SOVEREIGN RISK RATINGS AND MACROECONOMIC FUNDAMENTALS: A PANEL DATA APPROACH

Bruno Ferreira Frascaroli, Jailson da Conceio Teixeira de Oliveira[a,b]

[a]*Associate Professor. Graduate Program of Economics. Federal University of Paraba frascaroli.b@gmail.com, Cidade Universitria, Joo Pessoa-PB, 58051-900*
[b]*PhD Candidate, Graduate Program of Economics, Federal University of Paraba jailson.consultor@gmail.com, Cidade Universitria, Joo Pessoa-PB, 58051-900*

Abstract

The main purpose of this study is to examine the determinants of sovereign risk ratings produced by rating agencies. These ratings are among the most important tools for reducing asymmetric information in international financial markets. The macroeconomic fundamentals of the countries were considered: solvency, liquidity, economic development, and stability. A panel data model based on Rowland (2004) was estimated. Our main results are that promoting income growth and controlling inflation, which is associated with discipline in tax policy, are important to maintaining low levels of country risk. The growth of GDP per capita and the evolution of the CP level indicate a country's ability to generate income and thus strengthen its development, whereas the discipline of fiscal policy indicates a country's ability to honor its financial commitments. In addition, ratings in the current period are influenced by previous ratings, indicating the agencies' conservative behavior.

Keywords:
Sovereign Risk Ratings; Macroeconomic Fundamentals; Panel Data
JEL classification: G15, E44, D82

---

1. Introduction

This article examines the sovereign risk ratings produced by rating agencies. These ratings are simple risk measures associated with government bonds, which reflect countries' debts. Therefore, macroeconomic, political, and legal variables, among others, are included in the rating associated with each country's government bonds. However, the existence of asymmetric information in financial markets is inevitable, and this asymmetry will affect the returns of credit operations (Arezki and Sy (2011)).

In terms of macroeconomics, countries' indebtedness-i.e., the opportunity costs of their investments-have short-, medium-, and long-term implications for financing and economic policy, and other important decisions. For example, the importance of international credit market conditions to emerging countries such as Brazil is obvious. Because these countries are not self-sufficient in terms of financing, they become net borrowers in international financial markets.

Reinhart and Carmen M. Reinhart (2002) notes that fundraising conditions are critical, and rating agencies evaluate net borrower countries harshly because several international crises have occurred since the 1990s. A downgrade indicates to investors that the risk of acquiring bonds from this country has increased. This change further constrains that government's ability to attract foreign capital. The main purposes of this study are to analyze the sovereign risk ratings produced by rating agencies and to estimate the parameters based on countries' macroeconomic fundamentals. We assume that macroeconomic fundamentals reflect each country's conditions, and they will thus be used as rating determinants.

Our empirical analysis is based on Rowland (2004), and we estimated the parameters using econometric models for pooled data-also known as panel data models-from the observed ratings and their determinants for different countries. We used sovereign risk as a criterion for estimating fixed and random effects. We concentrate on the relationships between countries' ratings and their macroeconomic fundamentals. Using the estimated parameters, we tested the statistical significance of the regressors and then observed the degree of homogeneity among the sampled countries.

In addition, this study briefly analyzes the experimental estimations to find the best specification for the model following the traditional statistical assumptions. It is important to analyze changes not only temporal changes but also longitudinal changes-i.e., the time series of macroeconomic determinants-in robustness tests.

Following this brief introduction, Section 2 discusses the puzzles surrounding the issues of ratings agencies and ratings, as well as their possible impacts on the real economy. Section 3 describes the panel data method used, specifying its main technical aspects. The variables used in the estimations, the sample and the dataset construction are defined in Section 4. We analyze the results in Section 5, and finally, Section 6 concludes.

2. The sovereign ratings literature

A rating is an estimation of the probability of future default. There are two types of ratings: (1) sovereign ratings, which are the object of this study; and (2) corporate ratings, which are the risks associated with companies' stocks around the world. Sovereign ratings express the risk assumed by investors by acquiring bonds from a particular country, and they are based on analyses of countries' economic, social, and political circumstances. Sovereign ratings can be subjective because they involve judgments not only of current internal and external macroeconomic variables but also of their future values (Bhatia (2002)).

In other words, a sovereign risk rating describes a national government's credit risk (Poors (2011)). They represent assessments of relative risk based on issuers' ability and willingness to pay debts in full (**?**). Rating agencies are companies that are independent of government or private sector interests, which allows them to pursue the following principles: independence, objectivity, credibility, and freedom to disclose their ratings of the credit quality of debt issuances and issuers (Frenkel and Scholtens (2004)). Standard &

Poor's, Moody's Investors Service, and Fitch IBCA are the major rating agencies, representing approximately 80% of the ratings market, as the ratings market is concentrated and characterized by oligopolistic competition **?**. This market structure implies that each agency processes information with different returns of scale, resulting in barriers to entry.

Ratings attempt to reflect country-specific risk factors, which may affect an entity's ability to repay its debts in full and on time. The risk of sovereign intervention-for example, the risk that a country will impose exchange rate policies or enact debt moratoriums - is just one of a country's economic risks. The term economic risk refers to economic, political, and social factors, which influence the ratings of the country itself and those of the issuing entities located there (Frenkel and Scholtens (2004)).

Table 1 shows the rating scales created by the world's main rating agencies. The table includes a numerical scale ranging from 1 to 24 to represent the degree of risk. Countries in the 1-10 range belong to the low-risk, investment grade group. Countries above 10 are part of the higher-risk group, and the holders of their bonds are viewed as financial market speculators. Countries in the 22-24 range have defaulted on their debts; thus, their ratings are based on the possibility of partial or full loan recovery.

Table 1: Rating Systems

	Companies			Numerical
Classification	**Moody's**	**S&P**	**Fitch**	**Scale**
	Aaa	AAA	AAA	1
	Aa1	AA+	AA+	2
	Aa2	AA	AA	3
	Aa3	AA-	AA-	4
Investment Grade	A1	A+	A+	5
	A2	A	A	6
	A3	A-	A-	7
	Baa1	BBB+	BBB+	8
	Baa2	BBB	BBB	9
	Baa3	BBB-	BBB-	10
	Ba1	BB+	BB+	11
	Ba2	BB	BB	12
	Ba3	BB-	BB-	13
	B1	B+	B+	14
	B2	B	B	15
Speculative	B3	B-	B-	16
	Caa1	CCC+	CCC+	17
	Caa2	CCC	CCC	18
	Caa3	CCC-	CCC-	19
	-	CC	CC	20
	-	C	C	21
	Ca	SD	DDD	22
	C	D	DD	23
	-	-	D	24

Source: Standard & Poor's, Fitch, Moody's.

2.1. Rating criteria

Sovereign risk ratings are assigned to debt-issuing countries by agencies using criteria that are not always clear, i.e., there are no patterns for either the determinants of the ratings or the weights assigned to each determinant because ratings reflect both qualitative and quantitative determinants.

Qualitative determinants of ratings include political risks. For example, the integrity of leaders and the stability and transparency of institutions are judgments made by analysts about governments' decision-making behaviors during economic crises. However, Haque and Mathieson (1998) empirically demonstrate that political variables have no or very little impact on agencies' rating decisions.

On the other hand, the same quantitative determinants include measures of economic and financial performance and contingent liabilities, although judgments about the integrity of such data are qualitative in nature. There is no exact formula for combining scores to determine ratings. Moreover, the variables are interrelated, and their weights are fixed neither by government nor over time (Afonso and Gomes (2012)). Cantor and Packer (1996) observe that even for quantitative determinants, it is difficult to find a relationship between the weights assigned by Moody's and those assigned by Standard & Poor's because of the numerous criteria adopted by these agencies.

Standard & Poor's, for example, divides their determinants of sovereign ratings into categories, which are in turn divided into subcategories that include projections of economic growth, fiscal flexibility, monetary stability, and political risk. Each government is then rated on a scale from 1 (highest) to 6 with respect to each category analyzed (Poors (2011)). Some agencies, including Moody's, consider the probability of default in their ratings, i.e., the probability that a government will declare a moratorium on its debt.

Cantor and Packer (1996) seminal paper fits an econometric model to predict countries' ratings using macroeconomic time series data. However, following the 1997 Asian crisis, this econometric model lost its ability to predict ratings. Furthermore, the authors note that these quantitative models are limited in their ability to explain changes in ratings because it is difficult to incorporate qualitative variables. Using an ordered response model, Bissoondoyal-Bheenick (2005) analyzed the determinants of sovereign risk for a sample of 95 countries over the period from December 1995 to December 1999.

The sample was divided into two subsamples, the first of which was composed of 25 top-rated countries (Moody's Aaa to Aa3; Standard & Poor's AAA to AA) and the second of which was composed of 70 countries with lower ratings (Moody's A1 to C; Standard & Poor's A to CC). The study's primary conclusion is that the importance of macroeconomic variables may vary according to a country's degree of development. In the sample of highly rated countries, macroeconomic variables do not play important roles in determining ratings. In contrast, in riskier countries, gross domestic product (GDP) per capita, inflation, current account balance, and international reserves are particularly important.

Basu and Timmer (2013) analyze the evolution of sovereign credit during the global financial crisis by observing ratings changes between 2008 and 2012. Using econometric models, Standard & Poor's ratings are estimated using macroeconomic, structural, and governance variables. Overall, after the 2008 events, rating agencies seemed to attribute less importance to cyclical variables, such as GDP volatility, imports, and exports. However, structural factors such as the rule of law, which encompass the overall impact of governance, were more strongly emphasized.

2.2. The role of ratings and criticisms of their function

Sovereign risk rating has both direct and indirect effect on the credit quality of entities that operate in a particular location. In the presence of asymmetric information in global financial markets, the ratings produced by credit risk agencies send important signals to market participants. Markets sustain rating agencies for various reasons:

- Ratings must be credible, i.e., they are only valuable when they are reliable. Rating agencies finance themselves by charging debt issuers to prepare ratings; thus, they have no incentive to produce biased or unreliable ratings;
- Obtaining and interpreting information about debt issuers is costly. Therefore, rating agencies experience returns to scale upon obtaining and interpreting such information;
- Ratings can summarize information about the future creditworthiness of the debt issuer in a manner that is both clear and easy for market actors to understand.

According to Partnoy and Carmen M. Reinhart (2002), there are serious endogeneity problems in this market. Delays in ratings changes in the wake of market changes cause agents to anticipate such ratings changes. Thus, because agencies assess a debtor's future ability to pay, the effectiveness of ratings can be seriously impaired if the rating is performed after a change in market perception, as agents would no longer consider the ratings reliable indicators of any debt issuer's future ability to pay.

Another problem detected by Cantor and Packer (1996) is the strong convergence of Standard & Poor's and Moody's ratings: when these agencies assign different ratings, they vary by a single position on the scale, indicating that these classifications are conservative.

Partnoy and Carmen M. Reinhart (2002) notes that the existence of regulatory inefficiencies in financial markets might explain this paradox. Numerous legal rules and regulations are substantially dependent on ratings, particularly those assigned by a small group of rating agencies, the nationally recognized statistical rating organizations (NRSROs). However, the author notes that barriers to entry in the NRSRO market are prohibitive. Thus, the ratings assigned by NRSROs are valuable to financial market participants even if their informational content is not superior to the public information reflected in the market.

Agents who manage institutional investors' funds, for example, are subject to internal fund management rules that assign risks to portfolios based on NRSRO ratings. Thus, even when these ratings do not provide adequate information about the risks posed by certain issuers, fund managers are required to use them.

According to Ferri (1999), several financial market observers and institutions - for example, the World Bank and the International Monetary Fund - blamed ratings agencies for failing to warn the market about the 1997 Asian financial crisis. As in 1929, the agencies downgraded the sovereign risk ratings of some countries involved in the 1997 crisis, again engaging in behavior that was overly conservative based on the macroeconomic fundamentals.

Bone (2009) argues that before the 1997 Asian crisis, changes in these sovereign ratings were not significant and appeared to be historically stable. After the Asian crisis, the agencies issued abrupt downgrades that were not comparable to those that had been issued earlier, i.e., they acted procyclically. Ferri (1999) argue that such procyclical, conservative behaviors prolong the economic effects of a crisis because the agencies excessively downgrade the sovereign risk ratings of economies that already had low sovereign risk ratings.

According to the authors, such excessive downgrades would not occur in economies with better sovereign risk ratings. Instead, these economies experience improved rating classifications, which occurred during the 2008 financial crisis in the US. Similarly, Doluca (2014) analyzes whether agencies' ratings for countries are positively correlated with their financial gains in those countries, finding moral hazard or profit-maximizing bias, among the rating agencies. However, the results also show that agencies' reputational concerns seem to dominate their financial interests.

Sy (2009) provides a comprehensive discussion of the channels through which sovereign risk ratings impact other markets. In integrated financial markets, ratings downgrades should have effects beyond securities. According to the author, financial markets have increasingly used ratings, which contributed to the current financial crisis by worsening shortages of funds. He also calls attention to the need for better rating agency regulations to reduce conflicts of interest and increase transparency and competition.

Arezki and Sy (2011) examine the impact of sovereign risk ratings news events across countries and in European financial markets from 2007 to 2010. They find that downgrades have significant economic and statistical impacts on both countries and financial markets and that such announcements can lead to financial instability. Seventy-one rating announcements were made between October 2006 and April 2010, 29 of which were rating change announcements and 28 of which were downgrade announcements. Downgrades to nearly speculative ratings, such as Greece's downgrading by Fitch on December 8, 2009, had a systematic impact on the Eurozone countries.

Fatnassi and Hasnaoui (2014) analyze the stock market reactions of four European countries (Greece, Portugal, Spain, and Italy) to changes in their Fitch, Moody's, and Standard & Poor's ratings from June 2008 to June 2012 using panel data models. The results indicate that upgrades and downgrades affect the returns of both rated countries and other countries. However, the observed market reactions to foreign debt-issuing agent downgrades are stronger during the sovereign debt crisis period. In addition, rating agencies' negative news is more informative than their positive news.

According to Kiff (2012), rating agencies' risk classifications affect fundraising costs for bond issuance and thus influence financial stability. During the recent financial crisis, there was evidence of ratings instability. Thus, the authors recommend greater ratings accuracy and transparency regarding the quantitative parameters used in such classifications.

The effects of ratings agencies' classifications are not limited to countries' bonds. For example, Borensztein and Valenzuela (2013) investigate the influence of sovereign risk ratings on corporate risk ratings in developed and emerging economies from 1995 to 2009. The results show that sovereign risk ratings are important determinants of corporate risk ratings, especially in countries that have capital account restrictions and high political risk.

Finally, Bayar and Kili (2014) analyze the relationship between Turkey's sovereign risk ratings and foreign direct investment flows into the country from January 1995 to July 2013. Using a multivariate time series approach, the authors find a positive relationship between foreign direct investment flows and sovereign risk ratings, highlighting the Standard & Poor's ratings. In addition, the study reveals two-way causality between the sovereign risk ratings assigned by Standard & Poor's and foreign direct investment in Turkey. They also observe one-way causality between the ratings assigned by Fitch and Moody's and foreign direct investment inflows, i.e., foreign direct investment affects these classifications.

3. Panel data model

Panel data models are used when longitudinal observations are available - i.e., for individuals over a period - which yields information about possible individual heterogeneity. According to Wooldridge (2002), these models are widely used to investigate both structural changes and transition dynamics.

A panel data model has some important advantages, including the ability to mitigate collinearity problems and omitted variable bias while increasing degrees of freedom. It allows the analysis of both intertemporal dynamics and individual variable characteristics to better control for the effects omitted variables (Hsiao (1986)).

There are numerous approaches to assigning ratings using quantitative models. For example, Rowland (2004) uses pooled data analysis techniques, while Canuto and Porto (2012) estimate an econometric model for collective analysis of cross-sectional data. In line with the econometric model of Cantor and Packer (1996), Ferri (1999) estimate an ordinary least squares (OLS) model with two types of ratings cardinalization, and Bissoondoyal-Bheenick (2005) uses an ordered response model.

There are many ways to address this type of data, even when we consider that the dependent variable, the rating, is an ordinal variable. Among the problems faced by econometric models are cardinalization problems, which stem from attempts to cardinalize ratings in order to make them estimable, as econometric models are unable to address concepts. It would be impossible to introduce a rating variable into a model without addressing this issue. However, errors may be introduced when cardinalizing a rating because such transformations (regardless of whether they are linear or non-linear) establish quantifiable relationship among rating concepts. For example, assigning a rating equal to two (BBB=2) does not necessarily imply twice the risk of a rating equal to one (AAA=1). However, the ability to linearize ratings, provided they are still convex, enables their exploration using panel data models.

An alternative nonparametric method, such as the Artificial Neural Networks (ANNs) used in Frascaroli (2009), may be strongly recommended, depending on the type of response desired from the model. In this study, given these methodological choices, efforts were made to obtain information in parametric form in order to examine them in light of theories and facts related to rating classifications. Thus, estimation using a panel data model fits some model selection criteria, such as being supported by the data, i.e., offering a good fit, being comprehensive in the sense of having good explanatory power, and being consistent with formulations about ratings and recent relevant events.

The use of panel data in regressions has expanded with the advancement of econometrics, which has enabled considerable improvements in modeling and statistical tests. This body of literature includes dynamic models, nonlinear models, and models that include Markovian processes that consider discrete variables, among many others, all of which are widely used for various purposes.

However, panel data models have some limitations, as with any model that simplifies an observed phenomenon. For example, Arellano (2002) and Baltagi (1995) cite risks such as incomplete samples or measurement error. These problems are linked to bias resulting from poor model specification caused by the failure to consider an eventual differentiation of the coefficients along individual units and/or over time, among other limitations.

To achieve our objective using the available data, we attempted to set aside all of the problems described above, although there were no problems arising out of unbalanced panels.

3.1. The estimated model

To better understand the econometric methodology for static panel data, the basic equation that represents the estimated model is:

$$R_{it} = \alpha_{it} + \beta x_{it} + \epsilon_{it} \tag{1}$$

where R is the rating, x_{it} is the matrix of explanatory variables with k regressors without the constant, *i=1, ..., N* refers to cross-section unit (country), *t=1,...,T* refers to time (year), and ϵ_{it} is the error term such that $\epsilon_{it} \sim N(0, \sigma^2)$ in the absence of autocorrelation of *i.i.d.* (independently and identically distributed) residuals. The parameter $\alpha_i \sim N(0, \sigma^2)$ is a stochastic term inherent to the individual units that captures the individual effects and may or may not be correlated with the vector of explanatory variables (Cameron (2005)).

If $Cov(\alpha_i, x_{ij}) \neq 0$, a fixed effects model should be estimated. The unobserved effect may be eliminated based on the assumption that $E(\epsilon_{it}|x_i, \alpha_i) = 0$. This situation is known as strict exogeneity. For this purpose, the mean of equation (1) is obtained in time through the following equation:

$$\bar{R}_i = \alpha_i + \beta \bar{x}_i + \bar{\varepsilon}_i \tag{2}$$

Subtracting (2) from (1), we have:

$$R_{it} - \bar{R}_i = (x_{it} - \bar{x}_i)\, \beta + (\epsilon_{it} - \bar{\epsilon}_i) \tag{3}$$

where the fixed effect α_i is eliminated. Thus, OLS can be used to obtain the fixed effects estimator. However, if $Cov\,(\alpha_i, x_{ij}) = 0$, i.e., α_i is not correlated with the explanatory variables vector, it is preferable to model these effects as randomly distributed among observational units using a random effects model. Because the errors for the same individual in different periods are correlated, it is more appropriate to use the generalized least squares (GLS) estimator instead of OLS.

The choice of which model (fixed or random effects) to use requires identifying whether there is a correlation between α_i and the vector of explanatory variables. The Hausman test (Hausman (1978)) is used to detect the presence or absence of this correlation, and the null hypothesis assumes the non-correlation of α_{it} and the explanatory variables of the model. If the null hypothesis is accepted, the estimators of random and fixed effects will be consistent, but the random effects estimator is preferred, given that the fixed effects estimator is inefficient. In contrast, if the null hypothesis is not accepted, the fixed effects estimator is preferred because it is efficient and consistent, in which case the random effects estimator becomes inconsistent.

It is worth emphasizing that the static panel is subject to some problems, including endogeneity resulting from correlations between some explanatory variables and the error terms. Moreover, certain economic series can be related not only to each other but also to their own past values. Thus, a dynamic panel model is used through the generalized method of moments (GMM), which is suggested by Arellano and Bond (1991), Blundell and Bond (1998) to provide more robust estimations. The dynamic model specification includes the lagged values of the dependent variable (R_{it-1}) as an independent variable as follows:

$$R_{it} = \gamma R_{it-1} + \beta x_{it} + \alpha_i + \varepsilon_{it}, \quad i = 1, ..., N, \quad t = 1, ..., T \tag{4}$$

where γ is a scalar, α_i denotes the individual fixed effects (i.e., the effects associated with each country that are time invariant), and ϵ_{it} denotes time-varying shocks that specific to each country. The model assumes that $E(\alpha_i) = E(\epsilon_{it}) = E(\alpha_i \epsilon_{it})$ and $E(\epsilon_{it}\epsilon_{js})$ for each i, j, t, s with $\imath \neq j$.

The inclusion of the lagged dependent variable, along with the omission of individual fixed effects α_i and the likely endogeneity of the explanatory variables, makes traditional estimators biased and inconsistent. Thus, Arellano and Bond (1991) propose estimating equation (4) with the use of instruments via difference GMM (GMM-AB) to eliminate the fixed effects .

However, Blundell and Bond (1998) highlight that for a sample with small T, the lagged value instruments of the variable levels may be weak for the first differences, leading to non-consistent and biased GMM-AB estimators. To reduce this bias problem, Arellano and Bover (1995) and Arellano and Bover (1995) developed system GMM, which combines the set of difference equations (instrumented by their level lags) with the set of level equations (instrumented by lags of their own first differences).

To analyze the robustness of the estimated model, various tests are performed. The Sargan (1958) and Hansen (1982) tests were used to verify the power of the instruments.

The null hypothesis of the former is that the system GMM instruments are correlated with the error terms. The null hypothesis of the latter is that the instruments are valid; a third test, the difference-in-Hansen test, has the same null hypothesis and is used to verify exogenous instruments. Finally, given the sensitivity of the dynamic panel to correlation of residuals, first- and second-order autocorrelation tests developed by Arellano and Bond (1991) whose null hypothesis is the absence of second-order autocorrelation are also applied.

4. Sample selection and treatment

The sample was composed of the long-term foreign currency ratings assigned to emerging countries by Standard & Poor's from 1989 to 2011. Overall, 33 countries are considered: Argentina, Bolivia, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominican Republic, Egypt, El Salvador, Guatemala, India, Indonesia, Jamaica, Kazakhstan, Lebanon, Malaysia, Mexico, Mongolia, Morocco, Pakistan, Panama, Paraguay, Peru, Romania, Russia, South Africa, Thailand, the Philippines, Tunisia, Turkey, Uruguay, and Venezuela. Importantly, data access issues restricted the sample, primarily due to solvency and liquidity measures. Of the 23 ratings assigned by this agency (Table 1), 16 were included in the sample, i.e., the AAA, AA+, CCC+, CCC, C, and D ratings were included.

It is important to note that the study period begins in 1989; however, this does not mean that all of the countries had rating classifications for that year. Each country in the sample was included based on its first rating classification. Consequently, the estimates will be based on an unbalanced panel.

The variables used as macroeconomic determinants of ratings in this study were collected from the World Bank's annually updated World Development Indicators database. Because these observations refer to end-of-period statistics, end-of-period ratings were used for countries whose ratings were updated more than once per year. That is, when Standard & Poor's reviewed a country's rating more than once per year, only the last was used in the estimations. To simplify further reading of parameters, Table 2 summarizes the abbreviations for the variables included in the models.

Table 2: List of Variables

Group	Variable	Notation
	Ratings	R
Solvency	Long-term debt as a percentage of GDP	LTD/GDP
Liquidity	Level of total reserves as a percentage of GDP	R/GDP
	Total external debt as a percentage of exports of goods and services	ED/EXP
	Total debt service as a percentage of exports of goods and services	TDS/EXP
Development and Economic Stability	Growth rate of GDP per capita	G-GDP
	Evolution of the level of consumer prices	CP
	Economic openness index	EOI

Source: The authors' work based on Standard & Poor's and World Bank data.

Some of the determinants in similar studies, such as Cantor and Packer (1996), Canuto and Porto (2012), Rowland (2004), and Bissoondoyal-Bheenick (2005), were used as regressors in this study. It is possible to divide these determinants using the same criteria adopted by Rowland (2004) by adding one more variable category, which consists of variables that are directly related to the determinants of countries' development and economic stability indices. The descriptive statistics of the sample are shown in Table 3.

Table 3: Descriptive statistics of the variables analyzed

Variable	**Mean**	**Standard Deviation**	**Minimum Value**	**Maximum Value**
Ratings	11.16727	3.208768	4	22
LTD/GDP	0.335588	0.178071	0.030401	1.280983
R/GDP	0.175027	0.14652	0.012215	1.19413
ED/EXP	1.432037	0.85142	0.235754	4.5252
TDS/EXP	0.198022	0.135956	0.019754	1.15308
G-GDP	0.031139	0.041129	-0.14385	0.161962
CP	0.148751	0.895237	-0.01408	20.75887
EOI	0.697951	0.387886	0.149329	2.204074

Source: The authors' work based on Standard & Poor's and World Bank data.

In this sample, the countries with the worst ratings (SD) were Argentina and Russia, whereas China had the best rating (AA-). On average, the countries included in the sample are rated as speculative. With respect to solvency indicators, the average debt/GDP ratio was 33.5%, with a maximum value of 128.1% in Indonesia in 1998.

With respect to liquidity indicators, the average ratio of foreign reserves to GDP was 17.5%. The mean ratio of total external debt to exports was 143.2%, with a maximum value of 452.5% in Argentina in 2002. The total debt service as a percentage of exports of goods and services was 19.8%, on average, with a maximum value of 115.3% in Brazil in 1999.

Finally, regarding the development and economic stability variables, Brazil also exhibits the maximum observed inflation rate of 2,075.8% in 1994. The mean growth rate of GDP per capita was 3.1%. The highest growth rate over the study period was observed for Mongolia in 2011, while its economic openness index (EOI) averaged 69.7%, indicating that these countries' economies are relatively integrated into international trade.

Argentina, Brazil, and Russia were notable in the sample, as these economies faced major crises during the period analyzed: Brazil experienced price instability before the Real Plan (1994), Russia defaulted (1998), and Argentina had a crisis (2001).

5. Results

To identify the initial relationships between macroeconomic variables and ratings, Pearson's correlations were examined, and statistical significance was set at 5%. Table 4 shows the results.

Table 4: Pearson's Correlations

	R	LTD/GDP	R/GDP	ED/EXP	TDS/EXP	G-GDP	CP	EOI
R	1							
LTD/GDP	0.33*	1						
R/GDP	-0.22*	0.25*	1					
ED/EXP	0.45*	0.42*	-0.26*	1				
TDS/EXP	0.27*	0.31*	-0.21*	0.73*	1			
G-GDP	-0.28*	-0.20*	0.13*	-0.29*	-0.21*	1		
CP	0.11*	-0.02	-0.06	0.10*	0.06	-0.03	1	
EOI	-0.32*	0.24*	0.43*	-0.54*	-0.43*	0.11*	-0.09*	1

Source: The authors' work based on Standard & Poor's and World Bank data.

Table 4 indicates that the correlation between all the selected variables and ratings are significantly different from zero and exhibit the expected signs. Long-term debt as a percentage of GDP, total external debt and total debt service as a percentage of exports of goods and services, and the evolution of the consumer price (CP) level have positive correlations with the numerical rating. In other words, the deterioration of some of these variables may be associated with a sovereign risk rating downgrade. In contrast, variables such as the level of foreign reserves in relation to GDP, the GDP per capita growth rate, and the EOI are negatively correlated with the numerical rating, indicating that increases in these variables can improve sovereign risk ratings. After checking the significant correlations between these variables and ratings, static and dynamic models were estimated. Table 5 depicts the results.

Both fixed and random effects models were estimated. The Hausman test shown in Table 5 indicates that fixed effects provide a better fit because it rejects the null hypothesis of noncorrelation between the specific effects and the explanatory variables. Comparing the results of the fixed effects model with those of the system GMM, it appears that with the inclusion of the lagged dependent variable, total reserves level as a percentage of GDP, which proxies for a country's solvency, was no longer statistically significant. In contrast, the estimates for the EOI and total external debt as a percentage of exports of goods and services became statistically significant.

The estimation of the dynamic panel was performed using a 2-step system GMM model with robust errors to address the problem of proliferation of instruments, eliminating overidentification. The overidentification restriction is due to the number of instruments, which is smaller than the number of groups investigated. The model specification tests at the 5% significance level indicated that the estimation has no second-order autocorrelation problem [AR(2)], and the Hansen test confirms the validity of the instruments used. The difference-in-Hansen test indicates that the instruments are exogenous.

The estimated coefficient indicates that R_{it-1} is statistically significant and positive. This result suggests the existence of inertia in the rating process - i.e., the rating assigned in the previous period impacts the current rating. With respect to macroeconomic variables, long-term debt, a solvency proxy, affects the rating because it is statistically significant.

Table 5: Econometric Models of Ratings

	Fixed Effects			**System GMM**		
	Coef.	**Stand. Error**	**t**	**Coef.**	**Stand. Error**	**z**
Rit-1				0.658875	0.04306	15.3*
LTD/GDP	5.870104	1.073168	5.47*	2.969927	1.00682	2.95*
R/GDP	-9.82986	1.419841	-6.92*	-1.02699	1.042333	-0.99
ED/EXP	-0.35054	0.273669	-1.28	0.484701	0.274583	1.77***
TDS/EXP	0.695568	1.303729	0.53	-3.32766	2.165732	-1.54
G-GDP	-6.58869	2.474802	-2.66*	-7.31202	3.368324	-2.17**
CP	0.242964	0.100207	2.42**	3.293819	1.684917	1.95**
EOI	1.01402	0.916713	1.11	-0.75857	0.319174	-2.38*
CONS	10.74337	0.678492	15.83*	3.242181	0.509467	6.36*
No. of observations=550				No. of observations=516		
R2 = 0.2267				No. of groups: 33		
F test 21.36 (0.0000)				No. of instruments: 31		
Hausman test 22.76 (0.0019)				AR(1) (0.003)		
p-values in parentheses				AR(2) (0.724)		
*not rejected at 1%,significance.				Sargan (0.233)		
**not rejected at 5%,significance.				Hansen (0.540)		
***not rejected at 10%,significance.				Hansen-Diff. (0.905)		

Source: The authors' work based on Standard & Poor's and World Bank data.

The sign of its associated coefficient is positive, indicating that increases in the debt/GDP ratio increase the numerical scale of the assigned rating - i.e., the country would experience a sovereign risk rating downgrade. This result is consistent with the literature on this subject.

With respect to the variables used as liquidity proxies, only total external debt as a percentage of exports of goods and services was statistically significant and positive, thus indicating that increases in this variable contribute to sovereign risk rating downgrades. This result is consistent with the studies of Cantor and Packer (1996) and Canuto and Porto (2012).

All of the variables used to proxy for economic development and stability were statistically significant and exhibited the expected signs. GDP per capita growth (G-GDP) is associated with improvements in sovereign risk ratings and stands out among all of the variables included in this model because it has the strongest impact on ratings. These model results contrast with those of the fixed effects model, in which the impact of per capita GDP growth was smaller than that of reserves.

The magnitudes of the CP coefficients also differ between these two models. Its effect on ratings is stronger in the estimates obtained via system GMM, in which the second variable has the greatest impact. As in Cantor and Packer (1996), Canuto and Porto (2012), and Bissoondoyal-Bheenick (2005), GDP per capita and inflation are the most important economic variables used to assign ratings.

Finally, in the dynamic model, the coefficient associated with the EOI is statistically significant, although it was the variable with the smallest impact on ratings. The

EOI coefficient is negative, indicating that the higher this index value, the higher the sovereign risk rating, which is consistent with Rowland (2004), Canuto and Porto (2012), and Bissoondoyal-Bheenick (2005). According to Maltritz and Berlemann (2013), a country's economic openness is consistent with Ricardo's theory of comparative advantage in which an increase in international trade contributes to the generation of employment and income. The foreign market is a source of demand for a country and reduces the cost of domestic production, improving the country's international competitiveness.

6. Conclusions

This article examined the relationship between the sovereign risk ratings assigned by rating agencies and macroeconomic fundamentals. A panel data model was used because this method is most appropriate for accounting for the effects of country-specific variables, including liquidity, solvency, and development and economic stability indicators. The sample comprised an unbalanced panel of 33 countries using Standard & Poor's and World Bank data from 1989 to 2012.

Based on the economic literature on ratings and traditional statistical assumptions, we tried to identify the best model specification. A Hausman test indicated the use of a fixed effects model whose results were compared to those of a system GMM model. The included lagged dependent variable was statistically significant and positive, which suggests the existence of inertia in ratings, i.e., current ratings are influenced by the ratings assigned in the previous period. The conservative behavior of rating agencies explains this result.

The macroeconomic variables that had a significant impact on sovereign risk ratings included development and economic stability proxies - i.e., the growth of GDP per capita, the evolution of the CP level and the EOI - and solvency and liquidity proxies - i.e., long-term debt as a percentage of GDP and total external debt as a percentage of exports of goods and services, respectively.

Based on the magnitude of the estimated coefficients, promoting income growth and fighting inflation, which are associated with discipline in tax policy, suggest an optimal strategy for maintaining investment-grade ratings. The growth of GDP per capita and the evolution of the CP level indicate a country's ability to generate income and thus strengthen its development process, whereas the discipline of fiscal policy indicates a country's ability to honor its financial commitments.

Efforts to improve the model specification are suggested for future studies, which can occur through more robust statistical and econometric procedures or through combinations of function approximation models in which data panel techniques are combined with ANNs.

References

Furceri D. Afonso, A and P. Gomes. Sovereign credit ratings and financial markets linkages: application to european data. *Journal of International Money and Finance*, 31(3):606–638, 2012.

M. Arellano. *Panel data econometrics*. Oxford University Press: London, 2002.

M Arellano and S. Bond. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies*, 58(2):277–297, 1991.

M. Arellano and O. Bover. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1):29–51, 1995.

Candelon B. Arezki, R. and A. N. R. Sy. Sovereign rating news and financial markets spillovers: evidence from the european debt crisis. *IMF Working papers*, 68, 2011.

B. H. Baltagi. *Econometric analysis of panel data*. Wiley: Chichester, 1995.

DE S. Ratha D. Basu, K. and H. Timmer. Sovereign ratings in the post-crisis world: an analysis of actual, shadow and relative risk ratings. *Policy Research Working Paper Series*, 6641, 2013.

Y. Bayar and C. Kili. Effects of sovereign credit ratings on foreign direct investment inflows: evidence from turkey. *Journal of Applied Finance & Banking*, 4(2):91–109, 2014.

Ashok Vir Bhatia. Sovereign credit ratings methodology: An evaluation. *IMF working papers*, 170(2), 2002.

E. Bissoondoyal-Bheenick. An analysis of the determinants of sovereign ratings. *Global Finance Journal*, 15:251–280, 2005.

R. Blundell and S. Bond. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1):115–143, 1998.

Cowan K. B. Borensztein, E. A. and P. Valenzuela. Sovereign ceilings lite? the impact of sovereign ratings on corporate ratings. *Journal of Banking & Finance*, 37(11):4014–4024, 2013.

A. C. Cameron. *Microeconometrics methods and applications*. Cambridge University Press: New York, 2005.

R. Cantor and F. Packer. Sovereign ceilings lite? the impact of sovereign ratings on corporate ratings. *Economic Policy Review*, 2(2):37–53, 1996.

Santos P. F. P. Canuto, O. and P. C. S. Porto. Macroeconomics and sovereign risk ratings. *Journal of International Commerce, Economics and Policy*, 3(2), 2012.

H. Doluca. Is there a bias in sovereign ratings due to financial reasons? *The Empirical Economics Letters*, 13(7):801–814, 2014.

Ftiti Z. Fatnassi, I. and H. Hasnaoui. Stock market reactions to sovereign credit rating changes: evidence from four european countries. *Journal of Applied Business Research*, 30(3), 2014.

Liu L-G. Stiglitz J. E. Ferri, G. The procyclical role of rating agencies: evidence from the east asian crisis. *Economic Notes*, 28(3):335–355, 1999.

Silva-L. C. Silva Filho O. C. Frascaroli, B. F. Classificao de ratings de risco soberano de pases emergentes a partir de fundamentos macroeconmicos utilizando redes neurais artificiais [sovereign risk ratings of emerging countries based on macroeconomic fundamentals using artificial neural networks]. *Brazilian Review of Finance*, 7(1), 2009.

Karmann A. Frenkel, M. and B. (Eds.) Scholtens. *Sovereign risk and financial crises*. Springer International Publishing: New York, 2004.

L. Hansen. Large sample properties of generalized method of moments estimators. *Econometrica*, 50(3):1029–1054, 1982.

Mark-N. Haque, N. U. and D. J. Mathieson. The relative importance of political and economic variable in creditworthiness ratings. *IMF working papers*, 98(46), 1998.

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

C. Hsiao. *Analysis of panel data*. Cambridge University Press: London, 1986.

Nowak S. B. Schumacher L. Kiff, J. Are rating agencies powerful? an investigation into the impact and accuracy of sovereign ratings. *IMF Working papers*, 23, 2012.

D. Maltritz and M. (Eds.) Berlemann. *Financial crises, sovereign risk and the role of institutions*. Springer International Publishing Switzerland: Switzerland, 2013.

Giovanni Majnoni Partnoy, F. Richard Levich and (Eds.) Carmen M. Reinhart. *The paradox of credit ratings. In: Ratings, Rating agencies and the global financial system*. Kluwer Academic Press: New York, 2002.

Standard & Poors. Sovereign government rating methodology and assumptions. Technical report, Standard & Poors, 2011.

Giovanni Majnoni Reinhart, C. M. Richard Levich and (Eds.) Carmen M. Reinhart. *Sovereign credit ratings before and after financial crises. In Ratings, Rating agencies and the global financial system*. Kluwer Academic Press: New York, 2002.

P. Rowland. Determinants of spread, credit ratings and creditworthiness for emerging market sovereign debt: a follow-up study using pooled data analysis. *Working papers of Banco de la Republica de Colombia*, 2004.

J. Sargan. The estimation of economic relationships using instrumental variables. *Econometrica*, 26(3):393–415, 1958.

A. N. Sy. The systemic regulation of credit rating agencies and rated markets. *World Economics Data Papers*, 10(4):69–108, 2009.

J. Wooldridge. *Econometric analysis of cross-section and panel data*. The MIT Press: London, 2002.