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DETERMINANTS OF SOVEREIGN RATINGS: A COMPARISON OF CASE-BASED REASONING AND ORDERED PROBIT APPROACHES

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DETERMINANTS OF SOVEREIGN RATINGS:
A COMPARISON OF CASE-BASED REASONING AND ORDERED PROBIT APPROACHES

Emawtee Bissoondoyal-Bheenick[1], Robert Brooks[2] and Angela Y.N.Yip[3]

Abstract

The paper compares two alternative techniques for the modelling of the determinants of sovereign ratings, specifically, ordered probit and case-based reasoning. Despite the differences in approach the two alternative modelling approaches produce similar results in terms of which variables are significant and forecast accuracy. This suggests that either approach can be used, and that there is some robustness in the results. As regards significant variables, both models find that a proxy for technological development, specifically, mobile phone use, is the most important variable. Apart from the technology proxy, a range of conventional macroeconomic variables are found to be significant, in particular GDP and inflation. The models are then used to produce forecasts for 2002 and for a set of unrated countries. The forecast comparison indicates the critical role played by the technology proxy variable in the modelling.

JEL Codes: G15

Keywords: Sovereign Ratings, Ordered Response Models, Case-Based Reasoning

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1. Introduction

Sovereign credit ratings play an important part in determining countries' access to international capital markets and the terms of that access. As more countries are added to the list of rated sovereigns, the information content of ratings becomes even more important. Sovereign ratings help to foster the dramatic growth, the stability, and the efficiency of international and domestic markets. The ultimate value of a rating agency's contribution to that market efficiency depends on its ability to provide ratings that are clear, credible, accurate risk opinions based on a fundamental understanding of credit risk. When ratings meet investors' needs for reliable risk assessments, their value also extends to borrowers seeking flexible, economical funding in the capital markets, and to intermediaries, regulators, savers, governments, economists, the financial media, and a host of other market participants and observers.

The three big players of the rating agencies, which provide the default probability of countries, are Standard and Poor's, Moody's and Fitch Ratings. The increased importance of rating agencies has brought their work to the attention of a wider group of observers and also under criticism from many observers for their lack of timeliness in making rating changes. The Mexican crises of 1994-95 brought out that credit rating agencies, like almost anybody else, were reacting to events rather than anticipating them, an observation reinforced by rating performance before and during the Asian crisis (Reisen and von Maltzan, 1999). Following these criticisms, it has become vital that rating agencies provide more accurate analysis of political, economic and social aspects of each country. The ratings assigned to each country are therefore considered, among others, as being a key ingredient to determine the investment portfolio. As the Basel II uses sovereign ratings as a tool for determining overall risk in the standardized approach, reliability of ratings is a very important condition. Reliability of ratings can be tested in various ways. There has been much research work undertaken focusing on the market responses to announcements of rating, or outlook changes, and the stability of ratings (see for example Brooks, Faff, Hillier and Hiller (2004), Reisen and Von Maltzan (1999)). Each of these studies has tried to assess the impact of rating announcement on the stock market returns.

Another area, which has drawn significant attention in the area of credit ratings, is the determinants of sovereign ratings. The first systematic study of the relationship between sovereign credit ratings and their determinants is provided by Cantor and Packer (1996a), who examined the determinants of the levels of Moody’s and Standard and Poor’s ratings for 49 mature and emerging market economies as of 29 September 1995. After converting these ratings to a numerical scale (with the highest Aaa/AAA=16 and the lowest B3/B-=1), they regressed these ratings on a set of economic variables that had been identified by the agencies as influencing the level of sovereign rating. The results were impressive in terms of explanatory power. Cantor and Packer (1996a) add, however, that the regression achieves its high R^2 through its ability to explain large differences in rating. The model has little to say about small differences in ratings. Examining the separate explanatory variables, the Cantor and Packer (1996a) results indicate that higher ratings were associated with high per capita income, high GDP growth, low inflation, a low ratio of foreign currency external debt to exports, the absence of a history of defaults on foreign currency debt since 1970, and a high level of economic development (as measured by the IMF classification as an industrial country). The coefficients on the fiscal position and the external balance were not statistically significant. The methodology used by Cantor and Packer (1996a), that is Ordinary Least Squares, however, has been criticized in numerous research papers. The ordered response model has been argued to be more appropriate to the modeling of ratings on the basis that applies to dependent variables of a discrete, ordinal nature. The use of OLS technique assumes that the underlying dependent variables, ratings has been categorised into equally spaced discrete intervals rating categories. This implies that the risk differential between an AAA/Aaa and an AA+/Aa1 rating is the same as between BB-/Ba3 and B+/B1 rating. In simple terms, it can be explained as follows. If the responses are coded 0, 1, 2, 3, 4, then linear regression will treat the difference between a 4 and a 3 as being the same as the difference between a 3 and a 2. However, this is not the case since a rating of AAA/Aaa conveys different information as compared to a rating of AA+/Aa1. Hence the use of OLS method is argued to be an inappropriate for some multinomial choice variables, which are inherently, ordered such as ratings (see for example, Mckelvey and Zaviona (1975); Moon and Stotsky (1993), Bissoondoyal-Bheenick (2005)).

The literature on the determinants of sovereign ratings focuses primarily on a number of statistical approaches that can be used to model the determinants. Of the numerous works undertaken, none of the studies have focussed on the use of a completely different approach other than the traditional statistical models. Case-based reasoning (CBR) is a problem-solving and reasoning paradigm that uses past experiences to solve new problems, based on the assumption that the world as a whole is regular, consistent and predictable (Kolodner, 1993). Applications of CBR can be found in planning, design, diagnosis and classification, and legal reasoning (Marling et al., 2002).

The strength of CBR lies in its capability to provide an explanation and justification for its decision. To support financial decision-making, simply an `accept' or ‘reject’ format to a decision is not sufficient, what is also needed is some explanation. Comprehensibility is often crucial in solving financial problems. Depending on the retrieving methods, CBR is capable of explaining and justifying its decision in the form of relevant precedents and/or if-then rules. When a country is forecasted with a rating of ‘C’, CBR is able to provide examples of similar countries having a rating of ‘C’ in the past as a justification for its forecast and/or rules to trace the logic of a decision. The reasoning behind a decision or a solution is always clear and can be explained.

Yip (2005a, 2005b) has previously analyzed the use of nearest neighbour (NN) and decision tree induction (TI) as the CBR retrieving methods to predict business failure in Australia and the results are compared with that of discriminant analysis (DA) for performance evaluation. It is shown that CBR outperforms DA in terms of predicting failed companies and is a viable and competitive alternative in providing early warnings of those companies at risk of failing based on the data set. Applications of CBR can be extended to solve other financial problems and accordingly this study makes a comparison of a particular statistical model, based on ordered probit, and CBR. The main contribution of the paper to the existing literature on the determinants of sovereign ratings is that it is far more extensive than earlier studies in terms of the rating agencies included, and it uses a new approach to assess the quantitative factors contributing to the sovereign ratings of individual countries. The plan of this paper is as follows. In section 2, the data used and the modelling framework is outlined for both the ordered response model and CBR. Section 3 presents the empirical results of the analysis. Section 4 introduces the forecast ratings of the sample of countries for the year 2002 as well as the forecast ratings of weaker economies, which are not actually rated by the rating agencies, while the final section contains some concluding remarks.

2 Data and Modeling Framework

2.1 Data

In terms of the ratings utilised in this study, while most previous research has focused on the two oldest providers of ratings, namely Standard and Poor's and Moody's, this study extends the previous literature by including the sovereign ratings provided by Fitch ratings. The rating exercise includes a number of factors, which reflects the political and economic risk of each country. Economic risk addresses the government's ability to repay its obligation on time and is said to be determined by both quantitative and qualitative factors according to the rating agencies, while political risk addresses the sovereign's willingness to repay its debt. Currently, each of the agencies provides credit research and opinion on more than 90 countries and assigns ratings to the foreign and local currency debt of sovereign governments. However, the list of countries under consideration is not the same for each of the agencies and in the case of Fitch Ratings, the ratings assigned are currently available for approximately 80 countries. In this study the focus is to assess the determinants of ratings by focussing on these different categories of ratings, in particular, Standard and Poor's foreign currency ratings and local currency ratings (94 countries); Moody's bonds and notes ratings and bank deposits ratings (94 countries); and Fitch foreign currency ratings and local currency ratings (78 countries). The population of ratings used in this study is the ratings for the six different categories as of 31st December 2001. The forecast exercise is undertaken for the year 2002. The choice of this sample period reflects data availability, in particular the availability of economic variables included as potential determinants in this study.

In their statements on rating criteria on their websites and publications, the rating agencies indicate a number of criteria that can be used to assign credit ratings. Nonetheless, it is difficult to use the same criteria for the following reasons: some of the criteria are not quantifiable. Moreover, the rating agencies provide little guidance as to the relative weight assigned to each of the variables and the agencies rely on such a large number of criteria, which are not easily accessible. Second, the choice of the economic variables utilised as determinants of ratings reflects data availability for each of the countries. The economic variables were extracted from the World Bank database. The relationship between the variables that have been identified as potential determinants of sovereign ratings and countries ability and willingness to service its debt are detailed below:

- *GDP:* GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. A relatively high rate of economic growth suggests that a country's existing debt burden will become easier to service over time.
- *Inflation:* Inflation, as measured by the consumer price index, reflects the annual percentage change in the cost to the average consumer of acquiring a fixed basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The higher the level of inflation, the higher is public dissatisfaction and hence this affects the political and economic situation of the country.
- *Foreign Direct Investment/GDP:* Foreign direct investment is net inflows of investment to acquire a lasting management interest (10 percent or more of voting

stock) in an enterprise operating in an economy other than that of the investor. It is the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net inflows in the reporting economy.

- *Current Account/GDP:* Current account balance is the sum of net exports of goods, services, net income, and net current transfers. The current account balance is an important criteria considered by rating agencies, in particular for the low rated countries (speculative grade ratings)
- *Trade/ GDP:* Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product. The level of trade indicates the situation of the balance of trade of the country.
- *Real Interest Rates:* Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator.
- *Mobile Phones:* Mobile phones refer to users of portable telephones subscribing to an automatic public mobile telephone service using cellular technology that provides access to the public switched telephone network, per 1,000 people. This is used to proxy the level of technological advancement of the country.

2.2 Modelling Framework

In line with the argument presented above, sovereign ratings represent an ordinal ranking of creditworthiness. The ratings by Standard and Poor's, Moody's and Fitch ratings for the year 2001 are replaced by a numerical equivalent grade into broad categories (Aa1, Aa2, Aa3 are all combined into one category). Following Bissoondoyal-Bheenick (2005), it seems that the inclusion of more specific sub-identifiers does not lead to any differences in the analysis as compared to when the rating classes are grouped together. For example, Moody's appends numerical modifiers 1, 2, and 3 to each generic rating classification from Aa through Caa. The modifier 1 indicates that the obligation ranks in the higher end of its generic rating category; the modifier 2 indicates a mid-range ranking; and the modifier 3 indicates a ranking in the lower end of that generic rating category. For Standard and Poor’s and Fitch ratings, the modifiers are pluses and minuses. Table 1 provides a summary of the mapping of the ratings grade that has been carried out.

To motivate the ordered response model, consider the latent variable model,

$$y_i^* = x'_i \beta + \varepsilon_i \qquad (1)$$

where y_i^* is an unobservable latent variable that measures the risk level, x_i is a vector of explanatory variables, in this case, economic variables, β is a vector of unknown parameters and ε_i is a random disturbance term. If the distribution of ε_i is chosen to be normal, then ultimately this produces an ordered probit model. As usual, y_i^* is unobserved. What we assume is that y_i^* is related to the observed variable y_i, in this case, Moody’s Bonds and Notes, Moody’s Bank Deposits, Standard and Poor’s Foreign Currency Rating, Standard and Poor’s Local Currency Rating, Fitch Foreign Currency rating and Fitch Local Currency ratings in the following way.

$$y_i = \begin{cases} 0 \text{ if } y_i^* < \varepsilon_0 \\ 1 \text{ if } \varepsilon_0 < y_i^* \le \varepsilon_1 \\ 2 \text{ if } \varepsilon_1 < y_i^* \le \varepsilon_2 \\ 3 \text{ if } \varepsilon_2 < y_i^* \le \varepsilon_3 \\ \quad\vdots \\ 9 \text{ if } \varepsilon_8 < y_i^* \end{cases}$$

where the εs ($\varepsilon_0 < \varepsilon_1 < \varepsilon_2 < \varepsilon_3 < \ldots\ldots < \varepsilon_8$) are unknown (threshold) parameters to be estimated.

To estimate the model, the variables that constitute x_i must be selected, and in this case these are the economic variables are detailed above. Therefore the initial model to be estimated is:

$$y_i = \beta_1 \text{ GDP} + \beta_2 \text{ Inflation} + \beta_3 \text{ FDI /GDP} + \beta_4 \text{ Current Acc/GDP} + \beta_5 \text{ Real Interest Rate} + \beta_6 \text{ Trade/GDP} \quad (2)$$

This model includes only the standard variables from the macroeconomic and international finance settings. However, the world is now more of a knowledge economy, and as such, it is useful to augment the model with a variable that captures technological capacity. As such, in addition to the macroeconomic and international finance variables, another variable has been included in the study, specifically, the use of mobile phone as a proxy for the level of technological development in a country. While a number of possible proxies for technological development exist, they are all likely to be highly correlated. The mobile phone usage variable is a measure that is readily available and objective, and does capture the availability of technological infrastructure and its uptake. As such the second model estimated is as follows:

$$y_i = \beta_1 \text{ GDP} + \beta_2 \text{ Inflation} + \beta_3 \text{ FDI /GDP} + \beta_4 \text{ Current Acc/GDP} + \beta_5 \text{ Real Interest Rate} + \beta_6 \text{ Trade/GDP} + \beta_7 \text{ Mobile phones} \quad (3)$$

In addition to the ordered response model, this study also utilises CBR to model the determinants of sovereign ratings. CBR is a problem-solving and reasoning paradigm that is intuitively similar to the cognitive process humans follow in problem solving. People often recall past similar experiences, and reuse or modify solutions of these experiences to generate a plausible answer for a problem. However, in searching their memories, people may suffer from recalling the most recently solved cases (recency effects) or the early well-remembered cases (primacy effects) (Schank, 1982). CBR can compensate for the recency and primacy effects. A CBR system allows for a systematic search through all the stored cases for similar and relevant cases to generate a solution for a new problem.

In CBR, knowledge is represented by cases. A case is a conceptualized piece of knowledge representing an experience (Kolodner, 1993). It contains past lesson(s) as the content of the case and the context in which the lesson(s) can be used. A case usually includes a problem description, its corresponding solution and/or outcome. Depending on the specific problem to be solved, the case may not include all these parts. A representative set of cases forms a case base for a problem domain. Table 2 gives an example of the extracted cases and a problem to be solved in the current study.

The main processes in a CBR cycle are illustrated in Figure 1. They involve retrieving the most similar cases, reusing the solutions of the retrieved cases, revising the proposed solution if necessary, and retaining the new case (Aamodt & Plaza, 1994). When a new problem is encountered, it is represented as a new case. The system searches and retrieves one or more cases similar to the new case from the case base. A solution suggested by a similar case is reused or revised if necessary to solve the new case. When appropriate, the new case will be retained in the case base to expand the knowledge of the CBR system for future retrievals. Adding new knowledge to the system is as easy as adding a new case to the case base.

2.2.1 Case Matching and Retrieving

Among the processes in a CBR cycle, retrieving the most similar cases is the first and crucial step in CBR because without this subsequent steps cannot take place. The effectiveness of a CBR system depends greatly on its ability to retrieve the most similar and relevant cases in order to solve the new problem. The well known methods for case retrieval are nearest neighbour (NN) and decision tree induction (TI) (Watson and Marir, 1994; Main et al., 2001). When NN is used, the explanation for a decision is supported by similar cases, with the degree of similarity known. When TI is used, the justification is in the form of if-then rules as well as similar cases.

NN is a non-parametric method that assesses similarity between a target case and a stored case based on their attribute resemblance. Cases are ranked by their similarity to the new case. Those cases with higher scores are more similar to the new case and will be retrieved before the lower score cases. A total of *k* most similar cases to the new case, which is called the *k*-NNs, are to be found and retrieved. These similar cases can be cited when needed to justify the prediction. Citing relevant previous experiences or cases is also a way to justify a position (Kolodner, 1992).

Formally, given that X and Y are the target and stored case respectively with n number of attributes and x_i and y_i are the values for their ith attribute, the similarity measure typically used for NN assessment is the inverse of the weighted normalized Euclidian distance. A similarity score between X and Y is calculated by

$$SIM(X,Y) = 1 - DIST(X,Y) = 1 - \sqrt{\sum_{i}^{n} \delta(x_i, y_i)^2} \tag{4}$$

where

$$\delta(x_i, y_i) = \frac{|x_i - y_i|}{|max_i - min_i|} \tag{5}$$

By Equation (4), every attribute in the target case is matched to its corresponding attribute in the stored case. For symbolic attributes, $\delta(x_i, y_i) = 0$ if $x_i = y_i$; otherwise $\delta(x_i, y_i) = 1$. For numerical attributes, max_i and min_i are the maximum and minimum values of the ith attribute respectively. As such, the similarity score is normalized within the range of 0 to 1, where 0 is a total dissimilarity and 1 is an exact match. This calculation is repeated for every stored case in the case base. Those cases with higher scores are more similar to the target case and will be ranked before the lower score cases.

TI finds patterns among training cases and divides them into clusters based on similarity. A TI algorithm such as ID3 and C4.5 determines which attributes best divide the cases and generate a decision tree to organize the cases in memory (Quinlan, 1986; Quinlan, 1993). A path from the root to a leaf of the decision tree classifies a target case. The justification for the classification is in the form of similar cases at the leaf as well as the if-then rule formed by routing from the root down to the leaf.

ID3 uses information gain as a criterion for choosing the attribute that best divides the cases. It is calculated by the difference between entropy of a set of cases and its partitions built from an attribute. The entropy characterizes the impurity of a set of cases T with respect to the target attribute that has k outcomes. It is defined as

$$entropy(T) = \sum_{j=1}^{k} - p_j \times \log_2 p_j \tag{6}$$

where p_j is the proportion of T belonging to outcome j. If T is partitioned on attribute X with n values, the expected value of the entropy is the weighted sum over the subsets given by

$$entropy_x(T) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} \times entropy(T_i) \tag{7}$$

where T_i is the subset of T for which attribute X has value i. The information gain by branching on X to partition T is measured by

$$gain(X) = entropy(T) - entropy_x(T) \tag{8}$$

An attribute with a high information gain means that the attribute conveys reliable information for dividing the cases.

The information gain measure has a strong bias towards selecting attributes with many possible values over those with few values. To remedy for the bias, gain ratio instead of information gain is used to express the proportion of information generated by the split. The bias is rectified by normalizing the information gain

$$\textit{gain ratio(X)} = \textit{gain}(X) \,/\, \textit{split info(X)} \tag{9}$$

where

$$\textit{split info(X)} = -\sum_{i=1}^{n} \frac{|T_i|}{|T|} \times \log_2\left(\frac{|T_i|}{|T|}\right) \tag{10}$$

is the potential information generated by dividing T into n subsets. The attribute with the highest gain ratio is chosen for splitting the cases, subject to the constraint that the information gain must be at least as large as the average gain over all tests examined.

C4.5 extends ID3 by providing a method to deal with continuous attributes. The split on continuous attributes is restricted to binary. Given a continuous attribute X, a binary test on X results in two branches, corresponding to the conditions $X \leq Z$ and $X > Z$, where Z is the threshold value. C4.5 finds the threshold that has the greatest gain ratio and then compares this with that of the other attributes for deciding which attribute will be used for the next split.

A prototype system was developed to implement these retrieving methods for forecasting sovereign ratings. It is written in Java with part of its code adapted from Weka 3.2 (Witten & Frank, 2000). The code for implementing NN is revised based on Weka's IB1. IB1 finds the training case closest to the testing case based on distance. It is revised so that the training case is retrieved based on similarity rather than distance according to Equation (3). The number of k in the k-NNs is 1 in this study. In other words, only the training case with the highest similarity score is retrieved because the expectation of the *k*-nearest cases being similar may not hold for a large *k* with a limited sample size (Weiss and Kulikowski, 1991). The training case that has the highest similarity score with the testing case is found and retrieved, and its rating is reused as the forecasted rating of the testing case. The prototype system adapts its code from Weka's J4.8 for TI. J4.8 algorithm (Witten & Frank, 2000), a variant of C4.5, is used for building a decision tree for the training cases. By routing down the tree according to the values of the attributes tested in the successive nodes of the built tree, a testing case is forecasted with a rating. In the context of sovereign ratings forecasting, no revision or adaptation of the outcome is needed. The forecasted rating is compared with the actual rating of the testing case to decide whether or not the forecast is correct. The accuracy or misclassification in each class of ratings can be then obtained.

Missing values in data set is a common issue in practice and the data sets used in this study also have missing values in both the explanatory variables and the rating. IB1 and J4.8 have their own algorithms to deal with missing values. Both methods remove cases from analysis when the rating is missing. Therefore, the number of training cases for rating categories Moody's Bonds and Notes, Moody's Bank Deposits, Standard and Poor's Foreign Currency Rating, Standard and Poor's Local Currency Rating, Fitch Foreign Currency rating and Fitch Local Currency ratings is 94, 94, 94, 93, 78 and 77 respectively. When missing values occur in an explanatory variable, IB1 considered the distance as 1 when both values of the training and testing cases are missing, and the distance calculated based on the normalized value of the non-missing variable when only one value is missing. For J4.8, the calculation of gain ratio will take into consideration the probability that an explanatory variable's value is known in searching for the variable that best divides the cases. A training case in which the variable to be tested has a missing value is split into pieces using a weight based on the probability that the case belongs to a branch. The case is sent in parts down each branch until a leaf node is reached. When a testing case has a missing value for a decision node, J4.8 explores all possible outcomes and combines the resulting classifications arithmetically to reach a forecasted rating (Witten & Frank, 2000).

3. Determinants Results

3.1 Ordered Probits Model

An intuitive explanation of the modeling framework is as follows. Underlying the observed alphabetic grade for a country is an unobserved numerical score, y_i *. The value of this numerical score, in this case, rating 1-9, is determined by the set of explanatory variables according to the model (equation 1 and equation 2). The score then determines the alphabetic grade assigned through the assumed mapping. That is, the score is mapped to the observed alphabetic grade dependent upon which interval it falls into. The ordered response model (equation 1 and equation 2) is run for the sample of countries with each of the 6 dependent variables, namely, Standard and Poor's Foreign Currency Rating (SPFC), Moody's Bank Deposits (MBD), Moody's Bonds and Notes (MBN) and Standard and Poor's Local Currency Rating (SPLC), Fitch Foreign Currency ratings (FitchFC) and Fitch Local Currency Ratings (FITCH LC) for the year 2001. The results are reported in Table 3. Panel A of table shows the economic variables, which are significant for the year 2001 across the six rating categories using equation 2, that is by including mobile phones in the model. The variables GDP and mobiles phones are significant across the 6 rating categories. As expected, there is an inverse relationship between the numerical scores and GDP, that is as GDP increases, the ratings assigned (alphabetical ratings) are upgraded and the same applies in the case of mobile phones. Considering the other economic variables, in general, they produce insignificant results. The literature on the determinants of sovereign ratings suggest that in general we expect other economic variables to be significant, for instance the level of inflation, the level of debt, the current account balance (see Cantor and Packer (1996), Bissoondoyal-Bheenick (2005)). As such, the model is run by excluding the mobile phone factor (using equation 1). Panel B of table 3 reports the results.

The results reveal more significant variables when the model is modified. GDP, inflation and real interest rates are significant for all the rating agencies with anticipated signs. In addition, for Fitch ratings, the level of current account balance/GDP is significant for both the local and foreign currency ratings. A possible explanation is that given Fitch provide ratings to a lower number of countries than Moody's and Standard and Poor's, the number of high rated countries is lower. For the low rated countries, that is those countries generally with speculative grade ratings, the literature suggest that the level of current account balance is, in fact, a significant variable in the determinants of low rated countries (Bissoondoyal- Bheenick (2005)). This implies that for developing (emerging markets) countries, a larger range of indicators, including balance of payments measures, are relevant in assigning ratings, a claim supported by the rating agencies comments on the determinants of ratings.

3.2 The Most Important Determinants Selected by J4.8

NN does not itself select variables and all the variables are included in the analysis. TI has its own algorithms for distinguishing important variables from less important ones in building a decision tree. C4.5 selects the variables that best divide cases using gain ratio as the criterion. By examining the gain ratios of the explanatory variables at each decision node, an idea of the most significant variable at that node can be given. The variable being selected at the root node is considered as the most important variable among all because it is the most promising variable on which to divide all the cases.

Table 4 presents the gain ratios of the explanatory variables for the decision trees built with a depth of 2 levels only, i.e. the root node and nodes for its left and right branches across the rating categories. Panel A and B show the gain ratios using 7 and 6 variables respectively. Figures in bold denotes the variables that have the highest gain ratios and are selected as the most important variables for splitting at the nodes.

For example, for SPFC using 7 variables, mobile phones, with the highest gain ratio, is selected at the root level for classifying cases into two groups. As the branch to the left node means ≤ and to the right node means > a threshold value, the group branched to the left means countries with less mobile phones and the group branched to the right means countries with more mobile phones. The column of classified with ratings shows countries with more mobile phones are associated with higher ratings whereas those with less mobile phone have lower ratings. For those countries with less mobile phones and lower ratings in the left node, inflation is the selected variable to further divide the cases. For those countries with more mobile phones and higher ratings on the right, GDP is the selected variable for further splitting.

For all the rating categories using 7 variables, mobile phones is selected as the most significant variable in dividing all the cases, GDP is the selected variable for further dividing higher rating countries, and inflation is the selected variable, except for MBN and MBD where mobile phones is again selected, for further dividing lower rating countries.

With the removal of mobile phones as the explanatory variable, Panel B of Table 4 shows GDP or inflation is selected as the most significant variable at the root level. When GDP is selected, the left branch, with lower GDP, is associated with lower rating cases whereas the right branch, with higher GDP, is associated with higher rating cases, generally speaking. When inflation is selected, the left branch, with lower level of inflation, is associated with higher rating cases whereas the right branch, with higher level of inflation, is associated with lower rating cases, in general. By comparing Panel A and B of Table 4, mobile phones, better classifies lower and higher rating countries as reflected by less overlapping of ratings. Table 4 only shows the most important variables selected at the first 2 levels. The decision trees will be further expanded from the left and right nodes under the root node and other variables will be selected. Based on the data sample of this study, the decision trees for rating categories SPLC, FF and MBN (using 7 variables), and SPFC, SPLC, FF and FL (using 6 variables) utilize all the variables. Other rating categories (using 7 or 6 variables) leave out one or two variables in building the decision trees.

4. Forecasting

4.1 Forecast for the year 2002

This section provides a forecast of the ratings to be assigned to the full sample of countries for the year 2002. The models used under the ordered response model that is have been adjusted to consider only the statistically significant economic variables. Accordingly, from the model where mobile phones were included, the forecast model was based on GDP and mobile phones only and from the model where mobiles phones were excluded, the model has been re-estimated with the significant variables only that is with GDP, inflation and real interest rates. Hence the models were adjusted as follows:

$$y_i = \beta_1 \text{ GDP} + \beta_7 \text{ Mobile phones} + \varepsilon_I \quad (12)$$

$$y_i = \beta_1 \text{ GNP per capita} + \beta_2 \text{ Inflation} + \beta_3 \text{ Real Interest Rates} + \varepsilon_I \quad (13)$$

where y_i represents the observed grades for Moody's Bonds and Notes, Moody's Bank Deposits, Standard and Poor's Foreign Currency Ratings and Standard and Poor's Local Currency Ratings, Fitch Foreign Currency Ratings and Fitch local Currency ratings for the year 2001. Following equation (12), the forecast of the ratings is therefore based on the GDP and mobiles phones for the year 2002 and the parameter estimates for the year 2001 using the model in equation (12) for each of the six rating categories. The score then determines the alphabetic grade to be assigned through the assumed mapping. An illustration of the model using the numerical values for Standard and Poor foreign currency rating on the basis of equation 12 that is with the inclusion of mobile phones is detailed below. The number of rating categories for SPFC obtained from the model is eight, that is no observations are available for the numerical score 8 in the actual ratings. The numerical score to be assigned to each country is based on the limits points obtained from the model as follows:

$$y_i = \begin{cases} 1 & \text{if } y_i^* < -2.6218 \\ 2 & \text{if } -2.6218 < y_i^* \leq -2.2373 \\ 3 & \text{if } -2.2373 < y_i^* \leq -1.7621 \\ 4 & \text{if } -1.7621 < y_i^* \leq -1.2760 \\ 5 & \text{if } -1.2760 < y_i^* \leq -0.7236 \\ 6 & \text{if } -0.7536 < y_i^* \leq 0.3108 \\ 7 & \text{if } 0.3108 < y_i^* \leq 0.7642 \\ 8 & \text{No observations} \\ 9 & \text{if } y_i^* > 0.7642 \end{cases}$$

The numerical score then determined the alphabetical grade to be assigned for each country following the classification of the rating (table 1).

As far as CBR is concerned, the forecast has been undertaken under the two variants of the model, categorised under J48 and EQ-NN respectively. The CBR forecasts take the values for the explanatory variables for 2002 and select matching cases using the approaches detailed in section 2.2.1 to produce the forecasts for 2002. The results of the forecast of ratings for the year 2002 are reported in table 5. Panel A of the table indicates that, on average, based on quantitative factors only, there is a high degree of accuracy in the predictions for the ratings for the year 2002, under the three models. For the three models, ordered probit, J48 and EQ-NN, the percentage of hits is around 60 percent. The number of misses reported is up to 3 level differences, but most of the misses' fall between a one or two notch difference. Ratings are considered to be a quantitative as well as qualitative analysis by the rating agencies. These results are based on only the quantitative factors. However, for the model with mobile phones, it seems that the ordered response model seems to provide a higher percentage of hits as compared to J48 and EQ-NN, though this is not the case for Fitch Ratings. This is consistent with the literature where it has been argued that in the case of ordered data such as ratings, ordered probit models are an appropriate model, (see for example, Mckelvey and Zaviona (1975); Moon and Stotsky (1993), Bissoondoyal-Bheenick (2005)).

Panel B of table 5 report the forecast ratings for 2002 using the model without mobile phones. The results of J48 and EQ-NN reveal approximately the same percentage of hits (50 percent) as compared to the model with mobile phones, although the percentage of hits under the ordered probit model is lower in this case. The appraisal of each country's overall creditworthiness is both quantitative and qualitative ("Sovereign Credit Ratings: A Primer", (1998); "Moody's Country Credit Statistical Handbook", (2001)). The quantitative aspect of the analysis incorporates a number of measures of economic and financial performance and contingent liabilities, although judging the integrity of the data is a more qualitative matter. The social and political factors are considered as being the qualitative factors. The results suggest that, while GDP is important, the broad level of technological development, as represented by mobile phones, is perhaps more important.

4.2 Weaker Economies Forecast

This section analyses a set of weaker economies, which are not rated by any of the rating agencies. The forecast has been undertaken for a sample of 25 countries under the model without mobile phone and a sample of 32 countries with the model including mobiles. The estimates, using each of the models, that is ordered probit, J48 and EQ-NN, are made for the year 2002. Each of the models provides ratings as expected[1], that is most of the countries have a speculative grade ratings, given they are weaker economies which are unrated by the agencies. In terms of the ratings grades, most of the ratings assigned are in between the numerical grade 5 to 9. Table 6 reports a comparison of the ratings assigned by each of the model. In particular, a comparison is undertaken between OP and J48, OP and EQ-NN and J48 and EQ-NN. Panel A of table 6 reports the results of the model with mobiles and panel B reports the results of the model without mobiles. With regards to panel A, the results indicate that the ratings are more consistent between ordered probit and J48. The majority of the difference in the models is up to a single notch difference. In addition, in the model with mobile phones, it seems that the three models are consistent to some

[1] The results of the ratings assigned to each of the countries for each of the models is not reported in the paper, rather a comparison of the models is provided.

extent. Most of the variation is up to 2-notch differences only. Panel B of table 6, however indicates that the ratings assigned to the weaker economies are quite dispersed, with some of the ratings assigned completely different, as reported in the greater than 3 notches category. In this case, some of the difference is up to an 8-notch difference. Hence the models seem to provide completely different ratings, without a technology proxy variable included in the analysis.

5. Conclusion

This paper examines the quantitative determinants of sovereign ratings provided by the three main rating agencies, namely, Standard and Poor's, Moody's and Fitch ratings. An understanding of sovereign ratings has become important because of globalisation of markets and cross-border investments. The primary aim of this paper is to help better understand the economic variables used in the determination of sovereign ratings and to compare the different models that can be utilised to assess the significance of particular quantitative variables.

The paper compared two alternative techniques for the modelling of the determinants of sovereign ratings, specifically, ordered probit and CBR. Despite the differences in approach the two alternative modelling techniques produce similar results in terms of which variables are significant and forecast accuracy for 2002. This suggests that either approach can be used, and that there is some robustness in the results. As regards significant variables, both models find that a proxy for technological development, specifically, mobile phone use, is the most important variable. This role for a technology variable is clearly important in the modern knowledge economy. Apart from the technology proxy, a range of conventional macroeconomic variables are found to be significant, in particular GDP and inflation.

The models are used to produce forecasts for 2002. When mobile phone use is included in the analysis forecast accuracy is around 60%, with most forecast errors within a single notch. When mobile phone use is excluded, forecast accuracy is much lower (less than 40%). Forecasts are also produced for a set of unrated countries. When mobile phone use is included as a variable in the analysis, the forecasts produced by the different models are quite similar. In contrast, when mobile phone use is excluded from the analysis there is considerable variability across models in terms of forecast ratings.

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Table 1: Mapping of Rating Grades

Investment Grade Ratings	Moody's	Standard & Poor's	Fitch	Rating Grade 1-9
Highest Quality	Aaa	AAA	AAA	1
High Quality	Aa1	AA+	AA+	2
	Aa2	AA	AA	
	Aa3	AA-	AA-	
Strong payment capacity	A1	A+	A+	3
	A2	A	A	
	A3	A-	A-	
Adequate payment capacity	Baa1	BBB+	BBB+	4
	Baa2	BBB	BBB	
	Baa3	BBB-	BBB-	
Speculative Grade ratings				
Likely to fulfil obligations, Ongoing Uncertainty	Ba1	BB+	BB+	5
	Ba2	BB	BB	
	Ba3	BB-	BB-	
High Risk Obligations	B1	B+	B+	6
	B2	B	B	
	B3	B-	B-	
Poor standing and Subject	Caa1	CCC+	CCC+	7
To very high Credit Risk	Caa2	CCC	CCC	
	Caa3	CCC-	CCC-	
Near Default with some possibility of recovery	Ca	CC	CC	8
Lowest Rating	C	SD	C	9
			DDD	
			DD	
			D	

Table 2: This table presents an example of extracted cases and a problem represented in a fixed format of attribute-value pairs. A case is comprised of the values of the attributes that describe the situation of a country and the outcome is the rating. GDP, inflation and mobiles are the names of the attributes and the rating of the problem has yet to be determined.

		Iceland	**Bahrain**	**The Bahamas**	**Croatia**
Problem description	GDP	8,956,240,896	7,225,543,680	4,179,432,960	24,435,838,976
	Inflation	9	0	4	3
	Mobiles	865	462	197	535
	..	..	..	..	..
	..	..	..	..	..
	..	..	..	..	..
Outcome	Rating	Aa3	Ba1	A3	?

Table 3: Determinants of ratings using Ordered Response Model
This table shows the relative significance of the economic variables applied to the whole population of countries for the year 2001. Panel A resports the results of the model with mobiles phones included and panel B resports the results of the model by excluding mobile phone as a dertminant of ratings. Values in parenthesis are t-statistics.

PANEL A: 7 Economic Variables Model

	Eplantory Variables						
Dependent Variable	**Current Acc/ GDP**	**FDI/GDP**	**GDP**	**Inflation**	**Mobiles**	**Real Interest rates**	**Trade/ GDP**
SPFC	-0.0130	-0.0047	-0.0029**	0.0081	-0.0040*	0.0117	-0.0008
	(-0.6777)	(-0.1535)	(-1.6245)	-(0.2680)	(-6.7397)	-(0.6862)	-(0.8033)
SPLC	-0.0115	0.0281	-0.0236**	0.0281	-0.0036*	0.0221	-0.0041
	-(0.6017)	(0.9266)	-(1.6733)	(0.9282)	-(6.0098)	(1.2896)	-(1.2200)
MBN	-0.0052	-0.0172	-0.0036**	0.0042	-0.0038*	0.0213	0.0035
	-(0.2765)	-(0.4689)	-(1.8378)	(0.1357)	-(5.2970)	(1.2012)	(1.0020)
MBD	-0.0036	-0.0908	-0.0241**	-0.0111	-0.0041*	0.0112	0.0022
	-(0.1888)	-(0.2423)	-(1.7569)	-(0.3600)	-(6.3545)	(0.6381)	(0.6262)
FitchFC	-0.0254**	-0.0282	-0.0028**	0.0105	-0.0035*	0.0171	0.0026
	-(1.7778)	-(0.8881)	-(1.8638)	(0.3719)	-(5.6690)	(1.0186)	(0.7446)
FitchLC	-0.4954*	-0.0444	-0.0201**	0.0032	-0.0032*	0.0078	0.0039
	-(2.2679)	-(1.3997)	-(1.6554)	(0.0110)	-(5.1709)	(0.4590)	(1.1222)

PANEL B: 6 Economic Variables Model

	Explantory Variables					
Dependent Variable	**Current Acc/ GDP**	**FDI/GDP**	**GDP**	**Inflation**	**Real Interest rates**	**Trade/ GDP**
SPFC	-0.0232	-0.3343	-0.0003*	0.0685*	0.0678*	-0.0003
	(-1.2319)	(-1.1146)	(-2.3531)	(-2.2836)	(-4.1368)	(-0.9709)
SPLC	-0.0205	0.0007	-0.0004*	0.0810*	0.0688*	-0.0063
	(-1.0891)	(-0.0247)	(-2.2581)	(-2.6871)	(-4.1851)	(-1.9124)
MBN	-0.0156	0.0535	-0.0044*	0.0579*	0.0720*	0.0018
	(-0.8485)	(-14618)	(-2.4439)	(-1.9001)	-4.1975	-0.5239
MBD	-0.0151	-0.4877	-0.0039*	0.0049**	0.0680*	0.0005
	(-0.8199)	(-1.3225)	(-2.2248)	(-1.6598)	(-3.9988)	(-0.1483)
FitchFC	-0.0388**	-0.0487	-0.0004*	0.0633*	0.0566*	0.0002
	(-1.8248)	(-1.5432)	(-2.3829)	(-2.2704)	(-3.5083)	(-0.0505)
FitchLC	-0.0630*	-0.0633	-0.0032*	0.0510**	0.0462*	0.0018
	(-2.9417)	(-2.0167)	(-2.0332)	(-1.8320)	(-2.8189)	(-0.5122)

* Denotes statistical significance at 5 %
** Denotes statistical significance at 10%

Table 4 – The most important determinants selected by J4.8 for decision trees with a depth of 2 levels

This table presents the gain ratios of the explanatory variables for the decision trees built with a depth of 2 levels across the rating categories. Panel A and B show the gain ratios using 7 and 6 variables respectively. Figures in bold denotes the explanatory variables selected at the nodes for splitting.

Panel A: 7 EconomicVariables Model

Dependent Variable	Node	GDP	Inflation	Foreign Direct Investment/ GDP	Current Account/ GDP	Trade/ GDP	Real Interest Rates	Mobile Phones	Classified with Ratings
SPFC	**Root**	0.253	0.207	0.063	0.055	0.045	0.181	**0.542**	1, 2, 3, 4, 5 & 6
	Left	0.116	**0.194**	0.106	0.015	0.081	0.086	0.133	3, 4, 5 & 6
	Right	**0.340**	0.183	0.000	0.021	0.067	0.052	0.057	1, 2, 3 & 4
SPLC	**Root**	0.194	0.191	0.056	0.093	0.069	0.179	**0.544**	1, 2, 3, 4, 5 & 6
	Left	0.089	**0.260**	0.073	0.058	0.030	0.061	0.100	2, 3, 4, 5 & 6
	Right	**0.169**	0.064	0.031	0.026	0.028	0.050	0.097	1, 2 & 3
FF	**Root**	0.208	0.342	0.038	0.156	0.097	0.150	**0.584**	1, 2, 3, 4, 5, 6 & 7
	Left	0.222	**0.340**	0.094	0.177	0.125	0.098	0.117	4, 5, 6 & 7
	Right	**0.409**	0.065	0.005	0.013	0.035	0.040	0.128	1, 2, 3 & 4
FL	**Root**	0.134	0.313	0.145	0.056	0.066	0.153	**0.592**	1, 2, 3, 4, 5 & 6
	Left	0.104	**0.350**	0.125	0.063	0.046	0.096	0.152	3, 4, 5 & 6
	Right	**0.154**	0.091	0.017	0.098	0.049	0.015	0.085	1, 2, 3 & 4
MBN	**Root**	0.211	0.156	0.024	0.017	0.060	0.154	**0.481**	1, 2, 3, 4, 5, 6 & 7
	Left	0.080	0.105	0.018	0.047	0.048	0.059	**0.277**	3, 4, 5, 6 & 7
	Right	**0.306**	0.168	0.033	0.064	0.108	0.064	0.115	1, 2, 3 & 4
MBD	**Root**	0.198	0.179	0.033	0.021	0.047	0.165	**0.496**	1, 2, 3, 4, 5, 6 & 7
	Left	0.036	0.129	0.026	0.048	0.037	0.054	**0.280**	3, 4, 5, 6 & 7
	Right	**0.302**	0.080	0.003	0.031	0.087	0.080	0.194	1, 2, 3 & 4

Panel B: 6 Economic Variables Model

Dependent Variable	Node	GDP	Inflation	Foreign Direct Investment/ GDP	Current Account/ GDP	Trade/ GDP	Real Interest Rates	Classified with Ratings
SPFC	**Root**	**0.253**	0.207	0.063	0.055	0.045	0.181	1, 2, 3, 4, 5 & 6
	Left	0.043	**0.167**	0.017	0.018	0.068	0.131	3, 4, 5 & 6
	Right	0.172	**0.399**	0.143	0.079	0.111	0.162	1, 2 & 3
SPLC	**Root**	**0.194**	0.191	0.056	0.093	0.069	0.179	1, 2, 3, 4, 5 & 6
	Left	0.080	**0.202**	0.029	0.092	0.097	0.172	2, 3, 4, 5 & 6
	Right	0.103	**0.467**	0.138	0.085	0.146	0.184	1, 2, 3, 4 & 6
FF	**Root**	0.208	**0.342**	0.038	0.156	0.097	0.150	1, 2, 3, 4, 5, 6 & 7
	Left	**0.285**	0.165	0.081	0.104	0.051	0.195	1, 2, 3, 4, 5 & 6
	Right	0.109	**0.305**	0.175	0.131	0.152	0.133	3, 4, 5, 6 & 7
FL	**Root**	0.134	**0.313**	0.145	0.056	0.066	0.153	1, 2, 3, 4, 5 & 6
	Left	**0.194**	0.192	0.086	0.131	0.093	0.157	1, 2, 3, 4, 5 & 6
	Right	**0.358**	0.334	0.140	0.138	0.321	0.133	1, 3, 5 & 6
MBN	**Root**	**0.211**	0.156	0.024	0.017	0.060	0.154	1, 2, 3, 4, 5, 6 & 7
	Left	0.000	**0.092**	0.035	0.073	0.042	0.080	2, 3, 4, 5, 6 & 7
	Right	0.024	**0.346**	0.077	0.014	0.117	0.130	1, 2, 4 & 6
MBD	**Root**	**0.198**	0.179	0.033	0.021	0.047	0.165	1, 2, 3, 4, 5, 6 & 7
	Left	0.009	0.076	0.033	0.027	0.053	**0.104**	2, 3, 4, 5, 6 & 7
	Right	0.025	**0.133**	0.069	0.091	0.000	0.055	1, 2, 4 & 6

Table 5: Forecast ratings for the year 2002

This table reports the forecast rating assigned to each country for the year 2002. Panel A reports the percentage of hit and miss that each of the models have for the year 2002, using the mobile phone factor. Panel B reports the results for the models wihout the use of mobile phones. The degree of miss reported is up to 3-notch difference (maximum obtained). A rating notch is a one-level difference between the forecast rating and the actual rating.

Panel A: Model with Mobiles

	% of Hit			% of Miss								
Ratings				**1 Notch**			**2 Notches**			**3 Notches**		
	OP	**J 48**	**EQ-NN**	**OP**	**J 48**	**EQ-NN**	**OP**	**J 48**	**EQ-NN**	**OP**	**J 48**	**EQ-NN**
SPFC	66	55	55	14	29	26	19	11	13	1	5	6
SPLC	57	45	53	27	40	29	15	12	12	1	3	6
MBN	60	52	59	23	30	19	15	16	15	2	2	7
MBD	59	43	57	26	29	23	10	22	14	5	5	6
FicthFC	44	52	57	47	33	27	6	10	12	3	5	4
FitchLC	52	47	59	31	32	19	14	12	18	3	9	4

Panel B: Model without Mobiles

	% of Hit			% of Miss								
Ratings				**1 Notch**			**2 Notches**			**3 Notches**		
	OP	**J 48**	**EQ-NN**	**OP**	**J 48**	**EQ-NN**	**OP**	**J 48**	**EQ-NN**	**OP**	**J 48**	**EQ-NN**
SPFC	40	50	51	39	29	21	16	13	11	5	8	17
SPLC	46	43	48	36	33	23	14	17	14	4	7	15
MBN	37	37	48	36	26	19	13	22	12	12	15	20
MBD	40	36	47	33	31	20	17	15	13	4	18	19
FicthFC	42	48	57	41	31	22	10	13	8	6	8	13
FitchLC	46	46	56	32	23	18	16	13	14	6	18	12

Table 6: Forecast rating of weaker economies not rated by the rating agencies.
This table reports the forecast rating assigned to each country for the year 2002. Panel A reports the percentage of hit and miss that each of the models have for the year 2002, using the mobile phone factor. Panel B reports the results for the models wihout the use of mobile phones. The table compares the results of the three models, that is OP v J48, OP v EQ-NN and J48 and EQ-NN.

Panel A: Model With Mobiles - Percentage

	SPFC	SPLC	MBN	MBD	FicthFC	FitchLC
OP v J 48						
Hit	75	63	25	25	63	26
1 Notch	16	31	72	47	31	56
2 Notches	9	6	3	28	6	9
3 Notches	-	-	-	-	-	9
Greater than 3 Notches	-	-	-	-	-	-
OP v EQ-NN						
Hit	28	16	28	19	16	41
1 Notch	53	53	19	25	59	56
2 Notches	19	31	41	37	25	3
3 Notches	-	-	9	16	-	-
Greater than 3 Notches	-	-	3	3	-	-
J 48 v EQ- NN						
Hit	13	22	13	47	22	22
1 Notch	63	56	56	34	59	56
2 Notches	25	22	25	16	19	13
3 Notches	-	-	6	3	-	9
Greater than 3 Notches	-	-	-	-	-	-

Panel B: Model Without Mobiles - Percentage

	SPFC	SPLC	MBN	MBD	FicthFC	FitchLC
OP v J 48						
Hit	28	28	8	28	36	12
1 Notch	44	24	60	44	44	44
2 Notches	8	32	28	20	20	16
3 Notches	20	16	4	-	-	8
Greater than 3 Notches	-	-	-	8	-	20
OP v EQ-NN						
Hit	20	20	36	32	24	28
1 Notch	48	36	32	40	32	36
2 Notches	16	32	16	16	24	4
3 Notches	16	12	8	4	12	24
Greater than 3 Notches	-	-	8	8	8	8
J 48 v EQ- NN						
Hit	40	20	20	24	28	20
1 Notch	32	56	48	28	36	28
2 Notches	12	12	16	28	16	20
3 Notches	16	8	-	4	12	12
Greater than 3 Notches	-	4	16	16	8	20

Figure 1 – A general CBR cycle (adapted from Aamodt and Plaza, 1994)