Assessing country risk: a PD model based on credit ratings

Henrique F. Macedo, André L. S. Guimarães, Vicente S. Cardoso e Jorge C. C. O. Lima

Assessing country risk: a PD model based on credit ratings

Henrique F. Macedo, André L. S. Guimarães, Vicente S. Cardoso e Jorge C. C. O. Lima

BNDES – Brazilian Development Bank

Abstract

The purpose of this study is to examine the main determinants of the sovereign credit ratings provided by the three major rating agencies: Fitch Ratings, Moody's and Standard and Poor's. We follow the Shadow Rating approach in order to model the logit of the Probability of Default (PD) of the ratings, and apply cross section and panel data econometrics to select the most explanatory and robust variables.

Motivation

Understanding the determinants of the sovereign credit rating is important as it sheds light into what credit rating agencies monitor when they issue a rating . Also, because not all countries have a credit sovereign rating, a model that can be used to assess the credit worthiness of sovereigns is required. This study seeks to produce an econometric model that can use readily available data, in order to assess sovereign credit risk in a way that allows comparisons with well-know international rating scales.

Relevant Literature

A number of empirical studies have examined the impact of economic factors on the sovereign risk (e.g., Feder and Uy (1985), Cantor and Packer (1996), Larrain et al. (1997), Mulder and Perrelli (2001), Alfonso (2003) and Mellios and Paget-Blanc 2006).

The study follows a similar pattern, however the sample used is larger and more recent than those of previous studies. This is important as it allows for greater accuracy and relevance, especially in such a dynamic environment as that of international finance.

Methodology

The Shadow Rating approach followed Erlenmaier (2006). The notable difference is the use of the logit of the probability of default (PD) as dependent variable, as opposed to the use of the PD directly. The cross section and panel data econometrics modelling followed Wooldridge (2001), Singer and Willett (2003) and Frees (2004).

The shadow rating approach is typically used when default data are scarce and external ratings issued by the major international rating agencies (Standard and Poor's, Moody's or Fitch Ratings) cover significant portion of the loan portfolio of the institution holding the loan. The common purpose to all quantitative methodologies for risk classification is to identify risk factors that provide reliable indications about the probability of default (Moody's Investor Service, 2010).

The shadow rating approach does that indirectly, since there is insufficient data to develop an explicit model for predicting the probability of default, identifying the key factors and estimating weights for each factor in order to estimate external ratings. Furthermore, one must calibrate the model to a probability of default (Erlenmaier, 2006), in order to make the estimated model useful for credit risk management and compliant with regulatory demmands.

The development of the model followed six steps:

1. Data collection;
2. Mapping of external ratings to probability of defaults;
3. Analysis of risk factors and variable selection;
4. Model estimation;
5. Model validation; and
6. Model adjustment.

Step 1: Data Collection

We have collected data from the three major credit agencies, covering 123 countries with at least one year rating, from 1999 to 2009. We have also collected data for the same period from the World Economic Outlook database published by the International Monetary Fund, and the World Development Indicators database and Worldwide Governance Index, published by the World Bank.

The sample of sovereign ratings used for mapping the dependent variable was obtained from Bloomberg, taking the history of ratings issued by Standard & Poor's, Moody's and Fitch Ratings from 2000 to 2009. When there were multiple ratings issuued by the same rating agency for a given country and year, only the rating at the end of the year was used.

Table 1. Tested Variables

Variable	***Sources***
Current account balance (% GDP)	WDI, WEO
Net Foreign Direct Investment (% GDP)	WDI
Total Reserves (% External Debt)	WDI
Total Reserves excluding Gold (US$)	WDI
External Debt (% Exports)	WDI
External Debt (% GDP)	WDI
GDP Growth (% Annual)	WDI, WGI
Gross Domestic Savings (% GDP)	WDI
Gross Fixed Capital Formation (% GDP)	WDI
International Trade (% GDP)	WDI
Gross Domestic Product (US$)	WDI
GDP per Capita (PPP)	WDI
Domestic Credit to Private Sector ($ GDP)	WDI
Stocks Traded, Total Value (% GDP)	WDI
Real Exchange Rate (REER 2005)	WDI
Real Interest Rate (%)	WDI
Inflation (Consumer Price Index, %)	WDI
Cash Surplus or Deficit (% GDP)	WEO
Central Government Debt (% GDP)	WEO
Gross Public Debt (% GDP)	WEO
Public Sector Primary Surplus (% GDP)	WEO
Public Sector Primary Surplus (%GDP)	WEO
Research & Development Expenses (% GDP)	WDI
Unemployment (% of total labor force)	WDI
Long-term Unemployment (% total unemployment)	WDI
Gini Index	WDI
Voice and Accountability	WGI
Political Stability, No Violence	WGI
Government Effectiveness	WGI
Regulatory Quality	WGI
Rule of Law	WGI
Control of Corruption	WGI

Economic, political and social indicators assessed (Table 1) were obtained from databases such as the World Development Indicators (WDI) and Worldwide Governance Index (WGI) from the World Bank and World Economic Outlook (WEO) from the International Monetary Fund (IMF).

No indicator used was estimated. Observations with missing data were not used for estimation. When indicators were similar in multiple sources, the source selection took in consideration the coverage and periodicity of the series.

Importantly, the number of sovereign ratings is much lower than that of corporate ratings due to a natural limitation in the number of countries. Thus, we used data from 2000 to 2009 so that the sample was large enough to allow the estimation of robust parameters. During this period, at least 123 countries had a rating.

After data collection, we proceeded to the mapping of the dependent variable.

Step 2: Mapping of external ratings to probability of defaults

An important step in building a shadow rating model is to map the ratings issued by rating agencies to associate them with default probabilities. In this procedure we used the unsecured issuer ratings of long-term foreign currency because they indicate the credit risk without mitigants and are consistent with Basel II (BCBS, 2006). Moreover, the long-term ratings in foreign currency are more stable (Moody's Investor Service, 2010), and better aligned with the average term of repayment of the loan portfolio of BNDES.

Table 2. Sovereign ratings and five year PD (%), 1983-2009

Rating Moody's	***Rating. S&P***	***Moody´s PD (*) (%)***	***Equiv. S&P***	***Model PD (%)***
Aaa	AAA	0.000	AAA	0.002
Aa1	AA+	0.000	AA+	0.306
Aa2	AA	0.000	AA	0.610
Aa3	AA-	0.000	AA-	0.915
A1	A+	0.000	A+	1.219
A2	A	0.000	A	1.524
A3	A-	0.000	A-	1.828
Baa1	BBB+	2.437	BBB+	2.133
Baa2	BBB	2.437	BBB	2.437
Baa3	BBB-	2.437	BBB-	3.848
Ba1	BB+	8.079	BB+	5.258
Ba2	BB	8.079	BB	6.669
Ba2	BB-	8.079	BB-	8.079
B1	B+	10.572	B+	10.572
B2	B	10.572	B	16.044
B3	B-	10.572	B-	21.515
Caa – C	CCC+ - C	32.458	CCC+	26.987
Caa – C	CCC+ - C	32.458	CCC	32.458
Caa – C	CCC+ - C	32.458	CCC-	49.344
Caa – C	CCC+ - C	32.458	CC	66.229
Caa – C	CCC+ - C	32.458	C	83.115

Source: (*) Moody's Investor Service, 2010

In the mapping process we used the mean five year probability of default (PD), as shown in Table 2. The use of the mean five year PD is important because in shorter time horizons, credit events, especially for sovereign debt, are very rare. In addition, five year PDs show lower volatility (Moody's Investor Service, 2010) , and allow better estimation. Finally, we are interested in the Long Run Probability of Default.

As noted, the mean probability of default does not distinguish between modifiers (sublevels) and assigns a zero PD zero to ratings between AAA and A-. In order to distinguish the model PD in this region, a cubic interpolation was used, as reported in the last column of Table 2.

After mapping external ratings into default probabilities, we identified possible variables to use in model development.

Step 3: Analysis of risk factors and variable selection

Variable selection was performed by the analysis of various risk factors, from data collected as described in section 2. According to S&P (2011), risk factors related to the probability of default of a country are divided into 5 main categories:

1. Economic;
2. Political;
3. Fiscal;
4. External; and
5. Monetary.

Each explanatory variable can be related to more than one category (eg, related to both economic score and fiscal score). Thus, in order to facilitate the interpretation of the model, we sought to associate each selected variable to the predominant category.
In most cases, explanatory variables were ratios of Gross Domestic Product (GDP) or per capita. This ensures that country size would not a priori influence the credit risk. Furthermore, by using ratios, we avoided the need to treat differences in the value of money and different currencies. The only variable that does not fit the characteristics described previously is the base-10 logarithm of international reserves (in US$).

Given the large number of variables, there were numerous possible combinations of variables to explain the probability of default. Thus, only the variables most strongly correlated with the default probability were considered. In addition, several indicators showed high correlation with each other, suggestion a relationship with the same underlying risk factor. In this case, when two variables showed a correlation greater than 80%, the variable with the highest correlation with the remaining variables was excluded from the analysis in order to reduce multicollinearity.

After treatment of the data and the selection of variables, we estimated a model with seven explanatory variables, six of which are continuous variables and one is dichotomous. Table 3 lists the descriptive statistics of the variables used in the model.

These variables encompass (as proxies) the categories of risk factors previously cited. Balance on Current Account and Foreign Currency Reserves are related to External risk (flow and inventory, respectively), Income per Capita (PPP) is related to Economic risk, and Inflation to Monetary risk.

Table 3. Descriptive Statistics

Variable	***Minimum***	***Maximum***	***Mean***	***s.d.***
Current account balance (cab) (%)	-30.26	44.62	-1.17	9.56
Log_{10} GDP per capita (gdppc)	2.65	4.96	3.95	0.48
Cash surplus or deficit (gsd) (%)	-25.63	39.53	-0.84	5.62
WGI index (wgi) (%)	17.33	90.37	56.23	17.81
Inflation (inflation) (%)	-2.00	30.00	5.80	6.11
Log_{10} International reserves (trc)	6.99	12.38	9.76	0.84

We chose to bound inflation between -2% and 30%, in order to correct a distribution problem and also because we believe that inflation greater than 30% already represents a poor monetary policy. This helps to avoid distortions in countries with very high inflation. Along the same line, this treatment avoids excessively rewarding a large deflation, that may not represent good monetary policy.

The WGI index is formed by the simple arithmetic mean of three scores: Government Effectiveness, Regulatory Quality and Rule of Law. The mean was more explanatory than each individual score, and avoided the strong correlation between the three scores. The WGI index in the model represents Political risk.

Cash surplus or deficit was obtained from the IMF WEO and is formed by the simple arithmetic mean of the result in the reference year, the previous year and the estimate for the following year. The use of the 3-year average is important to decrease volatility, and to handle large differences such as those occurring in election years. The score represents Fiscal risk.

Finally, a dichotomous variable was used in order to correct the WGI index distribution, with value one for countries with WGI index greater than 75% (dwgi_m75) and zero otherwise.

Step 4: Model Estimation

Given the structure of the data with observations from the same countries for several years, the entire (pooled) sample violates the premise of independence of observations, as the rating of a country in a year is highly dependent on the rating of the previous year. In such scenario, panel methods are adequate (Wooldridge, 2001; Frees, 2004; Singer & Willett, 2003).

The modeling process employed panel data models with least squares method with random effects for the periods as indicated by the tests suggested by the literature (Hausman, 1978) in order to estimate the parameters that best fit the data.

Figure 1. Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	68.189097	6	0.0000

Correlated Random Effects - Hausman Test
Equation: Untitled
Test period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	2.993463	6	0.8097

Figure 2. Redundant Fixed Effects

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section and period fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	45.527917	(93,560)	0.0000
Cross-section Chi-square	1436.479290	93	0.0000
Period F	4.605626	(9,560)	0.0000
Period Chi-square	47.771734	9	0.0000
Cross-Section/Period F	41.753539	(102,560)	0.0000
Cross-Section/Period Chi-square	1439.926226	102	0.0000

The Hausman test aims to identify the need to handle random effects in the panel. From Figure 1, the null hypothesis was rejected for the cross section and not discarded for periods.

The random effects in periods aims to isolate the effect of the correlation that the ratings of these countries have with each other for various years.

The test of redundant fixed effects aims to verify whether it is necessary to handle fixed effects in the panel. The null hypothesis was rejected for the cross section and the periods, indicating that this effect should not be used (Figure 2).

The dependent variable was defined as the logit of the probability of default associated with ratings. The logit is defined as the natural logarithm of the odds ratio: LN (pd / (pd-1)), where PD is a probability of default associated with a rating (as per Table 1). In addition, a dummy was included, which is intended to adjust the WGI index distribution which is bimodal (or non-linear in relation to the logit). The final model is given by:

Formula 1. Estimated Model

$$\text{logit} = \alpha + \beta_1 \cdot \text{cab} + \beta_2 \cdot \text{gdppc} + \beta_3 \cdot \text{gsd} + \beta_4 \cdot \text{wgi} + \beta_5 \cdot \text{inflation} + \beta_6 \cdot \text{trc} + \beta_7 \cdot \text{dwgi\_m75} + \varepsilon$$

$$\text{and } PD = \frac{1}{1 + e^{-\text{logit}}}$$

Table 4 presents the selected variables. All variables are statistically significant and show the expected signs. Standard errors calculated for statistical inference are robust to heteroskedasticicty, following White (1980).

Table 4. Model Coefficients (n=886, Adjusted R^2 = 0.892)

Variable
Current account balance (cab) (% GDP)
Log_{10} GDP per capita (gdppc) (PPP)
Cash surplus or deficit (gsd) (% GDP)
WGI index (wgi) (%)
Inflation (inflation) (%)
Log_{10} International reserves (trc)
WGI dummy : WGI > 75 (dwgi_m75)

As the scores obtained from the model were in line with the expected default probabilities, it was not necessary to calibrate the estimated PDs, and we proceeded to model validation.

Step 5: Model Validation

The selected model has undergone several tests to assess its capacity to accurately estimate the ratings issued by major international rating agencies.

There are not sufficient sovereign ratings to test the model out-of-sample, since all available data was used to estimate the model. Instead, we used a hit-mismatch matrix, following Grün et al (2010), and verified the ability of the estimated model prior to adjustments, to correctly predict the ratings issued by international rating agencies.

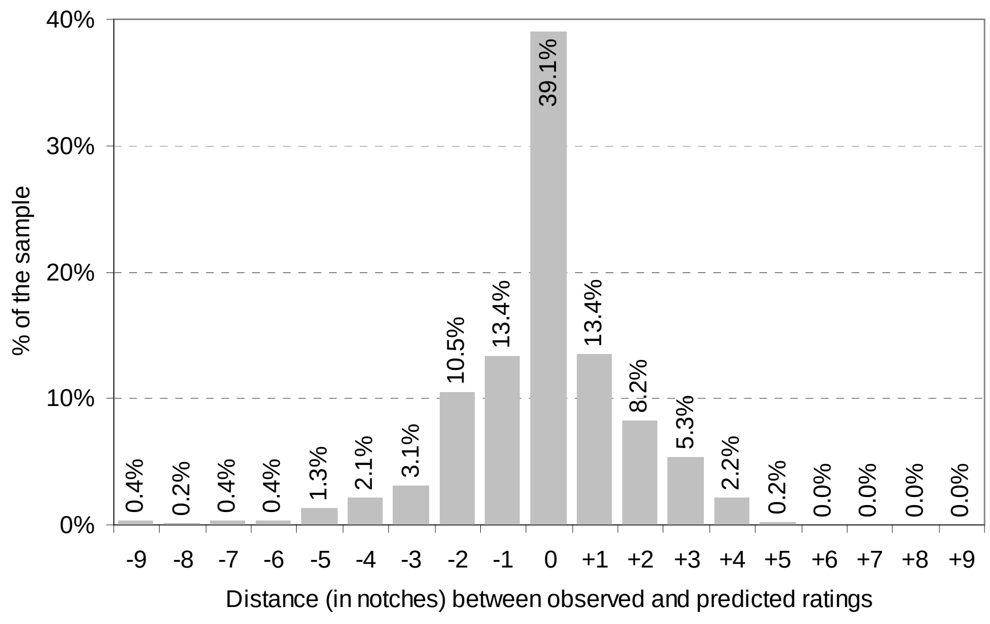
Based on this method, the estimated model shows a hit ratio of 93,0%; within three notches of the observed rating, that was considered satisfactory.

Table 5. Hit-mismatch matrix: predicted vs observed ratings, without modifiers

Predicted	Observed						
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**<=CCC**
AAA	**542**	44	17	8	0	0	0
AA	4	**36**	34	4	0	0	0
A	11	80	**313**	89	1	0	0
BBB	0	0	60	**309**	89	14	0
BB	0	0	2	119	**230**	74	7
B	0	0	0	11	148	**164**	51
<=CCC	0	0	0	0	9	18	**9**

Another similar manner, is to evaluate the distribution of the differences between predicted (model) and observed (agency) ratings. In this analysis, a difference of zero implies an exact match, and each integer represents a distance of one notch between estimated and observed ratings.

Graphic 2. Distribution of differences between predicted and observed ratings



Finally, we evaluated the accuracy of the model. In this evaluation, we used a tool known as continuous receiver operating characteristic (continuous ROC). This diagnostic test (Nguyen, 2007), allows to compare the accuracy of a measurement against a known gold standard, even if the measurement is continuous. Greater values of the area under the ROC curve indicate a better accuracy. The estimated model exhibited an area under the ROC curve of 88.28 %, which represents a good level of accuracy.

According to the above results, the model presented here performs well and yields scores close to the ratings published by international rating agencies.

It should be noted that, as the tests were performed in-sample, it is expected that the out-of-sample accuracy would be somewhat reduced. Such reduction should be minimized by the model adjustments presented in the next step.

Step 6: Model Adjustment

As mentioned in the previous section, the quantitative model does not capture some intrinsic features of certain countries only with political, economic and social variables. These unobserved characteristics sometimes are often responsible for the distance between predicted and observed ratings. Because these issues affect only a handful of countries, it is not possible to include them in the quantitative model (i.e., not statistically significant).

The main qualitative characteristic influencing ratings is the existence of recent default history. Countries that have defaulted recently may experience a difference of up to 9 notches between estimated and observed ratings. A second important influence is the use of hard currency, especially when a country belongs to a multilateral agreement, as the European Union, as inflation is often under control and the country is better protected from major devaluations. Thus, in order to supplement the quantitative model, we proposed the notch adjustments listed in Table 6.

Table 6. Adjustments after the quantitative model

Criteria	Adjustment to predicted rating
Default in the last 2 years?	If yes, move down 6 notches
Default in the last 3-5 years?	If yes, move down 4 notches
Default in the last 6-10 years?	If yes, move down 2 notches
Strong currency (i.e., Euro, US Dollar)	If yes, move up 1 notch

These adjustments significantly improve the ratings estimated from countries with some of the above features, which - in particular - are those outside the range of -3 to 3 sublevels difference in Graphic 2.

Conclusion

The presented model aims to produce ratings and default probabilities in the lack of a database containing a sufficient number of defaults.

The model contains six factors and a dummy variable. For 92% of the pooled sample (grouping the three agencies) the predicted rating is within three notches of the observed rating. Recent country's default (up to 10 years) turns out to influence the sovereign rating, although not statistically significant, because of the small number of defaults. Nonetheless, this credit event explains well most errors larger than 3 notches. The accuracy obtained by the model is good, especially considering that credit agencies uses qualitative judgments that are beyond the scope of this study.

Notwithstanding the limitations, the model presented here, based on the shadow rating approach, is easy to understand and apply, uses readily available information, and satisfactorily predicts country ratings issued by international rating agencies, and can be an useful tool for the assessment of sovereign credit risk.

References

Alfonso A. (2003), *Understanding the Determinants of Sovereign Debt Ratings: Evidence of the Two Leading Agencies*, Journal of Economics and Finance, 27, 56-74.

BCBS – Basel Committee on Banking Supervision. (2006). Basel II: *International Convergence of Capital Measurement and Capital Standards: a Revised Framework, Comprehensive Version (BCBS)*. June 2006 Revision.

Cantor, R.; Packer, F.; (1996), *Determinants and Impact of Sovereign Credit Ratings*, Reserve Bank of New York, Economic Policy Review, 2, 37-53.

Erlenmaier, U., The Shadow Rating Approach – Experience from Banking Practice, In: Engelmann, B.; Rauhmeier, R. (2006), *The Basel II Risk Parameters*, cap. IV, pp. 39-77.

Frees, E. (2004). *Longitudinal and panel data: analysis and applications in the social sciences*. Cambridge Univ Press, EUA.

Grün, B.; Hofmarcher, P.; Hornik, K.; Leitner, C.; Pichler, S. (2010) *Deriving Consensus Ratings of the Big Three Rating Agencies*. Research Report Series, Institute for Statistics and Mathematics, WU Vienna University of Economics and Business, Vienna.

Hausman, J. A. (1978). *Specification Tests in Econometrics*. Econometrica 46 (6): 1251–1271.

Larrain, G., Helmut, R.; Maltzan, J. (1997), *Emerging Market Risk and Sovereign Credit Ratings*, OECD Development Center, Technical Paper, 124.

Mellios, C.; Paget-Blanc, E. (2006), *Which factors determine sovereign credit ratings?* The European Journal of Finance, vol 12, pp 361 - 377

Moody's Investor Service (2010), *Sovereign Default and Recovery Rates 1893-2009*. Report Number: 124389, New York.

Mulder, C.; Perrelli, R. (2001), *Foreign Currency Credit Ratings for Emerging Market Economies*, IMF Working Paper, 01/191.

Nguyen, P. (2007), *nonbinROC: Software for Evaluating Diagnostic Accuracies with Non-Binary Gold Standards*, Journal of Statistical Software, 21.

Singer, J.; Willett, J. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford University Press, EUA.

Standard & Poor’s (2011), *Sovereign Government Rating Methodology and Assumptions*, New York.

White, H. (1980), *A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity*, Econometrica: Journal of the Econometric Society.

Wooldridge, J. (2001). *Econometric analysis of cross section and panel data*. The MIT press.