INSTITUTO UNIVERSITÁRIO DE LISBOA

How consistent are the sovereign credit ratings?

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Master in Finance

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this dissertation is dedicated to my parents, whose unwavering belief in me has been my greatest strength. Their support and encouragement have enabled me to pursue and achieve my academic goals.

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Resumo

A inevitável globalização dos mercados financeiros levou a um aumento da procura de classificações soberanas. Nesta tese avaliamos a consistência das classificações soberanas atribuídas pelas três principais agências internacionais, nomeadamente a Moody's, a Standard & Poor's e a Fitch, em períodos de tempo e níveis de classificação específicos. Utilizando a análise de dados em painel, examinamos a evolução das classificações ao longo de vários anos para garantir a sua consistência e contabilizar os efeitos não observados específicos do país. As nossas descobertas indicam que os modelos estimados, utilizando variáveis explicativas quantitativas, têm um bom desempenho dentro e entre agências, e têm um forte poder de previsão global dos ratings a atribuir.

Classificação JEL: C23; C25; E44; F30; F34; G15; H63

Palavras-chave: Classificações de crédito; Dívida soberana; Agências de notação; Dados do painel; Efeito aleatório; Sistema GMM.

Abstract

The inevitable globalization of financial markets has led to an increased demand for sovereign ratings. In this thesis, we assess the consistency of sovereign ratings assigned by the three main and well-known international agencies, namely Moody's, Standard & Poor's, and Fitch, across specific time periods and rating levels. Using panel analysis, we examine the evolution of ratings over several years to ensure their consistency and account for unobserved country-specific effects. Our findings indicate that the estimated models, using quantitative explanatory variables, perform well both within and between agencies, and they have a strong overall prediction power of future ratings.

JEL classification: C23; C25; E44; F30; F34; G15; H63

Keywords: Credit ratings; sovereign debt; rating agencies; panel data; random effect; System GMM.

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List of abbreviations

AGR 07 – the first approach (A for Afonso, G for Gomes, R for Rother, and 07 for 2007)

AGR 11 – the second approach (A for Afonso, G for Gomes, R for Rother, and 11 for 2011)

CDS – Credit default swaps

CRA – Credit Rating Agency

dh – default history

ed – external debt

er – external reserves

FE/FEM – fixed effects methodology

gd – government debt

GDP – Gross Domestic Product

GDPG – Gross domestic product growth

GDPP – Gross domestic product per capita

ge – government effectiveness

GMM – Generalized method of moments

LSDV – Least square dummy variables

OLS – Ordinary Least Squares

R – Sovereign credit ratings

RE/REM – Random effect methodology

S&P/SP – Standard and Poor's

VIF – Variance inflation factor

CHAPTER 1

1. Introduction

Setting the stage for the first section, we describe the crucial role that credit rating agencies play in the financial market and discuss their importance in guiding investment decisions given the possible negative effects of inconsistent ratings on investors, financial institutions, and the financial system's stability. A credit agency is an organization that collects data on companies and other organizations, such as countries, and uses that information to issue a credit rating—a classification that represents the borrower's creditworthiness. Rating agencies possess all the information required by both creditors and borrowers. For instance, they know the amount of money available to an assessed borrower, how many credits they have already used, and their repayment performance throughout the loan's life. These agencies, also known as credit rating agencies (CRAs), reduce information asymmetry between creditors and borrowers and facilitate the lender's decisions to determine whether to loan to an individual, business, or even country with low or high interest, according to their previous history and their likelihood of paying the debt back on time. In principle, a high credit rating means a lower interest rate (and vice versa). Furthermore, it offers prospective qualitative indicators of the likelihood of default and streamlines the assessment of a government's capacity and readiness.

Their significant guidance in investment decisions stems from several key functions. The risk assessment process first evaluates governmental bonds. Investors use these ratings to assess the probability of default and decide on whether to purchase a particular bond. Second, there is investment guidance. Rating agencies provide an effortless reference source for sorting out whether an investment meets the required criteria, given that investors typically have certain risk tolerances and investment objectives. These companies categorize their securities into various risk types, including investment-grade and speculative (junk)-grade. For example, when conducting open market operations, the European Central Bank can only accept bonds with at least one A rating from one of the major rating agencies as collateral. The third factor is market confidence, as higher-rated entities typically attract a larger pool of investors due to their perceived stability and reliability. This affects market liquidity and the cost of capital for the rated entities. Fourth, regulations bind many institutional investors, including pension funds and insurance companies, by dictating the minimum credit quality of investments they can hold. Credit ratings supplement these regulatory requirements for compliance. Fifth, in derivative pricing, specifically credit default swaps (CDS), credit rating agencies ease the pricing of credit default swaps in terms of the cost of protection priced in the CDS market. Sixth, information efficiency condenses complex financial information into a reduced and simplified standard format that allows investors to make a quick assessment of the credit risk associated with the investment.

The three most prominent rating agencies in the world for sovereign credit ratings are Moody's, Standard & Poor's, and Fitch[1]. Because of the substantial effect these three rating agencies have on the financial markets, it is essential to evaluate the solidity of their assessments.

The present thesis presents an empirical test for the coherence of country ratings; such consistency and reliability of ratings, more generally, have been under very rigorous criticism following the 2008 financial crisis[2] among ratings assigned by leading CRAs. In this context, we aim to investigate the existence of significant discrepancies in ratings for specific countries over time, utilizing a combination of pooled ordinary least square (OLS), fixed effect least square dummy variables (LSDV), random effects model, and generalized method of moments (GMM) techniques. Therefore, our analysis will contribute to the current debate on the credibility and predictive power of credit ratings.

To achieve the proposed goal, the study will only consider Middle Eastern countries, providing a longitudinal analysis that captures the long-term trends and shifts in these economies. Starting with 2002, we have compiled a comprehensive yearly data set on sovereign ratings, macroeconomic data, and qualitative variables such as GDP per capita, GDP growth, government debt, government effectiveness, external debt, external reserves, and default history (see, e.g., Afonso et al., 2007).

An overview of the consistency of the results of the sovereign credit ratings in relation to the two models undertaken shows that both models produce reliable and consistent results, although they differ in scope. "Model 1" covers economic indicators from 2002 to 2022 across 8 countries, and "Model 2" covers 2007 to 2022 across 10 countries, both of which exhibit highly coherent credit rating results. This robustness suggests that the resulting sovereign credit ratings for both models are strong and durable across time and different country samples. The findings thus support the validity of the credit rating estimation methods in the two models, meaning that they are most likely appropriate in reflecting real economic fundamentals.

We structure the remainder of the thesis as follows. Section 2 provides an overview of rating systems and reviews the relevant related literature. In Section 3, we discuss our methodological choices with regard to the econometric approaches used. The fourth section introduces the dataset and reports on the empirical analysis, notably in terms of estimation and prediction results. Section 5 summarizes the main findings of this thesis.

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[1] These are private companies, not government agencies. Moody's and Standard & Poor's both have their headquarters in New York, while Fitch has two official HQs, one in New York and the other in London. Each agency gives countries around the world a specific credit rating score. These range from a top mark of "AAA," which stands for "prime," down to the lowest reading of "D," which stands for "in default".

[2] At the height of the global financial crisis in 2008, critics accused rating agencies of misrepresenting the risks associated with mortgage-related securities. Critics alleged that they created complex but unreliable models to calculate the probability of default for individual mortgages as well as for the securitised products created by bundling these mortgages (see https://www.cfr.org/backgrounder/credit-rating-controversy).

CHAPTER 2

2. Literature review

Literature has well documented the relevance of sovereign credit ratings in determining a country's borrowing costs and economic stability. Cantor and Packer (1996) assert that these ratings are primarily determined by a range of economic factors, such as per capita income, GDP growth, inflation rates, fiscal balance, and levels of external debt. They discovered a strong correlation between the sovereign credit ratings and bond yield spreads, demonstrating the country's direct impact on borrowing costs. Kaminsky and Schmukler (2002) observe that sovereign credit ratings show wide economic spillover in the country risk and in the stock market performance of the emerging markets. Membership in international organizations might be relevant to raise the credibility of a country and, therefore, positively impact sovereign credit ratings, according to Dreher and Voigt (2011). Researchers have conducted some empirical studies on the determinant and impact of the sovereign rating on a few external indicators, such as foreign reserves, the current account balance, exports, and terms of trade, all of which appear to be significant factors in papers examining currency crises. Indicators of the government's fiscal policy, budget balance, and debt may also be significant, in addition to variables that evaluate the risk of politics such as social indexes or corruption.

To determine these ratings, credit rating agencies use specific procedures. As White (2010) observes, credit rating agencies have a significant role in financial markets since they assist in minimizing information asymmetry. However, she also raises several concerns about the potential conflicts of interest associated with CRAs, given that issuers, rather than investors, fund them in their business model, potentially compromising their objectivity. Moody's Investors Service 2019 establishes a framework for rating sovereign bonds. The rating focuses on making an unbiased determination between economic resilience, institutional framework, fiscal strength, and susceptibility to event risk.

Afonso, Gomes, and Rother (2011) have identified the short-run and long-run economic determinants that significantly influence sovereign credit ratings. Researchers have identified GDP per capita, GDP growth, government indebtedness, and external debt as critical variables that have a significant impact on sovereign ratings. Ciocchini, Durbin, and Ng's (2003) study on governance also links high spreads to high levels of corruption. On the other hand, Reinhart, Rogoff, and Savastano's (2003) "debt intolerance" hypothesis says that countries that have defaulted or have high debts are seen as risky and have lower credit ratings because of this. Numerous contexts have called into question the high degree of reliability and predictability of sovereign credit ratings.

Table 2-1 provides a summary of some of the associated research and findings.

Table 2-1: previous related studies of determinants of the sovereign credit ratings

Reference	Data	Explanatory variables	Agencies	Methodology
Cantor and Packer (1996)	Cross-section, 1995, 45 Countries	Per capita GDP, GDP growth, Inflation, current account surplus, government budget surplus, debt-to-exports, economic development, default history	S&P Moody's	Linear transformation of the data. OLS estimation.
Monfort and Mulder (2000)	Panel, 1995-1999 (half-yearly), 20 emerging markets	Debt-to-GDP, debt-to-exports, debt service-to-exports, debt reschedule, reserves, current account surplus, real effective exchange rate, export growth, short-term debt share, terms of trade, inflation, growth of domestic credit, GDP growth, government budget surplus, investment-to-GDP ratio, per capita GDP, US treasury bill rate, Spread over T-bonds, regional dummies	S&P Moody's	Linear transformation of the data. Two specifications: static (OLS estimation of the pooled data) and dynamic (error correction specification including as regressor the previous rating and several variables in first differences)
Eliasson (2002)	Panel, 1990-1999, 38 emerging markets	Per capital GDP, GDP growth, inflation, debt-to-exports ratio, government budget surplus, short-term debt to foreign reserves ratio, export growth, interest rate spread	S&P	Linear transformation of the data. Static specification and both fixed and random effects estimation. Dynamic specification.
Hu, Kiesel and Perraudin (2002)	Unbalanced panel, 1981-1998, 12 to 92 countries	Debt service-to-exports ratio, debt-to-GNP ratio, reserves to debt, reserves to imports, GNP growth, inflation, default history, default in previous year, regional dummies, nonindustrial countries dummy	S&P	Ordered probit on pooled data. Two scales: 1-8 and 1-14
Afonso (2003)	Cross-section, 2001, 81 countries	Per capita income, GDP growth, inflation, current account surplus, government budget surplus, debt-to-exports ratio, economic development, default history	S&P Moody's	Linear, logistic and exponential transformation of the data. OLS estimation.
Alexe et al. (2003)	Cross-section 1998, 68 countries	Per capita GDP, inflation, trade balance, export growth, reserves, government budget surplus, debt-to-GDP ratio, exchange rate, domestic credit-to-GDP ratio, government effectiveness, corruption index, political stability	S&P	Linear transformation and OLS estimation.
Canuto, Santos and Porto (2004)	Panel 1998-2002, 66 countries	Per capita GDP, GDP growth, inflation, government debt to receipts, government budget surplus, trade to GDP, debt-toexports ratio, economic development, default history	S&P Moody's Fitch	Linear transformation. OLS, fixed effects and first differences estimation.
Borio and Packer (2004)	Panel 1996-2003, 52 countries	Per capita GDP, GDP growth, inflation, corruption perception index, political risk index, years since default, frequency of high inflation periods, government debt-to-GDP ratio, debt-to-exports ratio, others	S&P Moody's	Linear transformation of data. OLS regression of average credit rating including year dummies as regressors.
Bissoondoyal-Bheenick, Brooks and Yip (2005)	Cross-section 2001, 60 countries	GDP, inflation, foreign direct investment to GDP, current account to GDP, trade to GDP, real interest rate, mobile phones	S&P Moody's Fitch	Estimate an ordered probit with 9 categories
Bissoondoyal-Bheenick (2005)	Panel 1995-1999, 95 countries	Per capita GDP, inflation, govt financial balance to GDP, government debt-to-GDP ratio, real effective exchange rate, export to GDP, reserves, unemployment rate, unit labour cost, current account to GDP, debt-to-GDP ratio	S&P Moody's	Estimate an ordered probit using two scales 1-21 and 1-9 for each year individually.
Butler and Fauver (2006)	Cross-section 2004, 93 countries	Per capita income, debt-to-GDP ratio, inflation, underdevelopment index, legal environment index, legal origin dummies	Institutional Investor	OLS estimation.
António Afonso, Pedro Gomes and Philipp Rother (2007)	Panel of 130 countries from 1970 to 2005	per capita GDP; GDP real growth rate; government debt; government effectiveness; external debt and external reserves; sovereign default indicators	S&P Moody's Fitch	employ panel estimation and random effects ordered probit approaches to assess the explanatory power of several macroeconomic and public governance variables.
Afonso, A., Gomes, P., & Rother, P. (2011)	panel data of 130 countries from 1995 to 2005	GDP per capita; GDP growth rate; Government debt-to-GDP ratio; Government balance; Inflation rate; Current account balance-to-GDP ratio; Exchange rate volatility; External debt-to-GDP ratio; Political stability	S&P Moody's Fitch	ordered probit model

Ferri, Liu, and Stiglitz (1999) contend that the tendency of CRAs to downgrade ratings during crises, as seen during the East Asian financial crisis, intensifies the negative impact of economic recessions. This procyclicality in behavior suggests that at times, CRAs inaccurately reflect the true state of the economy. Moreover, Gärtner, Griesbach, and Jung (2011) note that regional biases influenced the scoring of European countries during the debt crisis. "In this regard, peripheral countries scored lower than their economic fundamentals would warrant, as noted by Gärtner, Griesbach, and Jung in 2011. "Occasionally, the role of CRAs becomes unclear. As information producers, they carry out all correction and alteration needs and provide them to the market at no cost. On the other hand, their rating role involves taking precautionary measures to ensure rating stability. Unpredictable ratings are a cause for concern in terms of contracting because they may lead to costly renegotiation by the parties in question. Rating stability is what gives credit ratings their utility. In practice, ratings should change only when the fundamental credit risk changes, which occurs at a pretty slow rate, argue CRAs. Rating agencies employ approaches that give relatively little weight to transitory shocks that might affect a company's credit risk in the short term, as supported by the underpinning credit risk concept (Frost, 2007). Cantor and Mann (2007) wrote about the trade-off between the accuracy and stability of sovereign credit ratings. They also talked about the problems that come with making constant changes to the ratings, which can give a more accurate picture of the economy but also make market prices more volatile. In this sense, a proper balance between the two—precision and stability—is crucial for optimal functionality.

Scholars have conducted empirical investigations into the potential conflicts of interest that may arise from the dependence of credit rating agencies (CRAs) on issuer fees. Covitz and Harrison (2003) conducted a study to determine if the activities of rating agencies show systematic variations that suggest a preference for issuer interests, commonly known as the "conflict of interest hypothesis," or investor interests, also known as the "reputation hypothesis." Their findings indicate that reputational incentives, rather than conflicts of interest[3], exert the most significant impact on CRAs. These agencies' significant role in capital markets has raised several questions about the legitimacy of their operations. In his 2007 paper, Frost examines and evaluates several points: Should the rating process be more transparent and publicly communicated?

[3] A scenario arises when a Credit Rating Agency (CRA) has a financial incentive to assign a credit rating based on factors other than the issuer's creditworthiness.

Bishara (2011), with regard to the Middle East region, adduces reasons that problems in governance and corruption have continued to pose major obstacles to improved sovereign credit ratings. As a result, this study emphasizes increased governance and anti-corruption frameworks as a means of fostering economic development and stability in the region. Along similar lines, Elbadawi and Makdisi (2007) also stressed that weak institutions and deficiencies in democratic governance result in negative sovereign credit ratings for Arab countries. Such aspects would tend to depress their ratings, increasing economic vulnerability.

CHAPTER 3

3. Methodology

The methodology section of this thesis outlines the rating systems, transformation categories, independent variables, data used, and analytical techniques employed to assess consistency.

3.1. Overview of the rating systems

We will consider credit ratings from the three most prominent rating agencies in the world: Moody's, Standard & Poor's, and Fitch Ratings. Although these institutions do not use the same qualitative codes, there is a relative consensus in their rating levels, as shown in Table 3-1 S&P and Fitch use similar qualitative letter ratings in descending order from AAA to CCC-, while Moody's system goes from Aaa to Caa3.

Table 3-1: Moody's, S&P and Fitch rating system and linear transformations

Characterization of debt and issuer (source: Moody's)		Ratings			Linear transformation
		Moody's	S&P	Fitch	Scale 21
Highest quality	Investment grade threshold	Aaa	AAA	AAA	21
High quality		Aa1 Aa2 Aa3	AA+ AA AA-	AA+ AA AA-	20 19 18
Strong payment capacity		A1 A2 A3	A+ A A-	A+ A A-	17 16 15
Adequate payment capacity		Baa1 Baa2 Baa3	BBB+ BBB BBB-	BBB+ BBB BBB-	14 13 12
Likely to fill obligations, ongoing uncertainty	Speculative grade	Ba1 Ba2 Ba3	BB+ BB BB-	BB+ BB BB-	11 10 9
High credit risk		B1 B2 B3	B+ B B-	B+ B B-	8 7 6
Very high credit risk		Caa1 Caa2 Caa3	CCC+ CCC CCC-	CCC+ CCC CCC-	5 4 3
Near default with possibility of recovery		Ca	CC	CC C	2
Default		C	SD D	DDD DD D	1

3.2. Transforming rating categories

Typically, a qualitative grading scale expresses the rating categories, which requires a transformation into numerical values before the econometric analysis can commence. According to Cantor and Packer (1996), there are inherent problems in mapping credit ratings to numeric values. Although credit ratings are ordinal, i.e., they provide relative ranking, conversion to numeric values may sometimes be a problem because this transformation could give the impression of precision that does not exist in ordinal rating scales. However, they also highlight the frequent use of numerical linear transformations in empirical analyses. Similarly, Reisen and von Maltzan (1999) confirm that numerical linear transformations might result in a loss of qualitative information in the ratings, and researchers should be mindful of the potential distortions. Ferri et al. (1999), on the other hand, make both a linear and a nonlinear transformation, claiming that it is highly unlikely that there is a difference between the categories, with a similar conclusion from both models. Moreover, no such difference is said to exist, according to Standard & Poor's (see Beers and Cavanaugh, 1998), and a linear transformation will be used to classify the ratings into 21 groups (see Table 3-1 inserted above).

3.3. Explanatory variables

The sovereign credit ratings are key measures indicating a country's economic and financial stability. Credit rating agencies analyze a large number of factors related to a country's creditworthiness. Such factors can normally be broadly grouped into two categories: Economic factors include GDP growth rate, inflation rate, balance of current account, external debt, public debt, and fiscal balance. In addition, institutional factors include political stability, governance effectiveness, rule of law, corruption level, and independence of the central bank, among others, such as default history, economic diversification, market finance development, and demographic trends. Since the rating materializes from an analysis of a huge amount of data, finding a reduced set of variables that might explain a country's rating would be very useful. Afonso, Gomes, and Rother (2007) argued that per capita GDP, real growth rate of GDP, governmental debt, effectiveness of governance, external debt, external reserves, and indicators of sovereign default are significant factors that credit rating agencies use; therefore, these factors will be our variables.

Regarding GDP per capita, there is an expected positive impact on ratings. It is anticipated that more developed economies will be less vulnerable to external shocks and will have more stable institutions to prevent government overspending. Real GDP growth is also expected to have a positive impact on ratings. Higher real growth makes it easier for the government to pay its debts. Concerning government debt, the expected impact is negative. An increase in the amount of outstanding government debt suggests a higher cost of interest and should be associated with a higher default risk.

Government effectiveness also has a positive impact. A satisfactory delivery of public services and bureaucratic proficiency should have a positive impact on one's capacity to pay off debt. Voice and accountability, political stability, regulatory quality, rule of law, control of corruption, and government effectiveness are the six World Bank governance indicators that we originally used; only the last one proved to be significant.

External debt is expected to have a negative impact. The risk of further fiscal burdens increases with the amount of external debt owed by the entire economy. This risk can stem either directly from the need to sell off foreign government debt or indirectly from the need to support overly indebted domestic borrowers. Foreign reserves exert a positive impact. Having larger (official) foreign reserves should protect the government from having to default on its foreign currency obligations.

Finally, and as expected, the default history has a negative impact. Previous sovereign defaults could suggest that there is a strong case for using a default to lower the amount of debt that is outstanding. A dummy variable that represents a default's previous occurrence and a variable that counts the number of years when the previous default occurred are used to affect the model. It is anticipated that this variable, which assesses credibility restoration following a default, will have a favorable impact on the rating score.

3.4. Data description

Sovereign credit ratings play a crucial role in the global financial system, influencing countries' access to international capital markets, determining borrowing costs, and signaling economic stability to investors. These ratings, assigned by credit rating agencies (CRAs) like Moody's, Standard & Poor's, and Fitch, are critical in shaping the economic prospects of nations, particularly in emerging markets. However, the methodologies and consistency of these ratings have been subjects of debate among policymakers, economists, and scholars.

In this thesis, we conduct a study on MENA markets. These nations offer a diverse mix of economic structures, political contexts, and levels of development, making them ideal candidates for studying the consistency of the sovereign credit ratings assigned to them using the factors that influence sovereign credit ratings. The first model, dubbed "Model 1," encompasses Bahrain, Cyprus, Egypt, Israel, Kuwait, Lebanon, Turkey, and Tunisia, with data spanning from 2002 to 2022. Meanwhile, the second model, dubbed "Model 2," extends the data range from 2007 to 2022, incorporating additional countries like Morocco and Saudi Arabia. The choice of countries is based only on data availability.

Unlike its counterpart, Model 1 takes into account a longer historical period of 20 years, enabling the observation of a wider range of economic situations in credit ratings. This includes all possible financial crises, Arab springs, booms, and recessions, as well as political events or regional biases that have influenced the ratings. This could give more insight into the stability of sovereign credit ratings over time. Model 2 encompasses a larger number of countries (10 compared to 8) and thus has a broader geographical scope, given that the estimation period begins in 2007. The period is significant and covers the global financial crisis and subsequent economic conditions; therefore, it is highly relevant to recent economic history.

We use the CRA's ratings for the left-hand side of the equation and apply the World Bank's World Development Indicators to the explanatory variables (refer to Appendix A). We shall ignore the fluctuations of our explanatory variables during the year, as we shall do with the credit ratings, and use the yearly data[4] only as our main source. We will implement two distinct approaches for both "Model 1" and "Model 2," utilizing both static and dynamic analysis. The first approach, "AGR 07," uses the same explanatory variables as Afonso (2007). This approach, which includes government effectiveness as one of the key factors, was chosen because Elbadawi and Makdisi (2007) noted that weak institutions and deficiencies in democratic governance lead to negative sovereign credit ratings for Arab countries. Similarly, increased governance and anti-corruption frameworks continue to be major obstacles to improved sovereign credit ratings (Bishara 2011). For the second approach (ARG 11), we utilized the most recent key determinants of the sovereign credit rating, as previously introduced by Afonso et al. (2011), which are GDP per capita, GDP growth, government debt, and external debt.

3.5. Descriptive statistics and correlation analysis

The key components[5] of this analysis provide valuable insights into the factors influencing sovereign credit ratings. High GDP per capita, effective governance, and substantial external reserves are positively associated with better credit ratings. Conversely, high government and external debt negatively impact credit ratings. These findings, as shown in Figure 3-1 and Table 3-2, align with existing literature and offer a nuanced understanding of the determinants affecting sovereign creditworthiness.

[4] Because some monthly or even quarterly data is not published and we don't have access to it, we go with yearly data instead of average data, as with ratings.

[5] Key components are mean, median, mode, range, variance, standard deviation, sharpness, and kurtosis.

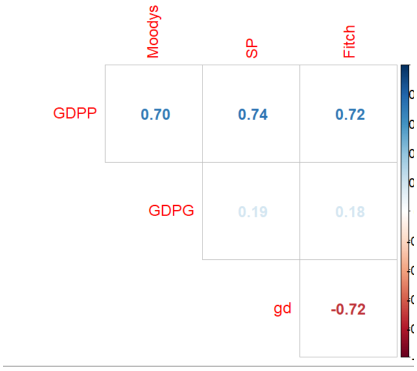

Table 3-2: Correlation matrix

	Moody's	S&P	Fitch
GDPP	0.701	0.736	0.719
GDPG	0.175	0.189	0.183
gd	-0.661	-0.673	-0.720
ge	0.550	0.575	0.554
ed	-0.343	-0.347	-0.299
er	0.096	0.097	0.080
dh	-0.224	-0.193	-0.202

Figure 3-1: Correlation matrix

3.6. Panel analysis

Because of the limited number of observations, a panel data model is the obvious choice to explore the influence of these independent variables over the credit ratings. The data structure in panel format is likely to bias the simple pooled OLS model, even though it yields different results. That's why the fixed effects model is a valuable tool for controlling unobserved heterogeneity, as it helps mitigate the omitted variable bias that can arise in pooled OLS models by including individual-specific intercepts. However, a fixed effects model can be less efficient when the assumption of uncorrelated individual effects and independent variables holds. This is because fixed effects models estimate a separate intercept for each country-specific effect, reducing the degrees of freedom. To find out if a fixed effects model is significantly better than a pooled OLS model, we use an F-test[6] to test the alternative hypothesis. This test assumes that at least one fixed effect is not zero, which shows that the fixed effects model is needed. If there is no correlation between the effects and the explanatory variables, which is unlikely in the case of country ratings and omitted qualitative variables, we will also consider a random effect model. This would imply that the qualitative variables are unrelated to the quantitative variables—that is, there is no correlation between, for example, the quality of institutions and the levels of democracy and corruption. We will perform the Hausman test, a critical tool for determining whether to use a fixed effects (FE) or random effects (RE) model in panel data analysis.

[6] See Hsiao, C. (1986). Analysis of panel data. Cambridge: Cambridge University Press.

3.6.1 Pooled ordinary least square (pooled OLS)

In terms of controlling unobserved heterogeneity and increasing the efficiency of estimations, panel data has this advantage[7] over purely cross-sectional or time series data. The equation is as follows:

$$Y_{it} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \mu_t + \omega_i + \varepsilon_{it} \tag{1}$$

where; i = 1,.., N (countries), t = 1,.., T (periods)

- X_1 [8]represents the first explanatory variable (GDP per capita), similarly X_2 represents the second explanatory variable (GDP growth), …, X_7 represent the final explanatory variable (default history).
- μ_t unobserved time dependent error term (factors affecting Y that vary with time but not across the country, e.g. improvement in the economic conditions).
- ω_i unobserved country dependent error term (e.g. Happiness, life satisfaction, well-being, quality of life, institutions, democracy, rule of law, political constraints, policy implications, panel econometrics, etc.).
- ε_{it} is an idiosyncratic (specific error term) that varies across all countries and times. This term encapsulates the random noise or individual deviations from the model that the country-specific or time-specific effects cannot explain.

The assumptions underlying the pooled OLS are as follows:

1) Regression coefficients are the same for all countries.
2) Regressors are non-stochastic i.e. errors are not correlated with explanatory variables: Cov(ν_{it}, X_{it})= 0 (this assumption is to be sure that our parameters are unbiased and consistent).
3) Error term $\nu_{it} \sim iid(0, \sigma_\nu^2)$ (the error term is identically independently distributed above a mean of zero and with a constant variance in the condition of homoscedasticity).

Using annual data, we pool all observations for the selected countries and estimate one big OLS regression, considering its core assumptions.

$$Y_{it} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \nu_{it} \tag{2}$$

where

$$\nu_{it} = \mu_t + \omega_i \tag{3}$$

[7] See Arellano, M. (2003), Baltagi, B. H. (2008), Wooldridge, J. M. (2010), Greene, W. H. (2012) & Hsiao, C. (2014).

[8] X_{i} is our explanatory variable, which is listed in Section 3.3 as follows: (GDPP, GDPG, gd, ge, ed, er, and dh). We will respect all necessary changes (centering, polynomial terms, etc.) later for the other equations.

3.6.2 Fixed effects lease square dummy variable (FE LSDV)

The fixed-effects[9] model takes into account the effect of country heterogeneity. This is achieved by using dummy variables to generate different intercepts for each country in the pooled data. These intercepts show what the countries are like.

To allow the intercept to vary among countries, we use the following differential intercept dummy (D) variable regression model:

$$Y_{it} = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_3 D_{3i} + \beta_4 D_{4i} + \beta_5 D_{5i} + \beta_6 D_{6i} + \beta_7 D_{7i} + \beta_8 X_{1,it} + \beta_9 X_{2,it} + \beta_{10} X_{3,it} + \beta_{11} X_{4,it} + \beta_{12} X_{5,it} + \beta_{13} X_{6,it} + \beta_{14} X_{7,it} + \varepsilon_{it} \tag{4}$$

where:

D1 = 1 if country 1, 0 otherwise.

D2 = 1 if country 2, 0 otherwise.

D3 = 1 if country 3, 0 otherwise.

D4 = 1 if country 4, 0 otherwise.

D5 = 1 if country 5, 0 otherwise.

D6 = 1 if country 6, 0 otherwise.

D7 = 1 if country 7, 0 otherwise.

Country 8 is the reference category, determined if D1= D2= D3= D4= D5= D6= D7= 0.

Since we have 8 countries, we need only 7 dummy variables to avoid the dummy variable trap, the situation of perfect collinearity[10].

LSDV intercepts are calculated as follows:

Country 8 is the reference category, determined if D1= D2= D3= D4= D5= D6= D7= 0.

$$Y_{it} = \beta_0 + \cancel{\beta_1 D_{1i}} + \cancel{\beta_2 D_{2i}} + \cancel{\beta_3 D_{3i}} + \cancel{\beta_4 D_{4i}} + \cancel{\beta_5 D_{5i}} + \cancel{\beta_6 D_{6i}} + \cancel{\beta_7 D_{7i}} + \beta_8 X_{1,it} + \beta_9 X_{2,it} + \beta_{10} X_{3,it} + \beta_{11} X_{4,it} + \beta_{12} X_{5,it} + \beta_{13} X_{6,it} + \beta_{14} X_{7,it} + \varepsilon_{it} \tag{5}$$

$$E(Y_4) = \beta_0 + \beta_8 X_{1,it} + \beta_9 X_{2,it} + \beta_{10} X_{3,it} + \beta_{11} X_{4,it} + \beta_{12} X_{5,it} + \beta_{13} X_{6,it} + \beta_{14} X_{7,it} + \varepsilon_{it} \tag{6}$$

[9] The term, fixed effect, is because although the intercept (β_{0i}) varies across countries, it's fixed over time; it is time invariant and as a result, has no subscript of t.

[10] Multicollinearity is the occurrence of high intercorrelations among two or more independent variables in a multiple regression model. When a researcher or analyst attempts to determine the most effective use of each independent variable to predict or understand the dependent variable in a statistical model, multicollinearity can lead to skewed or misleading results. In general, multicollinearity can lead to wider confidence intervals that produce less reliable probabilities in terms of the effect of independent variables in a model. For example, a dataset may include variables for income, expenses, and savings. However, because income is equal to expenses plus savings by definition, it is incorrect to include all 3 variables in a regression simultaneously.

The intercepts for country 1, 2, 3, 4, 5, 6 and 7 are calculated in the same way.

3.6.3 Random effect generalized least square model (RE GLS)

Because it incorporates the cross-sectional country-specific error component omega (ω_i) within the composite error term (υ_{it}) rather than the dummy variable as in the fixed effects model and permits a common intercept (β_0), the random effect model (REM) is also known as the error components model. Unlike in FEM, where each country has its own (fixed β_{0i}) intercept value, REM assumes it to be a random variable with a mean (β_0) as an average of all countries' intercepts and a random country-specific error term (ω_i) that measures the random deviation of each country's intercept from the common intercept (β_0), so that

$$\beta_{0i} = \beta_0 + \omega_i \tag{7}$$

Estimating with pooled OLS may result in serially correlated errors[11] even if Cov(ω_i, X_{it}) = 0. The Random effect model (REM) resolves this problem using a generalized least square (GLS) estimation approach that seeks to identify the degree to which serial correlation is a problem and then uses some weighted estimation to fix it by substituting the common error term (υ_{it}) and deriving the mean-corrected within group FE estimator, then transforming the equation by multiplying the means by the GLS parameter (λ).

$$\begin{aligned} Y_{it} - \lambda\bar{Y}_i = {} & \beta_0(1-\lambda) + \beta_1(X_{1,it} - \lambda\bar{X}_{1i}) + \beta_2(X_{2,it} - \lambda\bar{X}_{2i}) \\ & + \beta_3(X_{3,it} - \lambda\bar{X}_{3i}) + \beta_4(X_{4,it} - \lambda\bar{X}_{4i}) + \beta_5(X_{5,it} - \lambda\bar{X}_{5i}) \\ & + \beta_6(X_{6,it} - \lambda\bar{X}_{6i}) + \beta_7(X_{7,it} - \lambda\bar{X}_{7i}) + \upsilon_{it} - \lambda\bar{\upsilon}_i \end{aligned} \tag{8}$$

where λ is defined as

$$\lambda = 1 - \left(\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\omega^2}\right)^{\frac{1}{2}} \tag{9}$$

σ_ε^2 = Variance of idiosyncratic error term, ε_{it}

σ_ω^2 = Variance of country-specific term, ω_i

REM is set to be a quasi-demeaned model because the means ($\bar{Y}_i$ &$\bar{X}_i$) are weighted by GLS parameter, λ [0 ≤ λ ≤ 1].

If σ_ω^2 = 0, λ = 0 and REM estimator ≡ pooled OLS.

If $T\sigma_\omega^2 \rightarrow \infty$, λ = 1, REM estimator ≡ FEM.

If $T\sigma_\omega^2 \rightarrow \infty$, λ = 1, REM estimator ≡ FEM.

[11] individual errors components are neither correlated with each other nor autocorrelated across both cross-section and time periods. Even if Cov(ω_i , ε_{it}) = Cov(ω_i , ω_i) = Cov(ω_i , ε_{is}) = Cov(ε_{it} , ε_{is}) = 0,
we can't be certain that Cov(ω_i , ω_i) = Var(ω_i) = $\sigma_{\omega i}^2$ = 0 [typically, $\sigma^2 > 0$].

3.7. Dynamic regression analysis

Most economic variables, especially those that have to do with credit ratings, are of a discrete, bounded, and ordinal nature, and this puts some restrictions on the econometric methods applicable, making them tend toward dynamic relationships. This means that a variable's value in the present period depends on its value in the past. For instance, a country's previous credit rating might influence its current rating due to factors like reputation, investor expectations, or slow-moving economic conditions. This simply states that an order regression model appears to be the optimal option, but it does not take into account unobserved country heterogeneity because of a lack of qualitative assessment. By including the lagged dependent variables as explanatory variables to control for simultaneity bias, dynamic panel models explicitly account for endogeneity that may arise when explanatory variables correlate with the error term.

CHAPTER 4

4. Empirical analysis

4.1. Panel analysis results

Under the first approach (AGR 07), we looked at the linear relationship between the sovereign credit rating and the seven explanatory variables used in this method to see if simple or quadratic terms would work better. The ratings have a non-linear relationship with government debt, external debt, and external reserves. Refer to Figure 4-1. We checked for overfitting, multicollinearity (refer to Tables 4-1, 4-2, and 4-3), and robustness. By centering these variables, we can reduce multicollinearity by lowering the correlation between the linear and polynomial terms, centering and removing high VIF values (see Tables 4-4, 4-5, and 4-6) from the polynomial model's results. This ensures that the complexity of the model is warranted and does not adversely affect model reliability. Polynomial terms appeared to be the better choice for capturing non-linear effects, and improving fit is critical.

Following these changes, we will make a remediation for the main equations (2, 4, 6, and 8) to be reflected as follows and respectively.

Pooled OLS:

$$Y_{it} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_{3_{centered}}) + \beta_4 (X_{3_{centered^2}}) + \beta_5 X_4 + \beta_6 (X_{5_{centered}}) + \beta_7 (X_{6_{centered}}) + \beta_8 (X_{6_{centered^2}}) + \beta_2 X_7 + \nu_{it} \quad (10)$$

Fixed effects LSDV:

$$Y_{it} = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_3 D_{3i} + \beta_4 D_{4i} + \beta_5 D_{5i} + \beta_6 D_{6i} + \beta_7 D_{7i} + \beta_8 X_{1,it} + \beta_9 X_{2,it} + \beta_{10} \left(X_{3,it_{centered}}\right) + \beta_{11} \left(X_{3,it_{centered^2}}\right) + \beta_{12} X_{4,it} + \beta_{13} \left(X_{5,it_{centered}}\right) + \beta_{14} \left(X_{6,it_{centered}}\right) + \beta_{15} X_{7,it} + \varepsilon_{it} \quad (11)$$

LSDV intercepts:

$$E(Y_4) = \beta_0 + \beta_8 X_{1,it} + \beta_9 X_{2,it} + \beta_{10} \left(X_{3,it_{centered}}\right) + \beta_{11} \left(X_{3,it_{centered^2}}\right) + \beta_{12} X_{4,it} + \beta_{13} \left(X_{5,it_{centered}}\right) + \beta_{14} \left(X_{6,it_{centered}}\right) + \beta_{15} X_{7,it} + \varepsilon_{it} \quad (12)$$

Random effect GLS:

$$Y_{it} - \lambda \bar{Y}_i = \beta_0 (1 - \lambda) + \beta_1 (X_{1,it} - \lambda \bar{X}_{1i}) + \beta_2 (X_{2,it} - \lambda \bar{X}_{2i}) + \beta_3 \left(X_{3,it_{centered}} - \lambda \bar{X}_{3,it_{centered}}\right) +$$

$$\beta_4\left(X^2{}_{3,it_{centered}} - \lambda \bar{X}^2{}_{3,it_{centered}}\right) + \beta_5(X_{4,it} - \lambda \bar{X}_{4i}) + \beta_6\left(X_{5,it_{centered}} - \lambda \bar{X}_{5,it_{centered}}\right) + \beta_7\left(X_{6,it_{centered}} - \lambda \bar{X}_{6,it_{centered}}\right) + \beta_8(X_{7,it} - \lambda \bar{X}_{7i}) + v_{it} - \lambda \bar{v}_i \quad (13)$$

We followed the same strategy with approach 11 (AGR 11), taking into account all the adjustments needed with respect to the fewer predictors as in the first model.

Table 4-1: linear model, polynomial model & spline model comparison for government debt (gd)

	Dependent variable:		
	R		
	(1) Linear	(2) Polynomial	(3) spline
gd	−0.061***		
	(0.005)		
poly(gd, 2)1		−40.077***	
		(3.443)	
poly(gd, 2)2		10.315***	
		(3.443)	
ns(gd, df = 3)1			−10.135***
			(1.487)
ns(gd, df = 3)2			−19.283***
			(2.209)
ns(gd, df = 3)3			−15.519***
			(2.852)
Constant	15.870***	11.548***	17.507***
	(0.468)	(0.266)	(0.824)
Observations	168	168	168
R2	0.437	0.466	0.470
Adjusted R^2	0.434	0.460	0.460
Residual Std. Error	3.524 (df = 166)	3.443 (df = 165)	3.442 (df = 164)
F Statistic	128.960*** (df = 1; 166)	72.068*** (df = 2; 165)	48.430*** (df = 3; 164)
Note:			*p<0.1; **p<0.05; ***p<0.01

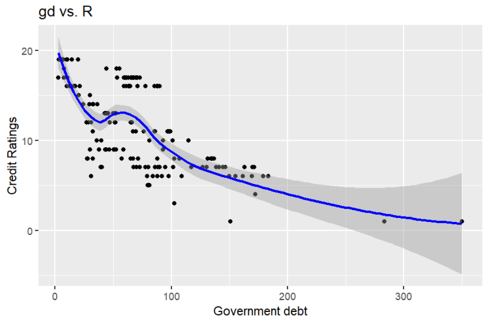

Figure 4-1: Nonlinearity check (gd vs R)

Table 4-2: Simple pooled OLS vs Quadratic terms pooled OLS		
	Dependent variable:	
	R	
	Simple	Quadratic
GDPP	0.0001***	0.00000
	(0.00002)	(0.00002)
GDPG	−0.018	0.036
	(0.044)	(0.035)
gd	−0.051***	−0.099***
	(0.004)	(0.007)
I(gdˆ2)		0.0002***
		(0.00003)
ge	0.970***	2.060***
	(0.327)	(0.299)
ed	−0.00002***	−0.00004***
	(0.00000)	(0.00001)
I(edˆ2)		0.000***
		(0.000)
er	0.00003***	0.0001***
	(0.00001)	(0.00001)
I(erˆ2)		−0.000***
		(0.000)
dh	−6.875***	−4.782***
	(1.715)	(1.369)
Constant	13.885***	16.009***`
	(0.564)	(0.582)
Observations	168	168
R2	0.797	0.876
Adjusted R^2	0.788	0.868
Residual Std. Error	89.680*** (df = 7; 160)	1.700 (df = 157)
F Statistic		111.114*** (df = 10; 157)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4-3: Comparison between Model 1 with simple pooled vs Model 2 with polynomial pooled		
	Model 1 **without** quadratic terms	Model 2 **with** quadratic terms
AIC	742.7842	667.6174
BIC	767.776	705.105

Table 4-4: VIF for pooled OLS with quadratic terms

GDPP	GDPG	gd	I(gd^2)	ge	ed	I(ed^2)	er	I(er^2)	dh
3.4179	1.3715	8.0085	7.2619	2.1682	31.6590	25.3800	10.8940	8.4197	1.2824

Table 4-5: VIF values after centering the polynomial pooled OLS

GDPP	GDPG	gd_centered	(gd_centered^2)	ge	ed_centered	I(ed_centered^2)	er_centered	I(er_centered^2)	dh
3.4179	1.3715	2.5932	2.2620	2.1682	17.9920	13.2270	4.8449	3.1355	1.2824

Table 4-6: VIF values after centering the polynomial pooled OLS and taking out the high VIF values

GDPP	GDPG	gd_centered	(gd_centered^2)	ge	ed_centered	er_centered	I(er_centered^2)	dh
3.4179	1.3715	2.5932	2.2620	2.1682	17.9920	4.8449	3.1355	1.2824

4.1.1 Moody’s

4.1.1.1 Model 1

In the first approach AGR 07, we first estimate the pooled OLS coefficients, which provide a baseline of the principal economic determinants of sovereign credit ratings without accounting for any unobserved heterogeneity between countries. To address this issue, we have also estimated a fixed effects model that incorporates country-specific dummy variables. An F-statistic of 11.0771 with a p-value of 3.14e-10 was also significant when testing the idea that this fixed effects model was better because it took into account factors that were unique to each country. We estimated a random effect model, assuming no correlation between the country-specific effects and independent variables. This assumption was strongly rejected by the Hausman test for randomness of effects, which yielded a chi-squared value of 229.66 and a p-value of 2.2e-16. If anything, this rejection further supports the estimation with the FE model when there is a correlation between individual effects and explanatory variables. Refer to Table 4-7.

In the second approach AGR 11. The pooled OLS regression shows that higher GDP per capita and GDP growth positively influence ratings, whereas higher government debt and external debt have a negative impact. The quadratic term for government debt highlights the potential nonlinearity in how debt levels affect sovereign credit ratings, where the adverse impact of debt diminishes at higher levels. The pooled model explained 76.3% of the variance within credit ratings, as shown in Table 4-7. Subsequently, we progressed into a fixed effects model to control for country-specific differences. The hypothesized model significantly increased the explained variance of the credit rating to 98.6%, thereby validating the differing levels of importance of GDP growth, governmental debt, GDP per capita, and external debt. An F-test comparing the fixed effects model to the pooled OLS model yields an F-statistic of 20.13883 with a p-value of 4.620074e-19. Hence, the fixed effects model does, in fact, do significantly better than the pooled OLS model in accounting for country-specific effects. We also estimated the RE model since it handles individual variability in a different manner. This model accounted for 61.7% of the credit rating variation. To this end, we conducted a Hausman test comparing the fixed effects model against the random effects model. The analysis yielded a Chi-square statistic of 98.605 with a P-value of 2.2e-16, rejecting the null hypothesis that the random effect is the best model for consistency. The fixed effects model generally fits the data better, as it gives a finer way of communicating the country-specific idiosyncratic influences around sovereign credit ratings that are inherently present.

Table 4-7: Panel estimations for Moody's – Model 1 **with** quadratic terms

	Dependent variable:					
	R					
	Pooled OLS		Fixed effects		Random effect	
	1st approach	2nd approach	1st approach	2nd approach	1st approach	2nd approach
GDPP	0.00002	0.0001***	−0.00002	−0.00001	0.00001	0.00004*
	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00002)	(0.00002)
GDPG	0.030	(0.043)	−0.026	0.076**	-0.012	0.079**
	(0.036)	(0.005)	(0.032)	(0.033)	(0.035)	(0.035)
gd_centered	-0.073***	-0.061***	−0.095***	-0.106***	-0.083***	-0.091***
	(0.004)	(0.005)	(0.007)	(0.008)	(0.006)	(0.007)
I(gd_centered2)	0.0002***	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
ge	2.252***		3.176***		2.717***	
	(0.299)		(0.605)		(0.432)	
ed_centered	−0.00002***	−0.00001***	−0.00001**	-0.00001***	−0.00002***	−0.00002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
er_centered	0.0001***		0.00000		0.00002**	
	(0.00001)		(0.00001)		(0.00001)	
I(er_centered2)	-0.000***					
	(0.000)					
dh	-4.920***		-5.937***		-5.720***	
	(1.402)		(1.202)		-(1.331)	
factor(code)1			8.914***	9.114***		
			(0.802)	(0.715)		
factor(code)2			9.658***	12.165***		
			(1.081)	(0.811)		
factor(code)3			11.235***	9.393***		
			(0.473)	(0.422)		
factor(code)4			12.771***	15.860***		
			(1.038)	(0.938)		
factor(code)5			11.676***	9.964***		
			(1.172)	(1.121)		
factor(code)6			14.257***	13.337***		
			(0.625)	(0.708)		
factor(code)7			8.755***	8.793***		
			(0.888)	(0.992)		
factor(code)8			8.309***	8.047***		
			(0.428)	(0.424)		
Constant	10.640***	8.727***			10.647***	10.080***
	(0.322)	(0.359)			(0.461)	(0.552)
Observations	168	168	168	168	168	168
R2	0.869	0.763	0.987	0.983	0.743	0.617
Adjusted R2	0.862	0.756	0.986	0.981	0.730	0.605
Residual Std. Error	1.741 (df = 158)	2.316 (df = 162)	1.481 (df = 152)	1.713 (df = 155)		
F Statistic	116.697*** (df = 9; 158)	104.234*** (df = 5; 162)	733.399*** (df = 16; 152)	671.175*** (df = 13; 155)	459.227***	261.278***
Note:				*p<0.1; **p<0.05; ***p<0.01		

4.1.1.2 Model 2

For ARG 07, before controlling for unobserved country-specific factors, a pooled OLS model revealed that GDP per capita, government debt, external debt, external reserves, and default history significantly affect credit ratings. The F-test, which compared the pooled OLS model to the fixed effects model, yielded substantial support for the latter. The fixed effects model pointed to the significant negative impact of government debt, as shown in Table 4-8, and defaults in history, but highlighted the positively significant effect of the government's effectiveness. The Hausman test rejected the RE model's applicability against the FE model, revealing that the RE model violated the assumption of no correlation between individual effects and regressors. In conclusion, the fixed effects model offers a consistent and practical approach to highlighting the country-specific observable and unobservable variables that determine sovereign credit ratings in this research.

AGR 11, the estimation of a pooled OLS model using GDP per capita and government debt, showed significant predictors of the credit rating, with an R-squared of 0.829. The fixed effects model had an F-statistic of 14.57414 (P- value = 1.251565e-16), which means it was a much better fit. This model yielded an R squared of 0.9873, which indicates substantial predictive power. We also estimated the RE model and found similar results, albeit with some variations in the levels of significance. The Hausman test comparing FE against RE provides a chi-square of 21.265, with P= 0.0007216. This rejects the RE model in favor of the FE model, because the former may be inconsistent. Therefore, we consider the fixed effects model to be the most suitable method for analyzing the factors influencing sovereign credit ratings in this dataset. See Table 4-8.

Table 4-8: Panel estimations for Moody's – Model 2 **with** quadratic terms

	Dependent variable:					
	R					
	Pooled OLS		Fixed effects		Random effect	
	1st approach	2nd approach	1st approach	2nd approach	1st approach	2nd approach
GDPP	0.0001***	0.0001***	0.00000	−0.00001	0.00002	0.00001*
	(0.00002)	(0.00001)	(0.00003)	(0.00003)	(0.00002)	(0.00002)
GDPG	0.009	(0.086)	−0.008	0.077**	-0.006	0.072**
	(0.037)	(0.038)	(0.029)	(0.031)	(0.030)	(0.032)
gd_centered	-0.075***	-0.076***	−0.099***	-0.104***	-0.091***	-0.093***
	(0.005)	(0.005)	(0.007)	(0.008)	(0.006)	(0.007)
I(gd_centered2)	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00003)	(0.00003)	(0.00002)	(0.00003)	(0.00003)	(0.00003)
ge	1.316***		3.004***		2.483***	
	(0.334)		(0.554)		(0.463)	
ed_centered	−0.00001***	−0.00001***	−0.00000**	-0.00001***	−0.00001***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
er_centered	0.0002***		-0.00000		0.00000	
	(0.0000)		(0.00000)		(0.00000)	
I(er_centered2)	-0.000***					
	(0.000)					
dh	-5.108***		-5.380***		-5.358***	
	(1.393)		(1.046)		-(1.121)	
factor(code)1			9.452***	10.186***		
			(0.809)	(0.837)		
factor(code)2			9.236***	11.957***		
			(1.052)	(0.989)		
factor(code)3			10.517***	8.988***		
			(0.481)	(0.434)		
factor(code)4			13.072***	15.966***		
			(1.136)	(1.186)		
factor(code)5			12.041***	11.139***		
			(1.227)	(1.129)		
factor(code)6			14.628***	13.415***		
			(0.641)	(0.721)		
factor(code)7			10.733***	9.838***		
			(0.429)	(0.403)		
factor(code)8			12.255***	10.645***		
			(1.245)	(0.870)		
factor(code)9			6.899***	8.586***		
			(1.446)	(1.657)		
factor(code)10			8.545***	8.354***		
			(0.431)	(0.420)		
Constant	10.623***	8.928***			10.511***	9.946***
	(0.349)	(0.303)			(0.481)	(0.526)
Observations	160	160	160	160	160	160
R2	0.879	0.829	0.991	0.987	0.761	0.679
Adjusted R2	0.872	0.824	0.990	0.986	0.749	0.669
Residual Std. Error	1.718 (df = 150)	2.019 (df = 154)	1.269 (df = 142)	1.507 (df = 145)		
F Statistic	121.471*** (df = 9; 150)	149.379*** (df = 5; 154)	888.667*** (df = 18; 142)	52.366*** (df = 15; 145)	481.546***	325.677***
Note:					*p<0.1; **p<0.05; ***p<0.01	

4.1.2 S&P

4.1.2.1 Model 1

Initially, the pooled OLS model for ARG 07 showed a positive correlation between GDP per capita and credit ratings, with negative coefficients indicating government debt and a history of defaults significantly enhancing the model. The study showed that government effectiveness and foreign exchange, as presented in Table 4-9, had significant positive effects. But if we switch to the FE LSDV model, which accounts for unobserved entity-specific heterogeneity, GDP per capita will change the sign and become negatively significant. This demonstrates the correlation between lower credit ratings and differences in GDP per capita within an entity. Government debt and default history continue to have significantly negative impacts, while government effectiveness and external reserves are positive and significant. An F-test for dominance of the fixed effects over the pooled OLS estimated the former to be far superior, providing evidence of the need to control for entity-specific effects. Under the assumption that such entity-specific effects were uncorrelated with the regressors, the random effect model exhibits slightly less explanatory power but also confirms government debt, government effectiveness, external debt, and default history as significant. Compared with the null hypothesis that the random effects model is consistent, the Hausman test again gave strong evidence that the fixed effects model should be chosen because of the possible correlation between entity-specific effects and explanatory variables.

The outcomes of our estimations for ARG 11 show that in the pooled OLS model, GDP per capita, GDP growth, government debt, and external debt are all significant factors that affect sovereign credit ratings. High GDP per capita and high GDP growth associate positively with ratings in sovereign credit ratings, while government and external debt associate negatively with ratings. It accounts for about 80.5% of the rating variance. The FE model recorded about 98.5% of the observed variance in credit ratings, as indicated in Table 4-9, and thus fit very strongly. The F-test comparing models show that this fixed effect model outperforms the pooled OLS model and is extremely significant at 4.877185e-17, proving that adding country-specific effects improves the model's fit. The RE model explained about 64% of the variability in credit ratings and showed almost similar significant results in all factors: GDP per capita, GDP growth, government debt, and external debt. Additionally, the Hausman test showed that the fixed effects model was preferable to the random effects model. It returns a chi-squared statistic of 95.427 with a p-value of 2.2e-16, indicating that the fixed effects model is more ideal in showing higher invariance, but the random effects model can turn out to be biased.

Table 4-9: Panel estimations for S&P – Model 1 **with** quadratic terms

	Dependent variable: R					
	Pooled OLS		Fixed effects		Random effect	
	1st approach	2nd approach	1st approach	2nd approach	1st approach	2nd approach
GDPP	0.00004**	0.0001***	−0.0001**	−0.00001	0.00000	0.0001***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
GDPG	0.058**	(0.108)	0.030	0.095**	.028	0.094**
	(0.034)	(0.038)	(0.031)	(0.030)	(0.033)	(0.033)
gd_centered	-0.070***	-0.059***	−0.080***	-0.092***	-0.076***	-0.080***
	(0.004)	(0.005)	(0.007)	(0.007)	(0.005)	(0.006)
I(gd_centered2)	0.0002***	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
ge	2.099***		2.506***		2.410***	
	(0.279)		(0.580)		(0.382)	
ed_centered	−0.00002***	−0.00001***	−0.00001**	-0.00001***	−0.00002***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
er_centered	0.00005***		0.00002***		0.00002**	
	(0.00001)		(0.00001)		(0.00001)	
I(er_centered2)	-0.000***					
	(0.000)					
dh	-3.106***		-3.853***		-3.684***	
	(1.307)		(1.153)		(1.252)	
factor(code)1			10.960***	9.932***		
			(0.769)	(0.660)		
factor(code)2			12.191***	12.835***		
			(1.037)	(0.748)		
factor(code)3			10.851***	9.260***		
			(0.454)	(0.389)		
factor(code)4			13.560***	15.801***		
			(0.995)	(0.865)		
factor(code)5			13.828***	11.008***		
			(1.124)	(1.033)		
factor(code)6			12.360***	11.751***		
			(0.600)	(0.653)		
factor(code)7			8.592***	8.218***		
			(0.851)	(0.915)		
factor(code)8			8.754***	8.030***		
			(0.411)	(0.391)		
Constant	10.111***	8.537***			10.372***	9.745***
	(0.301)	(0.321)			(0.404)	(0.476)
Observations	168	168	168	168	168	168
R2	0.884	0.806	0.988	0.985	0.768	0.640
Adjusted R2	0.877	0.800	0.987	0.984	0.756	0.629
Residual Std. Error	1.623 (df = 158)	2.070 (df = 162)	1.420 (df = 152)	1.580 (df = 155)		
F Statistic	133.405*** (df = 9; 158)	134.668*** (df = 5; 162)	801.453*** (df = 16; 152)	794.540*** (df = 13; 155)	524.899***	287.861***
Note:				*p<0.1; **p<0.05; ***p<0.01		

4.1.2.2 Model 2

In the first approach, the pooled OLS model shows that GDP per capita and external reserves have significant positive influences on credit ratings, while government debt and default history have insignificant negative effects. However, GDP growth is insignificant. It is shown that the fit is fairly great, R-square 0.871. Controlling for unobserved country-specific characteristics, the FE model produced a similar negative impact from government debt and default history, with a very high R-squared of 0.9899. According to Table 4-10. The F-test of pooled OLS vs. fixed effects pointed to a significant improvement by the fixed effects model—the F-statistic being 12,093, $p < 0.001$—thus supporting the use of this model. The RE model fitted reasonably well, with an R-squared value of 0.693, showing that GDP per capita, government debt, external debt, and default history are significant factors, while others like GDP growth and external reserves are not. Hausman's test represented the rejection of a random effects model in favor of a fixed effects model: chi-square = 24.019, $p = 0.002275$. Indeed, the latter is more appropriate since it controls for the correlations between regressors and individual-specific effects.

In the second approach. Based on Table 4-10, the pooled OLS regression explained 83.57% of the variation in credit ratings. The fixed effects LSDV model was applied, which presented that GDP growth positively influences credit ratings and government debt is still negatively significant. However, GDP per capita and external debt were insignificantly different from zero in this model. Fixed effects had a higher explanatory power, with an adjusted R-square value of 98.74%. The F-test of pooled OLS against fixed effects was significant: $F = 14.57438$, $p < 1.250888e{-16}$. This suggests that the fixed effects model is appropriate. Additionally, the RE model has been estimated where GDP per capita, GDP growth, government debt, and external debt are statistically significant predictors, as stated in Table 4-10, with 65.17% R-squared. However, the Hausman test confirmed that, with a chi-square of 23.512 and p-value of 0.0002693, the random effect model was inconsistent, and thus the fixed effects model should be preferred for this analysis.

Table 4-10: Panel estimations for S&P – Model 2 **with** quadratic terms

			Dependent variable:			
			R			
	Pooled OLS		Fixed effects		Random effect	
	1st approach	2nd approach	1st approach	2nd approach	1st approach	2nd approach
GDPP	0.0001***	0.0001***	-0.00001	−0.00001	0.00004	0.00001*
	(0.00002)	(0.00001)	(0.00003)	(0.00003)	(0.00002)	(0.00002)
GDPG	0.035	(0.089)	0.037	0.091**	.025	0.078**
	(0.037)	(0.036)	(0.031)	(0.029)	(0.032)	(0.030)
gd_centered	-0.070***	-0.068***	−0.084***	-0.086***	-0.079***	-0.081***
	(0.005)	(0.004)	(0.007)	(0.007)	(0.006)	(0.006)
I(gd_centered2)	0.0002***	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
ge	1.206***		1.257***		1.536***	
	(0.333)		(0.593)		(0.478)	
ed_centered	−0.00001***	−0.00001***	−0.00001	-0.00001***	−0.00001***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
er_centered	0.0001***		0.00000		0.00000	
	(0.0000)		(0.00000)		(0.00000)	
I(er_centered2)	-0.000***					
	(0.000)					
dh	-3.535***		-3.824***		-3.793***	
	(1.388)		(1.119)		-(1.167)	
factor(code)1			10.727***	10.821***		
			(0.866)	(0.791)		
factor(code)2			12.153***	12.998***		
			(1.126)	(0.934)		
factor(code)3			9.628***	8.822***		
			(0.515)	(0.410)		
factor(code)4			15.556***	16.654***		
			(1.216)	(1.121)		
factor(code)5			13.267***	12.713***		
			(1.313)	(1.218)		
factor(code)6			12.326***	11.641***		
			(0.686)	(0.681)		
factor(code)7			11.231***	10.691***		
			(0.459)	(0.381)		
factor(code)8			11.464***	11.263***		
			(1.333)	(0.823)		
factor(code)9			8.009***	8.557***		
			(1.548)	(1.567)		
factor(code)10			8.364***	8.118***		
			(0.461)	(0.397)		
Constant	10.283***	8.853***			10.336***	9.945***
	(0.348)	(0.286)			(0.493)	(0.501)
Observations	160	160	160	160	160	160
R2	0.871	0.836	0.990	0.989	0.693	0.652
Adjusted R2	0.863	0.830	0.989	0.987	0.677	0.640
Residual Std. Error	0.713 (df = 150)	1.908 (df = 154)	1.358 (df = 142)	1.425 (df = 145)		
F Statistic	112.510*** (df = 9; 150)	156.617*** (df = 5; 154)	770.471*** (df = 18; 142)	838.575*** (df = 15; 145)	340.791***	288.242***
Note:					*p<0.1; **p<0.05; ***p<0.01	

4.1.3 Fitch

4.1.3.1 Model 1

The main candidate for the first approach is a pooled OLS model, bundling several countries and ignoring country-specific effects. As noted in Table 4-11, the model's R-squared was 0.88, indicating that it will have a rather large explanatory power, but not for idiosyncratic—country-specific—variation. In the same breath, we undertook the fixed effects LSDV model with the inclusion of country-specific dummy variables.

We obtained a higher R-squared at 0.99 and subsequently emerged with better explanatory power when showing the importance of government debt, government effectiveness, and default history on the credit ratings. The F-test rejected the null hypothesis, indicating the FE model is more appropriate than the RE model. On the other hand, while the random effect model capturing individual-specific and idiosyncratic effects did turn out to be a reasonable fit based on an R-squared of 0.765, it was less useful in properly specifying the effects compared to the fixed effects model. The Hausman test confirmed that fixed effects outperform the RE model.

The second approach, pooled OLS model-based regression, indicates that the logarithm of GDP per capita, GDP growth, government debt, and external debt had a significant influence on sovereign credit rating, explaining 80.08% of the variation. This model does not account for country-specific effects. Most importantly, the fixed effects model had an unusually high R-squared of 98.68% as per Table 4-11. An F-test comparing the fixed effects model to the pooled OLS model revealed that the fixed effects model has a much better fit, with an F-statistic of 15.88673 and a p-value of 1.240794e-15. This affirms the use of fixed effects to account for variation at the country level. The R-squared value from the random effect model in Table 4-11 was 67.24%, providing very valuable results for GDP per capita and growth with positive and significant effects and negative effects associated with government and external debts. The Hausman test yielded results with a chi-square of 95.195 and a p-value of $< 2.2e-16$. This suggests that the fixed effects model is more consistent in controlling correlated regressors and individual effects than the random effect model.

Table 4-11: Panel estimations for Fitch – Model 1 **with** quadratic terms

	Dependent variable:					
	R					
	Pooled OLS		Fixed effects		Random effect	
	1st approach	2nd approach	1st approach	2nd approach	1st approach	2nd approach
GDPP	0.00004**	0.0001***	−0.0001**	−0.00001	-0.0000	0.0001***
	(0.00002)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
GDPG	0.028**	(0.084)	-0.0002	0.080**	-0.003	0.075**
	(0.033)	(0.036)	(0.029)	(0.029)	(0.031)	(0.032)
gd_centered	-0.073***	-0.064***	−0.082***	-0.094***	-0.080***	-0.082***
	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.006)
I(gd_centered2)	0.0002***	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00003)	(0.00003)	(0.00002)	(0.00003)	(0.00002)	(0.00003)
ge	1.933***		3.017***		2.555***	
	(0.276)		(0.538)		(0.386)	
ed_centered	−0.00002***	−0.00001***	−0.00001**	-0.00001***	−0.00001***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
er_centered	0.00004***		0.00001***		0.00001**	
	(0.00001)		(0.00001)		(0.00001)	
I(er_centered2)	-0.000***					
	(0.000)					
dh	-3.814***		-4.480***		-4.411***	
	(1.293)		(1.068)		(1.175)	
factor(code)1			11.072***	10.607***		
			(0.712)	(0.637)		
factor(code)2			12.163***	13.823***		
			(0.960)	(0.722)		
factor(code)3			11.677***	9.882***		
			(0.421)	(0.375)		
factor(code)4			13.041***	15.887***		
			(0.922)	(0.834)		
factor(code)5			14.526***	12.077***		
			(1.041)	(0.997)		
factor(code)6			12.840***	12.094***		
			(0.556)	(0.630)		
factor(code)7			8.022***	7.874***		
			(0.789)	(0.882)		
factor(code)8			9.169***	8.640***		
			(0.380)	(0.377)		
Constant	10.402***	9.091***			10.772***	10.073***
	(0.297)	(0.303)			(0.413)	(0.435)
Observations	168	168	168	168	168	168
R2	0.883	0.822	0.990	0.987	0.765	0.672
Adjusted R2	0.876	0.817	0.989	0.986	0.753	0.662
Residual Std. Error	1.606 (df = 158)	1.954 (df = 162)	1.316 (df = 152)	1.524 (df = 155)		
F Statistic	132.304*** (df = 9; 158)	149.924*** (df = 5; 162)	974.052*** (df = 16; 152)	890.118*** (df = 13; 155)	516.303***	332.511***
Note:				*p<0.1; **p<0.05; ***p<0.01		

4.1.3.2 Model 2

In AGR 07, the pooled OLS model, which excludes country collective effects, had a strong explanatory power, highlighted by an R-squared value of 0.9043, revealing the significant impacts of GDP per capita and government debt. Conversely, the fixed effects (LSDV) approach that accommodates country-specific dummy variables to account for unobserved heterogeneity showed an even better fit with an R-squared value of 0.9929. Although the random effect model was significant with regard to cross-country variation, it had lower R-squared values of 0.7809, indicating that most of the variance exists within countries. The Hausman test indicated a preference for the fixed effects model over the random effects model.

The AGR 11. The pooled OLS model reveals that GDP per capita and government debt are significant predictors with an R-square of 0.8719. Incorporating country-specific dummies, the fixed effects model identified a very substantial improvement in fit, with an R-square of 0.9909 as noted in Table 4-12. The results showed that GDP growth and government debt have significant effects, whereas GDP per capita and external debt do not. The value of the F-test statistic is 11.40909, while the p-value is 2.113089e-13, so the FE model fits significantly better than does the pooled model. The RE model's R-squared is 0.727.

The Hausman test results—a chi-squared value of 21.771 and a p-value of 0.0005787—suggest that FE is better than RE because the FE estimator stays accurate even when unobserved heterogeneity is present.

Table 4-12: Panel estimations for Fitch – Model 2 **with** quadratic terms

	Dependent variable:					
	R					
	Pooled OLS		Fixed effects		Random effect	
	1st approach	2nd approach	1st approach	2nd approach	1st approach	2nd approach
GDPP	0.0001***	0.0001***	-0.00001	0.00000	0.00003	0.0001*
	(0.00002)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
GDPG	0.007	(0.069)	0.002	0.067**	-0.005	0.057**
	(0.031)	(0.032)	(0.027)	(0.027)	(0.027)	(0.027)
gd_centered	-0.076***	-0.076***	−0.089***	-0.093***	-0.084***	-0.086***
	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.005)
I(gd_centered2)	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00002)
ge	1.193***		2.084***		1.837***	
	(0.283)		(0.509)		(0.398)	
ed_centered	−0.00001***	−0.00001***	−0.0000	-0.00001***	−0.00001***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
er_centered	0.0001***		0.00000		0.00000	
	(0.0000)		(0.00000)		(0.00000)	
I(er_centered2)	-0.000***					
	(0.000)					
dh	-4.006***		-4.289***		-4.287***	
	(1.177)		(0.961)		(1.006)	
factor(code)1			11.035***	11.160***		
			(0.743)	(0.726)		
factor(code)2			11.760***	13.213***		
			(0.967)	(0.857)		
factor(code)3			10.944***	9.690***		
			(0.442)	(0.376)		
factor(code)4			13.993***	15.779***		
			(1.043)	(1.029)		
factor(code)5			13.527***	12.454***		
			(1.127)	(1.118)		
factor(code)6			13.126***	12.118***		
			(0.589)	(0.625)		
factor(code)7			11.682***	10.827***		
			(0.394)	(0.350)		
factor(code)8			11.794***	11.637***		
			(1.144)	(0.755)		
factor(code)9			8.239***	9.157***		
			(1.329)	(1.437)		
factor(code)10			9.050***	8.677***		
			(0.396)	(0.364)		
Constant	10.757***	9.503***			10.844***	10.298***
	(0.295)	(0.249)			(0.398)	(0.418)
Observations	160	160	160	160	160	160
R2	0.904	0.872	0.993	0.991	0.781	0.727
Adjusted R2	0.899	0.868	0.992	0.990	0.769	0.719
Residual Std. Error	1.452 (df = 150)	1.658 (df = 154)	1.165 (df = 142)	1.307 (df = 145)		
F Statistic	157.543*** (df = 9; 150)	209.701*** (df = 5; 154)	1,102.483*** (df = 18; 142)	1,048.929*** (df = 15; 145)	538.290*	411.058***
Note:					*p<0.1; **p<0.05; ***p<0.01	

4.2. Dynamic analysis

Given the dynamic nature of the model and the presence of potential endogeneity in the explanatory variables, the Generalized Method of Moments (GMM) approach—both System GMM and Difference GMM—was considered a robust estimation method.

Such methods are perfectly suited to panel data models with lagged dependent variables. However, neither System GMM nor Difference GMM was able to provide consistent estimates after several attempts. Singularity problems: Warnings about singular matrices and excessive proliferation of instruments also plagued the models, resulting in impossible estimates. Of course, any actions that might have lowered the level of multicollinearity-centering of the lagged dependent variable would have changed the way time works in the model, so they weren't appropriate in this case. Although there is no high collinearity between the lagged dependent variable and other variables (as indicated in Table 4-13), the singularity issue remained.

Table 4-13: VIF values for collinearity between the lagged dependent variable and other variables

lag(R, 1)	gd_centered	I(gd_centered^2)	ge	ed_centered	er_centered	dh
6.305355	5.878862	2.517766	1.925616	3.497141	2.101536	1.118371

Therefore, to overcome this limitation of GMM, we used the random effect model as a complementary approach for such cases. Although GMM is specially set for handling endogeneity, the random effect model should be fit in this case since evidence from preliminary tests shows no apparent sign of the presence of significant endogeneity. In addition, it helped to reduce multicollinearity problems with the explanatory variables and generate, again, more interpretable coefficients without affecting the time dynamics.

The random effect model provides a more stable estimation framework for this analysis, particularly after centering the explanatory variables. Although it does not explicitly account for dynamic endogeneity, the overall stability and interpretability of the results make it a reliable alternative to GMM in this context.

Of course, extending the sample size is a clear direction for future research to apply System GMM or Difference GMM more robustly. Second, other methods, such as instrumental variables IV regression, would provide yet another way of addressing endogeneity.

4.3. Discussion

The panel analysis shows that the second approach (ARG 11), which uses GDP per capita, GDP growth, government debt, and external debt as explanatory variables (as talked about by Afonso et al. 2011), is the best overall approach because these variables do a decent job of showing how the credit rating changes. Combined with the FE LSDV, it outperforms pooled OLS and RE in the F-test and Hausman test. We will stick with model 1, as it provides a large time frame for test the consistency of the ratings (we will start with Moody's ratings) using the following methods.

4.3.1 Robustness check

Robustness checks ensure that our results are not sensitive to specific assumptions or models, and they're reliable across different models.

Clustered standard errors. Table 4-14 indicate that adjustments for potential clustering by country did not change the significance of key variables.

Heteroskedasticity robust standard errors. Once again, the significance of key coefficients remained unchanged. See Table 4-15

Alternative specifications. Using simple terms (Table 4-16) and quadratic terms (Table 4-7 mentioned above), the alternative model provided consistent results, reinforcing the robustness of the findings.

Table 4-14: Clustered standard errors for Moody's

	Dependent variable:
GDPP	−0.00001
	(0.00003)
GDPG	0.076
	(0.067)
gd centered	−0.106***
	(0.024)
I(gd centeredˆ2)	0.0002***
	(0.0001)
ed centered	−0.00001***
	(0.00000)
factor(code)1	9.114***
	(0.643)
factor(code)2	12.165***
	(0.860)
factor(code)3	9.393***
	(0.392)
factor(code)4	15.860***
	(0.944)
factor(code)5	9.964***
	1.590)
factor(code)6	13.337***
	(1.572)
factor(code)7	8.793***
	(1.019)
factor(code)8	8.047***
	(0.434)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-15: Heteroskedasticity robust standard errors for Moody's

	Dependent variable:
GDPP	−0.00001
	(0.00002)
GDPG	0.076
	(0.047)
gd centered	−0.106***
	(0.009)
I(gd centeredˆ2)	0.0002***
	(0.0002)
ed centered	−0.00001***
	(0.00000)
factor(code)1	9.114***
	(0.589)
factor(code)2	12.165***
	(0.794)
factor(code)3	9.393***
	(0.590)
factor(code)4	15.860***
	(0.642)
factor(code)5	9.964***
	(0.991)
factor(code)6	13.337***
	(0.689)
factor(code)7	8.793***
	(0.703)
factor(code)8	8.047***
	(0.416)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-16: Panel estimations for Moody's – Model 1 **without** quadratic terms

			Dependent variable:			
			R			
	Pooled OLS		Fixed effects		Random effect	
	1st approach	2nd approach	1st approach	2nd approach	1st approach	2nd approach
GDPP	0.0001***	0.0001***	−0.00003	−0.00001	0.00003	0.0001***
	(0.00002)	(0.00002)	(0.00003)	(0.00003)	(0.00002)	(0.00002)
GDPG	−0.018	0.080*	−0.028	0.077**	−0.027	0.072*
	(0.044)	(0.044)	(0.039)	(0.038)	(0.041)	(0.040)
gd	−0.051***	−0.049***	−0.057***	−0.066***	−0.056***	−0.061***
	(0.004)	(0.004)	(0.007)	(0.006)	(0.005)	(0.006)
ge	0.970***		2.627***		1.825***	
	(0.327)		(0.727)		(0.468)	
ed	−0.00002***	−0.00001***	−0.00001**	−0.00001**	−0.00002***	−0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
er	0.00003***		0.00001		0.00002**	
	(0.00001)		(0.00001)		(0.00001)	
dh	−6.875***		−6.932***		−6.998***	
	(1.715)		(1.446)		(1.559)	
factor(code)1			14.877***	15.478***		
			(0.939)	(0.878)		
factor(code)2			14.993***	17.341***		
			(1.436)	(1.064)		
factor(code)3			14.831***	14.096***		
			(0.749)	(0.796)		
factor(code)4			17.907***	21.274***		
			(1.490)	(1.180)		
factor(code)5			19.688***	18.677***		
			(1.088)	(1.106)		
factor(code)6			17.468***	17.488***		
			(1.170)	(1.229)		
factor(code)7			13.593***	14.277***		
			(1.349)	(1.427)		
factor(code)8			13.506***	14.016***		
			(0.605)	(0.610)		
Constant	13.885***	12.980***			15.034***	15.202***
	(0.564)	(0.610)			(0.707)	(0.806)
Observations	168	168	168	168	168	168
R2	0.797	0.742	0.981	0.976	0.663	0.544
Adjusted R2	0.788	0.736	0.979	0.975	0.649	0.533
Residual Std. Error		117.179*** (df = 4; 163)	1.789 (df=153)	1.986 (df = 156)		194.766***
F Statistic	89.680*** (df=7; 160)		532.475*** (df=15; 153)	537.808*** (df = 12; 156)	315.404***	
Note:					*p<0.1; **p<0.05; ***p<0.01	

4.3.2 Interaction terms

Interaction terms in regression models enable the evaluation of how the relationship between two variables varies based on the value of a third variable.

As noted in Table 4-17, the interaction term (GDP per capita) has a significant negative impact, with a p-value of 0.0132 when adding an interaction term between GDPP and GDPG with the main effects. When we only add the interaction term without the main effects, the interaction term (GDPP) shifts to be insignificant, with a p-value of 0.77.

Table 4-17: Interaction term estimation for Moody's with/without the main effect

	Dependent variable:	
	R	
	With effects	Without effects
GDPP	0.00002	
	(0.00003)	
GDPG	0.184**	
	(0.054)	
gd_centered	-0.106***	-0.108***
	(0.008)	(0.008)
I(gd_centered2)	0.0002***	0.0002***
	(0.00003)	(0.00003)
ed_centered	−0.00001***	−0.00001***
	(0.00000)	(0.00000)
factor(code)1	8.522***	9.121***
	(0.742)	(0.477)
factor(code)2	11.489***	12.088***
	(0.842)	(0.441)
factor(code)3	8.905***	9.735***
	(0.458)	(0.393)
factor(code)4	15.255***	15.775***
	(0.953)	(0.468)
factor(code)5	9.213***	9.678***
	(1.142)	(0.743)
factor(code)6	12.930***	13.619***
	(0.715)	(0.674)
factor(code)7	8.025***	9.325***
	(1.022)	(0.970)
factor(code)8	7.731***	8.138***
	(0.436)	(0.417)
GDPP:GDPG	−0.00001**	0.00000
	(0.00000)	(0.00000)
Observations	168	168
R^2	0.983	0.982
Adjusted R^2	0.982	0.981
Residual Std. Error	1.685 (df = 154)	1.737 (df = 156)
F Statistic	644.959*** (df = 14; 154)	706.753*** (df = 12; 156)
Note:		*p<0.1; **p<0.05; ***p<0.01

4.3.3 Prais-Winsten or Cochrane-Orcutt estimations

Sovereign ratings and economic variables are likely to have time dependence. If Moody's ratings are consistent over time, they may exhibit autocorrelation (i.e., this year's score depends on last year's rating). Using Prais-Winsten or Cochrane-Orcutt estimations helps correct for this issue, ensuring that our model provides accurate estimates of how your explanatory variables (GDP, debt, etc.) relate to the ratings. It improves the reliability of our time-series analysis by dealing with serial correlation in the residuals.

After 12 iterations, Prais-Winsten Regression indicates a significant level of autocorrelation in the residuals with ρ of 0.8477. Durbin-Watson statistics for the original model were 0.4922, indicating potential positive autocorrelation, while the transformed one was 1.425, suggesting improved autocorrelation but still concerning. GDPP and ed_centered showed no significant impact on ratings, with p values of 0.6595 and 0.2581, respectively. See Table 4-18.

Similarly, the Cochrane-Orcutt method on the main FE model revealed that GDPP is not significant, with a p-value of 0.1644. Durbin-Watson statistics for the original model were 0.5621, indicating strong positive autocorrelation, whereas the transformed model was 1.4637, suggesting some improvement but still potential issues. The Breusch-Godfrey test confirms the existence of serial correlation.

Table 4-18: Comparison between Prais-Winsten and Cochrane-Orcutt estimations

	Paris model	cochrane.orcutt model
Rho after 12 iterations	0.8477	
GDPP	-0.00001	-0.00003
	(00000)	(00000)
ed_centered	-0.0000	-0.00001***
	(00000)	(00000)
Observations	168	168
R2	0.8336	0.6622
Adjusted R2	0.8197	0.6496
Residual Std. Error	1.066 (df = 155)	1.0771 (df = 160)
F- Statistic	59.75 (df = 13; 155)	25.2 (df = 6; 160)
Durbin-Watson statistic (original)	0.4922	0.56214
Durbin-Watson statistic (transformed)	1.425	1.46372
LM test		12.439 (df =1)
Note:	*p<0.1; **p<0.05; ***p<0.01	

4.3.4 Stability of ratings response

We conduct stability tests to determine whether the relationship between ratings and explaining variables remains constant over time, or if these relationships change under different periods or economic regimes. Major events took place with the global economy during this 20-year period: financial crises, revolutions in the Arab world, debt crises, and pandemics. This presents an excellent opportunity to observe how the ratings of credit rating agencies (CRAs) responded to factors such as GDP growth and debt during these significant periods.

We begin by incorporating a temporal interaction between GDP per capita (GDPP) and the year to track the evolution of the correlation between GDPP and Moody's ratings (R). We begin by incorporating a temporal interaction between GDP per capita (GDPP) and the year to track the evolution of the correlation between GDPP and Moody's ratings (R). The GDPP has a negative coefficient (-0.0123), indicating that higher GDP per capita is associated with lower ratings. A negative coefficient (-0.2895) for the year term suggests that, on average, ratings decrease over time. Meanwhile, the interaction between GDPP and year is positive, indicating that the relationship between GDPP and ratings has become less negative over time as shown in Table 4-19.

Next, we created a dummy variable for the post-2008 period to assess whether macroeconomic impacts on ratings changed after the financial crisis. The coefficient for post_2008 is significantly negative, indicating a general decline in ratings following the financial crisis. The interaction terms between macroeconomic variables and the post_2008 variable are mostly not statistically significant, indicating that while the overall rating decline post-crisis is significant, the interaction with GDPP might not have a strong effect, as noted in Table 4-20.

As a final step, we have created a categorical variable for time periods—for instance, divided by decade: 1980, 1990, 2000, 2010, 2020—and checked the impact of that variable on ratings. As shown in Table 4-21, the coefficients for time_period2000s and time_period2010s are significantly positive, indicating higher ratings relative to the baseline period. Additionally, the coefficient of GDPP is positive, indicating a positive relationship, although its interaction with the time periods may not always be statistically significant. The interaction term of GDPG with 2010s, GDPG∗2010s, has a p-value < 0.001, which would imply that the responses of Moody's ratings to GDP growth manifest differently in the 2010s compared to the earlier decades. Turning to government debt, notice that both the linear and quadratic terms for the 2010s are significant, which provides evidence that the relationship between debt and ratings shifted in the 2010s relative to other periods. The interaction between GDPP and the 2010s is not significant ($p = 0.43$), implying that Moody's reaction to GDPP has not greatly changed across these time periods.

Put together, these three models portend a very complex interaction across the time variation of the macroeconomic variables and Moody's ratings, with a persistent decline since 2008 and shifting responses across the decades for GDP. These findings suggest that Moody's ratings are neither very stable nor predictable in nature over time, as their sensitivity for some major macroeconomic variables varies across different time periods, reflecting some temporal inconsistency.

Table 4-19: Time (year) interaction with GDPP

	Dependent variable
	R
GDPP	-0.013***
	(0.003)
year	-0.289***
	(0.045)
GDPG	0.016
	(0.030)
gd_centered	-0.085***
	(0.008)
I(gd_cetered)	0.0002**
	(0.00003)
ed_centered	0.00001
	(0.00000)
factory (code)1	591.927***
	(90.057)
factory (code)2	594.157***
	(89.963)
factory (code)3	591.589***
	(89.940)
factory (code)4	597.449***
	(89.901)
factory (code)5	593.186***
	(90.133)
factory (code)6	593.959***
	(89.740)
factory (code)7	586.640***
	(89.286)
factory (code)8	591.337***
	(90.094)
GDDP : year	0.00001***
	(0.00000)
Observations	168
R2	0.986
Adjusted R2	0.985
Residual Std. Errors	1.522 (df = 153)
F Statistics	740.145*** (df = 15; 153)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-20: Creating time dummy for post_2008 period

	Dependent variable
	R
GDPP	0.00004
	(0.00004)
Post_2008	-3.159***
	(0.667)
GDPG	-0.062
	(0.088)
gd_centered	-0.070***
	(0.011)
I(gd_cetered)	-0.0002**
	(0.0001)
ed_centered	-0.00002**
	(0.00001)
factory (code)1	11.118***
	(0.926)
factory (code)2	13.183***
	(1.017)
factory (code)3	11.428***
	(0.650)
factory (code)4	16.207***
	(1.104)
factory (code)5	11.535***
	(1.258)
factory (code)6	15.706***
	(0.871)
factory (code)7	10.266***
	(1.311)
factory (code)8	10.544***
	(0.704)
GDPP : post_2008	0.00002
	(0.00003)
post_2008 : GDPG	0.155*
	(0.094)
Post_2008 : gd_centered	-0.037***
	(0.010)
post_2008 : I(gd_centered^2)	0.0005***
	(0.0001)
post_2008 : ed_centered	0.00001
	(0.00001)
Observations	168
R2	0.988
Adjusted R2	0.986
Residual Std. Errors	1.463 (df = 149)
F Statistics	632.994*** (df = 19; 149)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-21: Creating a time variable (decades; 1980, 1990...,2020)

	Dependent variable
	R
GDPP	0.0001**
	(0.00003)
time_period2000s	11.860***
	(0.762)
time_period2010s	7.442***
	(0.653)
GDPG	-0.114***
	(0.044)
gd_centered	-0.060***
	(0.009)
I(gd_cetered)	-0.0003**
	(0.0001)
ed_centered	-0.00001**
	(0.00001)
factory (code)2	1.298**
	(0.544)
factory (code)3	-0.359
	(0.680)
factory (code)4	4.324***
	(0.612)
factory (code)5	0.908***
	(0.647)
factory (code)6	3.148***
	(0.998)
factory (code)7	-2.567*
	(1.460)
factory (code)8	-0.234
	(0.583)
GDPP : time_period2010s	0.00002
	(0.00002)
time_period2010s : GDPG	0.258***
	(0.057)
time_period2010s : gd_centered	-0.034***
	(0.007)
time_period2010s : I(gd_centered^2)	0.001***
	(0.0001)
time_period2010s : ed_centered	0.00001
	(0.00000)
Observations	152
R2	0.991
Adjusted R2	0.990
Residual Std. Errors	1.254 (df = 133)
F Statistics	807.314*** (df = 19; 133)
Note:	*p<0.1; **p<0.05; ***p<0.01

4.3.5 Time-series analysis on Moody's ratings

Timeseries analysis deals with variables that change with time relative to each other: for example, a trend, or seasonality, or some kind of lag where past values might influence present observations. Time-series analysis allows us to explore trends (e.g., whether ratings have become more stringent or lenient), persistence (e.g., how long a rating change lasts), and the potential lag effects of economic variables (e.g., how a change in GDP per capita this year affects ratings next year). It helps us uncover the dynamic behavior of Moody’s ratings and how they respond to evolving economic conditions.

A dynamic panel data model, which controls for the lagged dependent variable (two-way fixed effects model), reveals that the lag (R, 1) is highly significant, with an estimate of 0.7961. This indicates a strong positive autocorrelation in ratings, while GDPP and ed_centered are not significant. Refer to Table 4-22.

As seen in Table 4-23, we added a dummy variable representing year, and after running the FE model, we found that GDPG and ed_centered are not statistically significant, implying that in the fixed effects context, they don't have a significant impact on ratings. The dummy variables for countries are significant, whereas for years, they only started to be significant after 2011.

In Table 4-24, the fixed effects model with a lagged dependent variable (lagged_ratings) shows that lagged ratings have a significant positive effect (estimate: 0.4645), reinforcing the persistence in ratings over time. All the other explanatory variables are also significant, except for GDPP.

In general, GDPP was insignificant, whereas government debt (gd) and its square indicate a non-linear relationship, suggesting that the effect of gd on ratings varies at different levels. The lagged dependent variable highlights the significance of prior ratings in influencing current ratings. The inclusion of country and year fixed effects underscores the significance of unobserved heterogeneity in affecting ratings.

Table 4-22: Dynamic fixed effects (two-ways) model

	Dependent variable
	R
lag (R, 1)	0.796***
	(0.054)
GDPP	0.00002
	(0.00002)
GDPG	0.099***
	(0.025)
gd_centered	-0.016***
	(0.007)
I(gd_cetered)	0.0001**
	(0.00002)
ed_centered	-0.00000
	(0.00000)
Observations	160
R2	0.818
Adjusted R2	0.772
F Statistics	94.881*** (df = 6; 127)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-23: Fixed effects model with year dummies

	Dependent variable
	R
GDPP	0.0001***
	(0.00003)
GDPG	0.040
	(0.039)
gd_centered	-0.086***
	(0.009)
I(gd_cetered2)	0.0002**
	(0.00003)
ed_centered	-0.00000
	(0.00000)
factory (code)1	9.939***
	(0.856)
factory (code)2	11.944***
	(0.893)
factory (code)3	10.580***
	(0.714)
factory (code)4	15.295***
	(0.999)
factory (code)5	10.532***
	(1.230)
factory (code)6	12.986***
	(0.914)
factory (code)7	7.017***
	(1.089)
factory (code)8	10.054***
	(0.767)
factory (year) 2003	0.301
	(0.813)
factory (year) 2004	-0.063
	(0.822)
factory (year) 2005	-0.343
	(0.823)
factory (year) 2006	-0.516
	(0.832)
factory (year) 2007	-0.819
	(0.851)
factory (year) 2008	-1.020
	(0.874)
factory (year) 2009	-0.240
	(0.851)
factory (year) 2010	-0.339
	(0.851)
factory (year) 2011	-1.880**
	(0.872)
factory (year) 2012	-2.337***
	(0.877)
factory (year) 2013	-2.957***
	(0.887)
factory (year) 2014	-2.552***
	(0.883)
factory (year) 2015	-1.785**
	(0.858)
factory (year) 2016	-2.195**
	(0.865)
factory (year) 2017	-2.366***
	(0.891)
factory (year) 2018	-2.331
	(0.903)
factory (year) 2019	-2.606***
	(0.907)
factory (year) 2020	-2.252**
	(0.983)
factory (year) 2021	-2.757***
	(0.979)
factory (year) 2022	-3.435***
	(0.972)
Observations	168
R2	0.987
Adjusted R2	0.983
Residual Std. Errors	1.611 (df = 135)
F Statistics	300.240*** (df = 33; 135)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-24: Fixed effects model with lagged variable 1 way

	Dependent variable
	R
GDPP	-0.00003
	(0.00002)
GDPG	0.078***
	(0.027)
gd_centered	-0.058***
	(0.008)
I(gd_cetered2)	0.0001**
	(0.00003)
ed_centered	-0.00001***
	(0.00000)
R_lagged	0.464***
	(0.053)
factory (code)1	5.140***
	(0.763)
factory (code)2	7.127***
	(0.891)
factory (code)3	4.870***
	(0.623)
factory (code)4	9.357***
	(1.082)
factory (code)5	5.942***
	(1.023)
factory (code)6	6.859***
	(0.952)
factory (code)7	5.384***
	(0.894)
factory (code)8	4.205***
	(0.556)
Observations	167
R2	0.989
Adjusted R2	0.988
Residual Std. Errors	1.391 (df = 153)
F Statistics	946.362*** (df = 14; 153)
Note:	*p<0.1; **p<0.05; ***p<0.01

4.3.6 Comparing ratings across similar economic conditions

We investigate the consistency of the rating assignments by comparing the ratings for countries with comparable economic conditions under Moody's rating. For example, two countries with similar magnitudes of GDP, debt, and growth would receive similar ratings if Moody's had been consistent.

We introduced a pre- and post-Arab Spring model, which represents a sort of period interaction model. In this model, we introduced a period dummy (period), splitting the time into pre-crisis (before 2010) and post-crisis (2010 onwards), and interacting it with key macroeconomic variables. GDPP had a positive and significant impact in the pre-crisis period (p-value = 0.004261), indicating that GDP per capita had a stronger relationship with sovereign ratings before the crisis. In the post-crisis period, the effect of GDPP becomes insignificant (p = 0.136), suggesting its reduced importance in rating determination post-crisis. In terms of GDP growth (GDPG), both periods were significant, with a stronger negative interaction in the pre-crisis period (p = 0.000245) as indicated in Table 4-25. This implies that higher GDP growth was less important for ratings before the crisis. The linear term of government debt (gd) is negative and highly significant across periods, meaning higher debt levels consistently led to worse ratings, while the quadratic term is positive and significant, suggesting a nonlinear relationship—extremely high levels of debt might exacerbate the impact on ratings. External debt (ed) doesn't show a significant impact on ratings in either period. There are substantial country-level differences in ratings, with coefficients varying widely for different countries, indicating that country-specific factors play a significant role beyond the macroeconomic variables. There is a notable difference between the pre- and post-crisis periods, particularly in the relationship between sovereign credit ratings and GDPP and GDPG. Moody's credit ratings also appear to be less responsive to GDP per capita after the crisis, indicating changes in either criteria or methodology over time. Large interaction terms and coefficient shifts provide evidence of structural breaks in Moody's ratings' responsiveness to key economic indicators, implying that Moody's ratings are temporarily inconsistent.

We implemented a crisis dummy model for the global financial crisis (2008–2010) and interacted it with economic variables. The crisis dummy itself is significant (p = 0.049), indicating that the period during the financial crisis had a distinct impact on ratings. The interaction term between GDPP and the crisis dummy is not significant (p = 0.670) as per Table 4-26, indicating that there was no significant change in how GDPP affected ratings during the crisis. Turning to GDP growth was significant both before and during the crisis, but there was little evidence of a change during the crisis itself (interaction p = 0.192). In the case of government debt as well, there is a similar pattern like the period model: debt always receives a lower rating the more indebted it is. It is also found that the interaction term with the crisis dummy was insignificant, indicating that the effect of the debt did not differ in a fundamental way during the crisis. The external debt variable its interaction with the crisis dummy is insignificant, suggesting no distinct effect of external debt during the crisis period. This model provides weaker evidence of inconsistency than the period model, as most interactions with the crisis dummy are not significant. Still, the crisis itself affected ratings independently of the variables analyzed.

LSDV (pre- and post-2008) models. The pre-crisis model (before 2008) shows that GDPP is significant while GDP growth and government debt are insignificant, suggesting neither GDP growth nor debt levels play a large role in determining ratings pre-crisis. The post-crisis model (2008 onwards) showed that GDP per capita is no longer significant, while GDP growth and government debt with linear and non-linear terms become significant. These results indicate a clear shift in the determinants of Moody's ratings from the pre-crisis to post-crisis periods. In particular, Moody's emphasis on GDP per capita weakened, while government debt became a far more critical factor after the crisis. The findings suggest that Moody's rating criteria have not remained consistent over time. See Table 4-27.

Table 4-25: Pre and post Arab Spring 2010

	Dependent variable
	R
GDPP	0.00004
	(0.00002)
periodpost_crisis	8.318***
	(0.658)
periodpre_crisis	11.809***
	(0.778)
GDPG	0.113***
	(0.037)
gd_centered	-0.096***
	(0.007)
I(gd_cetered2)	0.0002***
	(0.00003)
ed_centered	-0.00000
	(0.00000)
factory (code)2	2.553***
	(0.534)
factory (code)3	-0.172
	(0.716)
factory (code)4	5.925***
	(0.572)
factory (code)5	1.187*
	(0.662)
factory (code)6	3.382***
	(0.850)
factory (code)7	-2.964***
	(1.258)
factory (code)8	-0.928
	(0.640)
GDPP : periodpre_crisis	-0.0001***
	(0.00002)
Periodpre_crisis : GDPG	-0.253***
	(0.067)
Observations	168
R2	0.987
Adjusted R2	0.985
Residual Std. Errors	1.513 (df = 152)
F Statistics	701.780*** (df = 16; 152)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-26: Pre 2008 model with LSDV "Crisis dummy"

	Dependent variable
	R
GDPP	-0.00001
	(0.00002)
crisis_dummy	1.805**
	(0.910)
GDPG	0.112***
	(0.036)
gd_centered	-0.098***
	(0.008)
I(gd_cetered2)	0.0002***
	(0.00003)
ed_centered	-0.00001***
	(0.00000)
factory (code)1	9.246***
	(0.707)
factory (code)2	11.970***
	(0.807)
factory (code)3	8.996***
	(0.438)
factory (code)4	15.741***
	(0.938)
factory (code)5	10.512***
	(1.128)
factory (code)6	12.941***
	(0.733)
factory (code)7	8.337***
	(1.020)
factory (code)8	7.993***
	(0.424)
GDPP : crisis_dummy	0.00001
	(0.00003)
crisis_dummy : GDPG	-0.151
	(0.115)
crisis_dummy : gd_centered	0.004
	(0.013)
crisis_dummy : I(gd_centered^2)	-0.0003
	(0.0002)
crisis_dummy : ed_centered	-0.00000
	(0.00000)
Observations	168
R2	0.984
Adjusted R2	0.982
Residual Std. Errors	1.678 (df = 149)
F Statistics	479.626*** (df = 19; 149)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-27: The pre- and post-financial crisis 2008 model

	Dependent variable	
	R	
	Pre 2008	Post 2008
GDPP	0.0001***	-0.00000
	(0.00003)	(0.00003)
GDPG	-0.023	0.102***
	(0.038)	(0.036)
gd_centered	-0.029	-0.108***
	(0.021)	(0.009)
I(gd_cetered2)	0.00004	0.0002***
	(0.0002)	(0.00003)
ed_centered	-0.00000	-0.00001**
	(0.00001)	(0.00001)
factory (code)1	11.288***	9.507***
	(1.230)	(0.952)
factory (code)2	13.775***	11.277***
	(0.657)	(1.116)
factory (code)3	11.478***	8.159***
	(0.457)	(0.459)
factory (code)4	14.435***	15.434***
	(0.727)	(1.372)
factory (code)5	12.275***	10.114***
	(1.428)	(1.465)
factory (code)6	8.705***	13.145***
	(2.086)	(0.763)
factory (code)7	7.992***	8.722***
	(0.884)	(1.984)
factory (code)8	11.910***	7.355***
	(0.697)	(0.466)
Observations	48	120
R2	0.999	0.985
Adjusted R2	0.998	0.983
Residual Std. Errors	0.567 (df = 35)	1.581 (df = 107)
F Statistics	2,017.155*** (df = 13; 35)	534.202*** (df =13; 107)
Note:		*p<0.1; **p<0.05; ***p<0.01

We applied the same procedures for S&P and Fitch as we did for Moody's (as per the discussion section), testing their consistency over time. Due to page constraints, we will only provide some tables, not all of them, as we did for Moody's, to validate our conclusions.

In terms of S&P, we applied the pre-and-post Arab Spring 2010 model, where Table 4-28 indicates that period dummies (pre-crisis and post-crisis) are highly significant, showing a substantial shift in ratings between these two periods. The positive coefficients imply that credit ratings improved over time, although the change was more pronounced in the pre-crisis period (12.92) than in the post-crisis period (9.02). GDP per capita and growth are both important, but government debt is not. The interaction terms (GDPP: preperiod crisis) and (preperiod crisis: GDPG) are statistically significant, suggesting that the effect of GDP per capita and GDP growth on credit ratings differed significantly between the pre- and post-crisis periods. As stated in Table 4-29, the pre-crisis model shows that GDP per capita, GDP growth, and external debt are not significant, whereas government debt is negatively significant. After 2008, GDP growth becomes significant, with a p-value of 0.00182, while the rest remains the same as before 2008. Based on the results, S&P sovereign credit ratings do not appear to be fully consistent over time. Before and after the 2008 financial crisis, credit rating factors changed. In particular, the importance of government debt in determining ratings increased after the crisis. GDP growth, which was not a significant factor before 2008, became a key variable in the post-crisis period. GDP per capita did not have a significant impact in either period, as did external debt.

Table 4-28: Pre and post Arab Spring 2010 estimations for **S&P**

	Dependent variable
	R
GDPP	0.0001***
	(0.00002)
periodpost_crisis	9.021***
	(0.573)
periodpre_crisis	12.921***
	(0.676)
GDPG	0.096***
	(0.032)
gd_centered	-0.083***
	(0.006)
I(gd_cetered2)	0.0002***
	(0.00002)
ed_centered	0.00000
	(0.00000)
factory (code)2	2.539***
	(0.464)
factory (code)3	-1.199*
	(0.623)
factory (code)4	5.075***
	(0.497)
factory (code)5	1.375**
	(0.576)
factory (code)6	0.880
	(0.739)
factory (code)7	-5.295***
	(1.094)
factory (code)8	-1.799***
	(0.557)
GDPP : periodpre_crisis	-0.0001***
	(0.00002)
Periodpre_crisis : GDPG	-0.156***
	(0.059)
Observations	168
R2	0.990
Adjusted R2	0.989
Residual Std. Errors	1.316 (df = 152)
F Statistics	934.144*** (df = 16; 152)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-29: The pre-and post-financial crisis 2008 model with LSDV estimations for S&P

	Dependent variable	
	R	
	Pre 2008	Post 2008
GDPP	-0.0000	0.00000
	(0.00002)	(0.00003)
GDPG	0.003	0.108***
	(0.026)	(0.034)
gd_centered	-0.036**	-0.086***
	(0.015)	(0.008)
I(gd_cetered2)	0.0002	0.0002***
	(0.0001)	(0.00003)
ed_centered	0.00001	-0.00001*
	(0.00001)	(0.00001)
factory (code)1	13.2629***	9.796***
	(0.850)	(0.893)
factory (code)2	15.983***	11.873***
	(0.454)	(1.046)
factory (code)3	11.750***	8.034***
	(0.316)	(0.430)
factory (code)4	15.936***	15.528***
	(0.503)	(1.286)
factory (code)5	14.815***	11.500***
	(0.987)	(1.374)
factory (code)6	7.886***	11.028***
	(1.442)	(0.715)
factory (code)7	7.024***	8.712***
	(0.611)	(1.860)
factory (code)8	12.336***	7.208***
	(0.482)	(0.437)
Observations	48	120
R2	0.999	0.987
Adjusted R2	0.999	0.985
Residual Std. Errors	0.392 (df = 35)	1.482 (df = 107)
F Statistics	4,247.557*** (df = 13; 35)	610.889*** (df =13; 107)
Note:		*p<0.1; **p<0.05; ***p<0.01

When it comes to Fitch, the results that we have obtained from the first model confirm that Fitch's sovereign credit ratings appear inconsistent over time. According to Table 4-30, GDP per capita has a positive and insignificant impact on ratings, whereas its interaction with the pre-crisis period is negative and significant, indicating that the relationship between ratings and GDPP was different before the Arab Spring 2010. External debt was significant in this model, while the coefficients for pre-2010 and post-2010 are highly significant, showing large differences in credit ratings between the two periods (pre-crisis = 13.15, post-crisis = 9.83). This suggests structural shifts in Fitch's credit rating approach between these periods, likely influenced by the 2008 financial crisis and the political stability of 2010. As shown in Table 4-31, GDP per capita, GDP growth, and government debt are all not significant, whereas external debt was marginally significant before 2008. After 2008, GDP per capita remained insignificant, while GDP growth became more significant after the crisis. In contrast to the pre-crisis model, external debt has a significant negative effect on ratings post-crisis (-1.005e-05, p = 0.04803). This suggests that Fitch became more concerned about external debt burdens after the financial crisis, reflecting greater awareness of vulnerabilities linked to external indebtedness.

Table 4-30: Pre and post Arab Spring 2010 estimations for Fitch

	Dependent variable
	R
GDPP	0.00003
	(0.00002)
periodpost_crisis	9.833***
	(0.578)
periodpre_crisis	13.147***
	(0.683)
GDPG	0.102***
	(0.033)
gd_centered	-0.085***
	(0.006)
I(gd_cetered2)	0.0002***
	(0.00003)
ed_centered	0.00000
	(0.00000)
factory (code)2	2.790***
	(0.469)
factory (code)3	-1.152*
	(0.629)
factory (code)4	4.527***
	(0.502)
factory (code)5	1.761***
	(0.582)
factory (code)6	0.682
	(0.746)
factory (code)7	-5.433***
	(1.105)
factory (code)8	-1.837***
	(0.563)
GDPP : periodpre_crisis	-0.0001***
	(0.00002)
Periodpre_crisis : GDPG	-0.201***
	(0.059)
Observations	168
R2	0.990
Adjusted R2	0.989
Residual Std. Errors	1.330 (df = 152)
F Statistics	953.447*** (df = 16; 152)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4-31: The pre-and post-financial crisis 2008 model with LSDV estimations for Fitch

	Dependent variable	
	R	
	Pre 2008	Post 2008
GDPP	0.00000	0.00000
	(0.00002)	(0.00003)
GDPG	0.036	0.083***
	(0.027)	(0.032)
gd_centered	-0.021	-0.092***
	(0.015)	(0.008)
I(gd_cetered2)	0.0002	0.0002***
	(0.0001)	(0.00003)
ed_centered	0.00001*	-0.00001**
	(0.00001)	(0.00001)
factory (code)1	13.837***	10.299***
	(0.895)	(0.836)
factory (code)2	17.306***	12.138***
	(0.478)	(0.980)
factory (code)3	11.412***	8.929***
	(0.333)	(0.403)
factory (code)4	15.612***	14.905***
	(0.529)	(1.205)
factory (code)5	16.411***	11.523***
	(1.038)	(1.286)
factory (code)6	6.468***	11.476***
	(1.518)	(0.670)
factory (code)7	6.320***	9.634***
	(0.643)	(1.742)
factory (code)8	12.683***	7.776***
	(0.507)	(0.410)
Observations	48	120
R2	0.999	0.989
Adjusted R2	0.999	0.987
Residual Std. Errors	0.412 (df = 35)	1.388 (df = 107)
F Statistics	3,957.279*** (df = 13; 35)	729.722*** (df =13; 107)
Note:		*p<0.1; **p<0.05; ***p<0.01

CHAPTER 5

5. Conclusion

This thesis sought to investigate the consistency of the sovereign credit ratings assigned by the three major credit rating agencies (CRAs)—Moody's, Standard & Poor's (S&P), and Fitch for the MENA market—because their assessments are intended to be forward-looking, focusing on long-term performance as a means of promoting stability. Their dominance in the financial markets has been evident for many years, raising questions about the integrity of their business model.

We used two models (Model 1, and Model 2) with a yearly data set to perform this analysis in ignorance of the fluctuations of our explanatory variables during the year, as we shall do with the credit ratings since some monthly or even quarterly data was not published. We conducted estimations for these two models using two different approaches. In the first approach (ARG 07), we utilized the key determinant of sovereign credit ratings as argued by Afonso et al. (2007). For the second approach (ARG 11), we utilized the most recent key determinants of the sovereign credit rating, as previously introduced by Afonso et al. (2011).

Regarding the methodological approach, we employed a variety of panel data models, including pooled OLS, fixed effects (FE) using the least squares dummy variable (LSDV) approach, and random effect (RE). The panel analysis's estimation results using pooled OLS, FE-LSDV, and RE estimates confirm that Moody's, S&P, and Fitch apparently relied on more or less similar sets of macroeconomic and financial variables, including GDP growth, government debt, inflation, and other country-specific economic indicators, for rating assignment.

We looked into dynamic panel data models to deal with the fact that credit ratings change over time. Specifically, we identified Difference GMM and System GMM as effective tools to address potential endogenous relationships using lagged dependent variables. Despite several adjustments—including limiting the number of instruments, collapsing the instrument matrix, and exploring alternative transformations—the GMM estimations remained unstable. Furthermore, we deemed it inappropriate to center the lagged dependent variable, a potential solution to multicollinearity, as it would distort the inherent time dynamics of the model. On the other hand, results obtained from the simple panel data models such as pooled OLS, FE-LSDV, and RE are coherent and interpretable. In this case, we chose the RE model as an alternative estimation method because it can control unobserved heterogeneity across countries and produce a stable solution.

Our study looked at how consistent Moody's, S&P, and Fitch ratings are for Middle Eastern countries. We did this using several different methods, including checks for robustness, interaction terms, Prais-Winsten or Cochrane-Orcutt estimations, stability of rating responses, time-series analysis, and comparing ratings across similar economic conditions. The results that we obtain confirm that the sovereign credit ratings assigned by Moody's, S&P, and Fitch for the MENA markets are not consistent over time.

Regardless, this dissertation lacks applicability to other cases and is limited by (i) the relatively small amount of time series data available for the Middle Eastern countries, (ii) ignorance of data and rating fluctuations due to non-publishing, and (iii) GMM issues due to the singularity of the matrix.

A larger dataset for the future may overcome some of the problems with GMM, whether in more countries or over a longer period of time. Other methods for dealing with endogeneity include IV regression or control functions.

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Appendix A

1. Countries

The ratings data are from Bloomberg terminal covering the period 2002 – 2022 for Moody's, S&P and Fitch. The countries are chosen due to the length of their rating series and their available econometric data, rather than anything else. The countries included in the estimations are Bahrain (BHR), Cyprus (CYP), Egypt (EGY), Israel (ISR), Kuwait (KWT), Lebanon (LB), Morocco (MAR), Saudi Arabia (SAU), Turkey (TUR) and Tunisia (TN).

2. Data source: Bloomberg Terminal, World Development Indicators 2001, World Bank

Credit Ratings (Ordinal)
Default History (Years)
GDP per capita (constant 1995 US$) (NY.GDP.PCAP.KD)
GDP growth (annual %) (NY.GDP.MKTP.KD.ZG)
Government debt (% of GDP) (GC.DOD.TOTL.GD.ZS)
Government effectiveness (GE.EST)
External debt, total (DOD, current US$) (DT.DOD.DECT.CD) in Millions
External reserves (FI.RES.TOTL.C) in Millions