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Sovereign credit ratings in South Africa: Does institutional quality matter?

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ABSTRACT

The study aimed to empirically assess whether governance quality influences sovereign credit scores in South Africa. The country faces a significant infrastructure financing gap that requires not only public sources but also the issuance of securities on global capital markets. Consequently, sovereign credit scores are a critical component of South Africa's development finance discourse. An Autoregressive Distributed Lag (ARDL) framework was applied to credit scores from Fitch, Standard & Poor's, and Moody's. The ARDL model is advantageous because it is efficient in both small and finite samples. Data for economic indicators were collected over 23 years, ending in 2023. Institutional quality was evaluated using governance indicators reported by the World Bank. The evidence indicates that, individually, corruption, politics, governance, freedom of expression, lawfulness, and regulatory quality do not significantly influence credit scores in South Africa. Variations in gross domestic product (GDP) and foreign investor activities also have an insignificant impact on ratings. In South Africa, sovereign scores are influenced by the reserves-to-external-debt ratio, the current account balance to GDP ratio, and inflation. From a policy perspective, although governance variables are individually insignificant, the government of South Africa should aim to improve institutional quality. Even though governance variables do not directly enhance credit scores, they reduce the likelihood of sovereign downgrades. Further research could explore whether governance variables collectively determine ratings in South Africa. The study could be expanded by including a broader sample that encompasses the least developed economies, thereby improving the generalizability of the results.

Contribution/Originality: This study represents one of the few comprehensive analyses examining the impact of institutions on sovereign ratings, employing the autoregressive distributed lag framework, a model seldom utilized in sovereign credit research within South Africa. In this regard, the study offers fresh perspectives relevant to academic research.

1. INTRODUCTION

South Africa is the second-largest economy in Africa. The country has a GDP of US$377.78 billion, according to the World Bank's 2023 estimates (World Bank, 2024a). South Africa needs to spend an estimated US$352 billion and US$273 billion between 2020 and 2030 on water and sanitation and transport infrastructure, respectively, if Sustainable Development Goals [SDGs] targets are to be achieved in these sectors (Development Bank of South Africa (DBSA), 2023). Essentially, this equates to spending a yearly average of between 8.7% and 11.2% on water, sanitation, and transport infrastructure (Development Bank of South Africa (DBSA), 2023). According to Development Bank of South Africa (DBSA) (2023) sustainable yearly budget financing structure should allocate

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US$73 billion on transport and US$68 billion on water and sanitation, US$22 billion on basic education and approximately US$23 billion on vocational education training. When the need to mitigate the negative effects of climate change is incorporated, the expenditure estimates are even higher. With this context, it is evident that the traditional state-led infrastructure financing model alone will not suffice to adequately finance infrastructure in South Africa. Thus, South Africa needs to financially innovate to bridge the infrastructure financing gap. Mundonde and Makoni (2023) and Mundonde and Makoni (2024) stated that most African countries are budget-constrained and cannot single-handedly finance the infrastructure development budgets. Thus, South Africa needs to supplement concessionary financing from international development agencies (IDAs) by selling securities on international debt markets.

In fact, the United Nations Development Program (UNDP) (2023) Reported an increasing trend in USD$ and EUR€ denominated Euro-bonds by African governments. Even though the trend abruptly stopped in 2020 due to the COVID-19 pandemic, it resumed in the following years. According to Mutize and Nkhalamba (2020), South Africa is the first African nation to issue bonds denominated in both local and foreign currencies on international markets. A snapshot of the recently issued Euro bonds is provided under Table 1.

Table 1. Recent Eurobonds by African countries.

Country	Yield to maturity	Date issued	Amount	Maturity date	Currency
Angola	10.6%	04 April 2022	1,750,000,000	14-Apr-32	US$
Nigeria	12.65%	24 March 2022	1,250,000,000	29-Apr-29	US$
South Africa	7.59%	20 April 2022	1,400,000,000	20 April 2032	US$
South Africa	8.74%	20 April 2022	1,600,000,000	20 April 2032	US$

Source: United Nations Development Program (UNDP) (2023).

Access to international capital markets provides African countries with additional foreign currency proceeds for investment. The weight of African borrowers on international bond indices is increasing (United Nations Development Program (UNDP), 2023). For instance, the constituents of emerging and underdeveloped nations in the widely tracked Emerging Market and Developing Economies [EMDEs] US$ bonds and the JP Morgan Emerging Market Bond Index Global [EMBIG] increased by 36% between 1992 and 2007. EMBIG further increased by 47% between 2007 and 2019 (International Monetary Fund, 2021). Currently, the continent has 22 Eurobond issuers, and the three largest issuers are Nigeria, Egypt, and South Africa.

The transition by African countries to a market-driven financing model brings to the fore the debate on the centrality of sovereign ratings in sustainable development finance. Whether a corporate or government entity, to become a fully-fledged participant in the global debt market, it is imperative for institutions to obtain a credit rating (United Nations Development Program (UNDP), 2023). Credit ratings have a bearing on public institutions' ability to finance budget shortfalls. A nation's borrowing cost is influenced by the premium that lenders demand as compensation for assuming default risk (International Monetary Fund, 2021). The premium charge is in part determined by a sovereign rating. Countries with good ratings tend to borrow on more favourable terms. Sychowiec, Bauhr, and Charron (2021) noted that credit ratings portray a picture of a country's willingness and ability to settle outstanding coupon and principal repayments. Ratings furnish international and domestic investors with additional information critical to formulating portfolio strategies, particularly where subnational entities are involved (Sychowiec et al., 2021). Furthermore, given the competition for funds among developing nations, the rating designation as non-investment often determines not just the cost but also the volume that the country can attract on the global debt market (International Monetary Fund, 2021; United Nations Development Program (UNDP), 2023). As a best practice, most international investors are mandated to purchase only investment-grade securities; the absence of such securities will constrain access to the international debt market (Mugobo & Mutize, 2016).

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With so much at stake in the context of SDGs financing and the post-COVID-19 pandemic economic recovery driving up demand for loanable funds, the relevance of objective and informed credit ratings cannot be underestimated. For this reason, credit rating agencies have come under immense scrutiny by academics as well as practitioners (Mugobo & Mutize, 2016; Mutize & Nkhalamba, 2020). Even though some of the criticism against CRA has been addressed to some extent through institutional reforms such as the Agency Reform Act of 2006 and the Dodd-Frank Act of 2010, the suspicion surrounding the accuracy and transparency of sovereign scores has never dissipated (Ozturk, 2014, 2016). Concerns around credit rating accuracy are critically important for African countries given the financing cost implications that rating misalignment can have on already fragile economies. Since credit premiums are tied to credit rating scores, it implies that transparent and fair credit risk assessment is highly beneficial to countries and national borrowers (Ozturk, 2014, 2016). Several researchers have emphasized the non-objective nature of the rating procedure and have provided evidence that developing countries, on average, are assigned lower ratings compared to developed countries (Mim, Nouira, & Rault, 2023; Mutize & Nkhalamba, 2020). Policy makers in developing countries have long been complaining about the continued adverse assessments from international CRAs: Standard & Poor's (S&P), Moody's, and Fitch. Addressing the 2023 Africa Climate Summit (ACS), President Ruto of Kenya attributed sustainable finance challenges to a biased credit rating system (Africa Peer Review Mechanism (APRM), 2023). His views are empirically supported by the earlier findings in Fuchs and Gehring (2017) that European and American CRA agencies assign favorable ratings to Western countries and to those nations resampling strong financial and cultural similarities with their home countries. Similarly, Chinese rating agencies tend to assign favorable scores to Chinese and BRICS entities (Fuchs & Gehring, 2017). President Ruto`s views are further compounded by the Africa Peer Review Mechanism (APRM) (2023) report of structural weakness in CRAs information verification procedures. International CRA undertook a rating action on Cameroon based on unverified information relating to delays in debt reservice repayments. Structural anomalies such as this only make the call for fair and transparent rating actions even louder.

South Africa was the first country in Africa to receive a rating from international credit rating agencies. At the inception of the post-apartheid era, the country was assigned a BB rating by Fitch. Moody's and S&P reciprocated and assigned South Africa a Baa3 and a BB with a stable outlook, respectively (Mugobo & Mutize, 2016; Mutize & Nkhalamba, 2020). Currently, S&P, Moody's, and Fitch rate the country at BB-, Ba2, and BB-, respectively. If the trend projected in Africa Peer Review Mechanism (APRM) (2023) were to result in 17 out of 22 rating actions by CRAs culminating in downgrades, the likelihood of a sovereign downgrade overhangs the South African financial markets. Takawira and Mwamba (2021) report that financial markets in South Africa are particularly elastic to downgrades. When the rating score deteriorated into speculative or junk territory in April 2017, yields on South Africa's 10-year bonds increased by 7.46% over a 5-day period (Mugobo & Mutize, 2016; Mutize & Nkhalamba, 2020). According to the South African Treasury, with a further downgrade, the country will not be included in the FTSE World Government Bond Index (WGBI). Furthermore, non-resident South Africans holding R800 billion worth of securities will likely exit the South African bond market (South African Treasury, 2020). This suggests that the understanding of rating dynamics in South Africa is critical, given the twin goals of diversifying sustainable funding options and enhancing the credit risk profiling of the nation.

Sychowiec et al. (2021) states that international CRAs are sensitive to institutions when evaluating sovereign credit risk. Broadly, the sovereign rating process has two categories: the ability and the willingness to pay (Ozturk, 2014, 2016). Whilst the latter can easily be measured through macroeconomic metrics, institutional quality is a recommended proxy for the propensity to settle outstanding debt obligations. For instance, lawfulness, control of corruption, and respect for property rights build investor confidence that a government is committed to debt repayment (Sychowiec et al., 2021). Governance factors pertinent to credit rating encompass not only the lawfulness, control of corruption, and respect for property rights. They include other components such as freedom of expression and accountability, government effectiveness, and the political environment (World Bank, 2024b). Arguments are

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provided in support of the view that developed countries can sustain higher debt levels due to the strength of their institutions that communicate positive sentiment to investors. Even though governance quality positively influences sovereign ratings (Mutize & Nkhalamba, 2020; Sychowiec et al., 2021) detailed studies on the subject is still lacking for South Africa. Through providing a comprehensive analysis of the influence of institutional quality on rating scores in South Africa, the study contributes to the existing literature on South Africa that has largely focused on macroeconomic factors as drivers of sovereign ratings (Mugobo & Mutize, 2016; Takawira & Motseta, 2021; Takawira & Mwamba, 2021). Methodologically, the study contributes to literature through applying the autoregressive distributed lag framework, a rarely adopted model in sovereign credit analysis in South Africa. In this regard, the study contributes valuable perspectives to academia. The researcher`s expectation is that, other than expanding the frontiers of academic literature, the research will contribute towards data-driven policy formulation. Empirical analytics play a significant role in achieving sustainable development targets. Domestic and international investors should find the study informative regarding governance-induced risks on South African government securities. In addition, the findings can serve as a basis for further research on sovereign credit ratings and institutional quality in developing countries.

The remainder of the article is organized as follows: Section 2 reviews the empirical literature. Methodological aspects of the study are discussed in Section 3, while the findings from the study are presented in Section 4. Finally, Section 5 concludes the article.

2. LITERATURE REVIEW

Researchers are reporting mixed findings on the interaction between the quality of institutions and rating scores. Sychowiec et al. (2021) states that empirical findings are even controversial in some instances. Even though, there is a strand of literature that posits that institutional quality positively relates to credit scores. On the basis that CRAs do not publicly disclose the weighting on institutional variables in their models, Ozturk (2014) applied ordered probit modeling on 93 developed and developing nations over an 11-year time frame ending in 2010. Institutional quality was measured through the six dimensions of corruption, effectiveness of governments, freedom of expression and accountability, political environment, compliance with the law, and regulatory quality (World Bank, 2024b). The study concluded that the six institutional measures are significant at the 1% level. The positive sign of the governance variables suggests that countries with a stable institutional environment receive high sovereign credit scores. Similarly, Ozturk (2016) proved, using a set of 93 developing, emerging, and developed countries, that governance variables strongly influence sovereign credit ratings. The researcher further provided evidence that sovereign credit ratings respond to developments in World Bank-reported governance indicators. In this case, sovereign credit scores can be improved subject to effective management of the institutional environment (Haspolat, 2015; International Monetary Fund, 2021).

For a panel of 27 developing African countries, Pretorius and Botha (2017) concluded that the ability to formulate and effectively implement policies that promote private sector investments is a critical driver of sovereign rating scores. The investigation used data collected between 2007 and 2014, and an ordered probit econometric framework was employed to arrive at the conclusion. Uniquely, data from an African-based credit rating agency, NKC African Economics was used in the study. The researchers asserted that NKC ratings offer distinct benefits, as NKC African Economics possesses a competitive advantage over international credit rating agencies due to its firsthand experience with the African business and economic environment. In any case, relative to the international CRAs, NKC rates more African nations (Pretorius & Botha, 2014; M. Pretorius & Botha, 2017). Holding the view that accuracy and transparency lack in the procedure through which Latin American countries are rated by the international CRAs (Enciso, Silva, Cruz, Piccoli, & Da Veiga, 2016) analyzed the influence of governance variables on rating scores for 10 Latin American countries. Using ordinal regression for data collected between 1996 and 2002. The results were that three governance variables: freedom of expression, quality of regulation, and government effectiveness

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significantly drive credit ratings in Latin America. Pretorius and Botha (2014) and M. Pretorius and Botha (2017) similarly reported government effectiveness as key driver of rating scores. Corruption, politics, and adherence to national laws were found to be insignificant. The finding contrast Ozturk (2014) and Ozturk (2016) who reported all six governance variables as highly significant at 1%.

Sychowiec et al. (2021) examined whether corruption directly affects subnational credit ratings in the United States. Using bribery convictions between 2001 and 2005, the study provided empirical evidence that, on average, the level of bribery does not directly lower subnational sovereign scores. This is because, in the United States of America, subnational entities receive federal grants, which allow states with higher corruption rates to maintain good credit ratings and cost-effective borrowings. The finding challenges the narrative that high corruption levels exert downward pressure on sovereign scores (Fuchs & Gehring, 2017; Haspolat, 2015; International Monetary Fund, 2021; Ozturk, 2016). However, only for states that have comparatively low federal finance support was corruption concluded to have a sizeable negative influence on sovereign credit ratings. In a more recent study, Mim et al. (2023) evaluated whether governance influences sovereign credit down grades and upgrades in developing countries. Data was collected over a 20-year period ending in 2020. Logistic regression was used in the estimation. The study concluded that, for a set of 29 developing countries, none of the governance variables impact the likelihood of sovereign rating improvement. Counterintuitively, the rule of law index even works to decrease the likelihood of a rating improvement. Mim et al. (2023) argued that in developing countries, socio-political tension resulting in deterioration of economic fundamentals increases with freedom of expression and demand for accountability. Given the mixed findings from the literature, how institutional quality impacts sovereign credit ratings in South Africa is an empirical question that the current study seeks to contribute towards.

3. METHODOLOGY

3.1. Data, Variables, and Sample

Secondary data is used to analyze the influence, if any, of the quality of institutions on sovereign credit. Ntsalaze, Boako, and Alagidede (2017); Osobajo and Akintunde (2019), and Takawira and Mwamba (2021) used secondary data to analyse credit rating scores in developing countries. For credibility reasons, credit scores reported by reputable international rating companies such as Moody's, Standard & Poor's, and Fitch are used in this study. Osobajo and Akintunde (2019) chronicles a long rating history for these CRAs. The first rating action by Moody's was in 1909, followed by Fitch in 1924 and lastly Standard & Poor's in 1941. The measurement of institutional quality follows that in Ozturk (2014), Ozturk (2016), and Enciso et al. (2016), where governance measures reported by the World Bank are used as a proxy for the quality of institutions.

The Worldwide Governance Indicators (WGI) data bank measures the institutional quality of approximately 205 global economies using information collected from a wide spectrum: specialized analysts, non-governmental organizations, public and private representative organizations, and international bodies (Enciso et al., 2016; Mundonde & Makoni, 2023, 2024). Institutional quality is disaggregated into six components: effectiveness of government policies, political environment, accountability and freedom of expression, ability to curb corruption, and adherence to laws and regulations. Governance variables are supplemented with a set of macroeconomic variables. Mim et al. (2023) adopted a similar approach when analyzing the impact of institutional quality on the likelihood of a downgrade in developing countries. Yearly data are collected from publicly available sources such as Statistics South Africa [Stats-SA], Thomson Reuters, Trading Economics database, South African Reserve Bank [SARB], and the World Bank data bank. Credit scores for South Africa are collected from CRA reports as published by the South African treasury. As in Osobajo and Akintunde (2019) and Mutize and Nkhalamba (2020), a rating scale is used to convert alphabetic CRA scores into numeric values, the average of which is the explained variable in the study. Appendix 1 summarizes the scale used by Sibanda (2018) and subsequently adopted in this study. Data is collected for the 23-year period ending in 2023. For a country that received its first rating in the 1990s, the researcher holds

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that the sample is wide enough for meaningful conclusions to be drawn. In summary, Table 2 presents the variables and the studies in which they were used.

Table 2. Explanatory variables.

Variable	Indicator	Data source	Reference
SCR	Sovereign credit rating	SA treasury; Trade economics	Takawira and Mwamba (2021); Enciso et al. (2016), and Sychowiec et al. (2021).
REXD	Reserves to external debt	World Bank WDI database	Afonso, Gomes, and Rother (2011); Ozturk (2016), and Mim et al. (2023)
CAGDP	Current account balance to gross domestic product	World Bank WDI database	Cantor and Packer (1996) and Afonso et al. (2011)
GDPG	Growth rate of gross domestic product	World Bank WDI database	Afonso et al. (2011) and Sychowiec et al. (2021)
Log FDI	Foreign direct investment	World Bank WDI database	Afonso et al. (2011); Takawira and Mwamba (2021) and Mim et al. (2023)
IFN	Inflation	World Bank WDI database	Afonso et al. (2011); Ozturk (2016) and Mim et al. (2023)
CC	Control of corruption	World Bank WDI database	Enciso et al. (2016); Ozturk (2016) and Sychowiec et al. (2021).
RQ	Regulatory quality	World Bank WDI database	Ozturk (2016); Enciso et al. (2016) and Mim et al. (2023).
GE	Government effectiveness	World Bank WDI database	Afonso et al. (2011); Enciso et al. (2016) and Mim et al. (2023).
PS	Political stability	World Bank WDI database	Ozturk (2016); Enciso et al. (2016) and Mim et al. (2023).
RL	Rule of law	World Bank WDI database	Ozturk (2016); Enciso et al. (2016) and Mim et al. (2023).
VA	Voice and accountability	World Bank WDI database	Ozturk (2016); Enciso et al. (2016) and Mim et al. (2023).

3.1.1. Model Specification

The study endeavors to determine whether, in South Africa, institutional quality influences sovereign scores. Given Afonso et al. (2011) and Mim et al. (2023) assertion that governance quality has long- and short-term impacts on sovereign scores, the Autoregressive Distributed Lag (ARDL) model is preferred for the study. The ARDL model is commonly used in empirical studies to estimate either a system of equations Saungweme and Odhiambo (2020) or single time series equations (Sibanda, 2018). The ARDL model is advantageous in that it is efficient in both small and finite samples. Saungweme and Odhiambo (2020) states that the model also produces long-run unbiased estimates. A generalized ARDL (p, q) model is outlined in Equation 1.

$$y_t = \alpha_0 + \sum_{i=1}^{p} \delta_i \, y_{t-i} + \sum_{i=1}^{q} \beta_i \, x_{t-i} + \varepsilon_t \qquad (1)$$

Where, respectively, p and q are the optimal lag values of the explained and explanatory variables, y_t' is the dependent variable that can be a vector or otherwise, x_t' represents the explanatory variables of either order *I(1)* or *I(0)* or a combination of *I(1) and I(0)*, and ε_t is the error correction term. Executing the ARDL is a multi-stage procedure that begins with establishing the order of integration in the series. Even though the universe of stationarity test is vast, the study uses the Augmented-Dickey-Fuller, a commonly applied methods in finance research (Mundonde & Makoni, 2023, 2024; Shrestha & Bhatta, 2018). The essence of unit root testing is making sure that the explanatory variables are not integrated of order two *I(2)*. ARDL is applicable with either *I(1) or I(0)* variables or even a combination of the two (Saungweme & Odhiambo, 2020). Multicollinearity is managed through variance inflation factor analysis. Only series with a variance inflation factor less than 5 are retained for further analysis. Moreover, the lag structure for the models is scientifically ascertained using information criteria. The Akaike Information Criterion (AIC) is used to find the optimal ARDL lag modeling. AIC is commonly used in finance and economics studies, hence its adoption in the current research (Shrestha & Bhatta, 2018). AIC is advantageous in that,

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when the assumptions on which the technique is based hold, the criterion enables accurate model selection. Compared to cross-validation of predictive performance, AIC is easy to compute.

Within the ARDL framework, estimating either an error correction or the short-run model depends on whether the series are cointegrating or non-cointegrating. To establish the cointegrating structure, the study uses the bound testing approach (Saungweme & Odhiambo, 2020; Shrestha & Bhatta, 2018). In line with Ozturk (2014), Ozturk (2016), and Mundonde and Makoni (2024), institutional variables are added individually to a base model. The models are specified below:

$$\Delta SCR_t = \alpha_0 + \beta_1 SCR_{t-i} + \beta_2 REXD_{t-i} + \beta_3 CAGDP_{t-i} + \beta_4 GDPGD_{t-i} + \beta_5 logFDI_{t-i} + \beta_6 IFN_{t-i} + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \varepsilon_t \quad (2)$$

$$\Delta SCR_t = \alpha_0 + \beta_1 SCR_{t-i} + \beta_2 REXD_{t-i} + \beta_3 CAGDP_{t-i} + \beta_4 GDPGD_{t-i} + \beta_5 logFDI_{t-i} + \beta_6 IFN_{t-i} + \beta_7 CC_{t-i} + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta CC_{t-i} + \varepsilon_t \quad (3)$$

$$\Delta SCR_t = \alpha_0 + \beta_1 SCR_{t-i} + \beta_2 REXD_{t-i} + \beta_3 CAGDP_{t-i} + \beta_4 GDPGD_{t-i} + \beta_5 logFDI_{t-i} + \beta_6 IFN_{t-i} + \beta_7 RQ_{t-i} + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta RQ_{t-i} + \varepsilon_t \quad (4)$$

$$\Delta SCR_t = \alpha_0 + \beta_1 SCR_{t-i} + \beta_2 REXD_{t-i} + \beta_3 CAGDP_{t-i} + \beta_4 GDPGD_{t-i} + \beta_5 logFDI_{t-i} + \beta_6 IFN_{t-i} + \beta_7 GE_{t-i} + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta GE_{t-i} + \varepsilon_t \quad (5)$$

$$\Delta SCR_t = \alpha_0 + \beta_1 SCR_{t-i} + \beta_2 REXD_{t-i} + \beta_3 CAGDP_{t-i} + \beta_4 GDPGD_{t-i} + \beta_5 logFDI_{t-i} + \beta_6 IFN_{t-i} + \beta_7 PS_{t-i} + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta PS_{t-i} + \varepsilon_t \quad (6)$$

$$\Delta SCR_t = \alpha_0 + \beta_1 SCR_{t-i} + \beta_2 REXD_{t-i} + \beta_3 CAGDP_{t-i} + \beta_4 GDPGD_{t-i} + \beta_5 logFDI_{t-i} + \beta_6 IFN_{t-i} + \beta_7 RL_{t-i} + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta RL_{t-i} + \varepsilon_t \quad (7)$$

$$\Delta SCR_t = \alpha_0 + \beta_1 SCR_{t-i} + \beta_2 REXD_{t-i} + \beta_3 CAGDP_{t-i} + \beta_4 GDPGD_{t-i} + \beta_5 logFDI_{t-i} + \beta_6 IFN_{t-i} + \beta_7 VA_{t-i} + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta VA_{t-i} + \varepsilon_t \quad (8)$$

In which Δ is a difference operator, SCR_t, represents sovereign scores, SCR_{t-i} is the sovereign scores lagged, $REXD_{t-i}$ is the lagged value of South Africa`s reserves to external debt, $CAGDP_{t-i}$ is the lagged value of the current account balance to gross domestic product ratio, $GDPGD_{t-i}$ is the lagged value of the gross domestic product, $logFDI_{t-i}$ is the lagged value of the natural logarithm of foreign direct investment, IFN_{t-i} is the lagged value of the inflation rate, CC_{t-i} is the lagged value of the corruption metric, RQ_{t-i} is the lagged value of the quality of regulation, GE_{t-i} is the lagged value of the effectiveness of the government, PS_{t-i}, lagged value of the measure of the political environment metric in South Africa, RL_{t-i} is the rule of law and VA_{t-i} is the lagged value of the freedom of expression and accountability and $\varepsilon_t$is the error term.

Bound cointegration technique, evaluate the assertion that:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$$
$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 \neq 0$$

The test is based on the Wald F-Statistic. The calculated F-Statistic is evaluated against the critical values listed in Pesaran, Shin, and Smith (2001). The decision criteria are as follows: If the calculated statistic is below the lower threshold, the null hypothesis of no cointegration remains accepted. If the Wald F-Statistic exceeds the upper bound, the series has a stable long-run equilibrium. If the test lies between the lower and upper bound values, the test is inconclusive (Pesaran et al., 2001). Having established a cointegrating relationship, the impact of institutional quality on sovereign scores is investigated using the error correction model outlined as:

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$$\Delta SCR_t = \alpha_0 + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \delta ECT_t + \varepsilon_t \quad (9)$$

$$\Delta SCR_t = \alpha_0 + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta CC_{t-i} + \delta ECT_t + \varepsilon_t \quad (10)$$

$$\Delta SCR_t = \alpha_0 + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta RQ_{t-i} + \delta ECT_t + \varepsilon_t \quad (11)$$

$$\Delta SCR_t = \alpha_0 + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta GE_{t-i} + \delta ECT_t + \varepsilon_t \quad (12)$$

$$\Delta SCR_t = \alpha_0 + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta PS_{t-i} + \delta ECT_t + \varepsilon_t \quad (13)$$

$$\Delta SCR_t = \alpha_0 + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta RL_{t-i} + \delta ECT_t + \varepsilon_t \quad (14)$$

$$\Delta SCR_t = \alpha_0 + \sum_{i=1}^{p} \gamma_1 \Delta SCR_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta REXD_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta CAGDP_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta GDPGD_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta logFDI_{t-i} + \sum_{i=1}^{q} \gamma_6 \Delta IFN_{t-i} + \sum_{i=1}^{q} \gamma_7 \Delta VA_{t-i} + \delta ECT_t + \varepsilon_t \quad (15)$$

Where all other variables are as specified in sections 2 to 8. Variable δECT_t is the error correction term, which captures the long-run relationship in the models. Having outlined the methodology, the subsequent section presents the findings.

4. RESULTS AND DISCUSSION OF FINDINGS

Variance inflation factor controls the negative effects of multicollinearity by retaining variables with a VIF less than 5 (Mundonde & Makoni, 2024). Table 3 reports the VIF results and the average VIF is 2.2725. Multicollinearity is thus adequately managed.

Table 3. Variance inflation analysis.

Explanatory variables	Acronym	VIF	1/VIF
Reserves to external debt	REXD	3.94	0.25
Current account balance to gross domestic product	CAGDP	3.39	0.30
Growth rate of gross domestic product	GDPG	2.51	0.40
Foreign direct investment	LogFDI	1.49	0.67
Inflation	IFN	1.31	0.76
Voice and accountability	VA	3.11	0.33
Corruption control	CC	1.80	0.56
Effectiveness of government	GE	2.25	0.44
Quality of regulation	RQ	2.11	0.48
Political environment	PS	3.45	0.29
Rule of law	RL	1.36	0.73
Average VIF		2.27	0.45

Table 4. ADF Unit root test.

Variable	Acronym	ADF stat	Order of integration
Sovereign credit rating	SCR	-3.914**	I(1)
Reserves to external debt	REXD	-3.883**	I(1)
Current account balance to gross domestic product	CAGDP	-3.347*	I(1)
Growth rate of gross domestic product	GDPG	-4.673***	I(0)
Foreign direct investment	LogFDI	-7.030***	I(0)
Inflation	IFN	-4.338**	I(1)
Corruption control	CC	-4.720***	I(1)
Quality of regulation	RQ	-8.935***	I(1)
Government effectiveness	GE	-4.427**	I(0)
Political environment	PS	-6.362***	I(1)
Rule of law	RL	-5.230***	I(1)
Freedom of expression and accountability	VA	-4.733***	I(1)

Note: *, ** and *** imply statistical significance at 10%, 5% and 1%, respectively.

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Although the ARDL bound test procedure does not require the series to be integrated of the same order, the approach is only applicable if the variables are either I(1) or I(0), or a combination of the two (Pesaran et al., 2001). The results of unit root tests are summarized under Table 4. The appropriateness of ARDL is justified on the grounds that the series are a combination of I(1) or I(0) variables (Saungweme & Odhiambo, 2020).

The optimal lags were determined using the AIC criterion, and the results of the test are summarized in Table 5. Lags are previous time points used as explanatory variables. Optimal lags are the number of lagged terms that minimize AIC, providing the best trade-off between fit and parsimony. The lag structure varies between a minimum of zero (GDP and log FDI) and a maximum of two (SCR, CAGDP, IFN, and RQ). The optimal lags for REXD, CC, GE, PS, RL, and VA are one. In this table, all variables have a single asterisk (*), indicating that their optimal lag selections are statistically valid at the 10% level sufficient for inclusion in the final model, though potentially less robust than if selected at a stricter level (e.g., 5% or 1%).

Table 5. AIC Optimal Lags.

Variable	Acronym	AIC	Lag
Sovereign credit rating	SCR	8.045*	2
Reserves to external debt	REXD	6.185*	1
Current account balance to gross domestic product	CAGDP	3.723*	2
Growth rate of gross domestic product	GDPG	4.869*	0
Foreign direct investment	LogFDI	1.253*	0
Inflation	IFN	4.396*	2
Corruption control	CC	5.437*	1
Quality of regulation	RQ	4.982*	2
Government effectiveness	GE	4.699*	1
Political environment	PS	6.441*	1
Rule of law	RL	5.452*	1
Freedom of expression and accountability	VA	3.839*	1

Note: * Imply statistical significance at 10%.

Table 6 presents the findings of the bound cointegration tests. The results are validated through the respective F-statistics of each model in relation to the Pesaran et al. (2001) asymptotic critical values. The null hypothesis of no-cointegration is rejected in favor of the alternative at the 1% level (Models 3 and 4) and the 5% level (Models 1, 2, 5, 6, and 7).

Table 6. Bound F-Test for cointegration.

Models tested for cointegration	F-statistic	Cointegration
Model 1	5.3**	☑
Model 2	5.1**	☑
Model 3	6.6***	☑
Model 4	9.2***	☑
Model 5	4.6**	☑
Model 6	4.9**	☑
Model 7	5.2**	☑

Note: ** and *** imply statistical significance at 10%, 5% and 1%, respectively.

The F-statistic values for each model are shown, and all are statistically significant at either the 5% () or 1% (*) level, as indicated by the asterisks. The presence of a check mark ☑ under the "Cointegration" column confirms that long-run relationships exist among the variables in each model.

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Specifically:

- Models 1, 2, 5, 6, and 7 show significance at the 5% level (F-statistics between 4.6 and 5.3), suggesting moderate evidence of cointegration.
- Models 3 and 4 show stronger significance at the 1% level (F-statistics of 6.6 and 9.2), indicating very strong evidence of long-term relationships among the variables in those models.

This confirms that in all seven models, the variables are not only correlated in the short term but also move together in the long run, justifying further estimation of long-run and error correction models.

Table 7. Error correction estimates.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
REXD	0.132*** (0.035)	0.107 (0.085)	0.1680* (0.073)	1.458*** (0.021)	0.145 (0.081)	0.171 (0.040)	0.089 (0.054)
CAGDP	0.232 (0.150)	0.097 (0.412)	0.326 (0.265)	0.322** (0.120)	0.260 (0.195)	0.318 (0.162)	0.099 (0.138)
GDPG	-0.036 (0.126)	-0.154 (0.355)	0.065 (0.258)	-0.022 (0.082)	-0.063 (0.158)	0.035 (0.130)	0.009 (0.093)
Log FDI	-0.489 (0.579)	-0.238 (0.987)	-0.965 (1.438)	-0.489 (0.331)	-0.693 (0.970)	-0.540 (0.529)	-0.409 (0.360)
IFN	0.148 (0.137)	0.097 (0.234)	0.327 (0.357)	0.285* (0.124)	0.176 (0.195)	0.229 (0.144)	-0.007 (0.118)
ADJ	-0.612** (0.282)	-0.457 (0.4216)	-0.499 (0.433)	-0.101** (0.41)	-0.552 (0.332)	-0.609** (0.249)	-0.866** (0.302)
CC		0.080 (0.203)					
RQ			-0.078 (0.130)				
GE				-0.061 (0.042)			
PS					-0.016 (0.104)		
RL						-0.098 (0.060)	
VA							-0.209 (0.223)

Note: *, ** and *** imply statistical significance at 10%, 5% and 1%, respectively: ADJ is the speed of adjustment.

Having confirmed that the series are cointegrated, the next step is to estimate the error correction model (Odhiambo & Muyambiri, 2018; Odhiambo & Saungweme, 2020). Table 7 presents the results of the error correction models, whilst Table 8 summarises the diagnostics.

Table 8. Diagnostic tests.

Diagnostics	Serial correlation	White test for heteroskedasticity		
	Durbin-Watson statistic	chi2(21)	Prob > chi2	Decision
Model 1	2.171	22	0.3995	Homoskedasticity
Model 2	2.059	22	0.3995	Homoskedasticity
Model 3	2.303	22	0.3995	Homoskedasticity
Model 4	2.024	22	0.3995	Homoskedasticity
Model 5	2.158	22	0.3995	Homoskedasticity
Model 6	2.044	22	0.3995	Homoskedasticity
Model 7	2.273	22	0.3995	Homoskedasticity

The primary aim of this research is to determine whether institutional quality influences credit scores in South Africa. Even though Auzturk (2016) reported a notable linkage between sovereign credit ratings and corruption, Model 2 shows that the control of corruption insignificantly relates to sovereign credit scores at 1%, 5%, and 10% levels in South Africa. The difference in findings may be explained by the fact that, as opposed to Auzturk (2016),

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who analyzed rating scores through a panel comprising developed and developing countries, the current study is conducted in a single-country setup. Nonetheless, our finding is like Enciso et al. (2016), who concluded that the control of corruption does not impact credit scores for a panel of Latin American countries. Furthermore, Sychowiec et al. (2021) reported that due to federal transfers, states with a high incidence of corruption can maintain favorable rating scores in the United States of America. Like the control of corruption, regulatory quality does not influence South Africa's sovereign rating scores. The finding is contrary to Butler and Fauver (2006) who showed that a standard deviation improvement in the quality of the legal environment improves a country`s ratings by 0.466 standard deviation. Afonso et al. (2011) and Enciso et al. (2016) provided evidence that government effectiveness improves sovereign rating in the long run. However, Model 4 shows this is not the case with South Africa. Political environment, adherence to laws, freedom of expression and accountability (Models 5, 6, 7 respectively) are concluded to be insignificant drivers of rating scores in South Africa. For developing countries, Mim et al. (2023) Stated that institutional quality is critical only as far as the probability of sovereign downgrade is concerned and not the improvement thereof. Other than the governance factors, Models 1, 3, and 4 show that the ratio of reserves to external debt significantly influences sovereign ratings at 1%, 10%, and 1%, respectively. High volume of reserves reduces the probability of default by the borrower (Afonso et al., 2011). Model 4 further provides evidence that the ratio of current account balance to gross domestic product and the level of inflation drive sovereign credit ratings. The significant positive relationship suggests that: "rapid accumulation of investment, which should lead to higher growth and improved sustainability over the medium term" (Afonso et al., 2011). On the other hand, the positive relationship between inflation and sovereign ratings can be explained by the observation that it reduces the real stock of outstanding government debt in domestic currency, leaving more resources to cover foreign debt obligations (Afonso et al., 2011).

5. CONCLUSION

The study aimed to empirically assess whether governance quality influences sovereign credit scores in South Africa. South Africa faces a significant infrastructure financing gap that requires not only public sources but also the issuance of securities on global capital markets to supplement public finances. In this context, sovereign credit scores become a critical component of South Africa's development finance discourse. An Autoregressive Distributed Lag (ARDL) framework was applied to data collected over 23 years, ending in 2023. The study concluded that, individually, the World Bank reported governance indicators do not influence sovereign credit scores in South Africa. However, macroeconomic variables such as the foreign reserves to debt ratio, current account balance to gross domestic product ratio, and the level of inflation significantly impact credit scores in South Africa. Conversely, the ratio of foreign direct investment and the growth rate of gross domestic product are insignificant. From a policy perspective, although governance variables are individually insignificant, the government of South Africa should seek to enhance institutional quality. This is based on the observation that, even if some governance variables do not directly improve rating quality, they reduce the probability of a sovereign downgrade. From a macroeconomic standpoint, the government should implement strategies to increase foreign currency reserves. A high reserves-to-debt ratio indicates a better capacity to settle liabilities when due. Additionally, South Africa, with its elevated levels of public debt, should actively pursue debt reduction strategies to avoid excessive costs when raising new funds. Debt reduction is instrumental in fostering positive investor sentiment and improving sovereign ratings. Furthermore, the government needs to target stable inflation rates that maintain a healthy balance between preserving investor value. Uncertainty around inflation indicates underlying macroeconomic imbalances that can negatively impact South Africa's ratings. Future research could explore whether governance variables collectively influence credit scores in South Africa. The study could also be expanded by including least developed economies, which would enhance the generalizability of the results.

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Appendix 1. Scale to convert alphabetic CRA scores into numeric values.

Rating description	Linear transformation	S&P	Fitch	Moody's
Prime	20	AAA	AAA	Aaa
	19	AA+	AA+	Aa1
High grade	18	AA	AA	Aa2
	17	AA-	AA-	Aa3
	16	A+	A+	A1
Upper medium grade	15	A	A	A2
	14	A-	A-	A3
	13	BBB+	BBB+	Baa1
Lower medium grade	12	BBB	BBB	Baa2
	11	BBB-	BBB-	Baa3
	10	BB+	BB+	Ba1
Non-investment grade speculative	9	BB	BB	Ba2
	8	BB-	BB-	Ba3
	7	B+	B+	B1
Highly speculative	6	B	B	B2
	5	B-	B-	B3
	4	CCC+	CCC+	Caa1
Substantial risks	3	CCC	CCC	Caa2
	2	CCC-	CCC-	Caa3
Extremely speculative	1	CC	CC	
Default imminent	1	C	C	Ca
	0	RD	DDD	
In default	0	SD	DD	C
	0	D	D	

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