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Modelling Sovereign Ratings in Indonesia: Analysis the Driving Factors Using the Panel Data Regression

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Abstract

Sovereign ratings serve as a concise reflection of a country's creditworthiness. They wield significant influence over various aspects of the economy, particularly affecting the interest rates at which governments can borrow when issuing new debt. This study aims to examine the impact of Real Gross Domestic Product (RGDP), General Government Debt (GGD), Current Account Balance (CAB), Net International Investment Position (NIIP), Foreign Exchange Reserves (FER), Credit Default Swap (CDS), and General Government Revenue (GGR) on sovereign ratings in Indonesia. The sample comprises four countries categorized in the same peer groupsas high-quality, medium-grade, and speculative investments with the data provided from 2004 to 2022. The research employs a panel data regression model. The results indicate that RGDP, Inflation, GGD, and CAB do not demonstrate statistical significance in their association with sovereign ratings, suggesting limited influence. In contrast, the FER variable exerts significant positive impacts and NIIP and FER variables exert significant negative impacts, underscoring their relevance in rating assessments. Conversely, despite its negative correlation, the CDS variable lacks statistical significance. Conversely, the CDS variable, despite its negative correlation, lacks statistical significance. Remarkably, when considering all variables collectively—RGDP, GGD, CAB, NIIP, FER, and CDS—they collectively wield a substantial influence on sovereign ratings, emphasizing the necessity of a comprehensive approach in comprehending these ratings.

Keywords: *Sovereign Ratings, Driving Factors, Panel Regression.*

1. INTRODUCTION

Credit Rating Agencies (CRAs) analyze and award a rank or grade to a government based on its capacity to satisfy its financial debt obligations, which is known as sovereign credit or debt ratings (Takawira & Mwamba, 2020). CRAs collect data from multiple sources, concerning the political, financial, economic, infrastructure, regional, local, and other related aspects of a nation (Saadaoui, 2022). They subsequently assess the country's ability to fulfill its debt obligations.

A sovereign credit rating is a grading system used to represent this evaluation. The nations with the greatest ratings are thought to be very creditworthy, and the ones with the lowest ratings are thought to be in default danger. The same corporation or sovereign

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entity is rated differently by three reputable credit rating agencies: Fitch, Moody's, and Standard & Poor's (Takawira & Mwamba, 2022). This variation has led researchers to question the specific indicators and criteria employed to assign sovereign credit ratings (Overes & Wel, 2021).

CRAs expanded their scope from rating only corporate entities to including sovereign ratings as well. This change left investors with a choice between utilizing publicly available credit scores or creating their own methods for credit scoring (Osobajo & Akintunde, 2019). Since a corporation cannot be rated higher than its home nation, corporate ratings have become reliant on sovereign ratings, effectively making sovereign credit ratings the ceiling for corporate ratings. International investors closely monitor sovereign credit rating movements, as this information is crucial for their investment decisions regarding specific countries (Gu et al., 2018).

Many stakeholders, including governments, authorities, debt issuers, investors, and borrowers, use sovereign ratings to assess an institution's willingness and ability to repay loans. High creditworthiness, a robust financial system, and general financial stability are all indicated by favorable credit ratings (Takawira & Mwamba, 2022). The earlier studies assessing financial stability mostly concentrated on exchange rates, market confidence, economic policies, and resource allocation, often overlooking the role of sovereign credit ratings (Bratis et al., 2020; Chauhan & Ramesha, 2018). However, some literature has pointed to the interconnectedness between SCRs and financial stability (Li et al., 2019).

Because of incidents involving mis-rating practices, CRAs have been the subject of investigation and criticism (Vu et al., 2022). Revisions to sovereign asset ratings may have a significant negative impact on stock markets. Sovereign ratings are of great significance to governments since favorable ratings can result in reduced interest rates and necessary access to global capital markets (Takawira & Mwamba, 2022).

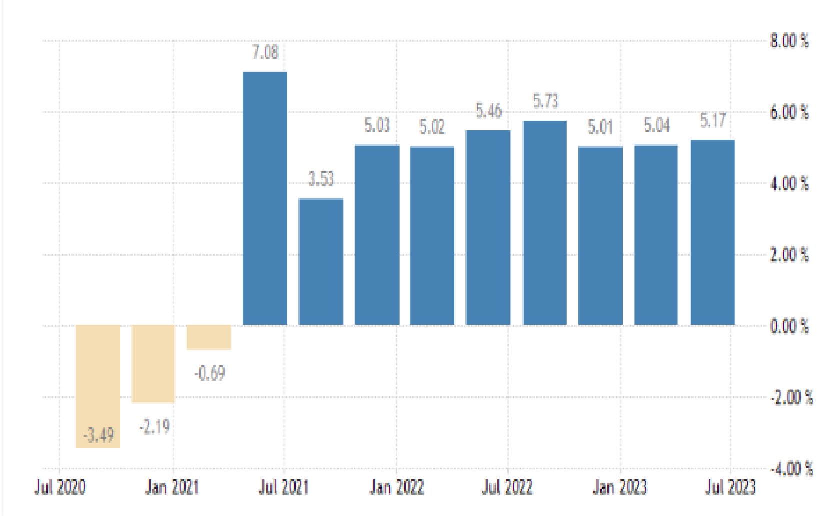

Figure 1. Indonesia GDP Annual Growth Rate

Source: (Statistic Indonesia, 2023)

Indonesia's economy grew strongly in the second quarter of 2023, rising 5.17% year over year and above market estimates of a 4.93% gain (Fig. 1). Building on a slightly adjusted 5.04% expansion in the first quarter, this growth represents the strongest pace of economic growth in three quarters and the ninth consecutive period of growth. Both government spending (10.62%) and fixed investment (4.63%) significantly increased. However, the net trade balance had a negative impact due to declines in both exports (-2.75%) and imports (-3.80%). The central bank projects economic growth for the full year 2023 in the range of 4.5% to 5.3%. Notably, in 2022, Indonesia's economy expanded by 5.31%, the highest growth rate since 2013.

Sovereign credit ratings are of paramount importance in evaluating a nation's creditworthiness, enabling investors to make informed decisions regarding their financial asset investments. A country's credit rating is determined through a complicated process conducted by specialized organizations that consider numerous factors from multiple angles. Researchers have shown a growing interest in understanding the factors influencing sovereign credit ratings, and numerous studies have sought to recognize and simulate these elements from a variety of perspectives. (Ramírez-Rondán et al., 2023).

In theory, the presence of CRAs helps address the agency problem stemming from information asymmetry between the investor (principal) and the issuer (agent). The signals provided by the CRA through credit ratings, investors can differentiate between issuers based on their degree of financial stability. The interest rate on bonds issued is directly correlated with creditworthiness (Ramírez-Rondán et al., 2023).

The effectiveness of CRAs depends on their reputation, which is closely connected to their capacity to create and supervise precise and unbiased credit ratings, thus dealing with the agency issues mentioned earlier. When it comes to sovereign credit ratings, this means evaluating not only macroeconomic elements however, institutional foundations and unpredictability. Uncertainty encompasses the risk associated with a government potentially acting in its self-interest at the expense of investors, thereby exacerbating the agency problem. This variable also encompasses both domestic and international systematic risks. Consequently, higher levels of uncertainty result in lower credit ratings.

Robust political structures force the government to make reliable promises not to take any steps that could jeopardize the interests of investors. Policies and rules that support the growth and stability of the country must also be adopted to maintain these institutions. Strong institutions essentially serve as buffers against the government deviating from beneficial policies or requiring the dissemination of precise and prompt information, thereby reducing the impact of unpredictable environments (Ramírez-Rondán et al., 2023).

Facet of the agency problem pertains to the interaction between CRAs, who function as principals, and issuers, who act as agents. One side of the argument is that issuers may provide CRAs with false information, especially if the rating agency has little access to the issuer's underlying factors. On the other hand, issuers may take advantage of opportunities after receiving a credit rating to hurt investors and damage CRAs' reputations. To mitigate CRAs routinely assess borrower credit risk, employ the threat of a downgrade as a tool for discipline, and are concerned about issuer moral hazard. Investors rely on the assessments provided by SCRs from CRAs to evaluate sovereign entities' willingness and ability to pay their debts (de Haan & Vermeulen, 2021). Because of this, the assessments made by the financial markets and corporate and sub-sovereign organizations are significantly impacted by SCRs (Ballester et al., 2021; Mohapatra et al., 2018; Tran et al., 2021). The financial system requires CRAs to play a critical role a comprehensive evaluation process because, as the famous quote suggests, “With great power comes great responsibility”. However, the existing literature offers a different perspective (Sahibzada et al., 2022).

As suggested by previous research that examined the consequences of credit rating downgrades often utilized panel regressions that grouped multiple nations together, without focusing on any specific nation. This research is aimed to unearth the influencing factors and subsequently construct a system or model capable of predicting or shaping generic credit ratings in Indonesia and its peer group countries. Such a system or model would prove invaluable to governments in their efforts to preempt rating downgrades and encourage rating upgrades, thereby restoring financial stability.

2. LITERATURE REVIEW

A sovereign credit rating assesses a nation's credit risk and indicates the probability that the nation will be able to fulfill its financial obligations. These ratings have a significant impact on public expenditure and the deficit because they establish the interest rate at which new debt can be issued by governments (Overes & van der Wel, 2023).

Most of the prior research concerning investment grade has delved into the factors influencing sovereign credit ratings, concentrating on factors including politics, society, and economy that affect a nation's ranking. Specifically, Fitch's sovereign ratings are determined through a blend of a sovereign rating model and a qualitative overlay (Fitch, 2023). The sovereign rating model is constructed through ordinary least squares estimation using economic and financial variables for all Fitch-rated sovereigns spanning from 2000 to 2019. However, it's important to note that the model's outcomes serve as an initial reference point for a country's rating in each rating review.

Acknowledging that quantitative models cannot comprehensively encompass all the relevant factors influencing sovereign creditworthiness, fitch employs a forward-looking qualitative overlay to account for factors that may not be fully captured by the sovereign rating model output for any specific rating (Fitch, 2023). As per the methodology description and prior research on determinants of sovereign credit ratings, the ultimate credit ratings are influenced by a blend of both objective and subjective information (Slapnik & Loncarski, 2019).

The majority of prior research has primarily concentrated on the impact of objective or "hard" information on sovereign credit ratings. Slapnik & Loncarski (2019) investigated sovereign credit ratings for 98 countries between 1996 and 2017. They employed ordered logistic regression (LR) with random effects and incorporated sentiment analysis of Moody's credit action reports as dependent variables.

The study found that textual sentiment, along with subjectivity, provided valuable insights not captured by traditional SCR determinants, especially when considering factors like governance and institutional quality. Study Takawira & Mwamba (2022) focuses on analyzing SCR using LR to determine their factors and forecast ratings in the future in South Africa. Macroeconomic indicators and SCRs in quarterly format from 1999 to 2020 are included in the dataset. The analysis emphasizes the importance of inflation, exchange rates, and HDDIR as influential variables in predicting credit ratings.

Proença et al. (2021) used an ordered probit model to study the factors influencing sovereign ratings in ten European nations. They covered the financial crisis in two different time periods for their analysis: 1995 to 2006 and 2007 to 2012. According to their findings, several factors, such as GDP per capita, rate of unemployment and balance of current accounts, reserves, government effectiveness, and debt levels, were important in determining the ratings of sovereign debt.

Mutize & Nkhalamba (2020) evaluated the importance of GDP as the main factor influencing long-term foreign currency sovereign ratings employing the binary estimation methods of probit and logit across thirty nations. Their findings refuted the widely held belief suggesting a rise in economic expansion within African countries is significantly raises the probability of sovereign credit rating upgrades. These divergent outcomes underscore the ongoing lack of consensus among researchers regarding the specific economic variables that exert influence over sovereign credit ratings.

De Moor et al. (2018) challenged the methodology employed in earlier research that primarily relied on quantitative variables for SCR analysis. Their study emphasized the importance of incorporating qualitative variables to enhance SCR models. Notably, their research holds significance because most previous studies on South Africa's sovereign ratings adopted a cross-sectional approach, which involved comparing or grouping South Africa with other countries.

According to the Overes & van der Wel (2023), a variety of statistical and machine learning models were used to predict sovereign credit ratings, including ordered logit (OL), support vector machines (SVM), classification and regression trees (CART), multilayer perceptron (MLP), Naïve Bayes (NB), and more. In order of decreasing random cross-validated accuracy, showed the highest predictive accuracy. The models' key variables varied slightly, as evidenced by the analysis of influential factors. Nevertheless, in accordance with economic theory, important factors including GDP per capita and regulatory quality were shared by the two best-performing models, MLP and CART, indicating a potential relationship between improved GDPs per capita and regulatory quality and higher credit ratings in Indonesia.

3. METHOD

This study is quantitative, and statistical methods were employed for data analysis. The research uses country ratings in local currencies from Moody's for Indonesia, Russia, Thailand, and the Philippines. Descriptive statistical tools such as mean, maximum, minimum, and standard deviation were used to understand the distribution of the collected research sample data. These tools helped in answering and testing the formulated hypotheses. To analyze the hypotheses, multiple regression analysis, specifically panel data regression analysis, was used. Time series data are combined with panel data regression with cross-sectional data, resulting in a dataset that includes multiple objects observed over various periods. This method improves efficiency, decreases multicollinearity between variables, increases degrees of freedom, and yields more varied and informative data. E-Views 10.0 was used for the data analysis.

4. RESULT

Descriptive statistics

Descriptive statistics is an approach that summarizes the information found in data sets, presents the information in a way that is easier to understand, and finds patterns in the data using numerical and graphical methods.

Table 1. Descriptive statistics

	Rating	RGDP	Inflation	GGD	CAB	NIIP	FER	CDS	GGR	GDPPC
Mean	11,62	4,01	5,09	31,55	18,67	-5,82	165,07	151,60	9,89	5385,38
Median	12	5	3,80	29,60	8,25	-1,10	115,89	120,80	7,65	3931
Maximum	14	8,50	17,10	68,40	120,29	34,70	473,11	741,15	36,90	15961
Minimum	6	-9,50	-0,90	7,90	-36,69	-43,80	12,98	25,30	0	1093
Std. Dev.	1,53	3,41	3,74	13,73	35,36	17,04	134,10	133,31	8,16	3636,78

Table 1 presents data on sovereign rating and various economic indicators from 76 observations. The sovereign rating scores range from 6 to 14, with an average of 11.62, and exhibit limited variability, as indicated by the small standard deviation of 1.53. RGDP values range from -9.50 to 8.50, with an average of 4.01, and display minimal variation with a standard deviation of 3.41. Inflation data, with values ranging from -0.90 to 17.10 and an average of 29.89, shows relatively low variability, as evidenced by a standard deviation of 13.34. GGD values vary from 7.90 to 68.40, with an average of 31.55, and exhibit limited variation with a standard deviation of 13.73. CAB data, ranging from -36.69 to 120.29 with an average of 18.67, demonstrates significant variation, reflected in a larger standard deviation of 35.36. NIIP data spans from -43.80 to 34.70, with an average of -5.82, and shows substantial variability, indicated by a standard deviation of 17.04. FER values range from 12.98 to 473.11, with an average of 165.07, and exhibit limited variation with a standard deviation of 134.10. CDS data varies from 25.30 to 741.15, with an average of 151.60, and displays relatively low variation, with a standard deviation of 133.31. GGR values range from 0 to 36.90, with an average of 9.89, and show limited variation with a standard deviation of 8.16. Lastly, GDPPC values span from 1093 to 15961, with an average of 5385.38, and demonstrate relatively low variation with a standard deviation of 3636.78.

The data reveals that sovereign rating scores have a relatively narrow range, indicating limited variability, while economic indicators such as RGDP and Inflation exhibit minimal variation. Additionally, variables like GGD and GDPPC display limited variation, while CAB demonstrates significant variability. Conversely, NIIP and FER exhibit substantial variation, and CDS and GGR display relatively low variation.

Table 2. Rating level

No	*Fitch*	*Rating*
1	AAA	20
2	AA+	19
3	AA	18
4	AA-	17
5	A+	16
6	A	15
7	A-	14
8	BBB+	13
9	BBB	12
10	BBB-	11
11	BB+	10
12	BB	9
13	BB-	8
14	B+	7
15	B	6
16	B-	5
17	CCC+	4
18	CCC	3
19	CCC-	2
20	SD	1

Selection of model panel tests

Chow test

Redundant Fixed Effects Tests
Equation: FEM
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	19.637833	(3,65)	0.0000
Cross-section Chi-square	49.034932	3	0.0000

The cross-section Chi-square statistic of 49.034932 with 3 degrees of freedom and a p-value of 0.0000, as well as the cross-section of statistic of 19.637833 with degrees of freedom (3,65) and a p-value of 0.0000, when the probability value is less than 0.05, indicating significance, the fixed effect model is the appropriate model, as demonstrated by the Redundant Fixed Effects Tests for the FEM equation.

Hausman test

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

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	176.616413	6	0.0000

When the probability value is below 0.05, indicating statistical significance, the fixed effect model is the most appropriate model in the Correlated Random Effects - Hausman Test scenario applied to the REM equation, according to the cross-sectional random Chi-Square Statistic of 176.616413, with 6 degrees of freedom and a p-value of 0.0000.

Classical assumptions test

Normality test

The purpose of the normality test is to ascertain whether the distribution of data follows or approximates a normal distribution. The researcher used the Jarque-Bera test by examining its significance value (sig.).

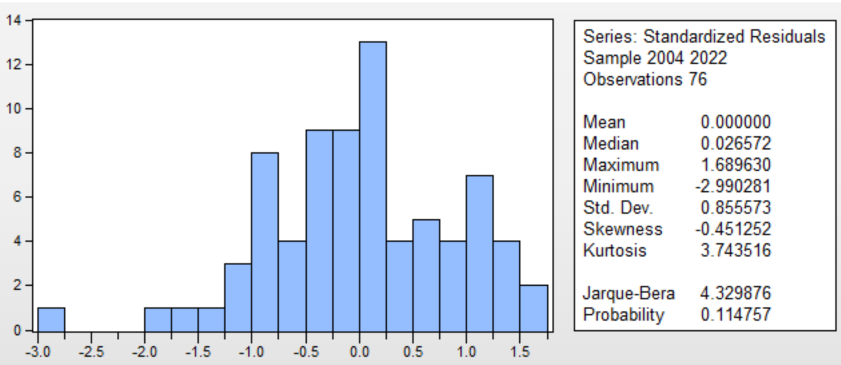

Figure 2 Normality test

Figure 2 shows the outcomes of the normalcy test. From these results, it can be concluded that the Jarque-Bera test yields a significance value (sig.) exceeding 0.05. This indicates that the distribution of residual data is normal or closely approximates a normal distribution.

Multicollinearity test

The multicollinearity test's goal is to determine whether or not the independent variables are correlated. Because this study contains multiple independent variables, the multicollinearity test must be performed.

Table 3. Correlation matrix

Correlation	RGDP	INFLATION	GGD	CAB	NIIP	FER	CDS	GGR	GDPPC
RGDP	1	0,15	0,11	-0,14	-0,30	-0,34	0,04	0,26	-0,32
INFL	0,15	1	-0,28	0,33	0,28	0,22	0,48	-0,16	0,18
GGD	0,11	-0,28	1	-0,60	-0,19	-0,72	-0,06	0,81	-0,68
CAB	-0,14	0,33	-0,60	1	0,63	0,76	0,15	-0,49	0,71
NIIP	-0,30	0,28	-0,19	0,63	1	0,48	0,11	-0,25	0,48
FER	-0,34	0,22	-0,72	0,76	0,48	1	0,05	-0,68	0,95
CDS	0,04	0,48	-0,06	0,15	0,11	0,05	1		
GGR	0,26	-0,16	0,81	-0,49	-0,25	-0,68	0,12	1	-0,69
GDPPC	-0,32	0,18	-0,68	0,71	0,48	0,95	0,08	-0,69	1

The data analysis highlights significant correlations, especially between GGR and GGD, as well as between FER and GDPPC, with correlation coefficients exceeding 0.8, indicating strong associations. To address potential multicollinearity, one variable from each highly correlated pair can be retained. Upon thorough examination of Table 3, it becomes evident that no independent variables display correlation values exceeding 0.8, affirming the absence of a noteworthy multicollinearity problem in the data.

Table 4. Correlation matrix

Correlation	RGDP	INFLATION	GGD	CAB	NIIP	FER	CDS
RGDP	1	0,15	0,11	-0,14	-0,30	-0,34	0,04
INFLATION	0,15	1	-0,28	0,33	0,28	0,22	0,48
GGD	0,11	-0,28	1	-0,60	-0,19	-0,72	-0,06
CAB	-0,14	0,33	-0,60	1	0,63	0,76	0,15
NIIP	-0,30	0,28	-0,19	0,63	1	0,48	0,11
FER	-0,34	0,22	-0,72	0,76	0,48	1	0,05
CDS	0,04	0,48	-0,06	0,15	0,11	0,05	1

The correlation matrix in Table 4 indicates that none of the correlation coefficients between variables exceed 0.8. This finding suggests that there is no significant multicollinearity present in the data. In other words, the independent variables included in the analysis do not have strong linear relationships with each other, which is a positive sign for the reliability of the regression analysis. High multicollinearity can lead to difficulties in identifying the individual each variable's impact on the dependent variable, and its absence is favorable when conducting statistical analyses.

Panel Regression Analysis

Dependent Variable: RATING
Method: Panel Least Squares
Date: 08/28/23 Time: 05:56
Sample: 2004 2022
Periods included: 19
Cross-sections included: 4
Total panel (balanced) observations: 76

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.50389	0.728072	14.42701	0.0000
RGDP	-0.044626	0.036849	-1.211049	0.2303
INFLATION	-0.033824	0.045958	-0.735973	0.4644
GGD	0.002356	0.017442	0.135084	0.8930
CAB	-0.000522	0.006001	-0.086941	0.9310
NIIP	-0.040760	0.011318	-3.601364	0.0006
FER	0.007678	0.001983	3.872384	0.0003
CDS	-0.000682	0.000942	-0.723974	0.4717

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.687949	Mean dependent var	11.61842
Adjusted R-squared	0.639941	S.D. dependent var	1.531597
S.E. of regression	0.919033	Akaike info criterion	2.802138
Sum squared resid	54.90041	Schwarz criterion	3.139481
Log likelihood	-95.48125	Hannan-Quinn criter.	2.936957
F-statistic	14.32994	Durbin-Watson stat	0.704315
Prob(F-statistic)	0.000000		

Simultaneous test

It is feasible to ascertain whether all independent factors taken together have a statistically significant impact on the dependent variable. by applying the F-statistic test. The F-test produced a result of 14.33, and the significance value (p-value) is less than 0.05, or more precisely, 0.000 is less than 0.05, based on the provided chart. This finding suggests that the factors RGDP, Inflation, GGD, CAB, NIIP, FER, and CDS have a statistically significant combined impact on the rating variable. To put it another way, the combination of these variables helps to explain why the rating variable varies.

Partial test

The regression analysis results indicate the following:

a. RGDP has a negative coefficient with a p-value of 0.23, signifying that it has a negative and statistically insignificant impact on the sovereign ratings. Specifically, sovereign ratings fall by 0.045 points for every percent increase in RGDP.

b. Inflation shows a negative coefficient with a p-value of 0.46, indicating a negative and statistically insignificant influence on the sovereign ratings variable. For each additional one percent increase in inflation, the sovereign ratings are expected to decrease by 0.034.

c. GGD has a positive coefficient with a p-value of 0.89, suggesting a positive yet statistically insignificant effect on the sovereign ratings. An additional unit of GGD leads to a mere 0.002 increase in the sovereign ratings.

d. CAB coefficient is negative with a p-value of 0.93, indicating a negative and statistically insignificant impact on the sovereign ratings. An extra billion USD in CAB corresponds to a rating decrease of 0.0005.

e. NIIP displays a negative coefficient with a significant p-value of 0.0006. Each additional unit of NIIP is linked to a substantial 0.04 decrease in the sovereign ratings.

f. FER exhibit a positive coefficient with a significant p-value of 0.0003, suggesting a positive and significant effect on the sovereign ratings. A billion USD increase in FER results in a rating increase of 0.007.

g. CDS has a p-value of 0.47 and a negative coefficient, implying a negative and statistically insignificant impact on the sovereign ratings. An extra unit of CDS corresponds to a rating decrease of 0.0007.

R squared test

The coefficient of determination expresses how much of the variability of the dependent variable can be explained by the independent factors, or R-squared. The adjusted R-squared value in the given model is 0.64 and is computed to lie between 0 and 1. This value indicates that approximately 64% of the variations observed in the sovereign ratings variable can be explained by the RGDP, GGD, CAB, NIIP, FER, and model components that include CDS variables. Factors impact the remaining 36% of the variability or variables that are not considered within the scope of this model.

5. DISCUSSION

RGDP has an insignificant impact on the sovereign ratings. The analysis reveals that RGDP exhibits a negative coefficient in its relationship with sovereign ratings, demonstrating that a rise in RGDP is typically accompanied by a decline in sovereign ratings. This relationship is statistically insignificant, implying that the observed negative impact could be due to random chance rather than a dependable pattern. Sovereign credit ratings wield substantial influence, as they possess the capacity to impact RGDP, either directly or indirectly. An elevation in credit rating can instill confidence in foreign capitalists, and stimulate a nation's economy, while a downgrade can exert profound repercussions, particularly on an already fragile economic situation (Rodríguez & Edgar, 2023). RGDP growth serves as a valuable gauge for evaluating a country's long-term debt sustainability (Benito et al., 2016). Notably, RGDP incorporates sovereign debt within its percentage distribution (Shopov, 2020). Using an ordered probit model, Proença et al. (2022) investigated the factors influencing sovereign ratings in ten European nations and discovered that RGDP per capita was a significant factor in determining sovereign debt ratings.

Inflation has a negative coefficient in its relationship with sovereign ratings, suggesting that a higher inflation rate is associated with lower sovereign ratings, a finding that initially aligns with conventional economic theory where higher inflation can erode a country's economic stability. This observation is not consistent with economic theories that suggest high inflation can be harmful to the economy. Moderate inflation has a positive impact on economic activity by increasing demand and lowering the real burden of debt, which explains the positive correlation between inflation and the rating (Su, 2023). Long-term negative effects of persistently high inflation include deteriorating purchasing power, warping price signals, and weakening investor confidence. The credit rating has significantly declined because of these factors. This emphasizes how crucial moderate inflation rates are to long-term economic stability and creditworthiness. Aras & Öztürk (2018) identified a noteworthy and positive relationship between Turkey's external debt, sovereign credit ratings, and inflation rate.

The GGD carries a positive coefficient in its relationship with sovereign ratings, implying that higher government debt levels are associated with higher sovereign ratings, which might seem counterintuitive since higher debt levels are often considered a risk factor. However, it's crucial to emphasize that this positive association is statistically insignificant. This suggests that the observed positive effect may not be a reliable or meaningful pattern but could result from random chance. This aligns with the conclusions of Cuestas et al. (2015), who hypothesized that the ratio of economic growth will probably be negatively impacted by the ratio of government debt to GDP. Additionally, they suggested that a high public debt burden usually has a nonlinear impact on growth, becoming noteworthy only after a certain threshold is crossed.

The CAB demonstrates a negative coefficient in relation to sovereign ratings, implying that a larger deficit in the current account balance relates to weaker sovereign ratings, which makes sense economically. However, it is essential to underscore that this negative relationship is statistically insignificant. This suggests that the observed negative impact on sovereign ratings may not be a reliable or meaningful pattern and could be attributed to random variation. This is not consistent with the findings of Proença et al. (2021), ratings of sovereign debt were found to be influenced by current account balance. If nations take out foreign loans to invest in capacity, they will be able to pay off their debts (Boumparis et al., 2022).

The study unveils a striking relationship between the NIIP and sovereign ratings. The negative coefficient signifies that a higher deficit in the international investment position is strongly related with lower sovereign ratings, aligning with conventional economic wisdom where a significant imbalance in international financial positions is viewed as a sign of potential credit risk. Importantly, this result carries significant statistical weight, indicating a highly unlikely occurrence by chance alone. These findings underscore the pivotal role of a nation's international financial health in shaping its creditworthiness and overall economic stability, emphasizing the importance of addressing deficits in the international investment position as a critical policy priority for governments aiming to enhance their sovereign ratings.

The study unveils a compelling relationship between FER and sovereign ratings. The positive coefficient indicates that higher levels of foreign exchange reserves are strongly associated with higher sovereign ratings, aligning with conventional economic wisdom where ample reserves are considered a sign of financial stability and ability to meet international obligations. What lends considerable weight to this result is the very low, signifying its high statistical significance. This implies that the observed positive impact on sovereign ratings is highly unlikely to be due to random chance, bolstering the reliability of the finding. These findings underscore the importance of maintaining robust foreign exchange reserves as a crucial factor in bolstering a country's creditworthiness and overall economic resilience, providing valuable insights for policymakers and investors alike.

CDS exhibit a negative coefficient in relation to sovereign ratings, suggesting that higher CDS values, which often indicate increased perceived credit risk, are associated with lower sovereign ratings. However, it is crucial to note that this relationship is statistically insignificant, implying that the observed negative impact on sovereign ratings may not be a reliable or substantial pattern but could be attributed to random variation. The practical significance of this relationship is extremely minimal in sovereign ratings. Rodríguez et al. (2019) a current account deficit may actually serve as a gauge of foreign willingness to close the gap through loans and investments, according to one theory. In this case, a greater current account deficit could be linked to either increased creditworthiness or brighter economic futures for the country, which would raise the sovereign rating.

6. CONCLUSION AND RECOMMENDATIONS

For the peer group countries as assessed, the RGDP variable lacks statistical significance despite its negative relationship with sovereign ratings, implying that RGDP fluctuations do not significantly impact sovereign ratings. Inflation, although negatively associated with sovereign ratings, does not hold statistical significance, indicating that changes in inflation rates have limited influence on sovereign ratings. GGD displays a positive yet statistically insignificant impact on sovereign ratings, suggesting that increases in GGD do not substantially affect sovereign ratings. Despite its negative correlation with sovereign ratings, the CAB lacks statistical significance, indicating that CAB variations do not strongly influence sovereign ratings. The NIIP shows a negative and statistically significant effect on sovereign ratings, signifying its significant impact. Likewise, FER has a positive and statistically significant influence on sovereign ratings, emphasizing their importance. CDS, though negatively linked to sovereign ratings, lacks statistical significance. However, when considering all variables together—RGDP, GGD, CAB, NIIP, FER, and CDS—they collectively have a significant impact on sovereign ratings, underscoring the need for a holistic approach in rating assessments. We offer several recommendations for future research endeavors. Firstly, the incorporation of panel structures into machine learning algorithms could prove highly beneficial in enhancing the predictive accuracy of sovereign credit rating models. This advancement holds the potential to refine the performance of ML models in this domain. Secondly, the expansion of the dataset to include additional explanatory variables holds promise for enhancing the accuracy of certain methods, particularly CART. Furthermore, the inclusion of more variables may yield deeper insights into the factors that significantly influence sovereign credit ratings. These recommendations pave the way for more robust and insightful research in sovereign credit rating modeling.

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