Estimating the weights assigned to determinants of emerging market sovereign ratings

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DEDICATION

To the Almighty God, Jesus Christ, my saviour.

You are the keeper of my heart and lover of my soul. Thank you for Your unconditional love towards me. I praise You for my daily strength, Your comfort in the shape of loved ones and Your lamp to my feet, guiding my each and every step. I pray that Your will be done now and forever.

Many are the plans in a man's heart, but it is the Lord's purpose that will prevail. *Proverbs 19:21*

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ABSTRACT

The recent global financial crisis uncovered numerous problems in the fundamental analytical structure and methodologies applied by the credit rating agencies. It reintroduced the debate concerning the accuracy, objectivity and diligence with which credit rating agencies assign sovereign credit ratings (sovereign ratings). Standard & Poor's, Moody's Investors Service (Moody's) and Fitch Ratings (Fitch) utilise more or less the same determinants in rating sovereigns worldwide. However, the weights assigned to each determinant differ for each of the three major credit rating agencies and hence the obstacle remains that sovereigns are rated differently by each agency. Changes in sovereign ratings influence flows of capital to emerging market economies. Sovereign ratings especially affect emerging market economies, since these economies are highly dependent on international capital flows to finance foreign currency expenditures. Sovereign default risk significantly influences flows of capital from developed economies to emerging market economies. Emerging market economies strive to maintain a stable and high rating, as long run foreign currency sovereign ratings are essential for the attraction of capital flows.

The first objective of this study was to scrutinise the effect of sovereign rating announcements, either an upgrade or a downgrade, on flows of capital to emerging markets. This study demonstrates the significance of sovereign rating changes on global market reactions. An upgrade through the investment grade barrier not only reduces a sovereign's global borrowing cost but also ensures funds from international investment. Granger causality tests determined that four emerging market economies, namely Cyprus, Hungary, Indonesia and Lithuania demonstrated changes in sovereign ratings that have an influence on flows of capital. Some of the economies suggest that bi-directional movements are possible as well, which gives the financial and capital account values the ability to forecast future ratings and vice versa. The timing of upgrades or downgrades across the three agencies was examined to establish whether rating changes occur simultaneously or whether a specific agency leads/follows with rating changes. Standard & Poor's was identified as the main leading agency that initiated 40.74% of rating changes followed by Fitch that led 33.33% and Moody's that led 25.93%. This study suggests that Standard &

Poor's is the leading agency, Moody's the primary following agency and Fitch the secondary following agency within the time period of 1998Q1-2014Q1, for the particular group of emerging market economies.

The second objective of this study was to examine the links between sovereign ratings and the weights assigned to the determinants within the sovereign rating methodologies. The analysis focused on Standard & Poor's, Moody's and Fitch in an attempt to verify which macro-economic variables have a significant influence on sovereign ratings. In addition, determining whether emerging market economies are rated differently by each credit rating agency. Three estimation techniques were applied to yield the empirical results. These three chosen methods are firstly the ordered probit method, secondly the Ordinary Least Squares (OLS) method with panel options fixed and random effects and thirdly the pooled OLS method with panel options fixed and random effects. The results of the empirical analysis found seven macro-economic variables significant, which has an imperative influence on sovereign ratings. These variables are fiscal balance as a percentage of GDP, external debt as a percentage of GDP, external debt as a percentage of exports, real GDP growth, real effective exchange rate and current account as a percentage of GDP.

Keywords: *Sovereign ratings, Capital flows, Emerging market economies, Macro-economic variables, Ordered Probit Model, OLS Model, Pooled OLS model, Fixed and Random effects, Granger causality*

UITTREKSEL

Die onlangse wêreldwye finansiële krisis het talle probleme in die fundamentele analitiese struktuur en metodologieë wat deur die kredietgraderingsagentskappe toegepas word blootgelê. Dit herbevestig die debat oor die akkuraatheid, objektiwiteit en deursigtigheid waarmee kredietgraderingsagentskappe kredietgradering toeken aan soewereine. Standard & Poor's, Moody's Investors Service (Moody's) en Fitch Ratings (Fitch) gebruik min of meer dieselfde determinante in hulle beoordelings wêreldwyd. Alhoewel, die gewig wat aan elke determinant toegeken word verskil vir elk van die drie groot kredietgraderingsagentskappe. Die hindernis bly dus staan dat soewereine verskillend beoordeel word deur elke agentskap. Veranderinge in soewereine kredietgraderings (soewereine graderings) beïnvloed vloeie van kapitaal na ontluikende markekonomieë. Soewereine graderings beïnvloed veral ontluikende markekonomieë, aangesien hierdie ekonomieë baie afhanklik is van internasionale kapitaalvloeie om buitelandse valuta uitgawes te finansier. Risiko van wanbetaling deur die soewereine beïnvloed vloeie van kapitaal vanaf ontwikkelde ekonomieë na opkomende mark ekonomieë. Ontluikende markekonomieë streef daarna om stabiele en hoë graderings te handhaa en die rede is dat langtermyn buitelandse valuta soewereine graderings noodsaaklik is om kapitaalvloeie vanaf globale markte aan te lok.

Die eerste doelwit van hierdie studie was om die effek van soewereine kredietgradering aankondigings, 'n opgradering of afgradering, op vloeie van kapitaal in ontluikende markte te ondersoek. Hierdie studie toon die belangrikheid van soewereine graderingveranderinge op die reaksie van die globale markte. 'n Opgradering deur die belegging graad lei nie net tot verminderde globale lenings koste vir 'n soewerein nie, maar verseker ook fondse vanaf internasionale beleggings. Granger oorsaaklikheidstoetse demonstreer dat vier ontluikende mark ekonomieë, naamlik Siprus, Hongarye, Indonesië en Litaue veranderinge in hulle soewereine kredietgraderings 'n invloed op die vloeie van kapitaal het. Sommige van die ekonomieë dui daarop dat wederkerige bewegings ook moontlik is, wat beteken dat die finansiële en kapitaalrekeningwaardes die vermoë het om toekomstige graderings te voorspel. Die tydsberekening van opgraderings of afgraderings deur die drie agentskappe is ondersoek. Daar word onderskei tussen die veranderinge in

die soewereine graderings wat óf gelyktydig óf individueel plaasvind en dit impliseer dat ‘n agentskap óf leiding neem óf ander agentskappe se veranderinge naboots. Standard & Poor's is geïdentifiseer as die leidende agentskap wat 40,74% van gradering veranderinge lei, gevolg deur Fitch wat 33,33% van die veranderinge lei en Moody's wat 25,93% van die leiding ïnisieer. Hierdie studie dui daarop dat Standard & Poor's die leidende agentskap is, Moody's die primêre nabootsende agentskap is en Fitch die sekondêre nabootsende agentskap was vir die tydperk 1998Q1-2014Q1 en vir die spesifieke groep van ontluikende markekonomieë.

Die tweede doelwit van hierdie studie ondersoek die verband tussen soewereine graderings en die gewigte wat aan die determinante binne die soewereine graderingsmetodologieë toegeken word. Die ontledings fokus op Standard & Poor's, Moody's en Fitch in 'n poging om te verifieer watter makro-ekonomiese veranderlikes ‘n beduidende invloed op soewereine graderings het. Daarbenewens word ook bepaal of die ontluikende markekonomieë verskillende gewigte toegeken word deur elke kredietgradering agentskap. Drie tegnieke is aangewend om die empiriese resultate op te lewer. Hierdie drie gekose metodes is eerstens die geordende probit-metode, tweedens die gewone kleinstekwadrate-metode met paneel vaste opsies en ewekansige effekte en derdens die saamgevoegde kleinstekwadrate-metode met paneel vaste opsies en ewekansige effekte. Die resultate van die empiriese ontleding bepaal dat sewe van die makro-ekonomiese veranderlikes ‘n beduidende effek op soewereine graderings het. Hierdie veranderlikes is fiskale balans as 'n persentasie van die BBP, buitelandse skuld as 'n persentasie van die BBP, buitelandse skuld as 'n persentasie van uitvoere, , reële BBP-groei, reële effektiewe wisselkoers en die lopende rekening as 'n persentasie van die BBP.

Sleutelwoorde: *Soewereine gradering, Kapitaalvloeie, Ontluikende markekonomieë, Makro-ekonomiese veranderlikes, Geordende probit-model, Gewone kleinstekwadrate-model, Saamgevoegde gewone kleinstekwadrant-model, Vaste en ewekansige effekte, Granger-oorsaaklikheid*

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1.1 BACKGROUND

The recent global financial crisis that began in 2007 with the subprime crisis, gave rise to the hypothesis formulated by Wehinger. This hypothesis states that the distresses fuelled by the subprime crisis should be seen as a potential explanation for the acceleration of the European sovereign debt crisis that unfolded in 2010 (Wehinger, 2010). The subprime crisis was in turn triggered by a real estate crisis in which a combination of increasing interest rates and decreasing house prices led to defaults on subprime mortgages. The banking sector had an unprecedented exposure to the real estate market since it participated in credit derivatives and securitisation of mortgages. A mass default of these mortgages resulted in numerous banks ending up on the verge of bankruptcy (Lin & Treichel, 2012).

The governments of developed economies were consequently forced to intervene. Various rescue plans were implemented to re-establish investors' confidence and reduce levels of market panic that had not been seen since 1929. Ureche-Rangau and Burietz (2012) stress the fact that such intensified market fright tends to have a domino effect on emerging market economies. These rescue plans included the provision of mass liquidity, capital injections into banks and guaranteeing the debt of some banks as methods of restoring confidence in the financial system (Gennaioli, Martin & Rossi, 2010). The longer-term dire consequences of these financing strategies only manifested itself much later in numerous European governments. These governments were unable to refinance their own debt, thereby establishing the link between the subprime mortgage crisis and the European sovereign debt crisis. Sovereign risk inherent in emerging markets mostly depend on the financial health of developed markets for foreign exchange, be it through export earnings or capital flows. A study by Arellano and Kocherlakota (2008) support the validity of this argument by proposing that an international banking crisis must ultimately become a sovereign debt crisis. This is even more so for emerging market economies.

1.1.1 Sovereign ratings

A country's sovereign credit rating is a major determinant of its ability to access international debt markets. According to Pescatori and Sy (2007) a country that experiences a significant downgrade of its sovereign credit rating will automatically find itself in a sovereign debt crisis. Sovereign ratings are assigned and published by credit rating agencies and the opinions of the famed big three, namely Standard & Poor's, Moody's and Fitch are the most influential. Sovereign ratings serve as both a qualitative and quantitative indicator of a government's creditworthiness. A sovereign rating is therefore an opinion of the future ability and willingness of a government to service its debt obligations (Basu, De, Ratha & Timmer, 2013).

1.1.2 The European sovereign debt crisis

The worldwide economic downturn uncovered numerous problems in the fundamental analytical structure and methodologies applied by the credit rating agencies. It reintroduced the debate concerning the accuracy, objectivity and diligence with which credit rating agencies assign sovereign ratings. According to Ryan (2012) the role that the credit rating agencies played in the financial market might have precipitated and even escalated the crisis. As a result, scepticism arose concerning the credibility of the credit rating agencies. On January 13, 2012 Standard & Poor's rapidly downgraded nine investment grade member states of the European Union (EU) and fourteen other EU economies were assigned negative outlooks. The PIIGS economies, namely Portugal, Ireland, Italy, Greece and Spain were the worst rated economies during the European sovereign debt crisis. The unintended consequence of rating downgrades was the increased international borrowing costs for these sovereigns that ultimately contributed to the already unstable market environment (Gärtner, Griesbach & Jung, 2011). Arezki, Candelon and Sy (2011) argue that these sovereign downgrades came about too rapidly and marked economies too many notches down the credit curve.

1.1.3 Sovereign spill-over effects on emerging market economies

The European Union Committee (2012) states that market reactions to changes in Sovereign ratings might cause (i) "cliff effects" (ii) encourage herd behaviour amongst investors and (iii) generate systematic disruptions. It explains why Arezki, Candelon and Sy (2011) reason that sovereign downgrades have the potential of economic and statistical spill-over effects. These spill-over effects are primarily dependent on the nature of the rating announcement, the country involved and the credit rating agency that assigned the specific rating. Kaminsky and Reinhart (2001) established that domestic markets are highly vulnerable to crises elsewhere when a central group of related economies are already affected. Due to the dependency on exports the assumption was made that all emerging market economies were highly susceptible to the downgrades and the anticipated economic crisis of the EU Member States. Consequently, sovereign credit risk has become a major threat to global financial stability.

Changes in sovereign ratings, either upgrades or downgrades, have a substantial influence on a country's capital flows. Kirabaeva and Razin (2010) established that capital flows are explained by a combination of foreign portfolio investment (FPI), foreign direct investment (FDI) and debt flows from bonds and bank loans. Remarkably, sovereign downgrades have a strong association with capital outflows, whilst sovereign upgrades are not as associated with capital flows as in the case of downgrades (Gande & Parsley, 2004).

1.2 PROBLEM STATEMENT

From the background it is evident that two major matters are under scrutiny, namely (i) the numerous problems uncovered by the global financial crisis in the fundamental analytical structure and methodologies applied by credit rating agencies, and (ii) the remarkable influence that changes in sovereign ratings have on flows of capital to emerging market economies.

The first problem is substantiated through the recent global financial crisis, which exposed various obstacles faced by the credit rating agencies. Standard & Poor's, Moody's and Fitch utilise more or less the same determinants in rating sovereigns worldwide. The major determinants of sovereign ratings according to eminent literature include the following eight determinants: per capita income, GDP growth rate, inflation, fiscal balance, external debt, economic development, default history and the current account balance. However, the weights assigned to each determinant differ for each of the three major credit rating agencies and hence, the obstacle remains that sovereigns are rated differently by each agency.

The second problem pertains to the manner in which changes in sovereign ratings influence flows of capital to emerging market economies. Sovereign ratings especially affect emerging market economies, since these economies are highly dependent on international capital flows to finance foreign currency expenditures. Reinhart and Rogoff (2004) therefore argue that sovereign default risk, which is ordinarily measured by sovereign ratings, significantly influence the flows of capital from developed economies to emerging market economies. It is of significance to emerging market economies to maintain a stable and high rating, as long run foreign currency sovereign ratings are essential for the attraction of capital flows (Kim & Wu, 2007).

1.3 MOTIVATION

The global financial crisis shed light on the flaws in the rating methods applied by the credit rating agencies. Ever since the start of the crisis, the role played by the credit rating agencies came under intense scrutiny and as a result became the newest topic of dispute. According to Sinclair (2010) the subprime crisis is the greatest threat experienced by the credit rating agencies in their century of existence. Not only did market participants and policymakers hold the credit rating agencies responsible for partly escalating the crisis, but the credit rating agencies themselves also acknowledged their errors during the period of financial instability (Uitzig, 2010). In the face of such convincing evidence, sovereign ratings assigned and published by the credit rating agencies is significant to all global investors and hence further examination on this subject matter is essential.

In current and past studies performed on sovereign ratings, few have examined the weights assigned to the determinants of sovereign ratings concerning emerging market economies. The seminal study done by Cantor and Packer (1996) determined which quantitative indicators weighed heavier during the process of determining sovereign ratings. The study examined sovereign ratings of Standard & Poor’s and Moody’s for 23 industrial- and 26 developing economies on September 1995. Six variables, namely per capita income, GDP growth rate, inflation, external debt, economic development and default history were established as the determinants of sovereign ratings. Conversely, no systematic relationship was found between sovereign ratings and current deficits or fiscal deficits. The statistical results demonstrated through means of a regression analysis that Standard & Poor’s and

Moody's mainly share the same sovereign rating determinants, although the weights assigned to some determinants differ for each agency.

The importance of this study lies in the fact that global investors should identify and be aware of the potential differences in weights assigned to the individual determinants of sovereign ratings for Standard & Poor's, Moody's and Fitch. The increased transparency of sovereign ratings should meaningfully assist investors in better assessing the risk of investing in emerging market economies. Global investors should therefore refer to the sovereign ratings of all three credit rating agencies and diligently do their own research in order to make a highly informed investment decision.

In addition to the methodological problems experienced by credit rating agencies, the global financial crisis turned global investors' attention to the emerging market economies. Emerging market economies drew attention due to the rapid economic growth and high returns that characterise such economies (Davis, Aliaga-Diaz, Thomas & Tolani, 2013). Ghosh, Kim, Qureshi and Zalduendo (2012) who identify numerous factors as significant in increasing the likelihood of capital inflow episodes to emerging market economies, strengthen this argument. These factors include larger global risk appetite, lower United States interest rates, as well as the attractiveness of the particular emerging market economy itself as an investment destination.

This precise event occurred during the global financial crisis where the United States Federal Reserve pursued an unconventional policy named Quantitative Easing (QE). QE involved purchasing a substantial quantity of long-term treasuries and bonds in order to stimulate economic activity during the crisis. Gagnon, Raskin, Remache, and Sack (2010) claim that QE led to great reductions in interest rates and hence lower return on investments. Global investors sought alternative investments as the developed world experienced a major slowdown. Resultantly, emerging market funds surged in 2007-2008 as the emerging market sovereign bond spreads decreased. However, in September 2008, followed by the high profile collapse of Lehman brothers, numerous emerging market economies experienced severe distress and only embarked on the road to recovery in late 2009 and 2010 (Ahmed & Zlate, 2013). Therefore, Bonizzi (2013) argues that emerging market economies experience volatility problems with capital flows. This is the result of periods of large capital inflows followed by sudden interruptions of capital outflows and financial crises.

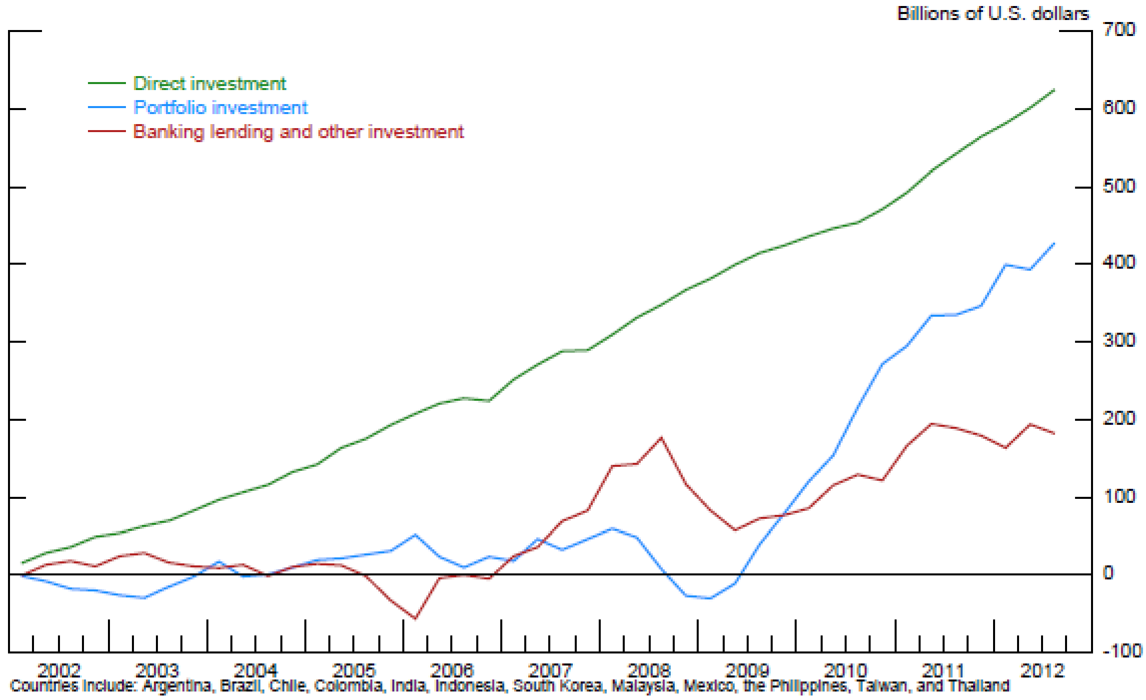

Figure 1.1: Cumulative net inflows to emerging market economies

Source: Ahmed and Zlate (2013)

The main studies in literature regarding the flows of capital for emerging market economies include Kim and Wu (2007), who examined the influence of historic sovereign ratings on international flows of capital to emerging market economies. The primary result indicates that long run foreign currency sovereign ratings are significant for attracting flows of capital. This study applied sovereign ratings from Standard & Poor's for the time period 1995-2003 in 51 emerging market economies by estimating a panel data framework. It is evident that sovereign credit risk has a major influence on flows of capital regarding their long run foreign currency sovereign rating.

In agreement, Larrain, Reisen and Maltzan (1997) demonstrated within a panel data analysis that changes in sovereign ratings have a material influence on global financial markets. In their study a significant “announcement effect” was observed when emerging market economies’ sovereign bonds were put on negative watch. These findings suggest that negative sovereign rating announcements have the ability to diminish private flows of capital into emerging market economies.

1.4 OBJECTIVES

Given that the recent financial crisis highlighted the challenges faced by the credit rating agencies, the main objective of this study is to examine links between sovereign ratings and the weights assigned to the determinants within the sovereign rating methodologies. The study examines Standard & Poor’s, Moody’s and Fitch in an attempt to verify whether each rating agency rates emerging market economies differently. In addition, the second main objective scrutinise the effect of sovereign rating announcements, either an upgrade or downgrade, on flows of capital in emerging markets. This potentially demonstrates the significance of sovereign rating changes on global market reactions.

In order to reach the main objective the following secondary objectives are formulated, viz. to:

- Theoretically determine the particular role of credit rating agencies in the current global economic environment.
- Access the timing of upgrades or downgrades across the three agencies, in order to establish whether rating changes occur simultaneously or whether a specific agency leads/follows with rating changes.
- Examine categorised emerging market economies, to determine whether the weights assigned to the individual macro-economic variables differ within the emerging markets.

1.5 METHODOLOGY

This research, pertaining to the objectives, consists of two phases, viz. firstly a literature review and secondly an empirical study.

1.5.1 Phase 1: Literature review

The aim of the literature review is to examine the role of the credit rating agencies in the current global economic environment. Subsequently, to identify the determinants with which sovereign ratings are assigned, for example (Erdem & Varli, 2014). In addition, to determine if the weights assigned by each credit rating agency is different, as suggested by Cantor and Packer (1996) and also by Alsakka and Gwilym (2012). Furthermore, literature on changes in sovereign ratings is critically analysed in an attempt to determine the relationship between sovereign ratings and flows of capital to emerging market economies, as pointed out by Kim and Wu (2007).

1.5.2 Phase 2: Empirical study

The findings of the literature study have been empirically tested by applying estimation techniques such as Granger causality, OLS, ordered probit and pooled OLS. Asteriou and Hall (2007) define the term causality as the ability to determine the future values of a variable by using past values of another variable. OLS is a generalised linear modelling technique used when modelling multiple explanatory variables as well as categorical explanatory variables (Hutcheson, 2011). Ordered probit models originate from the multinomial models, which are especially useful when ranks such as ratings are measured and the dependent variable is an ordinal variable (Matthies, 2013). The majority of new studies on economic or business issues tend to apply the ordered probit model and this method is therefore essential for this study since it is well-adjusted to modelling sovereign ratings. See chapter 4 for a comprehensive discussion of the methods used.

The specific design that is applied is a panel data analysis due to the cross-sectional component (economies) and the time series component (sovereign ratings and macro-economic determinants expressed in years). The macro-economic variables presented in this study are obtained from the database of the International Monetary Fund (International Financial Statistics, IFS), the World Data Bank as well as the Economic Intelligence Unit (EIU). Sovereign ratings have been attained from Moody's Sovereign Bond Rating History, Standard & Poor's Sovereign Rating and Country T&C Assessment Histories and Emerging Markets Traders Association for Fitch Ratings. The March 2014 FTSE Global Equity Index Series: *Regional*

Classification includes American, European, Asian and African economies. The March 2014 FTSE Global Equity Index Series: *Country Classification* includes advanced and secondary emerging market economies and frontier economies. The entire empirical analysis is performed using EViews 8.

1.6 CHAPTER LAYOUT

Chapter 1 dealt with the problem statement together with the background as an introduction to the study. In addition, motivations for further examination on this particular subject matter were presented.

Chapter 2 provides the literature study with an extensive evaluation of the credit rating agencies in the current global economic environment. Furthermore, an assessment of previous literature on the determinants of sovereign ratings is conducted. An explanation of the expected influence of each macro-economic variable on emerging market economies' sovereign ratings is given. Finally, a discussion of the potential discrepancy between the weights assigned to each determinant by each agency.

Chapter 3 deals with the influence of sovereign rating announcements, upgrades and downgrades, on the flows of capital to emerging market economies.

Chapter 4 presents a discussion of the methodology, the data used in the study and the results of the empirical analysis.

Chapter 5 concludes the study with a conclusion of the topic, limitations of the study and recommendations for future studies on this particular subject matter.

2. THE CREDIT RATING INDUSTRY

2.1 INTRODUCTION

Sovereign ratings reflect the relative likelihood of default, which serves as a measure of credit risk faced by a sovereign. Sovereign ratings have the ability to either improve or weaken a given country's cost of capital and thus the interest rate a sovereign attains in the global markets (Afonso, Gomes & Rother, 2011). A sovereign credit rating determines to what extent a country is capable, as well as willing, to reimburse its international debt in the specified time period. The eminent big three credit rating agencies use both qualitative and quantitative variables in their rating methodologies. Qualitative variables refer to political and cultural conditions in an economy, whereas quantitative variables refer to macro-economic factors that influence an economy. The wide range of variables gives an indication of the economic, social and political conditions in each economy (Pretorius & Botha, 2014).

The International Monetary Fund's (IMF) 2010 Global Financial Stability Report puts emphasis on sovereign default risk as the most critical risk threatening the global economy. Erdem and Gwilym (2014) agree with the statement made by the IMF and argue that the recent global financial crisis intensified the international conspicuous scrutiny of the methodologies applied by the credit rating agencies. In particular, the allocation of different weights to macro-economic variables that potentially leads to different ratings assigned to each sovereign.

This chapter serves as a means to accomplish the literature objective of examining the role of the credit rating industry in the global economic environment. The chapter is structured as follows. At the outset, the two critical defects of the industry, i.e. the oligopolistic structure of the market and the existing conflict of interest are evaluated. In addition, one of the key objectives credit rating agencies long to achieve, namely rating stability, is assessed while attempting to keep procyclicality[1] at bay. Furthermore, the investment grade threshold is explored to determine the likely implication it has for emerging market economies and a description of the debt ceiling. Macro-economic variables used by credit rating agencies to assign sovereign

[1] Procyclicality is an economic quantity that positively correlates with the overall state of the economy.

ratings are correspondingly examined. A brief literature review of this subject matter is executed to establish the weights assigned to each macro-economic variable. The empirical results yielded from past studies are scrutinised to determine the most significant variables used to determine sovereign ratings. To conclude this chapter, a comprehensive description of each variable included within the empirical study is given together with the chapter summary. Empirical methods are used in chapter 4 to access the significance of relationships between the macro-economic variables and sovereign ratings of the three big agencies.

2.2 THE CREDIT RATING INDUSTRY

Hill (2010) argues that the credit rating industry suffers from two precarious weaknesses, the first being the oligopolistic market structure and the second an existing conflict of interest. The elaboration of these two weaknesses inherent to the credit rating industry does not form part of the main objectives of this study. The purpose of the exploration of these two problems is to provide a background of the credit rating industry's operations. The oligopolistic market structure and the inherent conflict of interest cause a lack of transparency in the credit rating industry, which the objectives of this study aim to address.

2.2.1 Oligopolistic market structure

The credit rating industry fits the profile of an oligopolistic market structure in every traditional aspect. The traditional characteristics include a small number of market participants, high barriers to entry and excessive profit.

2.2.1.1 A small number of market participants

Strong barriers to entry support the maintenance of a small number of market participants within the credit rating industry. According to the US Securities and Exchange Commission (2015), credit rating agencies are granted the opportunity to register with the commission as nationally recognised statistical rating organisations (NRSROs). The Office of Credit Ratings (OCR) supports the commission in achieving its objectives. These objectives include the protection of investors, the promotion of capital formation and the preservation of efficient, fair and orderly markets. These objectives are accomplished through revision by the credit rating agencies that are registered with the commission. Once registered, credit rating agencies have the responsibility to comply with the requirements set by the NRSROs.

As shown in table 2.1 below, there are currently ten credit rating agencies registered with the NRSRO. However, this number is misleading for the reason that three agencies essentially dominate the market, whilst the other seven have a small market share. Standard & Poor’s, Moody’s and Fitch together represent 95 percent of the market, based on revenues. Standard & Poor’s and Moody’s each hold a 40 percent share, while Fitch occupies the remaining 15 percent (Marandola & Sinclair, 2014).

Table 2.1: Status of registrants on 31 December 2014

NRSRO	Registration date	Principal office
A.M. Best Company, Inc. (“A.M. Best”)	September 24, 2007	U.S.
DBRS, Inc. (“DBRS”)	September 24, 2007	U.S.
Egan-Jones Ratings Co. (“EJR”)	December 21, 2007	U.S.
Fitch, Inc. (“Fitch”)	September 24, 2007	U.S.
Japan Credit Rating Agency, Ltd. (“JCR”)	September 24, 2007	Japan
Kroll Bond Rating Agency, Inc. (“KBRA”)	February 11, 2008	U.S.
Moody's Investors Service, Inc. (“Moody’s”)	September 24, 2007	U.S.
Morningstar Credit Ratings, LLC (“Morningstar”)	June 23, 2008	U.S.
Standard & Poor's Ratings Services (“S&P”)	September 24, 2007	U.S.

H. R Ratings de Mexico, S.A. de C.V.	November 5, 2012	Mexico

Source: U.S. Securities and Exchange Commission (2015: 6)

2.2.1.2 Barriers to entry

Oligopolies are typically characterised by one or more barriers to entry. These barriers come in many different forms and for credit rating agencies the specific barriers include government certification, reputational capital and cost spreading (White, 2011).

<u>Government certification</u>

Government certification is the most crucial barrier to entry for the reason that the Securities and Exchange Commission (SEC) only certifies selected credit rating agencies that apply to the NRSOR. The SEC rejected the majority of NRSOR applicants between 1975 and 2006 and in addition refused to publicise any formal criteria of admittance (Jack & Gannon, 2012).

<u>Reputational capital</u>

The reputational risk faced by the credit rating agencies is an essential barrier to entry. Hunt (2009) states that a respectable reputation is achieved through maintained objectives and accurate assessments of creditworthiness. These elements are the building blocks to achieve success as a credit rating agency. Although, a favourable reputation remains to be a timely process, as it cannot be established overnight. Potential entrants are therefore hesitant to enter the market.

<u>Cost spreading</u>

Large NRSORs have the ability to perform financially intensive analyses across sovereigns that require legal, marketing, analytical and administrative expenses. Contrariwise, smaller NRSORs do not have the same financial abilities as larger NRSORs, earn smaller after tax profit margins (Jack & Gannon, 2012) and are therefore reluctant to enter the market.

2.2.1.3 Interdependence

According to Bayar (2014) the small number of market participants in the oligopolistic market leads to interdependence between the members. Therefore, the decisions and actions of one credit rating agency have consequences that affect the other agencies in the oligopoly. The finest example of interdependence in the credit rating oligopoly is seen with changes in ratings. As soon as one agency announces a rating change, be it an upgrade or downgrade, it immediately effects the way in which the other agencies view their own rating and as a result their rating change will be soon to follow. Chapter 3 explores this aspect in further detail.

2.2.1.4 Price setting and high profitability

Nielsen, Raimondos-Moller and Schjelderup (2003) argue that oligopolists tend to have some freedom to exercise price control, which allows the agencies to earn above average revenues. The rating agencies charge their preferred fees because there are no restrictions on fees earned in the rating industry. The big three credit rating agencies are characterised by their high profitability, especially the two powerhouses Standard & Poor's and Moody's. This is evident as according to Wilmers (2011), the pre-tax profit margins for both agencies from 2008 to 2010 surpassed 45 percent. In the absence of competitors and threat of new entry, these levels of profit are expected to continue.

2.2.1.5 Consequences of an oligopolistic market structure

The credit rating industry is characterised by few market participants, existing barriers to entry, interdependence between agencies and price setting that generates excessive profit. It can therefore be established that the credit rating industry has an oligopolistic market structure as it meets every criteria. Market participants should be mindful of the negative consequences that such a market structure entails (Hill, 2010).

The first negative consequence of an oligopolistic market structure is inefficiency, since the power of price setting creates higher than average profit margins that are not determined by the efficient market. This scenario results in decreased productivity which translates to methodological errors and inaccurate ratings (Hill, 2010). The second element is increased complacency as an absence of fear of exclusion from the industry exists. Credit rating agencies have become more conscious of their exclusive and authoritative position, which leads to cutting corners as to achieve short-term instead of long-term objectives. The final issue at hand is suppressed innovation. The problem presented itself as soon as the big three agencies adopted a nearly similar methodology that made it just about impossible for new agencies to enter with pioneering tools to measure credit risk (McClintock & Calabria, 2012).

2.2.2 The inherent conflict of interest

The oligopolistic nature of the credit rating industry is certainly troubling and a challenge all in itself, but the industry's most infamous trait is the continuing conflict of interest. Valentina, Cornaggia and Kimberly (2011) reason that the conflict of interest is rooted within the issuer-pay model itself. Agencies are paid by the issuers to assign ratings to their financial responsibilities. At all times the issuers long to attain as high as possible ratings, since higher ratings result in lower interest rates. However, these circumstances are a cause for concern as the interest of the issuers and the interest of the investors are conflicted. The issuers aspire towards favourable ratings, whilst the investors seek accurate ratings. Such conflicting desires create challenging conditions for large agencies to assign their ratings. The big three agencies are torn between serving the issuers that influence agency earnings, which may possibly jeopardise market-share in the industry; and serving the public investors, seeking exact ratings to make knowledgeable financial decisions.

The reputational capital theory argues that the risk of excessively high ratings is prevented by the fear of lost reputation. According to Macey (2010) the reputational capital theory is unsound for various reasons. The big three credit rating agencies are able to sacrifice some reputational capital for they are imbedded within the oligopoly and barriers are too high for entry. The agencies display herding behaviour, which refers to the ratings of one agency being tracked by those of another agency (see Chapter 3 for an elaboration on this particular subject matter). The agencies are therefore protected against unique reputational harm of a single agency since the impression of a systematic effect is assumed. Finally, reputation is unlikely to restrain agencies from issuing imprecise ratings for the reason that agencies have not amassed reputational capital for sovereign they have not rated before. Therefore, agencies, in this regard, risk nothing by issuing erroneous ratings.

2.3 RATING STABILITY

The International Monetary Fund (IMF) (2010) states that the credit rating agencies aim to keep the higher rating grades as stable as possible and that the higher rated sovereigns are, as a rule, kept more stable than the lower rating grades. The main motive for rating stability is a result of market participants' aversion to the prospective transaction costs associated with frequent rating changes. The sought after stability may well be achieved by the rating agencies when the 'through the cycle' (TTC) method is applied, rather than the 'point in time' (PIT) method.

According to Topp and Perl (2010) the TTC method is based on the capability of an issuer to endure a cyclical trough. In other words, credit rating agencies assess the default risk in the worst stage of the industry cycle, which is defined as the stress scenario. The stress scenario entails a stress test that uses historic default rates in the credit rating industry. As soon as ratings have been assigned, they are only altered in response to an adjustment of the stress scenario, for instance unforeseen policies and secular trends. TTC ratings are therefore less volatile than PIT ratings for the reason that TTC ratings emphasise the importance of permanent default risk and are just about independent from cyclical changes in the creditworthiness of a sovereign.

On the contrary, the PIT method purely considers the current position of an issuer and captures the essence of the short term predictive power, explicitly valid over a one year time horizon (Kiff, Kisser & Schumacher, 2013). PIT ratings are constructed by quantitative financial information and additional information regarding the state of the economic cycle. This information is converted into rating categories by means of statistical procedures, i.e. scoring models. PIT ratings have a main shortcoming as a result of the strong relationship between internal ratings and the capital endowment. The recent financial crisis highlighted this drawback, which forced volatile capital endowments that lead to procyclical effects.

2.4 EMERGING MARKET INVESTMENT GRADE STATUS

In contrast to developed economies that are customarily rated above investment grade, emerging market economies strive to achieve investment grade status. This status firstly enlarges the number of potential investors and secondly reduces the financial responsibilities faced by sovereigns. A third advantage is lower borrowing costs of corporates (Jaramillo, 2010). Table 2.2 below illustrates the investment grade threshold of each of the three credit rating agencies.

Table 2.2: Investment grade threshold

STANDARD & POOR'S	MOODY'S	FITCH
INVESTMENT GRADE		
AAA	Aaa	AAA
AA+	Aa1	AA+
AA	Aa2	AA
AA-	Aa3	AA-
A+	A1	A+
A	A2	A
A-	A3	A-
BBB+	Baa1	BBB+
BBB	Baa2	BBB
INVESTMENT GRADE THRESHOLD		
BBB-	**Baa3**	**BBB-**
NON-INVESTMENT GRADE		
BB+	Ba1	BB+
BB	Ba2	BB
BB-	Ba3	BB-
B+	B1	B+
B	B2	B
B-	B3	B-
CCC+	Caa1	CCC+
CCC	Caa2	CCC
CCC-	Caa3	CCC-
CC	Ca	CC
C	C	C
D	D	D

Source: Compiled by author

As observed in table 2.2 above, Standard & Poor's and Fitch's investment grade threshold is at BBB- and Moody's investment grade threshold is at Baa3. A sovereign rating acts as a benchmark for activities in the capital market. Sovereign ratings evaluate the economic environment and subsequently assist as a baseline for estimating risk associated with investment opportunities. Beers and Chambers (2003) therefore argue that foreign currency sovereign ratings are analogous to a debt ceiling for foreign currency sub-sovereign entity ratings. Regulations prevent institutional investors from investing in non-investment grade economies and for this reason investment grade status is particularly essential to emerging market economies. As soon as the investment grade threshold is broken, sub-sovereign entities obtain increased global investment and are included in structured investment funds (Ketkar & Ratha, 2009).

2.5 THEORETICAL DETERMINANTS OF SOVEREIGN RATINGS

A brief literature review is now presented regarding the central objective of this study that is establishing the different weights assigned by each agency to the macro-economic variables. Zheng (2012) states that each credit rating agency seems to have different subjective weights attached to the macro-economic variables, which leads to the differences in their ratings. According to Shen, Huang and Hasan (2012) the main concern with different weights is the inconsistencies, since the same sovereign ought to receive roughly equivalent ratings regardless of the rating agency. The credit rating agencies provide little to no guidance as to how they assign relative weights to each individual macro-economic variable. They do however provide information about the particular macro-economic variables that are used in their decision-making. It is therefore difficult for investors to identify the relationship between the credit rating agencies' criteria and the actual credit rating, as the weights are not fixed across credit rating agencies (Elkhoury, 2008).

Numerous variables have been theoretically identified as potential determinants of sovereign ratings. These variables are divided into solvency, liquidity, and dummy variables. Table 2.3 below presents the potential sovereign credit rating variables, established by previous studies.

Table 2.3: Potential sovereign credit rating variables

SOLVENCY VARIABLES Solvency variables reflect an economy's long-run ability to remunerate its debt.	
VARIABLE	**DEFINITION**
1. Real GDP growth rate	High economic growth rates generally produce a robust fiscal position, which suggest that a country's debt responsibilities become easier to service over the long-term.
2. Current account balance as percentage of GDP	A large current account deficit is an indication that an economy is heavily reliant on inflows from global funds. Persistent current account deficits increase global indebtedness and may result in a situation where economies are no longer able to service their debt.
3. Fiscal balance as percentage of GDP	A large fiscal deficit points towards a government that lacks the will or capability to increase the tax burden to finance current expenses, as well as its debt service. The probability that an external shock might generate a sovereign default is augmented with a weakened fiscal position.
4. Debt to exports ratio	A higher debt burden increases the difficulty of servicing debt. Exports are an essential source of foreign exchange and economies with large current account earnings are less susceptible to external shocks when servicing debt.
5. Debt to GDP ratio	A higher debt burden not only enlarges the transfer effort that a country has to make over time to service its debt burden, but also relates to a higher risk of default.

6. GDP per capita	The higher an economy's GDP per capita, the higher the sovereign credit rating assigned to the particular country.
7. Openness	Economic openness refers to liberated trade relations by means of abolished tariffs or non-tariff barriers. Openness is reflected in the balance of payments. The one side refers to exports of domestic products on global markets, whilst the other side refers to imports that sustain an economy through quality resources.
LIQUIDITY VARIABLES Liquidity variables reflect an economy's short-run ability to remunerate its debt. Even though an economy has the ability to pay back its long-term financial obligations, it does not necessarily mean that funds are available for short-run debt servicing.	
VARIABLE	**DEFINITION**
1. Foreign reserves as percentage of imports	Global debt has to be reimbursed out of foreign reserves. As a result, low foreign reserve levels increase an economy's risk of default. This variable determines to what extent foreign reserves are able to finance an economy's imports.
2. Inflation rate	A high inflation rate indicates operational problems in an economy's governmental finances. Numerous governments have reverted to inflationary finance of the fiscal deficit when government were found incapable or unwilling to raise the tax burden or cut spending. The inflation rate can for that reason be seen as a measure of governmental discipline. Public discontent with a high inflation rate may perhaps generate political instability.

3. Debt-service-to-GDP ratio	An economy's debt service is reliant on the level of debt, the yield as well as the debt composition. Large remunerations can be difficult to settle in times when international liquidity conditions are constricted or global risk appetite is lower than usual.
4. Debt-service-to-reserves ratio	Since global debt is reimbursed out of foreign reserves, the debt service to reserves ratio is a crucial measure of an economy's debt servicing abilities.
5. Debt-service-to-exports ratio	Exports are a fundamental source of foreign exchange. Economies with large export earnings are less susceptible to external shocks when servicing debt.
6. Exports as a percentage of GDP	Economies with large export earnings generally have a lower default risk rating.
7. Real effective exchange rate	Sovereign ratings are positively associated with real effective exchange rate appreciation and negatively associated with bond market liquidity.
DUMMY VARIABLE Theoretical models of creditworthiness frequently include regional or country-specific dummy variables that assume the value of one if a condition is met and zero if otherwise.	
VARIABLE	**DEFINITION**
1. Default history	The default variable assumes the value of one for the years an economy is in default on its foreign currency debt obligations and the value zero if otherwise. A default has a tremendous effect on a country's creditworthiness.

Source: Rowland and Torres 2004 (20) and UNCTAD 2008 (7)

Alsakka and Gwilym (2012) constructed a hypothesis which states that dissimilarities in sovereign ratings occur due to agencies assigning different weights to the same macro-economic determinants. The big three credit rating agencies are under scrutiny and each is dealt with individually.

Standard & Poor's assigns heavier weights to the following variables: reserve to imports ratio and investment to GDP, whilst fiscal balance, openness, GDP per capita and foreign reserves are not as crucial to Standard & Poor's as the other variables.

Moody's assigns heavier weights to the following variables: external debt, openness, foreign reserves, fiscal balance, and GDP per capita. However, the reserve to imports ratio and investment to GDP is not as important to Moody's as the other variables.

Fitch assigns heavier weights to the following variables: fiscal balance, foreign reserves, GDP per capita, reserves to imports and openness. Conversely, investment to GDP is not as significant as the other variables.

The results yielded from the study indicate substantial variances in the relative weights assigned to variables and so Alsakka and Gwilym (2012) cannot reject the formulated hypothesis and therefore accepts it.

2.6 EMPIRICAL RESULTS OF PREVIOUS STUDIES

The big three credit rating agencies apply a combination of qualitative and quantitative elements such as political, social and economic variables in their rating methodologies. However, these rating methodologies are not explicitly publicised. For this reason numerous studies have been performed to determine the most influential and fitting variables, as there are a vast number of variables, along with the weights assigned to each variable by each individual agency.

The seminal paper by Cantor and Packer (1996) is one of the first and foremost studies to assess the weights assigned to variables of sovereign ratings by Standard & Poor's and Moody's. This study employs a cross-section analysis performed on 23 industrial- and 26 developing economies. The results indicate that Moody's places more weight on external debt and less weight on default history as variables that impact negatively on sovereign ratings. Whereas Standard & Poor's places more weight on per capita income as a variable that impacts sovereign ratings positively. An OLS analysis is applied and six macro-economic variables are found significant in explaining sovereign ratings. These variables include inflation, per capita income, external debt, default history, GDP growth and the level of economic development.

The Cantor and Packer results are verified by Monfort and Mulder (2000), but their study solely evaluates emerging market economies. Their study contributes an assessment of the Asian crisis and found the relationship between sovereign ratings and macro-economic variables instable during crisis periods. Furthermore, autocorrelation is observed that has not been mentioned in earlier studies.

Likewise the emphasis is on emerging market economies which examine sovereign ratings of Standard & Poor's and Moody's. Feasible Generalised Least Squares (FGLS) and Pooled Ordinary Least Squares (POLS) panel data regressions are used. The results reveal the ratio of investment to GDP as the most significant variable to explain rating changes. In addition, the ratio of debt to exports is also identified as an important determinant (Mulder & Perelli, 2001).

Similarly to Cantor and Packer (1996) and Monfort and Mulder (2000), Eliasson (2002) found the same small number of macro-economic variables significant in determining sovereign ratings. Eliasson (2002) purely used macro-economic variables, as socio-political variables were not available to include in the study. A random effect (RE) panel data model with country specific omitted variables was applied.

Afonso (2003), like Mulder and Perelli (2001) includes Standard & Poor's and Moody's sovereign ratings in an empirical study. A total of 81 developed as well as developing economies are used and the sovereign ratings are converted linearly, logistically and exponentially. Afonso (2003) found the logistical model most accurate, the results are mainly aimed at economies ranked on the upper end of the rating scale. The study established external debt, default history, GDP per capita, inflation rate, level of economic development and real growth rate as relevant variables in determining sovereign ratings.

The Cantor and Packer (1996) study also forms the benchmark for the Rowland (2004) study that tests for significant inconsistencies between the yielded results of both studies. The author only focused on developing economies; however, he also applied credit ratings assigned by Standard & Poor's and Moody's. Rowland (2004) included identical variables to those of Cantor and Packer (1996) and ultimately determined that the same criterion is used when assessing developing and developed economies.

An innovative researcher altered the empirical modelling framework on this subject matter, by incorporating a panel ordered probit model (see Bissoondoyal-Bheenick, 2005). The motivation for this pioneering model is based on the dependent variables (sovereign ratings) that are of an ordinal nature. Prior to the panel ordered probit model, the OLS technique had been applied, but Bissoondoyal-Bheenick (2005) argues that the OLS technique assumes the dependent variable to be divided into equally spaced intervals, which is not fitting for qualitative ratings. This study performed an extensive analysis with 95 developing and developed economies. The results found the inflation rate and GDP per capita as the most important variables in assigning sovereign ratings and moreover indicated that a discrepancy exists between the weights allocated to variables of developed- and developing economies. The final results attained by Bissoondoyal-Bheenick (2005) are with regards to low rated economies. The study found the current account balance and the level of foreign reserves to be most influential factors in determining sovereign ratings for low rated economies.

Bissoondoyal-Bheenick (2005) inspired other studies to empirically incorporate the ordered response models as well, these studies include Afonso, Gomes and Rother (2009), Pfarr, Schmid and Schneider (2011) and Teker, Pala and Kent (2013).

An ordered probit, ordered logit as well as random effects model is applied by Afonso *et al*. (2007). Conclusions were drawn that the random effects ordered probit model had been the most efficient model, although all three models were competent when rating forecasts were made. Afonso *et al*. (2007) find real GDP growth, government effectiveness (public service delivery and competency of government), GDP per capita, government debt and external reserves to be the most significant determinants of sovereign ratings. In addition to the significant determinants, the study shows that foreign reserves and external debt are more pertinent for low rated economies, whilst inflation is more relevant for high rated economies.

Another study focusing on the difference between low and highly rated economies is the one by Gültekin-Karakaş, Hisarciklilar and Ozturk (2011), who likewise applied an ordered probit model. The study only involves data from Moody's as rating agency and examined 93 economies, both developed and developing economies. The main contributions of this study is the insertion of the dummy variable for the level of income in economies together with the results that suggest an inconsistency between ratings assigned to low income and high income economies. According to Gültekin-Karakaş *et al*. (2011), low income economies are inclined to receive lower sovereign ratings than high income economies, despite the fact that all variables are kept stable.

An essential study using a panel framework employing 35 emerging market economies in order to measure the influence that investment grade status has on economies was executed. The outcome of the study indicates that 5 to 10 percent reductions in spreads follow an upgrade to the investment grade class. Still no influence occurs with movements in the non-investment grade class, *ceteris paribus*, (Jaramillo and Tejada, 2011).

Alsakka and Gwilym (2012) utilise a unique dataset of six global credit rating agencies to examine emerging market economies. Three reasons are proposed in explaining the vast difference between the sovereign ratings assigned by each of the six rating agencies. Firstly, each agency allocates different weights to each macro-economic variable. Secondly, an evident disagreement exists between the rating agencies about the opaqueness of certain issuers. The third reason is found with regards to smaller rating agencies that tend to favour the issuers of their "home region".

Credit rating agencies consider governance indicators when assigning sovereign ratings in Ozturk (2014). The author uses ordered response models to empirically estimate the outcomes of the study, which stipulates that regulatory quality and government effectiveness are major determinants of sovereign ratings (Ozturk, 2014).

Pretorius and Botha (2014) not only employ international credit rating agencies, Standard & Poor's and Fitch, but also a South African research unit (NKC) since the primary focus group is African economies. Their methodological approach consists of a panel model with pooled OLS, fixed effects (FE), random effects (RE) and an ordered probit estimation. The results show an overlapping of three variables among the chosen corporations, namely external balance, corruption as a governance indicator and foreign reserves.

The importance of sovereign ratings is stressed by Erdem and Varli (2014) in attracting investments and so capital inflows. The study establish GDP per capita, reserves as a percentage of GDP, governance indicators and the budget balance as a percentage of GDP as the most significant variables in determining emerging market sovereign ratings by Standard & Poor's.

2.7 TARGETED VARIABLES

Although several studies have examined the subject matter of sovereign ratings there have not been many country-category studies on emerging market economies. One of the core contributions of this study to the existing literature is the influence of sovereign ratings assigned by the big three agencies on different categories within emerging market economies. The March 2014 FTSE Global Equity Index Series: *Regional Classification* (Americas, Europe, Asia-pacific and Africa) and according to the March 2014 FTSE Global Equity Index Series: *Country Classification* (advanced and secondary emerging markets economies and the frontier economies). The following variables together with their expected signs of influence are included in this section as potential determinants of the selected emerging market economies:

- Fiscal balance as a percentage of GDP (+)

  The fiscal balance is a representation of government's expenditures and revenues expressed as a portion of the gross domestic product. A budget surplus occurs when revenues exceed expenditures, whilst a budget deficit is the exact opposite. The data is normalised by dividing the fiscal balance by the gross domestic product, which enables easy comparisons across various economies. The fiscal balance gives an indication of whether a government borrows or saves money. Economies with high fiscal deficits relative to their gross domestic product have difficulty raising sufficient funds to finance government expenditure in comparison to economies with lower deficits (Jacobs, Schoeman & van Heerden, 2002). Fiscal balance has a positive influence on sovereign ratings that resultantly increases the sovereign credit rating of an economy.

- Current account as a percentage of GDP (-)

  The current account is a composite of all transactions of economic value that take place between non-resident and resident entities. The main classifications include export services, goods as well as primary and secondary income (IMF, 2012). The current account has a negative influence on sovereign ratings that result in a diminished sovereign rating of an economy.

- Inflation (-)

  The consumer price index measures inflation which is a reflection of the quarterly percentage change that the general consumer has to pay in order to obtain a basket of services and goods. Inflation may be altered or fixed at specified intervals, for instance quarterly (Labonte, 2011). Inflation has a negative influence on sovereign ratings, therefore decreasing the sovereign rating of an economy.

- GDP per capita (+)

  GDP per capita refers to the sum of gross value added altogether by resident producers in an economy plus all taxes on product, minus all subsidies that are not counted in the value of the products divided by a country's population.

Calculations are made without deductions for depreciation of fictitious assets or for diminution and deprivation of natural resources (World Bank, 2014). GDP per capita has a positive influence on sovereign ratings and hence increases the sovereign rating of an economy.

- Corruption index, proxy for economic development (+)

The corruption index is a measurement of the perceived levels of public sector corruption. The corruption index acts as a proxy for economic development in each country. Economic development is defined as the sustained and intense actions of policy-makers together with communities that promote better living standards and economic health in an economy. In addition, it also refers to qualitative and quantitative changes in an economy (Transparency International, 2014). The corruption index has a positive influence on sovereign ratings and therefore increases the sovereign rating of an economy.

- External debt as a percentage of GDP (-)

External debt is a government's fixed-term, predetermined obligations to others that are not settled in a specific period. External debt is also defined as the amount of a government's foreign liabilities reduced by the quantity of financial derivatives and equity that is held by a government. External debt includes foreign liabilities for instance money and currency deposits, securities that are not shares and loans (World Bank, 2014). External debt has a negative influence on sovereign ratings and resultantly decreases the sovereign rating of an economy.

- External debt as a percentage of exports (-)

External debt refers to the amount of a government's foreign liabilities reduced by the quantity of financial derivatives and equity that is held by a government. The total amount of external debt is measured as a proportion to exports services, goods and income (Tomz & Wright, 2012). External debt has a negative influence on sovereign ratings and therefore decreases the sovereign rating of an economy.

- Reserves as % of imports (+)

  Total reserves are compiled by monetary gold, exceptional drawing rights, reserves of IMF members held by the IMF and holdings of foreign exchange under the control of monetary authorities. The gold component of these reserves is valued at year-end (December 31) London prices. Reserves as a percentage of imports give an indication of the number of months of imported goods and services an economy is able to finance (World Bank, 2014). Reserves have a positive influence on sovereign ratings, which increases the sovereign rating of an economy.

- Real GDP Growth (+)

  The Gross Domestic Product is a measurement of the monetary value of final goods and services that are produced in an economy in a given time period. It includes all the output that is produced within the borders of a country. The quarterly growth rate of the gross domestic product is expressed in percentage and at market prices. The value is based on the constant local currency (Callen, Cherif, Hasanov, Hegazy & Khandelwal, 2014). Real GDP growth has a positive influence on sovereign ratings and therefore increases the sovereign rating of an economy.

- Real effective exchange rate (-)

  The real effective exchange rate is equivalent to the nominal effective exchange rate. A measurement of the value of a particular currency against a weighted average of numerous foreign currencies that is divided by an index of costs or a price deflator (World Bank, 2014). The real effective exchange rate has a negative influence on sovereign ratings that resultantly decreases the sovereign rating of an economy.

- Default history (-)

  Default can narrowly be defined as a violation of the legal terms of contract, for instance failing to service debt within the specified period. Broadly it can be defined as voluntary restructurings of debt that reduce the creditors’ value of the debt. The default history variable assumes the value of one for the years an economy is in default on its foreign currency debt obligations and assumes the value zero if otherwise (Tomz, 2012). Default history has a negative influence on sovereign ratings and hence decreases the sovereign rating of an economy.

- Openness (+)

  Global trade is dependent on economic openness of the given economies involved. The extent to which an economy is open to trade is determined by the exchange rate, macro-economic policies of governments involved and external trade conditions. Openness in an economy is econometrically calculated as a ratio that includes the sum of a specific country's exports plus imports as a fraction of the gross domestic product (Stensnes, 2006). Openness has a positive influence on sovereign ratings and therefore increases the sovereign rating of an economy.

The expected relationships between the macro-economic variables and the Sovereign ratings as specified in literature and based on previous studies together with economic theory, will be empirically estimated. The results of the relationships together with the interpretations are given in chapter 4.

2.8 CHAPTER SUMMARY

This chapter addressed the main objective of this study by means of conducting a literature and empirical review of past studies with regards to the industry in which sovereign credit rating agencies operate. The two essential problems of the industry, namely the oligopolistic structure of the market and the existing conflict of interest are examined and established as two of the factors that triggered the recent global financial crisis. The oligopolistic market structure leads to three major negative consequences: firstly decreased productivity that gives rise to inaccurate ratings and methodological errors. Secondly, a few market participants create the opportunity for agencies to cut corners as agencies are fully conscious about their authoritative and exclusive position in the industry. Thirdly, any innovation to reconstruct rating methodologies within the industry is supressed as a result of restricted market entry. With regards to the inherent conflict of interest, the reputational capital theory is found to be unsound, for the reason that the agencies are able to sacrifice some reputational capital as barriers are too high for entry.

One of the main objectives of credit rating agencies, namely rating stability, is discussed and it is found that there are two available methods to rate sovereign. These methods are either the TTC method or the PIT method. The TTC method is best applied when the objective of rating stability needs to be met. In addition, it is observed that the investment grade threshold that is at BBB- for Standard & Poor's and Fitch and Baa3 for Moody's is essential to emerging market economies. As the investment grade threshold is broken, sub-sovereign entities obtain increased global investment for the reason that they are once again included in structured investment funds. Theoretical macro-economic variables that credit rating agencies use to assign sovereign ratings are established as the following: real GDP growth rate, current account balance as percentage of GDP, fiscal balance as percentage of GDP, debt to exports ratio, debt to GDP ratio, GDP per capita, foreign reserves as percentage of GDP, inflation rate, debt-service-to-GDP ratio, debt-service-to-reserves ratio, debt-service-to-exports ratio, real effective exchange rate and default history expressed as a dummy variable.

A brief literature review of previous studies on this subject matter determined the weights assigned to each macro-economic variable. Standard & Poor's assigned heavier weights to reserve to imports ratio and investment to GDP, whilst fiscal balance, openness, GDP per capita and foreign reserves are not as crucial to Standard & Poor's as the other variables. Moody's assigned heavier weights to external debt, openness, foreign reserves, fiscal balance, and GDP per capita. Whereas the reserve to imports ratio and investment to GDP is not as important to Moody's as the other variables. Fitch assigned heavier weights to fiscal balance, foreign reserves, GDP per capita, reserves to imports and openness. Although investment to GDP is not as significant as the other variables.

This study focuses on the following variables, as presented in literature, to determine each variable's potential influence on sovereign ratings, viz. fiscal balance as a percentage of GDP, current account as a percentage of GDP, inflation, GDP per capita, corruption index, proxy for economic development, external debt as a percentage of exports, external debt as a percentage of GDP, reserves as a percentage of imports, real GDP growth, real effective exchange rate, default history and openness. Chapter 4 empirically tests the relationships between sovereign ratings and the macro-economic variables to ultimately determine the most significant variables used by the big three credit rating agencies.

3. SOVEREIGN CREDIT RATING CHANGES AND CAPITAL FLOWS

3.1 INTRODUCTION

Chapter 3 clarifies the other main objective of this study. This chapter serves as a means to contextualise the influence that changes in sovereign ratings (assigned by credit rating agencies, Standard & Poor’s, Moody’s and Fitch) have on emerging market economies. Sovereign ratings from the first quarter of 1998 to quarter one of 2014 are analysed to identify possible patterns or trends in the data. Kim and Wu (2007) emphasise the significance of long run foreign currency sovereign ratings on attracting capital flows to emerging market economies. An assessment will determine whether changes in sovereign ratings influence emerging market capital flows from both the capital and financial accounts and/or vice versa.

The selected emerging market economies are firstly classified according to the March 2014 FTSE Global Equity Index Series: *Regional Classification* and secondly according to the March 2014 FTSE Global Equity Index Series: *Country Classification.* Grouping emerging market economies according to the above-mentioned classifications enables sovereign ratings to be scrutinised in an attempt to ascertain similarities and/or differences between the emerging market economies within each classification.

Table 3.1 below demonstrates the different rating scales applied by Standard & Poor’s, Moody’s and Fitch. It provides an interpretation of each rating to comprehend the financial significance that each symbol represents. An explicit distinction is made between the investment grade and non-investment grade rating symbols. This information is essential to enable global investors to make informed investment decisions.

Together with the variation of sovereign credit rating scales applied by the credit rating agencies, the Basel Committee on Banking Supervision also have their own sovereign credit rating scale. Basel is responsible for the regulation of global banking, with the aim of minimising credit risk. Nouy (2012) explains the Basel II Standardised Approach that effectively captures the level of sovereign risk exposure measured as a percentage. A regulatory matrix demonstrates this approach with risk-weights for each sovereign rating classification (see Table 3.1).

Table 3.1: Long run foreign currency sovereign credit rating scale

INTERPRETATION	STANDARD & POOR'S	MOODY'S	FITCH	BASEL APPROACH
Investment grade				
Highest quality	AAA	Aaa	AAA	0%
High quality	AA+	Aa1	AA+	0%
	AA	Aa2	AA	0%
	AA-	Aa3	AA-	0%
Strong payment capacity	A+	A1	A+	20%
	A	A2	A	20%
	A-	A3	A-	20%
Adequate payment capacity	BBB+	Baa1	BBB+	50%
	BBB	Baa2	BBB	50%
	BBB-	Baa3	BBB-	50%
Non-Investment grade				
Likely to fulfil obligations, ongoing uncertainty	BB+	Ba1	BB+	100%
	BB	Ba2	BB	100%
	BB-	Ba3	BB-	100%
High-risk obligations	B+	B1	B+	100%
	B	B2	B	100%
	B-	B3	B-	100%
Vulnerable to default	CCC+	Caa1	CCC+	150%
	CCC	Caa2	CCC	150%
	CCC-	Caa3	CCC-	150%
Near or in bankruptcy or default	CC	Ca	CC	150%
	C	C	C	150%
	D	D	D	150%

Source: Compiled from International Monetary Fund (2010), Duker (2012) and Nouy (2012)

Section 3.2 presents the data used in this study with an explanation of the specific emerging market economies as well as the chosen time period for this section of the study. A brief description of the sources used is also given. A numerical code assigned to each category of rating scales in section 3.2 enables the comparison of different sovereign ratings. Therefore, transforming text into numeric data.

3.2 DATA

This study makes use of quarterly data from the first quarter of 1998 to quarter one of 2014 (1998Q1-2014Q1) for 34 emerging and frontier market economies. The Asian crisis ended in the last quarter of 1997. Therefore, this study uses the first quarter of 1998 as the commencement date for the time period of the empirical analysis, until the end of the first quarter in 2014. The 34 included economies represent all the emerging market and frontier economies for which sovereign ratings are assigned by the three main credit rating agencies, Standard & Poor's, Moody's and Fitch. Sovereign ratings are obtained from Moody's Sovereign Bond Rating History, Standard & Poor's Sovereign Rating and Country T&C Assessment Histories and Emerging Markets Traders' Association for ratings assigned by Fitch.

The flows of capital data, expressed in capital and financial account values are obtained from the International Monetary Fund's (IMF's) statistical database (International Financial Statistics, IFS). The March 2014 FTSE Global Equity Index Series: *Regional Classification* and the March 2014 FTSE Global Equity Index Series: *Country Classification* are both applied to the emerging market economies.

Sovereign ratings require quantitative values in order to make comparisons between the credit rating agencies. The sovereign rating scales are assigned a numerical code that ranges between 0 and 22 to attain the Explicit Credit Rating (ECR). Table 3.2 displays the ECR, which is fundamental in the calculations of the following section as well as the empirical study presented in chapter 4.

Table 3.2: Explicit Credit Rating

MOODY'S	STANDARD & POOR'S AND FITCH	ECR
Aaa	AAA	22
Aa1	AA+	21
Aa2	AA	20
Aa3	AA-	19
A1	A+	18
A2	A	17
A3	A-	16
Baa1	BBB+	15
Baa2	BBB	14
Baa3	BBB-	13
Ba1	BB+	12
Ba2	BB	11
Ba3	BB-	10
B1	B+	9
B2	B	8
B3	B-	7
Caa1	CCC+	6
Caa2	CCC	5
Caa3	CCC-	4
Ca	CC	3
C	C	2
SD/RD	SD/RD	1
D	D	0

Source: Compiled by author

Figures 7.1-7.34 (Appendix A) provide a graphical representation of the sovereign ratings assigned by Standard & Poor's, Moody's and Fitch to the selected 34 emerging market economies. The x-axis signifies the time period, ranging from 1998Q1-2014Q1. The y-axis signifies the sovereign ratings expressed in numerical values.

Based on an in-depth analysis of the graphs, the following conclusions are made concerning the leading and following rating agencies: The term *leading agency* refers to the credit rating agency that initiates and assigns a rating change, whilst the term *following agency* refers to the other two rating agencies that react to the leading agency's rating change. Standard & Poor's was observed to be the main leading agency that initiated 40.74% of the rating changes within the first quarter of 1998 to quarter one of 2014 for the 34 emerging market economies. Fitch led 33.33% of the rating changes, whilst Moody's only led 25.93% for the 34 emerging market economies within the same time period. This study concluded that Standard & Poor's is the leading agency, whereas Moody's is the primary following agency and Fitch the secondary following agency.

As observed from the graphs, a small number of emerging market economies defaulted within this particular time period. Sri-Lanka in 1996, Russia in 1998 and Argentina in 2002. Hatchondo, Martinez and Sapriza (2007) legally define a default episode as scheduled debt not paid beyond the specified grace period, within the stipulated debt contract. According to the credit rating agencies, the duration of a default episode is a measurement of the time lapse between the actual default event and the restructuring of the debt. Debt restructuring refers to a process that is accessible for a sovereign entity entangled in financial distress. The sovereign is therefore able to renegotiate and diminish its unsettled and outstanding debt in an attempt to rehabilitate and reinstate liquidity in order to continue with sovereign operations.

Table 3.3 and table 3.4 below present the March 2014 FTSE Global Equity Index Series: *Regional Classification* and the March 2014 FTSE Global Equity Index Series: *Country Classification.* The grouping of selected emerging market economies establishes possible similarities and/or differences between the sovereign ratings of the emerging market economies within each classification.

The following section presents the data descriptives evaluating the sovereign ratings as on March 2014. The purpose is to comprehend the future ability and willingness of the emerging market economies' governments to service their debt obligations.

Table 3.3: March 2014 FTSE Global Equity Index Series: Regional Classification

THE AMERICAS	ASIA-PACIFIC	EUROPE	AFRICA
Argentina	China	Czech Republic	South Africa
Brazil	India	Bahrain	Egypt
Chile	Indonesia	Bulgaria	Morocco
Colombia	Malaysia	Croatia	
Mexico	Philippines	Cyprus	
Peru	Sri Lanka	Estonia	
	Taiwan	Hungary	
	Thailand	Lithuania	
		Malta	
		Poland	
		Romania	
		Russia	
		Slovakia	
		Slovenia	
		Tunisia	
		Turkey	
		UAE	

Source: FTSE Global Equity Index Series Regional Classification (2014)

Table 3.4: March 2014 FTSE Global Equity Index Series: Country classification

ADVANCED EMERGING MARKETS	SECONDARY EMERGING MARKETS	FRONTIER MARKETS
Brazil	Chile	Argentina
Czech Republic	China	Bahrain
Hungary	Colombia	Bulgaria
Malaysia	Egypt	Croatia
Mexico	India	Cyprus
Poland	Indonesia	Estonia
South Africa	Morocco	Lithuania
Taiwan	Peru	Malta
Thailand	Philippines	Romania
Turkey	Russia	Slovakia
	UAE	Slovenia
		Sri Lanka
		Tunisia

Source: FTSE Global Equity Index Series Country Classification (2014)

3.3 DATA DESCRIPTIVES

This section comprehensively describes sovereign ratings assigned by Standard & Poor's, Moody's and Fitch for the selected emerging market economies, at the end of March 2014.

Table 3.5: March 2014 FTSE Global Equity Index Series: Regional Classification

	THE AMERICA'S		
	STANDARD & POORS	**MOODY'S**	**FITCH**
Argentina	CCC+ [6]	Caa1 [6]	CC [3]
Brazil	BBB- [13]	Baa2 [14]	BBB [14]
Chile	AA- [19]	Aa3 [19]	A+ [18]
Colombia	BBB [14]	Baa3 [13]	BBB [14]
Mexico	BBB+ [15]	A3 [16]	BBB+ [15]
Peru	BBB+ [15]	Ba1 [12]	BBB+ [15]
TOTAL AVERAGE RATING: 13.4	**Standard & Poor's average rating: 13.7**	**Moody's average rating: 13.3**	**Fitch average rating: 13.1**
	ASIA-PASIFIC		
China	AA- [19]	Aa3 [19]	A+ [18]
India	BBB- [13]	Baa3 [13]	BBB- [13]
Indonesia	BB+ [12]	Baa3 [13]	BBB- [13]
Malaysia	A- [16]	A3 [16]	A- [16]
Philippines	BBB- [13]	Baa3 [13]	BBB- [13]
Sri Lanka	B+ [9]	B1 [9]	BB- [10]
Taiwan	AA- [19]	Aa3 [19]	A+ [18]
TOTAL AVERAGE RATING: 14.5	**Standard & Poor's average rating: 14.4**	**Moody's average rating: 14.6**	**Fitch average rating: 14.4**
	EUROPE		
Czech Republic	AA- [19]	A1 [18]	A+ [18]
Bahrain	BBB [14]	Baa2 [14]	BBB [14]
Bulgaria	BBB [14]	Baa2 [14]	BBB- [13]
Croatia	BB [11]	Ba1 [12]	BB+ [12]
Cyprus	B [8]	Caa3 [4]	B- [7]
Estonia	AA- [19]	A1 [18]	A+ [18]
Hungary	BB [11]	Ba1 [12]	BB+ [12]
Lithuania	A- [16]	Baa1 [15]	BBB+ [15]
Malta	BBB+ [15]	A3 [16]	A [17]
Poland	A- [16]	A2 [17]	A- [16]
Romania	BB+ [12]	Baa3 [13]	BBB- [13]
Russia	BBB [14]	Baa1 [15]	BBB [14]
Slovakia	A [17]	A2 [17]	A+ [18]
Slovenia	A- [16]	Ba1 [12]	BBB+ [15]
Tunisia	B [8]	Ba3 [10]	BB- [10]
Turkey	BB+ [12]	Baa3 [13]	BBB- [13]
UAE	AA [20]	Aa2 [20]	AA [20]
TOTAL AVERAGE RATING: 14.2	**Standard & Poor's average rating: 14.2**	**Moody's average rating: 14.1**	**Fitch average rating: 14.4**

	AFRICA		
South Africa	BBB [14]	Baa1 [15]	BBB [14]
Egypt	B- [7]	Caa1 [6]	B- [7]
Morocco	BBB- [13]	Ba1 [12]	BBB- [13]
TOTAL AVERAGE RATING: 10.8	**Standard & Poor's average rating: 10**	**Moody's average rating: 11**	**Fitch average rating: 11.3**

Source: Compiled by author

From the sovereign ratings given in the table above it is evident that the Asia-Pacific region is assigned the highest average sovereign rating by all three credit rating agencies. The average rating for the economies included in the Asia-Pacific region is 14.5, in other words a sovereign credit rating of BBB+ for Standard & Poor's and Fitch, and a sovereign credit rating of Baa1 for Moody's. Referring to the economies within this region such as China and Taiwan, who are highly competitive economies with numerous successes in the international sphere, this result is expected. The majority of the economies within the Asia-Pacific region are as investment grade economies and therefore experience higher ratings.

Africa, on the other hand, is the lowest rated region with an average rating of 10.8, signifies a sovereign credit rating of BB for Standard & Poor's and Fitch, and a sovereign credit rating of Ba2 for Moody's. Egypt has a non-investment grade status, while both South Africa and Morocco linger on the brink of potentially becoming non-investment grade economies as well.

Table 3.6: March 2014 FTSE Global Equity Index Series - Country classification

	ADVANCED EMERGING MARKETS		
	STANDARD & POOR'S	**MOODY'S**	**FITCH**
Brazil	BBB- [13]	Baa2 [14]	BBB [14]
Czech Republic	AA- [19]	A1 [18]	A+ [18]
Hungary	BB [11]	Ba1 [12]	BB+ [12]
Malaysia	A- [16]	A3 [16]	A- [16]
Mexico	BBB+ [15]	A3 [16]	BBB+ [15]
Poland	A- [16]	A2 [17]	A- [16]
South Africa	BBB [14]	Baa1 [15]	BBB [14]
Taiwan	AA- [19]	Aa3 [19]	A+ [18]
Thailand	BBB+ [15]	Baa1 [15]	BBB+ [15]
Turkey	BB+ [12]	Baa3 [13]	BBB- [13]
TOTAL AVERAGE RATING = 15.4	**Standard & Poor's average rating: 15**	**Moody's average rating: 15.5**	**Fitch average rating: 15.7**

	SECONDARY EMERGING MARKETS		
Chile	AA- [19]	Aa3 [19]	A+ [18]
China	AA- [19]	Aa3 [19]	A+ [18]
Colombia	BBB [14]	Baa3 [13]	BBB [14]
Egypt	B- [7]	Caa1 [6]	B- [7]
India	BBB- [13]	Baa3 [13]	BBB- [13]
Indonesia	BB+ [12]	Baa3 [13]	BBB- [13]
Morocco	BBB- [13]	Ba1 [12]	BBB- [13]
Peru	BBB+ [15]	Ba1 [12]	BBB+ [15]
Philippines	BBB- [13]	Baa3 [13]	BBB- [13]
Russia	BBB [14]	Baa1 [15]	BBB [14]
UAE	AA [20]	Aa2 [20]	AA [20]
TOTAL AVERAGE RATING= 14.2	**Standard & Poor's average rating: 14.5**	**Moody's average rating: 14.0**	**Fitch average rating: 14.3**
	FRONTIER MARKETS		
Argentina	CCC+ [6]	Caa1 [6]	CC [3]
Bahrain	BBB [14]	Baa2 [14]	BBB [14]
Bulgaria	BBB [14]	Baa2 [14]	BBB- [13]
Croatia	BB [11]	Ba1 [12]	BB+ [12]
Cyprus	B [8]	Caa3 [4]	B- [7]
Estonia	AA- [19]	A1 [18]	A+ [18]
Lithuania	A- [16]	Baa1 [15]	BBB+ [15]
Malta	BBB+ [15]	A3 [16]	A [17]
Romania	BB+ [12]	Baa3 [13]	BBB- [13]
Slovakia	A [17]	A2 [17]	A+ [18]
Slovenia	A- [16]	Ba1 [12]	BBB+ [15]
Sri Lanka	B+ [9]	B1 [9]	BB- [10]
Tunisia	B [8]	Ba3 [10]	BB- [10]
TOTAL AVERAGE RATING = 12.6	**Standard & Poor's average rating: 12.7**	**Moody's average rating: 12.3**	**Fitch average rating: 12.7**

Source: Compiled by author

In all three classifications, the advanced, secondary emerging economies and frontier economies, the sovereign ratings of Standard & Poor's and Fitch remain nearly similar. Moody's does not follow the general trend set by Standard & Poor's and Fitch. As expected, the advanced emerging economies received the highest average rating, followed by the secondary emerging economies and lastly the frontier markets. There is, however, the exception of Estonia, rated as highly as an advanced emerging economy, but listed with the frontier markets. A possible explanation for this could be that Estonia's economy has recently excelled within the sovereign ratings' criteria and could potentially advance to a better performing category of economies.

According to Parts (2013), former Estonian prime minister, the Estonian economy has undergone an efficient recovery since the global recession. Evidence of improvement is visible in increased domestic demand because of enhanced market share within the trade-partner countries, which gives rise to export earnings. The debt burden of businesses and households has diminished significantly as private savings and investments improved. In addition, the unemployment rate has declined from 10.2% in 2012 to 8.8% in 2014.

3.4 INVESTMENT VS NON-INVESTMENT GRADE

Table 3.7 below divides the emerging market economies at the end of March 2014, into either investment grade or non-investment grade because of their sovereign credit rating. Emerging market economies aim to gain investment grade status for the reason that it decreases the financing costs together with the default risk of a sovereign. Consequently, it attracts a larger pool of potential global investors to the particular emerging market economy (Jaramillo, 2010).

Adams, Mathieson and Schinasi (1999) explain that sovereign ratings adopted the Basel Committee risk-weighting scheme as a regulatory strategy. It attempts to limit the exposure to non-investment grade ratings because non-investment grade sovereigns pose immense risk and potential financial loss to investors. Therefore, it base investment grade ratings as the primary investment decision.

Table 3.7: Investment and non-Investment grade, March 2014

INVESTMENT GRADE:	NON-INVESTMENT GRADE:
Bahrain	Argentina
Brazil	Croatia
Bulgaria	Cyprus
Chile	Egypt
China	Hungary
Colombia	Sri-Lanka
Czech Republic	Tunisia
Estonia	
India	
Indonesia	
Lithuania	
Malaysia	
Malta	

Mexico Morocco Peru Philippines Poland Romania Russia Slovakia Slovenia South Africa Taiwan Thailand Turkey UAE	

Source: Compiled by Standard & Poor's, Moody's and Fitch sovereign ratings (2014)

3.5 THE IMPACT OF RATING CHANGES ON CAPITAL FLOWS

Changes in sovereign ratings are essential as they signify valued information. Gande and Parsley (2004) performed their study on emerging market economies and their main findings focused on the effects that either an upgrade or downgrade of sovereign ratings have on capital flows. A sovereign downgrade has a strong association with outflows of capital that depart from the downgraded sovereign back to the initial investor.

Larrain, Reisen and Maltzan (1997) argue that during an economic boom cycle, sovereign ratings improve which reinforce exhilarated investor expectations that ultimately result in excessive inflows of capital. As anticipated within an economic bust cycle, sovereign downgrades give rise to panic amongst investors, which immediately drive flows of capital out of an economy.

Findings regarding the relationship between sovereign credit rating changes and capital flows have been consistent in literature, therefore leading to the conclusion that changes in sovereign ratings have a significant influence on the movement of capital flows. In addition to this, the possibility of this relationship behaving in a *vice versa* manner is also scrutinised.

Figures 7.35-7.42 and Table 7.1-7.24 (Appendix B) graphically illustrate emerging market economies' sovereign ratings, either upgraded from the non-investment grade barrier into investment grade or downgraded from the investment grade barrier into non-investment grade. In addition, capital- and financial accounts, and/or vice versa express the relationship that these changes in sovereign ratings have on capital flows. Within the given time period, 1998Q1-2014Q1, only four emerging market economies breached the investment barrier. These economies are Cyprus, Hungary, Indonesia and Lithuania.

Before commencing with the graphical illustrations, the capital and financial accounts are defined. The capital account refers to the net private and public global investments that flow freely in or out of an economy. It includes portfolio flows, foreign direct investments and bank borrowing (Kose & Prasad, 2004). The financial account refers to financial assets such as bonds, equity, currency, gold and derivatives. A liberal financial account refers to the integration of an economy with other economies, which increase the likelihood of spill over effects from troubled economies to the home economy. The potential outcome is measured against the benefit of lowered funding costs, increased efficiency and access to international capital markets (International Monetary Fund, 2008).

Applying Granger causality tests, it establishes the direction of causality between the sovereign ratings and capital flows. Asteriou and Hall (2007) state that the term *causality* refers to the ability to use one variable's past values to forecast future values of another variable. Observing two variables as in this instance, a VAR model can capture the relationship between changes in sovereign ratings and capital flows. This is when the possibility exists that the dependent variable could influence the independent variable or contrariwise, with various lags intervals.

3.6 INTERPRETATION OF GRANGER CAUSALITY RESULTS

3.6.1 Cyprus' financial account

Standard & Poor's, Moody's and Fitch: The null hypothesis that the financial account does not granger cause the ratings for Cyprus by Standard & Poor's, Moody's and Fitch, cannot be rejected since all the probability values are greater than 0.05. Stated differently, forecasting historic values of the financial account cannot be used to future values of the ratings for Cyprus by the three rating agencies.

The null hypothesis that the ratings do not granger cause the financial account can be rejected on the 95 percent level of significance for all three rating agencies. In other words historic values of Cyprus' ratings from Standard & Poor's, Moody's and Fitch can be used to forecast future values of the financial account or at least are expected to impact on the subsequent capital flows. Applying the same principal for the capital and financial account of each country, the conclusions are presented below.

3.6.2 Cyprus' capital account

Standard & Poor's, Moody's and Fitch: The null hypothesis that the capital account does not granger cause the ratings for Cyprus by Standard & Poor's, Moody's and Fitch can be rejected since all the probability values are smaller than 0.05, except that Fitch and Moody's is significant on the 90 percent level of significance.

The null hypothesis that the ratings do not granger cause the capital account can be rejected at the 95 percent level of significance for all three rating agencies. A bi-directional feedback exists between the ratings and the capital account and previous values of the capital account can be used to forecast future ratings for Cyprus and vice versa.

3.6.3 Hungary's financial account

Standard & Poor's, Moody's and Fitch: The null hypothesis that the financial account does not granger cause the ratings for Hungary by S Standard & Poor's, Moody's and Fitch cannot be rejected since all the probability values are greater than 0.05. Accordingly, historic values of the financial account cannot be used to forecast future values of the ratings for Hungary by the three rating agencies.

The null hypothesis that the ratings do not granger cause the financial account can be rejected on the 95 percent level of significance for all three rating agencies. Therefore, historic values of Hungary's ratings from Standard & Poor's, Moody's and Fitch can be used to forecast future values of the financial account.

3.6.4 Hungary’s capital account

<u>Standard & Poor’s, Moody’s and Fitch:</u> The null hypothesis that the capital account does not granger cause the ratings for Hungary by Standard & Poor’s, Moody’s and Fitch can be rejected since all the probability values are smaller than 0.05. Consequently, historic values of the capital account can be used to forecast future values of the ratings for Indonesia by the three rating agencies.

The null hypothesis that the ratings do not granger cause the capital account can be rejected on the 95 percent level of significance for all three rating agencies. Hence, there is a bi-directional feedback between the ratings and Hungary’s capital account and that previous values of the capital account can be used to forecast future ratings and vice versa.

3.6.5 Indonesia’s financial account

<u>Standard & Poor’s, Moody’s and Fitch:</u> The null hypothesis that the financial account does not granger cause the ratings for Indonesia by Standard & Poor’s, Moody’s and Fitch cannot be rejected since all the probability values are greater than 0.05. Therefore, historic values of the financial account cannot be used to forecast future values of the ratings for Indonesia by the three rating agencies.

The null hypothesis that the ratings do not granger cause the financial account can be rejected on the 95 percent level of significance for Moody’s and Fitch, but rejected for Standard & Poor’s. In other words, historic values of Indonesia’s ratings from Fitch and Moody’s can be used to forecast future values of the financial account.

3.6.6 Indonesia’s capital account

<u>Standard & Poor’s, Moody’s and Fitch:</u> The null hypothesis that the capital account does not granger cause the ratings for Indonesia by Standard & Poor’s, Moody’s and Fitch cannot be rejected since all the probability values are greater than 0.05. Accordingly, historic values of the capital account cannot be used to forecast future values of the ratings for Indonesia by the three rating agencies.

The null hypothesis that the ratings do not granger cause the capital account can be rejected on the 95 percent level of significance for all three rating agencies.

Consequently, historic values of Indonesia’s ratings from Standard & Poor’s, Moody’s and Fitch can be used to forecast future values of the capital account.

3.6.7 Lithuania’s financial account

Standard & Poor’s, Moody’s and Fitch: The null hypothesis that the financial account does not granger cause the ratings for Lithuania by Moody’s can be rejected since the probability values are smaller than 0.05; however it cannot be rejected for Standard & Poor’s and Fitch. Hence, historic values of the financial account for Lithuania can be used to forecast future values of Moody’s ratings for Lithuania.

The null hypothesis that the ratings do not granger cause the financial account can be rejected on the 95 percent level of significance for all three rating agencies. Therefore, historic values of Lithuania’s ratings from Standard & Poor’s, Moody’s and Fitch can be used to forecast future values of the financial account.

3.6.8 Lithuania’s capital account

Standard & Poor’s, Moody’s and Fitch: The null hypothesis that the capital account does not granger cause the ratings for Lithuania by Fitch can be rejected since the probability values are smaller than 0.05 and Moody’s on the 90 percent level of significance. However it cannot be rejected for Standard & Poor’s. Consequently, historic values of the capital account for Lithuania can be used to forecast future values of Moody’s and Fitch ratings for Lithuania.

The null hypothesis that the ratings do not granger cause the financial account can be rejected on the 95 percent level of significance for Standard & Poor’s and 90 percent level of significance for Fitch. The null hypothesis for Moody’s cannot be rejected. Accordingly, historic values of Lithuania’s ratings from Standard & Poor’s and Fitch can be used to forecast future values of the capital account.

3.7 CHAPTER SUMMARY

Chapter 3 examined the relationship between changes in sovereign ratings and flows of capital to emerging market economies. Sovereign ratings affect emerging market economies, since these economies are highly dependent on international capital flows to finance foreign currency expenditures. In addition, emerging market economies aim to achieve investment grade status, because this promotes flows of capital into emerging markets. An upgrade through the investment grade barrier not only reduces a sovereign's global borrowing cost but also ensures funds from international investment. Granger causality tests determined that four emerging market economies, namely Cyprus, Hungary, Indonesia and Lithuania demonstrated changes in sovereign ratings that have an influence on flows of capital. Some of the economies suggest that bi-directional movements are possible as well, meaning the ability of financial and capital account values to forecast future ratings and vice versa. Furthermore, Standard & Poor's is identified as the main leading agency that initiated 40.74% of rating changes followed by Fitch that led 33.33% and Moody's that led 25.93%. In conclusion, this study suggests that Standard & Poor's is the leading agency, Moody's the primary following agency and Fitch the secondary following agency within the time period of 1998Q1-2014Q1, for the particular group of emerging market economies.

4. METHODOLOGY AND RESULTS

4.1 INTRODUCTION

In chapter 1, the main objective of this study was identified as obstacles in the fundamental analytical structure and methodologies applied by Standard & Poor's, Moody's and Fitch. As discussed in chapter 2, numerous earlier studies highlighted the main determinants of sovereign ratings, but only a small number of academics focused their attention on the potential differences in weights assigned to the individual determinants. The latter is significant as it became increasingly valuable to global investors who now have access to public information through available resources. As a result, the investors are able to identify and be mindful of the potential differences in weights assigned to the individual determinants. The increased transparency of sovereign ratings should meaningfully assist investors by improving the risk assessment of investments in emerging markets.

The objective of the empirical analysis is firstly to determine the key determinants of sovereign ratings, followed by an assessment of the weights assigned to each of the key determinants by Standards and Poor's, Moody's and Fitch. This chapter starts with a discussion of the reasoning behind the chosen methods, followed by a description of the data used in the methodological approaches. Lastly, the chapter presents an interpretation and conclusion of the empirical study's results.

4.2 ARGUMENTS FOR THE CHOSEN ESTIMATION TECHNIQUES

The empirical analysis of the study follows the estimation techniques of three influential studies, viz. the seminal paper by Cantor and Packer (1996) and the studies done by Alsakka and Gwilym (2012) and Erdem and Varli (2014). One of the earliest studies that attempted to determine the main macro-economic determinants of sovereign ratings together with the weights assigned to each individual determinant is that of Cantor and Packer (1996). The study follows an OLS approach with a cross-section analysis of 23 industrial and 26 developing economies. The Cantor and Packer (2006) results indicate that the main macro-economic indicators considered in the evaluation of sovereign ratings are per capita income, GDP growth, inflation, external debt, level of economic development, and default history. Cantor and Packer (1996) established that in comparison to Standard & Poor's, Moody’s assigns heavier weight to external debt and less weight to default history as elements with a negative impact on sovereign ratings. Furthermore, Moody’s assigns less weight to GDP per capita as a positive element compared to Standard & Poor’s.

Alsakka and Gwilym (2012) used an extensive set of emerging market economies in Central Asia and Europe. An ordered probit model is utilised as an estimation technique to evaluate their hypothesis. Their hypothesis states that variations in sovereign ratings occur due to agencies assigning different weights to the same macro-economic determinants. The results established that Standard & Poor’s assigns heavier weights to the following variables: Foreign reserves and investment to GDP ratio. However, fiscal balance, openness and GDP per capita are not as fundamental to Standard & Poor’s. Moody’s assigns heavier weights to the following variables: External debt, openness, fiscal balance, and GDP per capita. Conversely, foreign reserves are not as crucial to Moody’s. Fitch assigns heavier weights to the following variables: Fiscal balance, foreign reserves, GDP per capita, foreign reserves and openness.

Erdem and Varli (2014) performed one of the first studies that examined sovereign ratings in particular country-categories. Emerging markets are chosen as the specific country-category and for this reason the study done by Erdem and Varli (2014) is extremely relevant and influential in an empirical sense to this study. Quarterly panel data of sovereign ratings by Standard & Poor’s is utilised for the period 2002-2011 for eight emerging market economies. As with Cantor and Packer (1996), Erdem and Varli (2014) also made use of the OLS estimation technique that includes panel options fixed and random effects. In addition to the OLS analysis, an ordered probit model is estimated, followed by a pooled OLS model that includes panel options fixed and random effects with an AR (1) disturbance term. The OLS and pooled OLS models’ results conclude that fiscal balance, governance indicators, GDP per capita and foreign reserves significantly influence sovereign ratings. The ordered probit model yielded similar results to the two linear models, except that external debt was also found to be a significant determinant in assessing sovereign ratings.

4.3 DATA

Quarterly data from the first quarter of 2004 to the first quarter of 2014 is utilised in the empirical estimations of this study. Macro-economic data is obtained from the database of the International Monetary Fund (International Financial Statistics, IFS) as well as the Economic Intelligence Unit (EIU). Sovereign ratings are obtained from Moody's Sovereign Bond Rating History, Standard & Poor's Sovereign Rating and Country T&C Assessment Histories and Emerging Markets Traders Association for Fitch Ratings. The March 2014 FTSE Global Equity Index Series: *Regional Classification* includes 16 emerging markets from Europe, America, Asia and Africa and the March 2014 FTSE Global Equity Index Series: *Country Classification* includes 14 emerging markets divided into the advanced economies, secondary economies and frontier economies.

The European sample includes 328 observations, the American sample includes 164 observations, the Asian sample includes 123 observations and the African sample includes 41 observations. The advanced sample includes 246 observations, the secondary sample includes 123 observations and the frontier sample includes 205 observations. The March 2014 FTSE Global Equity Index Series: *Country Classification* (advanced, secondary and frontier economies combined) include 573 observations and the March 2014 FTSE Global Equity Index Series: *Regional Classification* (European, American, Asian and African economies combined) include 656 observations.

Table 4.1: March 2014 FTSE Global Equity Index Series: Regional classification

The America's	Asia-Pacific	Europe	Africa
Argentina	China	Czech Republic	South Africa
Brazil	India	Bulgaria	
Mexico	Indonesia	Hungary	
Peru		Lithuania	
		Poland	
		Russia	
		Slovakia	
		Slovenia	

Source: Compiled by author

Table 4.2: The March 2014 FTSE Global Equity Index Series: Country classification

Advanced Emerging	Secondary Emerging	Frontier Markets
Brazil	China	Argentina

Czech Republic Hungary Mexico Poland South Africa	Peru Russia	Bulgaria Lithuania Slovakia Slovenia

Source: Compiled by author

The following variables are used following the studies done by Cantor and Packer (1996) and Erdem and Varli (2014): GDP per capita (GDPPC), real GDP growth (RGDP), fiscal balance as a percentage of GDP (FISGDP), current account balance as a percentage of GDP (CAGDP), real effective exchange rate (REER), openness (OPEN) foreign reserves as a percentage of imports (FORIMP), external debt as a percentage of exports (DEXP), external debt as percentage of GDP(DGDP), inflation (INFL), corruption index (CI) and default history (DH).

4.4 DATA DESCRIPTIVES

The following section gives a description of the data to comprehend the properties of the data as well as the potential problems in dealing with the data. EViews 8 is the statistical software used to perform the descriptive statistical section of the study, which includes tables, graphs and estimations. Figures 7.43-7.50 (Appendix C) give graphical representations of multiple graphs of variables in levels. The x-axis signifies the time in years and the y-axis signifies the values of each individual graph.

Figure 7.43 suggests for advanced economies that Standard & Poor’s, Moody’s, Fitch, DEXP, FORIMP, OPEN, DGDP and CI may have a trend in the data and therefore formal unit root tests have to be done to determine whether the data is stationary. However, the graphs indicate that FISGDP, INFL, REER, RGDP, DH and GDPPC show no clear trend in the data and therefore suggest stationarity in these variables.

Figure 7.44 suggests for secondary economies that Standard & Poor’s, Moody’s, Fitch, FORIMP, OPEN, GDPPC, DGDP and CI may have a trend in the data and therefore formal unit root tests have done to determine whether the data is stationary. However, the graphs indicate that FISGDP, INFL, DEXP, REER, RGDP, DH and show no clear trend in the data and therefore suggest stationarity in these variables.

Figure 7.45 suggests for frontier economies that Standard & Poor's, Moody's, Fitch, INFL, DEXP FORIMP, OPEN, GDPPC, DGDP, RGDP and CI may have a trend in the data and therefore formal unit root tests have to be done to determine whether the data is stationary. However, the graphs indicate that FISGDP, DH and show no clear trend in the data and therefore suggest stationarity in these variables.

Figure 7.46 suggests for European economies that Standard & Poor's, Moody's, Fitch, DEXP FORIMP, OPEN, DGDP, and CI may have a trend in the data and therefore formal unit root tests are done to determine whether the data is stationary. However, the graphs indicate that FISGDP, INFL, GDPPC, RGDP, DH and show no clear trend in the data and therefore suggest stationarity in these variables.

Figure 7.47 suggests for Asian economies that Standard & Poor's, Moody's, Fitch, DEXP, GDPPC, RGDP, OPEN, DGDP, and CI may have a trend in the data and therefore formal unit root tests are done to determine whether the data is stationary. However, the graphs indicate that FISGDP, INFL, FORIMP, DH and show no clear trend in the data and therefore suggest stationarity in these variables.

Figure 7.48 suggests for American economies that Standard & Poor's, Moody's, Fitch, DEXP, FORIMP, GDPPC, OPEN, DGDP, CAGDP and CI may have a trend in the data and therefore formal unit root tests are done to determine whether the data is stationary. However, the graphs indicate that FISGDP, RGDP and DH show no clear trend in the data and therefore suggest stationarity in these variables.

Figure 7.49 suggests for FTSE economies that Standard & Poor's, Moody's, Fitch, DEXP, FORIMP, INFL, OPEN, DGDP, and CI may have a trend in the data and therefore formal unit root tests are done to determine whether the data is stationary. However, the graphs indicate that FISGDP, RGDP and DH show no clear trend in the data and therefore suggest stationarity in these variables.

Figure 7.50 suggests for regional economies that Standard & Poor's, Moody's, Fitch, DEXP, FORIMP, GDPPC, OPEN, DGDP, and CI may have a trend in the data and therefore formal unit root tests are done to determine whether the data is stationary. However, the graphs indicate that INFL, RGDP and DH show no clear trend in the data and therefore suggest stationarity in these variables.

Ultimately, the graphical representation of the variables indicate that Standard & Poor's, Moody's, Fitch, DEXP, FORIMP, OPEN, DGDP, CI and CAGDP potentially have unit roots. On the contrary, FISGDP, INFL, REER, RGDP, DH and GDPPC seem to be stationary. However, formal unit root tests follow to empirically determine stationarity.

4.4.1 Unit root tests

QMS (2009) defines panel data as data characterised by both a time series dimension ($t_1, t_2 \ldots t_T$) and a cross-section dimension ($i_1, i_2 \ldots 1_N$).The existence of a time series component creates problems with stationarity and this subject matter refers to properties (mean, variances and expectations) that remain constant over time. On the other hand, non-stationarity pertains to properties that vary over time and do not remain constant (Nason, 2011). Recent literature indicates that panel based unit root tests possess higher power that the individual time series unit root tests. Firstly, QMS (2009) states that varying degrees of heterogeneity between N and the power of the test increases as the N increases. Secondly, no absolute certainty exists concerning the validity of rejecting a unit root and lastly the cross sectional elements improve the properties of unit root test in comparison to the standard Augmented Dickey Fuller (ADF).

Tests for the level of integration of each variable are done by means of three panel unit root tests, namely Levin, Lin and Chu (2002) (LLC), Im, Pesaran and Shin (2003) (IPS) and Hadri (2000). The test equation estimates all three specifications, namely (i) individual intercept, (ii) individual intercept and trend and (iii) none.

4.4.1.1 Levin, Lin and Chu (2002)

The simple ADF specification is the starting point of the LLC (2002) test:

$$\Delta Y_{i,t} = a_i + \rho Y_{i,t-1} + \sum_{k=1}^{n} \emptyset_k \Delta Y_{i,t-k} + \delta_i t + \theta_t + u_{it}$$

The model appropriates two-way fixed effects, firstly a_i and secondly θ_t, therefore both unit-specific time trends and unit-specific fixed effects are included. The unit-specific fixed effects are an essential factor since it allows heterogeneity, as the coefficient of the lagged Y_i is limited to homogeneity through every unit of the panel (Asteriou & Hall, 2007). The power of a unit root test is the probability of rejecting the null hypothesis, if false. The null hypothesis is that a series contains a unit root. The Levin, Lin and Chu test specify the null hypothesis as follows:

$$H_0: \rho = 0$$

$$H_1: \rho < 0$$

H_0: Is that of a unit root, thus the series is non-stationary.

H_1: Stipulates the alternate hypothesis of no unit root and therefore, the series is stationary.

LLC (2002) is classified as a first-generation panel unit root test, which is based on cross-sectional independency that assumes no co-integration between cross-sections. This assumption derives from conditions stating that the pooled OLS estimator of ρ follows a standard normal distribution under the null hypothesis. The LLC test can hence be considered as a pooled ADF test with different lag lengths throughout the sections in the panel (Asteriou & Hall, 2007).

4.4.1.2 Im, Pesaran and Shin (2003)

Nell (2011) indicates that IPS (2003) is also a first generation test; however, not as restrictive as LLC (2002) due to heterogeneous coefficients of the $Y_{i,t-1}$ variable. Separate estimates for each i section are given permitting for different stipulations of the parametric values, the lag lengths and the residual variance. The model with individual effects and no time trend is as follows:

$$\Delta Y_{i,t} = a_i + \rho_i Y_{i,t-1} + \sum_{k=1}^{n} \emptyset k \Delta Y_{i,t-k} + \delta_i t + u_{it}$$

In comparison to the LLC test, the IPS test uses separate unit root tests for n, instead of pooling the data. Hence, the test is based on the ADF test statistics' average across groups (Hurlin & Mignon, 2007). The null hypothesis is given as:

$$H_0: \rho_i = 0 \text{ For all } i\text{'s}$$
$$H_1: \ \rho < 0 \text{ For no less than one } i$$

H_0: All the individual effects follow a unit root process, thus all series are non-stationary.
H_1: The alternate hypothesis specifies that some, but not all, individual effects follow a unit root process, thus only a fraction of the series is stationary.

Hoang and McNown (2006) state that the IPS test combines the evidence that the unit root hypothesis of N unit root tests performs N cross-section units. The test assumes that T is similar for all cross-section units and thus a balanced panel is required to determine the $\bar{t}$ test statistic. The $\bar{t}$ test statistic is the average of the individual ADF $\bar{t}$ test statistic for testing that $\rho_i = 0$ for all i , represented as t_{pi}.

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_{pi}$$

IPS (2003) indicates that under certain assumptions, t_{pi} converges to a statistic represented as t_{iT}. It assumes independent and identically distributed random variables *(iid)* that have finite mean and variance. Values are calculated for the mean $(E[t_{iT} \mid \rho_i = 1])$ as well as for the variance (Var $[t_{iT} \mid \rho_i = 1])$ of the t_{iT} statistic. Additionally, it calculates different values of N and lags in the expansion term of the equation (ADF*). Furthermore, the IPS statistic tests for unit roots in panels based on the values acquired for the mean and variance:

$$t_{IPS} = \frac{\sqrt{N}\ (\bar{t} - 1/N \sum_{i=1}^{N} E_{[tiT|\rho i=0]})}{\sqrt{(\text{Var}_{\ [t_{iT} \mid \rho_i=0]})}}$$

The equation demonstrates the standard normal distribution as $T \rightarrow \infty$ followed by $N \rightarrow \infty$ successively (QMS, 2009). Monte Carlo simulations suggest that the execution of the small sample IPS test is more beneficial than the LLC test (Nell, 2011).

4.4.1.3 Hadri Test (2000)

The Hadri Test is also a first-generation test and assumes that all series are stationary around a deterministic trend. The null hypothesis is as follows:

H_0: Stationarity – series does not comprise a unit root.

The equation for the model is expressed as:

$$\mathrm{Y_{it}} = \alpha_i + \delta_i t + r_{it} + u_{it}$$

Where u_{it} is a stationary process and $r_{it} = r_{i,t-1} + u_{it}$ with $u_{it} \backsim$ *iid* $(0,\sigma_u^2)$

Therefore the r_{it} is a random walk model that constantly substitutes r back in the model: $Y_{it} = \alpha_i + \delta_i t + u_{it}$ with $u_{it} = \sum_{j=1}^{t} u_{it} + \varepsilon_{it}$

Therefore, the null hypothesis is presented as $\sigma_u^2 = 0$, which is the variance of the random walk factor. If the variance u_{it} is zero, r_{it} turns into a constant and consequently Y_{it} is stationary. The Hadri test allows for homoscedasticity across panels and heteroskedastisity adjustments across units. Test statistics follow a standard normal law.

4.4.1.4 Unit root test results

Table 4.3: Results of the unit root test concerning the advanced economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-1.4879	0.5348	**DSP**	-4.4239	0.0000
MOODYS	-1.4263	0.5826	**DMOODYS**	-4.0347	0.0000
FITCH	-1.7267	0.2862	**DFITCH**	-4.4647	0.0000
FISGDP	-4.7224	0.0000			
INFL	-2.7732	0.0003			
DEXP	-1.8881	0.1575	**DDEXP**	-4.6505	0.0000
FORIMP	-1.8569	0.1789	**DFORIMP**	-4.3323	0.0000
OPEN	-0.522	0.9968	**DOPEN**	-4.6300	0.0000
REER	-5.1454	0.0000			
RGDP	-2.7731	0.0003			
DGDP	0.1302	1.0000	**DDGDP**	-4.1155	0.0000

CI	-1.4346	0.5920	**DCI**	-4.5348	0.0000
GDPPC	-2.6426	0.0011			

Source: Compiled by author

Table 4.3 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor's, Moody's, Fitch, DEXP, FORIMP, OPEN, DGDP and CI. As a result, these series are non-stationary in levels, however the formal test results indicate stationarity in first differences. Therefore, S&P, Moody's, Fitch, DEXP, FORIMP, OPEN, DGDP and CI each contains one unit root (integrated of order one, I (1)). Obversely, the formal test results establish that FISGDP, INFL, REER, RGDP and GDPPC do not contain a unit root and are resultantly stationary in levels (integrated of order zero, I (0)).

Table 4.4: Results of the unit root test concerning the secondary economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-1.4767	0.5332	**DSP**	-4.9058	0.0000
MOODYS	-1.0008	0.8417	**DMOODYS**	-4.7249	0.0000
FITCH	-2.0159	0.1693	**DFITCH**	-4.6728	0.0000
FISGDP	-7.3804	0.0000			
INFL	-3.4775	0.0001			
DEXP	-3.0358	0.0017			
FORIMP	-2.1487	0.1125	**DFORIMP**	-6.6079	0.0000
OPEN	-2.1359	0.1173	**DOPEN**	-6.5684	0.0000
REER	-5.0173	0.0000			
RGDP	-2.9264	0.0034			
DGDP	-4.8482	0.0000			
CI	-1.0204	0.8324	**DCI**	-4.2891	0.0000
GDPPC	-1.6031	0.4362	**DGDPPC**	-4.9105	0.0000

Source: Compiled by author

Table 4.4 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor's, Moody's, Fitch, FORIMP, OPEN, GDPPC and CI. Hence, these series are I (1) variables since the null hypothesis of a unit root in first differences can be rejected. Contrariwise, the formal test results establish that FISGDP, INFL, DEXP, REER, RGDP and DGDP do not contain a unit root and are resultantly stationary in levels, i.e. I (0).

Table 4.5: Results of the unit root test concerning the frontier economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-1.6594	0.3641	**DSP**	-4.0264	0.0000
MOODYS	-1.4658	0.5536	**DMOODYS**	-3.8514	0.0000
FITCH	-1.6027	0.4183	**DFITCH**	-4.2114	0.0000
FISGDP	-2.8018	0.0007			
INFL	-1.7846	0.2549	**DINFL**	-4.2650	0.0000
DEXP	-1.1510	0.8202	**DDEXP**	-4.1136	0.0000
FORIMP	-1.9428	0.1462	**DFORIMP**	-5.0542	0.0000
OPEN	-1.5838	0.4367	**DOPEN**	-6.2654	0.0000
RGDP	-2.1930	0.0470			
CI	-1.3492	0.6647	**DCI**	-4.3712	0.0000
GDPPC	-2.1729	0.0519	**DGDPPC**	-5.8882	0.0000

Source: Compiled by author

Table 4.5 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor's, Moody's, Fitch, INFL, DEXP FORIMP, OPEN, GDPPC, DGDP, RGDP and CI. Consequently, these series are I (1) variables since the null hypothesis of a unit root in first differences can be rejected. In contrast, the formal test results establish that FISGDP, INFL, DEXP, REER, RGDP, DH do not contain a unit root and are resultantly stationary in levels, i.e. I (0).

Table 4.6: Results of the unit root test concerning the European economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-1.3121	0.7437	**DSP**	-4.2589	0.0000
MOODYS	-1.1727	0.8283	**DMOODYS**	-4.2846	0.0000
FITCH	-1.7814	0.2050	**DFITCH**	-4.4217	0.0000
FISGDP	-3.7156	0.0000			
INFL	-2.6762	0.0001			
DEXP	-1.4155	0.6287	**DDEXP**	-4.0537	0.0000
DGDP	0.0860	1.0000	**DDGDP**	-6.9690	0.0000
FORIMP	-1.8953	0.1184	**DFORIMP**	-4.7691	0.0000
OPEN	-1.0186	0.9429	**DOPEN**	-5.3623	0.0000
RGDP	-2.4212	0.0023			
CI	-1.4169	0.6273	**DCI**	-4.4804	0.0000

GDPPC	-2.9651	0.0000			

Source: Compiled by author

Table 4.6 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor's, Moody's, Fitch, DEXP, FORIMP, OPEN, DGDP, and CI. Accordingly, these series are I (1) variables since the null hypothesis of a unit root in first differences can be rejected. Conversely, the formal test results establish that FISGDP, INFL, GDPPC, RGDP, DH do not contain a unit root and are resultantly stationary in levels, i.e. I (0).

Table 4.7: Results of the unit root test concerning the Asian economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-2.0149	0.1698	**DSP**	-4.8911	0.0000
MOODYS	-0.6575	0.9129	**DMOODYS**	-4.9679	0.0000
FITCH	-1.6074	0.4330	**DFITCH**	-4.6583	0.0000
FISGDP	-7.4818	0.0000			
INFL	-2.9795	0.0024			
DEXP	-2.0370	0.1609	**DDEXP**	-4.6281	0.0000
DGDP	-4.8850	0.0000			
FORIMP	-2.3778	0.0494	**DFORIMP**		
OPEN	-1.9744	0.1908	**DOPEN**	-3.7838	0.0000
RGDP	-2.2091	0.0922	**DRGDP**	-4.7456	0.0000
CI	-1.0751	0.8046	**DCI**	-4.6395	0.0000
GDPPC	-1.5993	0.4391	**DGDPPC**	-4.8000	0.0000

Source: Compiled by author

Table 4.7 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor's, Moody's, Fitch, DEXP, GDPPC, RGDP, OPEN and CI. Hence, these series are I (1) variables since the null hypothesis of a unit root in first differences can be rejected. Conversely, the formal test results establish that FISGDP, INFL, FORIMP and DGDP do not contain a unit root and are resultantly stationary in levels, i.e. I (0).

Table 4.8: Results of the unit root test concerning the American economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-1.9704	0.1577	**DSP**	-4.5203	0.0000
MOODYS	-1.4457	0.5656	**DMOODYS**	-3.7662	0.0000
FITCH	-1.5166	0.5030	**DFITCH**	-4.7632	0.0000
FISGDP	-5.1668	0.0000			
INFL	-2.8654	0.0014			
DEXP	-1.7084	0.3374	**DDEXP**	-5.6198	0.0000
DGDP	-3.5979	0.0000			
FORIMP	-1.0731	0.8400	**DFORIMP**	-5.6419	0.0000
OPEN	-1.5054	0.5129	**DOPEN**	-6.4934	0.0000
RGDP	-3.0847	0.0002			
CI	-1.3487	0.6485	**DCI**	-4.4960	0.0000
GDPPC	-1.2116	0.7539	**DGDPPC**	-3.6506	0.0000

Source: Compiled by author

Table 4.8 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor's, Moody's, Fitch, DEXP, FORIMP, GDPPC, OPEN and CI. As a result, these series are I (1) variables since the null hypothesis of a unit root in first differences can be rejected. Conversely, the formal test results establish that FISGDP, RGDP and DGDP do not contain a unit root and are resultantly stationary in levels, i.e. I (0).

Table 4.9: Results of the unit root test concerning the FTSE economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-1.5606	0.4326	**DSP**	-4.3823	0.0000
MOODYS	-1.3413	0.7546	**DMOODYS**	-4.1264	0.0000
FITCH	-1.7581	0.1604	**DFITCH**	-4.4150	0.0000
FISGDP	-4.5950	0.0000			
INFL	-2.8245	0.0000			
DEXP	-1.2575	0.8628	**DDEXP**	-4.6191	0.0000
DGDP	-0.1445	1.0000	**DDGDP**	-4.0431	0.0000
FORIMP	-1.7059	0.2192	**DFORIMP**	-5.0565	0.0000
OPEN	-1.2616	0.8591	**DOPEN**	-5.6349	0.0000
RGDP	-2.5967	0.0000			
CI	-1.3079	0.8115	**DCI**	-4.4619	0.0000

Source: Compiled by author

Table 4.9 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor’s, Moody’s, Fitch, DEXP, FORIMP, OPEN, DGDP, and CI. Resultantly, these series are I (1) variables since the null hypothesis of a unit root in first differences can be rejected. Obversely, the formal test results establish that FISGDP, RGDP and INFL do not contain a unit root and are resultantly stationary in levels, i.e. I (0).

Table 4.10: Results of the unit root test concerning the regional economies

LEVELS	T-STATISTIC	T-PROBABILITY	FIRST DIFFERENCES	T-STATISTIC	T-PROBABILITY
SP	-1.6282	0.3201	**DSP**	-4.4551	0.0000
MOODYS	-1.1778	0.9066	**DMOODYS**	-4.2257	0.0000
FITCH	-1.6760	0.2503	**DFITCH**	-4.5601	0.0000
FISGDP	-4.8558	0.0000			
INFL	-2.7873	0.0000			
DEXP	-1.6179	0.3364	**DDEXP**	-4.5862	0.0000
DGDP	-0.3680	1.0000		-4.0879	0.0000
FORIMP	-1.7726	0.1380	**DFORIMP**	-5.0527	0.0000
OPEN	-1.3396	0.7816	**DOPEN**	-5.3482	0.0000
RGDP	-2.5557	0.0000			
CI	-1.3303	0.7933	**DCI**	-4.5164	0.0000
GDPPC	-2.2340	0.0010			

Source: Compiled by author

Table 4.10 indicates that the null hypothesis of a unit root cannot be rejected for Standard & Poor’s, Moody’s, Fitch, DEXP, FORIMP, OPEN, DGDP, and CI. Therefore, these series are I (1) variables since the null hypothesis of a unit root in first differences can be rejected. In contrast, the formal test results establish that INFL, RGDP, FISGDP and GDPPC do not contain a unit root and are resultantly stationary in levels, i.e. I (0).

4.4.2 Analysing the correlation between variables

After considering the properties of individual time series, the analysis proceeds to multiple series, commencing with correlation. Correlation analysis is an essential and widely employed statistical method in economic data. The term *correlation* refers to the extent to which two quantitative variables are either connected or associated. The correlation coefficient is denoted as the *r* coefficient. The *r*-value necessitates both a scale and direction that can either be positive or negative and ranges between -1 and 1. A correlation coefficient with a value of zero indicates no direct relationship between two variables. A positive correlation coefficient points towards a mutual increase of both variables, thus as the one variable increases the other variable corresponds with an increase in value as well. A negative correlation coefficient specifies an inverse relationship between two variables, thus as the one variable increases the other variable decreases (Taylor, 1990).

Correlation matrix estimations are performed to determine the relationships between variables for each of the country-categories. The correlation matrices are imperative, as high correlation amongst variables is the source of multicolinearity. Farrar and Glauber (2005) established that multicolinearity occurs when two or more variables are correlated and results in redundant and spurious information of the response. According to Field (2013) a correlation of $r > 0.8$ is regarded as high correlation between two variables, whilst a correlation of $r < 0.3$ is considered low correlation. Field's (2013) correlation benchmarks are used to compare and interpret the correlation matrices given below. Tables 4.11-4.18 represent the results of the correlation matrix for each country-category:

Table 4.11: Correlation matrix - advanced economies

	DSP	DMOODYS	DFITCH	DCI	DDEXP	DDGDP	DFORIMP	DOPEN	FISGDP	GDPPC	INFL	REER	RGDP
DSP	1.000	0.168	0.279	-0.007	0.034	0.025	-0.048	-0.063	0.168	0.034	0.046	0.139	0.199
DMOODYS	0.168	1.000	0.197	-0.023	0.035	0.118	0.016	-0.148	0.085	0.039	0.051	0.105	0.052
DFITCH	0.279	0.197	1.000	-0.054	0.060	-0.095	-0.025	0.022	0.181	0.047	0.002	0.133	0.171
DCI	-0.007	-0.023	-0.054	1.000	0.096	0.026	0.059	-0.010	-0.046	-0.007	-0.080	0.067	0.104
DDEXP	0.034	0.035	0.060	0.096	1.000	0.010	0.342	-0.166	0.051	-0.024	0.028	0.140	-0.050
DDGDP	0.025	0.118	-0.095	0.026	0.010	1.000	0.129	-0.025	-0.043	-0.237	-0.020	-0.102	-0.027
DFORIMP	-0.048	0.016	-0.025	0.059	0.342	0.129	1.000	-0.259	0.009	-0.017	0.030	-0.294	-0.270
DOPEN	-0.063	-0.148	0.022	-0.010	-0.166	-0.025	-0.259	1.000	-0.189	-0.091	-0.023	-0.211	0.086
FISGDP	0.168	0.085	0.181	-0.046	0.051	-0.043	0.009	-0.189	1.000	0.072	0.061	0.093	0.195
GDPPC	0.034	0.039	0.047	-0.007	-0.024	-0.237	-0.017	-0.091	0.072	1.000	0.259	-0.013	0.210
INFL	0.046	0.051	0.002	-0.080	0.028	-0.020	0.030	-0.023	0.061	0.259	1.000	0.042	-0.036
REER	0.139	0.105	0.133	0.067	0.140	-0.102	-0.294	-0.211	0.093	-0.013	0.042	1.000	0.074
RGDP	0.199	0.052	0.171	0.104	-0.050	-0.027	-0.270	0.086	0.195	0.210	-0.036	0.074	1.000

Source: Compiled by author

Table 4.12: Correlation matrix - secondary economies

	DSP	DMOODYS	DFITCH	DCI	DDGDP	DEXP	DFORIMP	DGDPPC	DOPEN	FISGDP	INFL	REER	RGDP
DSP	1.000	0.252	0.018	-0.141	0.038	-0.006	0.008	0.219	0.050	0.104	-0.040	0.028	0.170
DMOODYS	0.252	1.000	-0.074	-0.023	0.091	0.015	-0.125	0.002	0.098	0.052	0.046	-0.009	0.130
DFITCH	0.018	-0.074	1.000	-0.022	0.052	0.144	-0.151	0.009	0.006	-0.019	-0.003	0.061	0.209
DCI	-0.141	-0.023	-0.022	1.000	-0.180	-0.073	0.037	-0.345	-0.066	-0.062	-0.087	0.047	-0.057
DDGDP	0.038	0.091	0.052	-0.180	1.000	0.019	-0.093	-0.001	-0.329	-0.068	0.010	-0.029	-0.003
DEXP	-0.006	0.015	0.144	-0.073	0.019	1.000	0.059	0.036	0.022	0.173	-0.237	0.092	-0.100
DFORIMP	0.008	-0.125	-0.151	0.037	-0.093	0.059	1.000	-0.074	-0.679	0.124	0.050	-0.019	-0.068
DGDPPC	0.219	0.002	0.009	-0.345	-0.001	0.036	-0.074	1.000	0.017	0.029	0.038	0.024	-0.017
DOPEN	0.050	0.098	0.006	-0.066	-0.329	0.022	-0.679	0.017	1.000	0.131	0.043	-0.068	0.040
FISGDP	0.104	0.052	-0.019	-0.062	-0.068	0.173	0.124	0.029	0.131	1.000	0.349	0.133	0.068
INFL	-0.040	0.046	-0.003	-0.087	0.010	-0.237	0.050	0.038	0.043	0.349	1.000	0.042	-0.381
REER	0.028	-0.009	0.061	0.047	-0.029	0.092	-0.019	0.024	-0.068	0.133	0.042	1.000	0.126
RGDP	0.170	0.130	0.209	-0.057	-0.003	-0.100	-0.068	-0.017	0.040	0.068	-0.381	0.126	1.000

Source: Compiled by author

Table 4.13: Correlation matrix - frontier economies

	DSP	DMOODYS	DFITCH	DCI	DDEXP	DFORIMP	DGDPPC	DINFL	DOPEN	DRGDP	FISGDP
DSP	1.000	0.307	0.113	0.004	-0.453	-0.077	0.178	0.044	0.015	0.120	0.114
DMOODYS	0.307	1.000	0.178	0.084	-0.176	-0.049	0.070	-0.013	0.003	-0.019	0.214
DFITCH	0.113	0.178	1.000	-0.045	-0.028	-0.042	0.018	0.001	0.002	-0.069	0.126
DCI	0.004	0.084	-0.045	1.000	0.000	0.093	0.091	-0.079	-0.096	-0.087	0.033
DDEXP	-0.453	-0.176	-0.028	0.000	1.000	0.220	-0.226	-0.090	-0.246	-0.014	-0.230
DFORIMP	-0.077	-0.049	-0.042	0.093	0.220	1.000	-0.290	-0.027	-0.046	-0.268	-0.017
DGDPPC	0.178	0.070	0.018	0.091	-0.226	-0.290	1.000	0.103	-0.133	0.257	0.130
DINFL	0.044	-0.013	0.001	-0.079	-0.090	-0.027	0.103	1.000	-0.078	-0.067	0.038
DOPEN	0.015	0.003	0.002	-0.096	-0.246	-0.046	-0.133	-0.078	1.000	-0.008	0.019
DRGDP	0.120	-0.019	-0.069	-0.087	-0.014	-0.268	0.257	-0.067	-0.008	1.000	-0.037
FISGDP	0.114	0.214	0.126	0.033	-0.230	-0.017	0.130	0.038	0.019	-0.037	1.000

Source: Compiled by author

Table 4.14: Correlation matrix - European economies

	DSP	DMOODYS	DFITCH	DCI	DDEXP	DDGDP	DFORIMP	DOPEN	FISGDP	GDPPC	INFL	RGDP
DSP	1.000	0.291	0.243	0.032	-0.073	-0.083	-0.005	0.018	0.138	0.165	-0.008	0.231
DMOODYS	0.291	1.000	0.420	0.060	-0.067	-0.077	-0.040	0.002	0.175	0.114	0.100	0.248
DFITCH	0.243	0.420	1.000	0.033	-0.141	-0.131	-0.095	-0.001	0.129	0.095	0.012	0.276
DCI	0.032	0.060	0.033	1.000	0.059	0.092	0.037	-0.070	-0.027	-0.088	-0.061	0.051
DDEXP	-0.073	-0.067	-0.141	0.059	1.000	0.749	0.220	-0.248	-0.229	-0.185	-0.182	-0.238
DDGDP	-0.083	-0.077	-0.131	0.092	0.749	1.000	0.131	-0.028	-0.299	-0.069	-0.137	-0.156
DFORIMP	-0.005	-0.040	-0.095	0.037	0.220	0.131	1.000	-0.012	0.062	0.038	0.055	-0.064
DOPEN	0.018	0.002	-0.001	-0.070	-0.248	-0.028	-0.012	1.000	0.008	0.008	0.026	-0.045
FISGDP	0.138	0.175	0.129	-0.027	-0.229	-0.299	0.062	0.008	1.000	0.297	0.388	0.401
GDPPC	0.165	0.114	0.095	-0.088	-0.185	-0.069	0.038	0.008	0.297	1.000	0.455	0.111
INFL	-0.008	0.100	0.012	-0.061	-0.182	-0.137	0.055	0.026	0.388	0.455	1.000	0.169
RGDP	0.231	0.248	0.276	0.051	-0.238	-0.156	-0.064	-0.045	0.401	0.111	0.169	1.000

Source: Compiled by author

Table 4.15: Correlation matrix - Asian economies

	DSP	DMOODYS	DFITCH	DCI	DDEXP	DDGDP	DFORIMP	DGDPPC	DOPEN	DRGDP	FISGDP	INFL
DSP	1.000	0.065	0.082	0.072	-0.071	0.037	0.002	0.125	-0.032	-0.025	0.081	-0.073
DMOODYS	0.065	1.000	-0.068	0.038	-0.042	0.103	-0.034	0.115	-0.097	0.086	0.064	-0.016
DFITCH	0.082	-0.068	1.000	0.149	0.096	0.062	0.015	0.109	-0.222	-0.074	-0.006	-0.107
DCI	0.072	0.038	0.149	1.000	0.156	-0.233	0.107	-0.221	0.163	-0.203	0.112	-0.107
DDEXP	-0.071	-0.042	0.096	0.156	1.000	-0.008	0.533	-0.054	-0.002	-0.217	0.017	0.012
DDGDP	0.037	0.103	0.062	-0.233	-0.008	1.000	-0.297	0.888	-0.684	0.074	-0.096	0.021
DFORIMP	0.002	-0.034	0.015	0.107	0.533	-0.297	1.000	-0.235	0.020	-0.117	-0.012	0.006
DGDPPC	0.125	0.115	0.109	-0.221	-0.054	0.888	-0.235	1.000	-0.836	0.042	-0.290	-0.050
DOPEN	-0.032	-0.097	-0.222	0.163	-0.002	-0.684	0.020	-0.836	1.000	0.103	0.397	0.023
DRGDP	-0.025	0.086	-0.074	-0.203	-0.217	0.074	-0.117	0.042	0.103	1.000	-0.053	-0.122
FISGDP	0.081	0.064	-0.006	0.112	0.017	-0.096	-0.012	-0.290	0.397	-0.053	1.000	-0.098
INFL	-0.073	-0.016	-0.107	-0.107	0.012	0.021	0.006	-0.050	0.023	-0.122	-0.098	1.000

Source: Compiled by author

Table 4.16: Correlation matrix - American economies

	DSP	DMOODYS	DFITCH	DCI	DDEXP	DFORIMP	DGDP	DGDPPC	DCAGDP	DOPEN	FISGDP	INFL	RGDP
DSP	1.000	0.190	0.075	-0.047	-0.145	-0.064	0.170	0.270	-0.063	-0.022	0.145	0.037	0.174
DMOODYS	0.190	1.000	-0.005	-0.039	-0.047	-0.150	0.120	0.099	0.176	-0.170	0.003	-0.071	-0.025
DFITCH	0.075	-0.005	1.000	-0.137	-0.047	-0.043	0.008	-0.011	-0.008	0.038	0.117	0.113	0.166
DCI	-0.047	-0.039	-0.137	1.000	0.114	0.113	-0.019	-0.020	-0.145	-0.022	-0.046	0.026	-0.033
DDEXP	-0.145	-0.047	-0.047	0.114	1.000	0.290	-0.176	-0.087	-0.007	-0.046	-0.359	0.036	-0.042
DFORIMP	-0.064	-0.150	-0.043	0.113	0.290	1.000	-0.131	-0.089	0.005	-0.154	-0.026	-0.055	-0.107
DDGDP	0.170	0.120	0.008	-0.019	-0.176	-0.131	1.000	0.770	0.001	-0.027	0.304	-0.097	0.192
DGDPPC	0.270	0.099	-0.011	-0.020	-0.087	-0.089	0.770	1.000	0.000	0.014	0.201	-0.149	0.234
DCAGDP	-0.063	0.176	-0.008	-0.145	-0.007	0.005	0.001	0.000	1.000	-0.060	0.083	0.006	-0.057
DOPEN	-0.022	-0.170	0.038	-0.022	-0.046	-0.154	-0.027	0.014	-0.060	1.000	-0.153	-0.036	0.045
FISGDP	0.145	0.003	0.117	-0.046	-0.359	-0.026	0.304	0.201	0.083	-0.153	1.000	0.000	0.218
INFL	0.037	-0.071	0.113	0.026	0.036	-0.055	-0.097	-0.149	0.006	-0.036	0.000	1.000	0.132
RGDP	0.174	-0.025	0.166	-0.033	-0.042	-0.107	0.192	0.234	-0.057	0.045	0.218	0.132	1.000

Source: Compiled by author

Table 4.17: Correlation Matrix - FTSE economies

	DSP	DMOODYS	DFITCH	DCI	DDEXP	DDGDP	DFORIMP	DOPEN	FISGDP	INFL	RGDP
DSP	1.000	0.242	0.129	-0.002	-0.123	0.002	-0.029	0.013	0.133	-0.057	0.203
DMOODYS	0.242	1.000	0.140	0.018	-0.047	0.081	-0.070	0.004	0.126	-0.034	0.176
DFITCH	0.129	0.140	1.000	-0.041	-0.057	-0.036	-0.050	0.002	0.105	-0.021	0.178
DCI	-0.002	0.018	-0.041	1.000	0.053	0.021	0.053	-0.060	-0.019	0.014	0.040
DDEXP	-0.123	-0.047	-0.057	0.053	1.000	0.018	0.155	-0.026	-0.203	0.016	-0.046
DDGDP	0.002	0.081	-0.036	0.021	0.018	1.000	0.014	0.002	-0.059	-0.035	-0.055
DFORIMP	-0.029	-0.070	-0.050	0.053	0.155	0.014	1.000	-0.010	0.035	-0.018	-0.068
DOPEN	0.013	0.004	0.002	-0.060	-0.026	0.002	-0.010	1.000	0.009	0.008	-0.028
FISGDP	0.133	0.126	0.105	-0.019	-0.203	-0.059	0.035	0.009	1.000	0.019	0.311
INFL	-0.057	-0.034	-0.021	0.014	0.016	-0.035	-0.018	0.008	0.019	1.000	-0.030
RGDP	0.203	0.176	0.178	0.040	-0.046	-0.055	-0.068	-0.028	0.311	-0.030	1.000

Source: Compiled by author

Table 4.18: Correlation Matrix - regional economies

	DSP	DMOODYS	DFITCH	DCI	DDEXP	DDGDP	DFORIMP	DOPEN	FISGDP	INFL	RGDP
DSP	1.000	0.242	0.129	-0.002	-0.123	0.002	-0.029	0.013	0.133	-0.057	0.203
DMOODYS	0.242	1.000	0.140	0.018	-0.047	0.081	-0.070	0.004	0.126	-0.034	0.176
DFITCH	0.129	0.140	1.000	-0.041	-0.057	-0.036	-0.050	0.002	0.105	-0.021	0.178
DCI	-0.002	0.018	-0.041	1.000	0.053	0.021	0.053	-0.060	-0.019	0.014	0.040
DDEXP	-0.123	-0.047	-0.057	0.053	1.000	0.018	0.155	-0.026	-0.203	0.016	-0.046
DDGDP	0.002	0.081	-0.036	0.021	0.018	1.000	0.014	0.002	-0.059	-0.035	-0.055
DFORIMP	-0.029	-0.070	-0.050	0.053	0.155	0.014	1.000	-0.010	0.035	-0.018	-0.068
DOPEN	0.013	0.004	0.002	-0.060	-0.026	0.002	-0.010	1.000	0.009	0.008	-0.028
FISGDP	0.133	0.126	0.105	-0.019	-0.203	-0.059	0.035	0.009	1.000	0.019	0.311

INFL	-0.057	-0.034	-0.021	0.014	0.016	-0.035	-0.018	0.008	0.019	1.000	-0.030
RGDP	0.203	0.176	0.178	0.040	-0.046	-0.055	-0.068	-0.028	0.311	-0.030	1.000

Source: Compiled by author

The results obtained from table 4.11-4.18 above indicate a high correlation amongst a few of the variables. These variables include DDEXP and DDGDP that show a correlation of 0.749 within the group of European economies. In addition, DDGDP and DGDPPC display a correlation of 0.888 as well as DOPEN and DGDPPC with a correlation of -0.836, within the group of Asian economies. Furthermore, DDGDP and DGDPPC indicate a correlation of 0.770. This suggests that the empirical models may have potential problems with multicolinearity and therefore these combinations of variables should not be estimated together in order to prevent spurious results.

4.5 THE CHOSEN ESTIMATION METHODS

The next section provides a thorough discussion of the chosen methods used in the conduct of the empirical analysis of the study. Each model portrays its theory with unique tests and methods inherent to its methodological approach. The results are summarised and graphically illustrated, concluding this part of the empirical study.

4.5.1 OLS model

Hutcheson (2011) explains that the OLS regression is a generalized linear estimation method that models a single response variable recorded on an interval scale. The OLS method applies to both singular and multiple explanatory variables as well as categorised explanatory variables. The regression is presented below:

$$Y_{it} = \beta X_{it} + \alpha_i + u_{it}$$

Y_{it} signifies the emerging market sovereign rating, whilst X_{it} symbolises the vector of macro-economic variables. Additionally, t represents the period of time and i the specific country. Furthermore, β is a vector of the coefficients and α_i signifies the individual error terms for each of the emerging economies. The disturbance term u_{it} is independent across the periods of time and different countries. The OLS approach has a fundamental drawback since this technique assumes that ratings have equally spaced intervals. In other words, the theory argues that an upgrade from level 7 to level 8 possesses the same value or significance as an upgrade from level 2 to level 3 (Erdem & Varli, 2014). The previous chapter gives evidence that this argument regarding the value of a certain rating is false. For that reason, the ordered probit model is employed to address this particular shortcoming of the OLS technique. However, in order to compare the results of all the available techniques, the OLS results are reported, with results from the other techniques, despite the critique against OLS.

4.5.2 Ordered probit model

Jackman (2000) states that the ordered probit model is an ordered response model that applies the probit link function. The primary principle of the ordered probit model is the latent continuous metric that underlies the ordinal response. Teker, Pala and Kent (2013) portray the ordered probit model as follows:

$$y_{it}^{*} = X_{it}\beta + \gamma Z_{it} + u_{it}$$

The sovereign ratings are represented by y_{it}^{*}, which is the unobserved latent variable of specific country i, in period t. The vector of time variant explanatory variables is expressed by X_{it} with β as a vector of unidentified parameters. Dummy variables are constant regressors of time and are denoted by Z_{it} and u_{it} the disturbance term has a standard normal distribution (Jackman, 2000).

Long and Freese (2006) assume that y_{it}^{*} relates to the identified variable y_i, which is the sovereign credit rating, in the following manner:

$$y_i = \begin{cases} 1 \; if \; y_{it}^{*} < \tau 1 \\ 2 \; if \; \tau 1 \leq y_{it}^{*} \leq \tau 2 \\ 3 \; if \; \tau 2 \leq y_{it}^{*} \leq \tau 3 \\ 4 \; if \; \tau 3 \leq y_{it}^{*} \leq \tau 4 \end{cases}$$

The threshold parameters, otherwise known as cut-points are given as τ_m.

4.5.3 Pooled OLS

The pooled OLS technique is the third and final model applied in this section of the empirical analysis. The basic version of the pooled model is illustrated below:

$$y_{it} = \alpha + \acute{X}_{it}\beta + u_{it},\ i = 1,\ldots., N, \quad t = 1,\ldots.,T.$$
$$E[\varepsilon_{it}\,|x_{i1}, x_{i2}, \ldots., x_{iTi}] = 0,$$
$$Var[\varepsilon_{it}\,|x_{i1}, x_{i2}, \ldots., x_{iTi}] = \sigma_\varepsilon^2$$
$$Cov\left[\varepsilon_{it}, \varepsilon_{js}\middle|x_{i1}, x_{i2}, \ldots., x_{iTi}\right] = 0 \text{ if } i \neq j \text{ or } t \neq s.$$

The assumptions of the conventional model, namely homoscedasticity, stringent exogeneity of X_{it}, freedom across observations i and zero conditional mean of the disturbance term u_{it}, are applicable (Greene, 2010). The pooled OLS is inconsistent when the true model is the fixed effects model. The model is thus altered to:

$$y_{it} = \alpha + \acute{X}_{it}\beta + (\alpha_i - \alpha + u_{it})$$

The pooled OLS is suitable if the constant-coefficients or random effects models are fitting.

Erdem and Varli (2014) indicate a prevalent empirical problem in all three estimation techniques, which pertain to sovereign ratings. The challenge with sovereign ratings is that the rating information does not always represent the current situation in a country for the reason that ratings represent data from the past. Rating assessments may therefore take several months to complete when a watch-period is publicly announced. In such cases, an autoregressive ARMA structure can prove useful.

In order to comprehend the functioning of a univariate ARMA model it is beneficial to divide the different fragments that the model is made up (Ling, 2006). Firstly, the AR (1) (autoregressive of order one) model signifies that a level of the dependent variable's present observations are dependent on the level of its lagged observations. The AR (1) model is given as:

$$X_t = \emptyset X_{t-1} + \varepsilon_t$$

Where ε_t ~ W N(0, σ_t^2). In a similar manner AR(p) (autoregressive of order p) is shown as:

$$\mathrm{X_t} = \emptyset_1 \mathrm{X_{t-1}} + \emptyset_2 \mathrm{X_{t-2}} + \cdots + \emptyset_\mathrm{p} \mathrm{X_{t-p}} + \varepsilon_\mathrm{t}$$

Secondly, the MA(1) (moving average of order one) models the observations of a random/explanatory variable at time t, which is not only affected by the shock at time t, but additionally the shock that has taken place prior to time t. The MA(1) model is illustrated as follows:

$$\mathrm{X_t} = \epsilon_\mathrm{t} + \theta\, \epsilon_{\mathrm{t-1}}$$

Once more ε_t ~ W N(0, σ_t^2). As with AR(p) equation, the MA(p) (moving average of order *p*) equation is presented as:

$$\mathrm{X_t} = \epsilon_\mathrm{t} + \theta_1\, \epsilon_{\mathrm{t-1}} + \ldots + \theta_\mathrm{p}\, \epsilon_{\mathrm{t-p}}$$

A general ARMA model is the result when these two models AR(1) and MA(1) are combined:

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \varepsilon_t + \theta_1\, \epsilon_{t-1} + \cdots + \theta_p\, \epsilon_{t-p}$$

However, the ARMA model can be presented in a more concise manner when lag operators are included. The index is moved back one time unit as a lag operator (implied by L) is applied. Similarly, the time unit is moved back *k* times by applying it *k* times.

$$Lx_t = x_{t-1}$$
$$L^2 x_t = x_{t-2}$$
$$L^k x_t = x_{t-k}$$

The ARMA model can be rewritten using lag operators as follows:

$$AR(1): (1 - \emptyset L)x_t = \varepsilon_t$$
$$AR(p): (1 - \emptyset_1 L - \emptyset_2 L^2 - \cdots - \emptyset_p L^p)x_t = \varepsilon_t$$

$$MA(1): x_t = (1 + \theta L)\varepsilon_t$$
$$MA(q): x_t = (1 + \emptyset_1 L + \emptyset_2 L^2 + \cdots + \theta_q L^q)\varepsilon_t$$

Where $\emptyset_0 = 1,\ \theta_0 = 1$ defines log polynomials:

$$\emptyset(L) = 1 - \emptyset_1 L - \emptyset_2 L^2 - \cdots - \emptyset_p L^p$$
$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_q L^q$$

The ARMA process can now be written in a more succinct manner with the lag polynomials:

$$AR: \emptyset(L)x_t = \varepsilon_t$$
$$MA: x_t = \theta(L)\varepsilon_t$$
$$ARMA: \emptyset(L)x_t = \theta(L)\varepsilon_t$$

4.6 RANDOM AND FIXED EFFECTS

4.6.1 Random effects

Schmidheiny (2014) gives a description of the subject, random effects, stating that the individual-specific effect is a random variable. In addition, it does not correlate with the explanatory variables. The random effects model is demonstrated below:

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + v_{it}$$

The random effects model has a few crucial features that are listed as follows:

1. *Unrelated effects*

   $E(c_i|X_i, z_i) = 0$

   The assumption is made that the individual specific effect is a random variable that does not correlate with the explanatory variables' timeframe that includes the past, present and future period for the same individual.

2. *Variance effect*

   $V(c_i|X_i, z_i) = \sigma_c^2 < \infty$ [Homoscedastic]

   $V(c_i|X_i, z_i) = \sigma_{c,i}^2(X_i, z_i) < \infty$ [Heteroscedastic]

The individual specific effect is assumed to have a constant variance.

3. *Identifiability*

   Rank (W) = K+M+1 < NT and E $(W'_i W_i) = Qww$ is finite. The characteristic element is $w'_{it} = [x'_{it}\ z'_i]$

   Rank(W) = K+M+1 < NT and E$(W'_i \Omega_{v,i}^{-1} W_i)$ = Q_{WOW} is finite, where $\Omega_{v,i} = V(v_i|X_i, z_i)$

   The assumption is made that the regressors together with a constant are not flawlessly collinear, but that all the regressors, excluding the constant, possess non-zero variance and few extreme values.

4.6.2 Fixed effects

According to Cameron and Trivedi (2013), fixed effect (FE) models define the individual effect as random with the possibility of correlation with the explanatory variables. Linear regression models eliminate the individual effect by either mean-differencing or first differencing. FE models control for the effects of time-invariant variables with time-invariant effects (William, 2015). The fixed effect model is shown below:

$$y_{it} = \beta_1 x_{it} + a_i + u_{it}$$
$$\bar{y}_i = \beta_1 \bar{x}_i + a_i + \bar{u}_i$$
$$(y_{it} - \bar{y}_i) = \beta_1(x_{it} - \bar{x}_i) + (u_{it} - \bar{u}_i)$$
$$\ddot{y}_{it} = \beta \ddot{x}_{it} + \ddot{u}_{it}$$

The fixed effect model, like the random effect model, also has a few essential characteristics that are presented as follow:

1. *Related effects*

   The fixed effect model explicitly states the absence of the unrelated effects found in the random effect model.

2. *Effect variance*

   The fixed effect model assumes the absence of the constant variance as established in the random effect model.

3. *Identifiability*

   Rank ($\bar{X}$) = K < NT and E ($\ddot{x}'_i \ddot{x}_i$) is finite and the characteristic element:

   $\ddot{x}_{it} = x_{it} - \bar{x}_i$ and $\bar{x}_i = 1/\mathrm{T} \sum_t x_{it}$

   The assumption is made that the time-varying explanatory variables are not flawlessly collinear and that non-zero variance exist, in other words, there is variation over time for each individual. Few extreme values exist and therefore x_{it} do not include any time-invariant or constant variables.

4.6.3 The Hausman specification test

Clark and Linzer (2012) observe that the core of the Hausman test is based on the random effect model. The objective of the Hausman test is to detect a violation in the assumption that the regressors are orthogonal to the unit effects of the random effect model. The null hypothesis of the Hausman Test states that the random effect model is the preferred model due to its efficiency. The alternative hypothesis specifies that the random effect model becomes inconsistent, whilst the fixed effect model is consistent (Erdem & Varli, 2014). If there is no correlation between the explanatory variables and the unit effects, it causes the estimates of β in the fixed effects model ($\hat{B}_{FE}$) to be similar to estimates of β in the random effects model ($\hat{B}_{RE}$). Consequently, the Hausman test statistic H is used as a measurement to determine the difference between the random effect estimate and the fixed effect estimate:

$$H = \left(\hat{B}_{RE} - \hat{B}_{FE}\right)' [Var\left(\hat{B}_{FE}\right) - Var\left(\hat{B}_{RE}\right)]^{-1} (\hat{B}_{RE} - \hat{B}_{FE}).$$

Under the null hypothesis of orthogonality, H is distributed chi-square with degrees of freedom equal to the amount of explanatory variables in the model. A test result of p < 0.05 is an indication that at orthodox levels of significance, the difference between the two models is large enough to reject the null hypothesis. Resultantly, the random effects model is rejected and the fixed effects model accepted. However, if the test result does not suggest a significant difference p > 0.05, the random effects estimator is accepted instead of the fixed effects model (Clark & Linzer, 2012).

4.7 TESTING FOR CO-INTEGRATION

Ericsson (1991) defines co-integration as a statistical property that may possibly exemplify the long-term behaviour of economic time series as introduced by Engle and Granger (1987). For a long run relationship or equilibrium to exist, the requisite is a linear combination of Y_t and X_t that is a stationary variable *I* (0). QMS (2009) supplies a mathematical approach to co-integration in to comprehend the subject matter at hand.

The regression is given as follows:

$$Y_t = \beta_1 + \beta_2 X_t + u_t$$

With residuals: $$\hat{u}_t = Y_t - \hat{\beta}_1 - \hat{\beta}_2 X_t$$

If $\hat{u}_t$ ~ *I*(0), at that point variables Y_t and X_t are understood to be cointegrated in the long run.

4.7.1 The Kao Co-integration Test

The null-hypothesis of the Koa Test is that of no-co-integration. In other words, if the null-hypothesis is rejected the result is the existence of co-integration, which indicates that the variables move together over time. Kao (1999) presents both ADF and DF-type of tests to measure co-integration in a panel data structure. The model is as follows:

$$Y_{it} = a_i + \beta X_{it} + u_{it}$$

The residual based co-integration test is applied to the model:

$$u_{it} = e u_{it-1} + v_{it}$$

Where ρ is given as:

$$\hat{\rho} = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T} u_{it}\, u_{it-1}}{\sum_{i=1}^{N}\sum_{t=2}^{T} u_{it}^2}$$

With its corresponding t statistic:

$$t_\rho = \frac{(\hat{\rho}-1)\sqrt{\sum_{i=1}^{N}\sum_{t=2}^{T} u_{it}^2}}{1/(NT)\sum_{i=1}^{N}\sum_{t=2}^{T}(u_{it} - \hat{\rho}\, u_{it-1})^2}$$

Kao suggests four types of DF- tests, the first two DF_ρ and DF_t have a robust exogenous relationship between regressors and errors. An endogenous relationship between the regressors and errors exists for the last two tests DF_ρ^* and DF_t^*. Koa's four tests are stipulated below:

$$DF_\rho = \frac{\sqrt{N}\,T(\hat{\rho}-1) + 3\sqrt{N}}{\sqrt{10.2}}$$

$$DF_t = \sqrt{1.25}\,t_p + \sqrt{1.875N}$$

$$\mathrm{DF}_{\rho}^{*} = \frac{\sqrt{N}\,T(\hat{\rho}-1) + 3\sqrt{N}\,\hat{\sigma}_v^2/\hat{\sigma}_{0v}^2}{\sqrt{3 + 36\hat{\sigma}_v^4/(5\hat{\sigma}_{0v}^4)}}$$

$$\mathrm{DF}_{t}^{*} = \frac{t_\rho + \sqrt{6N}\,\hat{\sigma}_v/2\hat{\sigma}_{0v}}{\sqrt{\hat{\sigma}_{0v}^2/(2\hat{\sigma}_v^2) + 3\hat{\sigma}_v^2/(10\hat{\sigma}_{0v}^2)}}$$

In addition, Koa also proposes an ADF that has the same null hypothesis as the DF tests which is that of no-co-integration, as mentioned earlier in the chapter. The regression is as follows:

$$u_{i,t} = \rho u_{i,t-1} + \sum_{j=1}^{n} \phi j \Delta u_{i,t-j} + v_{it}$$

The ADF test statistic is estimated below, where $tADF$ signifies the ADF statistic of the regression given above:

$$\mathrm{ADF} = \frac{tADF + \sqrt{6N}\,\hat{\sigma}_v/(2\hat{\sigma}_{0v})}{\sqrt{\hat{\sigma}_{0v}^2/(2\hat{\sigma}_v^2) + 3\hat{\sigma}_v^2/(10\hat{\sigma}_{0v}^2)}}$$

4.7.2 Kao Co-integration test results

The Kao Co-integration test estimations are performed on all the country-categories for all three credit rating agencies.[2] The results for each country-category are summarised below – based on data of the three credit-rating agencies**:**

[2] The results are available from the author on request

- Advanced economies: Reject the null-hypothesis for each rating agency since 0.000 < 0.05. The results therefore indicate the existence of co-integration, which suggests that the variables move together over time.
- Secondary economies: Reject the null-hypothesis for each rating agency since 0.000 < 0.05. The results therefore identify the existence of co-integration, which suggests that the variables move together over time.
- Frontier economies: Reject the null hypothesis for each rating agency since 000 < 0.05. The results therefore indicate the existence of co-integration, which suggests that the variables move together over time.
- European economies: Reject the null hypothesis for each rating agency since 0.000 < 0.05. The results therefore indicate the existence of co-integration, which suggests that the variables move together over time.
- Asian economies: Reject the null hypothesis for each rating agency since 0.000 < 0.05. The results therefore indicate the existence of co-integration, which suggests that the variables move together over time.
- American economies: Reject the null hypothesis for each rating agency since 0.000 < 0.05. The results therefore indicate the existence of co-integration, which suggests that the variables move together over time.
- FTSE economies: Reject the null hypothesis for each rating agency since 0.000 < 0.05. The results therefore indicate the existence of co-integration, which suggests that the variables move together over time.
- Regional economies: Reject the null hypothesis for each rating agency since 0.000 < 0.05. The results therefore indicate the existence of co-integration, which suggests that the variables move together over time.

4.8 DISCUSSION OF ORDERED PROBIT, OLS AND POOLED MODELS

The objective of this chapter is to determine which macro-economic variables have a significant influence on sovereign ratings of Standard & Poor's, Moody's and Fitch. The estimation process started with a detailed description of the data followed by graphs that are given as an illustration to suggest either stationarity or non-stationarity within the data. The graphical representation is, however, not enough to determine unit roots and therefore three different formal unit root test are performed as a means to prevent spurious result. The three tests are Levin, Lin and Chu

(2002), Im, Perseran and Shin (2003) and Hadri (2000). After the results were obtained from the unit root tests, correlation matrices were done to eliminate variables that would cause multicolinearity, which yields false results. South Africa is the only economy included in the group of African economies and therefore cannot be empirically estimated on its own. South Africa is henceforth included in the estimations of the advanced economies, the March 2014 FTSE Global Equity Index Series: *Regional Classification* and in the March 2014 FTSE Global Equity Index Series: *Country Classification*. Accordingly, the following variables of each country category remained and are used in further estimations, after the unit root tests.

- **Advanced economies**: STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, REER, RGDP, DGDP, DH, CI, and GDPPC.
- **Secondary economies**: STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, REER, RGDP, DGDP, DH, CI and GDPPC.
- **Frontier economies:** STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, RGDP, DH, CI and GDPPC.
- **European economies:** STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, RGDP, DGDP, DH, CI and GDPPC.
- **Asian economies:** STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, RGDP, DGDP, DH, CI and GDPPC.
- **American economies:** STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, RGDP, DGDP, CAGDP, DH, CI and GDPPC.
- **March 2014 FTSE Global Equity Index Series: *Country Classification*:** STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, RGDP, DGDP, DH, and CI.
- **March 2014 FTSE Global Equity Index Series: *Regional Classification*:** STANDARD & POOR’S, MOODY’S, FITCH, FISGDP, INFL, DEXP, FORIMP, OPEN, RGDP, DGDP, CI, DH and GDPPC.

The chosen estimation techniques are (i) the ordered probit method followed by the (ii) OLS method with panel options fixed and random effects and (iii) the pooled OLS method with panel options fixed and random effects. Only some of the country-categories were able to estimate AR(1) and MA(1) models and these few models will be identified in the discussion of each result that follows. The AR model will be indicated as (AR1) and the MA model will be indicated as (-1). Before interpreting the results, the literature and theoretic background with regard to the expected sign of each variable is mentioned briefly as a full discussion of each variable has been given in chapter 2.

The expected signs are as follows: Fiscal balance as a percentage of GDP (+), Current account as a percentage of GDP (-), Inflation (-), GDP per capita (+), Corruption index, proxy for economic development (+), External debt as a percentage of GDP (-), External debt as a percentage of Exports (-), Reserves as a percentage of Imports (+), Real GDP Growth (+), Real Effective Exchange Rate (-), Default History (-) and Openness (+).

4.8.1 Ordered probit model estimation results

Table 4.19 represents the estimation results of the ordered probit model for all country-categories. The variables included in the results of the country-categories differ for each rating agency, according to the significance of each variable. The results of each of the three credit rating agencies are specified with the coefficient and probability of each macro-economic variable.

Table 4.19: Ordered probit model-Standard & Poor's, Moody's and Fitch (Appendix D: Table 7.25-7.60)

ORDERED PROBIT MODEL ESTIMATION RESULTS *– ADVANCED ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP	0.0432	0.0971			0.0502	0.0587
FISGDP(-1)	0.0433	0.0983				
RGDP	0.0912	0.0209			0.0883	0.0337
REER					0.0466	0.0812
DOPEN			-1.0453	0.0853		
ORDERED PROBIT MODEL ESTIMATION RESULTS						

– SECONDARY ECONOMIES						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP					0.1010	0.0171

ORDERED PROBIT MODEL ESTIMATION RESULTS

– FRONTIER ECONOMIES

VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP	0.0433	0.0808	0.0968	0.0047	0.0627	0.0173
DRGDP	0.0715	0.0704				
DDEXP			-0.0105	0.0784		

ORDERED PROBIT MODEL ESTIMATION RESULTS

– EUROPEAN ECONOMIES

VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP			0.0633	0.0130		
RGDP	0.1451	0.0003	0.0818	0.0005	0.1039	0.0000
RGDP(-1)	-0.0666	0.0925				

ORDERED PROBIT MODEL ESTIMATION RESULTS

– AMERICAN ECONOMIES

VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP	0.0489	0.0943				
RGDP					0.1022	0.0092
DDEXP					-0.0009	0.0880

ORDERED PROBIT MODEL ESTIMATION RESULTS

– FTSE ECONOMIES

VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP	0.0808	0.0000	0.0673	0.0001	0.0944	0.0000
DDEXP	-0.0012	0.0112			-0.0011	0.0507
DDEXP(-1)					-0.0010	0.0660
FISGDP			0.0434	0.0207		
FISGDP(-1)			0.0426	0.0210		

ORDERED PROBIT MODEL ESTIMATION RESULTS

– REGIONAL ECONOMIES

VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP	0.0262	0.0960	0.0343	0.0711		
FISGDP(-1)			0.0309	0.0996		
RGDP	0.0742	0.0000	0.0690	0.0001	0.0945	0.0000

DDEXP	-0.0011 0.0321		-0.0011 0.0477
DDEXP(-1)			-0.0009 0.0791

Source: Compiled by author

A p-value refers to the probability of attaining an observed effect under a null hypothesis. The p-value is interpreted by scrutinising whether the value is smaller than the particular threshold value. The specific threshold value is defined as a value that is either less than (< 0.05) for a confidence interval of 95% or less than (< 0.1) for a confidence interval of 90% or less than (< 0.01) for a confidence interval of 99% that is reported as statistically significant (Crombie, 2009). The sign of the coefficient, either positive or negative, indicates the direction in which the macro-economic variables influence the three rating agencies' sovereign ratings. See appendix E for a complete discussion of the estimation results.

4.8.1.1 Advanced economies

- *Standard & Poor's:* FISGDP, the previous quarter of FISGDP and RGDP influences the sovereign ratings of Standard & Poor's. The variable that has the largest influence is RGDP, according to the assessment of the coefficient and probability.
- *Moody's:* Based on the assessment of the coefficient and probability values, DOPEN predominantly influences Moody's sovereign ratings negatively.
- *Fitch:* FISGDP, RGDP and the REER positively influence the sovereign ratings of Fitch. This study determines that RGDP is the most influential variable when assigning sovereign ratings by Fitch.

4.8.1.2 Secondary economies

- *Fitch:* The only credit rating agency within the secondary economies that experienced a significant relationship with a macro-economic variable is Fitch. RGDP is the most influential variable that has a positive influence on sovereign ratings assigned by Fitch.

4.8.1.3 Frontier economies

- *Standard & Poor's:* According to the coefficient and probability values, FISGDP and DRGDP are variables that positively influence the sovereign ratings of

Standard & Poor's. This study identifies DRGDP as the variable that mostly influences the sovereign ratings of Standard & Poor's.

- *Moody's:* DDEXP has a negative effect on Moody's sovereign ratings. However, FISGDP has a positive and predominant relationship.
- *Fitch:* A positive relationship between FISGDP and the sovereign ratings of Fitch exists.

4.8.1.4 European economies

- *Standard & Poor's:* This study identifies RGDP as the main determining variable that has a positive influence on sovereign ratings assigned by Standard & Poor's. On the contrary, the previous quarter of RGDP is the main determining variable that has a negative influence. RGDP is therefore the most influential variable when assigning sovereign ratings by Standard & Poor's.
- *Moody's:* FISGDP and RGDP both have a positive relationship with sovereign ratings assigned by Moody's. Although, the variable that has the most dominant influence is RGDP.
- *Fitch:* This study identifies RGDP as the main and only variable that influences the sovereign ratings of Fitch in a positive manner.

4.8.1.5 American economies

- *Standard & Poor's:* Based on the assessment of the coefficient and probability values, FISGDP is the only variable that has a positive and predominant effect on sovereign ratings assigned by Standard & Poor's.
- *Fitch:* DDEXP has a negative influence on sovereign ratings assigned by Fitch, whilst RGDP has shown a positive relationship. The variable that has the largest effect on Moody's ratings is the RGDP, according to the assessment of the coefficient and probability.

4.8.1.6 FTSE economies

- *Standard & Poor's:* The variables that have a significant influence on sovereign ratings assigned by Standard & Poor's are RGDP and DDEXP. A positive relationship exists between RGDP and sovereign ratings, whilst a negative relationship exists between DDEXP and sovereign ratings. RGDP has the most influence on sovereign ratings assigned by *Standard & Poor's*.

- *Moody's:* Three variables mainly affect the sovereign ratings assigned by Moody's, namely RGDP, FISGDP and the previous quarter of FISGDP. Positive relationships exist with all three variables and the most influential variable is RGDP, according to the assessment of the coefficient and probability.
- *Fitch:* A positive relationship exists between RGDP and sovereign ratings assigned by Fitch. Conversely, two variables that have a negative influence are identified as well, namely FISGDP and DDEXP. The variable that has the largest influence on sovereign ratings assigned by Fitch is FISGDP.

4.8.1.7 Regional economies

- *Standard & Poor's*: This study determines that both FISGDP and RGDP have a positive impact on sovereign ratings assigned by Standard & Poor's. However, DDEXP is determined as a variable that has a negative influence. The variable that predominantly influences the sovereign ratings of Standard & Poor's ratings is FISGDP.
- *Moody's:* Based on the assessment of the coefficient and probability values, RGDP, FISGDP and the previous quarter of FISGDP have a positive influence on sovereign ratings assigned by Moody's. However, the most significant determinant is FISGDP.
- *Fitch:* DDEXP and the previous quarter of DDEXP have negative affects n sovereign ratings assigned by Fitch. In contrast, FISGDP shows a positive influence. The previous quarter of DDEXP is determined as the most influential variable when assigning sovereign ratings by Fitch.

4.8.2 OLS model

Table 4.20 represent the estimation results of the OLS model for all country-categories. The table below demonstrates the estimated coefficients and probability of each macro-economic for each rating agency.

Table 4.20: OLS model-Standard & Poor's, Moody's and Fitch[3]

OLS MODEL ESTIMATION RESULTS – *ADVANCED ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP	0.0094	0.0533			0.0092	0.0259
RGDP	0.0173	0.0103			0.0119	0.0373
REER	0.0085	0.0691			0.0069	0.0834
DOPEN			-0.3010	0.0221		
OLS MODEL ESTIMATION RESULTS – *SECONDARY ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP					0.0141	0.0252
OLS MODEL ESTIMATION RESULTS – *FRONTIER ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP	0.0166	0.0837	0.0165	0.0120	0.0244	0.0669
DRGDP	0.0285	0.0666				
DDEXP			-0.0026	0.0654		
AR(1)					-0.4853	0.0000
OLS MODEL ESTIMATION RESULTS – *EUROPEAN COUNTIRES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP	0.0321	0.0001	0.0184	0.0000	0.0211	0.0000
RGDP(-1)	-0.0170	0.0396				
AR(1)					-0.1099	0.0539
OLS MODEL ESTIMATION RESULTS – *AMERICAN ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP	0.0215	0.0755				
DOPEN			-0.2843	0.0425		
RGDP					0.0440	0.0452
OLS MODEL ESTIMATION RESULTS – *ASIAN ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	

[3] Detailed results are available from author on request

	COEF	PROB	COEF	PROB	COEF	PROB
DOPEN					-0.0017	0.0338
OLS MODEL ESTIMATION RESULTS *– FTSE ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DDEXP	-0.0004	0.0068				
RGDP	0.0189	0.0000	0.0121	0.0006	0.0232	0.0000
FISGDP			0.0064	0.0716		
OLS MODEL ESTIMATION RESULTS *– REGIONAL ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DDEXP	-0.0004	0.0034				
FISGDP			0.0066	0.0465		
RGDP			0.0123	0.0002	0.0220	0.0000

Source: Compiled by author

4.8.2.1 Advanced economies

- *Standard & Poor's:* Three variables have a positive relationship with sovereign ratings assigned by Standard & Poor's and these variables FISGDP, RGDP and REER. RGDP has the largest influence on sovereign ratings by Standard & Poor's.
- *Moody's:* The only significant variable in determining the sovereign ratings of Moody's is DOPEN and it has a negative effect on the sovereign ratings.
- *Fitch:* This study identifies three variables that have positive influences on sovereign ratings assigned by Fitch. These variables include FISGDP, RGDP and REER. The most influential variable of the three is RGDP.

4.8.2.2 Secondary economies

- *Fitch:* The only credit rating agency within the secondary economies that experienced a significant relationship with macro-economic variables is Fitch. A positive relationship exists between RGDP and sovereign ratings assigned by Fitch.

4.8.2.3 Frontier economies

- *Standard & Poor's:* Based on the assessment of the coefficient and probability values, FISGDP and DRGDP have a positive impact on sovereign ratings assigned by Standard & Poor's. The predominant variable between the two significant variables is identified as DRGDP.

- *Moody's:* This study determines both a negative and positive relationship between the macro-economic variables and sovereign ratings assigned by Moody's. A positive relationship exists with FISGDP, whilst a negative relationship exists with DDEXP. The variable that has a predominant effect on Moody's sovereign ratings is FISGDP.
- *Fitch:* FISGDP has a positive influence on sovereign ratings assigned by Fitch. Whereas the previous quarter of the dependent variable Fitch, AR(1), predominantly influence sovereign ratings in a negative manner.

4.8.2.4 European economies

- *Standard & Poor's:* The sovereign ratings assigned by Standard & Poor's are positively influenced by RGDP and negatively influenced by past values of RGDP. Ultimately, real GDP growth is determined as the most influential variable.
- *Moody's:* RGDP is the only significant variable and has a positive relationship with sovereign ratings assigned by Moody's.
- *Fitch:* Based on the assessment of the coefficient and probability values, FISGDP has a positive impact on sovereign ratings assigned by Fitch. On the contrary, the previous quarter of the dependent variable Fitch, AR(1), has a negative influence on sovereign ratings assigned by Fitch.

4.8.2.5 Asian economies

- *Fitch:* The only credit rating agency within the Asian economies that experienced a significant relationship with a macro-economic variable is Fitch. RGDP has a negative influence and is the most influential variable in determining sovereign ratings assigned by Fitch.

4.8.2.6 American economies

- *Standard & Poor's:* This study identifies a positive relationship between FISGDP and sovereign ratings assigned by Fitch. FISGDP is the only significant variable and therefore has the largest influence on sovereign ratings

- *Moody's:* DOPEN is the only variable found to be significant and has a negative impact on sovereign ratings assigned by Moody's, based on the assessment of the coefficient and probability values.
- *Fitch:* A positive relationship exists between RGDP and the sovereign ratings assigned by Moody's. RGDP is therefore the predominant determinant of sovereign ratings.

4.8.2.7 FTSE economies

- *Standard & Poor's:* This study determines a positive relationship between RGDP and sovereign ratings assigned by Standard & Poor's, but also a negative relationship with DDEXP. RGDP is the main variable influencing ratings of *Standard & Poor's*, according to the assessment of the coefficient and probability.
- *Moody's:* RGDP and FISGDP both have positive relationships with sovereign ratings assigned by Moody's. Based on assessment of the coefficient and probability, RGDP has the largest influence on sovereign ratings assigned by Moody's.
- *Fitch:* RGDP is the only variable that is significant and shows a positive relationship with sovereign ratings assigned by Fitch.

4.8.2.8 Regional economies

- *Standard & Poor's:* According to the assessment of the coefficient and probability, DDEXP is identified as the only significant variable. DDEXP has a negative influence on sovereign ratings assigned by Standard & Poor's.
- *Moody's:* Two variables demonstrate a positive influence on sovereign ratings assigned by Moody's. These variables are FISGDP and RGDP and this study identifies RGDP as the variable that has the largest influence on sovereign ratings.
- *Fitch:* Based on the assessment of the coefficient and probability values, RGDP demonstrates a positive relationship with sovereign ratings assigned by Fitch.

4.8.3 OLS fixed and random effects models

Table 4.21 represents the estimation results of the OLS fixed and random effects for all country-categories. The Hausman specification test is applied and the results obtained from the test are given in brackets, next to each variable. The Hausman test statistic H is used as a measure to determine the difference between the random effect estimate and the fixed effect estimate, selecting the most efficient estimate (Clark & Linzer, 2012). Pretorius and Botha (2014) found that in most cases the random effects model turns out to be the most appropriate model. The three credit-rating agencies are specified with the coefficient and probability of each macro-economic variable.

Table 4.21: OLS models, the Hausman Specification Test with fixed and random effects-Standard & Poor's, Moody's and Fitch[4]

OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– ADVANCED ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP [RANDOM]	0.0161	0.0217				
REER [RANDOM]	0.0088	0.0612			0.0067	0.0897
DOPEN [RANDOM]			-0.3316	0.0107		
DDGDP [RANDOM]					-0.0001	0.0635
OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– FRONTIER ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP [RANDOM]			0.0190	0.0108	0.0432	0.0601
DRGDP [RANDOM]	0.0246	0.0827				
DDEXP [RANDOM]	-0.0134	0.0000				
OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– EUROPEAN ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP[RANDOM/FIXED]	0.0156	0.0002	0.0156	0.0139	0.0184	0.0000
OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– ASIA ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DOPEN [RANDOM]					-0.0018	0.0330
OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– AMERICAN ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB

[4] Detailed results are available from author on request

DOPEN [RANDOM]			-0.3055	0.0321		
RGDP [RANDOM]					0.0483	0.0633
OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– FTSE ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP [RANDOM]	0.0180	0.0001	0.0129	0.0008	0.0235	0.0003
DDEXP [RANDOM]	-0.0003	0.0112				
OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– REGIONAL ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
RGDP [RANDOM]			0.0132	0.0005	0.0235	0.0002
DDEXP [RANDOM]	-0.0004	0.0063				

Source: Compiled by author

4.8.3.1 Advanced economies

- ***Standard & Poor's:*** RGDP and REER both influence the sovereign ratings of Standard & Poor's positively. The most influential variable is RGDP, according to the assessment of the random effect coefficient.
- ***Moody's:*** DOPEN is the only variable found to be significant. DOPEN negatively influences the sovereign ratings assigned by Moody's.
- ***Fitch:*** Based on the assessment of the coefficient and probability values, the sovereign ratings of Fitch are influenced by REER and DDGDP. REER demonstrates a positive relationship, whilst DDGDP demonstrates a negative relationship. This study identifies REER as the variable that has the largest influence on sovereign ratings assigned by Fitch.

4.8.3.2 Frontier economies

- ***Standard & Poor's:*** The sovereign ratings of *Standard & Poor's* are positively influenced by DRGDP and negatively influenced by DDEXP. DRGDP has shown to be the predominant determinant of sovereign ratings assigned by Standard & Poor's.
- ***Moody's:*** Based on the assessment of the coefficient and probability values, FISGDP is the only variable found to be significant. FISGDP has a positive influence on sovereign ratings assigned by Moody's.

- *Fitch:* FISGDP demonstrates a positive relationship with sovereign ratings assigned by Fitch. FISGDP is the variable that has the largest influence in this regard.

4.8.3.3 European economies

- *Standard & Poor's:* RGDP is the only variable that was found to be significant. The sovereign ratings assigned by Standard & Poor's are therefore largely influenced by RGDP, which has a positive influence.
- *Moody's:* According to the assessment of the coefficient and probability values, RGDP is the only variable found to be significant. Therefore, RGDP is the main variable that influences sovereign ratings assigned by Moody's.
- *Fitch:* The sovereign ratings assigned by Fitch are predominantly influenced by FISGDP, which has a positive impact on sovereign ratings.

4.8.3.4 Asian economies

- *Fitch:* DOPEN is the only variable found to be significant. DOPEN has a negative impact on sovereign ratings assigned by Fitch, according to the assessment of the coefficient and probability values.

4.8.3.5 American economies

- *Moody's:* According to the assessment of the coefficient and probability values, DOPEN has a negative influence on sovereign ratings assigned by Moody's.
- *Fitch:* This study determines a positive relationship between RGDP and sovereign ratings assigned by Moody's. RGDP is the most influential variable in this regard.

4.8.3.6 FTSE economies

- *Standard & Poor's:* Two variables demonstrate a relationship with sovereign ratings and these variables are RGDP and DDEXP. RGDP has a positive influence, whilst DDEXP has a negative influence. RGDP is the main variable influencing sovereign ratings assigned by Standard & Poor's.
- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The variable that has the largest impact on sovereign ratings in this regard is thus RGDP.

- *Fitch:* The sovereign ratings assigned by Fitch are predominantly influenced by RGDP, which has a positive influence on sovereign ratings.

4.8.3.7 Regional economies

- *Standard & Poor's:* DDEXP is determined as the most influential variable that has a negative influence on sovereign ratings assigned by Standard & Poor's.
- *Moody's:* Based on the assessment of the coefficient and probability values, a positive relationship exists between RGDP and sovereign ratings assigned by Moody's.
- *Fitch:* This study demonstrates a relationship between RGDP and sovereign ratings assigned by Fitch. RGDP has a positive influence and is also the variable that has the largest impact on sovereign ratings, in this regard.

4.8.4 Pooled OLS models

Table 4.22 represents the estimation results of the pooled OLS model for all country-categories. The three credit rating agencies are specified with the coefficient and probability of each macro-economic variable.

Table 4.22: Pooled OLS models-Standard & Poor's, Moody's and Fitch[5]

POOLED OLS MODEL ESTIMATION RESULTS – *ADVANCED ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DDEXP?	-0.0002	0.0223			-0.0002	0.0147
DRGDP?	0.0159	0.0231				
REER?	0.0089	0.0575			0.0073	0.0709
POOLED OLS MODEL ESTIMATION RESULTS – *SECONDARY ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DRGDP?					0.0147	0.0483
POOLED OLS MODEL ESTIMATION RESULTS – *FRONTIER ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	

[5] Detailed results are available from the author on request

	COEF	PROB	COEF	PROB	COEF	PROB
FISGDP?					0.0244	0.0669
DRGDP?	0.0287	0.0679				
DDGDP?	-0.0063	0.0449	-0.0040	0.0508		
AR(1)					-0.4853	0.0000
POOLED OLS MODEL ESTIMATION RESULTS *– EUROPEAN ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DFISGDP?	0.1179	0.0934				
DRGDP?	0.4707	0.0000			0.0092	0.0989
DDGDP?	0.1179	0.0934			-0.0030	0.0211
POOLED OLS SQUARES MODEL ESTIMATION RESULTS *– ASIAN ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DFISGDP?						
DOPEN?					-0.0030	0.0019
DRGDP?			0.01640	0.0255	0.0131	0.0135
POOLED OLS MODEL ESTIMATION RESULTS *– AMERICAN ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DOPEN?			-0.2465	0.0782		
DCAGDP?			-0.0006	0.0359		
POOLED OLS MODEL ESTIMATION RESULTS *– FTSE ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DRGDP?	0.0160	0.0075				
POOLED OLS MODEL ESTIMATION RESULTS *– REGIONAL ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DRGDP?	0.0166	0.0083	0.0105	0.0446		

Source: Compiled by author

4.8.4.1 Advanced economies

- ***Standard & Poor's:*** Two variables that have an influence on sovereign ratings assigned by Standard & Poor's are DDEXP and DRGDP. DDEXP has a negative relationship, whereas DRGDP has a positive relationship with sovereign ratings. DRGDP is determined as the most influential variable when assigning sovereign ratings by Standard & Poor’s.

- *Fitch:* According to the assessment of the coefficient and probability values, REER has a positive influence, whilst DDEXP has a negative influence on sovereign ratings assigned by Fitch. REER has the largest impact in this regard.

4.8.4.2 Secondary economies

- *Fitch:* DRGDP is the only variable that is found to be significant. DRGDP has a positive influence on sovereign ratings assigned by Fitch.

4.8.4.3 Frontier economies

- *Standard & Poor’s:* This study demonstrates an existing relationship between DRGDP and sovereign ratings assigned by Standard & Poor’s, according to the assessment of the coefficient and probability.
- *Moody’s:* The variable that has the most predominant effect on sovereign ratings as assigned by Moody’s is DDGDP. DDGDP has a negative impact in this regard.
- *Fitch:* FISGDP and the previous quarter of the dependent variable Fitch, an AR(1) model has an influence on sovereign ratings assigned by Fitch. FISGDP has a positive impact, whilst the AR1 model, that is the previous quarter of the dependent variable Fitch, has a negative influence. Fitch is predominantly influenced by FISGDP, based on the assessment of the coefficient and probability.

4.8.4.4 European economies

- *Standard & Poor’s:* According to the assessment of the coefficient and probability, three variables have an influence on sovereign ratings assigned by Standard & Poor’s. These variables are DFISGDP that has a positive impact, RGDP that also has a positive impact and DDEXP that has a negative impact. FISGDP is determined as the most influential variable when assigning sovereign ratings by Standard & Poor’s.
- *Fitch:* Two variables influence sovereign ratings assigned by Fitch. These variables are DRGDP and DDEXP. DRGDP has a positive influence, whilst

DDEXP has a negative influence. The variable that has the main influence on Fitch is DRGDP.

4.8.4.5 Asian economies

- *Moody's:* This study demonstrates an existing relationship between DRGDP and sovereign ratings assigned by Moody's. DRGDP has a positive influence in this regard.
- *Fitch:* Based on the assessment of the coefficient and probability values, DOPEN and DRGDP both influence sovereign ratings assigned by Fitch. RGDP has a positive impact, whereas DOPEN has a negative impact. DRGDP has the largest influence on sovereign ratings assigned by Fitch.

4.8.4.6 American economies

- *Moody's:* DOPEN and DCAGDP influence the sovereign ratings assigned by Moody's. DOPEN as well as DCAGDP has a negative influence. The variable that has the largest effect on sovereign ratings assigned by Moody's is openness.

4.8.4.7 FTSE economies

- *Standard & Poor's:* DRGDP is the only variable found to be significant and consequently, the sovereign ratings assigned by Standard & Poor's are influenced by DRGDP. DRGDP has a positive impact, according to the assessment of the coefficient and probability.

4.8.4.8 Regional economies

- *Standard & Poor's:* This study demonstrates an existing relationship between DRGDP and sovereign ratings assigned by Standard & Poor's. DRGDP has a positive influence in this regard.
- *Moody's:* The sovereign ratings assigned by Moody's are influenced by DRGDP. DRGDP has a positive impact, based on the assessment of the coefficient and probability.

4.8.5 Pooled OLS fixed and random effects models

Table 4.23 represents the estimation results of the pooled OLS fixed and random effects model for all country-categories. The three credit rating agencies are specified with the coefficient and probability of each macro-economic variable.

Table 4.23: Pooled OLS fixed and random effects models-Standard & Poor's, Moody's and Fitch[6]

POOLED OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS – *ADVANCED ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
REER? [RANDOM]	0.0082	0.0793			0.0067	0.0635
DRGDP? [RANDOM]	0.0185	0.0232				
DDEXP? [RANDOM]	-0.0002	0.0266				
DDGDP? [RANDOM]					-0.0001	0.0897
DOPEN? [RANDOM]			-0.3314	0.0107		
POOLED OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS – *FRONTIER ECONOMIES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DRGDP? [RANDOM]	0.0285	0.0706				
DDGDP? [RANDOM]	-0.0056	0.0790				
DFISGDP? [RANDOM]					0.0398	0.0712
POOLED OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS – *EUROPEAN COUNTIRES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DDGDP? [RANDOM]					-0.0026	0.0441
POOLED OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS – *ASIAN COUNTIRES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DOPEN?[RANDOM]					-0.0032	0.0020
DFISGDP?[RANDOM]					0.0149	0.0199
POOLED OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS – *AMERICAN COUNTIRES*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	

6 Detailed results are available from the author on request

	COEF	PROB	COEF	PROB	COEF	PROB
DOPEN? [RANDOM]			-0.2701	0.0580		
DCAGDP?[RANDOM]			-0.0006	0.0354		
POOLED OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– FTSE CLASSIFICATION*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DRGDP? [RANDOM]	0.0192	0.0049				
POOLED OLS: FIXED/RANDOM EFFECTS MODEL ESTIMATION RESULTS *– REGIONAL CLASSIFICATION*						
VARIABLE	**STANDARD & POORS**		**MOODYS**		**FITCH**	
	COEF	PROB	COEF	PROB	COEF	PROB
DRGDP? [RANDOM]	0.0192	0.0078				

Source: Compiled by author

4.8.5.1 Advanced economies

- *Standard & Poor's:* REER, DRGDP and DDEXP demonstrate an existing relationship with sovereign ratings assigned by Standard & Poor's. REER and RGDP have a positive impact, whilst DDEXP has a negative impact. DRGDP is the most influential variable when assigning sovereign ratings by Standard & Poor's.
- *Moody's:* Two variables, namely REER and DDEXP sovereign ratings assigned by Moody's. Both variables have a negative impact and REER predominantly influences sovereign ratings in this regard.
- *Fitch:* DRGDP and DDGDP are found to be significant. Therefore, a positive relationship exists between DRGDP and sovereign ratings and a negative relationship exists between DDGDP and sovereign ratings.

4.8.5.2 Frontier economies

- *Standard & Poor's:* Based on the assessment of the coefficient and probability values, DRGDP has a positive impact and DDEXP has a negative impact on sovereign ratings. DRGDP is determined as the most influential variable when assigning sovereign ratings by Standard & Poor's.
- *Fitch:* DFISGDP is the only variable found to be significant. The sovereign ratings assigned by Fitch are predominantly influenced by DFISGDP, which has a positive influence.

4.8.5.3 European economies

- *<u>Fitch:</u>* DDGDP has the most influential impact on sovereign ratings assigned by Fitch. DDGDP demonstrates a negative influence based on the assessment of the coefficient and probability values.

4.8.5.4 Asian economies

- *<u>Fitch:</u>* This study demonstrates two variables that have an existing relationship with sovereign ratings. These variables are DDGDP that has a positive influence and DOPEN that has a negative influence. DDGDP is identified as the variable that has the largest influence on sovereign ratings assigned by Fitch.

4.8.5.5 American economies

- *<u>Moody's:</u>* DOPEN and DCAGDP are two variables that have a relationship with sovereign ratings assigned by Moody's. DOPEN has a negative impact, as well as DCAGDP. DOPEN is determined as the variable that has the most influence on sovereign ratings assigned by Moody's.

4.8.5.6 FTSE economies

- *<u>Standard & Poor's:</u>* DRGDP is the only variable found to be significant. DRGDP has a positive influence on sovereign ratings assigned by Standard & Poor's, based on the assessment of the random effects coefficient.

4.8.5.7 Regional economies

- *<u>Standard & Poor's</u>* - based on the assessment of the coefficient and probability values, DDEXP is found to be significant. DDEXP has a negative influence on sovereign ratings assigned by Standard & Poor's.

Lastly, Appendix E gives a complete discussion of the ordered probit, OLS and pooled OLS models' results.

4.9 CHAPTER SUMMARY

To conclude chapter 4, a brief summary is given concerning the results obtained in this chapter. There were two main objectives in this chapter. The first was to determine which macro-economic variables are significant and therefore have an effect on sovereign ratings of Standard & Poor's, Moody's and Fitch. The second objective was to identify which variables weigh the most in the decision making of each individual rating agency when assigning sovereign ratings for emerging market economies.

The results of the empirical analysis found seven macro-economic variables significant, which has a significant influence on sovereign ratings. These variables are fiscal balance as a percentage of GDP, external debt as a percentage of GDP, external debt as a percentage of exports, real GDP growth, real effective exchange rate and current account as a percentage of GDP. Cantor and Packer (1996) conclude that the main macro-economic indicators considered in the evaluation of sovereign ratings are per capita income, GDP growth, inflation, external debt, level of economic development, and default history. Erdem and Varli (2014) conclude their results from both the OLS analysis and the pooled OLS model. The results indicate that that the fiscal balance as a percentage of GDP, governance indicators, GDP per capita and reserves as a percentage of GDP has a significant influence on sovereign ratings.

The empirical results of this study indicate that the signs of the coefficients and the expected signs, according to literature, are in line with one another, with the only exception of openness. According to literature, the sign of the coefficient of openness should be positive; however, in this study the sign is empirically estimated as negative. A potential explanation for the negative sign could refer to the particular economies included within the study. Emerging market economies tend to have trade deficits, suggesting that the country's imports account to more than its exports. Economies that experience such trade deficits are termed import dependent economies and in this study, it includes Brazil, Bulgaria, India, Mexico, Poland, Slovakia, South Africa and Lithuania.

Three estimation techniques were applied to yield the empirical results. These three chosen methods are the ordered probit method followed by the OLS method with panel options fixed and random effects and the pooled least squares method with panel options fixed and random effects. There are only a few country categories that were able to estimate an AR(1) or MA(1) model. The ordered probit model yielded the same results as the two linear models, except external debt as a percentage of exports is also found to be a significant factor in the assessment of a sovereign's credit ratings. Regarding the methodological approach, the preferred model proved to be the ordered probit model, because of the discrete and ordinal nature of the dependent variable that is credit ratings. The favoured model is in line with other studies such as Amato and Furfine (2004), Bissoondoyal-Bheenick (2005), Hung, Cheng, Chen and Huang (2013) and Pretorius and Botha (2014).

The following are results of the summary of the three estimation techniques for each country-category. The results suggest that Standard & Poor's weights the (i) real GDP growth as the main influential variable as a variable that has a positive influence on sovereign ratings. Followed by (ii) external debt as a percentage of exports, that has a negative influence on sovereign ratings. In addition, (iii) fiscal balance as a percentage of GDP has a positive influence on sovereign ratings. Furthermore, (iv) the real effective exchange rate has a negative influence on sovereign ratings.

Moody's firstly weights the (i) real GDP growth as the most influential variable, that has a positive influence on sovereign ratings. Secondly, (ii) openness that has a negative influence on sovereign ratings, (iii) thirdly, fiscal balance as a percentage of GDP that has a positive influence on sovereign ratings and (iv) lastly, external debt as a percentage of exports, that has a negative influence on sovereign ratings.

Fitch weights the (i) real GDP growth as the most influential variable that has a positive influence on sovereign ratings. Moreover (ii) fiscal balance as a percentage of GDP has a positive influence on sovereign ratings. Additionally, (iii) the real effective exchange rate has a negative influence on sovereign ratings and (iv) finally, openness that has a negative influence on sovereign ratings. In comparison to previous studies regarding the weights assigned to macro-economic variables, Cantor and Packer (1996) establish that Moody's assigns more weight to external debt and less weight to default history as negative sovereign elements than Standard & Poor's does. In addition, Moody's assigns less weight to GDP per capita as a positive sovereign element. The empirical outcomes of this study did not, however, find the same variables significant as Cantor and Packer (1996), but the results from the study done by Alsakka and Gwilym (2012) are more in line with this study. A possible explanation could be based on the similarity of the samples of both Alsakka and Gwilym (2012) and this study. The results established that Standard & Poor’s assigns heavier weights to the following variables: Reserve to imports ratio and investment to GDP, Moody’s assigns heavier weights to the following variables: External debt, exports to imports, foreign reserves, fiscal balance, and GDP per capita. Fitch assigns heavier weights to the following variables: Fiscal balance, foreign reserves, GDP per capita, reserves to imports and exports to imports.

The groups of emerging market economies each conclude different results. Within the March 2014 FTSE Global Equity Index Series: *Country Classification*, the secondary economies produced the least number of significant variables for all three agencies. The Hausman specification test with fixed and random effects could not be estimated with the secondary economies. A possible explanation for the lack of significant variables could be the small panel of three emerging markets (China, Peru and Russia) in the secondary economies. Concerning the advanced and frontier economies, Standard & Poor’s assigns more weight to the variables in the advanced economies with the ordered probit model and thus rate the advanced economies more strictly than the frontier economies. However, the least squares and pooled model suggest the opposite. Standard & Poor’s assigns heavier weight to the variables in the Frontier economies and thus the Frontier economies are rated stricter than the advanced economies. A comparison between the advanced and frontier economies could not be done for Moody’s as there are not any similar variables in the different models.

Within the March 2014 FTSE Global Equity Index Series: *Regional Classification*, the Asian economies produced the least amount of significant variables for all three agencies. As with the secondary economies, a possible explanation for the lack of significant variables could be the small panel of three emerging markets (China, India and Indonesia) in the Asian economies. On the contrary, the European economies produced a large number of significant variables for all the estimation models (Ordered probit, least squares and Pooled). The European economies consist of eight emerging markets and a possible explanation for the satisfactory results could be the large panel. The March 2014 FTSE Global Equity Index Series: *Country Classification* and the March 2014 FTSE Global Equity Index Series:

Regional Classification produced the most beneficial results. These two groups have the largest panels and that probably explains the number of variables found to be significant for all three agencies.

5. CONCLUSION

5.1 INTRODUCTION

The recent global financial crisis highlighted numerous problems inherent the fundamental analytical structure and methodologies applied by Standard & Poor's, Moody's and Fitch. Research questions that this study addressed were to determine whether the weights assigned to each macro-economic variable are different for each credit rating agency and to determine the influence of changes in sovereign credit rating on capital flows to emerging market economies.

The first objective analysed if and how the weights assigned to macro-economic variables differ across the rating agencies. The second objective examined the effect of sovereign rating changes on capital flows to emerging market economies. In order to reach the main objectives this study identified the following secondary objectives: (i) with the assistance of theoretical information, the particular role of credit rating agencies in the current global economic environment; (ii) an assessment of the timing of upgrades or downgrades across the three agencies to determine whether a specific rating agency leads or follows rating changes or do the three agencies change ratings simultaneously, and (iii) categorising the emerging market economies in order to determine how the weights differ across country-categories.

This chapter provides conclusions concerning each of these objectives. Firstly, by providing conclusions regarding the two main objectives of this study and secondly, present a conclusion of the secondary objectives. This chapter additionally identifies the limitations of this study and concludes with some recommendations for future studies.

5.2 CONCLUSIONS

This section provides insight into the different weights assigned to the individual macro-economic variables and gives clarity on the potential differences amongst the three credit rating agencies.

5.2.1 Conclusions concerning the macro-economic variables that have an imperative influence on sovereign ratings

The results of the empirical analysis found seven macro-economic variables significant. These variables are fiscal balance as a percentage of GDP, external debt as a percentage of GDP, external debt as a percentage of exports, real GDP growth, real effective exchange rate and current account as a percentage of GDP

5.2.2 Conclusions concerning individual macro-economic variable weighting

The results of the three estimation techniques for each country-category establish that Standard & Poor's assigns heavier weights to (i) real GDP growth (positive factor) as the main influential variable, followed by (ii) external debt as a percentage of exports (negative factor), (iii) fiscal balance as a percentage of GDP (positive factor) and (iv) the real effective exchange rate (negative factor).

Moody's assigns heavier weights to (i) real GDP growth (positive factor) as the most influential variable, followed by (ii) openness (negative factor), (iii) fiscal balance as a percentage of GDP (positive factor) and (iv) external debt as a percentage of exports (negative factor).

Fitch assigns heavier weights to (i) real GDP growth (positive factor) as the most influential variable, followed by (ii) fiscal balance as a percentage of GDP (positive factor), (iii) the real effective exchange rate (negative factor) and (iv) openness (negative factor).

The results of this study, regarding the signs of the coefficients, are in line with the results of other studies. Openness is the only variable that does not have a similar link to theory. The empirical estimation suggests a negative sign for openness, whereas eminent literature suggests a positive sign. The specific choice of economies can potentially contribute to the negative sign. Economies such as Brazil, Bulgaria, India, Mexico, Poland, Slovakia and South Africa normally experience trade deficits. A trade deficit suggests that a country's imports account for more than its exports. Economies such as these are termed import dependent economies.

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5.2.3 Conclusions concerning rating changes on capital flows to emerging market economies

Eminent literature and empirical estimations indicated that flows of capital expressed through capital and financial accounts to emerging market economies are essential. Sovereign ratings particularly affect emerging market economies since these economies are highly dependent on international capital flows to finance foreign currency expenditures. Therefore, these economies aspire towards investment grade status because it reduces a sovereign's financing costs and default risk. Investment grade status attracts a greater pool of potential global investors seeking to capitalise on the emerging market economy. Capital flows change most significantly when economies upgrade from the non-investment grade barrier into investment grade or downgrade from the investment grade barrier into non-investment grade. This study produced four emerging market economies that breached the investment barrier, which include Cyprus, Hungary, Indonesia and Lithuania.

Granger causality established the direction of causality between the sovereign ratings and capital flows. Causality refers to the ability of a variable's past values to forecast another variable's future values. This study observed a bi-directional relationship between the dependent and independent variables. Therefore, not only do changes in sovereign ratings have an influence on the movement of capital flows, but so too do flows of capital affect sovereign ratings.

5.2.4 Conclusion concerning credit rating agencies' role in the current global economic environment

The recent global financial crisis drew attention to the weaknesses in the credit-rating industry. The role played by the credit rating agencies came under intense scrutiny during and after the financial crisis since acknowledging their errors partly contributed to escalating the crisis. The credit rating industry faces two major struggles, the first being the oligopolistic market structure and the second the inherent conflict of interest. The first problem results in three negative outcomes. Firstly, decreased productivity results in inaccurate ratings and methodological errors. Secondly, the oligopolistic market structure characterised by few market participants enables rating agencies to misuse their power because of their exclusive position in the industry. Lastly, restricted market entry prohibits any innovation to reconstruct rating methodologies within the industry.

The inherent conflict of interest stems from the issuer-pay model itself, because issuers pay agencies to assign ratings to their financial responsibilities. These circumstances are a cause for concern since conflict exists between the interest of issuers and investors. The issuers long to attain high ratings singe higher ratings produce a low interest rate in the global markets. In contrary, the investors seek accurate ratings with the goal of attaining lucrative investments. The big three agencies therefore face a major challenge assigning ratings because they are torn between serving the issuer that influence agency earnings and serving the public investors, seeking exact ratings to make knowledgeable financial decisions.

5.2.5 Conclusions concerning the timing of sovereign credit-rating changes

An analysis of the timing of credit-rating changes executed by the big three credit rating agencies resulted in a kind of hierarchy. The order starts with the leading agency followed by the primary following agency and lastly the secondary following agency. The leading agency refers to the credit-rating agency that initiates and assigns a rating change, whilst the other two rating agencies react to the leading agency's rating change and therefore follow the lead. The analysis incorporated the time period from 1998Q1-2014Q1, observing 34 emerging market economies. The results suggested that Standard & Poor's is the main leading agency that initiated 40.74% of the rating changes within the period followed by Fitch that led 33.33% of the rating changes and lastly Moody's led 25.93% of changes. Therefore, the analysis concludes that Standard & Poor's is the leading agency, Moody's is the primary following agency and Fitch the secondary following agency, for the specified time period and groups of economies.

5.2.6 Conclusions concerning the weights assigned to the individual macro-economic variables within each country-category.

Each group of emerging market economies attained different results. The secondary economies that form part of the March 2014 FTSE Global Equity Index Series: *Country Classification* of emerging market economies produced the smallest number of significant variables for all three agencies. A likely explanation for the deficiency of significant variables may be the small panel with just three emerging markets in the secondary country category. However, advanced and frontier economies yielded more significant variables. The results indicate that Standard & Poor’s assigns heavier weights to the variables in the advanced economies with the ordered probit model and thus rate the advanced economies stricter than the frontier economies. However, the least squares and pooled model suggest the opposite. Standard & Poor’s assigns a heavier weight to the variables in the frontier economies and thus rates frontier economies stricter than the advanced economies. A comparison between the advanced and frontier economies is not possible for Moody’s because there are no similar variables in the different models.

The Asian economies that form part of the March 2014 FTSE Global Equity Index Series: *Regional Classification* of emerging market economies produced the smallest number of significant variables for all three agencies. Likewise, for the secondary economies, a possible explanation for the lack of significant variables could be the small panel of three emerging markets in the Asian country category. In contrast, the European economies produced a large number of significant variables with all three estimation models, i.e. ordered probit, least squares and pooled. The European economies consist of eight emerging markets and a possible explanation for the satisfactory results could be the large panel. The March 2014 FTSE Global Equity Index Series: *Country Classification* and the March 2014 FTSE Global Equity Index Series: *Regional Classification* produced the most meaningful results. These two groups have the largest panels and that probably explains the amount of variables found to be significant for all three agencies.

5.3 LIMITATIONS AND RECOMMENDATIONS

This section concludes this study with an assessment of the limitations of the study as well as recommendations for future studies.

5.3.1 Limitations

Limitations of the study are firstly the availability and quality of data regarding emerging market economies, especially African emerging market economies. The original data is in the national currency and not in standardised dollar terms;

therefore, the challenge arises with the accuracy of exchange rate conversion. The macro-economic data becomes more restricted as data points move further back in time and therefore less data points are available to estimate results.

The second limitation of this study is the absence of individual economy results. This study purely focused on estimations within a panel data framework and did not aim to obtain results concerning individual emerging market economies. Thirdly, the chosen macro-economic variables did not explain the sovereign ratings in an absolute manner and hence a certain part of the model remains undefined.

Fourthly, openness as a macro-economic variable resulted in opposite outcomes than those found in theory. The empirical estimation of this study indicates a negative sign for openness, whereas eminent literature indicates a positive sign.

Lastly, this study only employed macro-economic variables as stipulated in literature and other related studies. This study did not include any macro-economic variables beyond those identified by other studies.

5.3.2 Recommendations

This study considers the limitations as the key to identify future research and recommendations. Primarily, future studies can attempt to explore African emerging markets in more detail and therefore enlarge the emerging market economies sample.

Furthermore, in order to achieve more in-depth results about emerging markets, future studies could estimate individual economy results. It can enhance the results for the explanation of sovereign ratings because individual economies may produce additional macro-economic variables that are significant. The challenge would ultimately be the use of the appropriate empirical models to attain the desired result.

In addition, empirical models can add instrumental variables as a mean to capture the undefined statistics in the model. Moreover, openness as a macro-economic variable could be scrutinised in more detail. It could prove useful to future studies to determine whether openness may have both a positive and a negative influence on sovereign ratings. Lastly, future studies can employ potential new macro-economic variables identified by qualitative research excluded from models to date. This could hypothetically lead to other possibilities of sovereign credit rating determinants.

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7. APPENDICES

7.1 APPENDIX A: GRAPHICAL REPRESENTATION OF THE SOVEREIGN RATINGS ASSIGNED BY STANDARD & POOR'S, MOODY'S AND FITCH FOR THE TIME PERIOD 1998Q1 - 2014Q1

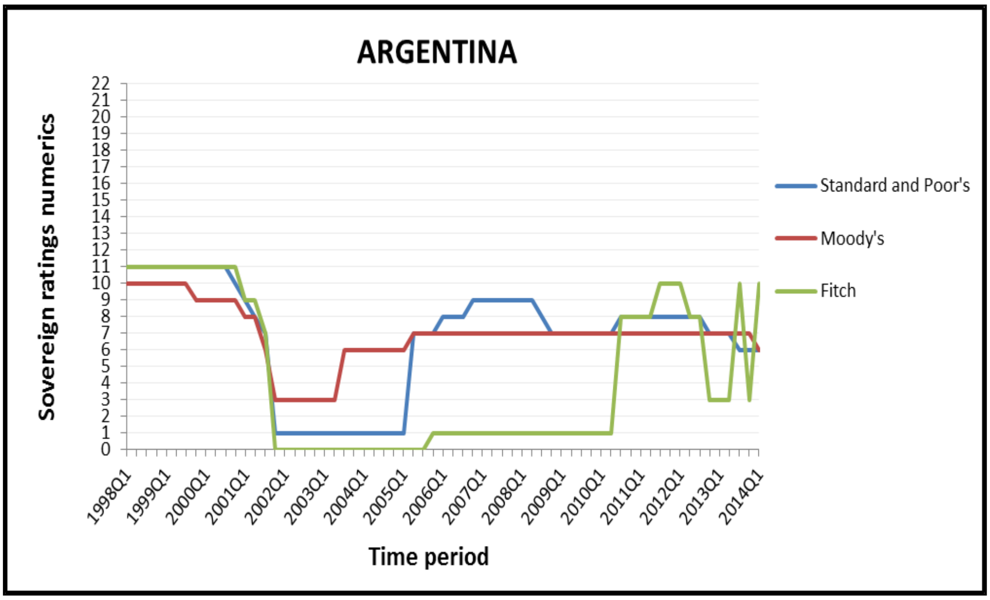

Figure 7.1: Argentina

Source: Compiled by author

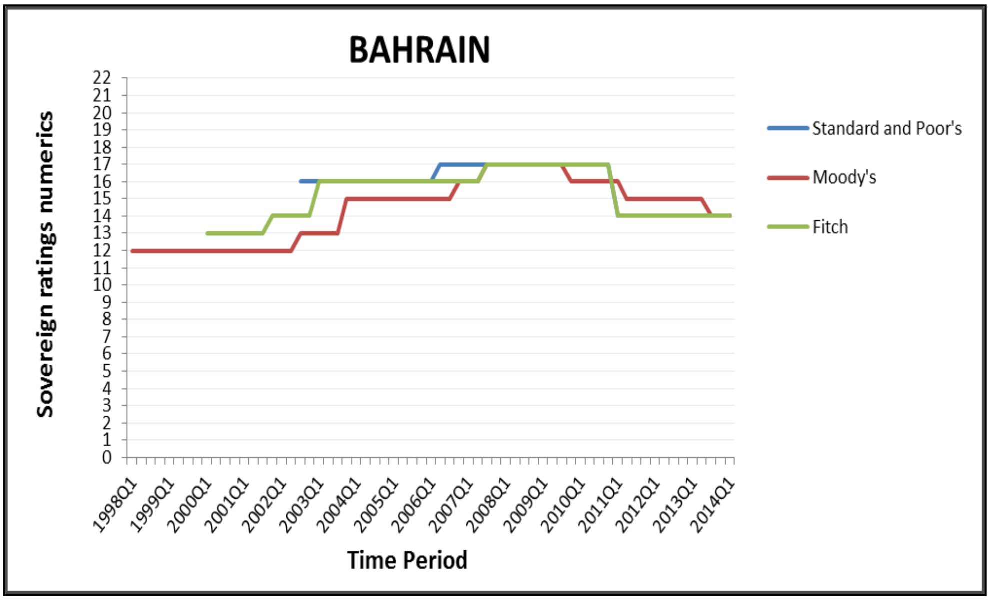

Figure 7.2: Bahrain

Source: Compiled by author

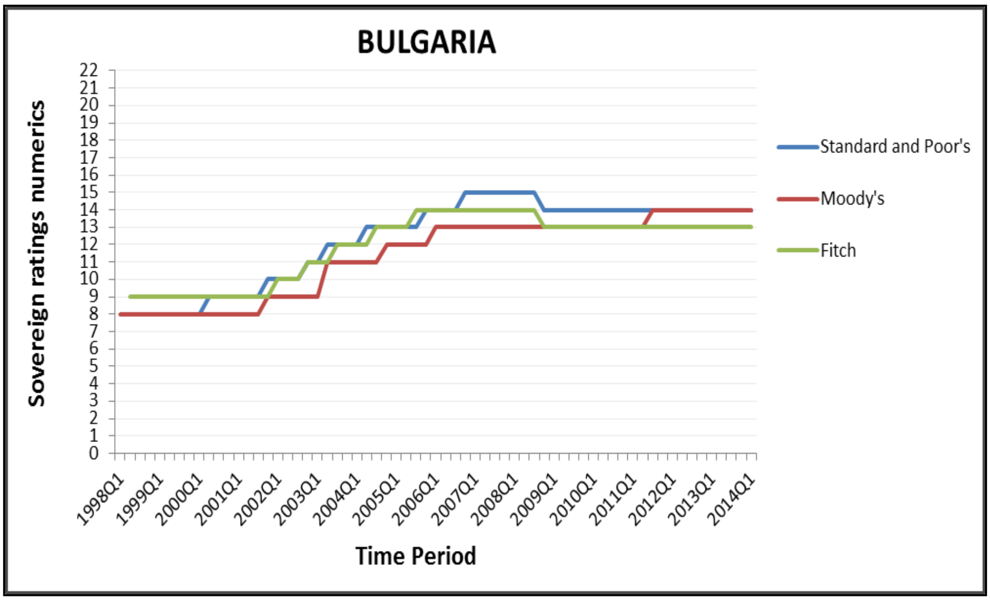

Figure 7.3: Bulgaria

Source: Compiled by author

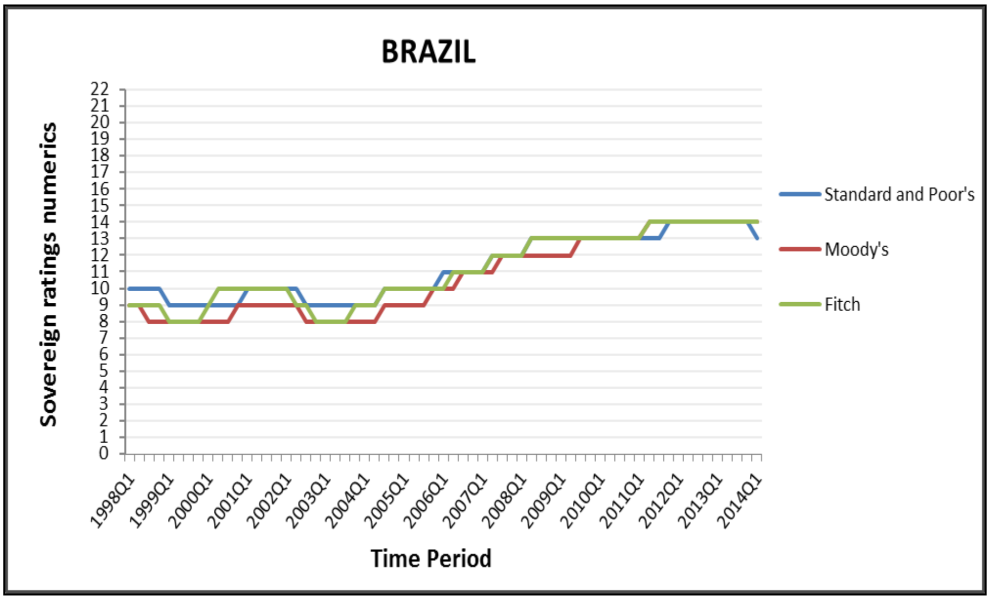

Figure 7.4: Brazil

Source: Compiled by author

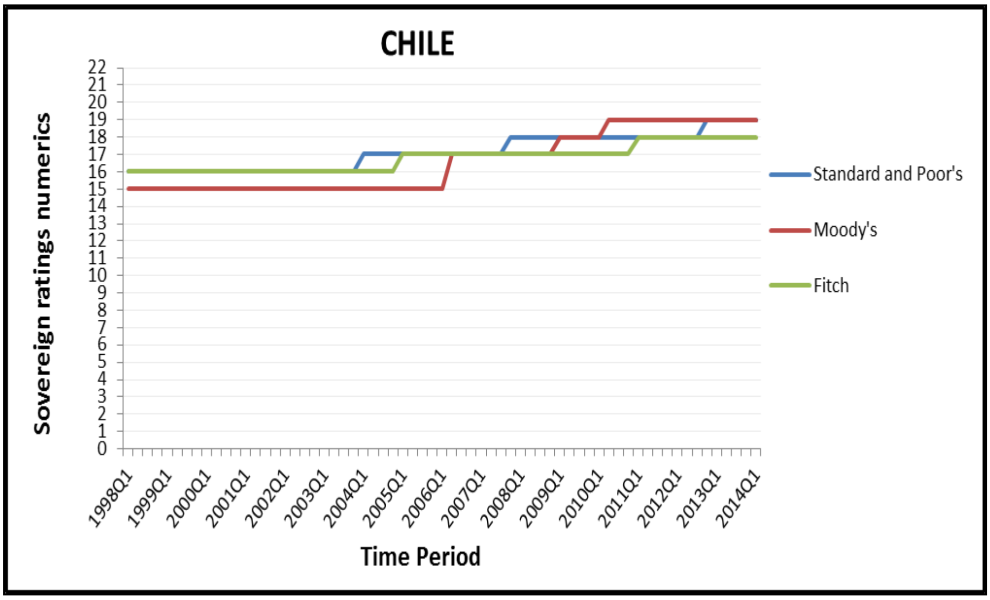

Figure 7.5: Chile

Source: Compiled by author

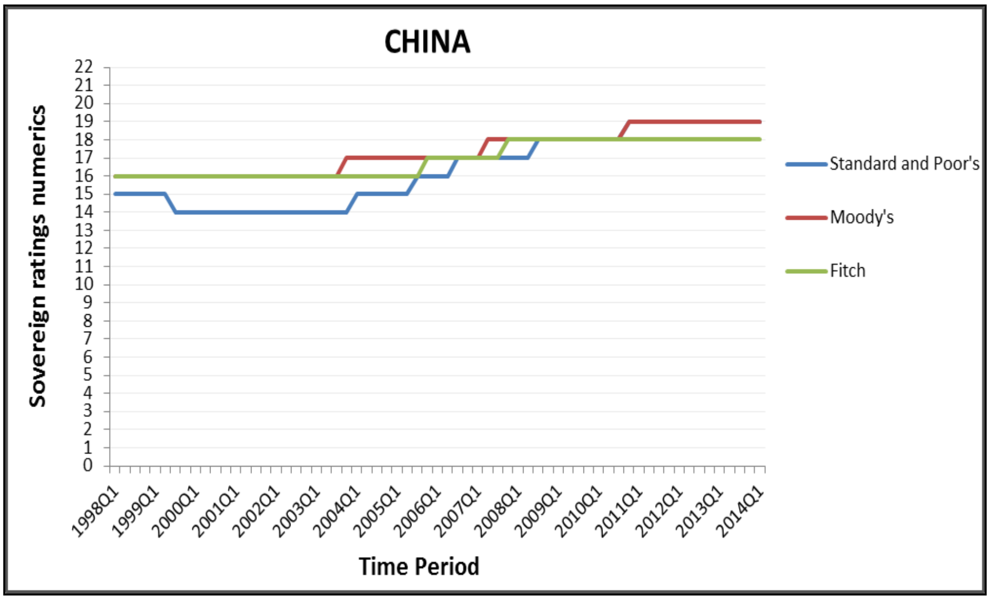

Figure 7.6: China

Source: Compiled by author

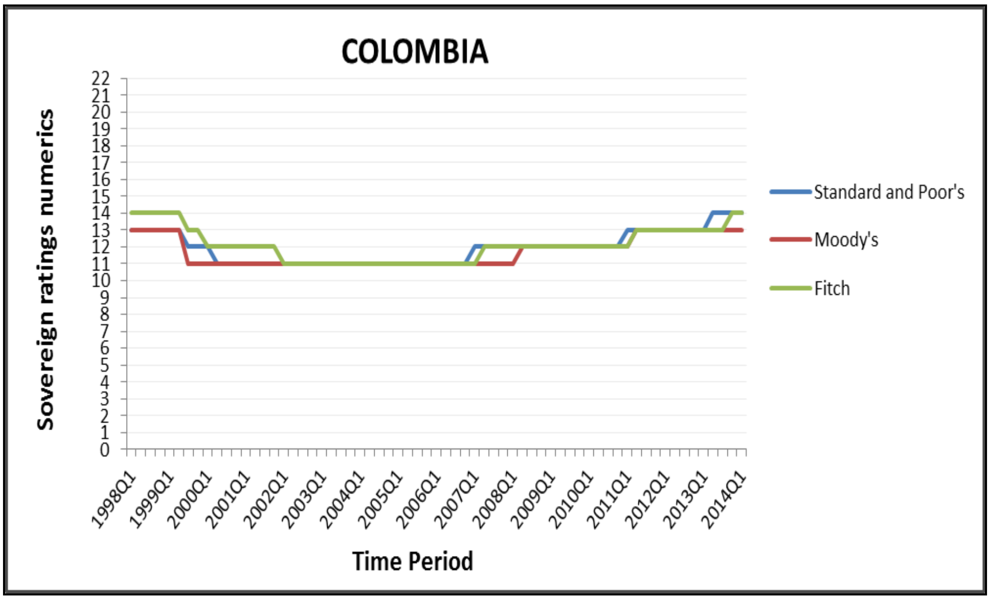

Figure 7.7: Colombia

Source: Compiled by author

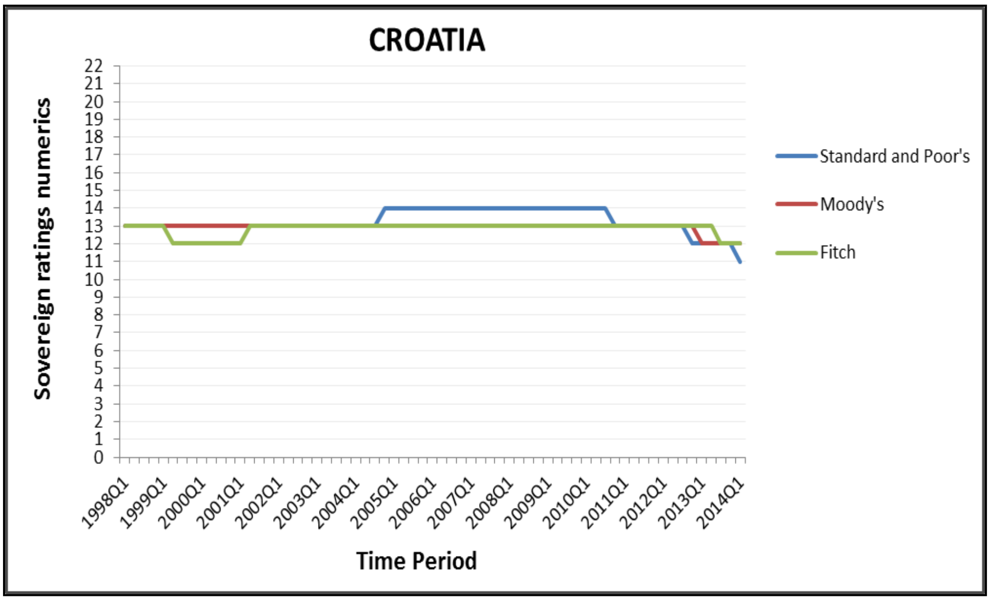

Figure 7.8: Croatia

Source: Compiled by author

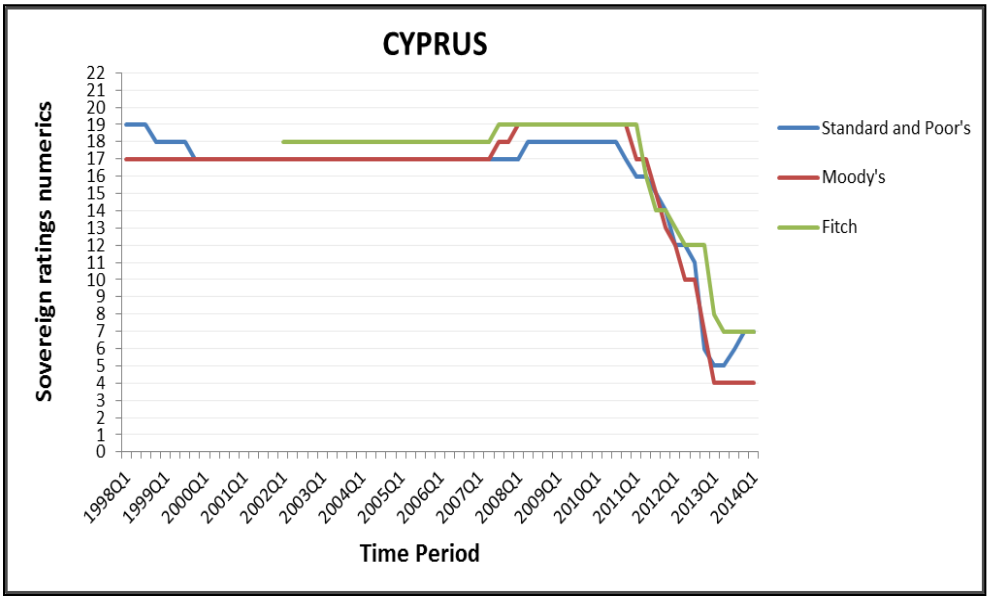

Figure 7.9: Cyprus

Source: Compiled by author

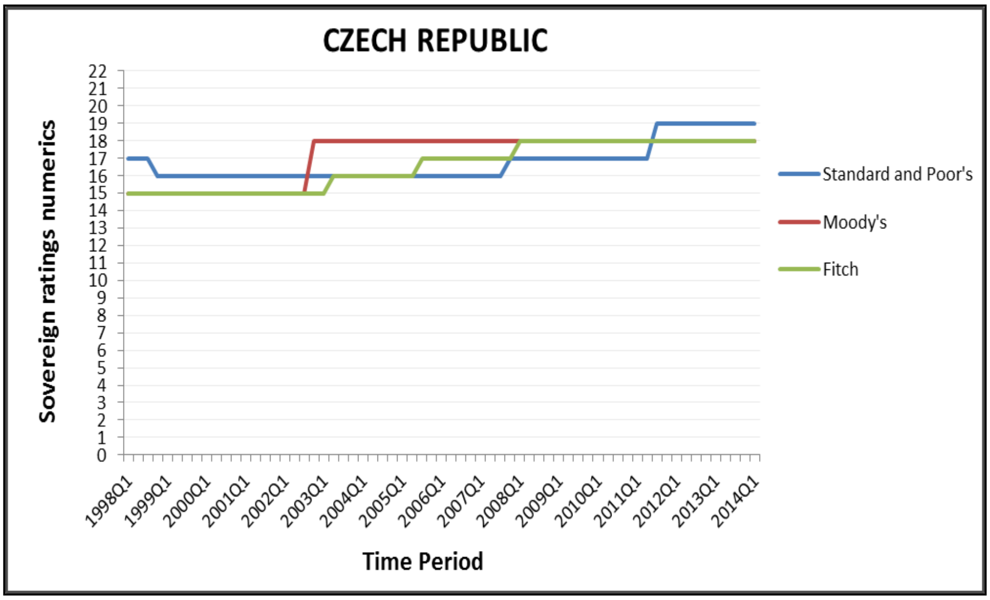

Figure 7.10: Czech Republic

Source: Compiled by author

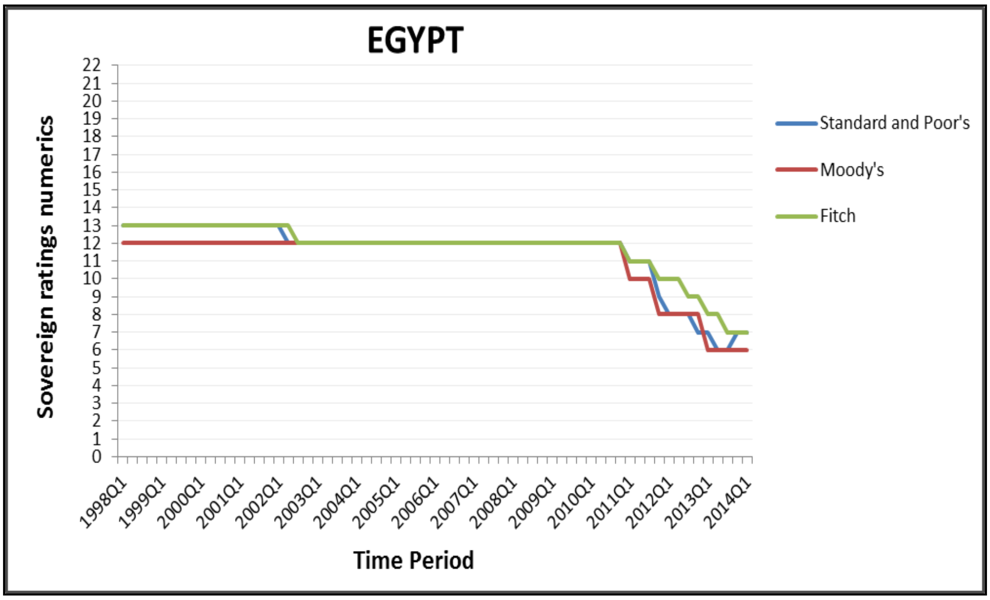

Figure 7.11: Egypt

Source: Compiled by author

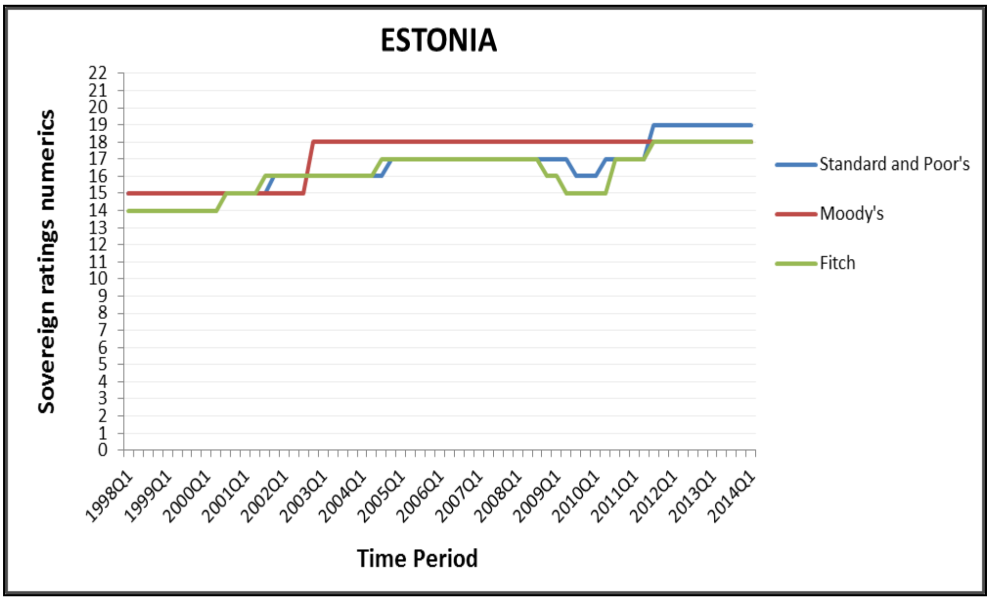

Figure 7.12: Estonia

Source: Compiled by author

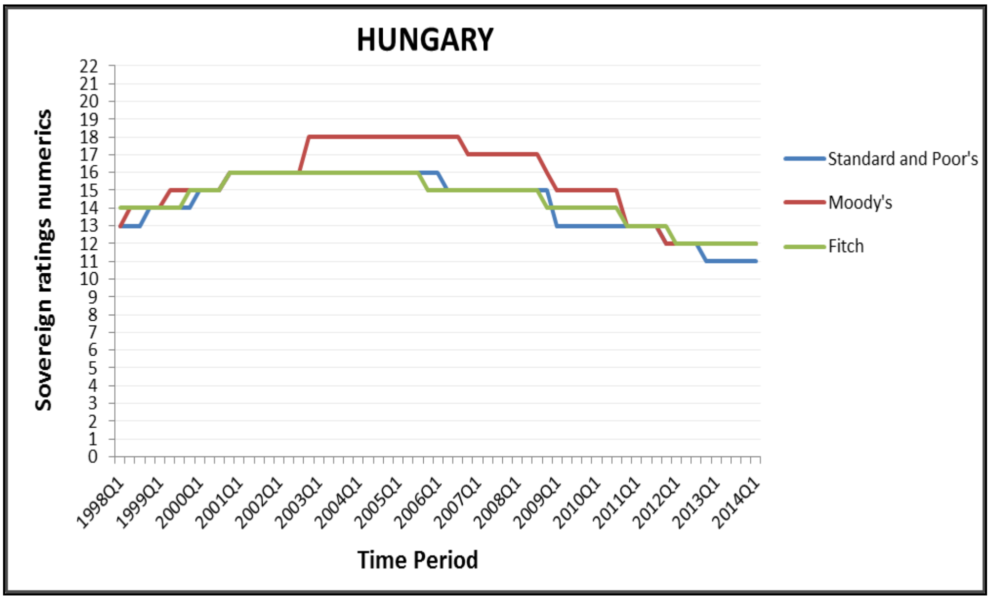

Figure 7.13: Hungary

Source: Compiled by author

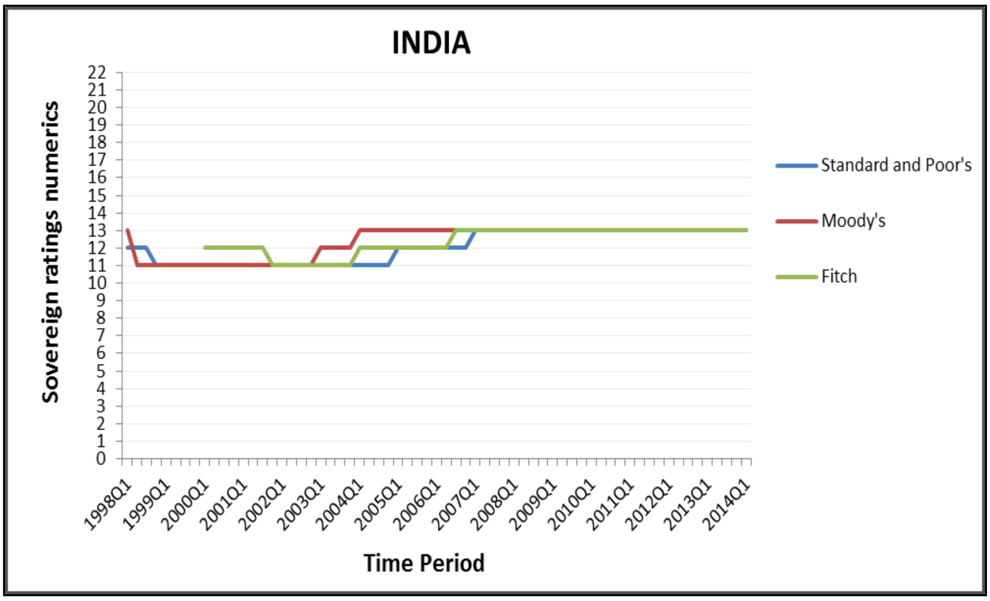

Figure 7.14: India

Source: Compiled by author

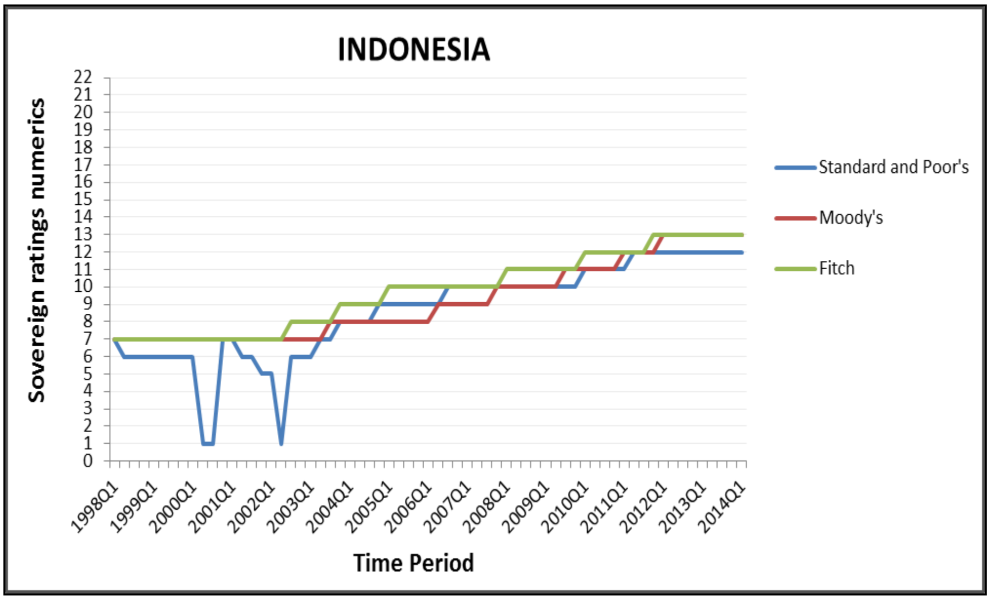

Figure 7.15: Indonesia

Source: Compiled by author

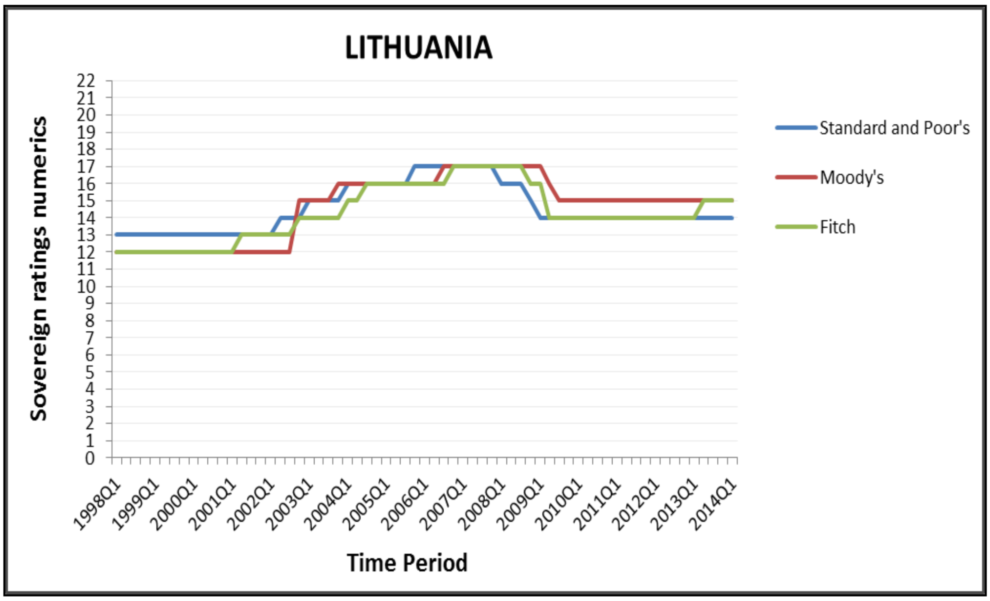

Figure 7.16: Lithuania

Source: Compiled by author

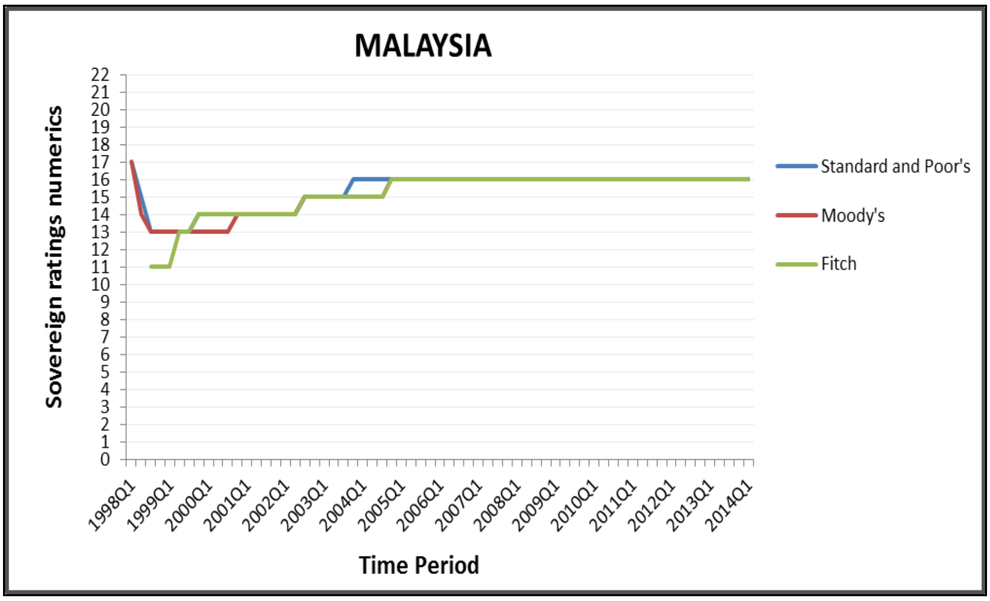

Figure 7.17: Malaysia

Source: Compiled by author

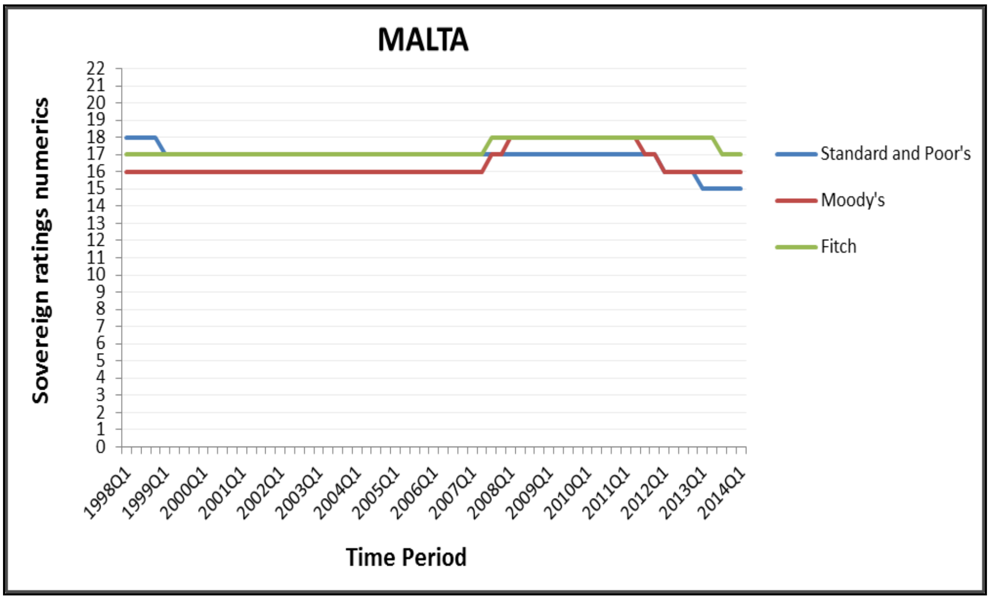

Figure 7.18: Malta

Source: Compiled by author

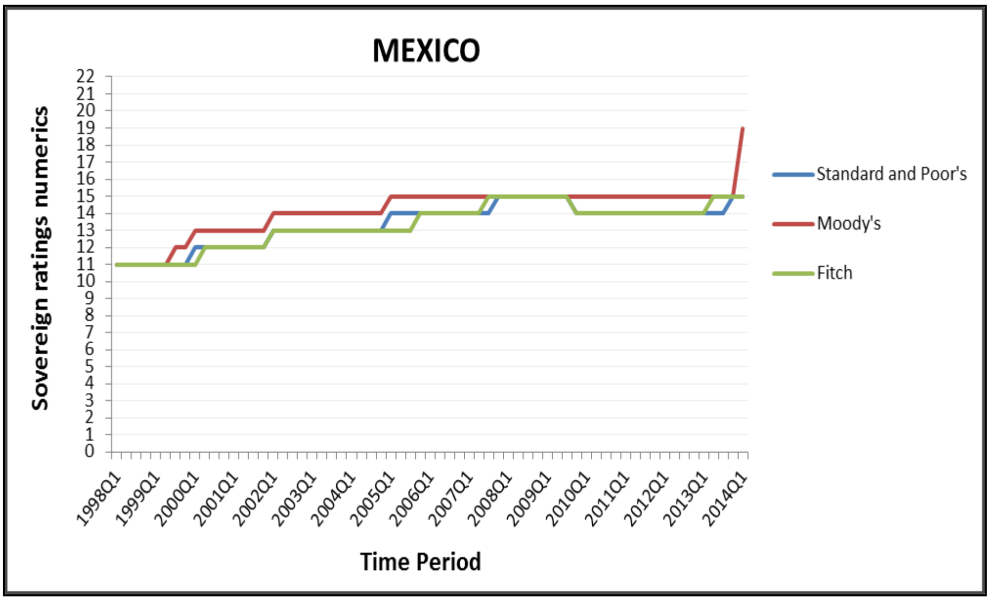

Figure 7.19: Mexico

Source: Compiled by author

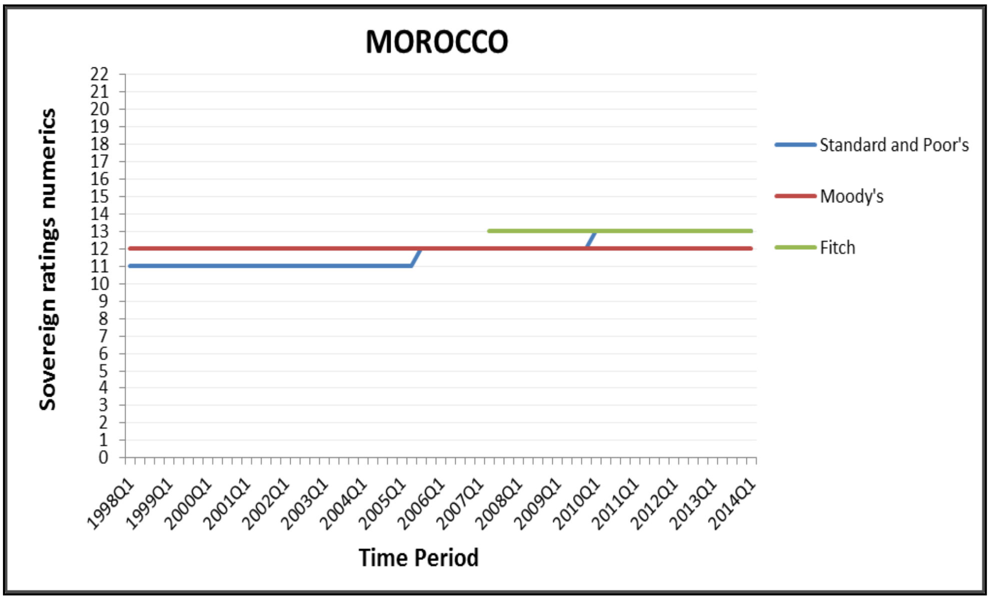

Figure 7.20: Morocco

Source: Compiled by author

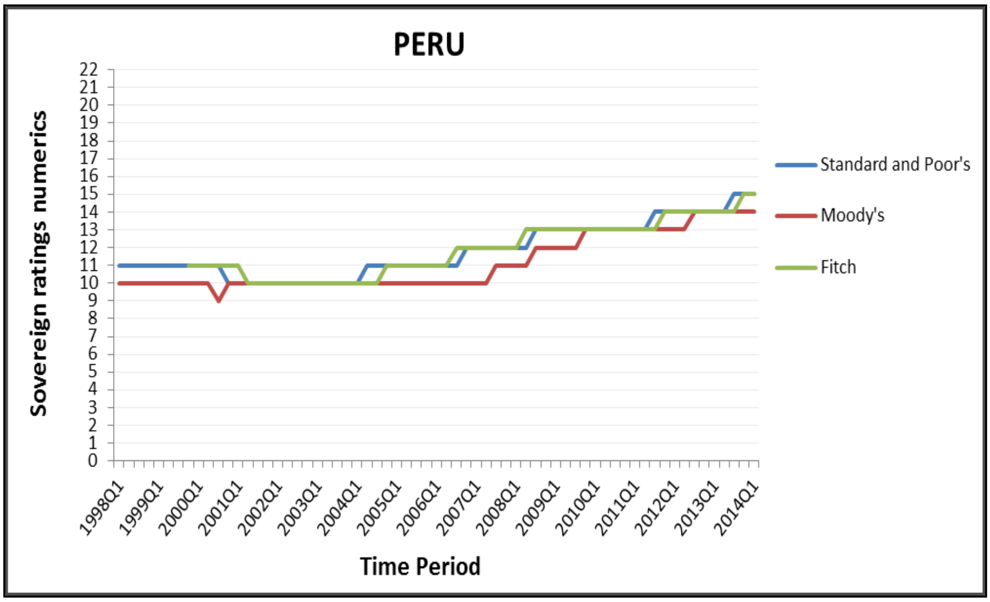

Figure 7.21: Peru

Source: Compiled by author

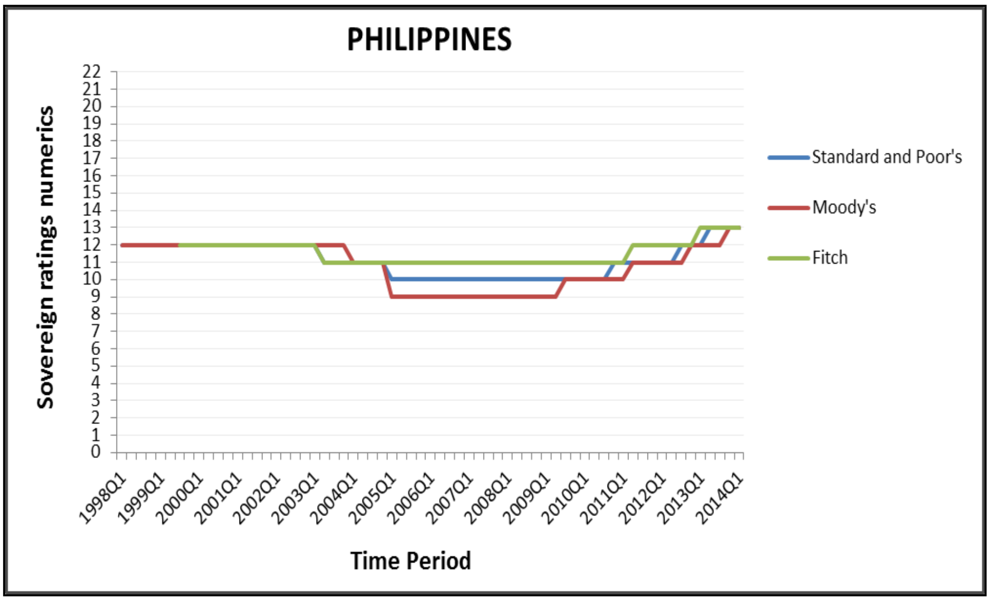

Figure 7.22: Philippines

Source: Compiled by author

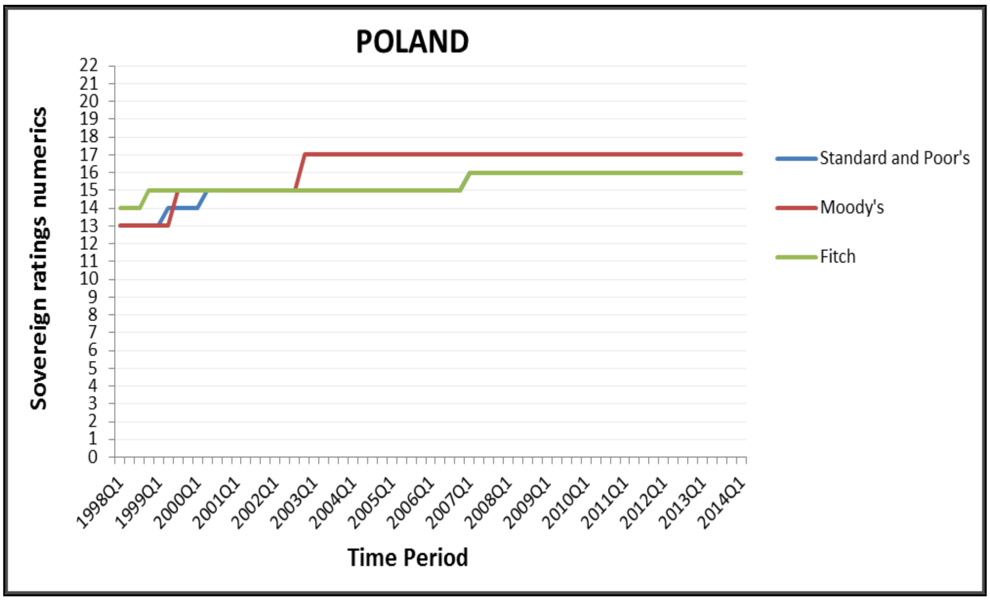

Figure 7.23: Poland

Source: Compiled by author

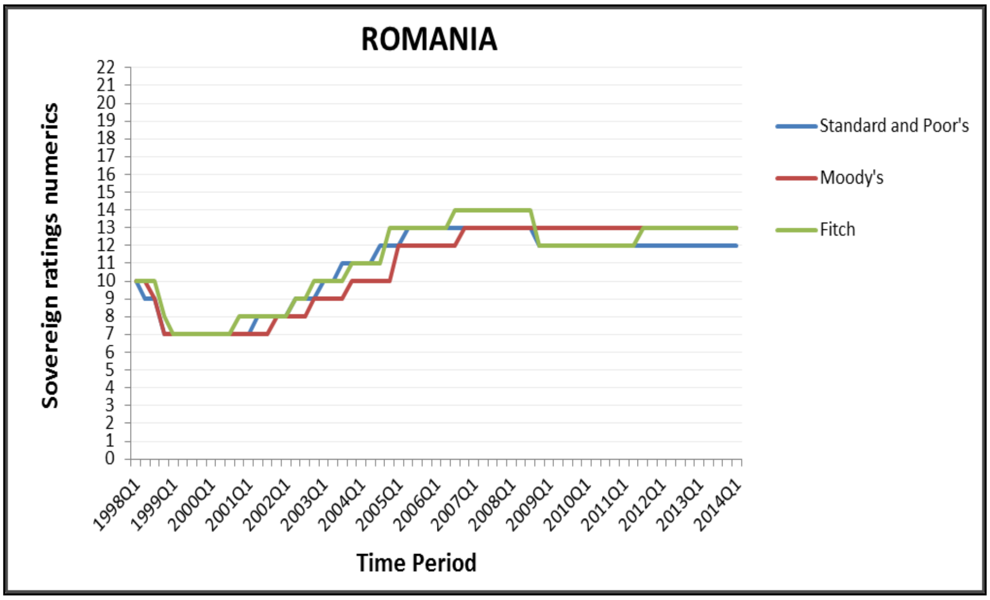

Figure 7.24: Romania

Source: Compiled by author

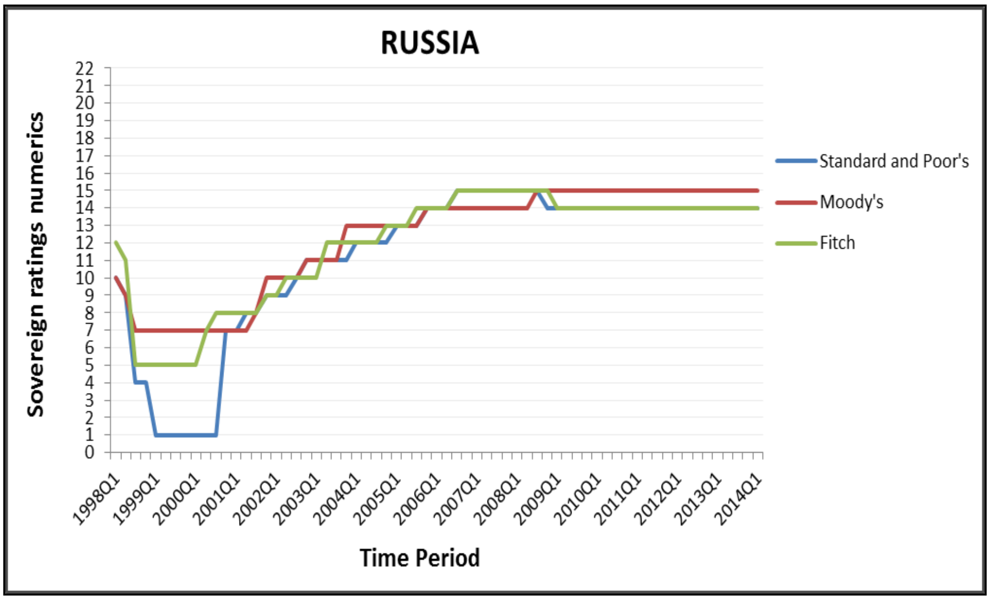

Figure 7.25: Russia

Source: Compiled by author

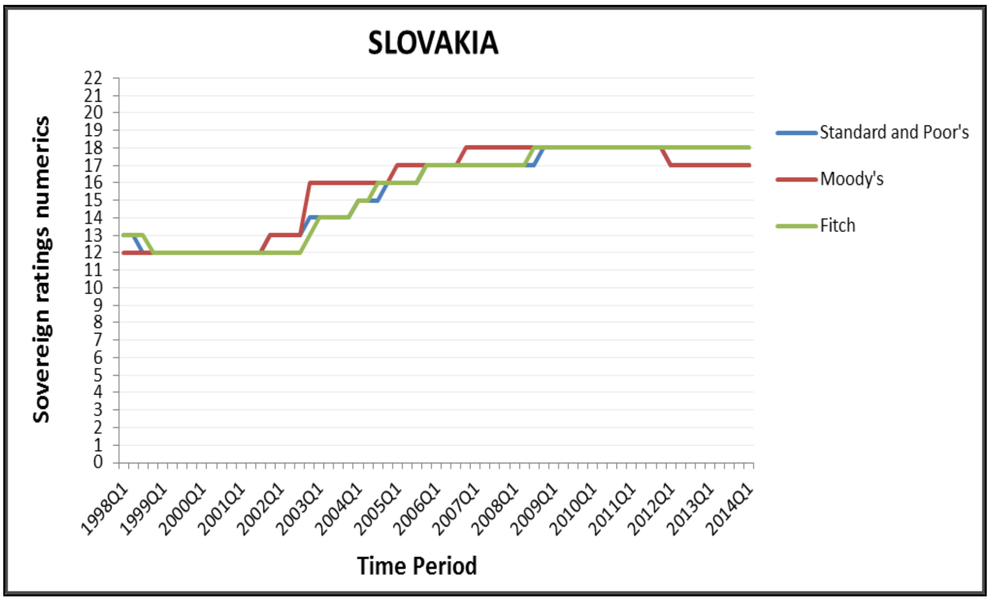

Figure 7.26: Slovakia

Source: Compiled by author

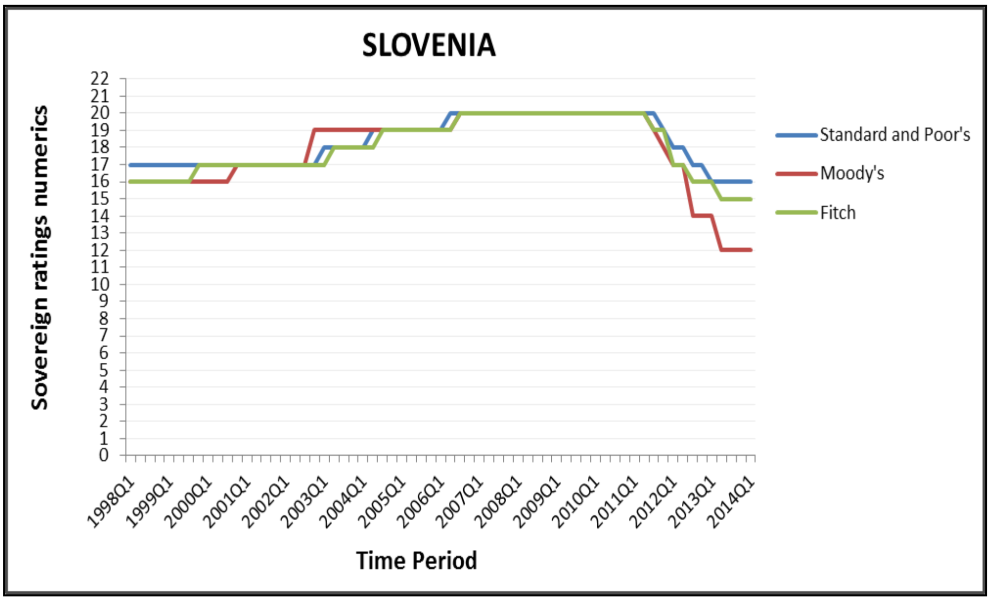

Figure 7.27: Slovenia

Source: Compiled by author

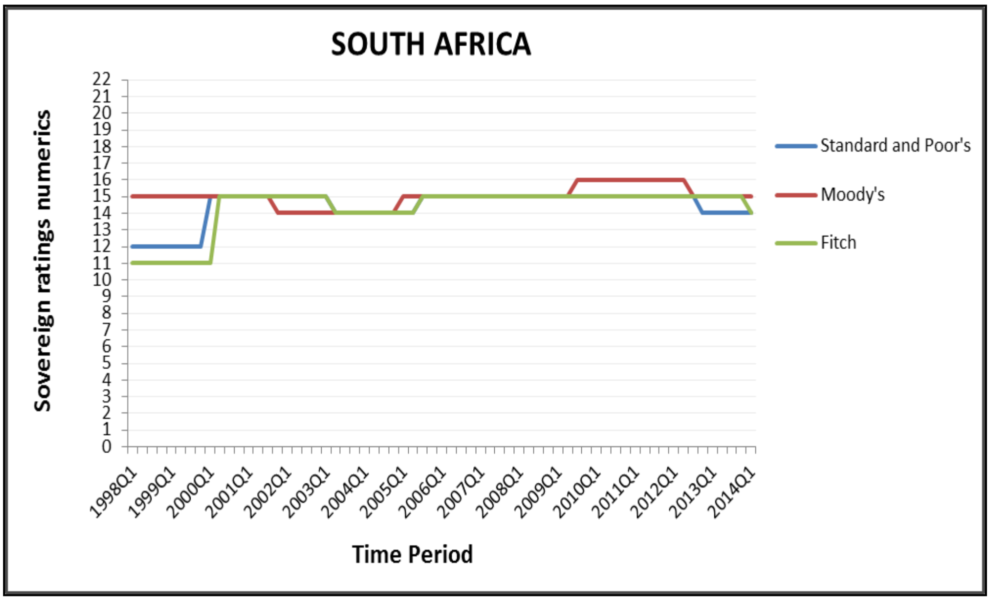

Figure 7.28: South Africa

Source: Compiled by author

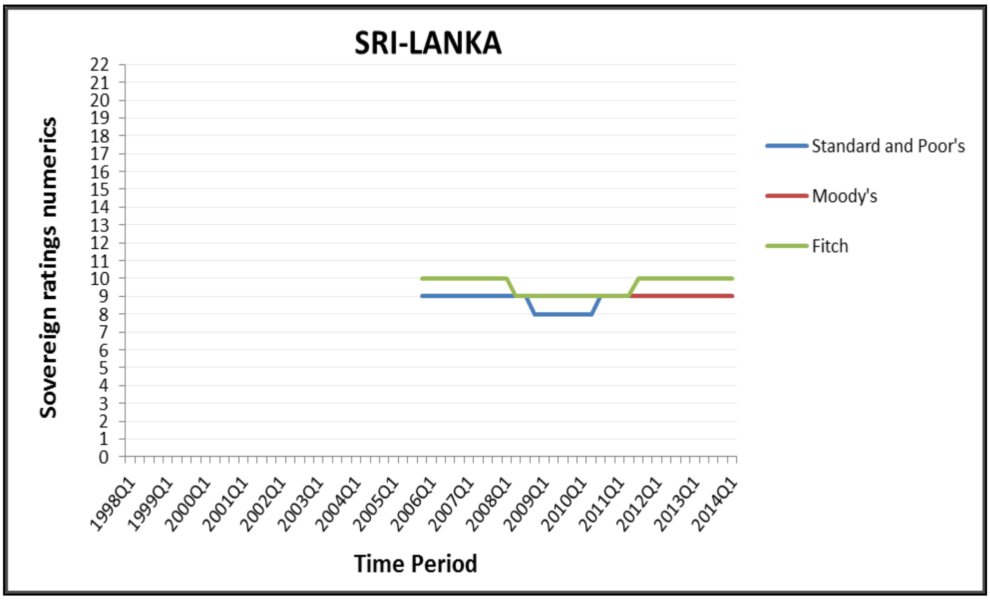

Figure 7.29: Sri - Lanka

Source: Compiled by author

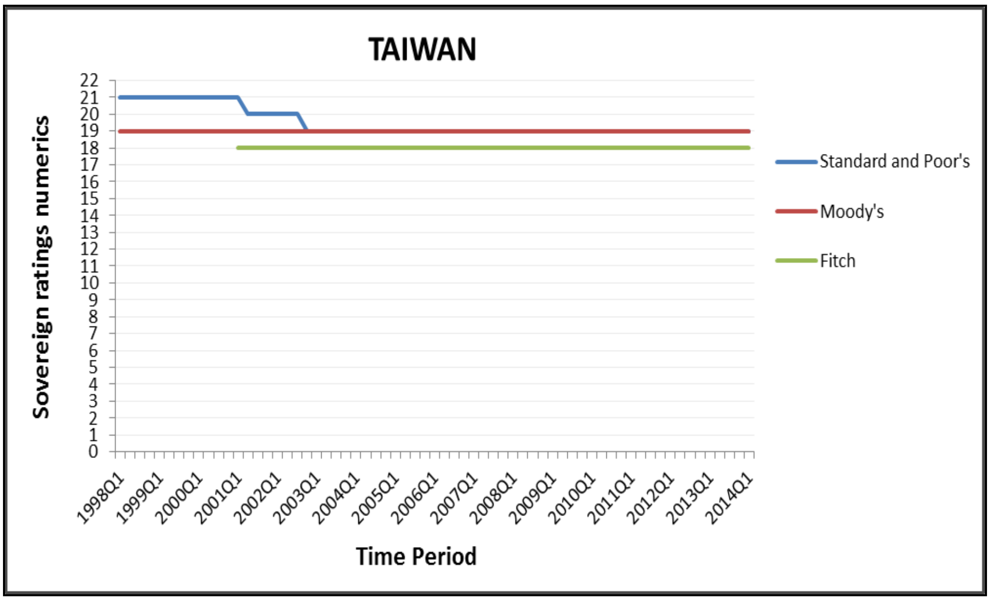

Figure 7.30: Taiwan

Source: Compiled by author

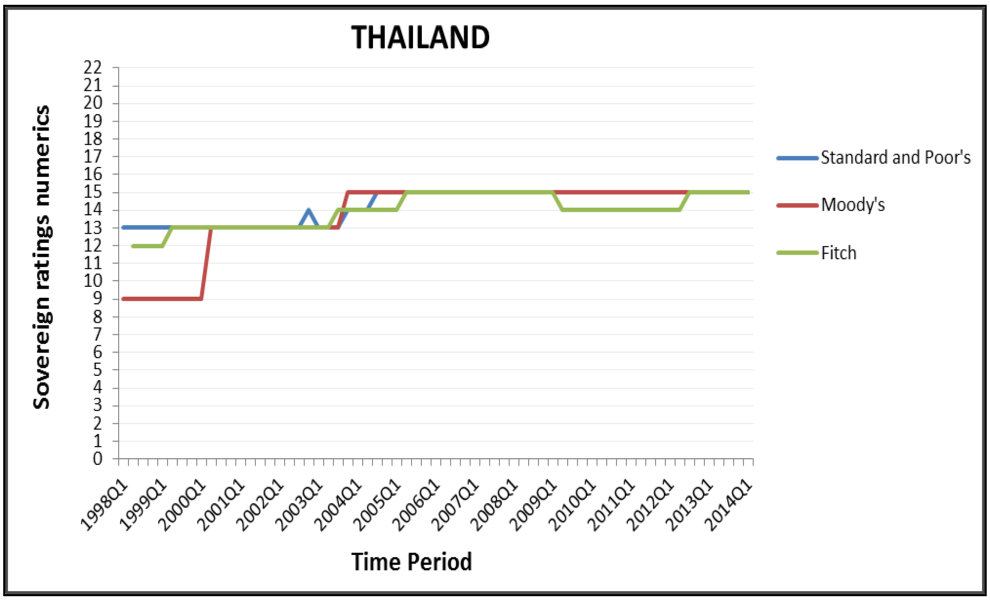

Figure 7.31: Thailand

Source: Compiled by author

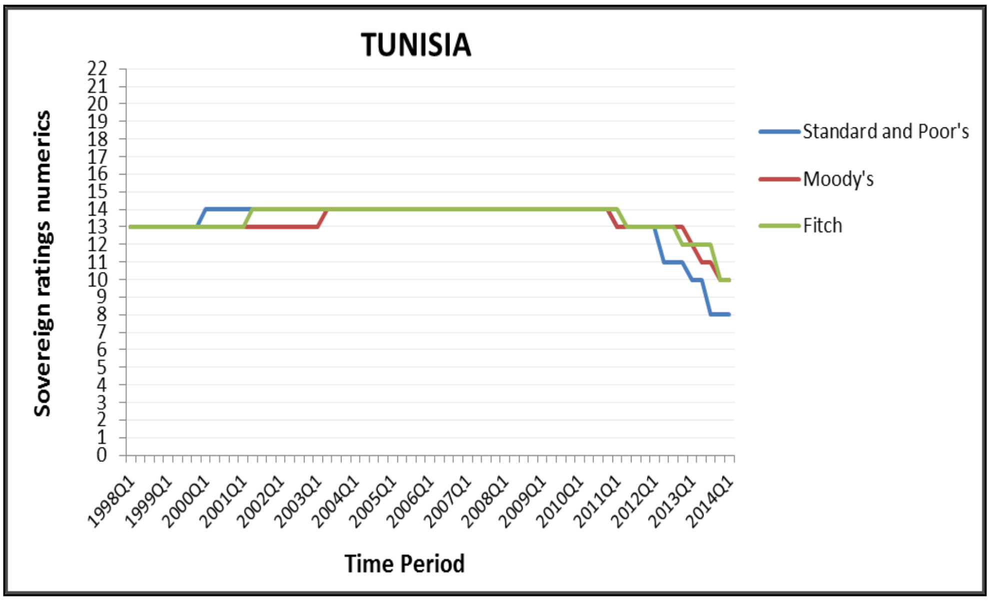

Figure 7.32: Tunisia

Source: Compiled by author

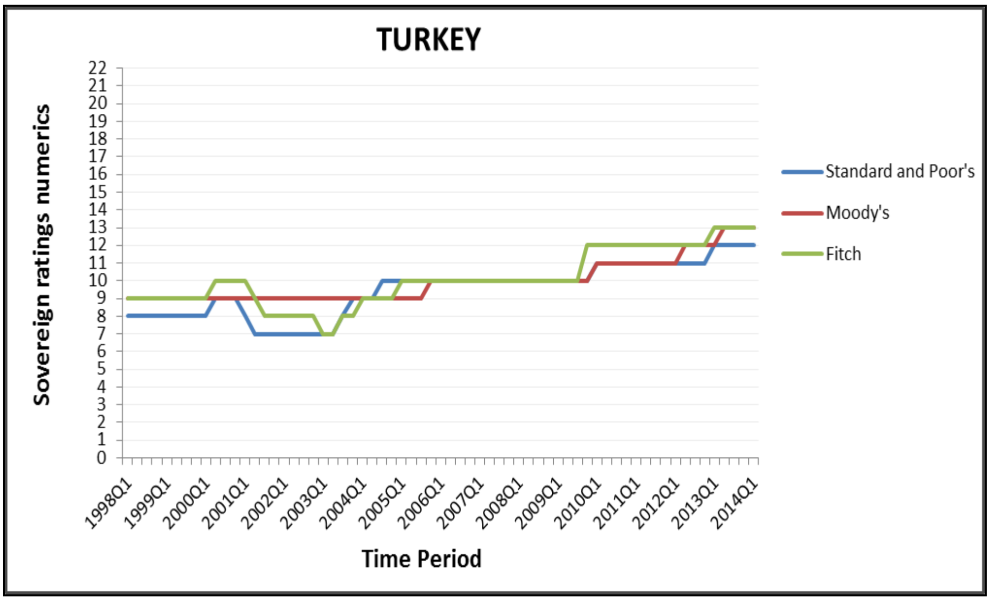

Figure 7.33: Turkey

Source: Compiled by author

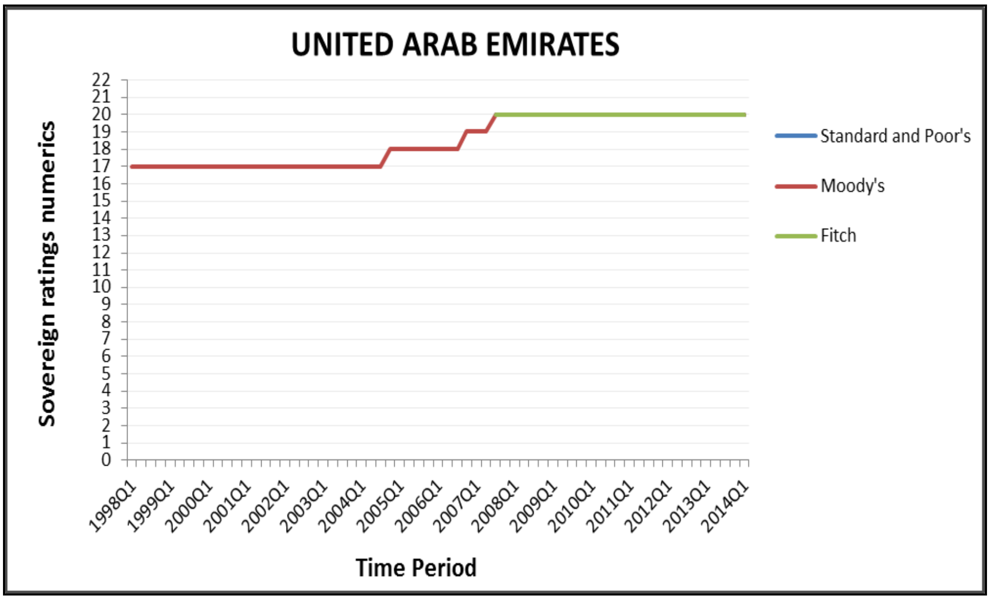

Figure 7.34: United Arab Emirates

Source: Compiled by author

7.2 APPENDIX B: ECONOMIES' BREACHING THE INVESTMENT BARRIER

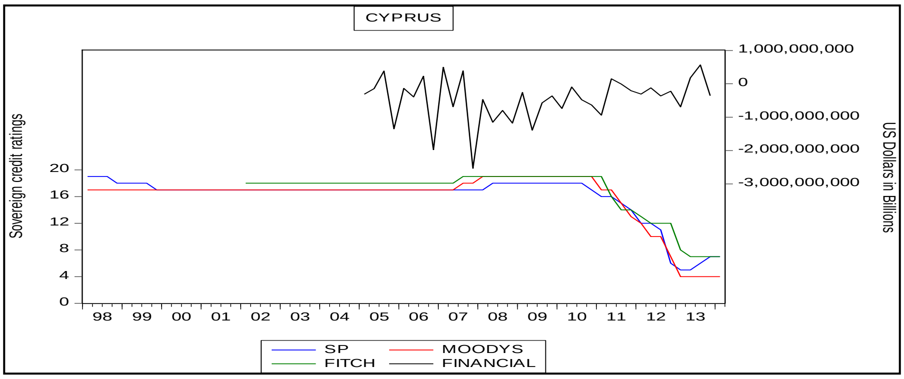

Figure 7.35: Cyprus' sovereign ratings and financial account

Source: Compiled by author

Table 7.1: Granger causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: MOODYS			
Excluded	Chi-sq	df	Prob.
FINANCIAL	0.992745	1	0.3191
All	0.992745	1	0.3191
Dependent variable: FINANCIAL			
Excluded	Chi-sq	df	Prob.
MOODYS	8.080073	1	0.0045
All	8.080073	1	0.0045

Table 7.2: Granger causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: FITCH		
Excluded	Chi-sq	dfProb.
FINANCIAL	0.391103	2 0.8224
All	0.391103	2 0.8224
Dependent variable: FINANCIAL		
Excluded	Chi-sq	dfProb.
FITCH	9.262734	2 0.0097
All	9.262734	2 0.0097

Table 7.3: Granger Causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: SP		
Excluded	Chi-sq	dfProb.
FINANCIAL	0.000752	1 0.9781
All	0.000752	1 0.9781
Dependent variable: FINANCIAL		
Excluded	Chi-sq	dfProb.
SP	6.087372	1 0.0136
All	6.087372	1 0.0136

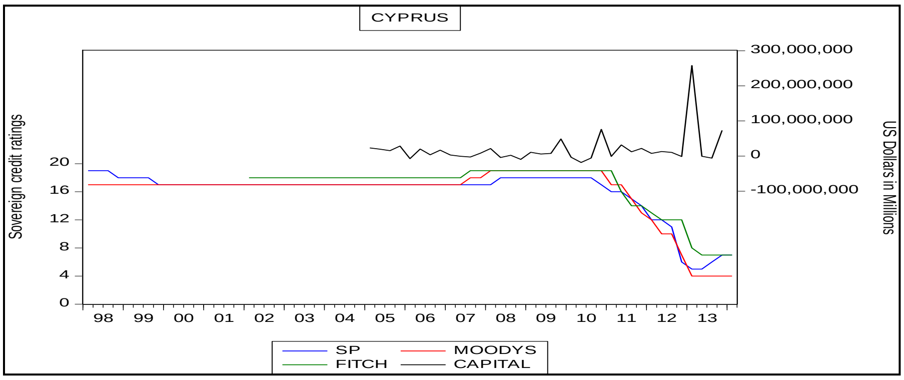

Figure 7.36: Cyprus' sovereign ratings and capital account

Source: Compiled by author

Table 7.4: Granger Causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: MOODYS			
Excluded	Chi-sq	df	Prob.
CAPITAL	6.907777	3	0.0749
All	6.907777	3	0.0749
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
MOODYS	29.74160	3	0.0000
All	29.74160	3	0.0000

Table 7.5: Granger Causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: FITCH			
Excluded	Chi-sq	df	Prob.
CAPITAL	9.121090	4	0.0581
All	9.121090	4	0.0581
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
FITCH	10.54771	4	0.0321
All	10.54771	4	0.0321

Table 7.6: Granger Causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: SP			
Excluded	Chi-sq	Df	Prob.
CAPITAL	14.48824	4	0.0059
All	14.48824	4	0.0059
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
SP	60.18283	4	0.0000
All	60.18283	4	0.0000

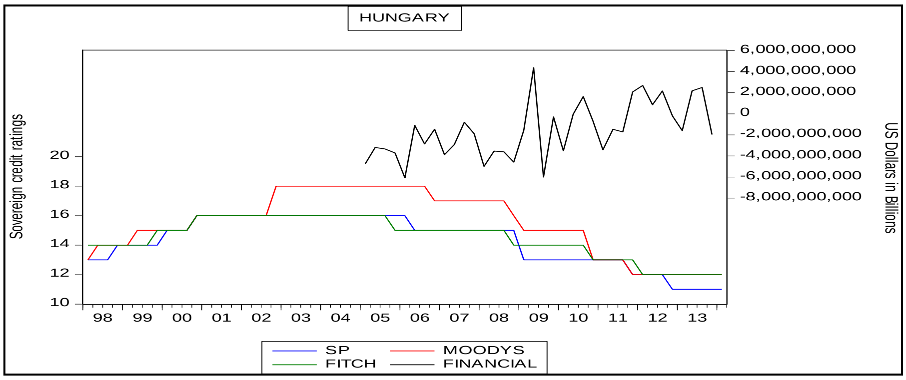

Figure 7.37: Hungary's sovereign ratings and financial account

Source: Compiled by author

Table 7.7: Granger Causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: MOODYS

Excluded	Chi-sq	df	Prob.
FINANCIAL	4.876920	3	0.1810
All	4.876920	3	0.1810

Dependent variable: FINANCIAL

Excluded	Chi-sq	df	Prob.
MOODYS	15.63474	3	0.0013
All	15.63474	3	0.0013

Table 7.8: Granger Causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: FITCH

Excluded	Chi-sq	df	Prob.
FINANCIAL	2.199761	1	0.1380
All	2.199761	1	0.1380

Dependent variable: FINANCIAL

Excluded	Chi-sq	df	Prob.
FITCH	13.87324	1	0.0002
All	13.87324	1	0.0002

Table 7.9: Granger Causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: SP

Excluded	Chi-sq	df	Prob.
FINANCIAL	0.758551	1	0.3838
All	0.758551	1	0.3838

Dependent variable: FINANCIAL

Excluded	Chi-sq	df	Prob.
SP	18.50159	1	0.0000
All	18.50159	1	0.0000

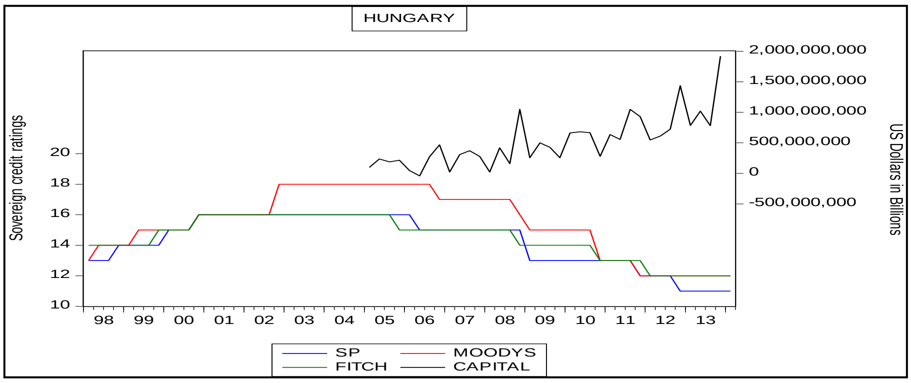

Figure 7.38: Hungary's sovereign ratings and capital account

Source: Compiled by author

Table 7.10: Granger Causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: MOODYS			
Excluded	Chi-sq	df	Prob.
CAPITAL	4.851452	1	0.0276
All	4.851452	1	0.0276
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
MOODYS	19.62157	1	0.0000
All	19.62157	1	0.0000

Table 7.11: Granger Causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: FITCH			
Excluded	Chi-sq	df	Prob.
CAPITAL	6.660918	2	0.0358
All	6.660918	2	0.0358
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
FITCH	13.29934	2	0.0013
All	13.29934	2	0.0013

Table 7.12: Granger causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: SP			
Excluded	Chi-sq	df	Prob.
CAPITAL	11.90197	2	0.0026
All	11.90197	2	0.0026
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
SP	10.02989	2	0.0066
All	10.02989	2	0.0066

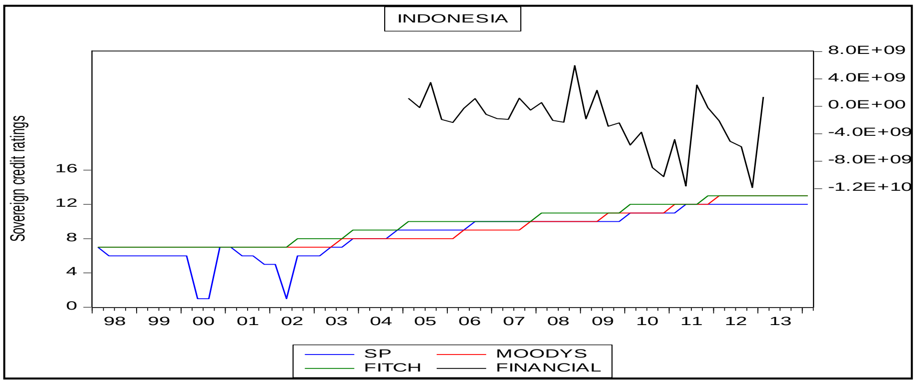

Figure 7.39: Indonesia's sovereign ratings and financial account source: Compiled by author

Table 7.13: Granger Causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: MOODYS

Excluded	Chi-sq	df	Prob.
FINANCIAL	4.11E-06	1	0.9984
All	4.11E-06	1	0.9984

Dependent variable: FINANCIAL

Excluded	Chi-sq	df	Prob.
MOODYS	5.090197	1	0.0241
All	5.090197	1	0.0241

Table 7.14: Granger Causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: FITCH

Excluded	Chi-sq	df	Prob.
FINANCIAL	1.058900	1	0.3035
All	1.058900	1	0.3035

Dependent variable: FINANCIAL

Excluded	Chi-sq	df	Prob.
FITCH	6.276887	1	0.0122
All	6.276887	1	0.0122

Table 7.15: Granger Causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: SP

Excluded	Chi-sq	df	Prob.
FINANCIAL	6.942711	3	0.0737
All	6.942711	3	0.0737

Dependent variable: FINANCIAL

Excluded	Chi-sq	df	Prob.
SP	2.138004	3	0.5443
All	2.138004	3	0.5443

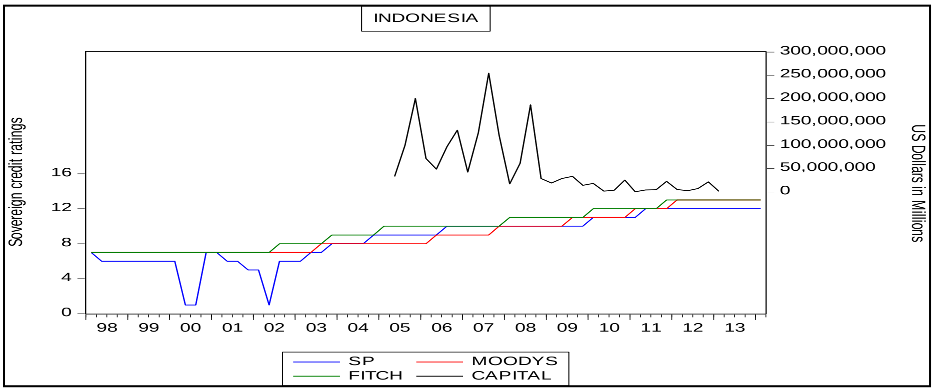

Figure 7.40: Indonesia's sovereign ratings and capital account

Source: Compiled by author

Table 7.16: Granger Causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: MOODYS			
Excluded	Chi-sq	df	Prob.
CAPITAL	0.458159	1	0.4985
All	0.458159	1	0.4985
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
MOODYS	10.16084	1	0.0014
All	10.16084	1	0.0014

Table 7.17: Granger Causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: FITCH			
Excluded	Chi-sq	df	Prob.
CAPITAL	1.950064	2	0.3772
All	1.950064	2	0.3772
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
FITCH	15.78466	2	0.0004
All	15.78466	2	0.0004

Table 7.18: Granger Causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: SP			
Excluded	Chi-sq	df	Prob.
CAPITAL	3.838032	2	0.1468
All	3.838032	2	0.1468
Dependent variable: CAPITAL			
Excluded	Chi-sq	df	Prob.
SP	7.141028	2	0.0281
All	7.141028	2	0.0281

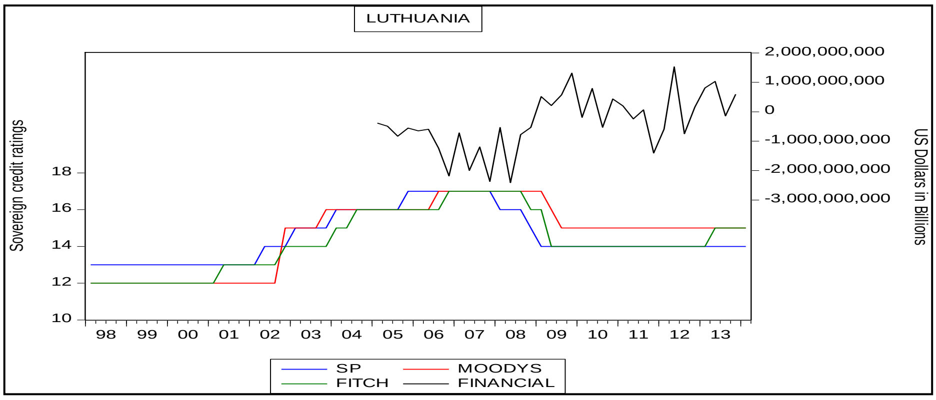

Figure 7.41: Lithuania's sovereign ratings and financial account

Source: Compiled by author

Table 7.19: Granger Causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: MOODYS			
Excluded	Chi-sq	df	Prob.
FINANCIAL	7.081603	2	0.0290
All	7.081603	2	0.0290
Dependent variable: FINANCIAL			
Excluded	Chi-sq	df	Prob.
MOODYS	8.271765	2	0.0160
All	8.271765	2	0.0160

Table 7.20: Granger Causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: FITCH			
Excluded	Chi-sq	df	Prob.
FINANCIAL	2.584597	1	0.1079
All	2.584597	1	0.1079
Dependent variable: FINANCIAL			
Excluded	Chi-sq	df	Prob.
FITCH	13.66931	1	0.0002
All	13.66931	1	0.0002

Table 7.21: Granger Causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests Dependent variable: SP			
Excluded	Chi-sq	df	Prob.
FINANCIAL	5.003820	3	0.1715
All	5.003820	3	0.1715
Dependent variable: FINANCIAL			
Excluded	Chi-sq	df	Prob.
SP	8.734402	3	0.0330
All	8.734402	3	0.0330

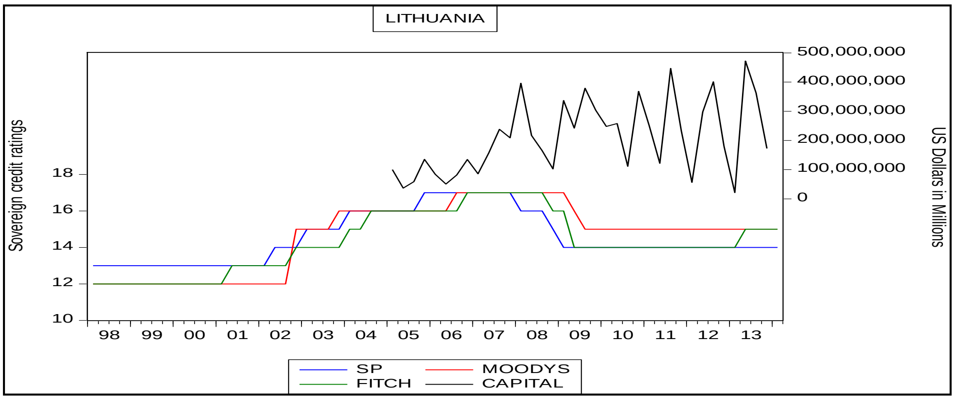

Figure 7.42: Lithuania's sovereign ratings and capital account

Source: Compiled by author

Table 7.22: Granger Causality-Moody's

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: MOODYS

Excluded	Chi-sq	df	Prob.
CAPITAL	3.190823	1	0.0741
All	3.190823	1	0.0741

Dependent variable: CAPITAL

Excluded	Chi-sq	df	Prob.
MOODYS	0.730231	1	0.3928
All	0.730231	1	0.3928

Table 7.23: Granger Causality-Fitch

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: FITCH

Excluded	Chi-sq	df	Prob.
CAPITAL	4.297224	1	0.0382
All	4.297224	1	0.0382

Dependent variable: CAPITAL

Excluded	Chi-sq	df	Prob.
FITCH	2.784482	1	0.0952
All	2.784482	1	0.0952

Table 7.24: Granger Causality-Standard & Poor's

VAR Granger Causality/Block Exogeneity Wald Tests
Dependent variable: SP

Excluded	Chi-sq	df	Prob.
CAPITAL	1.564083	2	0.4575
All	1.564083	2	0.4575

Dependent variable: CAPITAL

Excluded	Chi-sq	df	Prob.
SP	8.709676	2	0.0128
All	8.709676	2	0.0128

7.3 APPENDIX C: MULTIPLE GRAPHS OF VARIABLES IN LEVELS

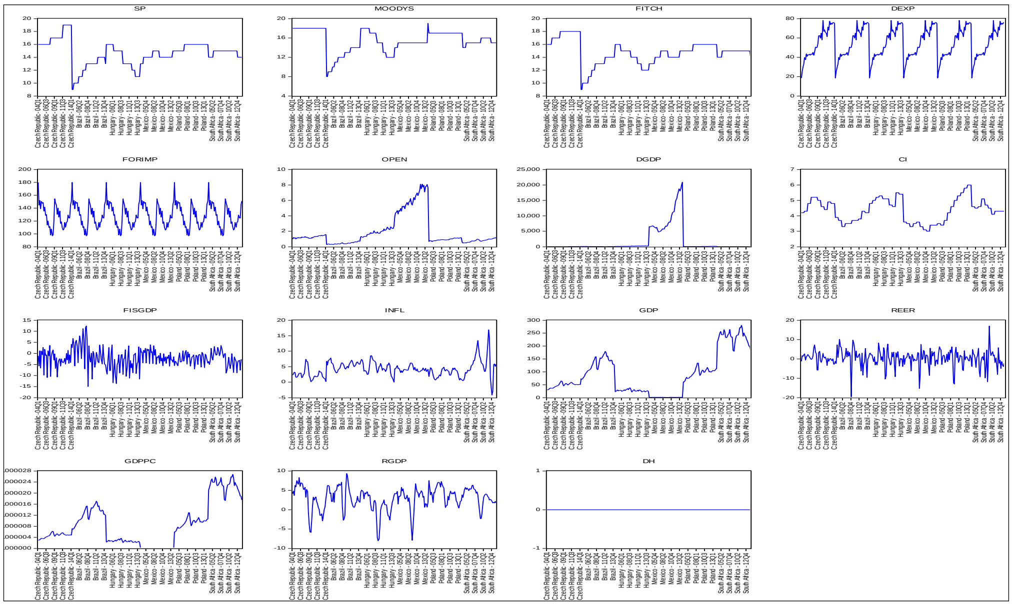

Figure 7.43: Multiple graphs of variables in levels-Advanced economies

Source: Compiled by author

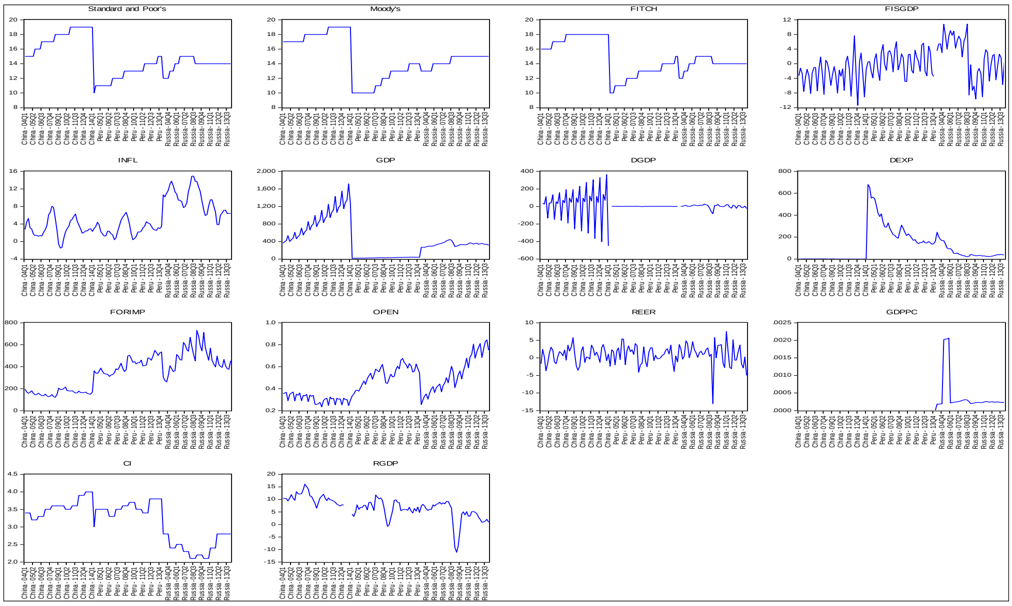

Figure 7.44: Multiple graphs of variables in levels-Secondary economies

Source: Compiled by author

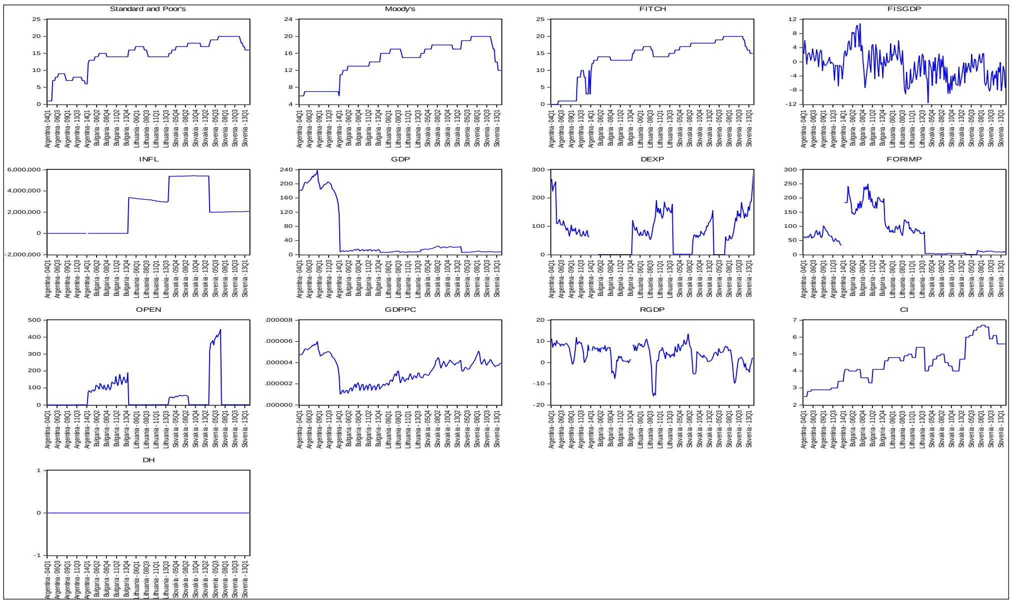

Figure 7.45: Multiple graphs of variables in levels-Frontier economies

Source: Compiled by author

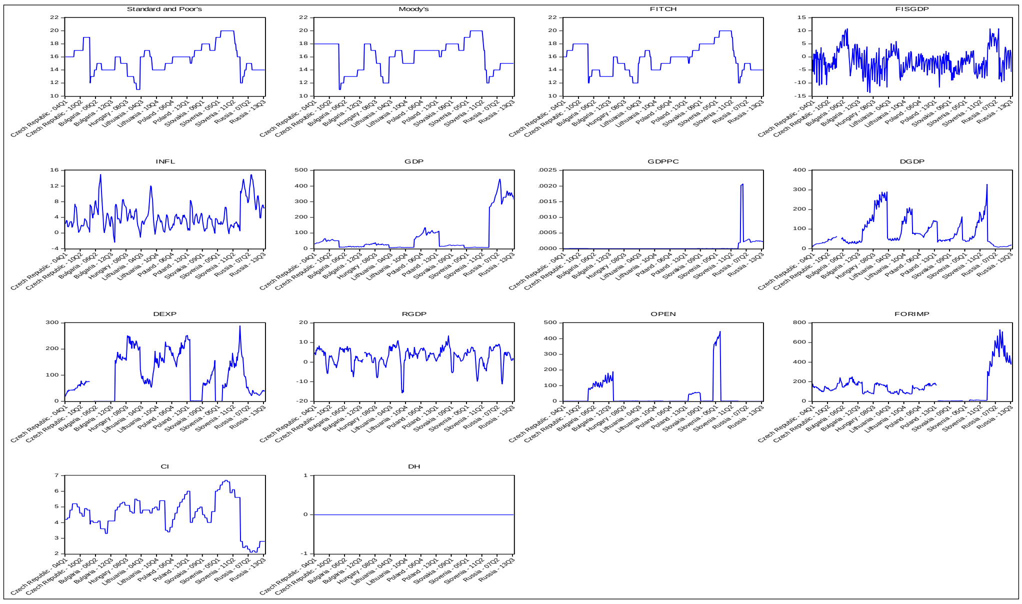

Figure 7.46: Multiple graphs of variables in levels-European economies

Source: Compiled by author

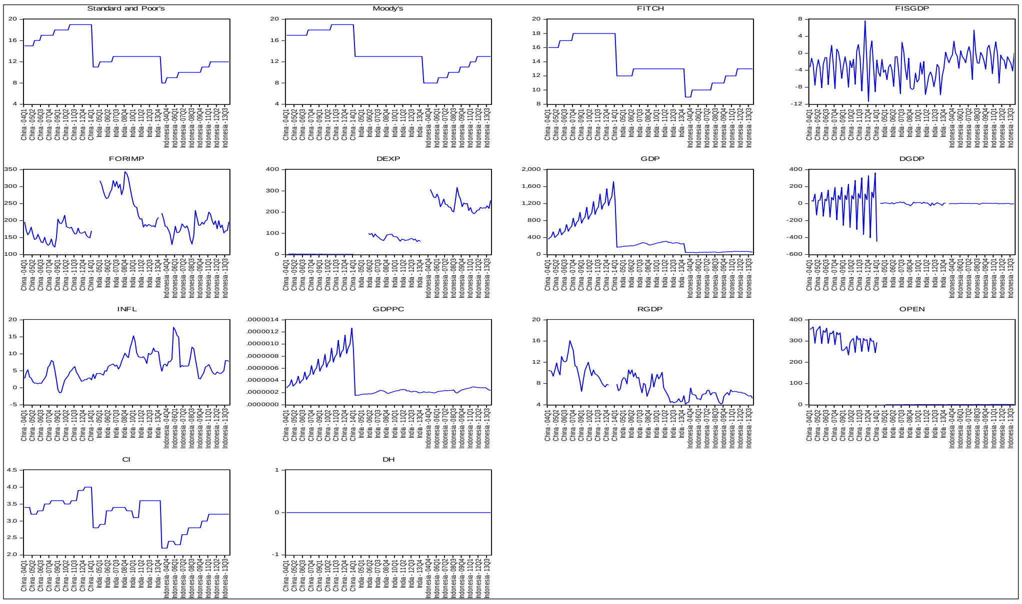

Figure 7.47: Multiple graphs of variables in levels-Asian economies

Source: Compiled by author

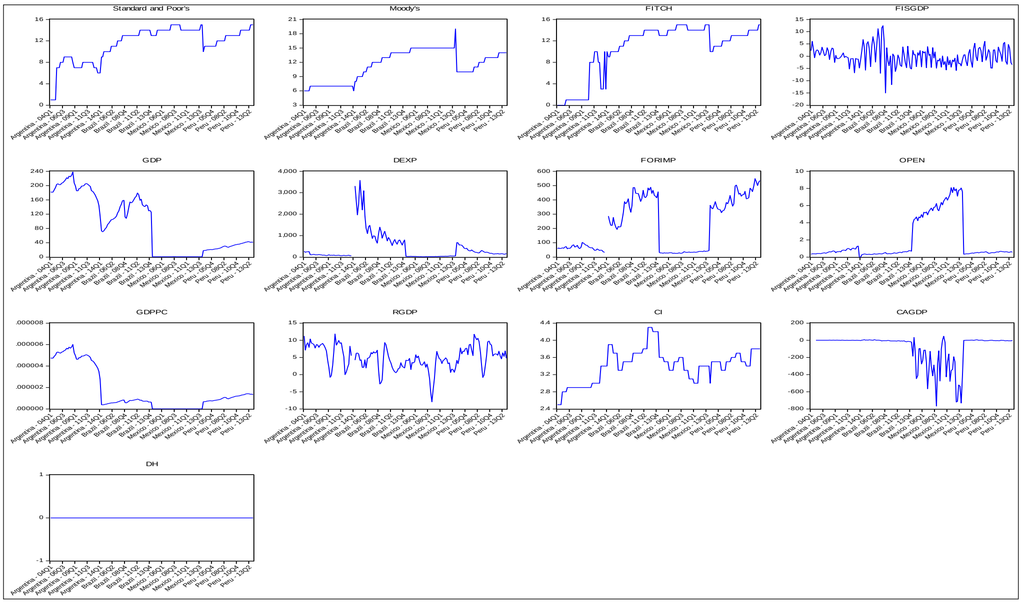

Figure 7.48: Multiple graphs of variables in levels-American economies

Source: Compiled by author

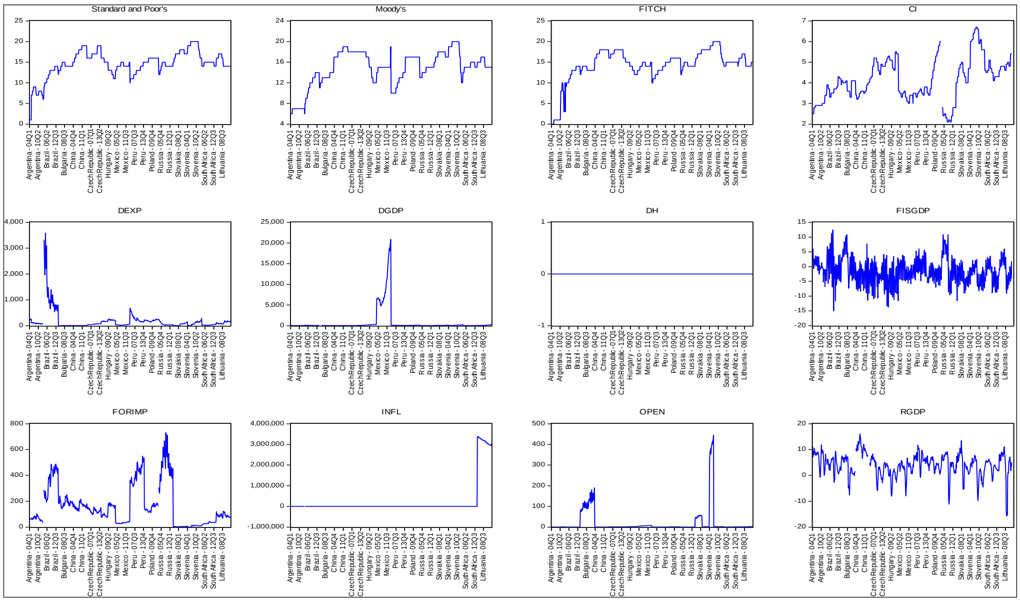

Figure 7.49: Multiple graphs of variables in levels-March 2014 FTSE Global Equity Index Series: Country Classification

Source: Compiled by author

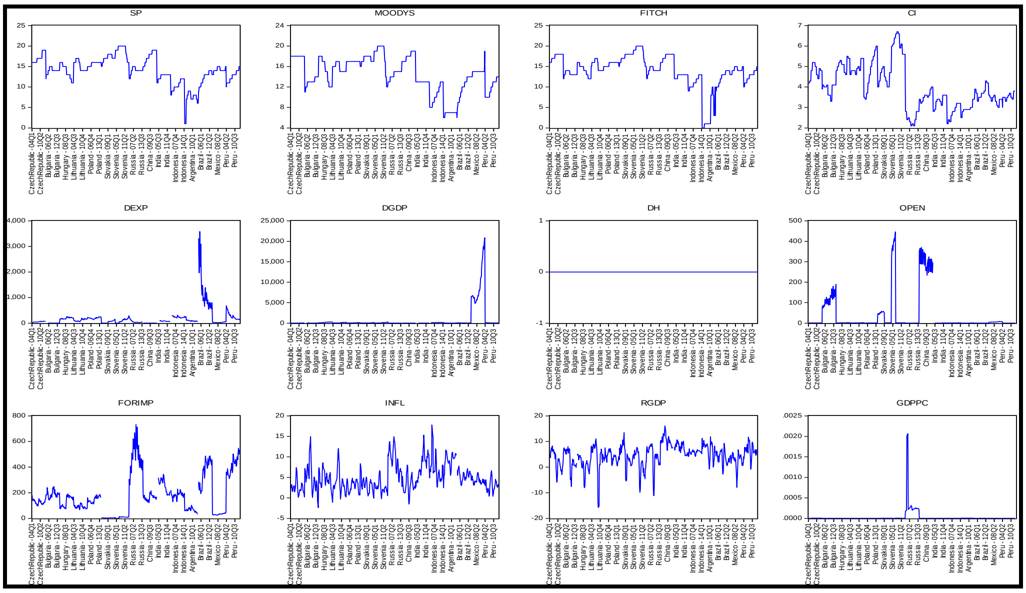

Figure 7.50: Multiple graphs of variables in levels-March 2014 FTSE Global Equity Index Series: Regional Classification

Source: Compiled by author

7.4 APPENDIX D: ORDERED PROBIT MODEL - STANDARD & POOR'S, MOODY'S AND FITCH

7.4.1 Advanced economies

Table 7.25: Standard & Poor's ordered probit model

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 07/19/15 Time: 21:22
Sample (adjusted): 2004Q2 2014Q1
Included observations: 240 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.043244	0.026063	1.659201	0.0971
FISGDP(-1)	0.043359	0.026227	1.653231	0.0983
RGDP	0.091275	0.039516	2.309817	0.0209
		Limit Points		
LIMIT_-1:C(4)	-2.894147	0.416178	-6.954103	0.0000
LIMIT_0:C(5)	-2.008622	0.224377	-8.951980	0.0000
LIMIT_1:C(6)	1.869954	0.218971	8.539741	0.0000
LIMIT_2:C(7)	2.893930	0.373902	7.739807	0.0000

Pseudo R-squared	0.094610	Akaike info criterion	0.701401
Schwarz criterion	0.802920	Log likelihood	-77.16816
Hannan-Quinn criterion	0.742306	Restr. log likelihood	-85.23198
LR statistic	16.12763	Avg. log likelihood	-0.321534
Prob(LR statistic)	0.001068		

Source: Compiled by author

Table 7.26: Standard & Poor's ordered probit model-Inclusion of all variables

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/02/15 Time: 10:38
Sample (adjusted): 2004Q2 2014Q1
Included observations: 240 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.039003	0.026559	1.468520	0.1420
RGDP	0.111894	0.042577	2.628063	0.0086
DCI	-0.327678	0.818384	-0.400396	0.6889
DDEXP	0.003337	0.025451	0.131099	0.8957
DFORIMP	0.007961	0.011560	0.688660	0.4910
DOPEN	-0.202918	0.683260	-0.296984	0.7665
INFL	0.030525	0.045730	0.667519	0.5044
REER	0.047100	0.030169	1.561206	0.1185

Limit Points				
LIMIT_-1:C(9)	-2.695317	0.470670	-5.726559	0.0000
LIMIT_0:C(10)	-1.748741	0.284019	-6.157130	0.0000
LIMIT_1:C(11)	2.170629	0.315734	6.874870	0.0000
LIMIT_2:C(12)	3.178639	0.428743	7.413852	0.0000
Pseudo R-squared	0.103401	Akaike info criterion		0.736824
Schwarz criterion	0.910856	Log likelihood		-76.41887
Hannan-Quinn criterion.	0.806946	Restr. log likelihood		-85.23198
LR statistic	17.62621	Avg. log likelihood		-0.318412
Prob(LR statistic)	0.024210			

Source: Compiled by author

Table 7.27: Moody's ordered probit model

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 20:52
Sample (adjusted): 2004Q2 2014Q1
Included observations: 240 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DOPEN	-1.045339	0.607438	-1.720899	0.0853
Limit Points				
LIMIT_-1:C(2)	-2.691587	0.338760	-7.945402	0.0000
LIMIT_0:C(3)	-2.018858	0.180072	-11.21141	0.0000
LIMIT_1:C(4)	1.735447	0.147627	11.75563	0.0000
LIMIT_4:C(5)	2.692986	0.360445	7.471276	0.0000
Pseudo R-squared	0.019199	Akaike info criterion		0.657302
Schwarz criterion	0.729816	Log likelihood		-73.87627
Hannan-Quinn criterion	0.686520	Restr. log likelihood		-75.32242
LR statistic	2.892298	Avg. log likelihood		-0.307818
Prob(LR statistic)	0.089004			

Source: Compiled by author

Table 7.28: Moody's ordered probit model-Inclusion of all variables

Dependent Variable: DMOODYS
Method: Panel Least Squares
Date: 06/03/15 Time: 13:06
Sample (adjusted): 2004Q2 2014Q1
Periods included: 40
Cross-sections included: 6
Total panel (balanced) observations: 240

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	-0.008485	0.057331	-0.147990	0.8825
FISGDP	0.003411	0.005987	0.569685	0.5694
RGDP	0.007451	0.008499	0.876790	0.3815
DCI	-0.087902	0.180365	-0.487356	0.6265
DDEXP	-7.50E-05	0.005168	-0.014511	0.9884
DFORIMP	0.000720	0.002422	0.297172	0.7666
DOPEN	-0.249652	0.145763	-1.712724	0.0881
INFL	0.006149	0.009654	0.636980	0.5248
REER	0.006796	0.006405	1.060983	0.2898

R-squared	0.035981	Mean dependent var	0.025000
Adjusted R-squared	0.002595	S.D. dependent var	0.376340
S.E. of regression	0.375851	Akaike info criterion	0.917533
Sum squared resid	32.63203	Schwarz criterion	1.048056
Log likelihood	-101.1039	Hannan-Quinn criterion.	0.970124
F-statistic	1.077740	Durbin-Watson stat	1.582841
Prob(F-statistic)	0.379486		

Source: Compiled by author

Table 7.29: Fitch ordered probit model

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 21:07
Sample (adjusted): 2004Q2 2014Q1
Included observations: 240 after adjustments
Number of ordered indicator values: 3
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.050240	0.026574	1.890526	0.0587
RGDP	0.088373	0.041618	2.123416	0.0337
REER	0.046647	0.026751	1.743765	0.0812
Limit Points				
LIMIT_0:C(4)	-1.973702	0.216116	-9.132602	0.0000
LIMIT_1:C(5)	1.967951	0.227533	8.649089	0.0000

Pseudo R-squared	0.100071	Akaike info criterion	0.607043
Schwarz criterion	0.679557	Log likelihood	-67.84522
Hannan-Quinn criterion.	0.636261	Restr. log likelihood	-75.38953
LR statistic	15.08862	Avg. log likelihood	-0.282688
Prob(LR statistic)	0.001742		

Source: Compiled by author

Table 7.30: Fitch ordered probit model-Inclusion of all variables

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/02/15 Time: 11:36
Sample (adjusted): 2004Q2 2014Q1
Included observations: 240 after adjustments
Number of ordered indicator values: 3

Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.053958	0.028002	1.926929	0.0540
RGDP	0.109462	0.045575	2.401814	0.0163
REER	0.066831	0.031424	2.126758	0.0334
DCI	-1.054581	0.787057	-1.339906	0.1803
DDEXP	0.018988	0.025525	0.743876	0.4570
DFORIMP	0.013551	0.012428	1.090332	0.2756
DOPEN	0.959057	0.689462	1.391022	0.1642
INFL	-0.014583	0.049836	-0.292628	0.7698
Limit Points				
LIMIT_0:C(9)	-2.028915	0.319202	-6.356210	0.0000
LIMIT_1:C(10)	2.059439	0.333197	6.180836	0.0000

Pseudo R-squared	0.131178	Akaike info criterion	0.629167
Schwarz criterion	0.774194	Log likelihood	-65.50004
Hannan-Quinn criterion	0.687602	Restr. log likelihood	-75.38953
LR statistic	19.77896	Avg. log likelihood	-0.272917
Prob(LR statistic)	0.011205		

Source: Compiled by author

7.4.2 Secondary economies

Table 7.31: Standard & Poor's ordered probit model-Inclusion of all variables

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/03/15 Time: 13:59
Sample (adjusted): 2004Q2 2014Q1
Included observations: 119 after adjustments
Number of ordered indicator values: 3
Convergence achieved after 9 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DGDPPC	1208.872	603.6512	2.002601	0.0452
FISGDP	0.027086	0.033054	0.819453	0.4125
DEXP	0.000636	0.001055	0.602633	0.5468
DCI	0.997417	1.476163	0.675682	0.4992
DOPEN	2.126602	3.254944	0.653345	0.5135
REER	0.000798	0.060825	0.013122	0.9895
Limit Points				
LIMIT_0:C(7)	-2.476274	0.432295	-5.728204	0.0000
LIMIT_1:C(8)	1.427907	0.215780	6.617432	0.0000

Pseudo R-squared	0.071912	Akaike info criterion	0.829698
Schwarz criterion	1.016529	Log likelihood	-41.36701
Hannan-Quinn criterion.	0.905564	Restr. log likelihood	-44.57227
LR statistic	6.410527	Avg. log likelihood	-0.347622
Prob(LR statistic)	0.378806		

Source: Compiled by author

Table 7.32: Fitch ordered probit model

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 21:30
Sample (adjusted): 2004Q2 2014Q1
Included observations: 116 after adjustments
Number of ordered indicator values: 3
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.101068	0.042402	2.383588	0.0171
Limit Points				
LIMIT_0:C(2)	-2.112164	0.474187	-4.454282	0.0000
LIMIT_1:C(3)	2.159569	0.395798	5.456238	0.0000

Pseudo R-squared	0.084271	Akaike info criterion	0.678916
Schwarz criterion	0.750129	Log likelihood	-36.37711
Hannan-Quinn. criterion	0.707824	Restr. log likelihood	-39.72477
LR statistic	6.695331	Avg. log likelihood	-0.313596
Prob(LR statistic)	0.009667		

Source: Compiled by author

7.4.3 Frontier economies

Table 7.33: Standard & Poor's ordered probit model

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 22:54
Sample (adjusted): 2004Q2 2014Q1
Included observations: 197 after adjustments
Number of ordered indicator values: 4
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.043395	0.024852	1.746180	0.0808
DRGDP	0.071561	0.039544	1.809639	0.0704
Limit Points				
LIMIT_0:C(3)	-1.615654	0.152835	-10.57126	0.0000
LIMIT_1:C(4)	1.484711	0.138859	10.69225	0.0000
LIMIT_6:C(5)	2.571071	0.358370	7.174350	0.0000

Pseudo R-squared	0.032550	Akaike info criterion	1.017263
Schwarz criterion	1.100593	Log likelihood	-95.20038
Hannan-Quinn criterion	1.050995	Restr. log likelihood	-98.40344
LR statistic	6.406126	Avg. log likelihood	-0.483251
Prob(LR statistic)	0.040638		

Source: Compiled by author

Table 7.34: Standard & Poor's ordered probit model-Inclusion of all variables

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/02/15 Time: 12:15
Sample (adjusted): 2004Q2 2014Q1
Included observations: 191 after adjustments
Number of ordered indicator values: 4
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DRGDP	0.059095	0.042174	1.401207	0.1612
DDEXP	-0.010046	0.005694	-1.764449	0.0777
DCI	0.301001	0.727678	0.413646	0.6791
DFORIMP	-0.005503	0.009839	-0.559302	0.5760
DINFL	6.31E-06	8.63E-06	0.731185	0.4647
DOPEN	-0.000179	0.003321	-0.053974	0.9570
FISGDP	0.028645	0.026277	1.090132	0.2757
		Limit Points		
LIMIT_0:C(8)	-1.621881	0.156905	-10.33673	0.0000
LIMIT_1:C(9)	1.525627	0.147778	10.32381	0.0000
LIMIT_6:C(10)	2.751674	0.458547	6.000855	0.0000

Pseudo R-squared	0.054799	Akaike info criterion	1.043708
Schwarz criterion	1.213985	Log likelihood	-89.67416
Hannan-Quinn criterion.	1.112678	Restr. log likelihood	-94.87306
LR statistic	10.39781	Avg. log likelihood	-0.469498
Prob(LR statistic)	0.167128		

Source: Compiled by author

Table 7.35: Moody's ordered probit model

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 23:00
Sample (adjusted): 2004Q2 2014Q1
Included observations: 192 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.096851	0.034269	2.826177	0.0047
DDEXP	-0.010537	0.005987	-1.759961	0.0784
		Limit Points		
LIMIT_-2:C(3)	-2.949936	0.387561	-7.611541	0.0000
LIMIT_-1:C(4)	-2.690993	0.316157	-8.511579	0.0000
LIMIT_0:C(5)	-2.049952	0.214353	-9.563455	0.0000
LIMIT_1:C(6)	1.863756	0.189247	9.848253	0.0000

Pseudo R-squared	0.107684	Akaike info criterion	0.702817

Schwarz criterion	0.804614	Log likelihood	-61.47044
Hannan-Quinn criterion.	0.744046	Restr. log likelihood	-68.88868
LR statistic	14.83648	Avg. log likelihood	-0.320159
Prob(LR statistic)	0.000600		

Source: Compiled by author

Table 7.36: Moody's ordered probit model-Inclusion of all variables

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/03/15 Time: 14:43
Sample (adjusted): 2004Q2 2014Q1
Included observations: 191 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.094937	0.034711	2.735092	0.0062
DRGDP	0.008140	0.051072	0.159391	0.8734
DDEXP	-0.010483	0.006237	-1.680719	0.0928
DCI	0.933609	0.814964	1.145584	0.2520
DFORIMP	-0.006193	0.011960	-0.517765	0.6046
DINFL	-2.92E-06	1.06E-05	-0.275905	0.7826
DOPEN	-0.001090	0.004389	-0.248347	0.8039
		Limit Points		
LIMIT_-2:C(8)	-2.955837	0.388456	-7.609193	0.0000
LIMIT_-1:C(9)	-2.698781	0.318761	-8.466475	0.0000
LIMIT_0:C(10)	-2.051412	0.217481	-9.432612	0.0000
LIMIT_1:C(11)	1.897638	0.194499	9.756525	0.0000

Pseudo R-squared	0.120571	Akaike info criterion	0.748806
Schwarz criterion	0.936110	Log likelihood	-60.51096
Hannan-Quinn criterion	0.824673	Restr. log likelihood	-68.80711
LR statistic	16.59230	Avg. log likelihood	-0.316811
Prob(LR statistic)	0.020223		

Source: Compiled by author

Table 7.37: Fitch ordered probit model

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 23:06
Sample (adjusted): 2004Q2 2014Q1
Included observations: 200 after adjustments
Number of ordered indicator values: 8
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.062732	0.026363	2.379515	0.0173

Limit Points				
LIMIT_-5:C(2)	-2.768378	0.371874	-7.444403	0.0000
LIMIT_-2:C(3)	-2.505647	0.290661	-8.620521	0.0000
LIMIT_-1:C(4)	-2.109940	0.210657	-10.01598	0.0000
LIMIT_0:C(5)	-1.771051	0.167617	-10.56604	0.0000
LIMIT_1:C(6)	1.417249	0.133149	10.64405	0.0000
LIMIT_2:C(7)	2.032227	0.205124	9.907284	0.0000
LIMIT_7:C(8)	2.148118	0.227352	9.448404	0.0000

Pseudo R-squared	0.025531	Akaike info criterion	1.198790
Schwarz criterion	1.330723	Log likelihood	-111.8790
Hannan-Quinn criterion	1.252181	Restr. log likelihood	-114.8102
LR statistic	5.862467	Avg. log likelihood	-0.559395
Prob(LR statistic)	0.015467		

Source: Compiled by author

Table 7.38: Fitch ordered probit model-Inclusion of all variables

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/03/15 Time: 14:56
Sample (adjusted): 2004Q2 2014Q1
Included observations: 191 after adjustments
Number of ordered indicator values: 7
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.058757	0.028826	2.038349	0.0415
DRGDP	0.009056	0.044287	0.204477	0.8380
DDEXP	-0.001336	0.006530	-0.204567	0.8379
DCI	-0.107675	0.767422	-0.140308	0.8884
DFORIMP	-0.003993	0.010271	-0.388758	0.6975
DINFL	-1.20E-06	9.51E-06	-0.126225	0.8996
DOPEN	-0.000407	0.003622	-0.112435	0.9105
Limit Points				
LIMIT_-2:C(8)	-2.761704	0.382305	-7.223815	0.0000
LIMIT_-1:C(9)	-2.192640	0.231736	-9.461798	0.0000
LIMIT_0:C(10)	-1.804777	0.177962	-10.14133	0.0000
LIMIT_1:C(11)	1.502280	0.144464	10.39902	0.0000
LIMIT_2:C(12)	2.122694	0.230023	9.228182	0.0000
LIMIT_7:C(13)	2.280921	0.267653	8.521945	0.0000

Pseudo R-squared	0.025787	Akaike info criterion	1.131701
Schwarz criterion	1.353060	Log likelihood	-95.07747
Hannan-Quinn criterion	1.221362	Restr. log likelihood	-97.59415
LR statistic	5.033350	Avg. log likelihood	-0.497788
Prob(LR statistic)	0.655893		

Source: Compiled by author

7.4.4 European economies

Table 7.39: Standard & Poor's ordered probit model

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 07/20/15 Time: 00:07
Sample (adjusted): 2004Q2 2014Q1
Included observations: 319 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.145197	0.040183	3.613397	0.0003
RGDP(-1)	-0.066697	0.039642	-1.682484	0.0925
Limit Points				
LIMIT_-1:C(3)	-2.879248	0.398192	-7.230799	0.0000
LIMIT_0:C(4)	-1.652166	0.139686	-11.82767	0.0000
LIMIT_1:C(5)	2.017089	0.161130	12.51837	0.0000
LIMIT_2:C(6)	3.084914	0.341017	9.046204	0.0000

Pseudo R-squared	0.087142	Akaike info criterion	0.750387
Schwarz criterion	0.821205	Log likelihood	-113.6867
Hannan-Quinn criterion	0.778669	Restr. log likelihood	-124.5393
LR statistic	21.70529	Avg. log likelihood	-0.356385
Prob(LR statistic)	0.000019		

Source: Compiled by author

Table 7.40: Standard & Poor's ordered probit model-Inclusion of all variables

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/03/15 Time: 15:03
Sample (adjusted): 2004Q2 2014Q1
Included observations: 312 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.028478	0.023390	1.217543	0.2234
RGDP	0.080281	0.023047	3.483305	0.0005
DDEXP	0.000693	0.007236	0.095838	0.9236
DCI	0.355738	0.614614	0.578799	0.5627
DFORIMP	0.000872	0.002937	0.296799	0.7666
DOPEN	0.002404	0.003875	0.620470	0.5349
INFL	-0.033863	0.030444	-1.112301	0.2660
Limit Points				
LIMIT_-1:C(8)	-3.016328	0.426920	-7.065321	0.0000
LIMIT_0:C(9)	-1.829950	0.223940	-8.171604	0.0000

LIMIT_1:C(10)	1.864001	0.225282	8.274088	0.0000
LIMIT_2:C(11)	2.904486	0.376902	7.706217	0.0000
Pseudo R-squared	0.085406	Akaike info criterion		0.778852
Schwarz criterion	0.910817	Log likelihood		-110.5009
Hannan-Quinn criterion	0.831594	Restr. log likelihood		-120.8196
LR statistic	20.63742	Avg. log likelihood		-0.354170
Prob(LR statistic)	0.004346			

Source: Compiled by author

Table 7.41: Moody's ordered probit model

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 23:19
Sample (adjusted): 2004Q2 2014Q1
Included observations: 319 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.081841	0.023597	3.468324	0.0005
FISGDP	0.063337	0.025490	2.484785	0.0130
		Limit Points		
LIMIT_-2:C(3)	-2.952626	0.356564	-8.280779	0.0000
LIMIT_-1:C(4)	-2.559671	0.251953	-10.15931	0.0000
LIMIT_0:C(5)	-1.884637	0.176569	-10.67365	0.0000
LIMIT_1:C(6)	2.313547	0.203138	11.38902	0.0000
Pseudo R-squared	0.135289	Akaike info criterion		0.600739
Schwarz criterion	0.671557	Log likelihood		-89.81783
Hannan-Quinn criterion	0.629021	Restr. log likelihood		-103.8704
LR statistic	28.10503	Avg. log likelihood		-0.281561
Prob(LR statistic)	0.000001			

Source: Compiled by author

Table 7.42: Moody's ordered probit model-Inclusion of all variables

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/03/15 Time: 15:11
Sample (adjusted): 2004Q2 2014Q1
Included observations: 312 after adjustments
Number of ordered indicator values: 5
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.062372	0.028444	2.192823	0.0283
RGDP	0.084321	0.025031	3.368624	0.0008

DDEXP	0.005473	0.007728	0.708234	0.4788
DCI	0.942054	0.719517	1.309287	0.1904
DFORIMP	-0.003444	0.003208	-1.073511	0.2830
DOPEN	0.001769	0.005102	0.346775	0.7288
INFL	0.024991	0.036209	0.690182	0.4901
		Limit Points		
LIMIT_-2:C(8)	-2.855674	0.392990	-7.266523	0.0000
LIMIT_-1:C(9)	-2.462339	0.304028	-8.099060	0.0000
LIMIT_0:C(10)	-1.783639	0.247298	-7.212516	0.0000
LIMIT_1:C(11)	2.530805	0.297718	8.500673	0.0000
Pseudo R-squared	0.150430	Akaike info criterion		0.614196
Schwarz criterion	0.746160	Log likelihood		-84.81451
Hannan-Quinn criterion	0.666938	Restr. log likelihood		-99.83225
LR statistic	30.03547	Avg. log likelihood		-0.271841
Prob(LR statistic)	0.000094			

Source: Compiled by author

Table 7.43: Fitch ordered probit model

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 23:28
Sample (adjusted): 2004Q2 2014Q1
Included observations: 319 after adjustments
Number of ordered indicator values: 4
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.103987	0.022046	4.716845	0.0000
		Limit Points		
LIMIT_-1:C(2)	-2.533581	0.290747	-8.714039	0.0000
LIMIT_0:C(3)	-1.684680	0.142595	-11.81440	0.0000
LIMIT_1:C(4)	2.101496	0.168426	12.47727	0.0000
Pseudo R-squared	0.102037	Akaike info criterion		0.697201
Schwarz criterion	0.744414	Log likelihood		-107.2036
Hannan-Quinn criterion	0.716056	Restr. log likelihood		-119.3853
LR statistic	24.36347	Avg. log likelihood		-0.336061
Prob(LR statistic)	0.000001			

Source: Compiled by author

Table 7.44: Fitch ordered probit model-Inclusion of all variables

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/03/15 Time: 15:21
Sample (adjusted): 2004Q2 2014Q1
Included observations: 312 after adjustments

Number of ordered indicator values: 4
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.010740	0.025560	0.420188	0.6743
RGDP	0.090884	0.024418	3.721930	0.0002
DDEXP	-0.007260	0.007286	-0.996307	0.3191
DCI	0.138958	0.593596	0.234096	0.8149
DFORIMP	-0.001906	0.002742	-0.694985	0.4871
DOPEN	-0.000353	0.004232	-0.083436	0.9335
INFL	-0.014323	0.031916	-0.448781	0.6536
Limit Points				
LIMIT_-1:C(8)	-2.691699	0.355326	-7.575301	0.0000
LIMIT_0:C(9)	-1.812006	0.227404	-7.968237	0.0000
LIMIT_1:C(10)	2.028130	0.240585	8.430004	0.0000

Pseudo R-squared	0.110894	Akaike info criterion	0.707247
Schwarz criterion	0.827216	Log likelihood	-100.3306
Hannan-Quinn criterion	0.755195	Restr. log likelihood	-112.8444
LR statistic	25.02757	Avg. log likelihood	-0.321572
Prob(LR statistic)	0.000750		

Source: Compiled by author

7.4.5 American economies

Table 7.45: Standard & Poor's ordered probit model

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/25/15 Time: 23:41
Sample (adjusted): 2004Q2 2014Q1
Included observations: 159 after adjustments
Number of ordered indicator values: 4
Convergence achieved after 12 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.048969	0.029270	1.673045	0.0943
Limit Points				
LIMIT_0:C(3)	-1.917023	0.206465	-9.284994	0.0000
LIMIT_1:C(4)	1.279187	0.137158	9.326340	0.0000
LIMIT_6:C(5)	2.617730	0.385572	6.789205	0.0000

Pseudo R-squared	0.059273	Akaike info criterion	1.041754
Schwarz criterion	1.138261	Log likelihood	-77.81948
Hannan-Quinn criterion	1.080945	Restr. log likelihood	-82.72273
LR statistic	9.806498	Avg. log likelihood	-0.489431
Prob(LR statistic)	0.007422		

Source: Compiled by author

Table 7.46: Standard & Poor's ordered probit model-Inclusion of all variables

Dependent Variable: DSP
Method: Panel Least Squares
Date: 06/04/15 Time: 15:08
Sample (adjusted): 2004Q2 2014Q1
Periods included: 40
Cross-sections included: 4
Total panel (unbalanced) observations: 153

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.083435	0.124651	0.669346	0.5043
FISGDP	0.016568	0.013894	1.192404	0.2351
GDPPC	19471.28	40279.60	0.483403	0.6295
DCAGDP	-0.000422	0.000438	-0.964013	0.3367
DCI	-0.247440	0.483646	-0.511614	0.6097
DDEXP	-0.000272	0.000261	-1.044540	0.2980
DFORIMP	-0.000657	0.002004	-0.327752	0.7436
DOPEN	-0.047457	0.239563	-0.198098	0.8432
INFL	-0.001634	0.028506	-0.057328	0.9544

R-squared	0.042141	Mean dependent var	0.104575
Adjusted R-squared	-0.011073	S.D. dependent var	0.608745
S.E. of regression	0.612107	Akaike info criterion	1.913202
Sum squared resid	53.95312	Schwarz criterion	2.091463
Log likelihood	-137.3599	Hannan-Quinn criterion	1.985614
F-statistic	0.791913	Durbin-Watson stat	1.369794
Prob(F-statistic)	0.610557		

Source: Compiled by author

Table 7.47: Fitch ordered probit model

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/26/15 Time: 00:02
Sample (adjusted): 2004Q2 2014Q1
Included observations: 158 after adjustments
Number of ordered indicator values: 7
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.102282	0.039248	2.606023	0.0092
DDEXP	-0.000949	0.000556	-1.705814	0.0880
		Limit Points		
LIMIT_-2:C(3)	-2.203976	0.384282	-5.735315	0.0000
LIMIT_-1:C(4)	-1.933443	0.306534	-6.307435	0.0000
LIMIT_0:C(5)	-1.756210	0.270942	-6.481863	0.0000
LIMIT_1:C(6)	1.856904	0.277187	6.699100	0.0000
LIMIT_2:C(7)	2.740702	0.350520	7.818959	0.0000
LIMIT_7:C(8)	2.907809	0.379159	7.669096	0.0000

Pseudo R-squared	0.061058	Akaike info criterion	1.071062
Schwarz criterion	1.226130	Log likelihood	-76.61386

Hannan-Quinn criterion	1.134037	Restr. log likelihood	-81.59591
LR statistic	9.964093	Avg. log likelihood	-0.484898
Prob(LR statistic)	0.006860		

Source: Compiled by author

Table 7.48: Fitch ordered probit model-Inclusion of all variables

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/04/15 Time: 15:26
Sample (adjusted): 2004Q2 2014Q1
Included observations: 157 after adjustments
Number of ordered indicator values: 7
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.096343	0.041835	2.302938	0.0213
DDEXP	-0.000525	0.000640	-0.819739	0.4124
DCI	-1.462451	1.230782	-1.188229	0.2347
DFORIMP	-0.000120	0.004954	-0.024242	0.9807
DOPEN	0.535257	0.625714	0.855434	0.3923
FISGDP	0.042315	0.034647	1.221306	0.2220
INFL	0.005645	0.045198	0.124901	0.9006
Limit Points				
LIMIT_-2:C(8)	-2.340171	0.514915	-4.544771	0.0000
LIMIT_-1:C(9)	-2.018333	0.414261	-4.872135	0.0000
LIMIT_0:C(10)	-1.828710	0.375847	-4.865564	0.0000
LIMIT_1:C(11)	1.880926	0.365861	5.141101	0.0000
LIMIT_2:C(12)	2.773565	0.437351	6.341741	0.0000
LIMIT_7:C(13)	2.941378	0.466886	6.299985	0.0000

Pseudo R-squared	0.081364	Akaike info criterion	1.118882
Schwarz criterion	1.371947	Log likelihood	-74.83221
Hannan-Quinn criterion	1.221660	Restr. log likelihood	-81.46011
LR statistic	13.25579	Avg. log likelihood	-0.476638
Prob(LR statistic)	0.066116		

Source: Compiled by author

7.4.6 March 2014 FTSE Global Equity Index Series: *Country Classification*

Table 7.49: Standard & Poor's ordered probit model

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/26/15 Time: 10:19
Sample (adjusted): 2004Q2 2014Q1
Included observations: 552 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.

DDEXP	-0.001268	0.000500	-2.535161	0.0112
RGDP	0.080823	0.015707	5.145533	0.0000
Limit Points				
LIMIT_-1:C(3)	-2.851915	0.353518	-8.067239	0.0000
LIMIT_0:C(4)	-1.581729	0.107330	-14.73707	0.0000
LIMIT_1:C(5)	1.934419	0.123981	15.60260	0.0000
LIMIT_2:C(6)	3.189402	0.263603	12.09928	0.0000
LIMIT_6:C(7)	3.431023	0.344825	9.950039	0.0000
Pseudo R-squared	0.072605	Akaike info criterion		0.820617
Schwarz criterion	0.875318	Log likelihood		-219.4904
Hannan-Quinn criterion	0.841990	Restr. log likelihood		-236.6741
LR statistic	34.36757	Avg. log likelihood		-0.397627
Prob(LR statistic)	0.000000			

Source: Compiled by author

Table 7.50: Standard & Poor's ordered probit model-Inclusion of all variables

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/04/15 Time: 16:28
Sample (adjusted): 2004Q2 2014Q1
Included observations: 550 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 10 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.024704	0.016244	1.520853	0.1283
INFL	-1.08E-07	8.21E-08	-1.318707	0.1873
RGDP	0.071939	0.016444	4.374743	0.0000
DDEXP	-0.001100	0.000526	-2.093118	0.0363
DCI	0.211424	0.494163	0.427843	0.6688
DFORIMP	-0.000375	0.002355	-0.159421	0.8733
Limit Points				
LIMIT_-1:C(7)	-2.985095	0.367799	-8.116103	0.0000
LIMIT_0:C(8)	-1.689018	0.124152	-13.60442	0.0000
LIMIT_1:C(9)	1.852479	0.130162	14.23205	0.0000
LIMIT_2:C(10)	3.110858	0.266500	11.67303	0.0000
LIMIT_6:C(11)	3.353055	0.347484	9.649537	0.0000
Pseudo R-squared	0.081000	Akaike info criterion		0.830179
Schwarz criterion	0.916377	Log likelihood		-217.2991
Hannan-Quinn criterion	0.863863	Restr. log likelihood		-236.4517
LR statistic	38.30521	Avg. log likelihood		-0.395089
Prob(LR statistic)	0.000001			

Source: Compiled by author

Table 7.51: Moody's ordered probit model

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 07/20/15 Time: 00:32
Sample (adjusted): 2004Q2 2014Q1
Included observations: 556 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.067331	0.000579	0.399072	0.0001
FISGDP	0.043461	0.018785	2.313610	0.0207
FISGDP(-1)	0.042691	0.018500	2.307634	0.0210
		Limit Points		
LIMIT_-2:C(4)	-3.148526	0.321216	-9.801901	0.0000
LIMIT_-1:C(5)	-2.787992	0.217296	-12.83037	0.0000
LIMIT_0:C(6)	-2.168425	0.133684	-16.22053	0.0000
LIMIT_1:C(7)	1.655279	0.095575	17.31922	0.0000
LIMIT_4:C(8)	2.921217	0.312736	9.340855	0.0000

Pseudo R-squared	0.053187	Akaike info criterion	0.652451
Schwarz criterion	0.714620	Log likelihood	-173.3813
Hannan-Quinn criterion	0.676734	Restr. log likelihood	-183.1210
LR statistic	19.47948	Avg. log likelihood	-0.311837
Prob(LR statistic)	0.000218		

Source: Compiled by author

Table 7.52: Moody's ordered probit model-Inclusion of all variables

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/04/15 Time: 16:33
Sample (adjusted): 2004Q2 2014Q1
Included observations: 550 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 10 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.044810	0.018637	2.404352	0.0162
INFL	-6.12E-08	9.37E-08	-0.652734	0.5139
RGDP	0.063193	0.017975	3.515558	0.0004
DDEXP	-0.000155	0.000604	-0.256733	0.7974
DCI	0.337575	0.591096	0.571099	0.5679
DFORIMP	-0.005028	0.002514	-2.000170	0.0455
		Limit Points		
LIMIT_-2:C(7)	-3.016181	0.333940	-9.032098	0.0000
LIMIT_-1:C(8)	-2.643657	0.229084	-11.54013	0.0000
LIMIT_0:C(9)	-1.984371	0.148458	-13.36652	0.0000
LIMIT_1:C(10)	1.987987	0.142827	13.91887	0.0000
LIMIT_4:C(11)	3.260888	0.328239	9.934503	0.0000

Pseudo R-squared	0.091548	Akaike info criterion	0.643445
Schwarz criterion	0.729643	Log likelihood	-165.9474
Hannan-Quinn criterion	0.677130	Restr. log likelihood	-182.6705
LR statistic	33.44637	Avg. log likelihood	-0.301722
Prob(LR statistic)	0.000009		

Source: Compiled by author

Table 7.53: Fitch ordered probit model

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 07/20/15 Time: 00:39
Sample (adjusted): 2004Q3 2014Q1
Included observations: 538 after adjustments
Number of ordered indicator values: 7
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.094576	0.016994	5.565391	0.0000
DDEXP	-0.001161	0.000586	-1.979781	0.0477
DDEXP(-1)	-0.000962	0.000548	-1.756047	0.0791
		Limit Points		
LIMIT_-2:C(4)	-2.851991	0.334060	-8.537374	0.0000
LIMIT_-1:C(5)	-2.343984	0.199259	-11.76350	0.0000
LIMIT_0:C(6)	-1.715435	0.119296	-14.37964	0.0000
LIMIT_1:C(7)	2.027530	0.134322	15.09459	0.0000
LIMIT_2:C(8)	3.152239	0.240745	13.09368	0.0000
LIMIT_7:C(9)	3.295999	0.272092	12.11353	0.0000

Pseudo R-squared	0.093053	Akaike info criterion	0.797062
Schwarz criterion	0.868792	Log likelihood	-205.4097
Hannan-Quinn criterion	0.825120	Restr. log likelihood	-226.4848
LR statistic	42.15006	Avg. log likelihood	-0.381802
Prob(LR statistic)	0.000000		

Source: Compiled by author

Table 7.54: Fitch ordered probit model-Inclusion of all variables

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/04/15 Time: 16:48
Sample (adjusted): 2004Q2 2014Q1
Included observations: 550 after adjustments
Number of ordered indicator values: 7
Convergence achieved after 10 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.021122	0.017219	1.226670	0.2199
INFL	1.38E-08	8.15E-08	0.169231	0.8656

RGDP	0.088200	0.017852	4.940490	0.0000
DDEXP	-0.000972	0.000568	-1.712519	0.0868
DCI	-0.314951	0.507493	-0.620602	0.5349
DFORIMP	-0.002117	0.002232	-0.948206	0.3430
Limit Points				
LIMIT_-2:C(7)	-2.944538	0.348120	-8.458402	0.0000
LIMIT_-1:C(8)	-2.425474	0.210638	-11.51490	0.0000
LIMIT_0:C(9)	-1.788577	0.132869	-13.46123	0.0000
LIMIT_1:C(10)	1.981409	0.142754	13.87987	0.0000
LIMIT_2:C(11)	3.083850	0.241861	12.75052	0.0000
LIMIT_7:C(12)	3.227994	0.273375	11.80794	0.0000
Pseudo R-squared	0.090589	Akaike info criterion		0.796597
Schwarz criterion	0.890632	Log likelihood		-207.0643
Hannan-Quinn criterion	0.833345	Restr. log likelihood		-227.6905
LR statistic	41.25231	Avg. log likelihood		-0.376481
Prob(LR statistic)	0.000000			

Source: Compiled by author

7.4.7 March 2014 FTSE Global Equity Index Series: *Regional Classification*

Table 7.55: Standard & Poor's ordered probit model

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/26/15 Time: 11:58
Sample (adjusted): 2004Q2 2014Q1
Included observations: 572 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DDEXP	-0.001113	0.000519	-2.142658	0.0321
FISGDP	0.026226	0.015757	1.664436	0.0960
RGDP	0.074223	0.016110	4.607172	0.0000
Limit Points				
LIMIT_-1:C(4)	-2.951293	0.365645	-8.071465	0.0000
LIMIT_0:C(5)	-1.680645	0.120643	-13.93074	0.0000
LIMIT_1:C(6)	1.885613	0.128892	14.62943	0.0000
LIMIT_2:C(7)	3.157506	0.264532	11.93618	0.0000
LIMIT_6:C(8)	3.397669	0.345052	9.846821	0.0000
Pseudo R-squared	0.077109	Akaike info criterion		0.805323
Schwarz criterion	0.866150	Log likelihood		-222.3224
Hannan-Quinn criterion	0.829052	Restr. log likelihood		-240.8977
LR statistic	37.15058	Avg. log likelihood		-0.388676
Prob(LR statistic)	0.000000			

Source: Compiled by author

Table 7.56: Standard & Poor's ordered probit model-Inclusion of all variables

Dependent Variable: DSP
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/04/15 Time: 16:57
Sample (adjusted): 2004Q2 2014Q1
Included observations: 571 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.076470	0.016288	4.694998	0.0000
FISGDP	0.029856	0.016253	1.836923	0.0662
DDEXP	-0.001119	0.000526	-2.127336	0.0334
DFORIMP	0.000144	0.002316	0.062228	0.9504
DOPEN	0.000409	0.003120	0.130957	0.8958
INFL	-0.025022	0.020406	-1.226204	0.2201
DCI	0.225486	0.502148	0.449042	0.6534
Limit Points				
LIMIT_-1:C(8)	-3.093430	0.386604	-8.001556	0.0000
LIMIT_0:C(9)	-1.810961	0.164877	-10.98370	0.0000
LIMIT_1:C(10)	1.771170	0.160108	11.06233	0.0000
LIMIT_2:C(11)	3.040090	0.281615	10.79521	0.0000
LIMIT_6:C(12)	3.277989	0.357361	9.172762	0.0000

Pseudo R-squared	0.080722	Akaike info criterion	0.817344
Schwarz criterion	0.908708	Log likelihood	-221.3518
Hannan-Quinn criterion	0.852989	Restr. log likelihood	-240.7887
LR statistic	38.87382	Avg. log likelihood	-0.387656
Prob(LR statistic)	0.000002		

Source: Compiled by author

Table 7.57: Moody's ordered probit model

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/26/15 Time: 12:56
Sample (adjusted): 2004Q2 2014Q1
Included observations: 592 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
FISGDP	0.046043	0.017691	2.602676	0.0092
RGDP	0.072769	0.017500	4.158323	0.0000
Limit Points				
LIMIT_-2:C(3)	-2.991551	0.336174	-8.898828	0.0000
LIMIT_-1:C(4)	-2.611159	0.226912	-11.50737	0.0000
LIMIT_0:C(5)	-1.979429	0.144501	-13.69834	0.0000
LIMIT_1:C(6)	2.028309	0.139059	14.58595	0.0000

LIMIT_4:C(7)	3.322729	0.323229	10.27979	0.0000

Pseudo R-squared	0.082900	Akaike info criterion	0.615014
Schwarz criterion	0.666846	Log likelihood	-175.0440
Hannan-Quinn criterion	0.635203	Restr. log likelihood	-190.8670
LR statistic	31.64592	Avg. log likelihood	-0.295683
Prob(LR statistic)	0.000000		

Source: Compiled by author

Table 7.58: Moody's ordered probit model-Inclusion of all variables

Dependent Variable: DMOODYS
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/04/15 Time: 17:00
Sample (adjusted): 2004Q2 2014Q1
Included observations: 571 after adjustments
Number of ordered indicator values: 6
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.069975	0.017936	3.901342	0.0001
FISGDP	0.042592	0.018764	2.269849	0.0232
DDEXP	-0.000202	0.000610	-0.330364	0.7411
DFORIMP	-0.005016	0.002515	-1.994444	0.0461
DOPEN	-0.001538	0.003052	-0.503869	0.6144
INFL	0.017016	0.023501	0.724067	0.4690
DCI	0.551715	0.599076	0.920944	0.3571
		Limit Points		
LIMIT_-2:C(8)	-2.928287	0.351673	-8.326742	0.0000
LIMIT_-1:C(9)	-2.550018	0.251829	-10.12598	0.0000
LIMIT_0:C(10)	-1.916819	0.183886	-10.42397	0.0000
LIMIT_1:C(11)	2.130935	0.189814	11.22645	0.0000
LIMIT_4:C(12)	3.428442	0.349025	9.822908	0.0000

Pseudo R-squared	0.097494	Akaike info criterion	0.631062
Schwarz criterion	0.722425	Log likelihood	-168.1681
Hannan-Quinn criterion	0.666706	Restr. log likelihood	-186.3347
LR statistic	36.33318	Avg. log likelihood	-0.294515
Prob(LR statistic)	0.000006		

Source: Compiled by author

Table 7.59: Fitch ordered probit model

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 05/26/15 Time: 13:27
Sample (adjusted): 2004Q2 2014Q1
Included observations: 573 after adjustments
Number of ordered indicator values: 7
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DDEXP	-0.001242	0.000533	-2.330744	0.0198
RGDP	0.093962	0.016975	5.535266	0.0000
Limit Points				
LIMIT_-2:C(3)	-2.852829	0.333936	-8.543043	0.0000
LIMIT_-1:C(4)	-2.345314	0.199420	-11.76069	0.0000
LIMIT_0:C(5)	-1.746359	0.121985	-14.31623	0.0000
LIMIT_1:C(6)	2.056310	0.135446	15.18181	0.0000
LIMIT_2:C(7)	3.156616	0.236434	13.35093	0.0000
LIMIT_7:C(8)	3.298992	0.268067	12.30660	0.0000
Pseudo R-squared	0.083197	Akaike info criterion		0.760266
Schwarz criterion	0.821012	Log likelihood		-209.8164
Hannan-Quinn criterion	0.783962	Restr. log likelihood		-228.8565
LR statistic	38.08031	Avg. log likelihood		-0.366172
Prob(LR statistic)	0.000000			

Source: Compiled by author

Table 7.60: Fitch ordered probit model-Inclusion of all variables

Dependent Variable: DFITCH
Method: ML - Ordered Probit (Quadratic hill climbing)
Date: 06/04/15 Time: 17:03
Sample (adjusted): 2004Q2 2014Q1
Included observations: 571 after adjustments
Number of ordered indicator values: 7
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
RGDP	0.087438	0.017553	4.981434	0.0000
FISGDP	0.027848	0.017209	1.618234	0.1056
DDEXP	-0.000957	0.000573	-1.670617	0.0948
DFORIMP	-0.001944	0.002227	-0.873201	0.3826
DOPEN	-0.002242	0.002670	-0.839752	0.4010
INFL	-0.011797	0.021486	-0.549027	0.5830
DCI	-0.142507	0.513271	-0.277644	0.7813
Limit Points				
LIMIT_-2:C(8)	-3.032254	0.374307	-8.100987	0.0000
LIMIT_-1:C(9)	-2.505488	0.242139	-10.34731	0.0000
LIMIT_0:C(10)	-1.891900	0.173510	-10.90372	0.0000
LIMIT_1:C(11)	1.935082	0.174008	11.12067	0.0000
LIMIT_2:C(12)	3.036781	0.264286	11.49052	0.0000
LIMIT_7:C(13)	3.177110	0.293966	10.80774	0.0000
Pseudo R-squared	0.091372	Akaike info criterion		0.773283
Schwarz criterion	0.872260	Log likelihood		-207.7723
Hannan-Quinn criterion	0.811898	Restr. log likelihood		-228.6659
LR statistic	41.78724	Avg. log likelihood		-0.363874
Prob(LR statistic)	0.000001			

Source: Compiled by author

7.5 APPENDIX E: DISCUSSION OF ORDERED PROBIT, OLS AND POOLED OLS MODELS' RESULTS

7.5.1 ORDERED PROBIT MODELS

7.5.1.1 Advanced economies

- *Standard & Poor's:* FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.0432 with a p-value of 0.0971 indicating statistical significance at the 90% confidence interval. Another positive relationship is established with the previous quarter of FISGDP (-1), which is designated as a MA(1) model and the coefficient is 0.0433 with a p-value of 0.0983 indicating statistical significance at the 90% confidence interval. Furthermore, a positive relationship is found with RGDP and the coefficient is 0.0912 with a p-value of 0.0209 indicating statistical significance at the 95% confidence interval.
- *Moody's:* Openness has a negative influence on sovereign ratings assigned by Moody's. The coefficient of openness is -1.0453 with a p-value of 0.0853 indicating statistical significance at the 90% confidence interval.
- *Fitch:* FISGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is 0.0502 with a p-value of 0.0587 indicating statistical significance at the 90% confidence interval. In addition, the relationship with RGDP is also positive and the coefficient is 0.0883 with a p-value of 0.0337 indicating statistical significance at the 95% confidence interval. Another positive relationship is found with REER and the coefficient is 0.0466 with a p-value of 0.0812 indicating statistical significance at the 90% confidence interval.

7.5.1.2 Secondary economies

- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of RGDP is 0.1010 with a p-value of 0.0171 indicating statistical significance at the 95% confidence interval.

7.5.1.3 Frontier economies

- *Standard & Poor's:* FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.0433 with a p-value of 0.0808 indicating statistical significance at the 90% confidence interval. Another positive relationship is established with DRGDP and the coefficient is

0.0715 with a p-value of 0.0704 indicating statistical significance at the 90% confidence interval.

- *<u>Moody's</u>*: DDEXP has a negative influence on sovereign ratings assigned by Moody's. The coefficient for DDEXP is -0.0105 with a p-value of 0.0784 at the 90% confidence interval. However, a positive relationship is established with FISGDP and the coefficient is 0.0968 with a p-value of 0.0047 indicating statistical significance at the 99% confidence interval.
- *<u>Fitch:</u>* FISGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is 0.0627 with a p-value of 0.0173 indicating statistical significance at the 95% confidence interval. FISGDP is the only variable found to be significant.

7.5.1.4 European economies

- *<u>Standard & Poor's</u>* RGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of RGDP is 0.1451 with a p-value of 0.0003 indicating statistical significance at the 99% confidence interval. Another relationship, however negative, is established with the previous quarter of RGDP (-1) that is designated as an MA(1) model and the coefficient is -0.0666 with a p-value of 0.0925 indicating statistical significance at the 90% confidence interval.
- *<u>Moody's</u>:* FISGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient of FISGDP is 0.0633 with a p-value of 0.0130 indicating statistical significance at the 99% confidence interval. An additional positive relationship is established with RGDP and the coefficient is 0.0818 with a p-value of 0.0005 at the 99% confidence interval.
- *<u>Fitch:</u>* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of RGDP is 0.1039 with a p-value of 0.0007 indicating statistical significance at the 99% confidence interval. RGDP is the only variable found to be significant.

7.5.1.5 American economies

- *<u>Standard & Poor's:</u>* FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.0489 with a p-value of 0.0943 indicating statistical significance at the 90% confidence interval.
- *<u>Fitch:</u>* DDEXP has a negative influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is -0.0009 with a p-value of 0.0092 indicating statistical

significance indicating statistical significance at the 99% confidence interval. However, a positive relationship is found with RGDP and the coefficient is 0.1022 with a p-value of 0.0880 at the 90% confidence interval.

7.5.1.6 March 2014 FTSE Global Equity Index Series: Country Classification

- *Standard & Poor's:* RGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of RGDP is 0.0808 with a p-value of 0.0112 indicating statistical significance at the 99% confidence interval. In addition, a contrary negative relationship is established with DDEXP, and the coefficient is -0.0012 with a p-value of 0.0001 indicating statistical significance at the 99% confidence interval.
- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient of RGDP is 0.0673 with a p-value of 0.0001 indicating statistical significance at the 99% confidence interval. An added positive relationship is found with FISGDP as well and the coefficient is 0.0434 with a p-value of 0.0207 indicating statistical significance at the 95% confidence interval. Finally, a positive relationship is also established with past values of FISGDP and the coefficient is 0.0426 with a p-value of 0.0210 indicating statistical significance at the 95% confidence interval.
- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of RGDP is 0.0944 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval. On the contrary, two negative relationships are found with DDEXP and the coefficient is -0.0011 with a p-value of 0.0507 indicating statistical significance at the 90% confidence interval, while the other negative relationship is found with past values of DDEXP and the coefficient is -0.0010 with a p-value of 0.0660 at the 90% confidence interval.

7.5.1.7 March 2014 FTSE Global Equity Index Series: Regional Classification

- *Standard & Poor's:* FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.0262 with a p-value of 0.0960 indicating statistical significance at the 90% confidence interval. In addition, another positive relationship is established with RGDP, and the coefficient is 0.0742 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval. On the contrary, a negative relationship is found with DDEXP and the coefficient is -0.0011 with a p-value of 0.0321 indicating statistical significance at the 95% confidence interval.

- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient of RGDP is 0.0690 with a p-value of 0.0001 indicating statistical significance at the 99% confidence interval. An additional positive relationship is found with FISGDP as well and the coefficient is 0.0343 with a p-value of 0.0711 indicating statistical significance at the 90% confidence interval. Finally, a positive relationship is also established with the previous quarter of FISGDP (-1) which is designated as a an MA(1) model and the coefficient is 0.0309 with a p-value of 0.0996 indicating statistical significance at the 90% confidence interval.
- *Fitch:* FISGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is 0.0945 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval. On the contrary, two negative relationships are found with DDEXP and the coefficient is -0.0011 with a p-value of 0.0477 indicating statistical significance at the 95% confidence interval, while the other negative relationship is found with past values of DDEXP and the coefficient is -0.0009 with a p-value of 0.0791indicating statistical significance at the 90% confidence interval.

7.5.2 OLS MODELS

7.5.2.1 Advanced economies

- *Standard & Poor's:* FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.0085 with a p-value of 0.0533 indicating statistical significance at the 95% confidence interval. Furthermore, a positive relationship is found with RGDP and the coefficient is 0.0173 with a p-value of 0.0103 indicating statistical significance at the 99% confidence interval. Another positive relationship is found with REER and the coefficient is 0.0094 with a p-value of 0.0691 indicating statistical significance at the 90% confidence interval.
- *Moody's:* DOPEN has a negative influence on sovereign ratings assigned by Moody's. The coefficient of DOPEN is -0.3010 with a p-value of 0.0221 indicating statistical significance at the 95% confidence interval.

- *Fitch:* FISGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is 0.0092 with a p-value of 0.0259 indicating statistical significance at the 95% confidence interval. In addition, the relationship with RGDP is also positive and the coefficient is 0.0119 with a p-value of 0.0373 indicating statistical significance at the 95% confidence interval. Another positive relationship is found with REER and the coefficient is 0.0069 with a p-value of 0.0834 indicating statistical significance at the 90% confidence interval.

7.5.2.2 Secondary economies

- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of RGDP is 0.0141 with a p-value of 0.0252 indicating statistical significance at the 95% confidence interval.

7.5.2.3 Frontier economies

- *Standard & Poor's:* FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.0166 with a p-value of 0.0837 indicating statistical significance at the 90% confidence interval, another positive relationship is established with DRGDP and the coefficient is 0.0285 with a p-value of 0.0666 indicating statistical significance at the 90% confidence interval.
- *Moody's:* DDEXP has a negative influence on sovereign ratings assigned by Moody's. The coefficient of DDEXP is -0.0026 with a p-value of 0.0654 indicating statistical significance at the 90% confidence interval. However, a positive relationship is established with FISGDP and the coefficient is 0.0165 with a p-value of 0.0120 indicating statistical significance at the 99% confidence interval.
- *Fitch:* FISGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is 0.0244 with a p-value of 0.0669 indicating statistical significance at the 90% confidence interval. An AR(1) model is found to be significant and has a negative coefficient of -0.4853 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval.

7.5.2.4 European economies

- *Standard & Poor's:* RGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of RGDP is 0.0321 with a p-value of 0.0001 indicating statistical significance at the 99% confidence interval. Another relationship, however negative, is established with the previous quarter RGDP (-

1) that is designated as an MA(1) model and the coefficient is -0.0170 with a p-value of 0.0396 indicating statistical significance at the 95% confidence interval.

- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient of RGDP is 0.0184 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval.
- *Fitch:* FISGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is 0.0211 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval. An AR(1) model is found to be significant and has a negative coefficient of -0.1099 with a p-value of 0.0539 indicating statistical significance at the 95% confidence interval.

7.5.2.5 Asian economies

- *Fitch:* DOPEN has a negative influence on sovereign ratings assigned by Fitch. The coefficient of DOPEN is -0.0017 with a p-value of 0.0338 indicating statistical significance at the 95% confidence interval.

7.5.2.6 American economies

- *Standard & Poor's:* FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.0215 with a p-value of 0.0755 indicating statistical significance at the 90% confidence interval.
- *Moody's:* DOPEN has a negative influence on sovereign ratings assigned by Moody's. The coefficient of DOPEN is -0.2843 with a p-value of 0.0425 indicating statistical significance at the 95% confidence interval.
- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of RGDP is 0.0440 with a p-value of 0.0452 indicating statistical significance at the 95% confidence interval.

7.5.2.7 March 2014 FTSE Global Equity Index Series: Country Classification

- *Standard & Poor's:* RGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of RGDP is 0.0189 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval. In addition, a contrary negative relationship is established with DDEXP, and the coefficient is -0.0004 with a p-value of 0.0068 indicating statistical significance at the 99% confidence interval.
- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient of RGDP is 0.0121 with a p-value of 0.0006 indicating

statistical significance at the 99% confidence interval. An added positive relationship is found with FISGDP as well and the coefficient is 0.0064 with a p-value of 0.0716 indicating statistical significance at the 90% confidence interval.

- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of RGDP is 0.0232 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval.

7.5.2.8 March 2014 FTSE Global Equity Index Series: Regional Classification

- *Standard & Poor's:* DDEXP has a negative influence on sovereign ratings assigned by Standard & Poor's. The coefficient of DDEXP is -0.0004 with a p-value of 0.0034 indicating statistical significance at the 99% confidence interval.
- *Moody's* FISGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient of FISGDP is 0.0066 with a p-value of 0.0465 indicating statistical significance at the 95% confidence interval. An added positive relationship is found with RGDP as well and the coefficient is 0.0123 with a p-value of 0.0002 indicating statistical significance at the 99% confidence interval.
- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of RGDP is 0.0220 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval.

7.5.3 OLS MODELS – FIXED AND RANDOM EFFECTS

7.5.3.1 Advanced economies

- *Standard & Poor's:* RGDP has a positive influence on the sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is 0.0161 with a p-value of 0.0217 indicating statistical significance at the 95% confidence interval. Furthermore, a positive relationship is found with REER and the Hausman test indicates the random effect model as the most suitable model. The coefficient for the random effect is 0.0088 with a p-value of 0.0612 indicating statistical significance at the 90% confidence interval.
- *Moody's:* DOPEN has a negative influence on the sovereign ratings assigned by Moody's. The Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.3316 with a p-value of 0.0107, indicating statistical significance at the 99% confidence interval.

- *Fitch:* REER has a positive influence on the sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is 0.0067 with a p-value of 0.0897, indicating statistical significance at the 90% confidence interval. In addition, the relationship with DDGDP is negative and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0001 with a p-value of 0.0635, indicating statistical significance at the 90% confidence interval.

7.5.3.2 Frontier economies

- *Standard & Poor's: D*RGDP has a positive influence on the sovereign ratings assigned by Standard & Poor's. The coefficient of DRGDP for the random effect is 0.0246 with a p-value of 0.0827, indicating statistical significance at the 90% confidence interval. Another relationship is established with DDEXP, however negative, and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0134 with a p-value of 0.0000, indicating statistical significance at the 99% confidence interval.
- *Moody's:* FISGDP has a positive influence on the sovereign ratings assigned by Moody's. The Hausman test indicates the random effect model as the most suitable model. The coefficient of FISGDP for the random effect is 0.0190 with a p-value of 0.0108, indicating statistical significance at the 99% confidence interval.
- *Fitch:* FISGDP has a positive influence on the sovereign ratings assigned by Fitch. The Hausman test indicates the random effect model as the most suitable model. The coefficient of FISGDP for the random effect is 0.0432 with a p-value of 0.0601, indicating statistical significance at the 95% confidence interval.

7.5.3.3 European economies

- *Standard & Poor's* RGDP has a positive influence on the sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of RGDP for the random effect is 0.0156 with a p-value of 0.0002, indicating statistical significance at the 99% confidence interval.
- *Moody's:* RGDP has a positive influence on the sovereign ratings assigned by Moody's. The Hausman test suggests the fixed effect model as the most suitable

model. The coefficient of RGDP for the random effect is 0.0156 with a p-value of 0.0139, indicating statistical significance at the 99% confidence interval.

- *Fitch:* FISGDP has a positive influence on the sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of FISGDP for the random effect is 0.0184 with a p-value of 0.0000, indicating statistical significance at the 99% confidence interval.

7.5.3.4 Asian economies

- *Fitch:* DOPEN has a negative influence on sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DOPEN for the random effect is -0.0018 with a p-value of 0.0330, indicating statistical significance at the 95% confidence interval.

7.5.3.5 American economies

- *Moody's:* DOPEN has a negative influence on sovereign ratings assigned by Moody's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DOPEN for the random effect is -0.3055 with a p-value of 0.0321, indicating statistical significance at the 95% confidence interval.
- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of RGDP for the random effect is 0.0483 with a p-value of 0.0633, indicating statistical significance at the 90% confidence interval.

7.5.3.6 March 2014 FTSE Global Equity Index Series: Country Classification

- *Standard & Poor's:* RGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of RGDP for the random effect is 0.0180 with a p-value of 0.0001, indicating statistical significance at the 99% confidence interval. In addition, a contrary negative relationship is established with DDEXP and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0003 with a p-value of 0.0112, indicating statistical significance at the 99% confidence interval.
- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The Hausman test suggests the random effect model as the most

suitable model. The coefficient of RGDP for the random effect is 0.0129 with a p-value of 0.0008, indicating statistical significance at the 99% confidence interval.

- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of RGDP for the random effect is 0.0235 with a p-value of 0.0003, indicating statistical significance at the 99% confidence interval.

7.5.3.7 March 2014 FTSE Global Equity Index Series: Regional Classification

- *Standard & Poor's:* DDEXP has a negative influence on sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DDEXP for the random effect is -0.0004 with a p-value of 0.0063, indicating statistical significance at the 99% confidence interval.
- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of RGDP for the random effect is 0.0132 with a p-value of 0.0005, indicating statistical significance at the 99% confidence interval.
- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is 0.0235 with a p-value of 0.0002, indicating statistical significance at the 99% confidence interval.

7.5.4 POOLED OLS MODELS

7.5.4.1 Advanced economies

- *Standard & Poor's:* DDEXP has a negative influence on sovereign ratings assigned by Standard & Poor's. The coefficient of DDEXP is -0.0002 with a p-value of 0.0223 indicating statistical significance at the 95% confidence interval. Furthermore, a positive relationship is found with DRGDP and the coefficient is 0.0159 with a p-value of 0.0231 indicating statistical significance at the 95% confidence interval. Another positive relationship is found with REER and the coefficient is 0.0089 with a p-value of 0.0575 indicating statistical significance at the 99% confidence interval.
- *Fitch:* DDEXP has a negative influence on sovereign ratings assigned by Fitch. The coefficient of DDEXP is -0.0002 with a p-value of 0.0147 indicating statistical

significance at the 95% confidence interval. In addition, a positive relationship is found with REER and the coefficient is 0.007301 with a p-value of 0.0709 indicating statistical significance at the 99% confidence interval.

7.5.4.2 Secondary economies

- <u>*Fitch:*</u> DRGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of DRGDP is 0.0147 with a p-value of 0.0483 indicating statistical significance at the 95% confidence interval.

7.5.4.3 Frontier economies

- <u>*Standard & Poor's:*</u> DRGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of DRGDP is 0.0287 with a p-value of 0.0679 indicating statistical significance at the 99% confidence interval. Another relationship is established, which is negative with DDGDP and the coefficient is -0.0063 with a p-value of 0.0449 indicating statistical significance at the 95% confidence interval.
- <u>*Moody's:*</u> DDGDP has a negative influence on sovereign ratings assigned by Moody's. The coefficient of DDGDP is -0.0040 with a p-value of 0.0508 indicating statistical significance at the 99% confidence interval. The sovereign ratings of Moody's for frontier economies are influenced by external debt as a percentage GDP.
- <u>*Fitch:*</u> FISGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of FISGDP is 0.0244 with a p-value of 0.0669 indicating statistical significance at the 95% confidence interval. An AR(1) model is found to be significant and has a negative coefficient of -0.4853 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval.

7.5.4.4 European economies

- <u>*Standard & Poor's:*</u> FISGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient of FISGDP is 0.4707 with a p-value of 0.0000 indicating statistical significance at the 99% confidence interval. Another positive relationship is established with DRGDP that is and the coefficient is 0.1179 with a p-value of 0.0934 indicating statistical significance at the 95% confidence interval. Finally, a positive relationship is also found with DDGDP and the coefficient is 0.1179 with a p-value of 0.0934 indicating statistical significance at the 90% confidence interval.

- *Fitch:* RGDP has a positive influence on sovereign ratings assigned by Fitch. The coefficient of DRGDP is 0.0092 with a p-value of 0.0989 indicating statistical significance at the 90% confidence interval. In addition, DDGDP is found to be significant and has a negative coefficient of -0.0030 with a p-value of 0.0211 indicating statistical significance at the 95% confidence interval.

7.5.4.5 Asian economies

- *Moody's:* DRGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient of DRGDP is 0.0164 with a p-value of 0.0255 indicating statistical significance at the 95% confidence interval.
- *Fitch:* DOPEN has a negative influence on sovereign ratings assigned by Fitch. The coefficient of DOPEN is -0.0030 with a p-value of 0.0019 indicating statistical significance at the 99% confidence interval. On the contrary, a positive relationship is established with DRGDP indicating statistical significance at the coefficient is 0.0131 and the p-values is 0.0135 indicating statistical significance at the 99% confidence interval.

7.5.4.6 American economies

- *Moody's:* DOPEN has a negative influence on sovereign ratings assigned by Moody's. The coefficient is -0.2465 with a p-value of 0.0782 indicating statistical significance at the 90% confidence interval. DCAGDP also has a negative relationship and the coefficient is -0.0006 and the p-value is 0.0359 indicating statistical significance at the 95% confidence interval.

7.5.4.7 March 2014 FTSE Global Equity Index Series: Country Classification

- *Standard & Poor's* DRGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient is 0.0160 with a p-value of 0.0075 indicating statistical significance at the 99% confidence interval.

7.5.4.8 March 2014 FTSE Global Equity Index Series: Regional Classification

- *Standard & Poor's* DRGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The coefficient is 0.0166 with a p-value of 0.0083 indicating statistical significance at the 99% confidence interval.

- *Moody's:* RGDP has a positive influence on sovereign ratings assigned by Moody's. The coefficient is 0.0105 with a p-value of 0.0446 indicating statistical significance at the 95% confidence interval.

7.5.5 POOLED OLS MODELS- FIXED AND RANDOM EFFECTS

7.5.5.1 Advanced economies

- *Standard & Poor's:* REER has a positive influence on sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of REER for the random effect is 0.0082 with a p-value of 0.0793, indicating statistical significance at the 90% confidence interval. Furthermore, a positive relationship is found with DRGDP and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is 0.0185 with a p-value of 0.0232, indicating statistical significance at the 95% confidence interval. Additionally, a negative relationship is established with DDEXP, and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0002 with a p-value of 0.0266, indicating statistical significance at the 95% confidence interval.
- *Moody's:* REER has a negative influence on sovereign ratings assigned by Moody's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of REER for the random effect is 0.3723 with a p-value of 0.0052, indicating statistical significance at the 99% confidence interval. Another negative relationship is found with DDGDP and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0025 with a p-value of 0.0477, indicating statistical significance at the 95% confidence interval.
- *Fitch:* DRGDP has a positive influence on sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DRGDP for the random effect is 0.0067 with a p-value of 0.0635, indicating statistical significance at the 90% confidence interval. In addition, a negative relationship is established with DDGDP and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0001 with a p-value of 0.0897.

7.5.5.2 Frontier economies

- *Standard & Poor's:* DRGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DRGDP for the random effect is 0.0285 with a p-value of 0.0706, indicating statistical significance at the 90% confidence interval. Another relationship however negative is established with DDGDP and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0056 with a p-value of 0.0790, indicating statistical significance at the 90% confidence interval.
- *Fitch:* DFISGDP has a positive influence on sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DFISGDP for the random effect is 0.0398 with a p-value of 0.0712, indicating statistical significance at the 90% confidence interval.

7.5.5.3 European economies

- *Fitch:* DDGDP has a negative influence on sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DDGDP for the random effect is -0.0026 with a p-value of 0.0441, indicating statistical significance at the 90% confidence interval.

7.5.5.4 Asian economies

- *Fitch:* DOPEN has a negative influence on sovereign ratings assigned by Fitch. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DOPEN for the random effect is -0.0032 with a p-value of 0.0020, indicating statistical significance at the 99% confidence interval. In addition, a positive relationship is found with DDGDP and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is 0.0149 with a p-value of 0.0199, indicating statistical significance at the 95% confidence interval.

7.5.5.5 American economies

- *Moody's:* DOPEN has a negative influence on sovereign ratings assigned by Moody's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DOPEN for the random effect is -0.2701 with a p-value of 0.0580, indicating statistical significance at the 95% confidence interval. Another relationship is identified that is also negative with DCAGDP and the Hausman test suggests the random effect model as the most suitable model. The coefficient for the random effect is -0.0006 with a p-value of 0.0354, indicating statistical significance at the 95% confidence interval.

7.5.5.6 March 2014 FTSE Global Equity Index Series: Country Classification

- *Standard & Poor's:* DRGDP has a positive influence on sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DRGDP for the random effect is 0.0192 with a p-value of 0.0049, indicating statistical significance at the 99% confidence interval.

7.5.5.7 March 2014 FTSE Global Equity Index Series: Regional Classification

- *Standard & Poor's:* DDEXP has a negative influence on sovereign ratings assigned by Standard & Poor's. The Hausman test suggests the random effect model as the most suitable model. The coefficient of DDEXP for the random effect is 0.0192 with a p-value of 0.0078, indicating statistical significance at the 99% confidence interval.