l_cargdp	-0.40493*	0.10377	-0.30472*	0.03078	0.04057	-0.02364	0.17103	-0.23906*	0.17925	**0.58071****	0.2735
l_iresgdp	-0.08473	-0.01315	0.25205*	-0.03223	0.00058	0.0514	**0.89487****	-0.15707	-0.02274	-0.02997	0.09856
l_cpsgdp	-0.08248	-0.08741	0.07931	-0.02066	**0.9361****	-0.04554	0.00144	0.05452	-0.01363	0.10021	0.08728
l_gdppcg95	-0.08901	-0.08613	0.01338	-0.12119	0.07429	**0.69466****	0.20487*	-0.09827	-0.0652	-0.07526	0.42017
l_gdpgr	-0.02258	0.08394	-0.06101	0.07548	-0.10696	**0.78625****	0.0433	-0.00831	-0.11712	-0.0279	0.33696
l_expgr	0.00948	0.09422	0.00277	-0.02994	-0.04274	**0.70087****	0.00013	-0.09335	-0.00465	0.08273	0.48151
l_inflcons	0.00879	0.07968	-0.02974	**0.9732****	0.00044	0.05298	-0.00211	-0.01334	-0.02396	0.00263	0.042
l_infldefl	0.00873	0.07349	-0.03356	**0.97667****	0.00115	0.05659	-0.0003	-0.00892	-0.02447	0.00223	0.03563
l_exchdev	0.06076	0.06561	-0.08441	**0.84431****	-0.01162	-0.20834*	0.00428	0.04118	-0.04188	0.03281	0.22393
l_iaexp	**0.85238****	-0.02486	-0.03552	0.04369	-0.01684	0.03297	-0.03461	-0.02905	-0.30535*	0.07476	0.16741
l_paexp	**0.9459****	-0.0331	-0.02933	0.02893	-0.0188	0.02063	0.00356	-0.00302	-0.12537	0.01614	0.0857
l_iad	**0.57337****	0.05442	0.12189	0.15136	-0.13414	-0.03469	-0.22291*	-0.21806*	-0.53957*	0.17497	0.19233
l_pad	**0.66746****	0.01293	0.13623	0.11864	-0.14091	-0.05711	-0.21351*	-0.28258*	-0.3708*	0.07802	0.22956
l_dsr	-0.26809*	-0.02981	0.25384*	0.02519	0.13861	-0.03147	-0.00574	0.114	0.0525	**0.78239****	0.21404
l_gegdp	-0.14641	0.00211	**0.49942****	0.02354	-0.0003	-0.25538*	0.3713	0.10125	0.02166	-0.19656	0.47615
l_uslibor	-0.04899	**0.63258****	0.04275	0.0593	0.13632	0.16445	-0.04529	-0.03843	0.13338	0.09155	0.51678
l_uklibor	0.00025	**0.95305****	-0.01995	0.05101	-0.01795	-0.01119	-0.02145	0.05739	0.00411	-0.00895	0.0844
l_imfremr	0.0225	**0.95959****	-0.03301	0.05492	-0.06869	-0.00521	-0.01748	0.0863	-0.0165	-0.01604	0.06155
l_imfsdrr	0.02182	**0.96102****	-0.03376	0.05434	-0.0669	-0.00675	-0.01918	0.08825	-0.01779	-0.01563	0.05864
l_iccpi	0.04271	**0.82493****	-0.02817	0.08017	-0.11259	0.12015	-0.02352	0.09815	-0.01023	0.01297	0.27287
l_oecdcpi	0.00052	**-0.56792****	0.0918	-0.01612	-0.02293	0.15291	-0.04752	0.01868	0.07731	-0.02838	0.63549
l_logGDPPC	**-0.50434****	-0.08747	0.15801	0.09526	0.08711	0.08659	0.26818*	0.32054*	-0.39233*	0.37647*	0.21854

*significant factor loadings ≥ ± 0.20

**highest significant factor loading for each variable