A Comparison of Country Credit Risk Ratings

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Abstract: A critical assessment and evaluation of country credit risk, which reflects the ability and willingness of a country to service its financial obligations, are essential concerns for the international financial community. The increasing incidence of debt rescheduling, especially by developing countries, and the impact of the debt crisis on the balance sheets and profits of international financial institutions, demand a critical assessment of such lending behaviour and business practices. This paper analyses the literature relating to empirical country credit risk models according to established statistical and econometric criteria used in estimation, evaluation and forecasting. Such an evaluation permits a critical assessment of the relevance and practicality of the country credit risk literature.

Keywords: Country credit risk; Empirical models; Econometric criteria; Statistical criteria; Estimation; Evaluation

1. INTRODUCTION

Following the rapid growth in international debt of less developed countries in the 1970s and the increasing debt rescheduling in the early 1980s, country credit risk, which reflects the ability and willingness of a country to service its financial obligations, has become a topic of major concern for the international financial community [Cosset and Roy, 1990]. Banks in developed countries, especially in the USA, are still managing the impact of the debt crisis on their balance sheets and profits. While banks have become more conscious in lending to less developed countries after the crisis, international bank lending has nevertheless resumed over the past decade. Political changes resulting from the fall of communism and the implementation of market-oriented economic and financial reforms have resulted in an enormous amount of external capital flowing into the emerging markets of Eastern Europe, Latin America, Asia, and Africa [Ramcharran, 1999].

The results of this lending spree, such as the Mexican devaluation of the peso in 1994, the recent cascade of devaluation and soaring numbers of troubled banks and borrowers in Asia and other countries, and Russia's debt overhang, demand a thorough re-assessment of the lending behaviour of international banks. These events have alerted banks to the fact that the globalisation of world trade and open capital markets are risky elements that can cause financial crises with rapid contagion effects, which threaten the stability of the international financial sector [Hayes, 1998]. Given these new developments, the need for a detailed assessment of country risk and its impact on international lending is crucial. A primary function of country risk assessment is to anticipate the possibility of debt repudiation, default or delays in payment by sovereign borrowers [Burton and Inoue, 1985]. Country risk assessment evaluates economic, financial, and political factors, and their interactions in determining the risk associated with a particular country. Perceptions of the determinants of country risk are important because they affect both the supply and cost of capital inflows [Brewer and Rivoli, 1990].

The plan of the paper is as follows. Section 2 provides a quantitative classification of empirical country credit risk models, which forms the database for this paper. The data are classified and described in Section 3. Various theoretical and empirical model specifications used in the literature are reviewed analytically in Section 4. Some concluding remarks are given in Section 5.

2. CLASSIFICATION OF COUNTRY CREDIT RISK MODELS

For purposes of evaluating the significance of empirical models of country credit risk, it is necessary to analyse such models according to established statistical and econometric criteria. The primary purpose of each of these empirical papers is to evaluate the practicality and relevance of the economic theory pertaining to country credit risk. An examination of the empirical impact and statistical significance of the results of the country credit risk models will be based on an evaluation of the descriptive statistics relating to the models as well as the econometric procedures used in estimation, testing and forecasting.

The paper reviews 30 published empirical studies on country credit risk [these papers are listed in Hoti, 2001]. A classification of the papers is given according to the data and sample sizes used, the pooled and cross-section nature of the data by both the number of countries and the number of time series observations used, the model specifications examined, the choice of dependent and explanatory variables considered, the number of explanatory variables used, econometric issues concerning the recognition, type and number of omitted explanatory variables, the number and type of proxy variables used when variables are omitted, the method of estimation, and the use of diagnostic tests of the auxiliary assumptions of the models.

3. CLASSIFICATION OF THE DATA

Scrutiny of the ECONLIT software package and the Social Science Citation Index for the most widely cited articles in the Country Credit Risk literature yields at least 30 published empirical papers over the last three decades in refereed journals. Although the first two papers were published in 1971 (in the Journal of International Economics) and 1977 (in the Journal of Development Economics), there were 10 papers published in the 1980s, a further 17 papers published in the 1990s, with the most recent paper having been published in 2001. Thus, the literature is essentially two decades old. There is no leading journal in the literature on country credit risk, with the Journal of International Business Studies and the Journal of Banking and Finance each publishing 3 papers, the Journal of Development Economics publishing 2 papers, and 22 other journals each publishing one paper on the topic. For further details, see Hoti [2001].

In Table 1, the 30 studies are classified according to the type of data used, namely cross-section or pooled, which combines time series and cross-section samples. Common sources of data are the International Monetary Fund, Bank for International Settlements, various sources of the World Bank, Euromoney, Institutional Investor, Moody's, Standard and Poor's, and various country-specific statistical bureaux. Two-thirds of the studies are based on pooled data, with the remaining one-third based on cross-section data. A classification (available on request) of the 20 studies using pooled data according to the number of countries, shows that it varies from 5 to 95 countries, with mean 43, median 42, and mode 47, with the frequency of occurrence of each number apart from the mode being 1. The same 20 studies using pooled data can be classified according to the number of annual and semi-annual observations (available on request). For the annual observations, the range of the 19 data sets is 5 to 24 years, with the mean, median and mode of the number of observations being 10.6, 11 and 5, respectively, with the frequency of occurrence of each number varying between 1 and 4. The range of the 4 data sets using semi-annual observations is 8 to 22 half-years, with the mean, median and mode of the number of observations being 17.25, 19.5 and 22, respectively.

Table1: Classification by Type of Data Used

Type of Data	Frequency
Pooled	20
Cross-section	10
TOTAL	30

The studies can also be classified using cross-section data according to the number of countries and the number of time series observations, respectively. One study did not report the number of countries used, while another study used data on 892 municipalities. Of the remaining 10 studies, the range is 18 to 143 countries, with mean 52.4, median 42, and no mode as each of the ten numbers occurred only once. There are 19 data sets using time series observations, with a range of 1 to 20, mean 4.7, median 2, and mode 1. Indeed, the most commonly used number of time series observations is 1, with a frequency of 9 in the 19 data sets, so that almost one-half of the cross-section data sets used are based on a single year.

4. THEORETICAL AND EMPIRICAL MODEL SPECIFICATIONS

The general country credit risk model typically estimated (and occasionally also tested and evaluated) is given as:

$$f(Y_t, X_t, u_t; \beta) = 0 \tag{1}$$

in which $f(.)$ is an unspecified functional form, Y is the designated (vector of) endogenous variables, X is the (vector of) exogenous variables, u is the (vector of) errors, β is the vector of unknown parameters, and $t = 1,...,n$

observations. As will be discussed below, equation (1) is typically given as a linear or log-linear regression model, or as a logit, probit or discriminant model. The elements of Y and X will also be discussed below. Defining the information set at time $t-1$ as $I_{t-1} = [Y_{t-1}, Y_{t-2},...; X_t, X_{t-1}, X_{t-2},...]$, the assumptions of the classical model are typically given as follows:

(A1) $E(u_t) = 0$ for all t;

(A2) Constant variance of u_t;

(A3) Serial independence (namely, no covariation between u_t and u_s for $t \neq s$);

(A4) X is weakly exogenous (that is, there is no covariation between X_t and u_s for all t and s);

(A5) u is normally distributed with mean 0 and constant variance;

(A6) Parameters are constant;

(A7) Y and X are both stationary processes, or are cointegrated if both are non-stationary.

Diagnostic tests play an important role in modern empirical econometrics, and are used to check the adequacy of a model through testing the underlying assumptions. The standard diagnostic checks which are used to test assumptions (A1) through (A7) are various tests of functional form misspecification, heteroscedasticity, serial correlation, exogeneity, third and higher-order moments of the distribution for non-normality, constancy of parameters and structural change, unit root tests, and tests of cointegration. There is, in general, little or no theoretical basis in the literature for selecting a particular model. In empirical analysis, however, computational convenience and the ease of interpretation of models are primary considerations for purposes of model selection. Of the 39 models given in the 30 studies and reported in Table 2, all but one are univariate models. The most popular model in the literature is the logit model, which is used 14 times, followed by the discriminant and probit models, which are used 6 and 5 times, respectively. Thus, almost one-half of the models used in the literature are probability-based models. Given the popularity of the linear and log-linear regression models in empirical economic research, it is somewhat surprising to see that the linear regression model is used only once, the log-linear regression model is used only twice, and both regression models are used in the same study only twice. The artificial neural network model, multi-group hierarchical discrimination model, random effect error component equations, naive model, combination model, G-logit model, classification and regression trees, cluster analysis, and system of equations, are used once each.

Table 2: Classification by Type of Model*

Model	Frequency
Only linear single equations	1
Only log-linear single equations	2
Both linear and log-linear single equations	2
Logit	14
Probit	5
Discriminant model	6
Others**	9
TOTAL	39

*More than one model was used in some studies. **Includes one entry for each of artificial neural network model, multi-group hierarchical discrimination model, random-effect error component equations, naïve model, combination model, G-Logit model, classification and regression trees, cluster analysis, and system of equations.

The dependent variable for purposes of analysing country credit risk is broadly classified as the ability to repay debt. Of the different types of dependent variables used, with more than one dependent variable being used in some studies, the most frequently used variable is debt rescheduling, which is used 19 times. This dependent variable is defined as the probability of debt rescheduling (as a proxy for debt default), the probability of general, commercial, official, and band debt rescheduling (in the current year or in the future), the probability of debt default, and discriminant score of whether a country belongs to a rescheduling or non-rescheduling group. Three types of dependent variable are used more than once, with the Institutional Investor country credit risk ratings being used 6 times, and Euromoney country credit risk ratings and fundamental valuation ratios being used 3 times each. The remaining 18 types of dependent variable, which were used once each, include significant payment arrears, Economist Intelligence Unit country credit risk ratings, Moody's country credit risk ratings, Moody's municipality credit risk ratings, propensity to obtain Moody's municipality credit risk ratings, S&P's country credit risk ratings, S&P's municipality credit risk ratings, propensity to obtain S&P's municipality credit risk ratings, average country credit risk ratings, country credit worthiness, bond spreads, relative bond spreads, credit risk ratings, income classification, spread over LIBOR, yield spreads of international bonds, stock returns, and secondary market price of foreign debt.

There are two types of explanatory variables used in the various empirical studies, namely economic and financial variables on the one hand, and socio-political variables on the other. Treating country credit risk variables as economic and/or financial variables, and regional differences as socio-political variables, Tables 3 and 4 present the numbers of each type of variable and their frequency. In Table 3, the number of economic and financial variables ranges from 2 to 18, with mean 7.96, median 7 and mode 6. Seven of the 15 sets of economic and financial variables have a frequency of one, with a frequency of 2 occurring 4 times and a frequency of 3 occurring 3 times. In Table 4, the number of socio-political variables ranges from 0 to 13, with mean 0.97, median 0 and mode 0. The absence of any socio-political variable occurs 18 times in the 30 studies. Of the remaining 6 sets of socio-political variables, 2 have a frequency of 1, 2 have a frequency of 2, and 2 have a frequency of 3. Hundreds of different economic, financial and socio-political explanatory variables have been used in the 30 separate studies. The set of economic and financial variables include indicators for country credit risk ratings, debt service, domestic and international economic performance, domestic and international financial performance, monetary reserves, and structural differences. The set of socio-political variables include indicators for country political risk ratings, domestic and international armed conflict, political events, and regional differences.

Table 3: Classification by Number of Economic and Financial Explanatory Variables*

Number	Frequency
2	3
3	3
4	1
5	1
6	6
7	2
8	2
9	2
10	1
11	1
12	2
13	3
14	1
15	1
18	1
TOTAL	30

*Country credit risk indicators are treated as economic and/or financial variables.

Table 4: Classification by Number of Socio-political Explanatory Variables*

Number	Frequency
0	18
1	3
2	2
5	2
6	3
11	1
13	1
TOTAL	30

*Regional differences are treated as socio-political variables.

The unavailability of the required data means that proxy variables have frequently been used in place of the unobserved variables. Tables 5 and 6 are concerned with the important issue of omitted explanatory variables in each of the 30 studies. It is well known that, in general, omission of relevant explanatory variables from a linear regression model yields biased estimates of the coefficients of the included variables, unless the omitted variables are uncorrelated with each of the included explanatory variables. For non-linear models, consistency replaces unbiasedness as a desirable statistical characteristic of an estimation method. In some studies, there is an indication of the various types of variables that are recognised as being important. Nevertheless, some of these variables have been omitted because they are simply unavailable. The classification in Table 5 is by recognition of omitted explanatory variables, where the recognition is explicitly stated in the study. Such an explicit recognition of omitted explanatory variables is used primarily as a check of consistency against the number of proxy variables used. Of the 30 studies in Table 5, exactly one-half did not explicitly recognise that any variables had knowingly been omitted, with the remaining 15 recognising that 29 explanatory variables had been omitted. The number of explanatory variables explicitly recognised as having been omitted varies from 1 to 8. Including and excluding the 15 zero entries for omitted explanatory variables give a mean number omitted of 0.97 and 1.93, respectively, median of 0.5 and 1, and mode of 0 and 1. Ten of the 15 studies which explicitly recognised the omission of explanatory variables noted that a single variable had been omitted.

Table 5: Classification by Recognition of Omitted Explanatory Variables*

Number Omitted	Frequency
0	15
1	10
2	2
3	1
4	1
8	1
TOTAL	30

*The classification is based on explicit recognition of omitted explanatory variables, and is used primarily as a check of consistency against the number of proxy variables used in the corresponding studies.

The classification in Table 6 is given according to the type of omitted explanatory variable, which is interpreted as predominantly economic or socio-political. Approximately two-thirds of the omitted explanatory variables are predominantly economic in nature, and the remaining one-third are predominantly socio-political. Perhaps somewhat surprisingly, very few studies stated dynamics as having been omitted from the analysis, even though most did not explicitly incorporate dynamics into the estimated specifications.

Table 6: Classification by Type of Omitted Explanatory Variables*

Omitted Variable	Frequency
Economic factors	19
Socio-political factors	10
TOTAL	29

*The various omitted variables are classified according to whether they are predominantly economic or socio-political in nature.

As some important economic, financial and socio-political explanatory variables have been omitted from one-half of the 30 studies, proxy variables have been used in most of these studies. Tables 7 and 8 are concerned with the issues of the number and type of proxy variables used. The problems associated with the use of ordinary least squares (OLS) to estimate the parameters of linear models in the presence of one or more proxy variables are generally well known in the econometrics literature, but extensions to non-linear models, which dominate the literature on country credit risk, are not yet available. Nevertheless, as a guide for analysis, the basic results are outlined below. These results are of special concern as one-half of the studies explicitly recognises the omission of at least one explanatory variable. In the case where only one proxy variable is used to replace a variable which is unavailable, the basic results are as follows: (1) the absolute bias in the estimated coefficient of the proxy variable is less than the case where the proxy variable is excluded; (2) the absolute bias in the estimated coefficient of the correctly measured variable is less than in the case where the proxy variable is excluded; (3) a reduction in measurement error is beneficial; and (4) it is preferable to include the proxy variable than to exclude it. When two or more proxy variables are used to replace two or more variables which are unavailable, it is not necessarily the case that the four basic results stated above actually hold. Thus, among other outcomes, the absolute bias in the estimated coefficients of both the correctly measured and incorrectly measured variables may be higher if two or more proxy variables are not used than when they are used, a reduction in measurement error may not be beneficial, and it may not be preferable to include two or more proxy variables than to exclude them. The reason for the different outcomes is that the covariation in two or more measurement errors may exacerbate the problem of measurement error rather than reducing it.

Table 7 classifies the 15 studies by the use of proxy variables, which ranges from 1 to 7. Including and excluding the 2 zero entries for the number of proxy variables used give a mean number omitted of 2.47 and 2.85, respectively, median of 2 in each case, and mode of 1 in each case. By comparison with Table 5, in which 10 of the 15 studies explicitly recognised the omission of a single explanatory variable, Table 7 shows that only 5 studies used a single proxy variable. Otherwise, the results in Tables 5 and 7 are reasonably similar. The classification in Table 8 is given according to the type of proxy variable used, which is interpreted as comprised of predominantly economic or socio-political factors. Three-fifths of the proxy variables are predominantly economic in nature, and the remaining two-fifths are predominantly socio-political, which is very similar to the results given in Table 6.

Table 7: Classification by Number of Proxy Variables Used*

Number	Frequency
0	2
1	5
2	3
3	1
4	1
6	2
7	1
TOTAL	15

*Two studies explicitly recognized the omission of explanatory variables but used no proxy variables.

Table 8: Classification by Type of Proxy Variables Used*

Proxy Variables	Frequency
Economic factors	22
Socio-political factors	15
TOTAL	37

*Some studies used both economic and socio-political proxy variables.

In Table 9 the classification is by method of estimation, in which more than one estimation method is used in some studies. Five categories are listed, namely OLS, maximum likelihood (ML), OLS and weighted least squares (WLS), discriminant methods, and others, which includes entries for, among others, propagation, regression-based techniques, approximation, minimax, Bayesian, optimum minimum distance, stepwise, optimisation, binary splits, and jack-knife methods. Even though logit and probit models in Table 2 are used 19 times in total, ML is used for estimation purposes only 12 times. Moreover, while linear and log-linear models are used only 5 times in total in Table 2, OLS is used 10 times in Table 9 (11 times if both OLS and WLS are included). Finally, while discriminant models are used 6 times in Table 2, discriminant estimation is used only twice in Table 9.

Table 9: Classification by Method of Estimation*

Method	Frequency
OLS	10
ML	12
OLS and WLS	1
Discriminant methods	2
Others**	14
TOTAL	39

*More than one estimation method was used in some studies. **Includes entries for, among others, propagation, regression-based technique, approximation, minimax, Bayesian, optimal minimum distance, stepwise, optimisation, binary splits, and jack-knife methods.

Finally, the classification in Table 10 is by use of diagnostics to test one or more auxiliary assumptions of the models. The role of diagnostic tests has become well established in the econometric literature in recent years, and plays an increasingly prominent role in modern applied econometrics [see McAleer, 1994 for further details]. Most diagnostic tests of the auxiliary assumptions are standard, and are available in most modern econometric software packages. Almost unbelievably, 27 of the 30 studies did not report any diagnostic tests whatsoever. Of the three which did report any diagnostic tests at all, there was one entry for each of WLS and heteroscedasticity, transformation for non-normality, and serial correlation. This is of serious concern, especially as the ML method is known to lack robustness to departures from the stated assumptions, but is nevertheless used 12 times. Models such as the logit and probit are also sensitive to departures from the underlying logistic and normal densities, respectively, so that the underlying assumptions should be checked rigorously. Sadly, this has been ignored in the country credit risk literature. Hence, the empirical results should be interpreted with caution and/or scepticism.

Table 10: Classification by Use of Diagnostics

Type of Diagnostics	Frequency
None	27
Others*	3
TOTAL	30

* Includes one entry for each of WLS and heteroscedasticity, transformation for non-normality, and serial correlation.

5. CONCLUDING REMARKS

This paper evaluated the significance of 30 published empirical papers in the country credit risk literature according to established statistical and econometric criteria used in estimation, evaluation and forecasting. Such an evaluation permits a critical assessment of the relevance and practicality of the literature.

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