An analysis of the determinants of sovereign credit ratings

by

Yao Chao Yang
12082602

Submitted in partial fulfilment of the requirements for the degree

MSc Actuarial Science

in the

Faculty of Natural and Agricultural Science

at the

University of Pretoria

Supervisors:

Dr F.J.C. Beyers
Dr R. Seymore
Dr A. De Freitas

2018

ABSTRACT

The study aims to quantitatively assess the extent to which sovereign ratings could be explained by a set of economic variables. A wide variety of factors could potentially bias a credit rating agency's decision. The analysis begins with replicating the results found in a seminal analysis by Cantor and Packer (1996). This analysis expanded by including more countries, dynamic over time and time lags. Multiple complementary statistical models and a Random Forest model are explored in this study. To ensure robustness of the model, out-sample-testing is applied. The results show that GNI per capita, GDP growth, total debt to GDP, inflation rate, default amount, default indicator, HDI, change in HDI and IMF indicator are statistically significant. It is observed that current account to GDP, GDP growth and inflation rate have a time-lagged effect on sovereign ratings. A further analysis by separating between developing and developed countries using the IMF indicator suggests that there is a discrepancy between developing countries ratings and developed country ratings. The model results also support the existence of subjective decisions or adjustments in sovereign risk assessment.

DECLARATION

I, Yao Chao Yang, declare that the thesis/dissertation, which I hereby submit for the degree MSc Actuarial Science at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

Date: 28 November 2018

ACKNOWLEDGEMENTS

I would like to thank my research supervisors Dr F.J.C. Beyers, Dr A. De Freitas and Dr R. Seymore for their continuous guidance, advice and valuable insights. I would also like to thank the research article co-authors, Prof R. van Eyden and Prof J.P. de Villiers, as it was a combined effort from all in completing the research article. In addition, I am grateful for the support of my managers at FNB.

Table of Content

List of Tables

Table of Figures

1 INTRODUCTION

As emerging markets expand and globalisation increase, global financial and economic integration has heightened the importance of sovereign ratings (Bissoondoyal-Bheenick, 2005; Haspolat, 2015). The increase in overseas investments has led to multifold demands for accurate financial information across different countries and consequently the demand for sovereign ratings. The sovereign ratings assigned to a country provide an indication of the government's financial ability and willingness to meet its debt obligations on time. In relation to the bonds issued by the country, sovereign ratings provide a measure of the quality of the bonds (Bissoondoyal-Bheenick, 2005; Polito and Wickens, 2014). Sovereign ratings are forward-looking opinions of the sovereign's capacity and willingness to service their debt in full and on time (S&P, 2016; Fitch Ratings, 2017). The study aims to quantitatively assess the extent to which sovereign ratings could be explained by economic variables.

Many investors around the world invest to meet their investment objectives, such as maximising profit or matching their assets and liabilities. A key principle in investment is to understand the risk involved in each asset class. The main objective of any investment is to select assets that maximise the investors' overall return for a given level of risk. For investors, credit ratings provide the most recent information on the likelihood of default by debt issuers, and therefore provide an indication of the riskiness of such assets. For issuers, ratings provide a guideline on the cost of capital as well as an independent assessment of the firm or the country from an external entity (Ho and Rao, 1993; Dimitrakopoulos & Kolossiatis, 2016). A low sovereign rating increases borrowing costs, which could affect a country's access to international capital (Luitel, et al., 2016).

Credit analyses often involve both quantitative and qualitative evaluation (Moody's, 2016). These assessments often look at the purpose of a loan, ability to repay the loan and the risks that could affect the ability to repay. It is important to determine the purpose of loans, as the use thereof may affect the prospect of a country. Payback ability assesses the government's expected source of repayment. The focus is on whether the source is sustainable and whether there are any alternative sources or refinancing plans. Risks that could impact the likelihood of repayment takes into account the macroeconomic condition of the country and the regulatory stability of the country (IFE: ST5 note, 2015). In the context of assessing the creditworthiness of sovereign issuers, more focus is placed on characteristics such as the sovereign's ability to modify the country's tax to generate revenue for debt servicing, the ability to restrict and reduce expenditure and the ability to recover after default events (Moody's, 2016).

A sovereign issuer refers to the government who oversees the fiscal authority (Fitch Ratings, 2017). National government, also considered as the largest borrowers in financial markets, issue short-term and long-term, as well as local and foreign bonds to generate funding for their financial obligations (Moody's, 2016). Common vanilla debts issued by the government are bonds, bills, notes, or a combination of them. The type of debt issued is based on the countries' market conditions, government policies, securities required, the term of the loan and the cost of fund (Moody's, 2016). In order for a government to gain easier access to the international market, they normally seek a credit rating score as it provides an independent view of its creditworthiness (S&P, 2011). Countries with sovereign ratings may enhance investments from local and overseas investors, as a sovereign rating provide investors a view on the government's ability to meet their debt obligations (Luitel, et al., 2016). Sovereign ratings are indicators of anticipated bond yields, as investors need an additional risk premium to compensate for the expected default. In an event of missing a coupon or principal repayment, this could result in an allocation of a default rating on the sovereign (Fitch Ratings, 2017).

Sovereign ratings are not only an important indicator for the government, but it is equally an important indicator for issuers under the sovereign's jurisdiction such as banks. Typically, the issuers' credit ratings are capped by the sovereign ratings (Bissoondoyal-Bheenick, 2005; Verster, et al. 2016). A movement in the sovereign rating may result in an issuer under its jurisdiction obtaining a rating below investment grade. Consequently, the issuer may face large institutional funds being withdrawn. This is possibly due to strict regulations prohibiting investments in assets with ratings below investment grade (Bissoondoyal-Bheenick, 2005). For example, certain pension funds might disinvest in assets that no long meet the regulatory requirements.

The main providers of sovereign credit ratings are Moody's, Standard and Poor's, and Fitch. The annual report in 2014 on Nationally Recognized Statistical Rating Organizations reported that the abovementioned three credit rating agencies held a total market share of 95% in the United States (SEC, 2015). In the European Union (EU), based on the annual turnover calculation of market shares, they held around 90% of the market share (ESMA, 2014).

Credit rating agencies act as information suppliers by processing various inputs to produce ratings. Sovereign ratings are published periodically or after a major event has occurred. The credit rating agencies use different symbols to represent each credit risk scale. Table 1 shows a summary of the different rating symbols used by the main credit rating agencies.

Table 1: Rating scales used by the credit rating agencies. The credit risk level is based on Moody's rating description.

	Moody's Ratings	Standard and Poor's Ratings	Fitch Ratings	
Investment Grade	Aaa	AAA	AAA	Lowest level of credit risk
	Aa1 Aa2 Aa3	AA+ AA AA-	AA+ AA AA-	Very low credit risk
	A1 A2 A3	A+ A A-	A+ A A-	Low credit risk
	Baa1 Baa2 Baa3	BBB+ BBB BBB-	BBB+ BBB BBB-	Moderate credit risk
Speculative Grade	Ba1 Ba2 Ba3	BB+ BB BB	BB+ BB BB	Substantial credit risk
	B1 B2 B3	B+ B B-	B+ B B-	High credit risk
	Caa1 Caa2 Caa3	CCC+ CCC CCC-	CCC+ CCC CCC-	Very high credit risk
	Ca	CC C	CC C	In or near default with some recovery
	C	SD D	DDD DD D	In default with little recovery
(Source: Moody's, 2016; Standard and Poor's and Fitch scales: https://www.cnb.cz)				

After the financial crisis in 2008, credit rating agencies were heavily criticised for their failure to accurately identify the risks associated with the different types of debt. The securities at the center of the financial crisis were subprime mortgage securities. Credit ratings issued by the credit rating agencies were under heavy scrutiny because insolvent financial institutions were issued favourable rating evaluations. Risky mortgage-related securities were wrongly approved by the credit rating agencies (Naciri, 2017). Moody's and Standard and Poor's were both heavily penalised by the U.S. Justice Department for their action in inflating the subprime mortgage securities' ratings (Scully and McLaughlin, 2017). Since bonds assigned with high credit ratings also carried a high risk, the reliability of the ratings assigned by the credit rating agencies remains a concern (Haspolat, 2015).

Although credit rating agencies make information on credit ratings available, such as the variables examined[1], and the general methodology applied, the precise steps in deriving the final ratings are not obtainable (Dimitrakopoulos & Kolossiatis, 2016; Verster, et al.,2016). Luitel et al. (2016) noted that the methodologies used by rating agencies are not disclosed in full nor in transparent manner. Moody's emphasises that the results from the factors considered in their assessments are not conclusive of the rating decision (Moody's, 2016). This has led to many rating users to question the methodology applied by the credit rating agencies and the criteria underlying the sovereign ratings. In particular, it is unclear how accurate the ratings resemble the probability of default by the country.

As mentioned, there have been many uncertainties with regards to the accuracy of credit rating agencies' risk assessment in identifying risk. In order to better understand the accuracy of credit rating agencies' risk assessment it is important to understand how credit rating agencies assign their sovereign credits ratings. A wide variety of factors could potentially bias a credit rating agency's decision. In this paper, the focus is on quantitatively assessing the determinants of sovereign credit ratings. The problem statements are stated below.

Problem statement

This research considers the following questions:

1. Can sovereign credit rating decisions by credit rating agencies be accurately explained and replicated by applying a statistical methodology using publicly available information and data?
2. Is there a group of determinants that influence sovereign credit ratings provided by Moody's and Standard and Poor's?

[1] More details on the variables considered by each of the three credit rating agencies are explained in section 2.3

The research aims to answer the above questions by:

1. Replicating the existing sovereign ratings analysis done by Cantor and Packer (1996) to examine whether the determinants are significant.
2. Testing different statistical modelling techniques and considering additional determinants.
3. Building a predictive model for sovereign ratings from the results obtained in (1).
4. Analysing the differences between developing and developed countries.
5. Applying the results obtained for countries as a case study.

Contributions to the current available literature are: (1) using more inclusive data – in terms of the number of years and the number of countries, to examine if the results from previous research[2] are consistent and up to date, and the determinants that are applicable; (2) compare the model ratings to the observed ratings; (3) investigate the extent to which economic factors impact South Africa's sovereign ratings by applying sensitivity tests and scenarios analysis.

[2] Research by Cantor and Packer (1996).

2 LITERATURE REVIEW

2.1 Background on sovereign ratings

The credit ratings industry expanded in the late 1800s when the classification of various bonds began – primarily railroad bonds. "History of Railroads and Canals in the United States" was published in 1860 by the forerunner of securities analysis Henry Varnum Poor. By 1890, Standard and Poor's predecessor, Poor's Publishing Company, published the "Poor's Manual" which analysed bonds (Partnoy, 2006).

John Moody made use of the details available and processed mass information into an understandable format with a hope that investors will be willing to pay for information. In 1909, John Moody published his first rating system for bonds in the book "Analysis of Railroad Investments". He began the assessment of the bonds issued by the railroad companies and assigning ratings to these bonds. The markets boomed in the 1920s, which led to an increase in demand for his ratings as well as Poor's (Nguyen and Knyphausen-Aufseß, 2014; Partnoy, 2006). Credit rating agencies generated revenue by charging the investors a fee for subscriptions. In 1930s, the economic depression caused a spike in sovereign defaults and stock market crashes, which resulted in many rating downgrades. As a result, the investors started losing interest in paying for ratings (Partnoy, 2006).

During 1975, the US Securities and Exchange Commission (SEC) decided to use ratings published by the major credit rating industries to assure capital regulatory requirements, particularly using the ratings when calculating the net capital requirement for debt securities. In doing so, the concept of Nationally Recognized Statistical Rating Organizations (NRSRO) was formed. Only credit ratings published by NRSRO agencies can be used when determining regulatory capital requirements. The reliance on credit ratings grew rapidly when the SEC increased the use of an NRSRO proxy for liquidity and creditworthiness regulatory requirements. Additional regulations resulted in NRSRO credit rating agencies becoming more relevant and important (Partnoy, 2006).

In 1975, the SEC stipulated that Moody's, Fitch and S&P ratings were to be adopted nationally. The SEC staff should not ask questions on firms' net capital calculation should firms determine their net capital using ratings provided by these credit rating agencies' ratings. When the SEC published the "2003 Concept Release", concerns were raised by the public on whether credit ratings (provided by previous NRSROs compliance rating agencies) should continue to be included in the regulations. The SEC was also requested to clarify the process of determining whose credit ratings to use and the level of oversight on the credit rating agencies (SEC, 2005). As of 2015, ten credit rating agencies[3] are registered as NRSROs (SEC, 2015).

2.1.1 The credibility of credit rating agencies

The credibility of ratings provided by the credit rating agencies is often questioned (Polito and Wickens, 2014; Haspolat, 2015; Luitel, et al., 2016; Scully & McLaughlin, 2017; Naciri, 2017) and criticism against the credit rating agencies on the misalignment of sovereign ratings was brought forward after the global financial crisis in 2008 (Gültekin-Karakas, et al., 2011). In 2011, the US SEC expressed their concerns about the credit rating agencies' ability to make timely and accurate disclosures. In the same period, the European Commission also proposed to have stricter rules in place for credit rating agencies in order to increase transparency and accountability (Polito and Wickens, 2014). Chen, et al. (2013) stressed that sudden changes to the sovereign ratings can affect the sovereign's real macroeconomic conditions by highlighting the immediate impact on the Euro and world stock markets after Fitch Ratings downgraded Spain's sovereign debt in 2010. This led to debates about the credit rating agencies' ability to foresee economic crises and how their involvement can exacerbate the economic condition when sudden changes are made to their ratings (Haspolat, 2015).

Dimitrakopoulos and Kolossiatis (2016) mentioned that credit rating agencies should see through a business cycle. The credit rating agencies should not assign good ratings only when favourable economic condition as the economic condition might deemed to expire or not to downgrade a country rating when they face short-term tight economic conditions. These studies stressed that credit rating agencies have, in the past, made decisions that exacerbated economic conditions (Chen, et al., 2013; Polito and Wickens 2014; Dimitrakopoulos and Kolossiatis, 2016).

[3] The Ten NRSROs credit rating agencies: A.M. Best Company, Inc.; DBRS, Inc.; Egan-Jones Ratings Company; Fitch Ratings, Inc.; HR Ratings de México; Japan Credit Rating Agency, Ltd.; Kroll Bond Rating Agency, Inc.; Moody's Investors Service, Inc.; Morningstar Credit Ratings, LLC; Standard & Poor's Ratings Services

The credit rating agencies run an issuer-pay business model, where the issuers of bonds need to pay to obtain a rating. In the case of a sovereign issuer, the sovereign country issuing the bond is the one that pays for the service of obtaining the ratings (Polito and Wickens, 2014). This type of business model appears to be contradictory and vulnerable to conflict of interest which can affect the quality and standard of the ratings (Luitel, et al., 2016; Naciri, 2017). Firstly, the issuer may be willing to pay to achieve a specific rating scale. Secondly, the credit rating agencies might be incentivised to push up the ratings in order to retain their customer base. Also, issuers with unsatisfactory ratings may decide to not be rated. This causes a conflict of interest with the rating users whose primary concern is the accuracy of the issuers' creditworthiness (Naciri, 2017).

The credit rating agencies emphasise that their ratings are prone to subjectivity and it represent their opinions about a borrower's creditworthiness. However, many studies conclude that the ratings are not an accurate representation of an issuer's creditworthiness (Nguyen and Knyphausen-Aufseß, 2014; Haspolat, 2015; Verster, et. al.,2016). Therefore, one of the aims of the study is assess whether credit rating decisions can be determined.

2.1.2 Emerging markets' credit ratings with a focus on South Africa

Investing in emerging markets' debt has attracted many investors due to beliefs that expected yield returns are higher as well as the ability to diversify their portfolios (Lazard Asset Management, 2017). Therefore, the accuracy of the credit ratings assigned to emerging markets' debts are often a concern for investors. As shown in Figure 1, on average, 59% of the countries in the emerging market are assigned a speculative grade rating, while only 9% of countries in the developed market are assigned a speculative grade rating. This raises a question around whether credit rating agencies apply a consistent rating assessment across all countries. Many studies attempt to address the inconsistencies pertaining to rating assessments of the emerging market countries by the rating agencies (Bissoondoyal-Bheenick, 2005; Gültekin-Karakas, et al.,2011; Luitel, et al., 2016).

Bissoondoyal-Bheenick (2005) grouped each country according to their financial stability histories to model the sovereign ratings separately. The results show that variables *net export to GDP*, *unemployment rate* and *unit of labour* *cost* are significant for high-rated countries (Moody's Aaa to Aa3 and S&P AAA to AA), whereas for low-rated countries (Moody's A1 to C and S&P A+ to CCC), *current account balance to GDP* and *foreign debt to GDP* were significant. Gültekin-Karakas et al. (2011) assessed countries in the developed and in the emerging markets separately. Countries were classified between high-income and low-middle-income based on the World Bank country classification. One example of inconsistency they found was GDP, which is highly significant for the high-income countries while it is insignificant for the low-middle-income countries. The authors conclude that high-income countries are more likely to be assigned a higher rating compared to low-middle income countries irrespective of the sovereigns' economic fundamental at the point of assessment. Both studies show that inconsistent weights are placed on the economic factors when assigning sovereign credit ratings to the emerging market countries.

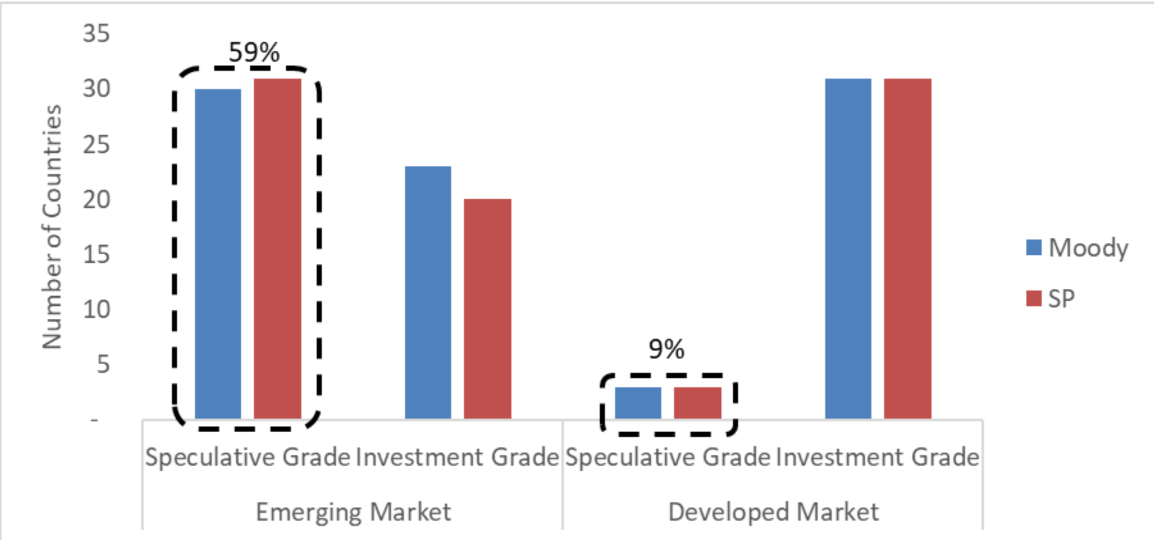
Luitel et al. (2016) made a comparison between ratings assigned by US-based (Moody's, Fitch and S&P) and Chinese-based (Dagong) rating agencies. The results show that, on average, US-based rating agencies assign AAA to the US, whereas Chinese-based rating agencies assign A+ rating to the US. A similar discrepancy can be observed for China's ratings assigned by Dagong compared to the ratings assigned by US-based rating agencies (on average, there is a difference of 5 to 6 notches with Dagong assigning the higher ratings). Luitel et al. (2016) continue to observe that US-based rating agencies favour countries in the UN General Assembly that have a high voting coincidence with the US, and countries that have similar geopolitics as the US. Dagong, on the other hand, favour the East Asian countries more. Luitel et al. (2016) noted that the emerging markets countries are subject to more frequent multi-notches rating movements. This often result in frequent rating downgrades or low ratings assigned to sovereigns.

Given that emerging markets, generally have a limited amount of quantitative data available, the sovereign credit risk assessment might place more weight on subjective judgments (Luitel, et al., 2016). This is different to the results observed by De Freitas et al. (2018), whose research examined the influence of whether a country is classified as developing country or advance economic based on credit ratings assigned by Moody's. They found that the developing countries' ratings were more directly explained by the model, whereas the developed countries' rating models showed a contrast (De Freitas, et al., 2018). This analysis is demonstrated in chapters 3.

Emerging market countries depend on the credit rating scores to gain access to international funding, hence the bias that may exist in their credit ratings due to subjective judgments can affect their access. Also as mentioned in chapter 1, the effect can extend to debt issuers under the South African government jurisdiction because of the sovereign ceiling that is observable. This places doubt on the accuracy of ratings assigned to companies within the South African jurisdiction (Verster, et al.,2016).

As shown in Figure 1, proportionally more emerging market countries are assigned speculative grade ratings, whereas developed market countries are assigned investment grade ratings. Therefore, it is interesting to analyse whether there are different rating assessments for countries with an emerging market compared to countries with a developed market. This study examines whether there are any difference between the modelling of emerging market countries and developed market countries. One of the aims is to investigate whether sovereign ratings, for a given set of similar set economic conditions, are assigned different ratings.

Figure 1: The distribution of ratings assigned to countries in emerging markets compared to countries in developed market using IMF classification for 2016.



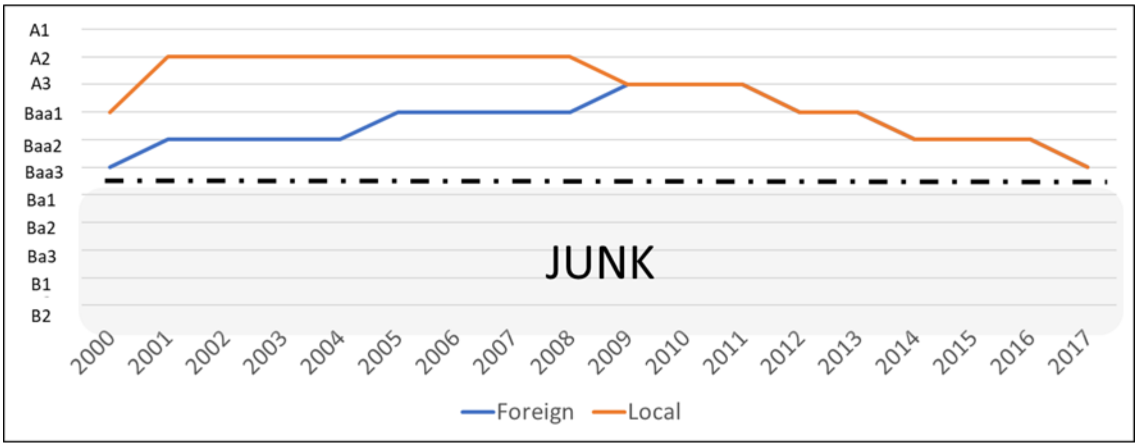
(Source: Moody's sovereign ratings data, S&P sovereign ratings data, IMF and own compilation. The data applied is discussed in chapter 4)

2.1.3 The differences between local and foreign debt credit ratings

Countries normally issue both local and foreign currency debts, and the rating agencies issue ratings to both types of debt (S&P, 2017; Moody's, 2016; Fitch Ratings, 2017). Foreign currency ratings assess the sovereign's ability to fulfil debt denominated in foreign currency (Capital Intelligence, 2018), whereas local currency ratings assess the sovereign's total debt denominated in their own currency. (Packer, 2003) However, there are certain exceptions, for example, if a local currency denominated bond is repaid in foreign currency, then a foreign currency rating might be more appropriate to be assigned for this bond. (Fitch Ratings, 2017)

Initially, sovereigns had low demand for obtaining local currency ratings for their debts, but in order to increase the investors' local currency bond pool, sovereigns are now also concerned about obtaining ratings for their local currency debts (Packer, 2003). Both local and foreign currency debts are generally assigned the same ratings (S&P, 2016; Moody's, 2016). The difference in ratings between local and foreign currency ratings is evident in that the issuers have different capacities to fulfil their debt obligation denominated in local currency compared to foreign currency (S&P, 2016). Moody's pointed out that an issue in a sovereign debt-servicing ability of one currency is likely to affect the debt-servicing ability of another currency, therefore the local and foreign currency ratings are closely related. A gap of larger than two notches (above or below) is rare (Moody's, 2016; Fitch Ratings, 2017). Figure 3 shows an example of Moody's ratings for South Africa's local and foreign sovereign ratings. The local and foreign ratings are aligned from 2009 onwards.

Figure 2 South Africa's local and foreign sovereign ratings. From 2009, the local and foreign ratings are aligned.



(Source: Moody's rating data)

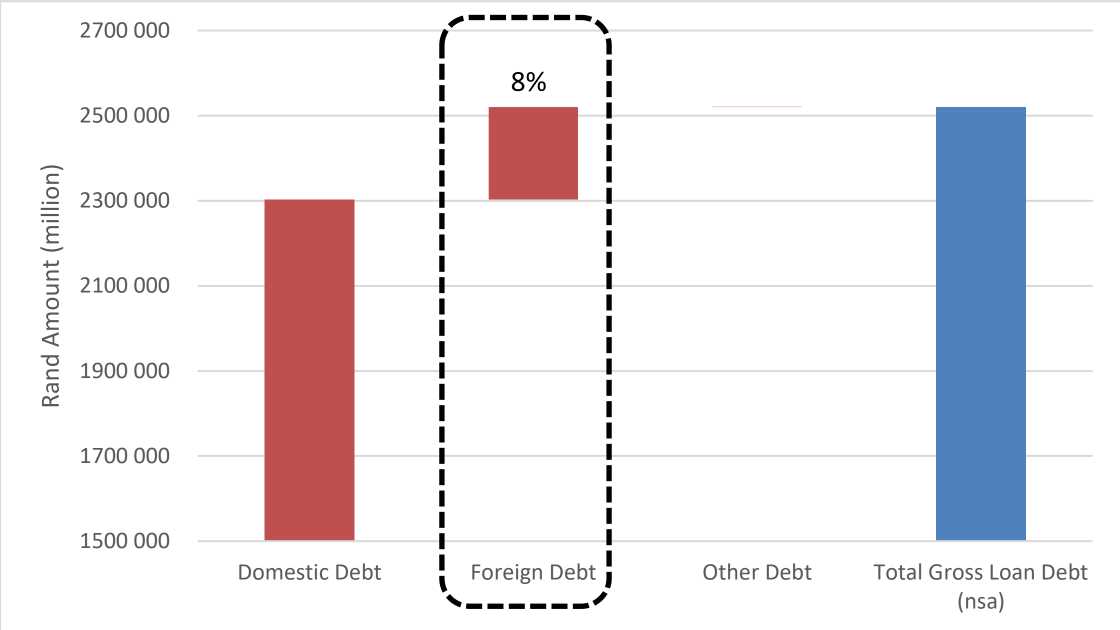
The sovereigns has a greater scope to selectively default on certain bonds (Fitch Ratings, 2017). This may affect the ratings assigned to local currency and foreign currency debt. Furthermore, since sovereigns need foreign currency to repay their external debts, the economy's ability to generate foreign currency and the market for local currency could affect the foreign ratings (Fitch Ratings, 2017). There is a possibility that local currency ratings can be rated above the foreign currency ratings if there exist a reliable and low-cost source of funding in an established domestic capital market (Fitch Ratings, 2017). Stable and low inflation could be a supporting factor for assigning local currency ratings above the foreign currency ratings. Local currency ratings might not receive a significant uplift if their currency is used in other countries. The focus of this study is on foreign sovereign ratings.

As mentioned in chapter 1, sovereigns with low ratings assigned may find that the servicing of debts are more expensive as a higher yield is expected to compensate for the higher risk of default. Another factor that could affect the debt-servicing amount is exchange rate. As shown in Table 2, South Africa's gross external debt at September 2017 was at USD 66.5 billion. The servicing of external debts for South Africa may become more expensive when the Rand exchange rate is weak. Figure 3 shows a summary of South Africa's total gross debt as at January 2018. South Africa's total gross debt amount is approximately R 2.5 trillion, of which 8% is foreign debt.

Table 2: Summary of South Africa's gross external debt.

Gross external debt		
	Sep-17	Dec-16
	$m	$m
1. General government	66 540	55 247
Long term	66 540	55 247
Debt securities	66 011	54 626
Loans	529	621
(Source: South African Reserve Bank)		

Figure 3: South Africa's total gross debt amount as at January 2018.



(Source: South African Reserve Bank and own compilation)

2.1.4 The uses of sovereign ratings

In relation to investment yield and credit rating scores, Cantor and Packer (1996) showed that there is a strong correlation between market-determined credit spreads and rating scores. This conclusion agrees in parts with the results by Ederington et al. (1987), they tested the correlation between corporate bond ratings and readily available financial accounting statistics. Moon and Stotsky (1993) support the results based on the correlation with municipal bond ratings. All three of the studies confirm that ratings may provide information to the market over and above information derived from publicly available financial statistics. Findings by Cantor and Packer (1996) did not show that ratings contribute towards predicting yields, which differs with the other two studies.

Hu et al. (2002) estimated transition probabilities matrices for sovereign issuers by comparing default experience with results from the modelling of sovereign ratings using an ordered probit technique. They mentioned that sovereign rating transition probabilities matrices could contribute towards the risk management of portfolios of emerging market credit exposures. The sovereign transition matrix can also be used in modelling credit portfolios and in pricing for calculating future loss distributions. However, Hu et al. (2002) acknowledge that the lack of data for countries assigned low ratings can make the construction of matrices difficult.

Regulations often link financial practices with credit ratings, which implies that an inaccurate rating may result in costly effects (Ozturk, et al., 2016). They further highlight that investment mandates of investment funds (for example, pension funds and mutual funds) often make use of credit ratings as a guideline on the eligibility of including an asset in their portfolio. The bond criteria for inclusion in the bond indices are often defined in terms of the credit rating score (e.g. in terms of investment-grade bond or sub-investment grade bond). These indices are commonly used by investment managers (or fund managers) as a benchmark or to track their portfolio performances (Ozturk, et al., 2016). The borrower's credit ratings are often related to the investment restrictions set by the regulation, the funding cost and the availability of funding from capital markets. For example, without obtaining an investment grade rating, the borrower may only be able to receive funding from a few investors as the regulation may prohibit certain investors from investing in assets below investment grade. Even if the funding was available to many investors, the cost is normally higher to compensate for additional risks involved. The collateral requirements for certain bonds issued are also a function of the quality of the borrower's credit rating (Ozturk, et al., 2016).

The cost of capital is an important indicator for a company investing in a project. Chen et al. (2013) mentioned that an investment project's net present value can be affected by a sovereign downgrade as the risk premium might change the cost of capital. A common framework in valuing a project is to calculate the net present value by using weighted average cost of capital (WACC) to discount future cash flows. Minardi et al. (2007) made use of the rating scores as an input in determining the market cost of debt. They stressed that better estimation of cost of capital can improve the budgeting decision process.

Chen et al. (2013) argue that sovereign ratings can be used as an indicator for the choices of investment. Investors might shift their investments from high-risk countries to less risky markets in other countries when sovereign ratings change. They found that temporary private investment growth is expected following a sovereign rating upgrade and the vice versa also holds following a sovereign rating downgrade.

Chen et al. (2015) showed that changes to a sovereign rating have a significant response from the country's economic growth viewpoint. The outcome of reassigning a sovereign rating within one-notch downgrade (upgrade) is an increase (decline) of about 0.6% (0.3%) in the country's five-year average annual growth rates. They also pointed out that sovereign rating revision impacts the cost of capital and the availability of credit as rating revisions may spark a flight-to-quality. Rating movements change the investors' preceptive of asset riskiness. Flight-to-quality may result in capital flows shift as investors move their investments to less risky assets.

Several studies concentrate on the accuracy of rating prediction. These studies rely on the assumption that the assessment of default risk done by the credit rating agencies are 100% accurate (Jackson, 1988). Ozturk (2014) recommends using internal resources to eliminate any concerns arising from the inaccuracies of external credit ratings sources. Duygun et al. (2014) also mentioned that there is a divergence when comparing the actual ratings with the estimated ratings. They argued, before the 2008 economic crisis, that there was a significant discrepancy between EU countries. This implies that credit rating agencies are biased toward certain countries. Amstad and Packer (2015) does not agree with the finding pertaining to bias by the authors above. However, they do accept that emerging economies, on average, are rated one notch below their deserved scale. Bartels and Weder di Mauro (2013) found that emerging market economies are assigned lower ratings by Moody's and Standard and Poor's compared to ratings assigned by Feri, a European credit rating agency. This adds to the earlier mentioned comparison done by Luitel et al. (2016).

When building a model, there is a tendency to select a statistical model that has the best prediction power and select predictor variables that are theoretically important without considering other viable variables. For example, factors such as wars and revolutions may have been accounted for in the past sovereign ratings which may no longer be applicable. Also, there is a need to consider factors that could influence the sovereigns' policy decisions differently, such as the current millennium period, fiscal discipline, debt management, productivity constrains, and the contingent liabilities arising from weak banking systems (Bissoondoyal-Bheenick, 2005). The abovementioned factors are not commonly considered. Therefore, it is crucial to note these changes when attempting to determine the sovereign ratings from historical data.

Another concern worth pointing out is that sovereign ratings provide a forward-looking evaluation of the country's future debt service capacity. Quantitative economic variables provide a view on historical performance. Thus, it is interesting to see how the future sovereign ratings are correlated to the current and past economic conditions. (Bissoondoyal-Bheenick, 2005)

As mentioned, sovereign ratings are an important indicator for determining the level of cost of borrowing (Dimitrakopoulos and Kolossiatis,2016; Luitel, et al., 2016). This would affect the amount of debt a sovereign can issue. Dimitrakopoulos and Kolossiatis (2016) mention that the procyclicality of ratings, which refers to downgrade ratings not justified in the macroeconomic condition, could further increase a volatility of the level of cost of borrowing.

2.1.5 Conclusion

Ozturk et al. (2016) highlighted that there are about USD 50 trillion outstanding sovereign debts which are rated by the different rating agencies. Sovereign ratings are commonly used as an indicative view on the state of a country's economy. Hence, it is important that sovereign ratings reflect an accurate view for all stakeholders using the information. Ratings are often treated as the source of sovereign riskiness and therefore, there is a demand for better understanding of the derivation of sovereign ratings. The next section considers literature about rating determinants and methodologies.

2.2 Evaluation of different credit rating determinants and methodologies

A substantial body of research has focused on quantifying the sources of variation in credit ratings. This section evaluates the different credit rating methodologies and the determinants of sovereign ratings applied in past literature studies. The rating methodologies applied by the three rating agencies (Moody's, S&P, Fitch Ratings) are also discussed.

2.2.1 Early research on credit ratings

Credit rating agencies have been assigning ratings since the early 1900s (Partnoy, 2006). They often insist that credit rating scores involve more than a mere financial analysis using a statistical model. Qualitative factors, for example, the political state of a country, also need to be taken into account together with judgmental evaluations when determining a credit rating. However, many empirical studies (Horrigan's,1996; West,1970; Pinches and Mingo,1973) showed that it is possible to generate a statistically reliable prediction of the credit ratings by using a set of financial determinants.

Horrigan (1966) conducted the first study on how the estimation of the determinants of the bond-issuing firm is used to predict the firm's ratings. This research was widely considered to be seminal in this field. The research was based on using the predictive power of accounting data by transforming it into more meaningful financial ratios to determine the corporate bond ratings. Horrigan (1966) modelled the bond ratings using an ordinary least-squares (OLS) regression, and 65% of the ratings variation was explained by the model.

From thereon, research on the statistical predictions of credit ratings have rapidly expanded. Many empirical studies adapted Horrigan's (1966) research as a reference and encouraged further research on modelling credit ratings by means of using different statistical techniques.

West (1970) used an OLS regression technique in an attempt to predict industrial bond ratings. Pinches and Mingo (1973) developed a multiple discrimination analysis (MDA) approach to model credit ratings. They considered ratings as a categorical variable which is more appropriate than assuming that ratings represent equal intervals in a measurement scale under an OLS regression. Katz (1976) also followed the MDA approach. Kaplan and Urwitz (1979) used ordered probit models that treat bond ratings as a latent variable. Kaplan and Urwitz (1979) argued that both MDA and OLS regression techniques remove the ordinal nature of bond ratings. Ederington et al. (1985) conclude that using an ordered or unordered logistic regression outperform the results obtained from OLS and MDA. One of the main reasons for the poorer performance when using the OLS regression as opposed to logistic regression is the assumption of interval scale on the dependent variable. This assumes that the rating categories are spread evenly. For example, using Moody's rating convention, the level of credit risk difference between an A+ and A is the same between B+ and B. However, this is not the case since the ratings express different credit risk information.

Ho and Rao (1993) examined the relationship between bond ratings and determinants using a logistic regression technique. Their study showed that ratings are more inclined to default risk during the period where the economy was unstable. They deduced that it may be rational for credit rating agencies to change their weightings on each determinant in response to changes in the economic environment. They further pointed out that coefficients for independent variables should be adjusted frequently.

The abovementioned studies focused on examining the relationship between corporate bond ratings and various financial variables. The rest of the section considers literature based on sovereign rating methodologies.

2.2.2 Sovereign Credit Ratings

In this section, previous literature studies on modelling of sovereign credit ratings are considered. The first section reviews studies that considered conventional statistical regression modelling techniques for modelling sovereign ratings. Section two investigates modelling sovereign ratings using advanced machine learning techniques.

2.2.2.1 Statistical techniques

The first systematic analysis of the determinants and impact of the sovereign credit rating was carried out by Cantor and Packer (1996). They applied a regression analysis using data from 49 countries and eight economic variables, namely:

- GNI per Capita,

- GDP growth,
- inflation,
- fiscal balance to GDP,
- current balance to GDP,
- external debt to GDP,
- default indicator, and
- development indicator.

The authors conclude that both Standard and Poor's and Moody's sovereign ratings may be explained by a set of quantitative determinants.

Cantor and Packer (1996) also conclude that there is a lack of direct relationship between GDP growth, external balance, fiscal balance and the sovereign ratings. They explained that this was because developing countries in the period of examination were growing at a faster rate than developed countries with mature economies. The independent variables considered were limited to macroeconomic factors, therefore Cantor and Packer (1996) stressed that a quantitative model may not be sufficient to explain all the variations. As mentioned earlier, this approach of modelling sovereign ratings may not be the most appropriate method as it is based on the assumption that rating scales are equally apart.

Bissoondoyal-Bheenick (2005) tested the relationship between ratings and quantitative economic variables by grouping the ratings based on the countries' financial stability histories. He argued that countries with long financial stability histories and countries that are still going through structural changes are more likely to be impacted by different economic variables. He conducted an ordered response model[4] from the period 1995-1999, which covered the period of the Asian Crisis[5]. The study classified 25 countries as financially stable countries and 70 countries as developing countries. He concluded that GNP per capita and inflation has been the most relevant economic variables.

To examine more determinants, Melliosa and Paget-Blancb (2006) performed a principal component analysis to identify the main factors affecting the ratings. They selected 49 factors, which included a combination of economic, political and social variables. Results demonstrated that the following variables have the

[4] Research by Gültekin-Karakas, et al. (2011), Erdem and Varli (2014) and Freitag (2015) also used the ordered response model. This model considers the ordinal nature of dependent variable.

[5] Resulted from the collapse of the Thai baht and currencies of many Asian countries in 1997 (Lai, 2000)

most influence on ratings:

- per capita income,
- government income,
- real exchange rate,
- default rate, and
- inflate rate.

These factors are then used in linear regression and logistic regression modelling. From the comparison of techniques, logistic regression performs better than linear regression. Another finding from Melliosa and Paget-Blancb (2006) is that corruption index appears to be an indicator for the quality of economic development and the governance of a country. Melliosa and Paget-Blancb (2006) acknowledge that the use of corruption index as proxy can only account for some aspects of political risks.

Haspolat (2015) examined the determinants affecting Moody's ratings using a multiple linear regression technique. The study found the following factors affecting the sovereign ratings positively:

- GDP per capita,
- governance quality,
- current account balance,
- growth performance and growth expectations,
- being an industrialised country, and
- having a reserve currency.

Whereas, the following factors had a negative effect on sovereign ratings:

- exchange rate volatility,
- interest payments,
- debt stock, and
- default occurrences.

Testing within one notch[6] scales on 2007 ratings, the predicted grades are 80% consistent. Based on the analysis on Greece and other countries' economic and social data, Haspolat (2015) also stated that Moody's does not always provide a rating in accordance with the rating manual.

Most studies focus on the attempt to predict ratings that a credit rating agency will likely assign to a country. Polito and Wickens (2014) aimed to develop a methodology to measure sovereign ratings that are transparent, independent

[6] One notch difference is one rating higher or one rating lower. For example, one notch higher than B1 is Ba3 (Moody's rating scale).

and timely. Transparency refers to the accessibility and ease of replication of information by the public. Independence refers to the fact that sovereign ratings are derived by using a model-base technique rather than relying on subjective evaluations. The timely term refers to the frequency of updating the model with the latest data for evaluation.

Polito and Wickens (2014) used a different approach to generate sovereign ratings. They derived the probability of default by calculating the debt-GDP ratio in relation to the maximum future debt limit. The application of the Black-Scholes and Merton's model allows for distance-to-default and probability of default to be calculated. The probability of default is then mapped into different credit rating scales. They found that low sovereign debt limits and uncertainty in the macroeconomic condition contributes to the probability of default and hence resulting in the possibility of a lower rating being assigned. When this was applied to data from 1970 to 2011, it showed that ratings would have been downgraded during the 1970 oil crisis and the 2008 Lehman's collapse. Polito and Wickens (2014) also found that sovereign borrowing capacity can be capped by the debt-GDP limits.

Dimitrakopoulos and Kolossiatis (2016) investigated the persistence of sovereign ratings. A test was conducted to determine whether past sovereign ratings have a direct impact on the latest ratings. A true state dependence refers to the dependency of sovereign ratings on the past ratings, whereas a spurious state dependence transpires when current ratings are unrelated to past ratings. A third state examines the cyclical effect of ratings which test whether there is a serial correlation. The serial correlation considers the impact of sovereign ratings on the economic environment which simultaneously impacts the sovereign financial solvency and the sovereign ratings. Considering the ordinal nature of sovereign ratings, the authors selected a dynamic ordered probit model and the results demonstrated a weak relationship between the latest ratings and the previous ratings assigned.

2.2.2.2 Machine learning techniques

Since the inception of the digital era, there has been an emergence of machine learning techniques to model and predict sovereign ratings. The first study to compare an artificial neural networks model for sovereign ratings to statistical models was conducted by Bennell et al. (2006). From their findings, they claim that artificial neural networks models have better predictive capability than statistical methodologies. Studies done by Bellotti et al. (2011), Chen et al. (2011) and Caporale et al. (2011) also obtained the same conclusion that machine learning methodologies attain superior predictive performance.

Research conducted by Ozturk et al. (2016) suggests that, in terms of the accuracy of prediction, machine learning classifiers outperform conventional statistical techniques. Their model predictability exceeds 90% when predicting sovereign ratings within one or two notches. Another finding in their research shows that there is a decline in prediction performance for ratings that are proximate to the investment and speculative grade threshold. The authors explained that this may be an indication of early warning signs to credit rating agencies.

De Freitas et al. (2018) modelled sovereign ratings using a Random Forest machine learning technique by categorising the countries between developing and advanced economic using the International Monetary Fund (IMF) convention. This approach is further explained in chapter 3.

Ozturk et al. (2016) pointed out that the main limitation of machine learning techniques is the lack of interpretability. This refers to the inability of machine learning based methods to derive the statistical relationship between sovereign ratings and independent variables. The statistical significance of each independent variable in determining the sovereign ratings cannot be produced.

2.2.3 Summary of different techniques

Logistic regression is a common technique applied in credit risk modelling. The predictability of a logistic regression model is relatively accurate, and the results do not differ significantly from other advanced techniques (Serrano-Cinca, et al., 2015). The OLS technique assumes that the explanatory variables and the sovereign ratings have a linear relationship, but from the probability of default perspective, the relationship is non-linear. The OLS technique considers the dependent variable as a continuous variable but ratings are categorical variable and therefore, it is an inadequate approach. (Fitch Ratings, 2017; Dimitrakopoulos and Kolossiatis, 2016).

One limitation associated with more complex models, such as artificial neural networks, other machine learning algorithms and data mining techniques, are the complexity in replicating the methodology. The amount of data required for machine learning algorithms to train is another constraint given that there are limited historic sovereign data. Many credit rating users are not equipped with the knowledge and the tools to perform these analyses on their own. Another problem in using advanced machine learning algorithms is the difficulty of statistically interpreting the relationship between the dependent and the independent variables. The results and outputs may be difficult to interpret by users without background knowledge in machine learning.

There are many different techniques to approach a problem, as seen in Table 3. Each technique has its own merits. It is important to examine the quality and the characteristic of the data when selecting an appropriate technique.

In this study, given the qualitative discrete ordinal nature of ratings, OLS regression, ordinal logistic regression and Random Forest model are applied to assess the relationship between economic variables and sovereign ratings.

Table 3: Summary of different techniques used to examine the determinants of credit ratings.

Methodologies	**Studies**
Linear regression	Horrigan (1966); West (1970); Cantor and Packer (1996); Haspolat (2015); Melliosa and Paget-Blancb (2006);
Logistic regression (ordered and unordered)	Pinches and Mingo (1973); Ederington's (1985); Katz (1976); Kaplan and Urwitz (1979); Hao and Rao (1993); Bissoondoyal-Bheenick (2005); Melliosa and Paget-Blancb (2006); Gültekin-Karakas, et al. (2011);Varli (2014); Freitag (2015); Dimitrakopoulos and Kolossiatis (2016)
Machine learning	Bennell et al. (2006); Bellotti et al. (2011); Chen et al. (2011); Caporale et al. (2011); Ozturk et al. (2016); De Freitas et al. (2018)
Probability of default model	Polito and Wickens (2014)

(Source: Own compilation)

2.3 The methodologies used by the three main credit rating agencies

Standard and Poor's assesses each sovereign's creditworthiness based on quantitative and qualitative factors. The quantitative factors include economic and financial indicators as well as incorporating contingent liabilities. The qualitative factors take into account the political changes and policy developments. This is important as it provides an indication of the sovereign's future debt servicing ability (Beers, 2004). Similarly, Moody's ratings also look at both quantitative and qualitative factors. Moody's mentions that quantitative measures provide useful information on economic trends and cyclical patterns. However, these measures are backward-looking, whereas sovereign ratings are forward-looking analyses on the probability of sovereign default. Therefore, scenario and stress testing are required to test the country's economic vulnerability. (Moody's, 2013) Nguyen & Knyphausen-Aufseß, (2014) note that, although there are distinctive features, in general, credit rating agencies follow similar approach in their assessment.

The sections below further outlines the different approaches published by the three rating agencies.

2.3.1 S&P sovereign credit rating methodology

As shown in Figure 4, Standard and Poor's use the following pillars as a foundation of sovereign risk assessment:

- institutional assessment,
- economic assessment,
- external assessment,
- fiscal assessment, and
- monetary assessment.

In most instances, it is expected that sovereign ratings will follow within one notch of the indicative ratings based on the scoring system. However, in some cases, this does not hold when one or more adjustments are made on the factors (S&P, 2017).

The institutional assessment analyse the government's policymaking capability as it affects the sovereign's ability to promote a balanced economic growth, reaction to shocks, and the public's finance sustainability. The economic assessment considers the following drivers:

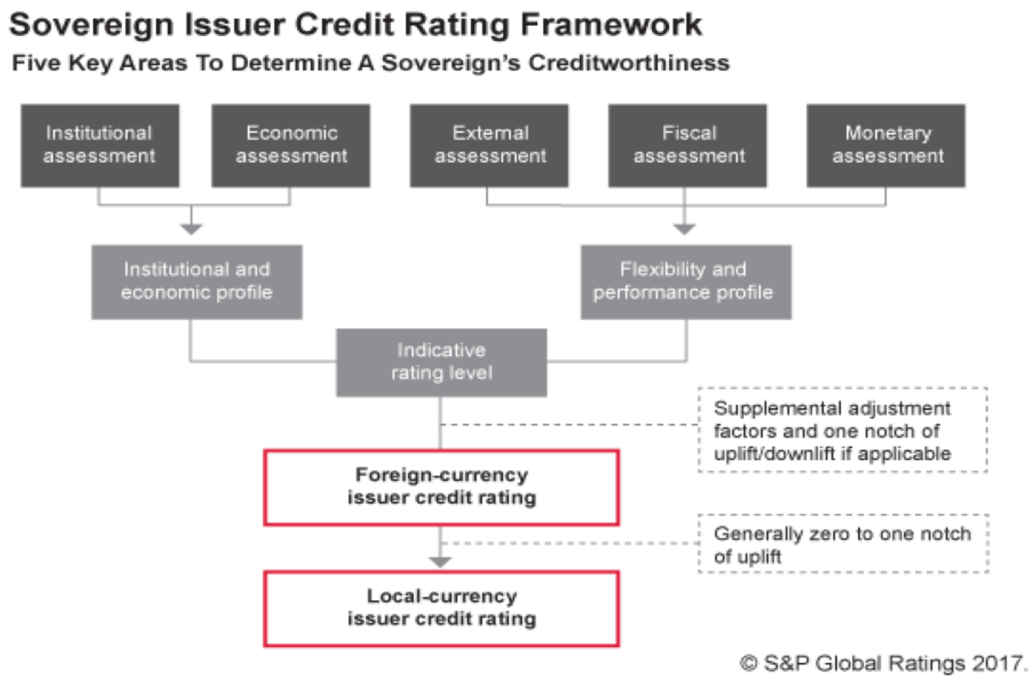
- income level,
- growth prospects, and
- economic diversity and volatility.

The most prominent measure of income is GDP per capita. A high GDP per capita could suggest that a country has a larger tax pool to draw from. Tax forms part of a large portion of the government's source of income. This will support the creditworthiness of the country. Growth prospects are measured by the real per capita GDP known as "trend growth". Standard and Poor's (2017) describes the "trend growth" as the sustainability of GDP growth over a period of time. Economic diversity and volatility assess the sovereign economic concentration risk and the vulnerability of the economy to risk events such as adverse weather conditions. The institutional assessment and economic assessment create an institutional and economic profile of the sovereign (S&P, 2017).

The external assessment examines the sovereign's ability to obtain external funding from aboard to meet their public obligations. The first measure looks at the degree of sovereign currency used in international transactions. Actively traded currencies and reserved currencies are attributable to better scores in an assessment. A sovereign currency is considered a reserved currency if it "accounts for more than 3% of the world's total allocated foreign exchange reserve" (S&P, 2017, p6). A sovereign currency is considered actively traded currency if it is "bought or sold in more than 1% of the foreign exchange market turnover" (S&P, 2017, p6). The assessment continues to assess the external liquidity and external indebtedness. To complete the assessment of the flexibility and performance profile of a sovereign, the fiscal assessment and the monetary assessment are required. The fiscal assessment considers the sovereign's debt burden and the sovereign's fiscal balance position and sustainability. The main consideration in the monetary assessment is the exchange rate as this may affect the country's monetary policy (S&P, 2017).

Although these five broad factors are generally assessed, Standard and Poor's (2017) mentions that supplemental adjustment factors are required periodically as certain credit risk factors tend to dominate a country's creditworthiness. The rating agency then makes judgmental adjustments to derive the indicative rating.

Figure 4: The five pillars used for sovereign credit analysis by S&P.



(Source: S&P, 2017)

2.3.2 Moody's sovereign credit rating methodology

Moody's (2016) highlights that there are four key factors as shown in Figure 5 used to update sovereign ratings, namely:

- the sovereign's economic strength,
- institutional strength,
- fiscal strength, and
- susceptibility to event risk.

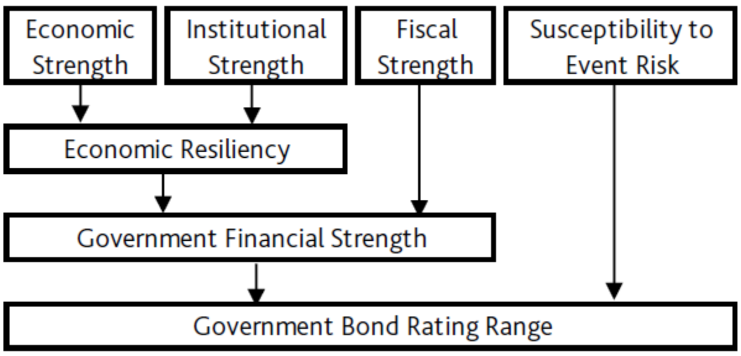
These factors are used in their scorecard by which the agency leverages off as a referencing tool. The scorecard provides a summary when assessing a sovereign's credit rating, however, Moody's stresses that it is not necessarily conclusive to the rating decision.

The four key factors considered in the sovereign risk analysis can further be broken down into rating sub-factors categories together with sub-factor indicators. Each of the sub-factors are assigned a weighting for calculating the scorecard. The sub-factor indicators are the different qualitative and quantitative indicators such as GDP growth and political risk (Moody's, 2016). Data and information for calculating or estimating the indicators are sourced from the International Monetary Fund, the Organization for Economic Cooperation and Development, the European Commission, the World Bank, and the Bank for

International Settlements. For some indicators, Moody's calculates an estimate based on the data provided by the national statistical source. The agency also applies an adjustment factor on a case-by-case assessment basis in instances whereby indicators are seen as outliers. The outcomes for each of the indicators are mapped into ranking categories. Once all the factors are taken into consideration, the rankings are then mapped into the respective rating symbols. Moody's emphasise that the scorecard results are not conclusive of their final credit rating decisions. (Moody's, 2016)

Figure 5 shows a summary of the different rating factors used as a proxy by the rating agency. The economic strength, institutional strength and fiscal strength factors assess the government's ability of resist medium-term shocks. The susceptibility to event risk factor considers the possible strain on government finance in an extreme event which could result in a sudden change to the sovereign's probability of default. (Moody's, 2016)

Figure 5: The four key factors considered by Moody's and the relationship of the factors.



(Source: Moody's, 2016)

2.3.3 Fitch Ratings sovereign credit rating methodology

Fitch Ratings considers a combination of a sovereign rating model and the qualitative overlay in their assessment of sovereign ratings. The sovereign rating model is the starting point of Fitch's assessment. There are four analytical pillars evident in Fitch's sovereign rating model analysis, namely:

- structural feature of the economy,
- macroeconomic performance,
- policies and prospect
- public finances, and

- external finances.

Based on the model, the structural feature of the economy which refers to the features that affect the economic vulnerability to shocks, generally carries the highest weighting in the model (Fitch Ratings, 2017). It is an ordinary least square regression model, which considers 18 variables where the data is based on historic, current and forward-looking possibilities. Data is collected from BIS, the IMF and the World Bank, and the sovereign national statistics. It sums up a final score which is mapped to a rating scale. It is imperative to conduct an annual review of the model to ensure that data is up to date with the estimation period.

Fitch Ratings (2017) acknowledges that the sovereign rating model cannot fully explain the influences on sovereign's creditworthiness, and therefore, they included a qualitative overlay in their assessment. This is to accommodate an adjustment for obscure factors and other unquantifiable factors. The process includes adjusting the rating notches derived from the output of a sovereign rating model. The adjustments are normally within the three notches range above or below. However, in the event of an extreme circumstance or rapid changes to a sovereign which is beyond the control of the model, the rating committee may extend the notch adjustment range based on subjective calls.

2.3.4 Discussion on credit rating agencies

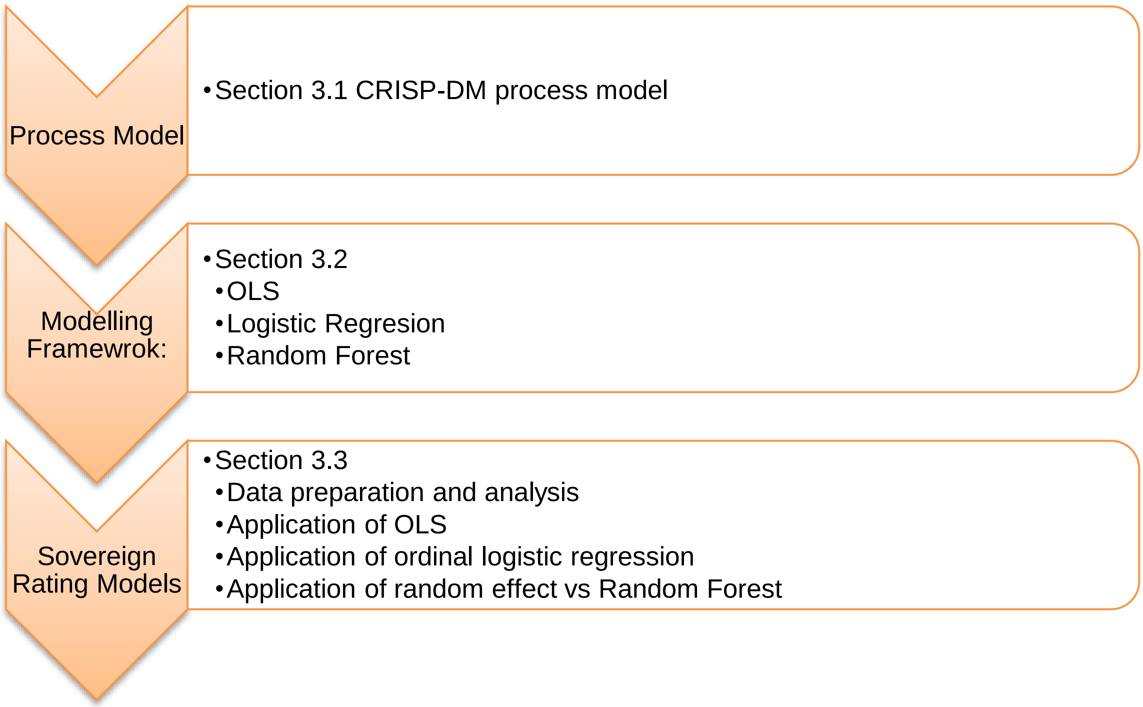
Verster, et al. (2016) noted that although the methodologies applied by the rating agencies are publicly available, the available information simply outline the key quantitative and qualitative factors considered. Dimitrakopoulos and Kolossiatis, (2016) also argue that the weights placed on each factor are not clearly defined and the subjective judgements made by the credit rating agencies are difficult to replicate. Another challenge is to obtain all the data used by the rating agencies, as some data are restricted and not accessible or freely available to the public.

Haspolat (2015) observed in their analysis that Moody's does not always assess a country according to the manual guide. The findings show that the ratings assigned does not reflect the countries' true economic, social and political situation. Haspolat (2015) further mentioned that similar arguments are applicable to other rating agencies such as Standard and Poor's and Fitch Ratings since an equivalent rating criteria is adopted. Nguyen and Knyphausen-Aufseß (2014) questioned whether the ratings are a result of the underlying factors fed into a methodology. Polito and Wickens (2014) found that the sovereign ratings methodology is based on the judgments of rating analysts. Luitel et al. (2016) noted that the subjective judgements and assessments are used in the absence of robust statistical modelling, which is based on the judgments of the rating committee. Polito and Wickens (2014) further claimed that the credit rating agencies do not make use of an economic model or a mathematical formula to determine sovereign ratings, but rather base decisions on mainly judgmental calls by risk analysts. They believe that the decisions are made by considering the economic and political factors in determining credit ratings. There is a sovereign risk unit within the credit rating agencies that issue, monitor and review ratings (Polito and Wickens, 2014).

3 DATA PREPARATION AND SOVEREIGN RATING MODELLING METHODOLOGY

In this chapter, the modelling framework applied to address the research question is explained. The rest of the chapter is as follow, section 3.1 explains the standard process model followed. Section 3.2 describe the different modelling methodology. Section 3.3 explores the models with sovereign ratings. This includes the data preparation and analysis. Section 3.4 considers different model metrics to assess the performance of models. Figure 6 shows the summarised flow for the rest of the chapter.

Figure 6 Summary of methodology followed

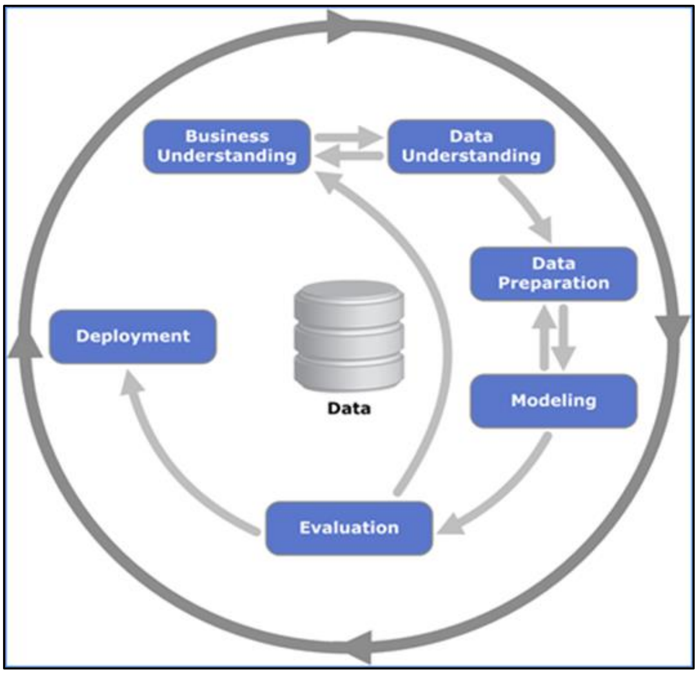


3.1 Process model

This study follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) process model (as shown in Figure 7) to address the research questions. The CRISP-DM was designed based on practical experience from real world data mining. CRISP-DM is a data mining model and a generic process model that can be adapted based on the needs of a specific problem (Shearer, 2000).

Chapters 1 and 2 outline the backgrounds of sovereign ratings and highlight the problems associated with the modelling and interpretation of credit ratings (business understanding). Chapter 3 analysis the data collected. An analysis of sovereign credit ratings and economic variables is conducted to examine any existing relationships (Data understanding). The data is then prepared for the modelling process (Data preparation). This is followed by the developing of sovereign rating models to explain the relative significance of the determinants and the relationship that may exist between sovereign ratings and economic variables (modelling). The model is then back tested to understand the difference between expected ratings and observed ratings (evaluation). Chapter 4 further evaluates the modelling results to determine whether the problem statement is addressed. Chapter 5 applies the ordinal logistic regression model on certain selected countries (Deployment). The chapter also performs sensitivity testing and scenario analysis.

Figure 7 The phases of the CRISP-DM reference model.



(Source: Shearer (2000))

3.2 Model Framework

In this section, conventional statistical modelling techniques and Random Forest techniques are defined and explained.

3.2.1 Ordinary Least Square Model

An Ordinary least squares (OLS) regression is a generalised linear model technique where the dependent variable (Y) can be represented as a linear

function of n independent variables (x_i).
The regression coefficient explains how Y changes as one unit of x_i changes. The dependent variable Y is represented by the line of best-fit. This line is computed using the least-square method. This is derived by minimising the sum of square of residuals (the difference between the observed Y and the model fit Y). This model is appropriate when the dependent variable can be represented as a scale interval variable (Hutcheson, 2011). Linear regression technique assumes that the dependent variables are nominal since categorical variables are converted to numeric numbers. The model assumes an equal interval level between each category. This removes the order and categorical nature of dependent variable.

3.2.2 Ordinal Logistic Regression (with and without random effect)

The primary aim of a logistic regression model is to model the dependent variable as a function of independent variables (Adeleke & Adepoju, 2010). A simple binary logistic regression explains the binary dependent variable *Y* as a function of X_i, the set of independent variables. A logistic regression model estimates the regression coefficients of the independent variables to predict the probability of an outcome event. An ordinal logistic regression technique is an extension of logistic regression (Menard, 2002). This technique allows for the ordinal nature of dependent variables. Sovereign ratings are ordinal as ratings can be ranked but the distances between the rankings are unknown. Considering the categorical and ordinal nature of sovereign ratings, the ordinal logistic modelling is applied to estimate the sovereign ratings in this study. Ordinal logistic regression model and ordinal logistic model are used interchangeably in this study.

Let $Y_{i,t}$ be the sovereign rating for country *i* and year *t*:

$$\ln\left(\frac{prob(Y_{i,t} \leq j)}{1 - prob(Y_{i,t} \leq j)}\right) = \alpha_j + \sum_{k=1}^{n} \beta_k X_{k,(i,t)} \; where\ j \in \{1, n-1\} \qquad (1)$$

where j is the sovereign rating scale from 1 to $n-1$. $X_{ik,t}$ are the k^{th} independent variables summarised in Table 6 for country i in year *t*. α_j is the threshold. A maximum likelihood estimation procedure is used to fit the model. β_k provides an indication of the sensitivity of each of K independent variable. The quantity on the left of the equation is called the logit. The coefficients of the independent variables indicate how the logit changes when independent variable changes by one unit.

An ordinal logistic regression with random effect is an extension of the standard ordinal logistic regression where the random effect is assumed to be independently and identically normal distributed. The extended formula is:

$$\ln\left(\frac{prob(Y_{i,t}\leq j)}{1-prob(Y_{i,t}\leq j)}\right) = \alpha_j + \sum_{k=1}^{n} \beta_k X_{k,(i,t)} + u_i \qquad (2)$$

$$where\ j \in \{1, n-1\}\ and\ u_t \sim N(0, \sigma^2)$$

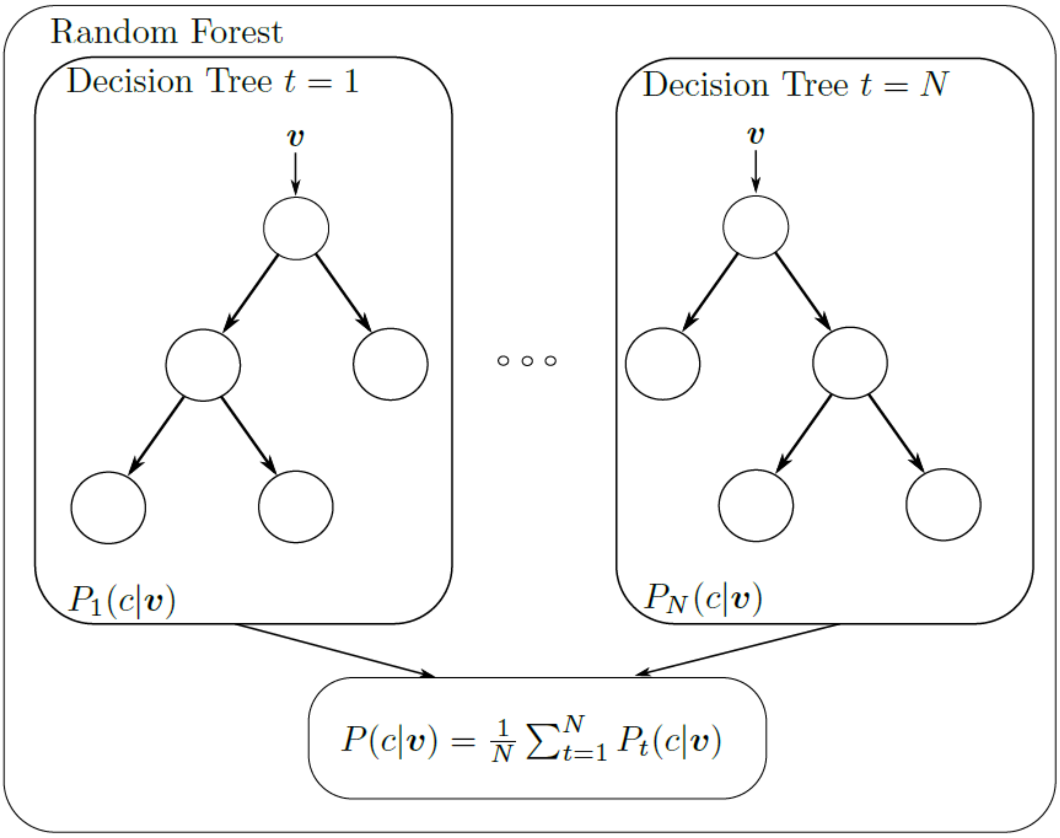
The training of the random effects OL model reduces to the estimation of the unknown parameters in (2) given a set of training data. This is achieved through either a frequentist approach of maximum likelihood estimation, or a Bayesian approach of Markov chain Monte Carlo (MCMC) sampling methods.

3.2.3 Random Forest Model

Supervised machine learning algorithms generate data driven models used for classification and regression. In this study, the machine learning algorithm used is the Random Forest. In contrast to the random effects OL model, the Random Forest is a nonparametric model. A Random Forest is an ensemble of predictive machine learning models, where each base model is a decision tree (Breiman, 2001).

The structure of a decision tree, illustrated in Figure 8, consists of a root node, connected with successive directional branches to nodes which each represent a choice between two alternatives. These are similarly connected to a final node for each branch, referred to as the leaf node, which represents a classification. A single decision tree is typically unstable and prone to overfitting (Bishop, 2006), but these disadvantages are alleviated with the Random Forest by accumulating the output decision of all the decision trees. In the context of classification, the output decision of the Random Forest is based on a vote over the predictions of the individual decision trees. The structure of a decision tree is learned from training data by selecting a variable at each step that optimally splits the training data according to a metric, for example, the Gini impurity used by the classification and regression tree (CART) algorithm (Breiman, 1984). To ensure decision tree diversity in the Random Forest, bootstrap aggregating is used to generate unique subsets of the training data for the learning of the structure of each decision tree. To further reduce correlation between the decision trees, each decision tree is also trained with only a random subset of the variables.

Figure 8 The structure of the Random Forest algorithm.



(Source: Own compilation)

The two parameters associated with the Random Forest are the number of decision trees, N, and the size of the subset of variables used by each decision tree, m_{try}. The Random Forest classification accuracy improves with an increase in N. The limitation to increasing N is the additional computational complexity and diminishing improvement in classification accuracy with larger values (Goldstein, et al., 2011). The value of m_{try} used by each decision tree is linked to the correlation between the decision trees. Optimal parameters are empirically selected based on the reduction of the out of bag (OOB) error (Goldstein, et al., 2011), which is the mean prediction error of the training samples using only the trees which did not have the training samples in their subset of training data. One of the advantages of the Random Forest algorithm is that it provides an internal estimate of variable importance. The most advanced measure of variable importance in Random Forests is the permutation accuracy importance (Strobl, et al., 2007). The importance of variable j is calculated by comparing the standard OOB classification accuracy and the OOB classification accuracy with the variable j randomly permuted. Let $B^{(n)}$ be the OOB sample for decision tree n, with $n \in \{1, \ldots, N\}$. The variable importance for each decision tree is

$$VI^{(n)}\left(x_{i,t}^{j}\right) = \frac{\sum_{(i,t)\in B^{(n)}} I(y_{i,t} = \hat{y}_{i,t}^{(n)})}{\left|B^{(n)}\right|} - \frac{\sum_{(i,t)\in B^{(n)}} I(y_{i,t} = \hat{y}_{i,t}^{\pi_{j},(n)})}{\left|B^{(n)}\right|} \tag{3}$$

where $\hat{y}_{i,t}^{(n)}$ is the predicted class for observation (i, t) before and $\hat{y}_{i,t}^{\pi_{j},(n)}$ after randomly permuting variable j. The total variable importance for each variable is

$$VI\left(x_{i,t}^{j}\right) = \frac{\sum_{n=1}^{N} VI^{(n)}\left(x_{i,t}^{j}\right)}{\sigma N} \tag{4}$$

where σ is the standard deviation of the differences.

3.3 Sovereign Credit Rating Data and Modelling

Before exploring the abovementioned modelling techniques on sovereign ratings, the dependent and independent variables are defined and analysed.

The dependent variable (sovereign ratings) and the independent variables (economic variables) are analysed in this section. The data collected is from the period 2000 to 2016. A total of 126 countries were considered for the analysis. A full list of countries selected can be found in the appendix. Cantor and Packer (1996) considered 49 countries in their study. The choice of the sample period is based on the availability of sovereign ratings data published by the credit rating agencies and macro-economic variables data for each country. The time period should include the impact of the global financial economic crisis on sovereign ratings.

The first part of data analysis considers the dependent variable sample. The total number of observed sovereign ratings considered is 3433. These observations include Moody’s and Standard and Poor’s ratings. There are countries which have not been considered throughout the whole period because the countries were not assigned in 2000. Ten macro-economic variables are then defined and plotted against the dependent variable to analyse the relationship. The selected variables are based on the variables considered by Cantor and Packer (1996). These variables broadly represent certain macroeconomic, political and social considered by the credit rating agencies (Fitch Ratings, 2017; Moody's, 2016, S&P, 2017). Countries with missing macro-economic variables for a specific year are excluded in the modelling process.

3.3.1 Dependent Variables

The dependent variable dataset is the foreign currency sovereign ratings from Moody's and Standard and Poor's for the period 2000 to 2016. When countries are assigned multiple ratings in a specific year, the most recent ratings for the year is selected. Moody's and Standard and Poor's use different symbols to represent their ratings, but for every Moody's rating symbol there is a counterpart in Standard and Poor's rating scales (as shown in Table 4). Therefore, for combined analysis, sovereign ratings are converted to numerical forms ranging from 0 to 20 (as summarised in Table 4). The sovereign ratings from Moody's and Standard and Poor's are combined to form a panel data sample which is used to analyse the main determinations considered by the ratings agencies.

As shown in Table 4, there is a poor representation for rating scales from 0-4. The frequency of rating scales between 0 to 4 is relatively low compared to other higher rating scales. Class imbalance occurs when one class has significantly less or more samples than the other classes i.e. the sample distribution is skewed. The existence of class imbalance may affect the model's ability to classify ratings in the minor ratings scale groups. To reduce the effect of class imbalances, data from rating scales 0 to 4 are clustered into one rating scale (visualised in Figure 9).

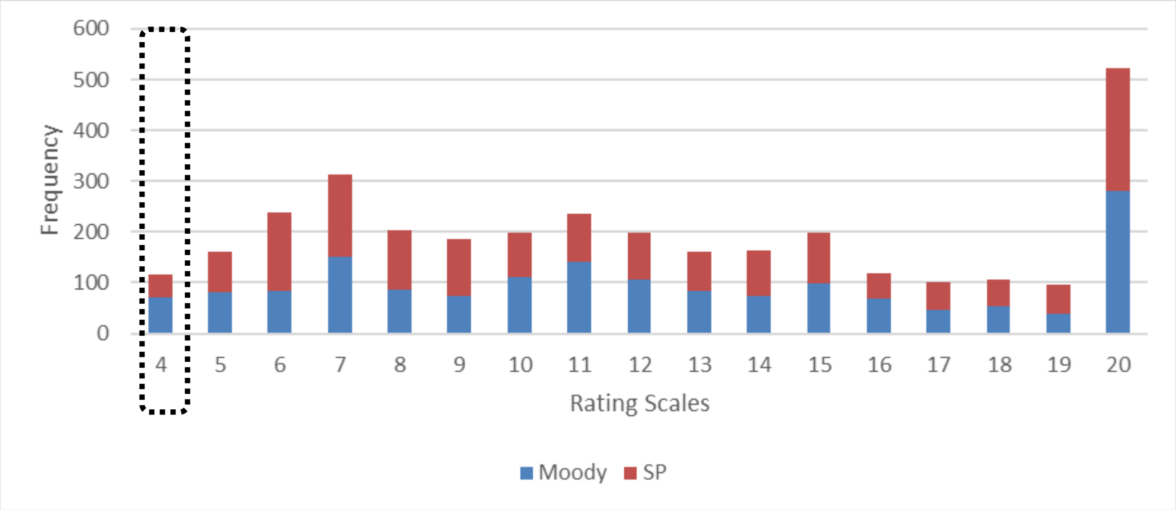
The initial analysis of independent variables in the later section is, however, based on the dataset without the grouping adjustment on the ratings.

Table 4: Summary of sovereign rating conversion. For every Moody's rating scale, there is a counterpart S&P scale. The frequency shows the combined number of observations for each of rating scales.

Conversion	Moody's Ratings	Standard and Poor's Ratings	Frequency	Adjusted
20	**Aaa**	**AAA**	522	522
19	**Aa1**	**AA+**	97	97
18	**Aa2**	**AA**	106	106
17	**Aa3**	**AA-**	102	102
16	**A1**	**A+**	118	118
15	**A2**	**A**	198	198
14	**A3**	**A-**	164	164
13	**Baa1**	**BBB+**	162	162
12	**Baa2**	**BBB**	198	198
11	**Baa3**	**BBB-**	236	236
10	**Ba1**	**BB+**	198	198
9	**Ba2**	**BB**	185	185
8	**Ba3**	**BB-**	203	203
7	**B1**	**B+**	313	313
6	**B2**	**B**	239	239
5	**B3**	**B-**	160	160
4	**Caa1**	**CCC+**	55	116
3	**Caa2**	**CCC**	16	
2	**Caa3**	**CCC-**	14	
1	**Ca**	**CC**	8	
0	**C**	**SD**	23	

(Source: Own compilation)

Figure 9: The distribution of rating scales split by Moody's and Standard and Poor's. This dataset shows the clustering of rating scales from zero to four.



(Source: Moody's, S&P sovereign ratings data and own compilation)

3.3.2 Independent Variables

The economic variables considered in this study are based on publicly available data (summarised in Table 5). Part of the study is to attempt to replicate and reproduce Cantor and Packer's (1996) findings. Therefore, the economic variables selected by Cantor and Packer (1996) are included: GNI per capita, GDP growth, inflation, fiscal balance, external balance, external debt, default indicator, and industrialised indicator. According to Moody's rating action report by Lindow (2016), these economic variables are commonly cited as determinants of sovereign ratings. Other economic variables[7] are considered in the model calibration to derive a sovereign rating model that may better explain the sovereign ratings. Although the rating agencies do not disclose the precise weighting applied to each factor, it may still be possible to measure the relationships that exist between them.

Economic variables provide an indication of the strength of an economy. Changes to the relative strength of an economy may affect the government's ability to fulfil their debt obligations in the near future. Otaviano, et al. (2004) mentioned that the prospect of an economy plays a significant role in the government's capacity and willingness to repay their debts. The government's primary source of income is tax received from the nation and the economic

[7] Summarised in Table 5.

prospect of a country will affect the amount of tax revenue available. Moody's emphasises that the economic strength or lack thereof of a country is a driver of possible sovereign defaults (Moody's, 2016).

In the next section, the independent variables (summarised in Table 5) are discussed in detail and its relationships with sovereign ratings are analysed. Table 6 summarises the lagged economic variables to be included in the ordinal logistic model. This examines whether any lagged effect on sovereign ratings exist. In the modelling section, variables in Table 5 and 6 are considered in the ordinal logistic model to examine whether the economic variables have a lagged effect on sovereign ratings and therefore, economic variables at time *t-1* and time *t-2* are also considered.

Table 5: Summary of independent variables[8].

Variable	Unit of measurement	Source
1. GNI per Capita	Dollars	World Bank
2. GDP growth	Percentage	World Bank
3. Inflation	Percentage	IMF
4. Fiscal balance	Percentage of GDP	IMF
5. Current balance	Percentage of GDP	IMF
6. Total debt	Percentage of GDP	IMF
7. Default indicator	Indicator variable	Bank of Canada
8. Development Indicator	Indicator variable	IMF
9. HDI	Index value	UNDP
10. Change in HDI	Percentage	Calculated
11. Default amount	USD amount	Bank of Canada

(Source: Own compilation)

Table 6: The independent lagged variables considered in the ordinal logistic model.

Variable at time t	Variable at time $t-1$	Variable at time $t-2$
GNI per Capita*(t)*	GNI per Capita*(t-1)*	GNI per Capita*(t-2)*
GDP growth *(t)*	GDP growth *(t-1)*	GDP growth *(t-2)*
Inflation rate *(t)*	Inflation rate *(t-1)*	Inflation rate *(t-2)*
Fiscal balance *(t)*	Fiscal balance *(t-1)*	Fiscal balance *(t-2)*
Current balance *(t)*	Current balance *(t-1)*	Current balance *(t-2)*
Total debt *(t)*	Total debt *(t-1)*	Total debt *(t-2)*
HDI *(t)*	HDI *(t-1)*	HDI *(t-2)*
Default amount *(t)*	Default amount *(t-1)*	Default amount *(t-2)*

(Source: Own compilation)

[8] Variables 1 to 8 are considered by Cantor and Packer (1996).

3.3.3 Analysis of Economic Variables vs Sovereign Ratings

In this section, the economic variables summarised in Table 5 are explained and the existing relationship between sovereign ratings and economic variables are analysed. The period of analysis is from 2000 and 2016. The graphs in this section plot countries' average sovereign rating over the period 2000 to and 2016 to the average of economic variable value. The red line shows the average economic variable value per rating scale. Table 7 shows the summary value of the red line and individual country values are tabulated in in appendix Table I.

3.3.3.1 GNI per capita[9]

This economic variable measures the average income per person in the country. The higher the average income, the higher the potential tax revenue. Governments with stable or growing tax base should be more capable of fulfilling their debt obligations.

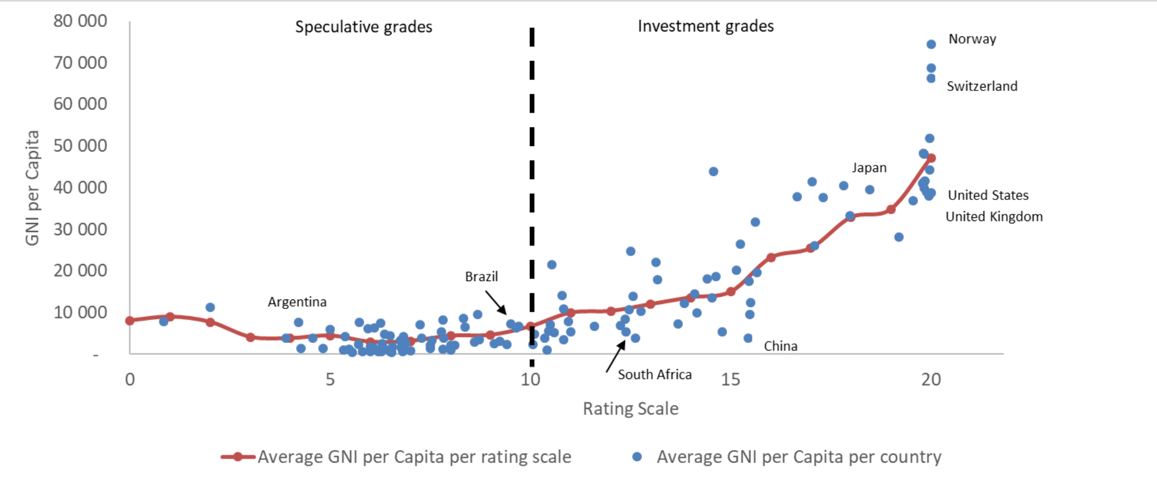
As shown in Figure 10, countries with high GNI per capita relate to a low risk assessment. This may be an indication that countries with high GNI per capita have more potential income and therefore reducing the sovereign's probability of default. Moody's indicate that countries with high income generally correlated to a low risk of default (Moody's, 2016). GNI per capita is also a good indicator for the economic development of a country. The economic history of a country and its institutional stability can determine how well they manage their debts and handle unexpected economic shocks. Countries with a long economic stability tend to have better financial instruments to deal with these situations (Otaviano, et al., 2004).

Figure 10 shows that most countries with a GNI per capita of less than \$12,000 fall under the speculative grade ratings. However, the sovereign bonds of countries with low income are not always deemed as a risky investment asset. China and South Africa are examples of countries where GNI per capita is less than \$6,000 but the sovereigns are assigned investment grade ratings on average. China had a high average GDP growth of 9.4% over the period 2000 to 2016 and the country has inflation well under control – average inflation rate of 2.3% (Worldbank data and IMF). In comparison, South Africa's average

[9] According to Worldbank data variable definition, this is formerly the GNP per capita

inflation rate of 5.9% and an average GDP growth of 3% over the period 2000 to 2016 (Worldbank data and IMF). These may be reasons as to why South Africa's average sovereign ratings are lower than China and are closer to speculative grade category.

Figure 10: Average GNI per capita per rating scale.



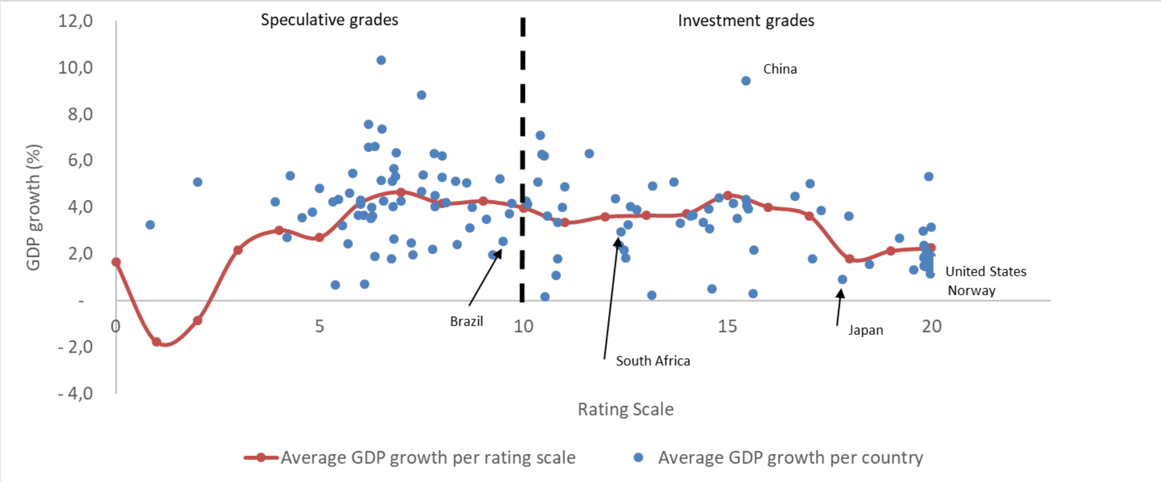
(Source: Worldbank data, and own compilation)

3.3.3.2 GDP growth

GDP growth describes the rate of change in GDP year on year. The WorldBank data defines GDP as "the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products" (Worldbank). GDP growth measures a country's economic growth. A relatively high and stable economic growth may suggest that the servicing of the existing debt burden will become easier over time (Cantor and Packer, 1996). As economies grow, the government's tax pool is expected to grow. Moody's emphasis that growth affects the debt servicing ability of a government (Moody's, 2016).

From Figure 11, there is no clear relationship observable between GDP growth and sovereign ratings. The average GDP growth is high for countries with speculative grades. Cantor and Packer (1996) observed that the emerging market economies tends to grow faster compared to developed market economies. This could be the reason why Figure 11 shows that speculative grade countries have a higher GDP growth as there are more emerging market countries in the speculative grade category.

Figure 11: Average GDP growth per rating scale.



(Source: Worldbank data and own compilation)

3.3.3.3 Inflation

The rate of change in consumer price index year on year. Inflation rate is one of the key indicators to measure a country's consistency in fiscal and monetary policies (Otaviano, et al., 2004).

There is a possibility that the government resorts to printing money as a means of financing their budgeted expenses, instead of financing budgeted expenses through tax revenue or issuance of debt (Cantor and Packer, 1996). This might result in a higher than normal market inflation. Moody's uses inflation as a proxy for policy credibility and effectiveness (Moody's, 2016). Otaviano, et al. (2004) explain that a failure in inflationary finance could affect the normal inflationary process negatively. This may affect the government's credibility adversely, which in turn affect the country's political stability. Therefore, a sovereign with good government policies tend to maintain the inflation rate at an acceptable level for the benefit of the nation.

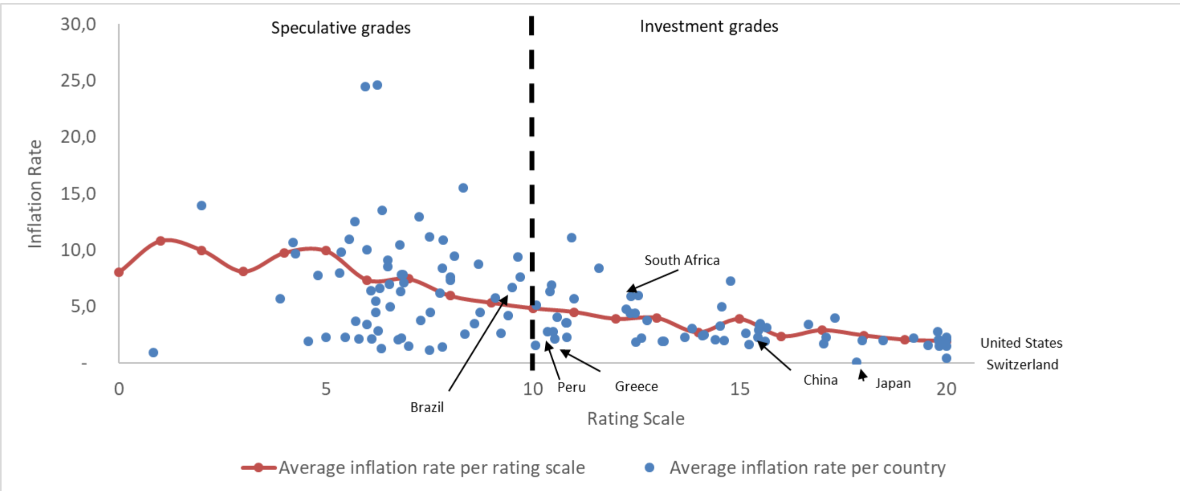
As the prices of goods and services increase, public dissatisfaction may increase due to customers' lower purchasing power. The same value of money would now purchase fewer items. Therefore, the demand for certain goods and services will reduce, affecting the country's economic growth. Also, a price increase in local goods and services can make the export less competitive and result in a decrease in export revenue. This could as a result affect the country's tax pool.

Figure 12 shows that the average inflation rate is lower for countries with higher investment grade ratings compared to countries with speculative grades. The inflation rate varies significantly for countries in the speculative grade, whereas, countries with investment grades have a flat average inflation rate around 3% to 5%. The volatility of inflation may be a concern for credit rating agencies when they perform risk assessments. Moody's has indicated that, in a low inflation environment, the government has more flexibility to react to stressed economic conditions (Moody's, 2016).

It can be seen from Figure 12 that none of the countries with sovereign ratings of AAA/Aaa had an inflation rate exceeding 5%. The highest observed average inflation rates are countries assigned with speculative grades. However, there are some exceptions where a country's inflation rate is reminiscent of countries with investment grade ratings. Peru is an example of this. Although Peru's average inflation rate is only 2.8%, Peru's sovereign ratings, on average over the period 2000 to 2016, is marginally above the speculative grade (data from: IMF, Moody's and S&P). The low inflation rate in Peru is a result of a series of structural reforms that was implemented in the 1990's. In addition to this, the government implemented conservative fiscal and monetary policies. Otaviano, et al. (2004) point out that Peru is considered a risky debtor because of their political uncertainty and their high concentration of raw materials export i.e. a lack of diversification of source of income.

Greece, on the other hand, had a relatively stable, and low inflation rate before defaulting in 2011 to 2012. Greece had an average rate of inflation of 2.13% over the period 2000 to 2016 (data from: IMF, Moody's and S&P).

Figure 12: Average inflation per rating scale.



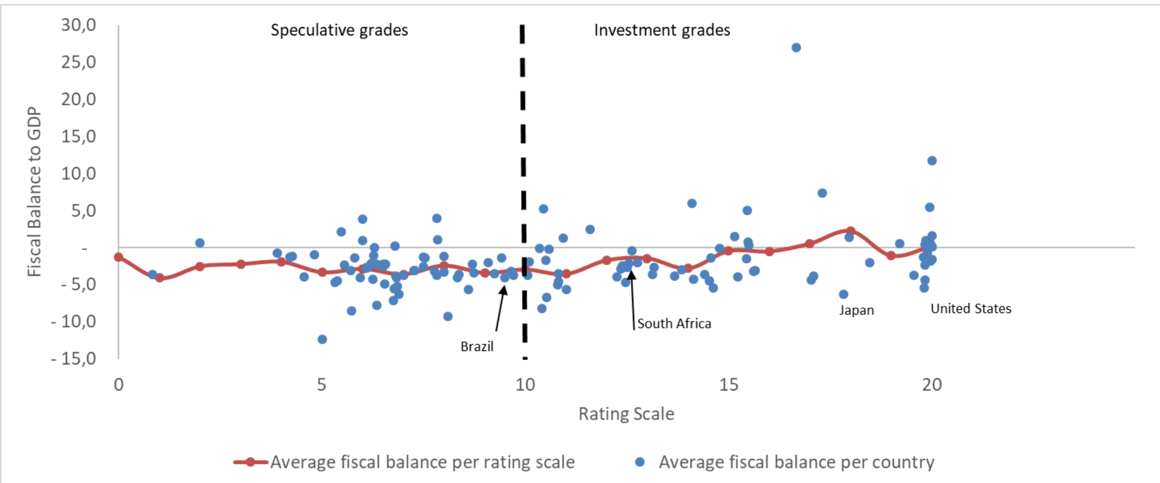
(Source: IMF and own compilation)

3.3.3.4 Fiscal balance to GDP

Government revenue less spending to GDP. Fiscal strength provides an indication of the government's financial health. Moody's assess indicators such as debt to GDP and debt to revenue in their fiscal strength factor (Moody's, 2016). These indicators considered by Moody's help to give an indication of government's available revenue to cover budgetary spending after taking into account debt. A fiscal deficit can result in the government issuing additional debt to cover their budgetary expense. This will then increase the government's indebtedness.

Although the average fiscal balance to GDP is negative across most of the rating scales, Figure 13 suggests that countries with investment grade ratings, on average, have a slightly higher fiscal balance. South Africa's average fiscal balance to GDP is at -2.44, whereas Brazil has an average ratio of -4.05. On the other hand, the US, which has a higher sovereign rating than Brazil and South Africa, has an average ratio of -5.38 (IMF, Moody's and S&P), therefore, a fiscal deficit. One of the reasons why the US is able to incur larger deficit could be that they have a good credit rating, as a result of being able to raise cheaper finance to cover their deficit compared to countries with lower rating scales. Countries with low rating scales may want to improve their sovereign ratings and opt for more conservative fiscal policies by restricting the level of borrowings (Cantor and Packer, 1996). By reducing the level of borrowing, the interest payment will decrease, freeing up government's revenue for other expenses.

Figure 13: Average fiscal balance per rating scale.



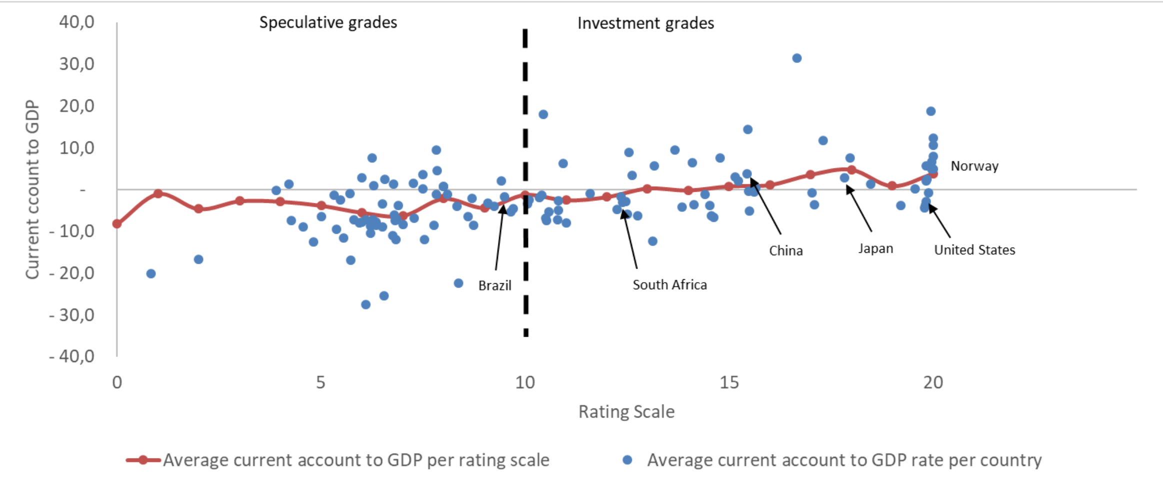
(Source: IMF and own compilation)

3.3.3.5 Current account

The current account consists of the sum of net exports of goods and services, net primary income, and net secondary income to GDP. The ratio provides a view of the countries' foreign trade activities. A deficit in the current account, may suggest there is a heavy reliance of funds from abroad. A large deficit relative to GDP may lead to a growth in foreign indebtedness (Cantor and Packer, 1996).

As shown in Figure 14 the average current balance between speculative and investment grades is close to zero with investment grades average having a current balance slighter higher above zero. This assumes that countries tend to have a sustainable balance of trade policy with the net external balance close to zero or positive. The current account balance is a factor in external balance. The value of imports and exports affect the demand and supply of local currency, and subsequently affecting the exchange rate. The exchange rate will have an impact on the value of foreign debt. Foreign debt repayment amounts can be affected by the exchange rate at the time of repayment. Otaviano, et al. (2004) emphasised that the rating agencies consider external balance variable as a good indicator of the level of integration with the world economy.

Figure 14: Average current account to GDP per rating scale.



(Source: IMF and own compilation)

3.3.3.6 Total government debt

This variable indicates the total government debt relative to GDP and includes both liabilities denoted in both domestic and foreign currency. A high debt to GDP ratio may suggest that the country does not have the ability to generate sufficient income from goods and services to pay back their debt. This economic variable differs to the external debt to export variable selected by Cantor and Packer (1996). The total government debt relative to GDP may be a better indicator of the government's ability to meet all their debt repayments.

Also, as shown in Figure 15, a few countries like the United States have a higher debt to GDP ratio compared to countries with speculative grades. As mentioned earlier, governments with a fiscal deficit are likely to issue debt in order to cover their budgetary expenses. Countries with good ratings are likely to enjoy the advantage of borrowing at a lower interest rate compared to countries with poor ratings. Therefore, from Figure 15, there is an increase in debt to GDP ratio closer to the AAA/Aaa[10] rating scale.

According to Checherita and Rother (2010), a high debt to GDP ratio will have a negative impact on economic growth. The impact may be more exemplified depending on the use of the government debt. The servicing of debt becomes onerous when the total debt of a country is relatively large in relation to its capacity to generate revenue. It may indicate a higher risk of default by the sovereign issuer (Otaviano, et al., 2004).

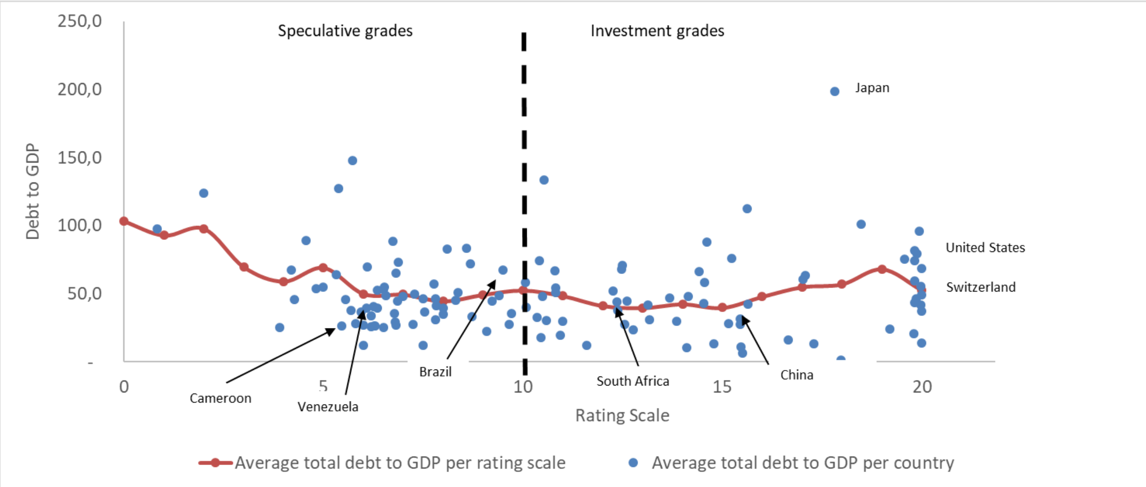
It is worth noting that the total indebtedness of the United States (average total debt to GDP ratio of 81.83) is equivalent to countries in the speculative grade category (data from: IMF, Moody's and S&P). A high rating assigned to the U.S government could be a result of their good reputation in terms of fulfilling their debt obligations, and their economic growth. These characteristics enable countries to issue a higher debt amount. As mentioned earlier, governments with speculative grade ratings may have more conservative borrowing policies or may have restricted access to international funding. For example, Venezuela has a debt to GDP ratio less than the average of investment grade countries, but on average the country is assigned ratings of those countries in the speculative grade category (data from: IMF, Moody's and S&P). This may be a result of Venezuela's historical record of economic and political instability (Otaviano, et al., 2004). However, a low debt to GDP ratio does not conclude that a country will not default. For example, Cameroon defaulted in 2004 to due poor budget management and the political uncertainties (Moody's, 2016).

---

[10] In Figure 4, AAA/Aaa is represented by 20.

Moody’s points out that a high debt burden may be a result of many issues within a country, but these debts become unsustainable when the country lacks the capacity to stimulate economic growth. This could affect the government’s future debt servicing ability (Moody's, 2016).

Figure 15: Average debt to GDP per rating scale.

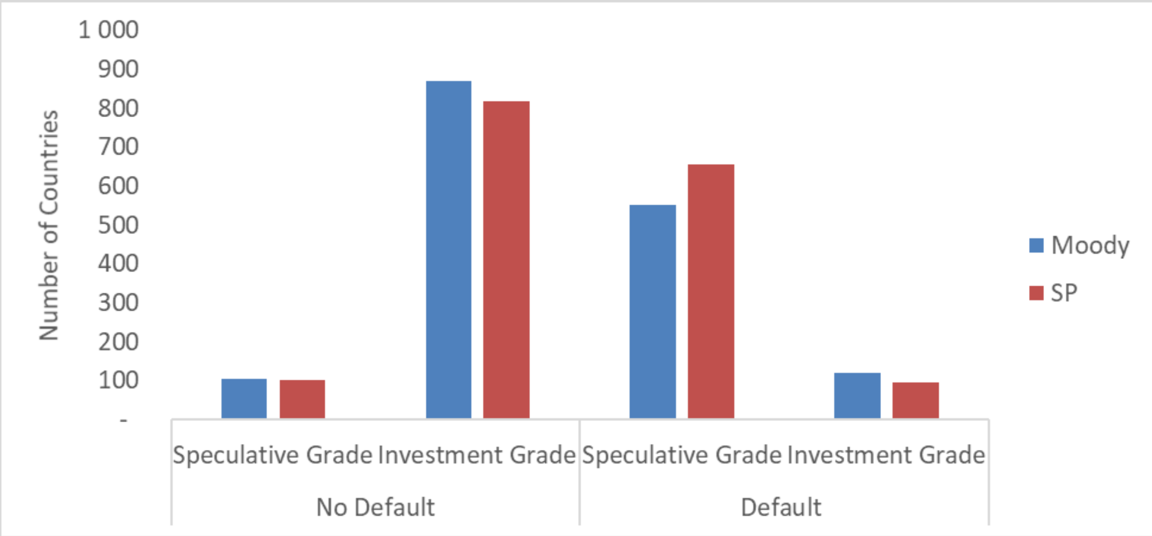


(Source: IMF and own compilation)

3.3.3.7 Default Indicator

This is an indicator variable of countries that has history of defaulting over the last five years. Countries with a recent default history could be considered riskier debtors. More than 80% of the defaults are from countries with speculative grade ratings. However, investment grade countries do not guarantee “no default”. For example, Greece has been assigned investment grade ratings before defaulting in 2011 to 2012 (data from: IMF, Moody’s and S&P). As shown in Figure 16, the sovereign ratings of countries without default histories are mainly investment grade ratings whereas the sovereign ratings of countries with default histories mainly falls under speculative grade ratings.

Figure 16: Default indicator split by speculative and investment grades.

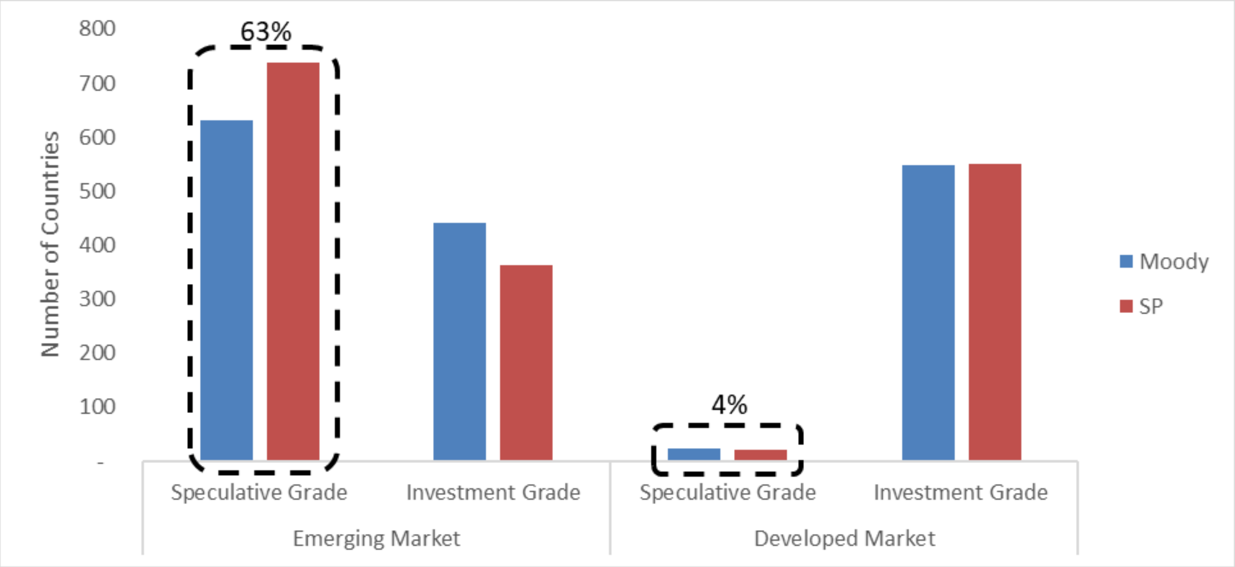


(Source: Bank of Canda default data and own compilation)

3.3.3.8 Development indicator

This is an indicator variable to classify a country as industrialised or not industrialised. This indicator is used as proxy to represent the level of country development. From Figure 17, 63% of the countries with speculative grade ratings are countries classified as emerging market by IMF. This may indicate that emerging market countries are generally considered as riskier debtors.

Figure 17: IMF development indicator, which classify countries as either emerging market or developed market. The countries are then split by speculative and investment grade.



(Source: IMF and own compilation)

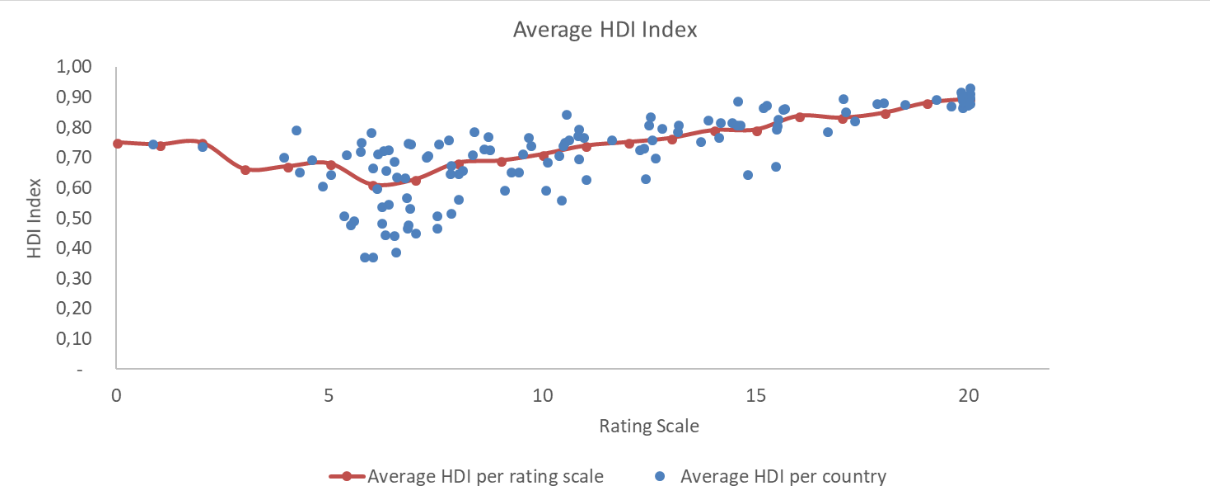
The following additional variables are not examined by Cantor and Packer (1996):

3.3.3.9 HDI

The Human Development Index (HDI) is a measure of achievement made on human development. The index incorporates the quality of life and longevity, education, and GNI per capita. This index was developed to emphasise that a country's development should be reflected in their people and not only on economic growth (United Nations Development Programme, 2016). It can assist in answering questions such as how countries with the same level of GNI per capita are able to end up with different human development outcomes. These issues can prompt debate about the government's priorities on national policies. Figure 18 indicates that, in general, countries with an investment grade rating have a higher HDI index score compared to countries with a speculative grade rating.

The change in HDI index year on year is also considered when modelling sovereign credit ratings.

Figure 18: HDI index per rating scale.



(Source: United Nations Development Programme and own compilation)

3.3.3.10 Default amount:

Default amount is the actual amount of default[11]. The difference between default amount and default indicator is that the default amount looks at the amount defaulted at annual intervals, whereas the default indicator classifies a country as defaulted irrespective of when the country defaulted. For example, a country that has defaulted by a small amount 5 years ago might be meeting all their debt obligations over the last 2 years. This variable could better reflect a country's possibility of default.

The abovementioned initial analysis of the economic variables with respect to sovereign ratings provide insights of the possible relationships that may exist. As mentioned earlier, the trends are based on data over the period of 2000 to 2016. In the modelling section, an ordinal logistic model is applied to test the hypothesis that combined economic variables are good antecedents for the sovereign ratings are defined. These variables are also considered in the Random Forest model.

[11] Similar to the term loss given default amount commonly used in credit analysis.

Table 7: The average of economic variables per rating scales for the period 2000 - 2016.[12]

Rating Scale	Average GNI	Average GDP Growth	Average Inflation rate	Average fiscal balance to GDP	Average Debt to GDP	HDI
0	8 083	1,7	8,04	-1,3	103,2	0,75
1	8 979	-1,8	10,82	-4,1	92,87	0,74
2	7 709	-0,9	9,98	-2,5	97,81	0,75
3	4 118	2,2	8,1	-2,2	69,65	0,66
4	3 820	3	9,77	-1,9	59,11	0,67
5	4 440	2,7	9,93	-3,3	69,17	0,68
6	2 952	4,2	7,34	-2,8	50	0,61
7	3 153	4,7	7,44	-3,6	49,46	0,63
8	4 409	4,2	5,95	-2,4	44,6	0,68
9	4 589	4,3	5,33	-3,4	49,38	0,69
10	6 663	4	4,84	-2,9	52,53	0,71
11	9 940	3,4	4,52	-3,5	48,46	0,74
12	10 341	3,6	3,9	-1,7	41,19	0,75
13	11 979	3,6	3,99	-1,4	39,65	0,77
14	13 620	3,7	2,7	-2,8	42,45	0,79
15	14 975	4,5	3,88	-0,4	39,77	0,79
16	23 146	4	2,38	-0,5	47,95	0,84
17	25 452	3,6	2,9	0,5	55	0,83
18	32 830	1,8	2,44	2,2	57,09	0,85
19	34 816	2,1	2,05	-1,1	68,15	0,88
20	47 142	2,3	1,94	0,2	52,62	0,9

(Source: IMF, Worldbank, Moody's and S&P ratings, and own compilation)

[12] These summaries the red line in each of the graphs where the graph shows the relationship between the rating scale and the average value of economic variable.

3.3.4 Application of modelling techniques

This research aims to examine whether sovereign ratings can be explained and predicted using a model. This section explores the modelling framework defined in the earlier section to model the relationship between sovereign ratings and economic variables.

3.3.4.1 Modelling Approach followed by Cantor and Packer (1996)

Cantor and Packer (1996) applied an ordinary least square (OLS) estimation technique in their investigation of the relationship between the economic variables and sovereign ratings. They converted the dependent variable (sovereign ratings) to scale variable. As mentioned, a sample of 49 countries were considered to show that a small group of economic variables can be used to explain the difference between the sovereign ratings. The economic variables are GNI per capita, GDP growth, inflation rate, fiscal balance, external balance, external debt, default indicator, and industrialised indicator. These variables are examined to see whether the study's results are in agreement with Cantor and Packer's (1996) results. The differences between this study and Cantor and Packer (1996) include the consideration of more countries, and the inclusion of macro-economic variables from 2000 to 2016.

3.3.4.2 Ordinal logistic regression model

In contrast to Cantor and Packer (1996), this study also consider ordinal logistic regression modelling approach. The selection of this model is based on the discrete and ordinal nature of sovereign ratings. Sovereign ratings are assumed to represent an ordinal nature which ranks the different level of credit risk. Ordinal regression model allows for this characteristic. Whereas, in the OLS technique, the model assumes that the ratings are categorised in rating categories that are evenly apart and assume that the dependent variable is continuous. Therefore, the OLS technique is argued to be less appropriate when modelling ratings which have an ordered nature (Bissoondoyal-Bheenick, 2005).

In ordinal logistic regression, indicator variables are converted to dummy variables. Since the industrialised variable and default variable are both indicator variables, dummy variables need to be created. Table 8 shows the dummy variables created for the two variables

Table 8: Conversion of categorical variables into dummy variables.

Categorical Independent Variables		
	Actual	Dummy value
Default indicator	no default	1
	default	-1
Development Indicator	developing	1
	developed	-1

(Source: Own compilation)

To provide a better explanation of the sovereign ratings at time t, economic variables at time $t, t-1\ and\ t-2$ listed in Table 6 are considered. For example, to explain the sovereign ratings in 2016, GDP growth in 2016, 2015 and 2014 are considered in the model. The reason for the inclusion of lag year variables is the change in economic variables might not reflect immediately in the sovereign ratings. Therefore, ratings at time t may reflect the lagged change in economic variables.

Since there are many independent variables to be examined, the final set of independent variables are selected via a stepwise variable selection in SAS procedure. The stepwise selection is a combination of backward elimination and forward selection where variables are added and removed by determining the maximum likelihood estimate of variables. This method allows for previously considered variables (Peduzzi, et al., 1980). After the stepwise variable selection, the variable selection is completed with a reasonability check of the signs of economic variables.

3.3.4.3 An analysis of ratings assigned to emerging market and developed countries.

As mentioned in the chapter 2, many studies found that developing and developed countries receive different risk assessment treatments by credit rating agencies (Bissoondoyal-Bheenick, 2005; Gültekin-Karakas, et al.,2011; Luitel, et al., 2016). In this study, the IMF development indicator variable is used in the modelling process to assess its significance. Taking the analysis a step further, this section analyse the Moody's ratings assigned for the time period 1998 to 2016 for 116 countries using the IMF classification to classify countries between developing and developed countries. In this study, developed countries and advanced economies are used interchangeably. The analysis assesses whether any inconsistences exist in rating assessment between developing and developed countries for similar economic conditions. This is done by employing a random effect logistic regression model using a country-specific random effect and a Random Forest model using the same variables as defined in the section 3.3.3. Since this analysis split countries up into two categories, an addition variable, the government effectiveness, is included. The government effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies (WorldBank Data).

3.4 Model fit metrics

The model examines the relationship between the sovereign ratings and the economic variables. The inclusion of various economic variables may result in multicollinearity amongst the independent variables. Multicollinearity affects the estimate of regression coefficients and inflates the variance. The overall model fit may be good, but the independent variables may lack statistical significance. One way of measuring multicollinearity is the variance inflation factor. This index measures the increase in variance due to multicollinearity. If the factor exceeds 5 it may imply a poor regression coefficient estimate and this could be a result of multicollinearity (Montgomery, 2001).

The ***R-squared statistic*** measures the distance between the observed results and the fitted regression line. Since in a linear regression model, the regression coefficients are estimated by minimising the least squared error, it is more appropriate to use R-squared as a measure of goodness of fit of such a model. In this case, R-squared explains how well the model explains the variation of dependent variable. For logistic regression modelling, the regression coefficients are calculated using the maximum likelihood estimation. Therefore R-squared may not be the best method to explain the goodness of fit. Hosmer and Lemeshow (2000) points out that the R-squared measure for logistic regression is based on comparing the fitted model to a model with only an intercept, and, therefore it does not assess the goodness-of-fit.

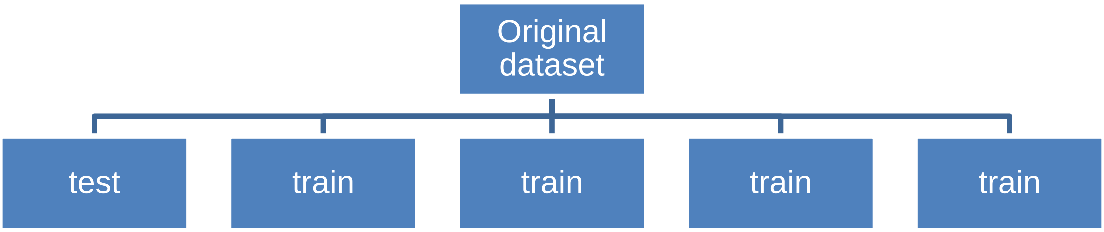
The ***C-statistic*** is another indicator to test how well a model fits the data. It measures the concordance between model estimate and the observed value.

The C-statistic also measures the ability of the model to rank sovereigns from high to low rating scales (Pencina and D’Agostino Sr, 2015). The value of the C-statistic is between 0.5 (random concordance) and 1 (perfect concordance). The higher the C-statistic value, the better the model discriminates the dependent variable. However, the C-statistic does not assess how accurate the model can predict the outcome (Pencina and D’Agostino Sr, 2015). The C-statistic is an equivalent to the measure of the area under the Receiver Operating Characteristic (ROC) curve. Hosmer and Lemeshow (2000) emphasis that ROC is more suitable for explaining classification accuracy. They explain that ROC measure the model’s discrimination ability between the outcome of interest and those that are not.

Out-of-sample five-fold accuracy test

To measure the predictability of the model, an out-of-sample n-fold cross validation is applied. The higher the n-fold, the larger the sample data is required for the results to be credible. The selection of five-fold is based on the amount of data entries available. As shown in Figure 19, the original dataset is randomly partitioned into five-folds and grouped between training dataset and test dataset. A training set is the set of data used to discover possible relationships. A test set is the set of data used to verify the strength of these potential relationships derived from the training set. In each iteration, it fits the model with *K* variables the training dataset. One-fold is left out and used to test the results of the fitted model with *K* variables. The overall accuracy is obtained from results of each test fold where the model estimates is compared to the actual observed sovereign ratings.

Figure 19: Partition of dataset into five-fold to group dataset between training and testing dataset.



(Source: Own compilation)

In the testing dataset, equation two is used to determine the probability of obtaining a specific rating scale. Since a logit model (1) produces cumulative probability of each rating scale from the highest rating scale (20) to the lowest rating scale (4), to calculate the probability of observing a specific rating, a conversion of the output of Equation (1).

$$P(Y_{i,t} = j) = P(Y_{i,t} \leq j) - P(Y_{i,t} \leq j+1), \tag{6}$$

where $Y_{i,t}$ is the sovereign rating of country *i* at time *t* and *j* is the rating scale $\in \{4,19\}$. $P(Y \leq j)$ is the cumulative probability of observing a sovereign rating of *j* or lower. Therefore, conversion from Equation (1):

$$P(Y \leq j) = \frac{\exp(\alpha_j + \sum_{k=1}^{n} \beta_k X_{k,t})}{1+\exp(\alpha_j + \sum_{k=1}^{n} \beta_k X_{k,t})} \qquad where\ j\ \in \{4,19\} \tag{7}$$

Equation (7) calculates a probability for each rating scale. The maximum of probabilities derived from equation (7) is considered as the most probable rating scale.

Similar out-of-sample testing approaches are followed for random effect and Random Forest model.

The critical evaluation of methodology by comparing the model rating with the observed ratings may be impacted by the class imbalance that exists in the ratings as mentioned in the earlier chapter. Hu, et al. (2002) point out that the existence of class imbalance might make prediction in the lower frequency classes difficult.

In the chapter 4, the modelling results are analysed. The section starts with a comparison of the results from Cantor and Packer (1996) followed by the results from the ordinal logistic regression model and then results from Random Forest.

4 RESULTS AND FINDINGS

In this chapter, the model results are analysed and interpreted. In section 4.1 Cantor and Packer's (1996) findings are replicated. It considers whether the economic variables considered by Cantor and Packer (1996) are still statistically significant. Section 4.2 discusses the results from the ordinal logistic model where more variables are examined. This section concludes by analysing the effect on model performance by adding the previous sovereign credit ratings. The IMF development indicator variable is statistically significant and therefore further analysis is done. In section 4.3, countries were separated between developing and developed and examined using random effect model and Random Forest model.

4.1 Modelling results from Cantor and Packer (1996)

The results are predominantly consistent with the findings by Cantor and Packer (1996). Variables 1 to 8 in Table 5 shows the economic variables investigated by Cantor and Packer (1996). As mentioned in chapter 2, the authors found the following variables statistically significant and have expected signs:

- per capita income,
- GDP growth,
- inflation,
- external debts,
- development index, and
- default history.

Although GDP growth has the anticipated sign, the variable was found to be significant at the 10% level. External balance and fiscal deficit were not significant.

Table 9 shows the replicated results using both linear regression and logistic regression. Of the individual regression coefficients for both models, all the variables, except fiscal balance, have the anticipated signs and are statistically significant at p-value less than 0.0001.

GNI per capita is consistent with the results from Cantor and Packer (1996). It shows that a high GNI per capita relates to a high rating. Since the variable range of GNI per Capita is substantially larger than other variables, the regression coefficient is relatively small compared with other variables.

The default indicator is significant in explaining the sovereign ratings. The result reflects that a country with histories of defaulting is more likely to obtain lower ratings than a country without default – there is a negative correlation between sovereign ratings and the default indicator.

Other variables that are consistent with the results from Cantor and Packer (1996) are inflation rate, and industrialised indicator. Lower inflation rates relate to higher ratings; and countries that are classified as industrialised or countries with a more developed economy are more likely to obtain higher ratings.

Cantor and Packer (1996) showed that the external balance is statistically insignificant. In this study, the current account balance variable used as a proxy for external balance, and from Table 9, it is seen that it is a statistically significant variable. The government normally aims to achieve a balance of payment close to 0 i.e. not excessively negative nor excessively positive. The positive correlation indicates a positive current account balance can improve the sovereign ratings.

Another variable considered statistically insignificant by Cantor and Packer (1996) is the GDP growth. Cantor and Packer (1996) explained that during their investigation period many of the developing economies tend to grow at a faster rate compared to developed and mature economies. The inclusion of historical data could eliminate this constraint. The model shows that GDP growth is significant at a 99.99% confidence interval. Table 9 shows that there is a positive correlation between GDP growth and sovereign ratings. A high GDP growth relates to a high rating.

Total debt to GDP has a negative correlation to the sovereign ratings. A high debt to GDP ratio relates to a low rating.

The fiscal balance has a negative correlation to the sovereign ratings. This means that the higher the government expenditure, the more likely it is to obtain a higher rating. This may be because countries with good ratings are likely to obtain a loan at a lower interest rate. This may encourage the government to borrow. So as debt increases, the overall interest payment expense also increases. Similarly, vice versa, a higher interest rate for countries with lower ratings will discourage the government to borrow.

The summary comparison between the linear regression technique and the ordinal logistic regression on the same variables are shown in Table 9. The model fit for both techniques are close which means that it is difficult to presume one model outperforms the other. Both models have an R-squared statistic of 0.78 i.e. 78% the variation in sovereign ratings can be explained by the independent variables. Also, both models produce regression coefficients in which the signs are consistent (+/-) with the economic theory except for fiscal balance. Fitch Ratings (2017) pointed out that OLS and logistic regression generally yield the same model performance, but the coefficients may be more difficult to interpret for logistic regression.

Table 9: The regression coefficient of the variables considered by Cantor and Packer (1996). This set of variables are tested under both linear and logistic regression.

	Linear Regression		Logistic Regression	
Variables	**Estimate**	**Pr > ChiSq**	**Estimate**	**Pr > ChiSq**
Current account to GDP	0.05117	<.0001	0.0283	<.0001
GNI per Capita	0.00009840	<.0001	0.000130	<.0001
GDP growth	0.06743	<.0001	0.0634	<.0001
Total debt to GDP	-0.02637	<.0001	-0.0223	<.0001
Fiscal balance to GDP	-0.02292	0.0262	-0.0330	<.0001
Inflation rate	-0.06780	<.0001	-0.0535	<.0001
Default indicator	-3.37054	<.0001	0.9806*	<.0001
IMF development indicator	3.29993	<.0001	-0.9053*	<.0001
R-squared		0.78		0.78
Adjusted R-squared		0.78		0.78

(Source: Own compilation. *The signs are due to dummy variables explained in section 3.3.4.2. Th dummy variable in Table 8 applies.)

4.2 Ordinal logistic regression modelling result

In the initial modelling step, all the variables from Table 6 are included in the model for variables selection. The initial model calibration includes independent variables from time *t*, *t-1* and *t-2* to capture the time lag effects of economic variables. As explained earlier, a stepwise variable selection is followed. Table 10 shows the final list of variables. Although the rating agencies may have placed substantial weights on fiscal balance, the model excluded fiscal balance in the variable selection. In Moody's report (2016), although the agency assesses the sovereign's fiscal strength, the fiscal balance variable is not part of the sub-factor indicators.

Table 10 shows the selected economic variables are statistically significant in explaining the sovereign ratings at time t and have the expected signs. Inflation is the only variable from time $t-1$ that shows a significance in explaining the sovereign rating at time t. Three variables from time $t-2$ are significant: Current balance to GDP ratio, GDP growth and inflation. These four time-lagged variables support the argument that some economic changes may only be reflected in the sovereign ratings at a later stage.

As expected, GNI per capita and GDP growth has a positive relationship with sovereign ratings. Inflation at time $t-1$ and $t-2$ are negatively related to the ratings. This is also consistent with the Cantor and Packer findings. As GNI per capita increases and GDP growth, the probability of ratings being upgraded increases. These two variables measure the prospect of economic growth. As inflation increases, the ratings are more likely to be downgraded.

The total debt to GDP ratio and default amount at time t together with default indicator have an inverse relationship with sovereign ratings. These variables provide an indication of a sovereign's indebtedness. An increase in total debt amount relative to the country's production (GDP) may increase the sovereign's likelihood of default. Therefore, as the signs suggest, the increase in total debt to GDP ratio and/or default amount relates to a lower rating.

Current account balance at time $t-2$ has a positive relationship with sovereign ratings. As current balance moves into positive, the chance of sovereign rating being upgraded increases. Industrialised country indicators show that the countries that are industrialised might benefit from a ratings upgrade.

As shown in Table 10, HDI at time t and change in HDI is positively related to the ratings. As standard of living, life quality and education within a country improves, the sovereign ratings might be improved. The change in HDI index from time $t-1$ and t positively correlated with sovereign ratings. Therefore, the larger the positive change, the better it reflects on the sovereign's ratings.

The summary of the ordinal logistic model is shown in Table 10. Comparing the ordinal logistic regression model's goodness-of-fit to the OLS technique approach by Cantor and Packer (1996), the ordinal logistic regression model has a better fit. The R-squared statistics of the ordinal logistic model shows that

80% of the variance can be explained by the model. The C-statistic is at 0.88. This shows that the model is good at ranking sovereign between high and low rating scales.

For the multicollinearity test amongst the selected economic variables, from Table 10 the variance inflation indices are below five. This indicates that the regression coefficients are not distorted by multicollinearity. The high variance inflation index between GNI per capita and HDI index may be as a result of a component of the HDI index as GNI per capita is one of the composite statistics. As shown in Table 11, there is a strong positive correlation between GNI per capita and HDI index.

Table 10: Summary of regression of coefficients under ordinal logistic regression. These variables are selected through the stepwise variable selection process.

Analysis of Maximum Likelihood Estimates			
Variables	**Estimate**	**Pr > ChiSq**	**Variance Inflation**
GNI per Capita	0.000108	<.0001	3.37968
GDP growth	0.0246	0.0247	1.38087
Total debt to GDP	-0.0184	<.0001	1.25399
Inflation rate	-0.0308	<.0001	1.49799
Default amount	-0.00005	<.0001	1.06506
Default indicator	0.8480*	<.0001	1.86329
HDI	5.6262	<.0001	3.21469
Change in HDI	49.7075	<.0001	1.54413
IMF development indicator	-0.8325*	<.0001	3.09548
Current account to GDP (t-2)	0.0335	<.0001	1.31165
GDP growth (t-2)	0.0571	<.0001	1.17975
Inflation rate (t-2)	-0.0411	<.0001	1.56128
Inflation rate (t-1)	-0.0286	0.0002	1.78320
C-Statistics		0.88	
R-Squared		0.80	
Adjusted R-Squared		0.80	

(Source: Own compilation. *dummy variable from Table 8 applies)

Table 11: Correlation coefficients of variables considered in the ordinal logistic model.

Pearson Correlation Coefficients													
	GNI	debt_GDP	GDP_growth	inflation	default	default_ind	HDI	HDI_rate	IMF_industrial_ind	inflation_t1	current_acc_t2	GDP_growth_t2	inflation_t2
GNI	1,00	0,14	- 0,25	- 0,29	- 0,02	- 0,56	0,75	- 0,33	0,75	- 0,29	0,33	- 0,22	- 0,30
debt_GDP	0,14	1,00	- 0,24	- 0,08	0,16	- 0,03	0,17	- 0,19	0,23	- 0,11	- 0,18	- 0,30	- 0,12
GDP_growth	- 0,25	- 0,24	1,00	0,06	- 0,08	0,14	- 0,26	0,47	- 0,22	0,03	0,12	0,20	0,08
inflation	- 0,29	- 0,08	0,06	1,00	0,05	0,32	- 0,26	0,14	- 0,30	0,56	- 0,05	0,12	0,42
default	- 0,02	0,16	- 0,08	0,05	1,00	0,11	0,03	- 0,03	0,01	0,05	- 0,02	- 0,12	0,04
default_ind	- 0,56	- 0,03	0,14	0,32	0,11	1,00	- 0,60	0,25	- 0,58	0,32	- 0,26	0,06	0,32
HDI	0,75	0,17	- 0,26	- 0,26	0,03	- 0,60	1,00	- 0,46	0,71	- 0,27	0,21	- 0,22	- 0,28
HDI_rate	- 0,33	- 0,19	0,47	0,14	- 0,03	0,25	- 0,46	1,00	- 0,24	0,13	0,01	0,15	0,15
IMF_industrial_ind	0,75	0,23	- 0,22	- 0,30	0,01	- 0,58	0,71	- 0,24	1,00	- 0,31	0,12	- 0,21	- 0,32
inflation_t1	- 0,29	- 0,11	0,03	0,56	0,05	0,32	- 0,27	0,13	- 0,31	1,00	- 0,06	0,13	0,56
current_acc_t2	0,33	- 0,18	0,12	- 0,05	- 0,02	- 0,26	0,21	0,01	0,12	- 0,06	1,00	0,05	- 0,06
GDP_growth_t2	- 0,22	- 0,30	0,20	0,12	- 0,12	0,06	- 0,22	0,15	- 0,21	0,13	0,05	1,00	0,09
inflation_t2	- 0,30	- 0,12	0,08	0,42	0,04	0,32	- 0,28	0,15	- 0,32	0,56	- 0,06	0,09	1,00

(Source: Own compilation)

4.2.1 Five-fold out-of-sample testing

The performance of the ordinal logistic model is analysed by applying a five-fold out-of-sample test technique. As explained in the earlier section, the sample dataset is split between a training and a test dataset. The model prediction percentage is calculated by combining the results of each test dataset. Table 12 shows the results of the ordinal logistic model by applying equation (2) to determine the model expected ratings. The model ratings are at a 25% exact match to the observed ratings. 55% of the model ratings are within one-notch of the observed ratings and 82% within 2-notches. This means 82% of the predicted ratings matches the observed sovereign ratings within 2-nothces. The model prediction results are compared to a random selection model i.e. assuming an equal probability of randomly selecting a rating scale. The probability of randomly selecting a rating scale in a group of 17 scales is 5.88%. Therefore, the ordinal logistic model performs significantly better than randomly selecting a rating scale.

Table 12: The accuracy of the ordinal logistic model to predict the observed sovereign ratings.

Notch differences	Model prediction	Expected from random selection
Exact match	25%	5.88%
1-notch difference	55%	17.6%
2-notches difference	82%	29.4%

(Source: Own compilation)

A confusion matrix provides a measure of the performance of the classification model. Table 13 is the confusion matrix of the ordinal logistic model determined from combining all the results of test dataset. The column shows the ratings from the model, whereas the rating scales on the row shows the observed ratings. Rating scale 7, 15 and 20 had an exact match with the observed ratings at a percentage greater than 50%. However, the model struggles to differentiate rating scales between 8 to 9 and 16 to 19. This could indicate a possibility that the model classifies the characteristics of rating scales between 8 to 9 to be the same characteristics as for rating scales 7 and 10. Similarly, the model classifies the characteristics for rating scales between 16 to 19 to be the same characteristics for rating scales 15 and 20. The number of observations in these ratings could also be a factor affecting the model's ability to differentiate.

Overall, the model's performance is better than randomly selecting a rating scale, which has a 5.88% chance of selecting the exact match. The model can differentiate ratings well within two-notch differences to the observed ratings. From the results of the ordinal logistic model, it outlines that, when the rating agencies assess sovereign risks, they may apply subjective judgments and not only consider economic factors. As mentioned earlier, there are subjective decisions that are not disclosed by the rating agencies. For example, Moody's mentions that unusual scales and factors are adjusted on a case-by-case assessment and there is no formulaic approach for these adjustments (Moody's, 2016). The section 4.2.2 considers results of adding the previous sovereign credit ratings in the model.

Table 13: The confusion matrix of ordinal logistic model.

Rating scale	**Model ratings**																	
Observed ratings	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**Exact match**
4	22	10	22	35			9	7	2	2								20%
5	22	14	29	60			6	9			1	1						10%
6	8	9	38	122			13	21										18%
7	15	8	55	133			17	34	1	1	1							50%
8			7	116			15	41		2	1							0%
9			5	127			8	22	5	4		3						0%
10			7	80			18	58	11	1	6	8					2	9%
11				35			33	88	25	9	3	22					12	39%
12				5			13	100	23	13	3	30					4	12%
13				7			21	64	14	4	2	36					11	3%
14				1			3	23	31	13	5	63					13	3%
15				1			8	17	17	10	5	107					22	57%
16								3	1	5	3	57					47	0%
17								2	5	7	1	45					42	0%
18											1	37					68	0%
19																	72	0%
20																	493	95%

(Source: Own compilation)

4.2.2 Performance of the ordinal logistic model by considering previous ratings

The last known sovereign ratings at *t-1* could be included to help model the sovereign ratings at time *t*. The argument for adding the sovereign rating at time *t-1* is that credit rating agencies anchors the latest known rating as the point of their assessment to help them derive a new rating. This approach is similar to the dynamic regression which models the noise as a time series. Fitting a logistic regression model, without grouping the rating scales, to the set of variables including the last ratings provides the results shown in Table 14. The results indicate that previous rating is considered a statistically significant variable. The model fit R-squared statistic shows that 98% of the variations in the rating scales can be explained by this model. This is a strong indication that the rating agencies may not start from scratch when assessing the new sovereign ratings. This provides backing to the claim that rating agencies use the last sovereign rating score as an anchor to perform their assessment.

Table 14: Regression coefficient of ordinal logistic model including the previous ratings.

Analysis of Maximum Likelihood Estimates			
Variables	**Estimate**	**Pr > ChiSq**	**Variance Inflation**
Previous rating	2.5192	<.0001	3.05294
GDP growth	0.1350	<.0001	1.34791
Total debt to GDP	-0.00931	<.0001	1.27412
Inflation rate	-0.0524	<.0001	1.15056
HDI	3.2028	<.0001	3.01789
Change in HDI	23.2921	0.0008	1.56896
IMF development indicator	-0.2538	0.0001	2.93458
C-Statistics		0.98	
R-Squared		0.97	
Adjusted R-Squared		0.98	

The five-fold cross validation results are shown in Table 15. Including the previous rating in the model increases the accuracy of the model of exact match to 71% and 91% with one-notch difference between model rating and observed ratings.

Table 15: Five-fold cross validation results.

Notch differences	Model performance
0	71%
1	91%
2	95%

Although the overall model fit is good, and the overall predictability is better than the ordinal logistic model, there are some concerns with including the previous ratings in the model. Although from Table 14, there is a weak multicollinearity between previous ratings and other independent variables, Table 16 indicates that there is a strong positive correlation between the current rating (dependent variable) and the previous ratings (independent variables). Economic changes may have already been captured by the previous ratings.

These factors may question the credibility of the results even if the variables are statistically significant.

Table 16: The correlation coefficient of variables included in the model which examines the significances of previous ratings.

Pearson Correlation Coefficients								
	Current rating	Previous rating	GDP_growth	Total debt to GDP	Inflation rate	HDI	Change in HDI	IMF_industrial_ind
Current rating	1,00	0,98	- 0,08	- 0,09	- 0,36	0,69	- 0,18	0,72
Previous rating	0,98	1,00	- 0,13	- 0,06	- 0,34	0,71	- 0,20	0,73
GDP_growth	- 0,08	- 0,13	1,00	- 0,26	0,02	-0,26	0,48	- 0,22
Total debt to GDP	- 0,09	- 0,06	- 0,26	1,00	- 0,56	0,17	- 0,21	0,22
Inflation rate	- 0,36	- 0,34	0,02	- 0,56	1,00	-0,26	0,11	- 0,30
HDI	0,69	0,71	- 0,26	0,17	- 0,26	1,00	- 0,45	0,71
Change in HDI	- 0,18	- 0,20	0,48	- 0,21	0,11	-0,45	1,00	- 0,23
IMF_industrial_ind	0,72	0,73	- 0,22	0,22	- 0,30	0,71	- 0,23	1,00

(Source: Own compilation)

4.3 Results from the analysis of ratings assigned to emerging market and developed countries

The ordinal logistic model's ability to accurately assign ratings compared to the observed ratings was assessed in the previous section. There are methods which could increase the accuracy of the model. This section considers possible methods that could improve the overall model's predictability. A machine learning algorithm can be used to model the credit rating agency decision process in a classification framework by treating each sovereign rating level as a class.

Table 17 summarise the variables considered in this analysis. It includes the expected signs for each variable based on the results obtained in earlier modelling.

For random effects OL models, the majority of variables which are statistically significant for the developing economies model are also shared by the developed countries model. This includes:

- GDP per capita,
- total debt/GDP, and
- government effectiveness.

In addition, the default indicator, and current account/GDP are significant for the developed countries model. The signs of the coefficients for the aforementioned variables were as expected.

For Random Forest models, the government effectiveness is the most important variable for both developing and developed countries. These results are congruent with the random effects OL models which both highlighted the government effectiveness as statistically significant.

The results were compared to a random effect ordered logistic regression. The prediction accuracy within one notch difference for a Random Forest model was at 79.26% for developing countries and 63.8% for developed countries. The random effect ordered logistic regression obtained 46.8% and 27.2% respectively. The random effect ordered logistic regression showed a poor model fit with McFadden R-squared for developing countries model at 0.41 and developed countries model at 0.45. This indicates that the model does not wholly capture the variation in sovereign ratings. The Random Forest is a non-parametric model, whereas the random effect ordered logistic regression is a parametric model. The parametric nature of regression models results in a moderate fit due to the inability of the model to sufficiently capture non-linear effects.

The out-of-sample performance for the models are obtained by using a five-fold cross validation. The out-of-sample classification performance for the random effects OL and Random Forest based models are compared in Tables 18 and 19 for the developing and developed countries, respectively. When comparing the prediction accuracy of the classes predicted by both developing and developed countries (B1 to Aa2), both the random effect OL and Random Forest have significantly improved per class prediction accuracy in the case of the developing economies. This is also reflected by the average prediction accuracy. The prediction accuracy is significantly more uniform between the classes for the developing countries, especially for the Random Forest i.e. the standard deviation of prediction accuracy is smaller for developing countries compared to developed countries. The prediction accuracy is only consistently high for the Aaa rating in the case of the developed countries. This indicates a lack of a standard approach to the assigning of credit ratings applicable for both developed and developing countries. Therefore, there is a discrepancy between developing countries model and the developed countries model.

The result shows that IMF development indicator variable is significant. This further highlights the inconsistences that exist when credit rating agencies assign ratings.

Table 17 Definition of variables analysed in the model of emerging market vs developed countries.

Variable	**Expected sign**
GDP per Capita	+
Real GDP growth	+
Inflation rate	-
Fiscal balance/GDP	+
Current account/GDP	+/-
Total debt/GDP	-
Default indicator	-
HDI rate	+
Government effectiveness	+

(source: own compilation)

Table 18 Per class prediction accuracy (%) for the developing countries models.

	Exact		1-Notch		2-Notches	
	OL	RF	OL	RF	OL	RF
Caa1	2.50	52.38	12.50	71.43	45.00	90.48
B3	8.86	53.57	26.58	78.57	68.35	88.10
B2	4.82	52.81	83.13	84.27	98.80	96.63
B1	52.41	64.24	80.69	79.47	85.52	87.42
Ba3	23.46	48.81	65.43	71.43	83.95	79.76
Ba2	7.46	44.78	53.73	61.19	95.52	86.57
Ba1	22.55	52.94	39.22	70.59	67.65	78.43
Baa3	31.45	52.42	66.94	76.61	72.58	87.10
Baa2	22.35	69.41	58.82	94.12	90.59	98.82
Baa1	17.65	62.32	36.76	85.51	79.41	91.30
A3	4.76	61.90	35.71	80.95	61.9	92.86
A2	9.43	73.58	18.87	81.13	30.19	92.45
A1	0.00	52.63	26.32	89.47	47.37	94.74
Aa3	4.55	63.64	9.09	81.82	59.09	86.36
Aa2	41.18	76.47	88.24	82.35	88.24	88.24
Average	16.90	58.79	46.80	79.26	71.61	89.28

Table 19 Per class prediction accuracy (%) for the developed countries models.

	Exact		1-Notch		2-Notches	
	OL	RF	OL	RF	OL	RF
B1	28.57	42.86	28.57	50.00	28.57	57.14
Baa3	0.00	20.00	0.00	20.00	0.00	33.33
Baa2	0.00	46.15	0.00	46.15	46.15	69.23
Baa1	0.00	23.53	6.67	29.41	13.33	52.94
A3	3.33	46.67	13.33	73.33	43.33	90.00
A2	4.88	65.85	34.15	90.24	34.15	90.24
A1	4.08	76.56	4.08	81.25	32.65	95.31
Aa3	0.00	20.83	25.00	54.17	41.67	58.33
Aa2	14.63	53.66	24.39	68.29	73.17	92.68
Aa1	5.41	70.27	72.97	91.89	72.97	91.89
Aaa	83.03	93.86	90.25	97.11	96.75	98.56
Average	13.08	50.93	27.21	63.81	43.89	75.42

5 APPLICATION OF THE MODEL

In this chapter, the ordinal logistic model is back-tested on the historical data sample for a few selected countries and the results are shown in Figures 20 to 27. A comparison between model ratings and the observed ratings for different countries are analysed. This is followed by sensitivity testing and scenario analysis for South African sovereign ratings.

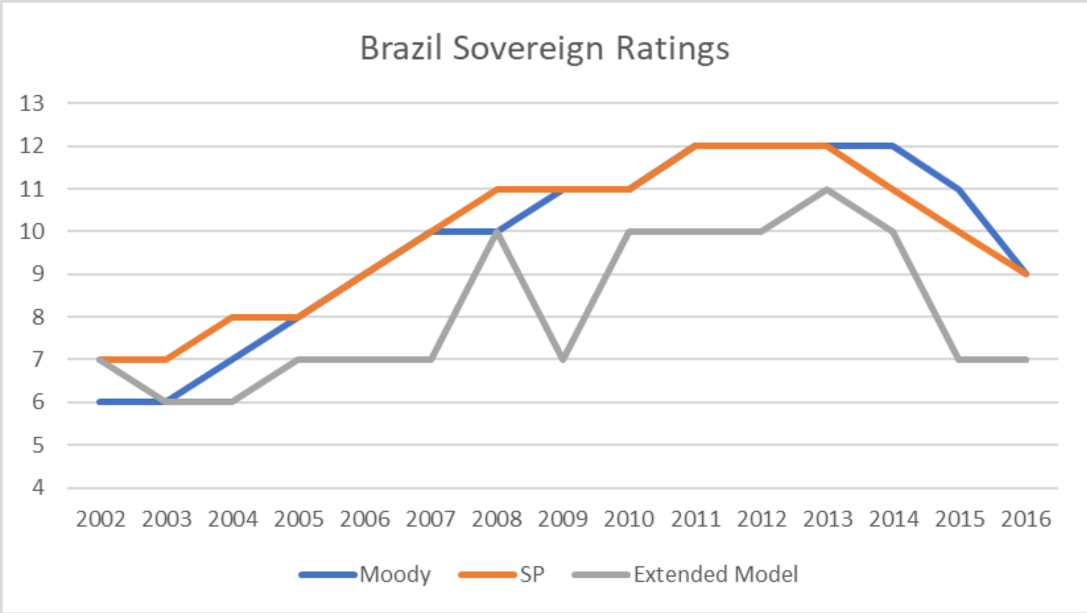
5.1 Illustration of model results on selected countries

This section looks at applying equation (2) using the regression coefficients in Table 10 to determine the model sovereign ratings. Based on the IMF development index, three developed country (Greece, US and Portugal) and five developing countries (South Africa, Brazil, Chile, Nigeria and Ghana) are included. Greece and Portugal experienced an economic financial crisis and therefore both are included to examine whether the model ratings identify a downgrade to their sovereign ratings. The extended model in Figure 20 – 27 refers to the ordinal logistic regression model.

5.1.1 Brazil

As shown in Figure 20, the model ratings for Brazil are within two-notches of the observed ratings except for the period between 2007 to 2009. The upgrade in 2008 was due to changes in GNI per capita and GDP growth. The downgrade in 2009 was due to the negative 0.13% GDP growth (Worldbank data). The downgrade in 2015 to 2016 was due to a high inflation rate of 10.7% (IMF data), and an increase in total debt to GDP ratio from 62% in 2014 to 73% in 2015 (IMF data). GDP growth in 2015 was at -3.77% compared to a positive 0.5% GDP growth in 2014 (Worldbank data).

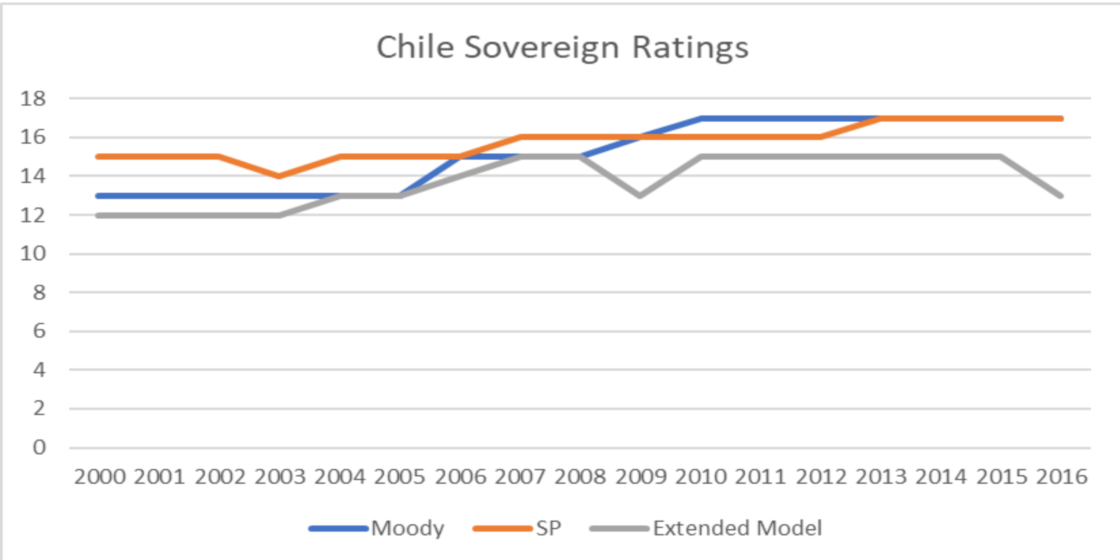
Figure 20: Brazil observed ratings vs model ratings.



5.1.2 Chile

As shown in Figure 21, the average notch difference between the observed ratings and model ratings is two. The downgrade in 2009 was due to negative GDP growth and lower GNI per capita. The downgrade in 2016 was due to an increase in total debt to GDP ratio from 17% in 2015 to 21% in 2016 (IMF data).

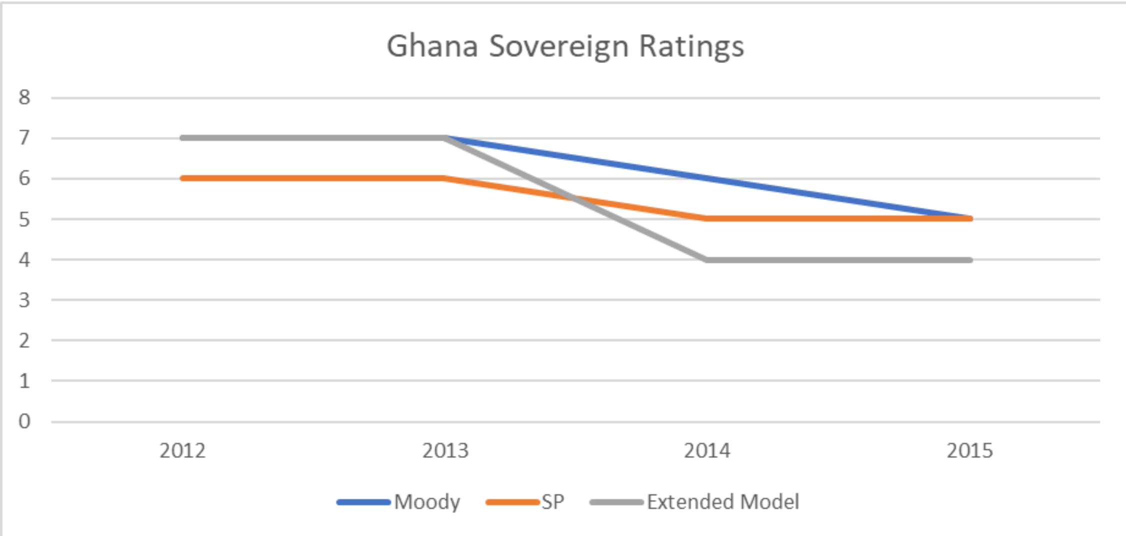
Figure 21: Chile observed ratings vs model ratings.



5.1.3 Ghana

Figure 22 shows the comparison of Ghana observed ratings to model ratings. The model ratings are on average within one-notch difference to the observed ratings. The main factors contributing to the downgrade in 2014 was the high total debt to GDP ratio and inflation. The total debt to GDP ratio increased from 57% in 2013 to 70% in 2014 (IMF data). Inflation increased from 13.5% in 2013 to 17% in 2014 (IMF data).

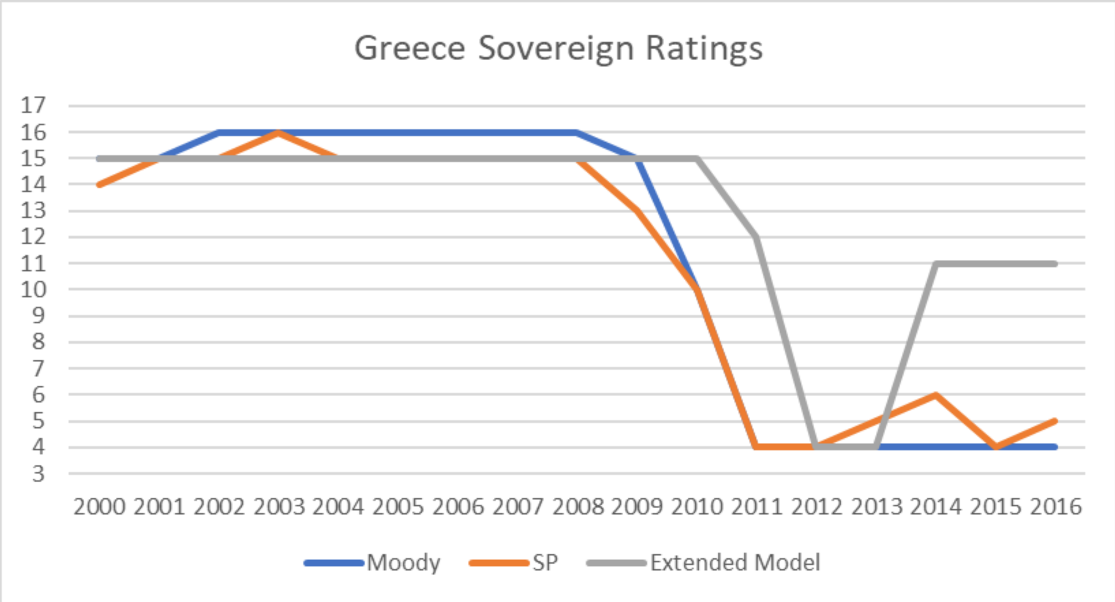
Figure 22: Ghana observed ratings vs model ratings.



5.1.4 Greece

Figure 23 shows that the model ratings for Greece and observed ratings between 2000 to 2009 are closely matched within one-notch. The Greece financial crisis occurred in late 2009 which led to sovereign ratings downgrade to junk status. The model gradually captures the downgrade to junk. This is due to a delayed reflection in the economic variables and the lagged variable included in the ordinal logistic model. The first downgrade experienced by the model rating in 2011 was due to a high percentage of total debt to GDP ratio of 172% in 2011 (IMF data). The high GNI per capita and low inflation between 2010 to 2012 neutralised some effects of the economic variables change. In 2012, there was a default in debt by Greece which resulted in a sovereign rating downgrade reflected by the model (Bank of Canda default data). The model rating produced an upgrade from 2013 to 2014. This is mainly due to the improvement of GDP growth from -3.24% to 0.74% and a decrease in inflation from -1.8% to -2.5%.

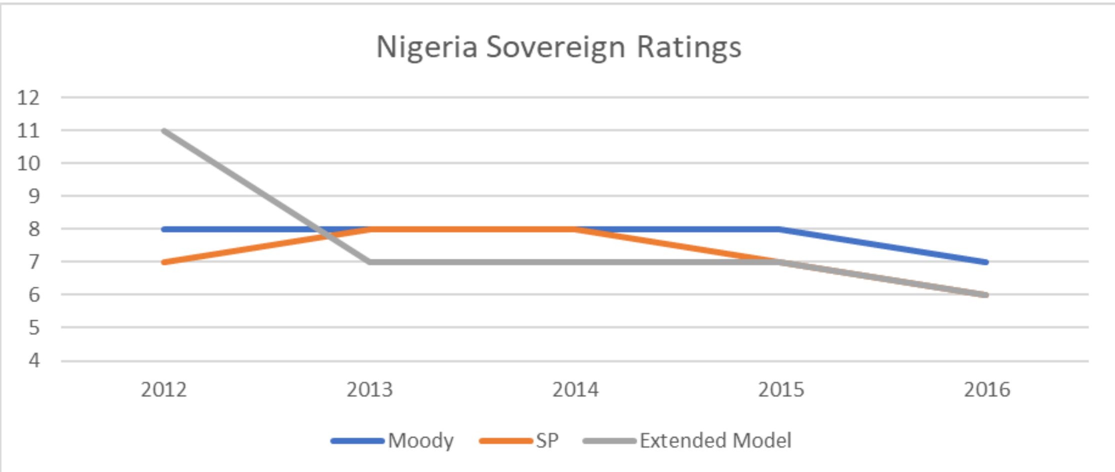
Figure 23: Greece observed ratings vs model ratings.



5.1.5 Nigeria

Figure 24 shows the observed ratings compared to the model ratings for Nigeria. From 2013, the model ratings are accurate within one-notch of the observed ratings. The downgrade in 2016 was due to negative GDP growth and an increase in total debt to GDP ratio from 13% in 2015 to 18% in 2016 (IMF data). Inflation rate increased from 9.6% in 2015 to 18.5% in 2016 (IMF data).

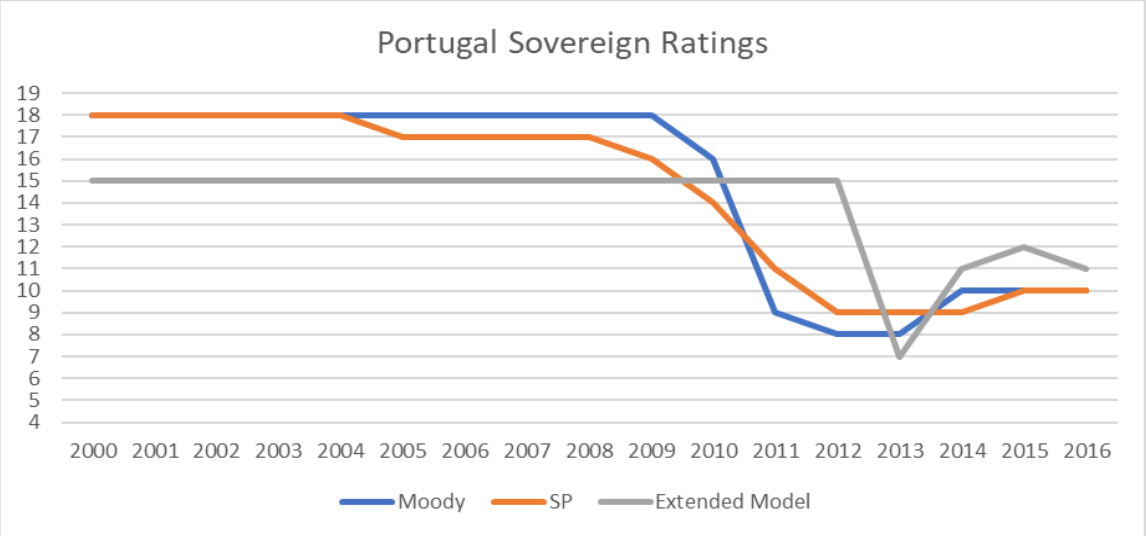
Figure 24: Nigeria observed ratings vs model ratings.



5.1.6 Portugal

As shown in Figure 25, the model ratings are within three-notches of observed ratings. The same is observed, as noted for Greece, where there was a delay in sovereign rating downgrade. Portugal's sovereign ratings was downgraded in 2011, and the model only reflects a downgrade to junk in 2013. The country defaulted on their debt in 2013 (Bank of Canda default data), which resulted in the model downgrading the ratings to junk.

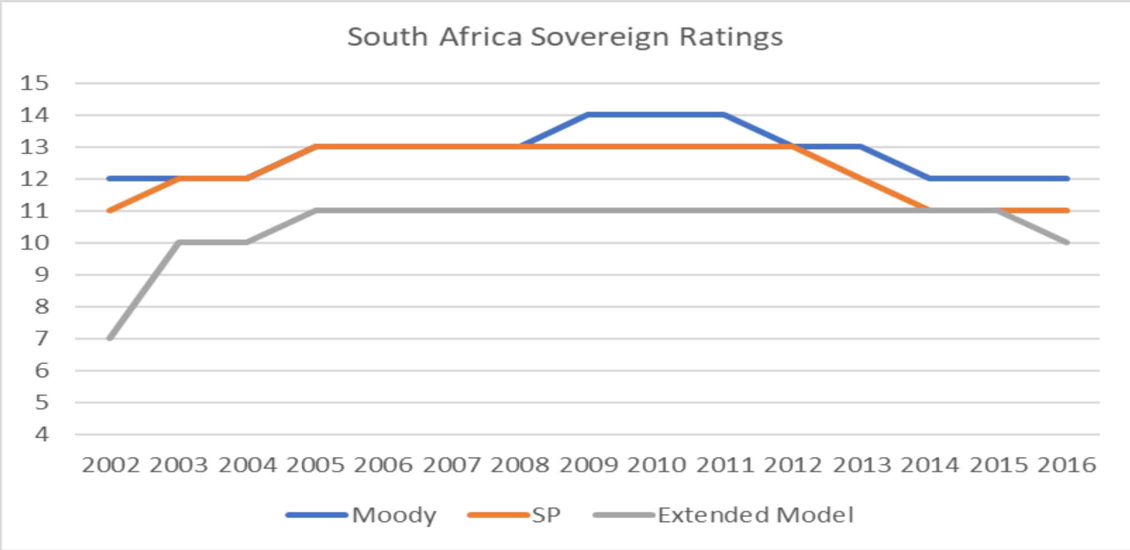
Figure 25: Portugal observed ratings vs model ratings.



5.1.7 South Africa

As shown in Figure 26, South Africa's observed ratings and model ratings on average have a difference of two-notches. In 2002, the model predicted a rating scale of seven (B1/B+), which is a rating in speculative grade, and the rating was upgraded to a rating scale of ten (Ba1/BB+) in 2003. This was due to low GNI per capita ($2690) in 2002 compared to $2940 in 2003 (Worldbank data). The total debt to GDP ratio was at 36% in 2002, which is higher than in 35% in 2003. Inflation was at 12.4% in 2002 and then dropped to 0.21% in 2003 (IMF data). The model predicted a flat rating scale of 11 (Baa3/BBB-) and a downgrade in 2016. The downgrade to speculative grade in 2016 was due to a low GNI per capita and GDP growth, coupled with high inflation and total debt to GDP ratio.

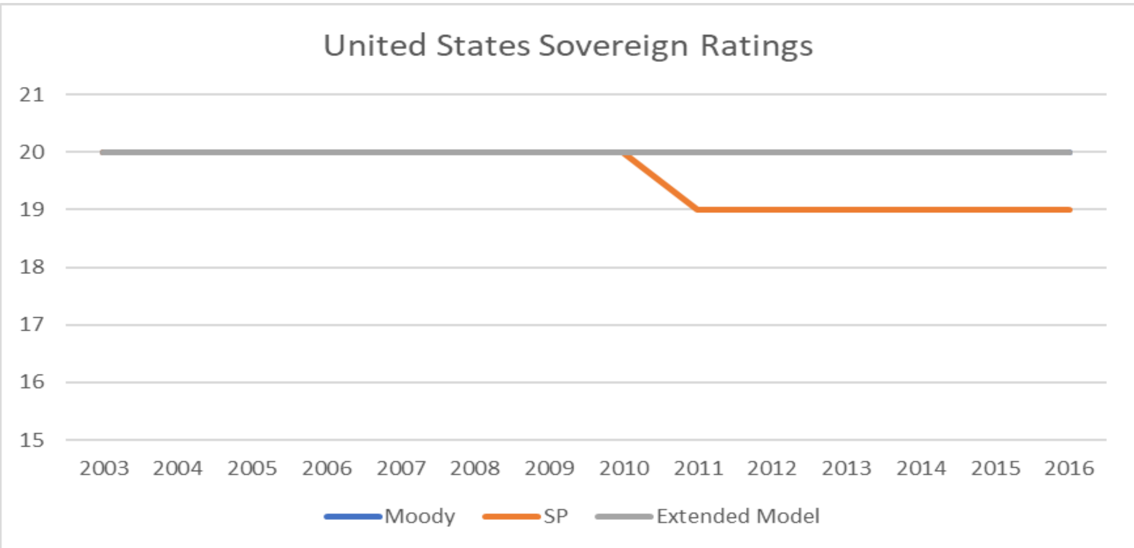
Figure 26: South Africa's observed ratings vs model ratings.



5.1.8 US

As shown in Figure 27, the model predicts the exact observed ratings as ratings assigned by Moody's. In 2011, S&P assigned a rating scale of 19 (AA+) for the downgrade, whereas Moody's kept the ratings at a rating scale of 20 (Aaa). Similarly, the model assigns a rating scale 20 (Aaa) which is consistent with the ratings assigned by Moody's.

Figure 27: US observed ratings vs model ratings.



Summary of the comparison between model ratings and observed ratings

- As seen from Figure 20 – 27, the model ratings obtained from ordinal logistic model follow the trend of the observed ratings.
- The model ratings are within two notches of the observed ratings or better.
- From Figure 23, 25, and 26 where the observed ratings change by more than two notches year on year, the model ratings are delayed in reflecting these changes. This lagged effect may be a result of lagged variables included in the model.
- There may be subjective judgements applied by credit rating agencies which are not reflected in the model ratings.

5.2 Sensitivity testing and scenario analysis: South Africa (SA)

In this section, sensitivity testing and scenario analysis are applied by using SA sovereign ratings and macro-economic variables. Table 20 shows the list of significant economic variables from the ordinal logistic model. The economic variables highlighted in orange are variables the government could influence through policy decisions. These variables are:

- GNI per capita,
- GDP growth,
- total debt to GDP ratio,
- inflation, and
- default amount.

GNI per capita and GDP growth could be enhanced, for example, by stimulating economic growth in the country through lower interest rates as this may lead to corporate taking on projects that they were unable to finance due to high interest rate. Total debt to GDP ratio will reduce if GDP growth increases or total debt decreases. The government can improve their budgeting process to reduce overspending. This may reduce the issuing of additional debt to financial deficits. Inflation can be controlled through monetary policy which involves changing the interest rate. The government should ensure that their debt repayments are made on time and that no default or missed payments occur.

Figure 28 shows the history of South Africa sovereign ratings assigned by Moody's and Standard and Poor's. In 2016, Standard and Poor's assigned South Africa one-notch above junk (rating scale 11) and Moody's assigned a rating at two-notches above junk (rating scale 12). The model assigns South

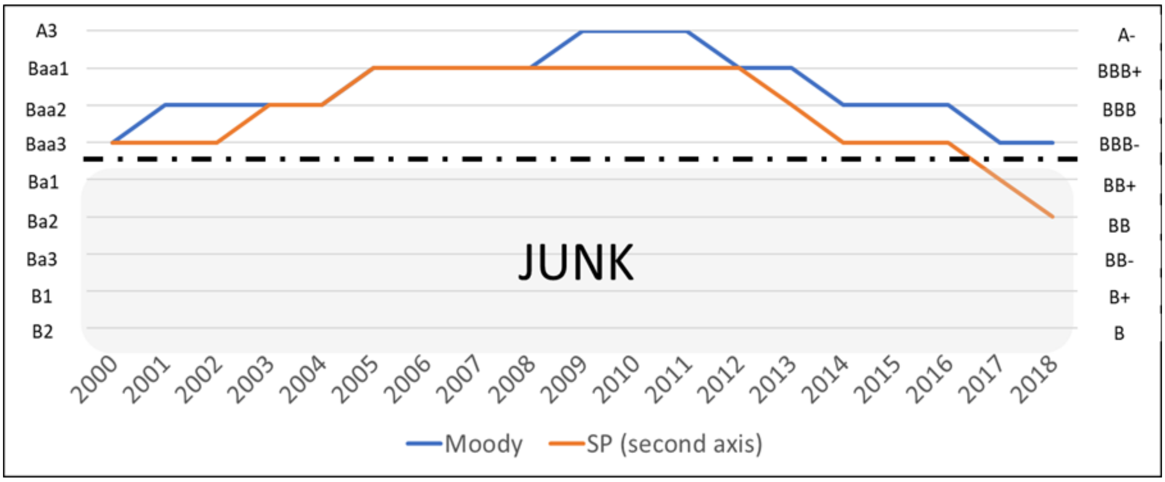
Africa a junk rating scale of 10 in 2016 (Figure 26). As shown in Figure 29, in 2016, South Africa was in a tight economic situation where the GDP growth was at 0.28% (Worldbank data); inflation rate sitting above the 4% - 6% desirable threshold at 6.7% (IMF data); GNI per capita sitting low at $5480, which is lowest at the lowest since 2012 (Worldbank data); total debt to GDP ratio rising to 2% (IMF data). As shown in Figure 29, the economic situation did not improve in 2017, which fuelled the downgrade to junk rating by Standard and Poor's.

Table 20: Summary of significant variables for the ordinal logistic model.

Variables	Odds ratio
GNI per capita	1.000
GDP growth	1.025
Total debt to GDP	0.982
Inflation	0.970
Default amount	1.000
Default indicator	5.452
HDI	277.613
Change in HDI	>999.999
IMF development indicator	0.189
Current account to GDP (t-2)	1.034
GDP growth (t-2)	1.059
Inflation rate (t-2)	0.960
Inflation (t-1)	0.972

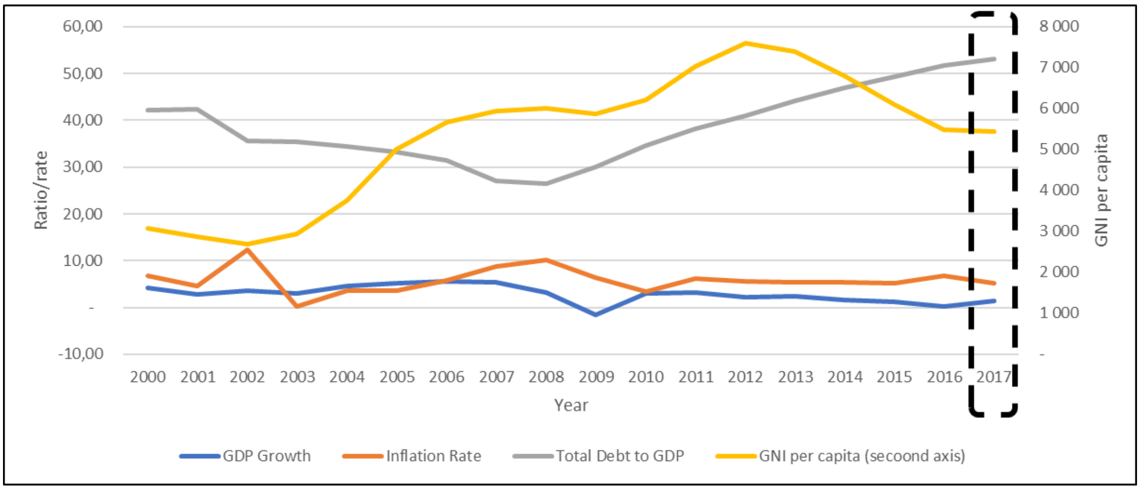
(Source: own compilation)

Figure 28: South Africa Sovereign ratings assigned by Moody's and S&P.



(Source: Moody's and S&P ratings)

Figure 29: South Africa historical view on economic variables. In 2016, there was a high debt to GDP ratio; low GDP growth, a decreased GNI per capita and an increase inflation.



(Source: IMF and Worldbank data)

To understand the impact of each of the factors highlighted in yellow in Table 20, sensitivity testing is applied by changing one variable each time and keeping the remaining variable constant. The sensitivity test results are the ratings obtained based on 2017 year-end economic values. The resulting modelling illustrate the possible outlook of South Africa's sovereign ratings.

As shown in Table 21, a change in GNI per capita from \$5430 to \$6000 shows no movement in model rating. If the GNI per capita decrease from \$5430 to \$4000, then model rating implies a downgrade for South Africa. Changes in GDP growth is not as significant. For both an increase in GDP growth from 1.32% to 3% or a decrease to -0.7%, the model rating remains unchanged. Similarly, for inflation, a decrease in inflation from 5.27% in 2017 to 4.5% or an increase to 5.5%, it results in the same model rating. For total debt to GDP ratio, a decrease from 53.1 to 40 will result a rating upgrade. Therefore, by managing the total amount of debt relative to GDP the sovereign rating can significantly improve. It is important to ensure that the government service all their debt obligation as a default will result in a rating downgrade.

However, it is not simple to obtain a better rating by simply maintaining a value for certain economic variables as there are interrelationship between economic variables. For example, an attempt by the government to manage growing inflation rate might require them to increase the interest rate and subsequently affect the economic growth.

Table 21: The sensitivity test of each variables. Each of the variables are sensibly adjusted under each sensitivity test to examine whether there are any changes on the model ratings.

Variable	Variable value in 2017	Sensitivity test value 1	Resultant rating 1	Sensitivity test value 2	Resultant rating 2
GNI per capita	5430	6000	no change	4000	downgrade
GDP growth	1.32	-0.7	no change	3	no change
Total debt to GDP	53.1	40	upgrade	55	no change
Inflation	5.27	5.5	no change	4.5	no change
Default indicator	0	1	downgrade		

(Source: IMF, World Data and own compilation)

The scenario analyses on the mixed changes in the economic variables are summarised in Table 22. The rating movement is determined by comparing the model ratings using 2017 economic variables outlined in Table 22 to the variables as described under each scenario.

In scenario 1 where the economic condition is optimistic with the GNI per capita is at $7000, GDP growth at 3%, debt to GDP ratio is at 40, inflation at 4% and no default on debt by the government then no rating movement is expected. In scenario 2, the model rating expects no change in favourable economic conditions with the GNI per capita is at $6000, GDP growth at 2%, debt to GDP ratio at 50, inflation at 4.5% and no default on debt by the government. In scenarios 3, a decrease in GNI per capita to $5200, a drop in GDP growth to 1%, an increase in total debt to GDP ratio at 58, inflation at 5.1%, and the government did not default on debt, then the model predicts the rating to remain unchanged. In scenarios 4 under a pessimistic economic condition with GNI per capita at $5200, GDP growth at 0%, an increase in total debt to GDP ratio at 65, inflation at 6%, and the government did not default on debt, then the model rating expects a rating downgrade.

Table 22: The scenario analysis for each variable. A mixed change in economic variables to mirror possible economic condition. The impact of each scenarios on the model ratings is then examined.

Scenarios	Economic condition	GNI per Capita	GDP growth	Total debt to GDP	Inflation	Resulting ratings movement
Value in 2017		5430	1.32	53.1	5.27	
Scenarios 1	Optimistic	7000	3	40	4	upgrade
Scenarios 2	Favourable	6000	2	50	4.5	no change
Scenarios 3	unfavourable	5200	1	58	5.1	no change
Scenarios 4	pessimistic	5200	0	65	6	downgrade

(Source: IMF, World Data)

Given this unstable economic condition and on-going political uncertainty, in 2018, Standard and Poor's downgraded South Africa from BB+ investment-grade rating into junk status, a rating of BB (S&P ratings, 2018). From the above sensitivity testing and scenarios analysis, South Africa's sovereign rating will remain unchanged if total debt to GDP ratio are maintained between 50%-58% and the government do not default on debt. However, the model indicates that South Africa might experience a rating downgrade in a pessimistic economic condition where the total debt to GDP ratio are increased to about 65%. Model suggests an upgrade is possible by enhancing a growth in GNI per capita and a decrease in total debt to GDP ratio to 40%. Although GDP growth and inflation changes might not have a significant impact, it is important to maintain it. The default indicator played a significant role in changing the rating. Therefore, to avoid further downgrades by the rating agencies, the government should ensure all their debts are serviced and there is no default on any debt repayments.

6 CONCLUSION AND FURTHER STUDIES

6.1 Conclusion

As mentioned in the literature review, many studies indicated that sovereign ratings assigned by credit rating agencies are often questioned (Polito and Wickens, 2014; Haspolat, 2015; Luitel, et al., 2016; Scully and McLaughlin, 2017; Naciri, 2017). Uncertainty about the accuracy of ratings to indicate default risk, as well as uncertainty about the methodologies followed by rating agencies necessitates critical evaluation of credit ratings decisions. Although credit rating agencies make their sovereign risk assessment methodologies available, there are constraints in replicating their ratings. One issue is the uncertainty about the exact data used by the rating agencies and whether such data is publicly available. Another issue is the subjective judgement applied by the rating agencies which cannot be explained by using a formula or model. This study assess the determinants of sovereign ratings using publicly available data, and develop sovereign rating model based on statistical methodology.

By replicating the methodology and economic variables applied by Cantor and Packer (1996), the results are mostly consistent with their findings. The consistent variables are:

- GNI per Capita,
- GDP growth,
- inflation,
- total government debt to GDP,
- IMF indicator, and
- default indicator.

The ordinal logistic model results, which include variables with lagged effects, show that GNI per capita, and GDP growth are significant variables with the expected positive relationship to ratings whereas inflation has a negative relationship. These variables provide an indication of a country's economic prospect. Total debt to GDP ratio and default amount have negative relationships with ratings. These two variables indicate the level of government indebtedness and the amount of default. Therefore, an increase is expected to impact the ratings negatively. Indicator variables HDI index and change in HDI, IMF development variables are also statistically significant. Finally, significant variables with time-lags are current account to GDP ratio, GDP growth and inflation. These variables have a lagged effect on the rating. Overall model fit suggests that sovereign ratings can be explained reasonably well by a selected group of economic variables.

To ensure the robustness of the model, a five-fold out-of-sample testing is completed. The model prediction shows that the model fits significantly better than randomly selecting a rating. An exact match model accuracy of 25% is obtained, compared to random selection probability of 5.88%. At 1-notch differences, the model prediction is at 55% accuracy whereas a random selection within 1-notch has a probability of 17.6%. This provides some evident that credit rating agencies' sovereign risk assessments are not purely based on economic variables. The subjective decision elements are not captured in the model. As mentioned in the earlier chapter, credit rating agencies themselves explain that there are elements of subjective adjustments in their risk assessment.

Sensitivity tests and scenario analysis for South Africa indicates the economic conditions under which the sovereign credit rating might change. If South Africa maintain its GNI per capita, GDP growth, total debt to GDP and inflation as at end of 2017, then a downgrade is unlikely to happen based on the results from ordinal logistic model. A small movement in these variables also show that no rating changes are expected. However, in a pessimistic economic condition where the total debt to GDP ratio are increased to about 65%, the model indicates that South Africa may face a downgrade. It is important that South Africa service all their debt obligations as a debt default will result in a rating downgrade.

The analysis on developing countries and developed countries shows that there is a clear discrepancy between the models. The developing countries model is generally consistent across the different ratings levels. In contrast, the developed countries model is not consistent across the different ratings levels. This also highlights the possible existence of subjective judgement in the rating assessment process.

Finally, a brief analysis on the inclusion of the previous known sovereign rating ratings suggest that credit rating agencies may use the previous known ratings as starting point in their risk assessment for determining the new sovereign credit ratings.

6.2 Further studies

To improve the predictive power of the model, other variables and methods can be considered. For example, as shown in earlier results, machine learning techniques such as Random Forests generally have a better predictive power than conventional statistical models. Although, there are limitations to using these techniques to make statistical inference, the use of these techniques will depend on the type of problem it will address. If the aim is to develop a predictive rating model, then machine learning techniques may be able to develop a model with a high predicting power.

For the logistic regression model, other considerations such as a random effect models mentioned earlier can also be tested. The grouping of the ratings into certain categories may also improve the results. For example, developing different models for developed and developing countries as considered in this study. Bissoondoyal-Bheenick (2005) grouped the ratings based on the countries' financial stability histories.

As shown in chapter 3, the random effects logistic regression approach can be applied to estimate the effect of covariates of a specific group, e.g. type of rating agencies (Moody's compared to S&P). Also, consider whether there is a correlation between the ratings assigned in a given year. For example, the rating assessments in 2010 might be tighter than the rating assessments in 2014. Further investigation on the inclusion of random effects in the model may reduce the correlation effect of panel dataset.

With respect to addressing and capturing subjective judgments, factors such as worldwide governance indicators, corruption indices, and government effectiveness can be considered. The weakness of using these indicators are the concerns with regards to the methodology followed in creating the indicators, which is mainly based on survey data and interviews that present individuals' perceptions (Williams and Siddique, 2008).

The consideration of the inclusion of previous ratings done in the chapter 3 suggests that a previously known rating is an important determinant of the new rating. However, this result differs with the findings by Dimitrakopoulos and Kolossiatis (2016). They showed that a weak relationship exists between the previous rating and the current rating. Further analysis using such as dynamic regression techniques could be investigated to examine the significance of previous known ratings.

Sovereign ratings are forward-looking indicators. There is room to derive a model that incorporates forward looking projections of the determinants of the sovereign ratings. Moody's (2016) points out that the country's future performance is considered when assessing a sovereign rating.

Although credit rating agencies refrain from giving a direct relationship between sovereign credit ratings and probability of default, it would be interesting to determine the relationship between sovereign credit ratings and its associated probability of default (PD). This involves developing a PD model where PD's are ranked and mapped into different ratings scales accordingly. This approach would provide the ability to assign a probability of default to a rating scale. Polito and Wickens (2014) considered an approach which involves mapping of probability of default into rating scales.

Dimitrakopoulos and Kolossiatis (2016) developed a dynamic panel ordered probit model to examine whether ratings are sticky or procyclical. They explained that ratings are considered procyclical if the observed ratings are higher than their model ratings before a financial crisis and during the crisis the observed ratings are lower than the model ratings. They tested the model before the financial crisis from 2000 to 2006 and after financial crisis from 2007 to 2011. The results show that ratings exhibit a stickiness behaviour (Dimitrakopoulos and Kolossiatis, 2016). Further analysis of the stickiness of credit ratings could lead to a better understanding of rating agency decisions.

7 BIBLIOGRAPHY

1. Adeleke, K. & Adepoju, A., 2010. *Journal of Mathematics and Statistics ,* 6(3), pp. 279-285.
2. Amstad, M. & Packer, F., 2015. Sovereign Ratings of Advanced and Emerging Economies After the Crisis. *BIS Quarterly Review,* pp. 77-91.
3. Bank, T. W., 2017. *World Data Bank.* [Online]
   Available at: http://databank.worldbank.org/data
   [Accessed 25 January 2017].
4. Bartels, B. & Weder di Mauro, B., 2013. *A Rating Agency for Europe – A good idea?,* s.l.: s.n.
5. Beers, D., 2004. *Sovereign Credit Ratings: A Primer,* London: s.n.
6. Bellotti, T., Matousek, R. & Stewart, C., 2011. A note comparing support vector machines and ordered choice models' predictions of international banks' ratings. *Decision support system,* 3(51), pp. 682-687.
7. Bennell, J., Crabbe, D., Thomas, S. & Gwilym, O., 2006. Modeling sovereign credit ratings: neural networks versus ordered probit. *Expert System Apply,* Issue 30, pp. 415-425.
8. Bishop, C., 2006. Pattern and Recognition and Machine Learning. *Springer.*
9. Bissoondoyal-Bheenick, E., 2005. An analysis of the determinants of sovereign ratings. *Global Finance Journal,* Issue 15, pp. 251-280.
10. Breiman, 1984. Classification and Regression Trees. *New York: Routhledge.*
11. Breiman, L., 2001. Random Forest. *Machine Learning,* 1(45), pp. 5-32.
12. Cantor, R. & Packer, F., 1996. Determinants and Impact of Sovereign Credit Ratings. *FRBNY Economic Policy Review.*
13. Capital Intelligence, 2018. *Foreign Currency and Local Currency Ratings.* [Online]
    Available at: http://www.ciratings.com/page/rating-definitions/foreign-local-currency-ratings
    [Accessed 30 January 2018].
14. Caporale, G., Matousek, R. & Stewart, C., 2011. EU banks rating assignments: is there heterogeneity between new and old member countries. *Rev. Int. Economics,* 1(19), pp. 189-206.
15. Chen, S., Chang, C. & Yang, S., 2012. The relation between sovereign credit rating revisions and economic growth. *Journal of Banking & Finance,* Issue 64, pp. 90-100.
16. Chen, S., Chen, H., Chang, C. & Yang, S., 2013. How do sovereign credit rating changes affect private investment?. *Journal of Banking and Finance,* Issue 37, pp. 4820-4833.

17. Chen, S., Härdleb, W. & Moro, R., 2011. Modeling default risk with support vector machines. *Quantative Finance,* 1(11), pp. 135-154.
18. Dimitrakopoulos, S. & Kolossiatis, M., 2016. State Dependence and Stickiness of Sovereign Credit Ratings: Evidence from a Panel of Countries. *Journal of Applied Economics,* 31(6), pp. 1065-1082.
19. Duygun, M., Ozturk, H., Shaban, M. & Tortosa-Ausina, E., 2014. *Quo Vadis, raters? A frontierapproach to identify misratings in sovereign credit risk,* Castellon: Economics Department, Universitat Jaume I.
20. Ederington, L. J., Yawitz, J. B. & Roberts, B. E., 1987. The informational content of bond ratings. *The Journal of Financial Research,* 10(3), pp. 211 -226.
21. Ederington, L., Yawitz, J. & Roberts, B., 1987. The Information Content of Bond Ratings. *Journal of Financial Research,* Issue 3, pp. 211-216.
22. European Securities and Market Authority, 2014. *Credit Rating Agencies' 2014 market share calculations for the purpose of Article 8d of CRA Regulation,* s.l.: s.n.
23. Fitch Ratings, 2017. *Sovereign Rating Criteria,* s.l.: https://www.fitchratings.com/site/dam/jcr.../Form%2025-101F1%20Item%205.pdf.
24. Goldstein, B. A., Polley, E. C. & Briggs, F. B. S., 2011. Random forests for genetic association studies. *Statistical Applications in Genetics and Molecular Biology,* 1(10).
25. Gültekin-Karakas, D., Hisarcıklılar, M. & Öztürk, H., 2011. Sovereign risk ratings: biased toward developed countries?. *Emerging Markets Finance and Trade,* 47(2), pp. 69-87.
26. Haspolat, F. B., 2015. Analysis of Moody's Sovereign Credit Ratings: Criticisms Towards Rating Agencies Are Still Valid?. *Procedia Economics and Finance,* Issue 30, pp. 283-293.
27. Ho, C. & Rao, P., 1993. Bond Ratings and their determinants in a Changing Environment. *Journal of Applied Business Research,* 9(1), pp. 133-139.
28. Horrigan, J. O., 1966. The determinantion of Long-Term Credit Standing with Financial Ratios. *Journal of Accounting Research,* Volume 4, pp. 44-62.
29. Hosmer, D. W. & Lemeshow, S., 2000. *Applied Logistic Regression.* 2 ed. New York: John Wiley & Sons, Inc..
30. Hutcheson, G. D., 2011. Ordinary Least-Squares Regression. *The SAGE Dictionary of Quantitative Management Research,* pp. 224-228.
31. Hu, Y.-T., Kiesel, R. & Perraudin, W., 2002. The estimation of transition matrices for sovereign credit ratings. *Journal of Banking & Finance,* Issue 26, pp. 1383-1406.
32. Jackson, J. D. & Boyd, J. W., 1988. A staticstical approach to modeling the

behavior of bond raters. *The Journal of Behavioral Economics,* 17(3), pp. 173-193.

33. Kaplan, R. & Urwitz, G., 1979. Statistical Model of Bond Ratings: A Methodological Inquiry. *Journal of Business,* 52(2), pp. 231-262.
34. Lai, Q., 2000. Currency Crisis in Thailand: The Leading Indicators. *The Park Place Economist,* Volume 8.
35. Lazard Asset Management, 2017. *Index Benchmark for emerging markets debt,* s.l.: Lazard Asset Management.
36. Lindow, K., 2016. *Rating Action: Moody's confirms South Africa's sovereign rating at Baa2 and assigns a negative outlook,* New York: Moody's Investors Service, Inc..
37. Luitel, P., Vanpee, R. & de Moor, L., 2016. Pernicious effects: How the credit rating agencies disadvantage emerging markets. *Research in International Business and Finance,* Volume 38, pp. 286-298.
38. Mellios, C. & Paget-Blanc, E., 2006. Which factors determine sovereign credit ratings?. *The European Journal of Finace,* 12(4), pp. 361-377.
39. Menard, S., 2002. In: *Applied Logistic Regression Analysis .* s.l.:Sage Publictation.
40. Minardi, A., Rinaldo, A. & Sanvicente, A. Z., 2007. A Methodology for Estimating Credit Ratings and the Cost of Debt for Business Units and Privately-held Companies.
41. Moody's, 2013. *Moody's Statistical Handbook: Country Credit,* s.l.: http://alleuropa.ru/fileserver/2013/78/153213.pdf.
42. Moody's, 2016. *Rating Methodolgy: Sovereign Bond Ratings,* s.l.: Moody's.
43. Moody's, 2016. *Rating Symbols and Definitions,* s.l.: https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_79004.
44. Naciri, A., 2017. Credit rating industry business model. In: *Sovereign Credit Rating: Questionable Methodologies.* Abingdon: Routledge.
45. Nguyen, J. M. & Knyphausen-Aufseß, 2014. The Impact of Sovereign Credit Ratings on Corporations: A Literature Review and Research Recommendations. *Financial Markets, Instituions & Instruments,* 3(23), pp. 125-178.
46. Otaviano, C., Pablo Fonseca P., d. S. & Paulo, C. S. P., 2004. *Macroeconomics and Sovereign Risk,* Washington: s.n.
47. Ozturk, H., 2014. The origin of bias in sovereign credit ratings: reconciling agency views with institutional quality. *J.Dev. Areas,* Issue 48, pp. 161-188.
48. Ozturk, H., Namli, E. & Erdal, J. I., 2016. Modelling sovereign credit ratings: The accuracy of models in a heterogeneous sample. *Economic Modelling,* Issue 54, pp. 468-478.

49. Packer, F., 2003. *Mind the gap: domestic versus foreign currency sovereign ratings,* s.l.: s.n.
50. Partnoy, F., 2006. How and Why Credit Rating Agencies are Not Like Other Gatekeepers. *Legal Studies Research Paper Series,* pp. 59-102.
51. Peduzzi, P., Hardy, R. J. & Holford, T. R., 1980. A Stepwise Variable Selection Procedure for Nonlinear Regression Models. *Biometrics,* 36(3), pp. 511 -516.
52. Pencina, M. J. & D'Agostino Sr, R. B., 2015. Evaluating Discrimination of Risk Prediction Models The C statistic. *JAMA Guide to Statistics and Methods,* 314(10), p. 1063.
53. Pinches, G. & Mingo, K., 1973. A Multivariate Analysis of Industrial Bond Ratings. *Journal of Finance,* 28(1), pp. 1-18.
54. Polito, V. & Wickens, M., 2014. Modelling the U.S. sovereign credit rating. *Journal of Banking & Finance,* Issue 46, pp. 202-218.
55. S&P, 2016. *S&P Global Ratings Definition,* s.l.: s.n.
56. S&P, 2017. *S&P Global Ratings,* s.l.: s.n.
57. Scully, M. & McLaughlin, D., 2017. *Bloomberg: Moody's Reaches $864 Million Subprime Ratings Settlement.* [Online]
Available at: https://www.bloomberg.com/news/articles/2017-01-13/moody-s-to-pay-864-million-to-settle-subprime-ratings-claims
[Accessed 20 March 2017].
58. Securities and Exchange Commission , 2015. *Annual Report on Nationally Recognized Statistical Rating Organizations,* s.l.: s.n.
59. Securities and Exchange Commission, 2005. *Definition of Nationally Recognized Statistical Rating Organization,* s.l.: s.n.
60. Serrano-Cinca, C., Gutiérrez-Nieto, B. & López-Palacios, L., 2015. Determinants of Default in P2P Lending. *PLOSONE,* 10(10).
61. Shearer, C., 2000. The CRISP-DM Model: The New Blueprint for Data Mining. *Journal of Data Warehouse,* 5(4), pp. 13 - 22.
62. Standard and Poor's, 2011. *Guide to Credit Rating Essentials ,* s.l.: s.n.
63. Stotsky, C.-G. M. a. J. G., 1993. Testing the Differences between the Determinants of Moody's and Standard & Poor's Ratings: An Application of Smooth Simulated Maximum Likelihood Estimation. *JOURNAL OF APPLIED ECONOMETRICS,* 1(8), pp. 51-69.
64. Strobl, C., Boulesteix, A. L., Zeileis, A. & Hothorn, T., 2007. Bias in random forest variable importance measures: Illustrations, sources and a solution. *BMC Bioinformatics,* 1(8), p. 25.
65. The credit rating of the Czech Republic, 2017. *Czech CNB national bank.* [Online]
Available at:
https://www.cnb.cz/en/monetary_policy/inflation_reports/2011/2011_IV/boxe

s_and_annexes/zoi_2011_IV_box_2.html
[Accessed 10 February 2017].
66. Transparency International, 2017. *Corruption Perception Index Overview.* [Online]
Available at: https://www.transparency.org/research/cpi/overview
[Accessed 03 February 2018].
67. United Nations Development Programme, n.d. *Human Development Reports.* [Online]
Available at: http://hdr.undp.org/en/content/human-development-index-hdi
[Accessed 14 August 2017].
68. United Nations Development Programme, 2016. *Human development report.* [Online]
Available at: http://hdr.undp.org/en/2016-report
[Accessed 25 August 2017].
69. West, R., 1970. An Alternative Approach to Predicting Corporate Bond Ratings. *Journal of Accounting Research,* pp. 118-127.

Working paper

1. Cristina Checherita and Philipp Rother, 2010. The impact of high and growing government debt on ecomonic growth an empirical investigation for Euro area. Working paper series No 1237.
2. De Freitas, A., Beyers, C., Seymore, R., van Eyden, R., de Villiers, J.P., Yang, J., 2018. Sovereign Credit Rating: An Analysis of Country Development Bias. Working paper.
3. Verster, T., de Jongh, R., Greenberg, S., Fourie, E., 2016. Assessing the relevance of emerging market obligor creditworthiness assigned by credit rating agencies. Working paper.

8 APPENDIX

Inclusion of known sovereign ratings

The sovereign ratings at time $t-1$ positively correlated to the sovereign ratings at time t. Therefore, if the country currently has a high rating, it is likely for the country to obtain a high rating again at time t. Like mentioned earlier, the current sovereign ratings contain information that is not publicly available. Hence, including the latest known sovereign ratings as an independent variable will improve the modelling of the sovereign ratings at time t. The R-squared on the model including the sovereign ratings at time $t-1$ is above 95%.

Table I: Economic Variables Summary

Country	Average Ratings	Average GNI per Capita per country	Average GDP growth	Average Inflation	Average fiscal balance to GDP	Average debt to GDP	Average HDI
Albania	7	4 294	2,65	2,2	-4,04	65,07	0,75
Angola	8	3 890	4,52	10,87	1,08	41,09	0,52
Argentina	4	7 593	2,72	10,68	-1,25	67,32	0,8
Armenia	9	3 513	4,01	4,49	-3,37	33,16	0,73
Australia	20	41 057	2,98	2,77	-1,23	20,71	0,92
Austria	20	41 329	1,49	1,87	-2,37	74,29	0,87
Azerbaijan	10	5 494	6,29	6,91	5,3	18,02	0,74
Bahamas, The	13	22 111	0,24	1,9	-3,57	41,49	0,79
Bahrain	13	17 823	4,9	1,94	-2,64	30,93	0,81
Bangladesh	8	977	6,2	7,61	-3,26	34,67	0,57
Barbados	11	14 051	1,07	3,59	-5	67	0,78
Belarus	6	6 179	3,67	24,5	-4,06	36,42	0,79
Belgium	18	39 471	1,55	2	-2,02	100,84	0,88
Belize	5	3 877	3,55	1,91	-3,97	89,05	0,7
Benin	6	701	3,98	2,85	-1,04	26,4	0,45
Bolivia	7	1 703	4,28	4,96	-2,19	48,77	0,64
Bosnia and Herzegovina	6	4 841	1,88	1,3	-2,21	39,5	0,73
Botswana	15	5 453	4,41	7,25	-0,05	13,14	0,65
Brazil	10	7 248	2,54	6,71	-4,05	67,24	0,72
Bulgaria	11	5 194	3,63	4,03	-0,15	30,57	0,76
Burkina Faso	6	583	5,46	2,12	-1,4	28,28	0,38
Cabo Verde	7	3 338	1,8	2,08	-7,16	88,67	0,64
Cambodia	6	859	6,58	5,48	-2,12	34,04	0,54
Cameroon	5	1 121	4,34	2,31	2,11	26,21	0,48
Canada	20	38 980	2,13	1,9	-0,59	79,31	0,9
Chile	15	9 555	4,06	3,34	0,81	11,2	0,81

China	15	3 814	9,42	2,31	-1,49	31,26	0,67
Colombia	10	4 711	4,13	5,15	-1,91	40,03	0,69
Costa Rica	10	6 692	4,18	7,65	-3,71	35,43	0,74
Cote d'Ivoire	8	1 475	8,82	1,13	-2,51	46,31	0,47
Croatia	11	10 849	1,79	2,26	-4,54	54,25	0,8
Cyprus	13	24 809	1,83	1,84	-2,64	70,61	0,84
Denmark	20	51 804	1,14	1,73	0,57	41,7	0,91
Dominican Republic	7	4 363	5,14	9,08	-2,58	25,02	0,69
Ecuador	4	3 869	4,25	5,66	-0,72	25,3	0,71
Egypt, Arab Rep.	8	2 169	4,19	9,45	-9,3	83,12	0,66
El Salvador	9	3 134	1,95	2,66	-3,49	44,89	0,66
Estonia	16	12 405	3,92	3,5	0,39	6,65	0,83
Ethiopia	7	575	10,32	8,57	-2,26	53,17	0,44
Fiji	7	3 848	1,97	3,78	-3,04	49,9	0,71
Finland	20	41 556	1,47	1,75	1,01	46,37	0,88
France	20	36 936	1,3	1,56	-3,72	75,58	0,88
Gabon	8	8 179	4,03	1,44	3,92	30,74	0,68
Georgia	8	3 351	5,38	4,51	-1,41	36,5	0,75
Germany	20	38 750	1,33	1,51	-1,53	68,79	0,9
Ghana	6	1 192	6,61	13,49	-7,81	52,38	0,55
Greece	11	21 549	0,16	2,13	-6,72	133,48	0,85
Grenada	1	7 915	3,24	0,92	-3,64	97,76	0,75
Guatemala	9	2 553	3,49	5,74	-1,99	22,23	0,6
Honduras	6	1 657	3,66	6,4	-2,69	39,32	0,6
Hong Kong SAR, China	18	33 269	3,63	1,97	1,45	1,09	0,89
Hungary	12	10 693	2,17	4,42	-4,72	68,13	0,81
Iceland	15	43 817	3,08	4,99	-1,35	58,07	0,89
India	10	1 024	7,08	6,37	-8,2	74,37	0,56
Indonesia	8	2 095	5,29	7,31	-1,19	39,58	0,65
Iran, Islamic Rep.	6	1 770	4,12	10,01	3,83	11,85	0,67
Iraq	5	5 960	4,8	2,31	-12,31	55,15	0,65
Ireland	17	41 485	5,01	1,72	-4,33	60,36	0,9
Israel	15	26 479	3,51	1,62	-3,9	76,05	0,88
Italy	16	31 698	0,3	1,93	-3,18	112,49	0,86
Jamaica	5	4 147	0,69	9,81	-4,5	127,5	0,71
Japan	18	40 405	0,91	0,05	-6,22	198,7	0,88
Jordan	9	2 853	5,06	3,46	-5,63	83,45	0,73
Kazakhstan	12	6 669	6,3	8,4	2,45	12,3	0,76
Kenya	7	1 043	5,31	7,85	-5,23	44,89	0,53
Korea, Rep.	15	20 209	4,18	2,61	1,51	28,27	0,87
Kuwait	17	37 872	4,48	3,42	27,03	16,01	0,79
Latvia	13	10 323	3,9	3,79	-2,02	23,76	0,8
Lebanon	6	7 615	4,6	3,71	-8,48	147,95	0,76

Lithuania	14	12 235	3,32	3,1	-2,95	29,87	0,83
Luxembourg	20	68 676	3,14	2,31	1,62	13,85	0,88
Madagascar	6	363	3,22	10,98	-2,37	45,97	0,49
Malaysia	14	7 188	5,07	2,25	-3,84	46,73	0,76
Mali	6	574	4,29	3,43	1,02	27,14	0,38
Malta	14	18 165	3,34	2,03	-3,56	66,13	0,82
Mauritius	12	6 833	4,37	4,75	-3,94	51,94	0,73
Mexico	12	8 476	2,36	4,4	-2,85	44,06	0,73
Moldova	4	1 355	5,34	9,68	-1,14	45,99	0,66
Montenegro	8	6 488	2,41	2,6	-3,56	50,61	0,79
Morocco	10	2 390	4,28	1,6	-3,76	58,46	0,6
Mozambique	7	494	7,36	6,99	-4,86	54,62	0,39
Namibia	11	5 327	4,87	5,72	-5,63	29,85	0,63
Netherlands	20	44 315	1,4	1,86	-1,75	55,49	0,9
New Zealand	19	28 111	2,67	2,22	0,56	23,89	0,9
Nicaragua	5	1 375	3,8	7,75	-0,91	54	0,61
Nigeria	8	2 144	4,69	11,14	-1,29	11,88	0,51
Norway	20	74 334	1,7	2,04	11,77	37,28	0,93
Oman	14	14 537	3,62	2,44	6,03	10,12	0,77
Pakistan	5	965	4,24	7,95	-4,72	64,09	0,51
Panama	11	7 086	6,2	2,75	-1,72	47,97	0,75
Papua New Guinea	7	1 047	4,04	6,3	0,19	29,32	0,47
Paraguay	6	2 460	3,64	6,62	0,06	26,5	0,66
Peru	10	3 884	5,09	2,81	-0,11	32,43	0,71
Philippines	9	2 249	5,22	4,21	-1,4	48,86	0,66
Poland	14	9 893	3,64	2,47	-4,27	47,91	0,82
Portugal	15	18 738	0,5	2,01	-5,39	87,86	0,81
Romania	10	6 320	3,74	9,41	-3,14	27,56	0,77
Russian Federation	11	7 835	3,98	11,12	1,27	19,37	0,77
Rwanda	6	668	7,56	4,5	-2,3	25,82	0,49
Saudi Arabia	15	17 546	4,33	2,92	5,08	27,64	0,8
Senegal	7	884	4,27	1,52	-3,7	48	0,45
Serbia	8	5 284	2,19	6,2	-3,15	57,24	0,76
Seychelles	2	11 242	5,07	13,93	0,7	123,68	0,74
Singapore	20	37 949	5,33	1,76	5,46	96,22	0,88
Slovak Republic	15	13 479	3,93	3,25	-4,48	42,95	0,81
Slovenia	16	19 667	2,16	3,11	-3,07	42,41	0,87
South Africa	12	5 322	2,96	5,9	-2,44	37,89	0,63
Spain	17	26 102	1,78	2,28	-3,79	63,26	0,86
Sri Lanka	7	2 771	6,34	7,15	-6,32	72,88	0,75
St. Vincent and the Grenadines	6	6 312	0,69	2,11	-2,74	69,92	0,72
Suriname	7	7 012	2,49	12,97	-3,06	27,39	0,71
Sweden	20	48 059	2,37	1,52	0,44	43,55	0,9

Switzerland	20	66 272	1,88	0,42	0,11	49,28	0,92
Thailand	13	3 885	4,03	2,22	-0,4	44,48	0,7
Trinidad and Tobago	13	13 816	3,23	5,96	-2,1	27,29	0,76
Tunisia	11	3 419	3,36	3,53	-3,47	50,6	0,7
Turkey	8	8 541	5,12	15,48	-4,04	45	0,71
Uganda	7	607	5,65	7,85	-3,86	26,64	0,48
Ukraine	6	2 313	2,43	12,53	-3,11	37,89	0,72
United Arab Emirates	17	37 688	3,85	3,96	7,43	13,15	0,82
United Kingdom	20	39 969	1,85	2,01	-4,31	59,66	0,89
United States	20	48 226	1,81	2,08	-5,38	81,83	0,91
Uruguay	9	9 507	3,12	8,72	-2,18	71,97	0,77
Venezuela, RB	6	7 534	3,53	24,65	-4,28	40,42	0,73
Vietnam	8	1 265	6,32	8,37	-3,68	46,1	0,65
Zambia	7	1 650	5,12	10,45	-5,54	35,54	0,57

Number of Observations

	current_acc	GNI	GDP_per_capita	GDP_growth	debt_GDP	fiscal	inflation	default	default_ind	HDI	HDI_rate	IMF_industrial_ind	current_acc_t2	GNI_t2	GDP_per_capita_t2	GDP_growth_t2	debt_GDP_t2	fiscal_t2	inflation_t2	default_t2	current_acc_t1	GNI_t1	GDP_per_capita_t1	GDP_growth_t1	debt_GDP_t1	fiscal_t1	inflation_t1	default_t1
current_acc	1.00000	0.34052	0.32886	0.04870	-0.13981	0.55229	-0.06487	0.01707	-0.25398	0.24123	-0.04536	0.15390	0.80829	0.32771	0.31585	0.00151	-0.08841	0.45304	-0.07343	0.02568	0.89752	0.33104	0.31947	0.01474	-0.10661	0.49762	-0.05385	0.02502
		<.0001	<.0001	0.0050	<.0001	<.0001	0.0002	0.3256	<.0001	<.0001	0.0090	<.0001	<.0001	<.0001	<.0001	0.9329	<.0001	<.0001	<.0001	0.1509	<.0001	<.0001	<.0001	0.4024	<.0001	<.0001	0.0022	0.1554
GNI	0.34052	1.00000	0.98716	-0.24999	0.14472	0.22358	-0.28654	-0.01844	-0.56422	0.74558	-0.33453	0.75133	0.33219	0.98480	0.97883	-0.22298	0.12569	0.23426	-0.30155	-0.02207	0.33680	0.99480	0.98669	-0.22644	0.13477	0.23320	-0.29486	-0.02234
	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	0.2884	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2170	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2045
GDP_per_capita	0.32886	0.98716	1.00000	-0.22812	0.11702	0.22468	-0.27811	-0.01942	-0.55282	0.72948	-0.32479	0.73553	0.31874	0.96778	0.97801	-0.21268	0.09948	0.22454	-0.28993	-0.02159	0.32356	0.97832	0.99070	-0.20522	0.10769	0.22789	-0.28479	-0.02169
	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	0.2635	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2271	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2181
GDP_growth	0.04870	-0.24999	-0.22812	1.00000	-0.24099	0.21204	0.05851	-0.07542	0.14117	-0.26457	0.47382	-0.22181	0.11686	-0.28158	-0.27189	0.20123	-0.10129	0.02978	0.08131	0.04981	0.10317	-0.27437	-0.26607	0.45951	-0.15078	0.08667	0.02883	0.00388
	0.0050	<.0001	<.0001		<.0001	<.0001	0.0007	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0958	<.0001	0.0053	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.1015	0.8258
debt_GDP	-0.13981	0.14472	0.11702	-0.24099	1.00000	-0.36783	-0.07870	0.16352	-0.03262	0.17322	-0.19436	0.22517	-0.18306	0.18240	0.15416	-0.29878	0.94454	-0.43936	-0.12355	0.14215	-0.16262	0.16231	0.13364	-0.28030	0.97812	-0.41695	-0.10570	0.16206
	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	0.0603	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
fiscal	0.55229	0.22358	0.22468	0.21204	-0.36783	1.00000	-0.05542	-0.00716	-0.13283	0.11354	0.03078	0.03826	0.51003	0.18510	0.17856	0.12442	-0.23855	0.69196	-0.07868	0.01281	0.53923	0.20225	0.19929	0.19495	-0.29770	0.81282	-0.05443	0.01008
	<.0001	<.0001	<.0001	<.0001	<.0001		0.0014	0.6800	<.0001	<.0001	0.0763	0.0276	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.4737	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0020	0.5671
inflation	-0.06487	-0.28654	-0.27811	0.05851	-0.07870	-0.05542	1.00000	0.04712	0.31803	-0.26369	0.13689	-0.30363	-0.04565	-0.28661	-0.27863	0.12188	-0.12249	-0.03581	0.41885	0.01961	-0.06369	-0.28259	-0.27559	0.12151	-0.10944	-0.07107	0.56048	0.02648
	0.0002	<.0001	<.0001	0.0007	<.0001	0.0014		0.0066	<.0001	<.0001	<.0001	<.0001	0.0106	<.0001	<.0001	<.0001	<.0001	0.0451	<.0001	0.2728	0.0003	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.1326
default	0.01707	-0.01844	-0.01942	-0.07542	0.16352	-0.00716	0.04712	1.00000	0.10775	0.02853	-0.02699	0.00660	-0.02333	-0.00613	-0.00602	-0.11798	0.15151	-0.06380	0.03615	0.19976	-0.00399	-0.01429	-0.01419	-0.11617	0.17046	-0.03867	0.05039	0.55987
	0.3256	0.2884	0.2635	<.0001	<.0001	0.6800	0.0066		<.0001	0.1004	0.1202	0.7040	0.1920	0.7318	0.7364	<.0001	<.0001	0.0004	0.0431	<.0001	0.8209	0.4170	0.4204	<.0001	<.0001	0.0281	0.0042	<.0001
default_ind	-0.25398	-0.56422	-0.55282	0.14117	-0.03262	-0.13283	0.31803	0.10775	1.00000	-0.60298	0.24844	-0.58240	-0.25978	-0.54360	-0.53070	0.06205	-0.01165	-0.13030	0.32353	0.11293	-0.25843	-0.55379	-0.54224	0.10011	-0.02210	-0.13369	0.32338	0.11142
	<.0001	<.0001	<.0001	<.0001	0.0603	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0005	0.5147	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2095	<.0001	<.0001	<.0001
HDI	0.24123	0.74558	0.72948	-0.26457	0.17322	0.11354	-0.26369	0.02853	-0.60298	1.00000	-0.46244	0.71447	0.21232	0.74012	0.72455	-0.22399	0.15131	0.10662	-0.27701	0.02762	0.22873	0.74297	0.72713	-0.23815	0.16389	0.11079	-0.26540	0.02693
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.1004	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.1224	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.1261
HDI_rate	-0.04536	-0.33453	-0.32479	0.47382	-0.19436	0.03078	0.13689	-0.02699	0.24844	-0.46244	1.00000	-0.24073	0.01106	-0.34632	-0.33775	0.14973	-0.11713	-0.00990	0.14696	-0.01225	-0.00885	-0.34636	-0.33749	0.24950	-0.14860	0.00045	0.13061	-0.00627
	0.0090	<.0001	<.0001	<.0001	<.0001	0.0763	<.0001	0.1202	<.0001	<.0001		<.0001	0.5361	<.0001	<.0001	<.0001	<.0001	0.5800	<.0001	0.4934	0.6151	<.0001	<.0001	<.0001	<.0001	0.9798	<.0001	0.7219
IMF_industrial_ind	0.15390	0.75133	0.73553	-0.22181	0.22517	0.03826	-0.30363	0.00660	-0.58240	0.71447	-0.24073	1.00000	0.12271	0.74069	0.72274	-0.21217	0.21322	0.01038	-0.31834	0.00487	0.13545	0.74535	0.72854	-0.21014	0.22060	0.02212	-0.30932	0.00481
	<.0001	<.0001	<.0001	<.0001	<.0001	0.0276	<.0001	0.7040	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	0.5616	<.0001	0.7852	<.0001	<.0001	<.0001	<.0001	<.0001	0.2090	<.0001	0.7846
current_acc_t2	0.80829	0.33219	0.31874	0.11686	-0.18306	0.51003	-0.04565	-0.02333	-0.25978	0.21232	0.01106	0.12271	1.00000	0.31689	0.30541	0.05044	-0.13048	0.54448	-0.05831	0.02355	0.90220	0.32427	0.31262	0.12164	-0.15808	0.54308	-0.05653	-0.00424
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0106	0.1920	<.0001	<.0001	0.5361	<.0001		<.0001	<.0001	0.0048	<.0001	<.0001	0.0011	0.1879	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0016	0.8127
GNI_t2	0.32771	0.98480	0.96778	-0.28158	0.18240	0.18510	-0.28661	-0.00613	-0.54360	0.74012	-0.34632	0.74069	0.31689	1.00000	0.98859	-0.24530	0.14579	0.21142	-0.29941	-0.01844	0.32191	0.99507	0.97982	-0.26671	0.16542	0.19832	-0.29069	-0.01317
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.7318	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	0.3024	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.4613
GDP_per_capita_t2	0.31585	0.97883	0.97801	-0.27189	0.15416	0.17856	-0.27863	-0.00602	-0.53070	0.72455	-0.33775	0.72274	0.30541	0.98859	1.00000	-0.22522	0.11640	0.21249	-0.28940	-0.01975	0.30951	0.98677	0.99060	-0.25954	0.13670	0.19430	-0.28275	-0.01326
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.7364	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	0.2693	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.4584
GDP_growth_t2	0.00151	-0.22298	-0.21268	0.20123	-0.29878	0.12442	0.12188	-0.11798	0.06205	-0.22399	0.14973	-0.21217	0.05044	-0.24530	-0.22522	1.00000	-0.24865	0.21518	0.09089	-0.06373	0.01182	-0.22898	-0.20925	0.45446	-0.28754	0.20014	0.13361	-0.11630
	0.9329	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0005	<.0001	<.0001	<.0001	0.0048	<.0001	<.0001		<.0001	<.0001	<.0001	0.0004	0.5087	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
debt_GDP_t2	-0.08841	0.12569	0.09948	-0.10129	0.94454	-0.23855	-0.12249	0.15151	-0.01165	0.15131	-0.11713	0.21322	-0.13048	0.14579	0.11640	-0.24865	1.00000	-0.38603	-0.07136	0.18004	-0.10470	0.13381	0.10471	-0.15203	0.97796	-0.30955	-0.10236	0.17883
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.5147	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
fiscal_t2	0.45304	0.23426	0.22454	0.02978	-0.43936	0.69196	-0.03581	-0.06380	-0.13030	0.10662	-0.00990	0.01038	0.54448	0.21142	0.21249	0.21518	-0.38603	1.00000	-0.03446	-0.00849	0.49812	0.22630	0.22260	0.08706	-0.42431	0.81778	-0.04743	-0.04031
	<.0001	<.0001	<.0001	0.0958	<.0001	<.0001	0.0451	0.0004	<.0001	<.0001	0.5800	0.5616	<.0001	<.0001	<.0001	<.0001	<.0001		0.0539	0.6348	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0080	0.0241
inflation_t2	-0.07343	-0.30155	-0.28993	0.08131	-0.12355	-0.07868	0.41885	0.03615	0.32353	-0.27701	0.14696	-0.31834	-0.05831	-0.29941	-0.28940	0.09089	-0.07136	-0.03446	1.00000	0.05420	-0.05253	-0.30039	-0.28966	0.02952	-0.10515	-0.05331	0.55952	0.04604
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0431	<.0001	<.0001	<.0001	<.0001	0.0011	<.0001	<.0001	<.0001	<.0001	0.0539		0.0024	0.0033	<.0001	<.0001	0.0987	<.0001	0.0029	<.0001	0.0100
default_t2	0.02568	-0.02207	-0.02159	0.04981	0.14215	0.01281	0.01961	0.19976	0.11293	0.02762	-0.01225	0.00487	0.02355	-0.01844	-0.01975	-0.06373	0.18004	-0.00849	0.05420	1.00000	0.02481	-0.02086	-0.02032	0.00475	0.16748	0.00900	0.02349	0.56017
	0.1509	0.2170	0.2271	0.0053	<.0001	0.4737	0.2728	<.0001	<.0001	0.1224	0.4934	0.7852	0.1879	0.3024	0.2693	0.0004	<.0001	0.6348	0.0024		0.1652	0.2435	0.2559	0.7905	<.0001	0.6149	0.1891	<.0001
current_acc_t1	0.89752	0.33680	0.32356	0.10317	-0.16262	0.53923	-0.06369	-0.00399	-0.25843	0.22873	-0.00885	0.13545	0.90220	0.32191	0.30951	0.01182	-0.10470	0.49812	-0.05253	0.02481	1.00000	0.32938	0.31762	0.05683	-0.13354	0.55118	-0.05486	0.02352
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0003	0.8209	<.0001	<.0001	0.6151	<.0001	<.0001	<.0001	<.0001	0.5087	<.0001	<.0001	0.0033	0.1652		<.0001	<.0001	0.0012	<.0001	<.0001	0.0018	0.1816
GNI_t1	0.33104	0.99480	0.97832	-0.27437	0.16231	0.20225	-0.28259	-0.01429	-0.55379	0.74297	-0.34636	0.74535	0.32427	0.99507	0.98677	-0.22898	0.13381	0.22630	-0.30039	-0.02086	0.32938	1.00000	0.98749	-0.24259	0.14611	0.21852	-0.29341	-0.02017
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.4170	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2435	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	0.2521
GDP_per_capita_t1	0.31947	0.98669	0.99070	-0.26607	0.13364	0.19929	-0.27559	-0.01419	-0.54224	0.72713	-0.33749	0.72854	0.31262	0.97982	0.99060	-0.20925	0.10471	0.22260	-0.28966	-0.02032	0.31762	0.98749	1.00000	-0.22135	0.11670	0.21944	-0.28402	-0.02127
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.4204	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2559	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	0.2270
GDP_growth_t1	0.01474	-0.22644	-0.20522	0.45951	-0.28030	0.19495	0.12151	-0.11617	0.10011	-0.23815	0.24950	-0.21014	0.12164	-0.26671	-0.25954	0.45446	-0.15203	0.08706	0.02952	0.00475	0.05683	-0.24259	-0.22135	1.00000	-0.24345	0.21193	0.07659	-0.06733
	0.4024	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0987	0.7905	0.0012	<.0001	<.0001		<.0001	<.0001	<.0001	0.0001
debt_GDP_t1	-0.10661	0.13477	0.10769	-0.15078	0.97812	-0.29770	-0.10944	0.17046	-0.02210	0.16389	-0.14860	0.22060	-0.15808	0.16542	0.13670	-0.28754	0.97796	-0.42431	-0.10515	0.16748	-0.13354	0.14611	0.11670	-0.24345	1.00000	-0.37697	-0.07512	0.17441
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.2095	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001
fiscal_t1	0.49762	0.23320	0.22789	0.08667	-0.41695	0.81282	-0.07107	-0.03867	-0.13369	0.11079	0.00045	0.02212	0.54308	0.19832	0.19430	0.20014	-0.30955	0.81778	-0.05331	0.00900	0.55118	0.21852	0.21944	0.21193	-0.37697	1.00000	-0.03530	-0.00690
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0281	<.0001	<.0001	0.9798	0.2090	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0029	0.6149	<.0001	<.0001	<.0001	<.0001	<.0001		0.0450	0.6953
inflation_t1	-0.05385	-0.29486	-0.28479	0.02883	-0.10570	-0.05443	0.56048	0.05039	0.32338	-0.26540	0.13061	-0.30932	-0.05653	-0.29069	-0.28275	0.13361	-0.10236	-0.04743	0.55952	0.02349	-0.05486	-0.29341	-0.28402	0.07659	-0.07512	-0.03530	1.00000	0.06292
	0.0022	<.0001	<.0001	0.1015	<.0001	0.0020	<.0001	0.0042	<.0001	<.0001	<.0001	<.0001	0.0016	<.0001	<.0001	<.0001	<.0001	0.0080	<.0001	0.1891	0.0018	<.0001	<.0001	<.0001	<.0001	0.0450		0.0003
default_t1	0.02502	-0.02234	-0.02169	0.00388	0.16206	0.01008	0.02648	0.55987	0.11142	0.02693	-0.00627	0.00481	-0.00424	-0.01317	-0.01326	-0.11630	0.17883	-0.04031	0.04604	0.56017	0.02352	-0.02017	-0.02127	-0.06733	0.17441	-0.00690	0.06292	1.00000
	0.1554	0.2045	0.2181	0.8258	<.0001	0.5671	0.1326	<.0001	<.0001	0.1261	0.7219	0.7846	0.8127	0.4613	0.4584	<.0001	<.0001	0.0241	0.0100	<.0001	0.1816	0.2521	0.2270	0.0001	<.0001	0.6953	0.0003	