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A SIMULATION ESTIMATION ANALYSIS OF THE EXTERNAL DEBT CRISES OF DEVELOPING COUNTRIES

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by

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Abstract

In this paper I develop models of the incidence and extent of external financing crises of developing countries, which lead to multiperiod multinomial discrete choice and discrete/continuous econometric specifications with flexible correlation structures in the unobservables. I show that estimation of these models based on simulation methods has attractive statistical properties and is computationally tractable. Three such simulation estimation methods are exposited, analyzed theoretically, and used in practice: a method of smoothly simulated maximum likelihood (SSML) based on a smooth recursive conditioning simulator (SRC), a method of simulated scores (MSS) based on a Gibbs sampling simulator (GSS), and an MSS estimator based on the SRC simulator.

The data set used in this study comprises 93 developing countries observed through the 1970–1988 period and contains information on external financing responses that was not available to investigators in the past. Moreover, previous studies of external debt problems had to rely on restrictive correlation structures in the unobservables to overcome otherwise intractable computational difficulties. The findings show that being able for the first time to allow for flexible correlation patterns in the unobservables through estimation by simulation has a substantial impact on the parameter estimates obtained from such models. This suggests that past empirical results in this literature require a substantial reevaluation.

KEYWORDS: Simulation Estimation, Maximum Simulated Likelihood, Simulated Scores, Gibbs Sampling, External Debt Crises

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1 Introduction

In this paper I employ simulation estimation methods to analyze econometrically the mounting external debt repayment problems of developing countries. These problems have received much attention recently, both in academic and policy circles, and in the media. The attention is well-deserved since even crude measures of external indebtedness and of repayment difficulties are steadily rising and lie well above historical standards. This paper studies both the incidence and the extent of external debt repayment problems, and attempts to quantify the impact of various factors that theory and past empirical findings suggest are precursors to such problems. Though the main modelling approach here follows McFadden et al. (1985) and Hajivassiliou (1987, 1989), simulation estimation methods developed recently allow me for the first time to introduce a flexible temporal correlation structure in the model unobservables. Such structures could not be accommodated with traditional maximum likelihood estimation methods because they necessitate repeated high-dimensional numerical integration.

In Section 2 I discuss the main issues from the theoretical and empirical literature on external debt and describes a theoretical approach based on credit rationing in the market for international lending. Several econometric problems with the existing literature are also discussed. In this section, I discuss issues specific to the longitudinal nature of my data set. In particular, the problems of persistent unobserved heterogeneity and state dependence are discussed, and past empirical evidence is reviewed. I then present the econometric models that I estimate and explain the intractability of maximum likelihood estimation methods for these limited dependent variable models with panel data. Data sources, definitions and descriptive statistics are relegated to a Data Appendix.

In Section 3 I describe the estimation methods of simulated scores (MSS) and smoothly simulated maximum likelihood (SSML) that are applicable to LDV models with flexible correlation structures in the unobservables. Such LDV models include the probit and Tobit models with panel data time-dependence used in this study, as well as multinomial choice models that do not impose restrictive assumptions on the substitutability among different alternatives such as the independence of irrelevant alternatives assumption (McFadden (1973)).

In Section 4 I discuss the empirical implementation of models of debt repayment crises and analyze the empirical findings. Section 5 concludes with a summary of the results and an evaluation of the MSS methodology in analyzing the empirical problem of debt repayment crises.

2 The Economic and Econometric Issues

2.1 An Overview

The mounting external debt repayment problems in the Third World are very serious. Figures 1 and 2 suggest that we may now be experiencing a substantial world debt crisis, since the external debt repayment problems in the Third World have been accelerating. Figure 1 shows that the gap between obligations and repayments that are falling into arrears is widening alarmingly; the fraction of debt-servicing obligations that are in arrears in each year exhibits an explosive growth. Figure 2 presents a similarly bleak picture by showing that the proportion of countries under analysis that are experiencing a repayments problem of some type (for example, obligations in arrears, or a need to request IMF assistance, or a rescheduling of repayments) exhibits the same deteriorating pattern.

In this paper, I analyze and model the determinants of external debt repayment problems of the developing countries within a framework of credit rationing and use the methods of simulated scores and smoothly simulated MLE to estimate reduced-form econometric models. A basic premise of the approach is that the specific cost charged to a country by international bankers (in the form of a "spread" over the London interbank offer rate (LIBOR)) does not perform the key role of clearing the market for international loans. Instead, the allocation of scarce credit among third world countries is essentially carried out through quantity offers and requests. The hypothesis that the spreads are exogenously determined is formally tested in Hajivassiliou (1987) using the approach of Hajivassiliou (1986a), and it is not rejected.[1]

A number of other studies, e.g., Eaton and Gersovitz (1980, 1981), have proceeded along disequilibrium lines and applied the standard switching regimes apparatus, which allows for the separate identification of supply and demand parameters. One of the problems with existing studies is that they neglect information on the classification of countries as supply constrained or demand constrained that is provided, for example, by the observation of a rescheduling. To solve this problem I examine models that use the actual incidence of repayment problems to classify regimes into constrained and unconstrained periods.

Information about the extent to which debt obligations fall in arrears is also valuable in assessing the severity of a lending constraint. There are two possible situations. First, if a country meets all its obligations promptly so that arrears are zero, that implies an absence of credit rationing, as the "notional" demand for new loans by this country, including loans to "roll over" debt, is less than the maximal supply of loans by bankers. A second possibility is a situation in which there is a positive level of excess demand. The country is constrained by the maximal new loans the bankers are willing to supply and tries to fill the excess demand gap for credit by letting its debt obligations fall into arrears. A rescheduling or an IMF conditionality-related program may also be necessary, depending on whether or not the bankers are willing to tolerate the required arrears.[2]

In McFadden et al. (1985) and Hajivassiliou (1987, 1989), a credit-rationing model with three

[1] Empirical evidence (Edwards (1984)) confirms that the spreads perform only a minor role in allocation of international credit, since they do not respond very significantly to usual indicators of creditworthiness. Theoretical reasons explaining why the interest rate cannot function as a pure price in this context are given in Hajivassiliou (1987). Although here I will not offer a full theoretical justification for the exogeneity assumption, it may be motivated by game-theoretic work on the bargaining problem with a "shrinking pie" as time goes by (see Binmore and Herrero (1984) and Shaked and Sutton (1984) for results and references), which implies that the eventual division will tend strongly to favour the short side of the market.

[2] It should be noted that when a country lets its debt repayments fall into arrears, this amounts in essence to *unilateral* rescheduling of its obligations. In contrast to this, a *formal* rescheduling agreement between a country and the international lenders signifies more severe problems. Frequently such agreements involve stipulations about the country's future macroeconomic policy.

regimes was introduced to combine information on arrears, which is valuable in assessing the severity of a lending constraint, and qualitative information about the incidence of repayment problems, like requests for reschedulings or involvement of the International Monetary Fund (IMF). A country is observed in the first regime if it faces no debt-repayments problems. In contrast, regimes 2 and 3 signify such problems, the difference being that in regime 2 the (positive) level of arrears are deemed tolerable by international lenders, hence no real debt crisis occurs. Regime 3 is characterized by a debt crisis, defined by a rescheduling arrangement of the obligations or involvement of the IMF. This 3-regime model simultaneously exhibits (a) a probit structure, since an indicator variable identifies the first regime of no debt repayment problems from the repayment problems regimes 2 and 3; (b) a tobit structure, in that the observed level of arrears can be either zero or positive; (c) a switching regressions aspect, as the new flow of lending to a country can be either equal to the notional demand for new funds in regime 1 or to the bankers' notional supply in regime 2; and, finally, (d) an endogenously missing data structure since when regime 3 is observed no attempts are made to identify the level of arrears and the new funds flowing to this economy. This model may be derived from a formal model of optimization subject to credit constraints.

In this paper I examine limited information reduced-form versions of these models that attempt to isolate the probit and the Tobit structures. Econometric analysis of the occurrence of external debt crises in the developing world using reduced-form models is desirable for many reasons. First, such analysis can provide a forecasting system that can be used to judge the creditworthiness of a given country in terms of future repayment problems. Second, the resolution of recent policy debates as to the desirability of alternative debt relief measures and the likely impact of newly developed institutions in international capital markets, as for example the recently established secondary market for external debt, require empirical evidence on which exogenous factors are the important forcing variables in these systems and which are the main determinants and precursors of repayment problems.[3]

2.2 Econometric Modelling Framework of External Debt Crises

Consider a random sample of N countries. A country i is observed over T_i periods, $t = 1, ..., T_i$. A data array (y_i, X_i) is observed, where y_i is a $T_i \times 1$ vector of limited dependent variables and X_i is a $T_i \times K$ array of exogenous variables. I assume y_i is an indirect observation on a latent vector y_i^* according to a many-to-one mapping $y_i = \tau(y_i^*)$, with y_i^* given by a linear model

$$y_i^* = X_i\beta + \epsilon_i. \tag{2.1}$$

The disturbance vector ϵ_i is assumed to be multivariate normal, independent of X_i, with the structure

$$\epsilon_i = \Gamma_i\eta_i, \tag{2.2}$$

[3]See Hajivassiliou (1989) and Ozler and Huizinga (1992) for investigations of secondary markets for international debt.

where Γ_i is a $T_i \times S_i$ parametric array of rank T_i, and η_i is a $S_i \times 1$ vector of independent standard normal variates. Let $\Omega_i = \Gamma_i \Gamma_i'$ and define:

$$D(y_i) = \{y_i^* | y_i = \tau(y_i^*)\}. \tag{2.3}$$

Then the likelihood of the observation is

$$\ell_i \equiv \ell(\theta; y_i) = \int_{D(y_i)} n(y_i^* - X_i\beta, \Omega_i) \quad dy_i^*, \tag{2.4}$$

where β, Ω_i are functions of a $k \times 1$ deep parameter vector θ, and

$$n(z, \Omega) = (2\pi)^{-T/2} |\Omega|^{-1/2} \exp[-z'\Omega^{-1} z/2] \tag{2.5}$$

is the multivariate normal density.[4] The asymptotically optimal parametric maximum likelihood estimator (MLE) would be defined as the vector θ that solves the score equations

$$\frac{1}{N} \sum_i s_i(\theta; y_i) \equiv \frac{1}{N} \sum_i \ell_{\theta i}(\theta; y_i)/\ell_i(\theta; y_i) = 0,$$

where $\ell_{\theta i}(\cdot)$ are the derivative vectors of the likelihood contribution ℓ_i.

Let us confine our attention to two specific mappings, the binomial discrete response model

$$y_{it} = \operatorname{sgn}(y_{it}^*), \tag{2.6}$$

and the Tobit or censored regression model

$$y_{it} = \max(0, y_{it}^*). \tag{2.7}$$

In the models of this paper, y_{it}^* measures the propensity of country i to run into a debt repayments crisis in year t, reflecting a gap between notional demand for and supply of external funds. In the probit case, y_{it} is a dummy variable signifying the occurrence of a debt "crisis" precipitated by a sufficiently big excess demand gap that cannot be "patched up" unilaterally by letting the debt obligations go into arrears. In the tobit case, y_{it} is the level of debt obligations in arrears, which is, of course, a variable left-censored at 0. Detailed definitions of the variables used are given in Section 4 and in the Data Appendix.

In view of (2.4) and (2.5), classical estimation by the method of maximum likelihood of either the binomial discrete response model (2.6) or the Tobit model (2.7), is computationally intractable when the number of time periods per individual, T_i, exceeds 3 or 4, the variance-covariance matrix Ω_i of the error vector ϵ_i is left unrestricted, and conventional numerical integration (e.g., multivariate quadrature) is used. A traditional approach in obtaining ML estimates is to restrict heavily the

[4]It should be noted that the assumption of a random sample implies that observations are independent across countries. This, of course, would be violated if there exist important world economy-wide effects. Observable such effects, like nominal international interest rates, a composite inflation rate for OECD countries, etc., were found to be statistically insignificant in McFadden et al. (1985). Unobservable such effects can be introduced as time-specific fixed effects.

structure of Ω_i in such a way as to make the evaluation of (2.4) computationally feasible. One extreme is to assume that the errors are independent across countries and across time periods for a given country, i.e.,

$$\Omega_i^{IID} = E\epsilon_i\epsilon_i' = \gamma_1^2 I_{T_i}, \tag{2.8}$$

where γ_1^2 is a variance parameter to be estimated. Despite its computational simplicity, such an assumption is often very inappropriate for a panel set of data. This issue has been neglected in most previous work on LDC debt performance, which has implicitly assumed that country-year shocks are all independently and identically distributed.

Temporal dependence can arise in at least two ways in a panel model of developing countries, and it can be a source of serious misspecification. First, heterogeneity that persists over time appears *a priori* important since countries differ in terms of colonial history and political, religious and financial institutions, all of which may affect a country's attitude toward borrowing and defaulting and lenders' attitudes toward the borrowing country. Such heterogeneity, which introduces serial correlation, seems a natural consequence of modelling debt performance as a function of a small number of macroeconomic variables. Second, serial correlation may be induced by learning processes that rely on a history of past repayment crises as a good predictor of future debt crises, by the role asset accumulation plays in the problem, or by a failure to address questions about the duration (actual or anticipated) of debt crises. In the models estimated in this paper, assuming erroneously that the error-terms are *i.i.d.* over time for a given country will in general yield inconsistent parameter estimates because of significant state-dependence found in previous investigations of such models (McFadden et al. (1985), Hajivassiliou (1987, 1989)).[5]

Another commonly used assumption, which allows some temporal dependence, is the one-factor analytic structure:

$$\Omega_i^{RE} = \gamma_1^2 I_{T_i} + \gamma_2^2 i_{T_i}' i_{T_i}, \tag{2.9}$$

where i_{T_i} is the $T_i \times 1$ vector of one's, and γ_1^2, γ_2^2 are variance parameters to be estimated. This implies that the integral in (2.4) can be written as a univariate integral of a product of cumulative normal distributions, which can be evaluated very efficiently through Gaussian quadrature methods (see Heckman (1981a), Butler and Moffit (1982), and Hajivassiliou (1984)). This assumption is made, for example, in Hajivassiliou (1987, 1989).

[5] Note that in the absence of state dependence, so that only exogenous variables appear as regressors in our models, under additional appropriate conditions, an erroneous imposition of this *i.i.d.* structure will give parameter estimates that are consistent up to scale and inefficient. See Hajivassiliou (1985, 1986b). For example, if the error-components are normally distributed and *i.i.d.* across individuals, ϵ will also be normal with $E\epsilon_{it}\epsilon_{is} = 0$ for $|t-s| > T_i$, since the only serial correlation in that case arises because of the persistence of the error components over all periods of observation for a given country. This would satisfy the weak dependence conditions of Ruud (1981) and White and Domowitz (1984) for consistency of misspecified MLE. An alternative consistent and inefficient approach in such a case would be to follow the conditional ML procedures of Andersen (1970) and Chamberlain (1980) for distributions that belong to the linear exponential family. A semiparametric alternative estimation method was given by Manski (1987). But the *a priori* important state-dependence in repayment crises models, confirmed in past work, violates the exogenous regressor assumption and makes correct modelling of the serial correlation structure important for consistency and not just for efficiency.

In this paper, I consider a third model for ϵ_i. This is the natural generalization of (2.9) that adds an autoregressive structure:

$$\epsilon_{it} = \alpha_i + \xi_{it}, \quad \xi_{it} = \rho\xi_{i,t-1} + \nu_{it} \qquad t = 1, ..., T_i$$

$$\nu_{it} \sim N(0, \sigma_\nu^2), \quad \xi_{i0} \sim N(0, \sigma_0^2), \quad \sigma_0^2 = \sigma_\xi^2 = \sigma_\nu^2/(1-\rho^2) \quad \text{by stationarity.} \tag{2.10}$$

$$\alpha_i \sim N(0, \sigma_\alpha^2), \quad \alpha_i \quad \text{and} \quad \xi_{it} \quad \text{independent.}$$

This one-factor plus AR(1) structure, with a variance-covariance matrix denoted by Ω_i^{AR1RE}, implies that (2.4) will involve a T_i-dimensional integral, thus rendering infeasible efficient classical estimation methods.[6] Hence, I turn to simulation estimation methods, which avoid the need for multidimensional integration.

3 Simulation Estimation of LDV Panel Data Models

In subsection 3.1 I exposit the methods of smoothly simulated maximum likelihood (SSML) and simulated scores (MSS) and show that they are applicable to the LDV models of this paper. In subsection 3.2 I discuss two simulation techniques to use in conjunction with these estimation methods, the Gibbs sampler (GSS) and the GHK/SRC simulator. These techniques make SSML and MSS continuous in the unknown parameters, thus further simplifying computation.

3.1 Simulation Estimation Methods

As can be seen from Hajivassiliou and McFadden (1990), the derivatives of the likelihood (2.4) of a typical observation with respect to the parameters β, Γ_i satisfy

$$\ell_\beta(\theta; y_i) \equiv \frac{\partial \ell(\theta; y_i)}{\partial \beta} = \ell(\theta; y_i) X_i' \Omega_i^{-1} E\{y_i^* - X_i\beta | y_i^* \in D(y_i)\} \tag{3.1}$$

$$\ell_\Gamma(\theta; y_i) \equiv \frac{\partial \ell(\theta; y_i)}{\partial \Gamma_i} = -\ell(\theta; y_i)\Omega_i^{-1}[I_{T_i} - E\{(y_i^* - X_i\beta)(y_i^* - X_i\beta)' | y_i^* \in D(y_i)\}\Omega_i^{-1}]\Gamma_i. \tag{3.2}$$

It will be useful for later analysis to write the derivatives (3.1)–(3.2) with respect to θ as

$$\ell_{i\theta} \equiv \ell_\theta(\theta; y_i) \equiv \frac{\partial \ell(\theta; y_i)}{\partial \theta} = \ell(\theta; y_i) E\{h(y_i^* - X_i\beta) | y_i^* \in D(y_i)\}, \tag{3.3}$$

where $h(u_i)$ is a vector of terms that are linear or quadratic in $u_i \equiv y_i^* - X_i\beta$, and depend on X_i and the mapping from the deep parameters θ to β and Γ_i.

For the general LDV model, the score of country i is

$$s_i \equiv s(\theta; y_i) \equiv \frac{\partial \ell n \ell(\theta; y_i)}{\partial \theta} = \ell_{i\theta}/\ell_i = E\{h(y_i^* - X_i\beta) | y_i^* \in D(y_i)\}. \tag{3.5}$$

[6] Computationally tractable but inefficient methods are available under special circumstances that are not satisfied in this paper. See the previous footnote.

The sets $D(y_i)$ in the leading cases of LDV models correspond to sets of linear inequality constraints on the elements of the latent vector y_i^*.[7]

In view of the assumption that the observations are *i.i.d.* across countries, the maximum likelihood estimator maximizes the sum of likelihood contributions (2.4) over subjects, i.e.,

$$\hat{\theta}_{MLE.1} \equiv \arg\max_{\theta} \left\{ \frac{1}{N} \sum_i \ell_i(\theta) = 0 \right\}, \tag{3.8}$$

or equivalently, is a root of the score equations (2.5), i.e.,

$$\tilde{\theta}_{MLE.2} \quad \text{solves} \quad \left\{ \frac{1}{N} \sum_i s_i(\theta) = \frac{1}{N} \sum_i [\ell_{i\theta}(\theta)/\ell_i(\theta)] = 0 \right\}. \tag{3.9}$$

Recall that by (3.5), at the true parameter vector θ^*, $E\{\frac{\partial ln \ell_i(\theta^*)}{\partial\theta}\} = E\{\ell_{i\theta}/\ell_i\} = E\{h(y_i^* - X_i\beta^*)|D(y_i)\} = 0$.

Consider a simulator $\tilde{\ell}_i \equiv \tilde{\ell}_i(\theta, R)$ for the likelihood contribution $\ell_i(\theta)$, based on R independent GHK/SRC simulations to be described in the next subsection. Then, the SSML/SRC estimator replaces hard-to-compute likelihood contributions with simulators $\tilde{\ell}_i(\theta, R)$, i.e., it is defined by:

$$\hat{\theta}_{SSML} \equiv \arg\max_{\theta} \left\{ \frac{1}{N} \sum_i \ln \tilde{\ell}_i(\theta, R) \right\}. \tag{3.10}$$

Next consider a simulator, $\tilde{s}_i \equiv \tilde{s}_i(\theta, R)$, for the score function $s_i(\cdot)$, satisfying the set of restrictions $y_i^* \in D(y_i)$, that is based on R independent draws according to r_G Gibbs resamplings also to be described in the next subsection. Then, the MSS1/GSS estimator replaces hard-to-compute conditional expectation terms in the logarithmic score with simulators $\tilde{s}_i(\theta, R, r_G)$:[8]

$$\hat{\theta}_{MSS.1} \quad \text{solves} \quad \left\{ \frac{1}{N} \sum_i \tilde{s}_i(\theta, R, r_G) = 0 \right\}. \tag{3.11}$$

Finally, consider a simulator $\tilde{\ell}_{i\theta}(\theta, R)$ for the derivative of a likelihood contribution $\ell_{i\theta}(\theta)$, based on R independent GHK/SRC draws, and a simulator $\tilde{\ell}_i(\theta, R)$ for the denominator probability based on the same R GHK/SRC draws. Then, the MSS2/GHK estimator is defined by:[9]

$$\tilde{\theta}_{MSS.2} \quad \text{solves} \quad \left\{ \frac{1}{N} \sum_i [\tilde{\ell}_{i\theta}(\theta, R)/\tilde{\ell}_i(\theta, R)] = 0 \right\}. \tag{3.12}$$

[7] See Hajivassiliou (1993) and Hajivassiliou and Ruud (1993) for explicit illustrations of this issue.

[8] See Ruud (1991) and Eggink et al. (1992) for combining these ideas with the EM algorithm and Hajivassiliou and McFadden (1990) for establishing the properties of this simulator.

[9] Another variant of this estimation method, MSS3/GHK, is to use an independent simulator for the denominator expression $\tilde{\ell}_i(\theta, R_d)$ based on R_d GHK/SRC draws that are distinct from the ones used for the numerator simulator, i.e., define

$$\tilde{\theta}_{MSS.3} \quad \text{solves} \quad \left\{ \frac{1}{N} \sum_i [\tilde{\ell}_{i\theta}(\theta, R)/\tilde{\ell}_i(\theta, R_d)] = 0 \right\}. \tag{3.13}$$

In this paper, I do not use MSS3/GHK because there exists strong evidence that the extra simulation noise introduced by the separate simulation of the numerator and denominator is very substantial in practice, compared to MSS2/GHK that uses the *same* R GHK underlying simulations to approximate the numerator and denominator expressions of the score.

Approaches along the MSS.2 and MSS.3 lines were introduced in van Praag and Hop (1987). It is important

Subsection 3.2 below summarizes the two simulation techniques used to construct the four simulation estimation methods defined by (3.10)–(3.13), namely the Gibbs sampling simulator (GSS) used to construct in MSS1/GSS, and the smooth recursive conditioning simulator (SRC/GHK) used to construct the SSML/GHK, MSS2/GHK, and MSS3/GHK estimators. The main asymptotic properties of these simulation estimators can be summarized as follows. First, the SSML/GHK estimator will be consistent and uniformly asymptotically normal (CUAN) with the number of observations $N \to \infty$, as long as R rises at least as fast as $\sqrt{N}$. Second, the MSS1/GSS estimator will be CUAN as $N \to \infty$, for any *finite* number of simulations R provided the number of Gibbs resamplings r_G used to calculate each simulation rises at least as fast as $\log N$. This result can be explained partly by the fact that the GSS approach generates *unbiased* draws for the whole score expression, as long as the number of Gibbs resamplings r_G rises without bound. Finally, using the GHK/SRC simulator to simulate the likelihood derivatives and the denominator likelihood probabilities R times guarantees that the MSS2/GHK estimator will be CUAN as long as R rises at least as fast as $\sqrt{N}$.[10] These asymptotic results are established in Hajivassiliou and McFadden (1990). Note that in case $\tilde{s}(\theta, R)$ is an unbiased simulator of the score, as for example with MSS1/GSS with $r_G \to \infty$, the resulting $\hat{\theta}_{MSS}$ is consistent and asymptotically normal for a *finite* number of simulations R. Another unbiased simulation method is discussed in Hajivassiliou and McFadden (1990) as simulator (3), and is based on acceptance-rejection arguments (Devroye (1986)). I do not apply this method in this paper, because it results in discontinuous optimization problems, which complicates substantially iterative search. It is important to point out that these asymptotic properties require that the same underlying random variates, used to simulate the $h(\cdot)$, $\ell(\cdot)$, and $\ell(\cdot)$ functions, be used throughout the iterative searches for the solution of (3.10)–(3.12). This important point was first made in McFadden (1989) and in Pakes and Pollard (1989).

These results are a marked improvement over the properties of the first simulation estimation method for LDV models developed by Lerman and Manski (1981). These authors explored the use of simulation in the context of estimating the classic discrete choice model and proposed the estimator: $\hat{\theta}_{LM} = \arg\max_\theta \frac{1}{N}\sum_i \ln \tilde{\ell}_i(\theta, R)$, such that the log-likelihood contributions ℓ_i are simulated unbiasedly ($E\tilde{\ell}_{ir} = \ell_i$) and consistently with R ($\tilde{\ell}_i(\theta, R) \to_p \ell_i(\theta)$ as $R \to \infty$). Lerman and Manski proposed using the empirical choice probabilities as the simulating function $\tilde{\ell}_i$. This simulator is a discontinuous function of the parameters and it is not bounded away from 0 and 1. Hence, because of these problems Lerman and Manski found that their estimator required a very large number of simulations for satisfactory performance.

that such approaches not rely on a frequency simulator for the denominator expression. The first reason is that since the frequency simulator is not bounded away from 0, the number of simulations used for approximating the denominator probability would then need to be very large for satisfactory performance. The second reason is that such an approach would yield discontinuous optimization problems. Both shortcomings can be overcome using the SRC simulator, which is smooth and bounded away from 0 and 1. See Hajivassiliou and Ruud (1993) for detailed discussions of these points.

[10] For the MSS3/GHK method, which is based on R GHK simulations of the numerator of the score and on R_d *separate* simulations of the denominator, the estimator will be CUAN for any finite number R of numerator simulations as long as the number of denominator simulations $R_d \to \infty$.

The simulation estimators I adopt here have several additional advantages over other simulation estimation methods in the early literature. The fact that MSS relies on the idea in Ruud (1986) that the score for the general linear exponential model can be written as conditional expectations which might be simulated directly, implies that MSS is generally applicable to any LDV model that can be written as a set of linear inequality constraints on the underlying latent variables, the distribution of which belongs to the linear exponential class. Hence, the method does not require the development of *ad hoc* simulation techniques for each type of LDV model that is under consideration. This generality of the MSS estimator improves on existing estimation methods of simulated moments (MSM) which require specialized arguments for different classes of LDV models. See, for example, the MSM approach developed by McFadden (1989) for the special case of the multinomial probit model. The case of multiperiod binary discrete response can be thought of as a multinomial probit model over the choice set $C = \{-1, +1\}^{T_i}$, with 2^{T_i} possible patterns of choice over time. The fact that T_i is fairly large in typical applications[11] renders intractable simple frequency simulators for choice-probabilities in the moment conditions.

A further considerable advantage of the simulation estimators considered here is that they are asymptotically efficient. This is because the MSS estimators simulate directly the conditional expectation expressions that appear linearly in the scores, and therefore they implicitly employ the optimal instrument functions in a generalized method of moments context. Similarly, the SSML estimator maximizes the full parametric log-likelihood function as $R \to \infty$, which makes it asymptotically efficient also. This issue was found to be critical in the Monte-Carlo experiments of Hajivassiliou and McFadden (1990) in that satisfactory efficiency of MSM estimators required good approximations to the optimal instruments, which in general is difficult to achieve.

3.2 Smooth Simulators for LDV Probabilities and Their Derivatives

This subsection describes the Gibbs sampling (GSS) and GHK/SRC simulation techniques. The techniques are discussed in greater detail elsewhere. For full discussion of the methods, see, *inter alia*, Börsch-Supan and Hajivassiliou (1993), Hajivassiliou and McFadden (1990), and Hajivassiliou et al. (1992). The Gibbs sampler simulator is based on a Markovian scheme that relies on easy-to-compute univariate truncated conditional normal densities to construct transitions. It has the desired truncated multivariate normal as its limiting distribution as the number of Gibbs resamplings $r_G \to \infty$. This simulator was developed by Hajivassiliou, relying on stochastic relaxation methods studied in Geman and Geman (1984). The GSS simulator is described in detail in Hajivassiliou et al. (1992) and its properties are established in Hajivassiliou and McFadden (1990). The GHK/SRC simulator is based on drawings from recursively truncated normals after a Cholesky transformation. It was first suggested by Geweke (1989), who relied on frequency (and thus discontinuous) simulation methods. Börsch-Supan and Hajivassiliou (1993) developed the current *continuous* form of the simulator and proved that it provides unbiased estimates for LDV

[11]For most countries in our sample, the number of time periods with available data is 17.

likelihood probabilities.[12]

3.2.1 The Smooth Recursive Conditioning Simulator (GHK)

Consider the $T \times 1$ random variate vector Y^* distributed as $N(\mu^*, \Omega)$ and consider the event $\mathbf{E} \equiv \{a^* \leq MY^* \leq b^*\}$, where $-\infty \leq a^* < +\infty$, $-\infty < b^* \leq +\infty$, $a^* < b^*$, the matrix M is non-singular, and the matrix Ω is positive definite. Define $a \equiv a^* - M\mu^*$, $b \equiv b^* - M\mu^*$, $\mu \equiv M\mu^*$, and let L be the (lower-triangular) Cholesky decomposition of $\Sigma \equiv M\Omega M' \equiv LL'$. For a vector e, let $e_{<j}$ denote the subvector of the first $j-1$ components, and for a matrix A, let $A_{j,<j}$ denote a vector containing the first $j-1$ elements of row j.

Draw sequentially $e_1 \sim N(0,1)$ s.t. $a_1 \leq l_{11} \cdot e_1 \leq b_1$, $e_2 \sim N(0,1)$ s.t. $a_2 \leq l_{21} \cdot e_1 + l_{22} \cdot e_2 \leq b_2$, $\cdots$, and $e_T \sim N(0,1)$ s.t. $a_T \leq l_{T1} \cdot e_1 + \cdots + l_{TT} \cdot e_T \leq b_T$. These univariate truncated normal variates are drawn according to the following smooth scheme: Let U be a uniform (0,1) random variable and let $\Phi(\cdot)$ denote the standard normal $N(0,1)$ cumulative distribution function. Define the random variable $e \equiv \Phi^{-1}((\Phi(b) - \Phi(a)) \cdot U + \Phi(a))$, where $-\infty \leq a < b \leq \infty$. As Proposition 1 in Hajivassiliou and McFadden (1990) proves, e is distributed $N(0,1)$ conditional on $a \leq e \leq b$.

Now let $e \equiv (e_1, \cdots, e_T)'$ and define

$Q_1 \equiv \text{Prob}(a_1/l_{11} \leq e_1 \leq b_1/l_{11})$,

$Q_t(e_1, \cdots, e_{t-1}) \equiv \text{Prob}((a_t - L_{t,<t} \cdot e_{<t})/l_{tt} \leq e_t \leq (b_t - L_{t,<t} \cdot e_{<t})/l_{tt} e_1, \cdots, e_{t-1})$.

The multiperiod LDV models examined in this paper have likelihood contributions given by (2.4) with linearly constrained regions (2.3) implied by the LDV models (2.6)–(2.7). Using the Cholesky decomposition above, we obtain

$$\begin{aligned} \ell(y, X; \beta, \Omega) &= \int_{a^*(y) \leq M(y) \cdot z \leq b^*(y)} n(z - X\beta, \Omega)\, dz \\ &= \text{Prob}[a^*(y) \leq M(y) \cdot Y \leq b^*(y);\ Y \sim N(X\beta, \Omega)] \\ &= \text{Prob}[a(y, X, \beta, \Omega) \leq L(y, \Omega) \cdot \nu \leq b(y, X, \beta, \Omega); \nu \sim N(0, I)]. \end{aligned}$$

Now consider a $T \times 1$ vector e_r drawn according to the sequential scheme described above, obtain R such vectors $e_r's$, and define the likelihood contribution simulator $\tilde{\ell}(e;\ y, X;\ \beta, \Omega;\ R)$

$$\tilde{\ell}(e; y, X; \beta, \Omega; R) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} Q_t(e_{1r}, \cdots, e_{t-1,r}).$$

As Lemma 1 of Hajivassiliou and McFadden establishes, the simulator $\tilde{\ell}(e; y, X; \beta, \Omega; R)$ is an unbiased estimator of $\ell(y, X; \beta, \Omega)$. Moreover, it is smooth, i.e., it is a continuous and differentiable function of the model parameters β and Ω and the underlying uniform random deviates.

[12]Keane (1990) independently developed a scheme of essentially the same form for the problem of approximating transition probabilities in panel discrete choice models. Another simulator for LDV probabilities that is smooth and bounded away from 0 and 1 is due to Stern (1992). Extensive Monte Carlo evidence in Hajivassiliou et al. (1992) shows that the GHK/SRC simulator strictly dominates the Stern simulator in terms of simulation root mean squared error.

3.2.2 The Gibbs Resampling Simulator (GSS)

Let the $T \times 1$ variate random vector Z describe the distribution of $Y^* \sim N(X\beta, \Omega)$ truncated on the event $\mathbf{E} \equiv a^* \leq M \cdot Y^* \leq b^*$.[13] For a matrix A, let $A_{-j,-j}$ denote the subarray excluding row j and column j. Similarly, for vector e, let e_{-j} be the subvector excluding component j.

Gibbs sampling is a Markovian updating scheme which proceeds as follows. Given an arbitrary starting set of values $Z_1^{(0)}, Z_2^{(0)}, \cdots, Z_T^{(0)}$, we draw $Z_1^{(1)} \sim [Z_1 | Z_2^{(0)}, \cdots, Z_T^{(0)}]$, then $Z_2^{(1)} \sim [Z_2 | Z_1^{(1)}, Z_2^{(0)} \cdots, Z_T^{(0)}]$, $Z_3^{(1)} \sim [Z_3 | Z_1^{(1)}, Z_2^{(1)}, Z_3^{(0)} \cdots, Z_T^{(0)}]$, $\cdots$, and so on, up to $Z_T^{(1)} \sim [Z_T | Z_1^{(1)}, \cdots, Z_{T-1}^{(1)}]$. Thus each variable is "visited" in the "natural" order and a cycle in this scheme requires T random variate generations. After r_G such iterations we would arrive at $Z^{(n)} \equiv (Z_1^{(n)}, \cdots, Z_T^{(n)})$. Proposition 3 in Hajivassiliou and McFadden (1990) establishes that $Z^{(n)}$ asymptotically has the true joint distribution of Z as r_G grows without bound. Let $Z_r^{(n)}$ be a vector drawn according to the Gibbs scheme after r_G resamplings. As explained in subsection 3.1, the logarithmic score, s_i, equals the expectation of $h(Z, X, \beta, \Omega)$ over the distribution of Z. It then follows trivially that $E\ h(Z_r^{(n)}, X, \beta, \Omega)$ converges to s_i as the number of Gibbs resamplings, r_G, grows to infinity. Hence, we define simulator (2) by $\tilde{s}_i(Z^{(n)}, y, X, \beta, \Omega, n, R) \equiv \frac{1}{R} \sum_r h(Z_r^{(n)}, y, X, \beta, \Omega)$, where R is the (finite) number of terminal simulations drawn, and r_G the number of Gibbs resamplings used for each simulation.

Though $\tilde{s}_i$ is unbiased for the true s_i only asymptotically with r_G, Hajivassiliou and McFadden (1990) prove that the MSS/GSS estimator is CUAN provided r_G rises at a rate at least as fast as $\log N$. It should be noted that, like the GHK simulator, the Gibbs sampling simulator is by construction continuous in the distributional parameters, β, Ω, a^*, M, and b^*.

4 Empirical Implementation of Debt Crises Models

In this paper I isolate the multiperiod probit and tobit reduced-form aspects of the 3-regime models of McFadden et al. (1985) and Hajivassiliou (1987, 1989). Recall that the probit side of the model relies on an indicator variable that identifies the first regime of no debt repayment problems from the repayment problems regimes. A debt "crisis" is precipitated by a sufficiently big excess demand gap between notional demand for and supply of external funds that cannot be "patched up" unilaterally by letting the debt obligations go into arrears. The tobit side of the model attempts to explain the level of debt obligations in arrears, which is, of course, a variable left-censored at 0.[14]

The dependent variables for the models I estimate are as follows: for the probit case, the

[13] For technical reasons, it is necessary to assume that the truncation region (a^*, b^*) of the multivariate normal distribution of Y^* is compact, which is equivalent to assuming $-\infty < a^* < b^* < +\infty$. This does not entail any loss of empirical generality, since one can consider a large compact rectangle defined by the limits of computing machine representation of floating point numbers. See Hajivassiliou and McFadden (1990) for details.

[14] The error terms of the probit and tobit reduced-form equations in general will be contemporaneously correlated, implying that some further efficiency gains can be achieved by joint estimation of the two sides. This, however, would introduce the risk of misspecification of one equation contaminating the estimation of the other. For this reason, in this paper I chose to estimate each reduced-form equation separately.

dummy variable PARIF for a repayment problem was defined to take the value 1 if IMF support was requested (either in the form of a standby agreement of second or higher tranche or use of the IMF Extended Fund Facility), if the bankers were approached to organize a rescheduling (including Paris Club, commercial banks, and aid-consortia renegotiations), or if a country let its external debt obligations (in principal or interest repayments) fall in significant arrears. This information was compiled from my own country-by-country investigations and from published and unpublished IMF sources. I used this information to examine carefully the reported dates of a rescheduling and to adjust them as necessary to reflect the key economic developments reflecting a debt crisis.[15] In the Tobit model, the dependent variable SARF was the total external debt obligations of a country in arrears.[16] See the Data Appendix for data sources and variable definitions. The final estimations employed 1338 country-year observations on 93 countries for the years 1970 to 1987, once observations with missing values for at least one variable were deleted.

I employ exogenous variables already identified in the literature as possible determinants of the incidence and extent of repayment problems. See Feder and Just (1977), Feder, Just and Ross (1981), Cline (1983), McFadden et al. (1985), and Hajivassiliou (1987, 1989).[17] One should bear in mind that since I estimate reduced-form models of excess credit demand, the signs of the coefficients are difficult to predict.

I begin with factors that are important in determining the creditworthiness of a country and hence the supply of lending, such as the ratio of outstanding debt to exports. This measures the extent to which exports, the main source of foreign exchange, can cover the external indebtedness of the country.

The ratio of reserves to imports is a measure of how long an economy can finance its imports by using its stock of reserves without seeking refuge in higher levels of external borrowing. This ratio may both indicate high creditworthiness and low demand for new loans, *ceteris paribus*, since existing stocks of reserves can be used to do such financing.

The ratio between debt service due and exports is considered as a further creditworthiness indicator, since it describes the ability of an economy to finance its yearly interest and principal obligations that are a pressing short run concern. I separate interest from principal repayments because the on-going "liquidity vs. solvency" controversy predicts different impacts of principal and interest obligations in precipitating debt crises.[18]

[15] See Hajivassiliou (1987) for a discussion of the issue of using detailed information about a country's economic situation to resolve lags between the request for a rescheduling and the eventual signing of such an agreement.

[16] Actual figures were obtained from confidential files at the World Bank. Arrears on principal of smaller than 1 percent of disbursed debt, and interest arrears of less than 0.1 percent of debt were treated as economically negligible and hence set to zero.

[17] To alleviate possible endogeneity issues, I lagged all explanatory variables by one year. This was also the approach followed in McFadden et al. (1985), and in Hajivassiliou (1987, 1989). It should be noted that in case significant residual serial correlation remains in the unobservables, this procedure will not be sufficient to overcome the endogeneity problem.

[18] According to the first view, the international capital markets are not frictionless, so that a debt crisis might be induced by a lack of liquidity to a financially sound borrower. The "solvency" view maintains that credit crises are manifestations of insolvency.

Real GNP per capita reflects both aid motivations by the suppliers of new lending and the degree of financial well-being of a country. As a measure of openness of the economy I employ the ratio of the current account balance relative to GNP. A high ratio of exports to GNP may be viewed as an undesirable characteristic by international bankers, because it reflects vulnerability to price shocks and to falling demand for its exported goods. On the other hand, the planners of a country with a highly open economy are more likely to be disciplined in their international financial dealings and less likely to repudiate, recognizing the severe losses from a drying-up of international credit.

Past repayment problems reflected in IMF arrangements, reschedulings or significant arrears outstanding could be strong indicators of a lack of creditworthiness. It is important to attempt to identify whether the significance of such past problems manifests learning by creditors in the face of uncertainty or whether they spuriously appear statistically significant if one fails to model satisfactorily the temporal dependence in the unobservables. Alternative measures based on the number of all past problems beginning from 1971 were tried to examine whether credit markets have "long memories."

The methods of MLE, SSML/GHK, MSS1/GSS, and MSS2/GHK were employed to estimate multiperiod binary probit and Tobit models under the correlation structures described in Section 2. Table 1 presents all estimates for the multiperiod probit model (2.6), while Table 2 gives the results for the censored model (2.7). The first column of each table gives ML estimates for the one-factor covariance structure (2.9), in which case the numerical integration problems involved are manageable. Columns 2 to 4 give the SSML/GHK, MSS1/GSS, and MSS2/GHK results respectively, for the one-factor plus AR(1) structure (2.10). All models are estimated with the set of independent variables discussed above. SSML/GHK is based on $R = 500$; MSS1/GSS uses $R = 10$ and $r_G = 20$; finally, MSS2/GHK uses $R = 500$ for the numerator derivatives and the denominator probabilities. In both tables, asymptotic t-statistics appear in brackets.

As already explained, the signs of the coefficients are difficult to predict *a priori*, since they correspond to reduced-form models of excess credit demand. Let me begin with a summary of the probit results in Table 1. The first finding is that, *ceteris paribus*, a country is more likely to request a rescheduling of its debt obligations, let its obligations go in arrears, or ask for IMF assistance, the greater the number of similar problems it has encountered in the previous year, and the higher its outstanding stock of debt relative to its exports. I also find that countries with high foreign reserves relative to imports are less likely to get into debt repayment problems. Bankers are seen to have "short memories" in the sense that the incidence of a debt problem in the immediately preceding period is a stronger predictor of similar problems in the future, compared to the cumulated number of problems in the whole observed past history. In general, the findings confirm results in past studies (McFadden et al. (1985), Hajivassiliou (1987, 1989)), that there is strong evidence of persistent unobservable country heterogeneity, which is attenuated but not eliminated by the inclusion of variables measuring the occurrence of problems in the preceding year.

Proceeding to Table 2, I present similar results that measure the severity and extent of credit constraints through the use of the multiperiod Tobit model. The coefficient estimates are somewhat better determined than in the probit case, presumably confirming the high informational content of the confidential arrears variable. Note in particular the statistically strong, negative sign of the coefficient of the current account to GNP ratio. The cumulated number of past problems is now statistically significant, suggesting stronger temporal dependence in the severity of crises.

The ratio of interest service due to exports has a significant and positive effect on the propensity to encounter debt repayment problems, while the ratio of principal service due to exports, even though generally less significant, has a negative sign. It is interesting to note that attempting to pool interest and principal repayments due into a single debt-service-due variable is statistically very strongly rejected; debt service due appears to be insignificant.[19]

The last three columns of each table are obtained through estimation by simulation and constitute the main innovation of this paper, since, in that case, the random-effects plus AR(1) error structure (2.10) renders estimation by classical ML methods totally infeasible. The second column gives the SSML/GHK results, while columns 3 and 4 report the two MSS methods, MSS1/GSS and MSS2/GHK respectively.

The results are quite reassuring since the two MSS estimates are close to one another as well as to the SSML estimates.[20] Moreover, the simulation estimates exhibit slightly lower accuracy compared to the ML estimates, as predicted by asymptotic theory. An important finding is the significant positive autocorrelation in the error (significant in both models, more strongly so in the Tobit case), which implies that the ML estimates are unreliable. Moreover, some of the variables that were found statistically not significant with the more restrictive correlated structures (e.g., CA/GNP) now become very important. The statistical significance of an observed history of problems is in most cases considerably reduced, whereas the random effects lose their significance somewhat. This suggests that the persistence arises more from the unobservables of the model (e.g., the magnitude of excess demand for credit in the previous period) rather than from the observed incidence of a repayments problem. Note that these estimates suffer from the long-standing problem of initial conditions in dynamic limited dependent variable models (see Heckman (1981b)). The reported

[19]Hajivassiliou (1989b) examines other issues that have important policy implications. For example, is an overvalued exchange rate one of the fundamental causes of external financing problems, or is overvaluation a very costly distortion that *arises from* very high levels of external indebtedness? Measures of overvaluation were constructed to investigate this issue, based on a discrepancy between official and black market exchange rates. Another issue analyzed in that study is the importance of world economic factors, which are exogenous to a developing country, in explaining the occurrence of external debt repayment problems. Such factors include the volume of import demand by industrialized countries, inflation in the OECD nations, and world interest rates. The findings have important policy implications on LDC "adjustment efforts" to stave off external financing crises. Finally, the models were investigated for the possibility of structural breaks occurring in the processes determining repayment problems over time. One popular view attributes part of the blame for the LDC repayment problems to the glut of "petrodollars" after the first 1973 major oil-shock. Only very weak evidence that such structural breaks occurred in the estimated relationships was found. Another possible structural break occurred after the much greater institutional involvement that followed the onset of defaults beginning in 1982. Some evidence that the probabilities of repayment problems worsened after 1981 was found.

[20]The random number generators were started from three different seeds, one each for SSML, MSS.1, and MSS.2, hence the three sets of simulation estimates were based on distinct underlying random draws.

results were obtained using Heckman's approximate solution, which assumes the same functional form for the distribution of the initial condition. Given that our data set is a "long" panel with approximately 14 years of observation per country, I do not expect the treatment of the initial conditions to make a substantial difference in estimation.[21]

5 Conclusion

In this paper I offered an econometric analysis of the incidence and extent of external debt repayment problems using simulation estimation methods. I exposited two such methods of estimation by simulation that, in contrast to most simulation estimation methods proposed in the literature, are continuous in the unknown parameter vectors and hence can be calculated by standard optimization methods. Furthermore, two of them, MSS2/GHK and SSML/GHK, are consistent and asymptotically normal (CAN) as $N \to \infty$ provided $\sqrt{N}/R \to 0$, while the third, MSS1/GSS, is CAN for any finite value of R, provided the number of Gibbs resamplings r_G used satisfies $\log N/r_G \to 0$. These methods allowed me for the first time to introduce an autocorrelation structure over time in the unobservables of the LDV models implied by credit-rationing theory, which can not be handled by traditional ML estimation methods because of high-dimensional integrals.

The main theoretical approach adopted was one of credit rationing in the market for international lending. Several econometric problems with the existing literature were discussed, in particular the issues of persistent unobserved heterogeneity and state dependence, which are specific to the longitudinal nature of our data set. The analysis attempted to quantify the impact of various factors that, because of theoretical arguments and past empirical findings, are believed to act as precursors to such problems. My results have shown that the restrictive correlation structures imposed by past studies, which are necessary to render feasible the classical method of MLE, resulted in unreliable econometric results.

I conclude that the simulation estimation techniques are likely to prove very useful in carrying out econometric analyses of LDV models with theoretically more appropriate correlation structures. There appears to be a strong case for a need to reevaluate the empirical results of the creditworthiness literature using such methods.

[21] In a separate line of research, McFadden and I are analyzing this issue and show that it can be addressed by adapting flexible functional form and semiparametric estimation methods, developed by Gallant and Nychka (1987). Simple tests of the adequacy of the distributional assumption for the initial condition can be devised by employing non-parametric density estimation methods.

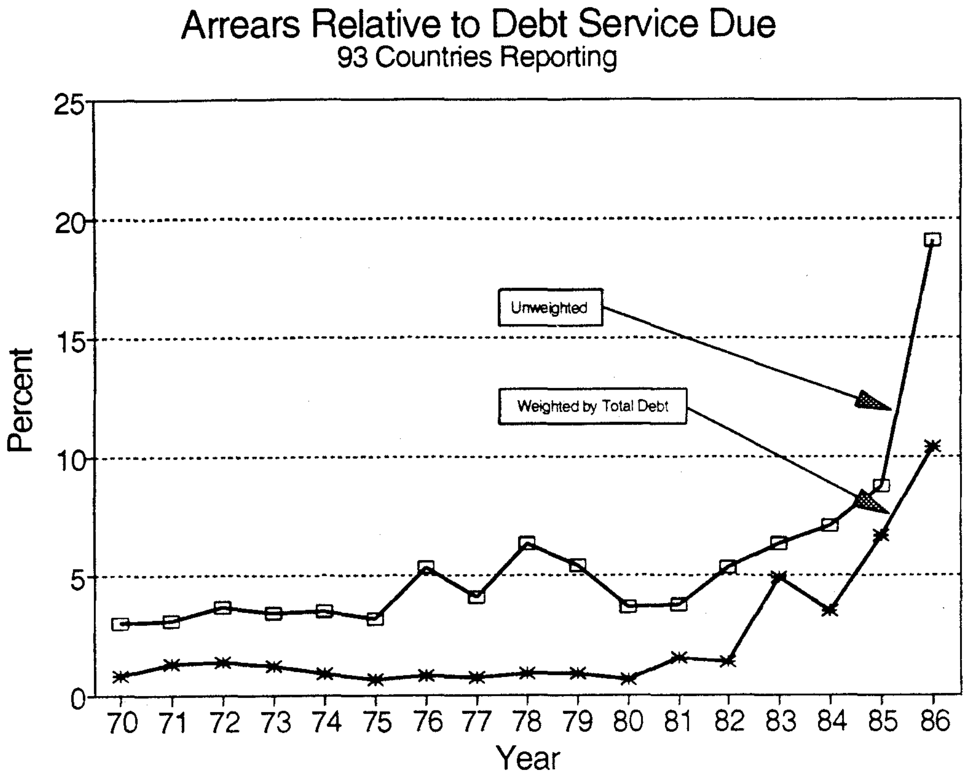
Arrears Relative to Debt Service Due
93 Countries Reporting
Percent
Year
Unweighted
Weighted by Total Debt
0
5
10
15
20
25
70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86

Figure 1

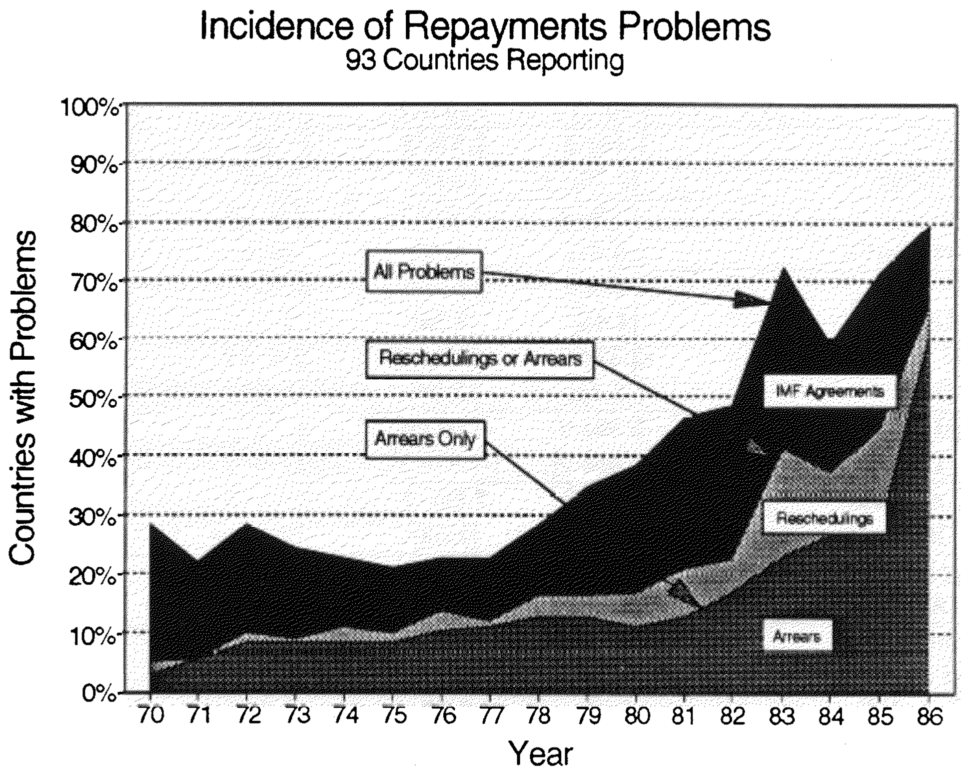
Incidence of Repayments Problems
93 Countries Reporting
Countries with Problems
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
All Problems
Reschedulings or Arrears
Arrears Only
IMF Agreements
Reschedulings
Arrears
70
71
72
73
74
75
76
77
78
79
80
81
82
83
84
85
86
Year

Figure 2

Table 1: Multi-Period Probit Models (Dependent Variable = PARIF)

	MLE	SSML/GHK	MSS1/GSS	MSS2/GHK
Constant	-1.16	-2.33	-2.31	-2.32
	[-10.17]	[-10.01]	[-10.27]	[-10.28]
Debt to	1.46e-3	1.37e-3	1.34e-3	1.39e-3
Exports Ratio	[2.76]	[2.47]	[2.49]	[2.48]
Reserves	-7.92e-2	-3.21e-2	-3.27e-2	-3.16e-2
to Imports Ratio	[-4.21]	[-4.43]	[-4.47]	[-4.41]
Interest	6.94e-2	3.57e-2	3.54e-2	3.58e-2
Service Due	[4.43]	[2.38]	[2.42]	[2.45]
Principal	-2.37e-2	-3.44e-2	-3.46e-2	-3.42e-2
Service Due	[-2.35]	[-2.26]	[-2.29]	[-2.31]
Per Capita	-5.39e-4	-1.22e-4	-1.21e-4	-1.24e-4
GDP in 1980 $'s	[-1.45e-2]	[-1.57e-3]	[-1.66e-3]	[-1.63e-3]
Current Account	4.40e-2	7.68e-2	7.64e-2	7.72e-2
to GNP Ratio	[0.11]	[2.59]	[2.62]	[2.64]
Past Significant	1.91	2.01	2.11	2.17
Interest Arrears	[7.02]	[6.47]	[6.44]	[6.57]
Past Significant	1.59	2.14	2.17	2.18
Principal Arrears	[5.34]	[4.78]	[4.87]	[4.55]
Past Reschedulings	1.45	0.67	0.64	0.62
or IMF involvement	[12.05]	[8.78]	[8.99]	[8.62]
Cumulated Significant	3.00e-2	3.61e-2	3.62e-2	3.55e-2
Interest Arrears	[0.62]	[0.46]	[0.33]	[0.74]
Cumulated Significant	6.12e-2	3.29e-2	3.22e-2	3.27e-2
Principal Arrears	[0.79]	[0.32]	[0.12]	[0.55]
Cumulated Reschedulings	4.27e-2	2.98e-2	2.91e-2	2.93e-2
or IMF Involvement	[1.73]	[1.59]	[1.77]	[1.44]
γ_1 (i.i.d.)	1	1	1	1
γ_2 (RE)	2.68	2.13	2.17	2.11
	[20.53]	[7.64]	[7.92]	[7.38]
$\rho(AR1)$	—	0.202	0.204	0.203
	—	[2.44]	[2.46]	[2.47]
loglikelihood at optimum	-498.54	-491.61	-491.94	—
constrained loglikelihood	-927.43	-921.27	-920.87	—
Pseudo R^2	0.463	0.466	0.467	—
Percent Correct Predictions	84.60	86.47	86.40	86.55

Table 2: **Multi-Period Tobit Models (Dependent Variable = SARF)**

	MLE	SSML/GHK	MSS1/GSS	MSS2/GHK
Constant	-2.40e-2	-3.21e-2	-3.27e-2	-3.25e-2
	[-11.99]	[-6.83]	[-6.74]	[-6.99]
Debt to	6.65e-6	4.53e-4	4.54e-4	4.51e-4
Exports Ratio	[1.56]	[2.49]	[2.38]	[2.40]
Reserves	-3.35e-4	-2.43e-4	-2.45e-4	-2.41e-4
to Imports Ratio	[-1.64]	[-2.92]	[-2.77]	[-2.82]
Interest	2.05e-4	2.42e-4	2.38e-4	2.43e-4
Service Due	[1.56]	[2.31]	[2.24]	[2.41]
Principal	-2.90e-5	-2.04e-5	-2.11e-5	-2.07e-5
Service Due	[-0.26]	[-1.83]	[-1.88]	[-1.81]
Per Capita	8.01e-4	7.24e-4	7.27e-4	7.20e-4
GDP in 1980 $'s	[1.64]	[1.44]	[1.42]	[1.41]
Current Account	-1.46e-2	-2.04e-2	-2.07e-2	-2.02e-2
to GNP Ratio	[-2.86]	[-3.25]	[-3.21]	[-3.29]
Past Significant	1.04e-2	7.42e-3	7.43e-3	7.41e-3
Interest Arrears	[5.41]	[4.21]	[4.27]	[4.20]
Past Significant	8.82e-3	5.82e-3	5.81e-3	5.87e-3
Principal Arrears	[4.02]	[2.47]	[2.50]	[2.53]
Past Reschedulings	1.76e-3	1.69e-3	1.71e-3	1.63e-3
or IMF involvement	[1.25]	[1.81]	[1.72]	[1.98]
Cumulated Significant	1.06e-3	6.28e-4	6.33e-4	6.37e-4
Interest Arrears	[3.25]	[2.37]	[2.17]	[2.48]
Cumulated Significant	-9.57e-4	-0.25e-3	-0.22e-3	-0.21e-3
Principal Arrears	[-1.54]	[-2.04]	[-2.01]	[-2.09]
Cumulated Reschedulings	9.93e-4	2.63e-3	2.61e-3	2.69e-3
or IMF Involvement	[3.81]	[3.45]	[3.59]	[3.63]
Amount of Significant	1.68	1.52	1.51	1.57
Past Interest Arrears	[3.14]	[2.63]	[2.88]	[2.93]
Amount of Significant	0.84	0.47	0.45	0.49
Past Principal Arrears	[8.80]	[6.92]	[7.03]	[6.88]
γ_1 (i.i.d.)	11.32	12.61	12.38	12.83
	[17.63]	[19.60]	[18.93]	[19.21]
γ_2 (RE)	12.66	6.53	6.27	6.92
	[14.31]	[3.27]	[3.96]	[3.83]
ρ (AR1)	—	0.293	0.287	0.289
	—	[2.91]	[3.03]	[2.93]
loglikelihood at optimum	554.880	557.399	557.880	—
constrained loglikelihood	227.560	236.321	237.642	—

Data Appendix
Data Sources, Description of Variables, and Descriptive Statistics

PART 1: Data Sources

Abbreviations for Data Sources (Computer Tapes)

BOP World Bank, World Tables, economic data sheet 2, balance of payments (1987)
ERP U.S. Council of Economic Advisers, 1985 Economic Report of the President
IMF IMF Annual Reports of the Director, various issues.
IFS International Monetary Fund, International Financial Statistics (1987)
WB World Bank, World Tables, economic data sheet 1 (1987)
WDT World Bank, World Debt Tables (1987)
WCY World Currency Yearbook, various issues.

All series consist of 1853 country-year observations, on 109 countries over the 1970-1986 period. All conversions between dollar and local currency values employed the period average exchange rate from IFS.

PART 2: Construction of Variables and Descriptive Statistics

Indicators of Repayment Problems	Mean	Standard Deviation
PSArI	(0.126)	(0.354)
Presence of "Significant" Arrears in Interest, 1970-1986, WB. "Significant" defined as greater than .001 of Total External Debt.		
PSArP	(0.069)	(0.262)
Presence of "Significant" Arrears in Principal, 1970-1986, WB. "Significant" defined as greater than .01 of Total External Debt.		
PRSSIMF	(0.293)	(0.541)
Occurrence of a Rescheduling Arrangement and/or IMF involvement, 1970-1986, IMF. IMF involvement defined as IMF support. IMF support is defined by an IMF standby agreement of second or higher tranche or use of the IMF Extended Fund Facility. Reschedulings include Paris Club, commercial banks, and aid-consortia renegotiations. This information was compiled from our own country-by-country investigations, and from published and unpublished IMF sources. The date of rescheduling was selected to reflect the key economic developments precipitating the rescheduling.		
SArI	(0.0003)	(0.0011)
Level of "Significant" Arrears in Interest, 1970-1986, WB. "Significant" defined as greater than .001 of Total External Debt.		
SArP	(0.0008)	(0.0050)
Level of "Significant" Arrears in Principal, 1970-1986, WB. "Significant" defined as greater than .01 of Total External Debt.		
SAr	(0.0011)	(0.006)
"Significant" Total Arrears in Principal and Interest, 1970-1986, WB. See above.		
Crisis3F	(0.723)	(1.154)
"Severity of Crisis" Indicator: 0=no repayments problem, 1=significant arrears only, 2=IMF or RSS, 1971-1987.		
PArIF	(0.419)	(0.647)
Binary Indicator, 0=no repayments problem, 1=significant arrears, IMF involvement, or rescheduling agreement, 1971-1987.		
SArF	(0.002)	(0.008)

"Significant" Total Arrears in Principal and Interest, 1971-1987, WB. See above.

CumPSArI	(0.727)	(2.096)
Cumulated number of past years with significant arrears in interest present.		
CumPSArP	(0.315)	(1.064)
Cumulated number of past years with significant arrears in principal present.		
CumRorI	(1.960)	(3.204)
Cumulated number of past years with a rescheduling or an IMF agreement in effect.		

Explanatory Variables	Mean	Standard Deviation
PCGDP80	(1.261)	(1.848)
Per Capita GDP, 1980 US$, 1970-1986, WB.		
DbttoExp	(176.991)	(232.814)
Total External Debt Relative to Exports, 1970-1986, WDT, IFS. Total debt includes public and private debt outstanding and disbursed, short-term debt, and use of IMF credit.		
REStoImp	(3.343)	(4.585)
International Reserves (Excluding Gold) Relative to Imports, 1970-1986, WDT.		
DSDtoExp	(11.994)	(15.403)
Total Debt Service Due Relative to Exports, 1970-1986, WDT, WB. Debt service due defined as interest and principal paid (TDS from WDT) plus outstanding interest and principal arrears.		
ISDtoExp	(4.871)	(6.763)
Interest Service Due Relative to Exports, 1970-1986, WDT, WB. Interest service due defined as interest paid (INT from WDT) plus outstanding interest arrears.		
PSDtoExp	(7.123)	(9.421)
Principal Service Due Relative to Exports, 1970-1986, WDT, WB. Principal service due defined as principal paid plus outstanding principal arrears.		
DSPTOEXP	(11.989)	(15.396)
Total Debt Service Paid Relative to Exports, 1970-1986, WDT.		
ISPtoExp	(4.870)	(6.762)
Total Interest Service Paid Relative to Exports, 1970-1986, WDT.		
PSPtoExp	(7.118)	(9.415)
Total Principal Service Paid Relative to Exports, 1970-1986, WDT.		
CAtoGNP	(-0.103)	(0.159)
Current Account Balance (Exports — Imports) Relative to GNP, 1970-1986, WDT.		

PART 3: Panel Summary Statistics. Years 1971-1979

Means of variables over individuals in a given year ($\frac{1}{N_t}\sum_i^{N_t} x_{it}$)

Year	1971	1972	1973	1974	1975	1976	1977	1978	1979
N_t	91	90	89	89	89	88	85	82	81
PSArI	0.044	0.067	0.090	0.101	0.090	0.091	0.071	0.085	0.111
PSArP	0.022	0.022	0.034	0.034	0.022	0.034	0.047	0.024	0.049
PRSSIMF	0.231	0.233	0.202	0.191	0.135	0.125	0.152	0.182	0.173
SArI	6.73e-5	3.17e-5	4.64e-5	6.32e-5	5.76e-5	7.21e-5	7.23e-5	9.92e-5	1.46e-4
SArP	5.85e-5	6.92e-5	9.81e-5	1.11e-4	1.28e-4	1.12e-4	3.24e-4	1.54e-4	4.54e-4
SAr	1.25e-4	1.07e-4	1.44e-4	1.74e-4	1.84e-4	1.84e-4	3.96e-4	2.53e-4	5.96e-4
Crisis3F	0.538	0.489	0.472	0.348	0.360	0.410	0.435	0.463	0.593
PArIF	0.297	0.289	0.281	0.213	0.236	0.261	0.259	0.293	0.346
SArF	1.43e-4	2.43e-4	1.74e-4	1.84e-4	2.83e-4	4.02e-4	2.44e-4	5.89e-4	9.92e-4
CumPSArI	0.055	0.111	0.169	0.270	0.360	0.432	0.471	0.573	0.691
CumPSArP	0.022	0.044	0.079	0.112	0.135	0.159	0.212	0.244	0.296
CumRorI	0.341	0.511	0.708	0.899	1.034	1.114	1.247	1.451	1.593
PCGDP80	1.032	1.066	1.119	1.151	1.197	1.228	1.300	1.312	1.341
DbttoExp	111.730	123.420	124.590	113.710	109.670	117.490	126.250	161.470	185.860
RestoImp	3.056	3.200	3.710	4.025	3.929	3.285	3.565	3.689	3.512
DSDtoExp	7.589	8.150	8.614	8.936	8.145	9.309	9.611	10.259	13.290
ISDtoExp	2.427	2.641	2.677	2.817	2.787	3.333	3.490	3.635	4.508
PSDtoExp	5.162	5.509	5.938	6.119	5.358	5.975	6.121	6.624	8.782
ISPtoExp	2.426	2.641	2.676	2.817	2.786	3.333	3.489	3.634	4.507
PSPtoExp	5.160	5.507	5.936	6.117	5.356	5.974	6.119	6.622	8.778
CAtoGNP	-0.078	-0.093	-0.092	-0.090	-0.095	-0.118	-0.100	-0.104	-0.123

Note: N_t = Number of Countries with Non-Missing Data

PART 3 (continued: Panel Summary Statistics. Years 1980-1987

Means of variables over individuals in a given year ($\frac{1}{N_t}\sum_i^{N_t} x_{it}$)

Year	1980	1981	1982	1983	1984	1985	1986	1987
N_t	78	77	74	72	69	68	65	51
PSArI	0.103	0.104	0.135	0.167	0.203	0.280	0.277	0.275
PSArP	0.039	0.054	0.125	0.029	0.059	0.185	0.569	0.051
PRSSIMF	0.377	0.446	0.472	0.580	0.515	0.554	0.471	0.243
SArI	9.92e-5	2.02e-4	4.68e-4	4.63e-4	8.48e-4	1.27e-3	8.27e-3	1.43e-4
SArP	1.78e-4	8.04e-4	1.06e-3	2.25e-4	5.54e-4	2.39e-3	1.01e-2	4.23e-4
SAr	2.77e-4	1.01e-3	1.53e-3	6.88e-4	1.40e-3	3.66e-3	1.09e-2	5.63e-4
Crisis3F	0.909	1.041	1.236	1.174	1.191	1.308	1.255	0.808
PArIF	0.481	0.581	0.681	0.652	0.647	0.815	0.784	0.436
SArF	9.67e-4	1.69e-4	9.34e-4	1.47e-3	3.50e-3	1.39e-3	1.09e-2	5.27e-4
CumPSArI	0.831	1.000	1.194	1.406	1.662	2.015	1.560	0.821
CumPSArP	0.364	0.432	0.556	0.507	0.574	0.785	1.137	0.346
CumRorI	2.078	2.595	3.139	3.855	4.324	4.831	5.314	1.744
PCGDP80	1.433	1.462	1.405	1.269	1.274	1.217	1.430	1.390
DbttoExp	186.850	207.730	257.240	277.880	273.120	311.100	282.520	186.500
RestoImp	3.512	2.834	2.613	2.700	2.619	2.797	3.465	3.827
DSDtoExp	12.53	14.03	15.617	16.23	16.27	19.31	21.774	13.65
ISDtoExp	5.332	6.251	7.692	8.326	8.106	9.141	10.397	5.024
PSDtoExp	7.200	7.777	7.925	7.902	8.163	10.164	11.377	8.630
ISPtoExp	5.331	6.250	7.690	8.323	8.101	9.134	10.394	5.023
PSPtoExp	7.197	7.772	7.917	7.893	8.151	10.146	11.347	8.626
CAtoGNP	-0.118	-0.127	-0.127	-0.110	-0.086	-0.094	-0.078	-0.112

Note: N_t = Number of Countries with Non-Missing Data

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