DETERMINANTS AND INFORMATIONAL VALUE OF SOVEREIGN CREDIT RATINGS

LIM KOK TIONG

FACULTY OF ECONOMICS AND ADMINISTRATION
UNIVERSITY OF MALAYA
KUALA LUMPUR

2021

DETERMINANTS AND INFORMATIONAL VALUE OF SOVEREIGN CREDIT RATINGS

LIM KOK TIONG

THESIS SUBMITTED IN FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF ECONOMICS AND ADMINISTRATION
UNIVERSITY OF MALAYA
KUALA LUMPUR

2021

UNIVERSITI MALAYA

ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: Lim Kok Tiong

Registration/Matric No: EHA160021

Name of Degree: Doctorate in Philosophy

Title of Project Paper/Research Report/Dissertation/Thesis (“this Work”):

Determinants and Informational Content of Sovereign Credit Ratings

Field of Study: Financial Economics

I do solemnly and sincerely declare that:

(1) I am the sole author/writer of this Work;
(2) This Work is original;
(3) Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract from, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the Work and its authorship have been acknowledged in this Work;
(4) I do not have any actual knowledge nor do I ought reasonably to know that the making of this work constitutes an infringement of any copyright work;
(5) I hereby assign all and every rights in the copyright to this Work to the University of Malaya (“UM”), who henceforth shall be owner of the copyright in this Work and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of UM having been first had and obtained;
(6) I am fully aware that if in the course of making this Work I have infringed any copyright whether intentionally or otherwise, I may be subjected to legal action or any other action as may be determined by UM.

10th August 2021

Candidate Signature Date

Subscribed and solemnly declared before,

Witness’s Signature Date 13 Aug 2021

Name:

Designation:

DETERMINANTS AND INFORMATIONAL VALUE OF SOVEREIGN CREDIT RATINGS

ABSTRACT

The sovereign credit ratings (SCRs) issued by Moody's, S&P, and Fitch in the form of alpha-numeric (i.e., Aaa, Aa1, Aa2, Aa3, etc.) and alpha-symbol (i.e., AAA, AA+, AA, AA-, etc.) are essential for rated countries to gain access to funds without the conditionality on collateral placement or the commitment on austerity measures. The SCR notches which are proxies of creditworthiness ranking on rated countries have been an integral part and a key determinant of the cost of borrowing. However, the prolonged implementation of zero-bound-policy-rate (ZBPR) and quantitative easing programme (QEP) raises the query on SCRs relevancy. This thesis examines the determination of SCRs and SCRs information value on sovereign bond yields (SBYs) and sovereign credit default swap spreads (SCDSs) of investment-grade rated countries. A sample of 32 investment grade multi-rated countries with quarterly and annual observations spanning from 2008 to 2017, when ZBPR and QEP were in effect, are used in this study. The empirical results show no evidence that the determination of SCRs was compromised when ZBPR and QEP were in effect. The SCRs determinants consist of GDP Growth, GDP Per Capita, Government Effectiveness Index, Inflation, Fiscal Balance, Debt to GDP, Reserve to GDP, and Financial Development Index continue to predict SCRs with high accuracy. However, the empirical results show that the SCRs information value was indeed disregarded, and rendered irrelevant on debts price discovery. The empirical estimates show that SCRs, irrespective of the credit rating agencies, are insignificant in the pricing of SBYs since 2008. The empirical estimates show that SCRs are also insignificant in pricing the SCDSs, but only from 2012 onwards. Since the SCRs is an essential enabler on the transmission of funds among countries and private sectors, the

results showing that SCRs information value was disregarded in SBYs and SCDSs pricing present broad and cascading implication on credit risk pricing. Therefore, the findings on SCRs information value being irrelevant when ZBPR and QEP were in effect provide an important revelation. This revelation must be assessed and mitigated by the credit rating agencies, policymakers, and institutional investors.

PENETAPAN DAN NILAI MAKLUMAT PERINGKAT KREDIT SOVEREIGN

ABSTRAK

Penarafan kredit berdaulat (SCR) yang dikeluarkan oleh Moody's, S&P, dan Fitch dalam bentuk alpha-numeric (iaitu, Aaa, Aa1, Aa2, Aa3, dll.) dan alpha-simbol (iaitu, AAA, AA +, AA, AA -, dan lain-lain) adalah penting bagi negara-negara dinilai untuk mendapat akses kepada dana tanpa syarat penempatan jaminan atau komitmen terhadap langkah berjimat cermat. Tahap SCR yang merupakan kedudukan pemeringkatan kelayakan kredit negara-negara dinilai telah menjadi bahagian yang tidak boleh dipisahkan dan penentu utama kos pinjaman. Namun, implementasi berpanjangan daripada *zero-bound-policy-rate* (ZBPR) dan program pelonggaran kuantitatif (QEP) menimbulkan pertanyaan mengenai relevansi SCR. Tesis ini mengkaji penentuan SCR dan nilai maklumat SCR untuk hasil bon berdaulat (SBYs) dan spread swap lalai kredit berdaulat (SCDSs) bagi negara yang diberi nilai gred pelaburan. Sampel 32 negara bertaraf gred pelaburan dengan cerapan suku tahunan dan tahunan dari 2008 hingga 2017 di bawah tempoh ZBPR dan QEP berkuatkuasa digunakan dalam kajian ini. Hasil empirik tidak menunjukkan bukti bahawa penentuan SCR oleh asas ekonomi telah dikompromikan ketika ZBPR dan QEP berkuatkuasa. Pemboleh ubah ekonomi termasuk Pertumbuhan KDNK, KDNK Per Kapita, Indeks Keberkesanan Kerajaan, Inflasi, Imbangan Fiskal, Nisbah Hutang KDNK, Nisbah Rizab KDNK, dan Indeks Pembangunan Kewangan terus meramalkan SCR dengan ketepatan yang tinggi. Walau bagaimanapun, hasil empirik menunjukkan bahawa nilai maklumat SCR memang diabaikan dan tidak relevan dalam penentuan harga hutang. Anggaran empirik menunjukkan bahawa SCR, tanpa mengira agensi penarafan kredit yang menerbitkannya, tidak signifikan dalam penetapan harga SBYs sejak tahun 2008. Anggaran empirik menunjukkan bahawa SCR juga tidak signifikan dalam penetapan harga SCDSs tetapi hanya dari tahun 2012 dan seterusnya. Oleh kerana SCR merupakan pemicu penting sebagai penyalur dana di antara negara dan sektor swasta, hasil kajian

yang menunjukkan bahawa nilai maklumat SCR tidak dihiraukan dalam harga SBYs dan SCDSs memberi implikasi yang luas kepada harga risiko kredit. Oleh itu, penemuan mengenai kesan ZBPR dan QEP yang menjadikan nilai maklumat SCR tidak relevan adalah wahyu penting dan mesti dinilai dan kesannya dikurangkan oleh agensi penilai kredit, pembuat dasar, dan pelabur institusi.

Acknowledgements

I have asked myself about whom I should be grateful for in the pursuit of my PhD. I struggled at first because I wanted this acknowledgement to be truly sincere from my experience. As Julie Andrews in the "*Sounds of Music*" has pointed out that the best place to start is the beginning. Here it goes…

It began in 2017, I decided to pursue my PhD with the anticipation to share my humble industry knowledge and to embrace new knowledge and skillsets that the University of Malaya and its associated scholars could offer me. The "Give" and "Take" was anticipated to be about 50:50 ratio.

I started to accumulate the "Take" part of the equation from Professor Dr Niaz and Professor Dr Cheong in my first semester. In subsequent semesters, I continued to accumulate more from Professor Dr Goh, Associate Professor Dr Kwek, Associate Professor Dr Lim, Associate Professor Dr Lau, and late Professor Dr Tan. The "Give" part of the equation did not make any traction, whatsoever.

Since the "Give" and "Take" were not in equilibrium, the negative attributes: doubts, frustration, ego, etc. cropped up. I thought to myself that I needed a counter-weight fast so that the equilibrium could be attained. As I was coaching my children about learning, an epiphany hit me. I realized that I was dead wrong about the 50:50 ratio. As a humble student, accumulating "Take" is a good and happy outcome. For that, I am grateful to my children for making me a better student, and my wife for holding the fort.

To my supervisors: Associate Professor Dr Kwek and Professor Dr Goh, I am grateful to have pursued my PhD under both of your supervision. Thank you for being accessible and the willingness to go the extra mile to make sure I get it right. Especially on this thesis submission, Professor Goh has been instrumental in helping me to beef up the paper. On many occasions, our discussion happened into the wee hours, and he had spent his CNY with my paper and me. I am deeply grateful to Professor Goh.

In addition, I would like to extend my gratitude to Professor Dr Niaz, Professor Dr Cheong, Professor Dr Evelyn, Associate Professor Dr Lim, Associate Professor Dr Lau, and late Professor Dr Tan for their contributions to my "Take" basket.

To my fellow PhD candidates, who had been helpful directly and indirectly, I am grateful to have taken the journey with you all. Finally, to the fellow administrators and supporting staff of the Faculty of Economics and Administration, thanks for the support and services.

Sincerely,

Lim Kok Tiong

Table of Contents

List of Figures

List of Tables

List of Abbreviations

No	Abbreviation	Description
1	BOE	Bank of England
2	BOJ	Bank of Japan
3	CRAs	Credit Rating Agencies
4	DD	Default Distance
5	ECB	European Central Bank
6	EDF	Expected Default Frequency
7	FD-GMM	First Differencing - GMM
8	FE	Fixed Effect Model
9	FED	US Federal Reserves
10	FOD-GMM	Forward Orthogonal - GMM
11	GFC	Global Financial Crisis
12	GMM	Generalized Method of Moment
13	IDRs	Sovereign Issuer Default Ratings - Fitch
14	NDAI	Non-Disclosure-Agreement obtained Information
15	NRSRO	Nationally Recognized Statistical Rating Organization
16	ODF	Observed Default Frequency
17	OLM	Ordered Logit Model
18	OPM	Ordered Probit Model
19	ORM	Ordered Respond Model
20	PAI	Publicly Available Information
21	QEP	Quantitative Easing Programme
22	RE	Random Effect Model
23	SBRs	Sovereign Bond Ratings - Moody's
24	SBYs	Sovereign Bond Yields
25	SCDSs	Sovereign Credit Default Swap Spreads
26	SCRM	Sovereign Credit Rating Methodology
27	SCRs	Sovereign Credit Ratings
28	SEC	US Securities Exchange Commission
29	SRs	Sovereign Ratings - S&P
30	ZBPR	Zero Bound Policy Rate

CHAPTER 1: INTRODUCTION

Although there are ten registered credit rating agencies (CRAs) in accordance with the Nationally Recognized Statistical Rating Organization (NRSRO) report in 2018[1], the "go-to" CRAs are the Moody's, S&P, and Fitch. These three CRAs command a combined 99% market share on sovereign credit ratings (SCRs). Countries rated with SCRs are equivalent to having the seal of approval to market the foreign currency-denominated bonds. Besides having the access to global funds, the SCR notches will also influence the borrowing costs or expected yields.

In the 1990s, Thomas Loren Friedman, the three-times "Pulitzer Price" winner columnist, raised the alarm regarding CRAs' influence. In his article (Friedman, 1996), he highlighted the concern of Moody's having the same influence as the US government. The popular quote from his article is presented below:

"*That makes Moody's one powerful agency. In fact, you could almost say that we live again in two-superpower world. There is the U.S. and there is Moody's. The U.S. can destroy a country by levelling it with bombs; Moody's can destroy a country by downgrading its bonds*.", Friedman, T. (1995, February 22). Foreign Affairs. New York Times, Section A, 19.

In accordance with the recently rated debts, S&P has rated more government debts than Moody's and Fitch's share is also gaining traction. Perhaps, the concern is not on Moody's alone but the oligopolist of these three leading CRAs. With the SCRs being fully integrated with the global financial system, and 159 or 82% of all countries are

[1] https://www.sec.gov/files/2018-annual-report-on-nrsros.pdf

already rated by them, however, the influence of these three leading CRAs cannot be denied.

The SCRs amongst these three leading CRAs are not strictly identical. For instance, the SCRs issued by Moody's are in the form of alpha-numeric (i.e., Aaa, Aa1, Aa2, Aa3, etc.) and SCRs issued by S&P and Fitch are in the form of alpha-symbol (i.e., AAA, AA+, AA, AA-, etc.). Despite their differences in forms, countries rated with Aaa by Moody's are having the same credit profile as those rated with AAA by S&P and/or Fitch. Countries rated with Aaa/AAA (i.e., US, Germany, etc.) are defined as having the highest credit quality in accordance with the SCRs ranking. Those rated with Aa1/AA+ are inferior to Aaa/AAA but superior to Aa2/AA, and so on. In retrospect, the highest credit quality means the lowest default risk therefore countries rated Aaa/AAA are rewarded with the lowest borrowing cost, followed by those rated Aa1/AA+, and so on.

On that note, the role of SCRs in risk-reward pricing convention is well established in the market application and empirical studies alike. For instance, the work of Ederington, Yawitz, and Roberts (1987) examined variables that explain corporate ratings, and the work of Cantor and Packer (1996) examined economic variables that explain SCRs issued by the three leading CRAs. On the other hand, the work of Jaramillo and Tejada (2011), Afonso, Arghyrou, and Kontonikas (2013), and Miricescu (2015) examined the "above and beyond" information value of SCRs in the pricing of SBYs.

Since the rollout of zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP), the measures to mitigate the 2008 global financial crisis (GFC), the economic variables that explain SCRs and SCRs information value on debts price discovery could have been affected. To our best knowledge, the effect of ZBPR and QEP on SCRs and SCRs information value is a research gap that has not been addressed.

1.1 Problem Statement

The sub-prime mortgage crisis that triggered the global financial crisis (GFC) in 2008 marked the beginning of the zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP). The ZBPR and QEP are rolled out by four major Central Banks: namely the US Federal Reserves (FED), Bank of England (BOE), European Central Bank (ECB) and Bank of Japan (BOJ). The common objective of ZBPR and QEP is for the Central Banks to steer their respective economies away from recession (e.g., U.S. corporate defaults due to sub-prime, European debt crisis, Japan stagflation, etc.). As the term ZBPR suggested, the policy rates of these four Central Banks were lowered to less than 1% region in 2008. Collectively from 2008 to 2017, these four Central Banks have also injected an aggregate of USD 12 trillion of fresh liquidity through QEP into the financial market. These two measures: ZBPR and QEP, may have warded off another corporate bankruptcy like the Lehman Brothers, or another country from defaulting after Greece in 2010, are not without consequences. The SCRs could be one of the casualties of these two measures.

This is because the currencies of these four Central Banks are designated reserves and international trade currency, therefore the spillover effect would be difficult to contain. Moreover, these four Central Banks are also the trend-setters, the concerted implementation of ZBPR would present a downward pressure on policy rates globally. Hence, with an unprecedented amount of fresh liquidity being offered at a cheap rate, countries can borrow more with a negligible decrease in debts serviceability ratio. For countries rolling over matured debts, the debts serviceability ratio also improved due to lower borrowing costs. Because of a credit conducive environment, the probability of sovereign default would also become negligible. Hence, these lead us to make the conjecture that the determinants of SCRs and SCRs information value on debts price discovery could have been affected when ZBPR and QEP are in effect.

1.2 Research Questions and Objectives

Based on this conjecture, this thesis aims to answer the question: "Are SCRs relevant on debts price discovery when ZBPR and QEP were in effect?". Guided by literature review and specific reference to the information theory advocated by Shannon (1948), the answer to this main question constitutes of three parts.

The first part is to examine whether the determination of SCRs was compromised when ZBPR and QEP were in effect. The second part of the answer will focus on the information value of SCRs on debts price discovery. The third part of the answer focuses on split-SCRs information value on debts price discovery. These three-part answers hereafter are referred to as the three research questions, together with the associated objectives are furnished in Table 1-1.

Table 1-1: List of Research Questions and Objectives

No	Research Questions	Research Objectives
1	Do CRAs interpret the economic variable of the countries seeking SCRs similarly?	To determine the economic variables that explain the SCRs issued by different CRAs.
2	Do SCRs convey information value on debts pricing?	To examine if SCRs produce "above and beyond" information value on debts pricing.
3	How do split-SCRs contribute to the SCRs information value on debts pricing?	To determine the role of split-SCRs on SCRs information value for debts pricing.

The empirical outcomes from each research question will form the collective answer to determine whether SCRs are relevant for debts pricing when ZBPR and QEP were in effect.

1.3 Organization of Study

In the following chapter, the works of literature reviewed for this paper is recorded and will serve as key references for subsequent chapters. In the nutshell, the pieces of literature are categorized into four themes: namely the theoretical perspective of sovereign credit ratings (SCRs), empirical studies on SCRs determinants, empirical studies on SCRs information value, and an overview on zero-bound-policy-rate (ZBPR) and quantitative easing programme (QEP).

In Chapter 3, the proprietary rating methodologies of Moody's, S&P, and Fitch are synthesized. The synthesis aims to detail the commonalities amongst these three leading CRAs in SCRs determination. The synthesis encompasses the scope of input variables, rating methodology, rating processes and procedures, and the discretion of the rating committee in determining the SCR notch for assignment. In addition, the considerations of Through-the-Cycle (TTC) philosophy, migration rates, cohorts, and default rates, are also key factors in SCRs determination, are also addressed in this synthesis. The debut of the SCRs function will provide a new perspective for interpreting the empirical findings.

The research methodology for this thesis is elaborated in Chapter 4. The theoretical research framework will be presented, followed by the demarcation of the three sub-questions on the research framework, and the empirical methods selected to tackle specific research questions are also discussed. The sample selection criteria and the selected sample will also be detailed in this chapter.

In Chapter 5, the SCRs function is put to test empirically. First, the set of eight economic variables are selected through the deliberation between the academically proven variables (i.e., principal component variables) and inputs considered by all three leading CRAs. Using the ordered response model (OPM), the predictive power of the set of selected eight economic variables are examined on SCRs issued by Moody's, S&P, and Fitch respectively. Subsequently, the weight of non-disclosure-agreement obtained information (NDAI) and sovereign credit rating methodology (SCRM) components in SCRs function is quantified for the first time in this thesis. The empirical outcomes in this chapter are aimed to address research question 1.

The SCRs information value in debts price discovery is examined in Chapter 6. The sovereign bond yields (SBYs) are selected as the dependent variable, and the SCRs by respective CRAs are examined in the context of "above and beyond" and standalone information value in SBYs pricing. Both panel and dynamic panel models are employed to produce empirical estimates. The empirical outcomes in this chapter are aimed to answer research question 2.

The third research question on split-SCRs information value on debt price discovery is tackled in Chapter 7. The sovereign credit default swaps spreads (SCDSs) will be the dependent variable, and the independent variables consist of the baseline regressors (i.e., SCRs determinants) and vector of SCRs by CRAs and paired SCRs. The standalone SCRs information value and the complementary information value of paired SCRs will be examined. Collectively, the empirical outcomes will determine the relevancy of SCRs information in SCDSs price discovery.

Finally, the empirical findings from research questions 1, 2, and 3 are summarized and presented as the collective answer to the main question "Are SCRs relevant on debts price discovery when ZBPR and QEP were in effect?". These are detailed in Chapter 8. The contributions, policy implications, and limitations of this thesis paper are also described in this chapter.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The pieces of literature reviewed for this thesis are summarized into four themes. The first theme focuses on the theoretical perspective of sovereign credit ratings (SCRs). The second theme focuses on the empirical studies on SCRs determinants. The empirical study on SCRs information value is categorized as the third theme. Finally, on the zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP), the emphasis is on information gathering.

2.2 Sovereign Credit Ratings (SCRs): The Theoretical Perspectives

The alpha-numeric SCRs (e.g., Aaa, Aa1, Aa2, Aa3, etc.) issued by Moody's (Emery, 2017) and the alpha-symbol SCRs (e.g., AAA, AA+, AA, AA-, etc.) issued by S&P (Ratings, 2016) and Fitch (FitchRatings, 2017) could be comprehended as default milestones that resemble the default distance advocated by Merton (1973). Whereas, the SCR default rates distribution resembles the expected default frequency (EDF) advocated by Vasicek (1977) and Kealhofer and Bohn (1993) on the KMV model, instead of the bell curve distribution in Merton's default distance model (1973). By tweaking some of the assumptions, these two models could be adapted to accommodate the SCRs default milestones. These models are discussed further in the following sections.

2.2.1Merton Distance to Default (DD) Model

The bonds pricing theory according to Merton (Merton, 1973) was constructed based on the following eight (8) assumptions:

Assumption 1:	The model is free of transaction costs, taxes, and hidden liabilities to the assets
Assumption 2:	The market is efficient
Assumption 3:	Borrowers and Lenders bear the same level of interest rate
Assumption 4:	No restriction on short-selling or its proceeds
Assumption 5:	Trading of assets is continuous
Assumption 6:	The capital structure under the Modigliani-Miller theorem[2]
Assumption 7:	The term structure is flat and known with certainty. For instance, the price of risk-free discounted bond in future at time t is $P_t = exp^{-r^t}$, and r is the risk-free interest rate at time t.
Assumption 8:	The value of the firm is not certain through time and follow the stochastic process

Among the eight assumptions, Merton has highlighted that only assumption five to assumption 8 are essential. Specifically, a firm's asset with the market value of A is derived from the function of asset value (V) and time (t), the future value of V is subjected to the processes of drift, volatility, and stochastic properties. Therefore, the function of $A = f(V, t)$ is written in the stochastic form as expressed on equation 2-1.

$$dA = [\,\alpha_A A - C_A]d_t + \sigma_A A dW_A \qquad \textit{2-1}$$

where α_A is the expected return of asset A at time t, C_A is the dollar pay-out (e.g., dividend to shareholders), σ_A is the variance of the return on the asset, and dW_A is the

---

[2] The exact terms of the theory were "The cost of capital, corporate finance and the theory of investment" by Modigliani and Miller (1958).

Brownian motion[3]. Subjecting equation 2-1 to Ito's process[4] of transformation, and substituting A with $exp^{r(T-t)}$, the lognormal process equation can be written as follow:

$$dA = \mu_A A_t dt + \sigma_A A_t d\omega_{A,t} \quad \text{2-2}$$

where A is the value of the asset, μ_A is the drift or expected return of the asset, σ_A is the variance of the asset, and $d\omega_{A,t}$ is the Weiner process of Brownian motion.

In the context of a firm's asset, the value of the asset A consists of equity and debt. Hence $A = D\ (V,t) + E\ (V,t)$, where D is the value of debt and E is the value of equity. The following conditions were observed by Merton (1973) in his discussion on pay-out rationales.

Condition 1:	$D(0,t) = E(0,t) = 0$, the non-negative values
Condition 2:	$D(V,t) \leq A$, reflecting the regularity of capital structure
Condition 3:	$E(V,t) \leq A$, reflecting the regularity of capital structure
Condition 4:	$D(V,t) = \min\ (Asset\ Value, Par\ Value\ at\ Maturity)$

Based on these conditions, especially on condition 4, Merton further assumed that there is no dividend pay-out (i.e., C_A from equation 1 is zero). Hence $D(V,t)$ is equivalent to the zero-coupon bond value as expressed on the following equation:

$$dD = Dexp^{-r(T-t)} \quad \text{2-3}$$

[3] The Brownian motion is also known as Weiner process, a stochastic process that observes four properties: 1) $W_0 = 0$, 2) time additive, 3) independent and identical distributed (iid), and 4) normally distributed. The existence of these properties was proven by N. Wiener.

[4] The Ito's process is a calculus method on stochastic processes by Kiyoshi Ito. It was adopted by Merton to model the option pricing theory that consist of drift, Brownian motion, time-additive, and Martingale properties.

In the event of liquidation, debtors have the first charge to the asset before shareholders hence the residual nature of $E(V,t)$ to shareholders is equivalent to $E(V,t) = \max(A(V,t) - D(V,t), 0)$. While condition 4 fulfils the requirement of bondholders, the management team, in accordance with the agency theory[5], would act in favour of $E(V,t)$. This is because the sole objective of the management team is to optimize shareholders' value.

For instance, in an event at time T where $A(T) - D(T) < 0$, which translates to no residual value left for the shareholders. In order to service $D(T)$ under such a condition, shareholders would need to inject more equity. In such a scenario, the management team would opt to default on $D(T)$ for the interest of shareholders. Therefore, the debtors of $D(T)$ would receive the minimum pay-out of either at par value of the debts (i.e., $A(V,t) - D(V,t) = 0$), or less than par upon filling to liquidate the firm (i.e., $A(V,t) - D(V,t) < 0$). The maximum payout to shareholders or $E(V,t) = \max(A(V,t) - D(V,t), 0)$ is motivated by the notion of maximizing shareholders' value.

The distance between the asset value $A(V,t)$ and debt value $D(V,t)$ is the default distance (DD). The DD is an essential measurement to safeguard the interest of debtholders, given that the management team will prioritize shareholders over bondholders. The default distance can be derived using Equation 2-4[6].

---

[5] According to agency theory, the management is the agent appointed by shareholders, the principal, to safeguard their interest and optimize shares' value. Therefore, the primary obligation is to the shareholders and not debtors.

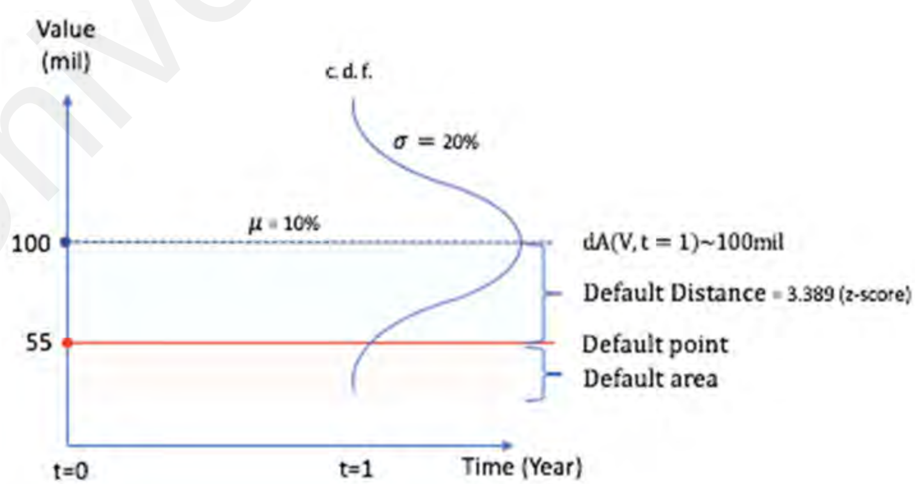
[6] Equation 4 is derived from d_2 of option pricing model described by Merton (1973). The full option pricing model is written as $c = SN(d_1) - N(d_2)Ke^{-rt}$, where c is the call premium, S is the current stock price, K is the strike price, N indicates the cumulative standard normal distribution, e is the exponential term, r is the risk-free rate or expected rate, and t is the time to maturity. The $d_1 = \frac{\ln(S/K) + \left(r + \sigma_S^2/2\right)t}{\sigma_S\sqrt{t}}$, and $d_2 = d_1 - \sigma_S\sqrt{t}$ where ln is the lognormal term, σ_S^2 is the variance from S, and σ_S is the standard deviation from S.

$$DD = \frac{ln\left(\frac{A}{D}\right)+(\mu-0.5\sigma_A^2)T}{\sigma_A\sqrt{T}} \qquad 2\text{-}4$$

where A is the firm's asset value, D is the debt value, μ is the expected return of the firm, σ_A is the volatility of the firm, and σ_A^2 is the standard deviation of the firm at time T. The probability of default is obtained from the normal distribution by the z-score from Equation 2-4.

For example, a firm ABC, a listed company, where the value of the firm $A(V,t)$ could be derived from the stock price multiplies with the total number of outstanding shares. Assuming at $t = 0$, the firm value was 100mil, growing at 10% at $t + 1$, with the variance of 20%, and debt maturing at $t + 1$ was 65mil at par. The function of firm value, default point and default distance on firm ABC based on Equations 2-2, 2-3, and 2-4 could be visualized in Figure 2-1.

Figure 2-1: Merton Default Distance (DD) Depiction



Note: The chart is illustrated by Author based on sample firm ABC.

The volatility adjusted value of the firm at time $t = 1$ is approximately 100mil, the debt value upon maturity is equivalent to the par value of 55mil, which is also known as the default point. The distance between firm value and default point at time $t = 1$ produced a z-score of 3.389 is the default distance. Based on the cumulative standard normal distribution table, a lookup on the z-score of 3.389 translates to 0.04% default probability at time $t = 1$.

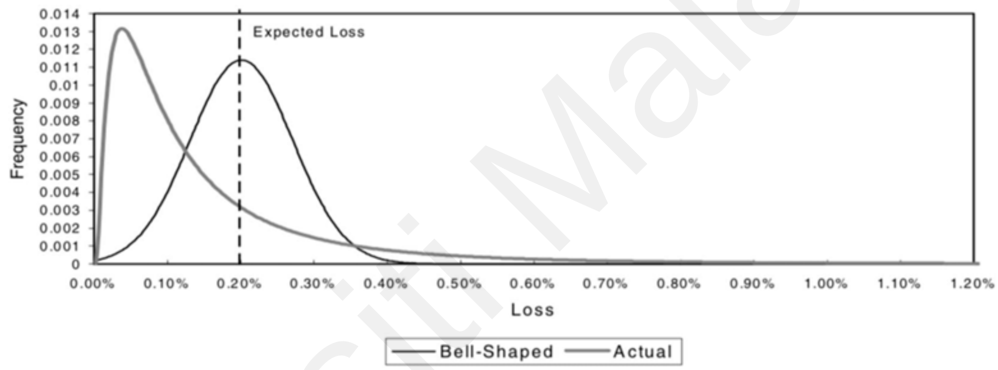
2.2.2 Kealhofer, Merton, and Vasicek (KMV) Model

The Kealhofer, Merton, and Vasicek (KMV) model is the first commercial model conceived from Merton's default distance (DD) model. For the KMV model to work, some of the original DD model's assumptions (see Section 2.2.1) are relaxed or revisited.

According to Vasicek (1977), the comprehensive liabilities consist of current liability, long-term liability, convertible debts, common equity, and preferred equity. The zero-coupon assumption is revisited, which is to address the impact of cash flow leakages in the asset component. In the nutshell, Vasicek highlighted that the original assumptions of the Merton model could have overstated the assets' value and understated the liabilities' value. Both values are essential for measuring the default distance.

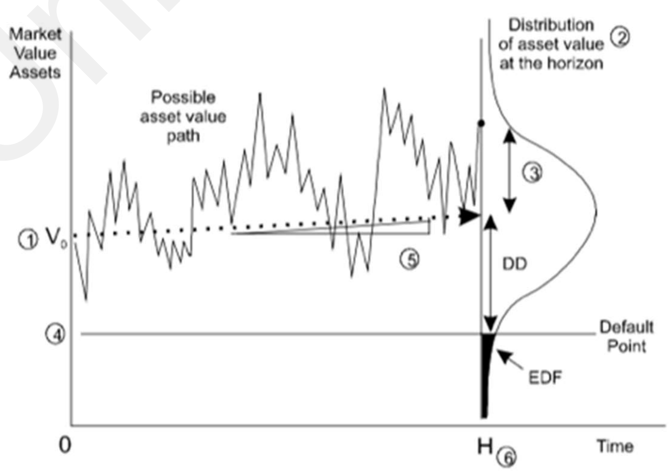
The whitepaper on "Portfolio management of default risk" by Kealhofer and Bohn (1993) echoed the argument regarding capital structure matters for measuring the default distance. For instance, the change in equity-debt ratio affects the asset volatility, the σ_A and σ_A^2 as expressed in Equation 2-4. In their original contribution, the authors pointed out that the default point is rather dynamic and does not observe the bell-curve distribution. Their observation on default point was in line with Black and Cox (1976) on the first passage of time to the barrier of default. The authors also highlighted that firms do not default instantaneously when $A(V,t) = D(V,t)$. The authors demonstrated with empirical data that the default point should constitutes of 100% of current liability plus 50% of long-term liability. Further observation was made on actual defaults to showcase the argument that default indeed do not follow lognormal distribution. This mean that the lookup on default probability based on z-score under the "bell curve" distribution is not realistic. As depicted in Figure 2-2, the actual default distribution is skewed with a fat-tail.

Figure 2-2: Empirical Loss Distribution Vs. Assumed Loss on Normal Distribution



Note: The chart on the Frequency Distribution Loss: Actual Vs. Bell-Shaped is sourced from (Kealhofer & Bohn, 1993) on page 16.

Figure 2-3: KMV Default Distance (DD) and Expected Default Frequency (EDF) Depiction



Legend:
1) The current asset value.
2) The distribution of the asset value at time *H*.
3) The volatility of the value of future assets at time *H*.
4) The level of the default point, the book value of the liabilities.
5) The expected rate of growth in the asset value over the horizon.
6) The length of the horizon, *H*.

Note: The chart is sourced from (Crosbie & Bohn, 2003) in Figure 8 on page 13.

Despite the refinement on asset value derivation, asset volatility adjustment, and default point calibration based on balance sheet approach advocated by Vasicek (1977) and Kealhofer and Bohn (1993), the works of Nazeran and Dwyer (2015), and Crosbie and Bohn (2003) argued that the structural framework of the Merton (1973) model and KMV Model are the same. The key deviation between the two models is the probability of default, this is termed as "Expected Default Frequency" or EDF. The EDF demarcation is shaded in black as in Figure 2-3.

Instead of referring to Gaussian distribution, the KMV model refers to the expected default frequency (EDF), a proprietary approach where the default probability is derived from the sample of 35,000 cross-sectional over 25 years of observations.

The probability of default (PD) based on Gaussian distribution is expressed in Equation 2-5, the PD based on KMV EDF monotonic function[7] is expressed in Equation 2-6, respectively.

$$PD_{A,t} = N[-DD] = N\left[-\frac{ln\left(\frac{A}{D}\right)+(\mu-0.5\sigma_A^2)T}{\sigma_A\sqrt{T}}\right] \qquad \textit{2-5}$$

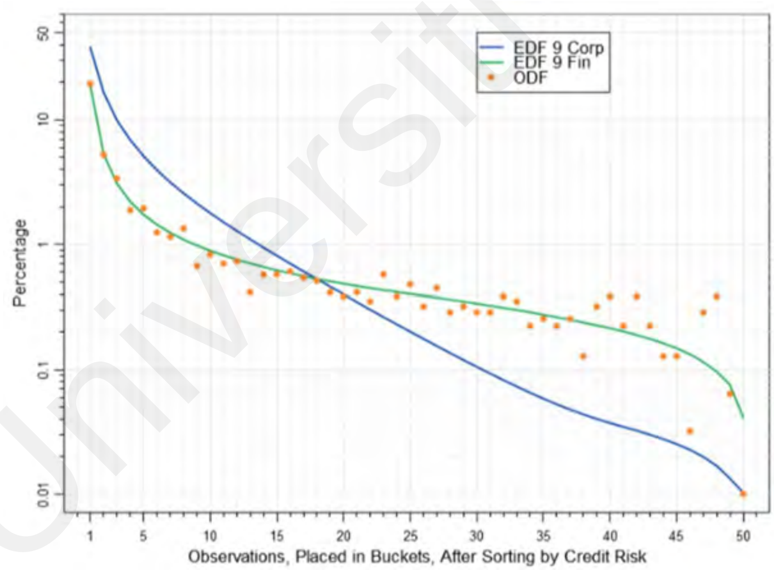
$$PD_{A,t} = M\left[-\frac{ln\left(\frac{A}{D}\right)+(\mu-0.5\sigma_A^2)T}{\sigma_A\sqrt{T}}\right] \qquad \textit{2-6}$$

[7] The monotonic function is a calculus function defined on a subset of the real numbers with real values, where the numbers in the subset are entirely non-increasing or non-decreasing is known as monotonic. For instance, the Figure 2-4 depicts the strictly decreasing monotone characteristic of default probability over the 50 credit risk buckets.

where PD_A is the probability of default for asset A at time t, N indicates the normal distribution, DD denotes the default distance, and M indicates the monotonic function of the EDF model in Equation 2-6.

The proprietary EDF model, known as the EDF credit metric, consists of different credit risk levels. The associated default probabilities are derived from the actual default frequency or the observed default frequency (ODF), the term applied in the KMV EDF model. The interaction between EDF and ODF can be visually observed from the chart depicted in Figure 2-4. Finding the default probability from the KMV perspective as described in Equation 2-6, the z-score is mapped against the EDF credit metric. The 12 rankings of the credit risk of the KMV model is depicted in Figure 2-5.

Figure 2-4: KMV EDF Credit Metric Interactive Chart



Note: This chart is sourced from (Nazeran & Dwyer, 2015) on Figure 5, page 18.

Figure 2-5: KMV EDF Credit Risk Ranking

Rank-ordering of 12 Hypothetical Firms

FIRM	A	B	C	D	E	F	G	H	I	J	K	L
Defaulte	No	No	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes
PD	1bp	3bps	10bps	40bps	70bps	1%	2%	5%	10%	20%	30%	50%

Note: This chart is sourced from (Nazeran & Dwyer, 2015) table 1, page 23.

With apparent constraint, the exact mapping from DD to KMV EDF credit metric is not elaborated further. Despite this limitation, the information thus far is sufficient to visualize the relation between the KMV EDF credit metric and the Merton Default Distance (DD) model. For instance, the interaction between the 50 credit risk levels and default probability could be observed from the chart in Figure 2-4, and the ranking of credit risk derived based on monotonic function as depicted in Figure 2-5 clearly shows that firms ranked “A” are of highest credit quality as compared to firms ranked “B”. The credit quality between firms that ranked “A” and “B” is further substantiated with the default probability at 1 basis point (bps) and 3 bps, respectively.

2.3 Sovereign Credit Ratings (SCR): Determinants

Empirically, one of the earliest studies on credit rating determinants was the work of Ederington et al. (1987). In the context of sovereign credit ratings (SCRs), the earliest and most cited literature was furnished by Cantor and Packer (1996). At that time, SCRs were mainly issued by Moody’s and S&P. The authors relied on announcements made by Moody’s and S&P for identifying the economic variables as potential SCR determinants. Their empirical model employed eight selected economic variables with a sample constituted of 49 countries rated by Moody’s and S&P. The cross-sectional regression model of eight covariates generated an impressive 90% predictive power.

Since then, the study of SCRs determinants has gained traction. Firstly, the number of rated countries has tripled since 1995. Fitch that domiciled in the United Kingdom has joined the dominance of Moody’s and S&P in SCRs universe. In the sphere of empirical research, new determinants were introduced and tested, and advanced methods were adopted by researchers. In the following subsections, the empirical research on SCRs determinants will be elaborated further.

2.3.1 Empirical Findings

The work of Cantor and Packer (1996) has served as the benchmark for many subsequent studies on SCRs determinants. The eight economic variables employed by the researchers were GNP per capita, GDP growth, Inflation, Fiscal balance, Current account balance, External debt, Economic development indicator, and Default history indicator. The cross-sectional model of these covariates was able to predict SCRs issued by Moody's with 90.2% accuracy, and SCRs issued by S&P with 92.6% accuracy.

In subsequent research, Afonso (2003) introduced External Debt-to-Export as an additional determinant of SCRs. With a sample of 81 countries, consisting of 29 developed countries and 52 developing countries, the set of nine determinants model was having 83% prediction accuracy on developed countries' SCRs and 86% on developing countries' SCRs issued by S&P. On SCRs issued by Moody's, the same set of determinants produced 85% prediction accuracy on developed countries and 87% prediction accuracy on developing countries.

The work of Rowland (2004) experimented with twelve SCR determinants. The empirical results showed that those statistical significance at 5% level were GDP per capita, Debt-to-Current Account Receivables, and Foreign Reserves-to-GDP in predicting SCRs issued by Moody's, and GDP per capita, GDP growth, Inflation, Debt-to-Current Account Receivables, and Foreign Reserves-to-GDP in predicting SCRs issued by S&P.

Recognizing the limitation in the cross-sectional method for handling the discreet nature of SCRs, the paper by Bissondoyal-Bheenick (2005) was the earliest to adopt the ordered response model (OPM) to study SCRs determinants. Focussing on SCRs issued by S&P, the author reported that only GNP per capita and Debt-to-GDP were statistically significant determinants on high-rated countries (i.e., AAA-rated countries) dataset. For low rated countries (i.e., from AA+ and lower SCR notches) dataset, the statistically significant determinants were GNP per capita, inflation, Fiscal Balance-to-GDP, and Current Balance-to-GDP.

The empirical results from Mellios and Paget-Blanc (2006) reported that 9 out of 13 selected determinants were significant at a 5% level. The ordered logistic model (OLM) generated estimates reported that the significant determinants were the Real effective exchange rate, Gross domestic savings, External Debt-to-Current external receivable, GNI per capita, Inflation, Trade dependency, Government revenue-to-GDP, Corruption index, and Default history indicator.

The work of Afonso, Gomes, and Rother (2009) tripled the number of determinants to a set of 24. Their empirical results generated using the ordered probit model and ordered logit model reported that only about half of those determinants were significant at the 5% level. The significant determinants of SCRs issued by Moody's were the GDP per capita, Inflation average, Government debt average, Government effectiveness average, External debt, External debt average, Current account, Reserves, Default history indicator, EU indicator, and Latin America & Caribbean indicator. As for SCRs issued by S&P, the significant determinants were the GDP per capita, Government debt, Government effectiveness average, Current account, Default history indicator, and Industrial indicator.

In a follow-up paper (Afonso, Gomes, & Rother, 2011), they reclassified the set of determinants into short-term and long-term determinants. The determinants that were significant in predicting SCRs issued by Moody's were the GDP per capita, GDP per capita average, GDP growth, Unemployment average, Inflation average, Government debt, Government debt average, Government balance, Government effectiveness average, External debt, Current account, Reserves, Default history, EU indicator, Industrial indicator, and Latin America & Caribbean indicator. For SCRs issued by S&P, the significant determinants were also identical to those reported on Moody's SCRs. The only exceptions were the Unemployment average and EU indicator. The Unemployment average was significant and the EU indicator was insignificant on SCRs issued by S&P. For SCRs issued by Fitch, there were 11 significant determinants, and they were mostly identical to those significant determinants on SCRs issued by Moody's and S&P.

In a recent study, Reusens and Croux (2017) repurposed the ten proven determinants to study the sample of 90 countries rated by Moody's, S&P, and Fitch. Their empirical results showed that EU indicator, External debt, GDP growth * Government debt, GDP growth, and Government debt were significant at 5% level in predicting SCRs issued by all three CRAs. The Fiscal balance was a significant determinant on SCRs issued by Moody's and S&P but not Fitch. The Economic development indicator and Default history indicator were significant determinants on SCRS issued by Moody's and Fitch but not S&P. The Inflation was a significant determinant on SCRs issued by S&P and Fitch but not Moody's.

By compiling the statistically significant determinants reported from 1996 to 2017 in Table 2-6, it becomes obvious that the core determinants of SCRs are less than ten and did not deviate much from the set of determinants employed by Cantor and Packer (1996). For instance, items 4 to 6 and items 11 to 13 as listed in Table 2-6 are about government debts. Although there are slight variations of emphasis when the determinants are measured in the form of short-term versus long-term determinants (e.g., Debt to GDP versus Debt to GDP average, Reserves versus Reserves average, etc.), but the core determinants remain relatively the same.

Table 2-1: List of Significant Determinants on SCRs issued by Moody's, S&P, and Fitch

		Moody's SCRs	S&P SCRs	Fitch SCRs
1	Corruption index	Y	Y	Y
2	Current account balance	Y	Y	Y
3	Current account balance average	Y	Y	Y
4	Debt-to-Current account receivables	Y	Y	
5	Debt-to-GDP	Y	Y	Y
6	Debt-to-GDP average	Y	Y	
7	Default history Indicator	Y	Y	Y
8	Developed Country (Dummy)	Y	Y	
9	Economic development indicator	Y		Y
10	Eurozone Membership indicator	Y	Y	Y
11	External debt	Y	Y	Y
12	External debt average	Y	Y	
13	External debt-to-Export	Y	Y	
14	Fiscal balance	Y	Y	Y
15	Fiscal balance average		Y	Y
16	GDP growth	Y	Y	Y
17	GDP growth * Government debt	Y	Y	Y
18	GDP per capita	Y	Y	Y
19	GDP per capita average	Y	Y	Y
20	GIP per capita	Y	Y	Y
21	Government effectiveness		Y	Y
22	Government effectiveness average	Y	Y	Y
23	Government revenue-to-GDP	Y	Y	Y
24	Inflation	Y	Y	Y
25	Inflation average	Y	Y	Y
26	Real exchange rate	Y	Y	Y
27	Real Interest Rate		Y	Y
28	Reserves	Y	Y	
29	Reserves average		Y	
30	Trade dependency	Y	Y	Y
31	Unemployment		Y	
32	Unemployment average	Y		Y

Note: The list of determinants is compiled from past studies (Afonso et al., 2009; Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Bissondoyal-Bheenick, Brooks, & Yip, 2006; Cantor & Packer, 1996; Mellios & Paget-Blanc, 2006; Reusens & Croux, 2017; Rowland, 2004). The tagging of "Y" indicates that the variable was examined and reported at least at a 5% significance level in earlier studies.

2.3.2Determinants Predictive Power

Selecting the correct set of economic variables as SCR determinants is only the first step, it is equally essential for the model to have robust predictive power on SCRs issued by varying credit rating agencies (CRAs). Hence, the eight-determinant model by Cantor and Packer (1996) that produced over 90% prediction accuracy on SCRs issued by Moody's and S&P was ground-breaking at that time. The works of Afonso (2003) and

Rowland (2004) also reported comparable success in using the same cross-sectional method and set of determinants in predicting SCRs from bigger sample sizes and in different timeframes.

However, scepticism started to surface for using the linear method over the discrete characteristic of SCRs. In accordance with Wooldridge (2002), the ideal econometrics method to study SCRs, which are discreet and risk-ranked, would be the ordered response model (OPM). The first paper employing the OPM was the work of Bissondoyal-Bheenick et al. (2006). With the six-determinant OPM, the model generated 40% prediction accuracy on SCRs issued by S&P and 42% prediction accuracy on SCRs issued by Fitch. Only half of the six determinants were reported significant at the 5% level; namely GDP growth, inflation, and real interest rate.

The work of Mellios and Paget-Blanc (2006) selected nine determinants and the ordered logit model (OLM) was used. The researchers reported all nine determinants were significant at a 5% level. The McFadden R^2[8] measurement was used to determine the nine-determinant OLM's predictive power. On average, the model generated 48% of fitness on SCRs issued by Moody's, S&P and Fitch.

With a sample of 66 countries with observations spanning from 1995 to 2005, Afonso et al. (2009) performed the OPM regressions using a set of 24 determinants to predict SCRs assigned by Moody's, S&P, and Fitch. Only about half of the determinants were reported significant at the 5% level. The 24-determinant model predicted SCRs issued by Moody's

---

[8] McFadden's pseudo R^2 is a logistic regression model that employs the maximum likelihood method: $R^2_{McFadden} = 1 - \frac{\log(Lc)}{\log(Lnull)}$. Where Lc denotes the likelihood value of the current fitted model and $Lnull$ denotes the likelihood value of the null model. The purpose of McFadden's pseudo R^2 is similar to a typical R^2 which is to measure the goodness of fit. For this case, the formal is most appropriate for discreet data such as $SCRs$.

with 47% accuracy, and 45% accuracy on SCRs issued by S&P and Fitch, respectively. On a follow-up paper (2011), the 24 determinants were reclassified into short-term and long-term determinants, the predictive power of their OPM models remained robust with prediction accuracy at 47% on SCRs issued by Moody's, 46% on SCRs issued by S&P, and 44% on SCRs issued by Fitch.

The empirical results reported by Reusens and Croux (2017) were rather interesting as compared to earlier studies. The authors examined the effect of multi-year and single-year observations of a sample of 90 countries, using a set of selected determinants in predicting the assigned SCR notches. The average predictive power of their OPM models generated 29% prediction accuracy on SCRs issued by Moody's, 28% on S&P's SCRs and 36% on Fitch's SCRs. Although the average predictive power of their models was below the 40% to 50% range as reported from earlier studies, their empirical results were commendable given the fact that the observation window from 2002 to 2015 inherited structural break events (i.e., 2008/2009 sub-prime crisis, 2010 European debt crisis, etc.). The outcome of their study suggests that the potency of the selected economic variables in predicting SCRs could be time-variant sensitive.

2.4 Sovereign Credit Ratings (SCRs): Information Value

The SCRs provides the information on default probability that was lacking previously when lending was extended to a borrowing country[9]. The consistency of SCR notches

[9] Prior to the existence of credit rating agencies (CRAs), a typically country borrowing was conducted through bilateral arrangement where the counterpart was another country. The borrowing country would need to pledge an asset as collateral deemed worthy by the counterpart. For the transaction to take place, the bilateral relationship between the borrowing country and lending country must first be established.

amongst the three leading credit rating agencies (CRAs) boosted the confidence and acceptability of institutional investors and policymakers alike[10]. On this basis, the SCRs is expected to produce significant information value about the rated countries and pricing for sovereign bond yields (SBYs). The borrowing cost for Aaa/AAA-rated countries should be the lowest as the outcome of having the highest credit quality profile, followed by countries rated with Aa1/AA+, and so on. In other words, the monotonous feature of SCRs is expected to reflect the discipline in risk pricing relative to the default rates in association with the respective SCR notches. The default rate distribution by SCR notches follows the loss distribution advocated by Kealhofer and Bohn (1993) and observes the default distance model by Merton (1973). The following subsections will focus on reviewing the past studies on the informational content of SCRs.

2.4.1 Information Value on Sovereign Bond Yields (SBYs)

In the study of SCRs information value, SCRs are treated as an independent variable instead of the dependent variable. SCRs should be on the right side of the equation so that the information value of SCRs could be measured. In this case, the dependent variable is the sovereign bonds, the rated instruments.

The work of Cantor and Packer (1996) provides the reference approach. Their study carried out four empirical steps. Firstly, the SCR was the dependent variable and a set of eight economic variables were selected as independent variables (see Section 2.3). In the

[10] The use of SCRs by institutional investors and even policy makers is evidenced. For instance, the classification of investment grade is the work of institutional investors. Investment grade assets, in this case, are sovereign bonds (SBs) issued by countries with SCRs rated from Aaa/AAA to Baa3/BBB-. SBs rated below Baa3/BBB- are considered speculative grade assets, and are prohibited in general from fund allocation considerations.

second step, the researchers replaced SCRs with sovereign bond yields (SBYs) as the dependent variable, and the same eight determinants were maintained as independent variables. The model for the second step is expressed in Equation 2-7. In step 3, the SCRs was introduced as an additional independent variable as expressed in Equation 2-8. In the final step, the SCRs were maintained while the set of eight determinants were excluded as the independent variables. The fourth step is expressed in Equation 2-9.

$$SBY_i = a + GNP_i + GDP_i + Inf_i + Fis_i + CAB_i + ED_i + EDI_i + DHI_i + e_i \quad \textit{2-7}$$

$$SBY_i = a + GNP_i + GDP_i + Inf_i + Fis_i + CAB_i + ED_i + EDI_i + DHI_i + AvgSCR_i + e_i \quad \textit{2-8}$$

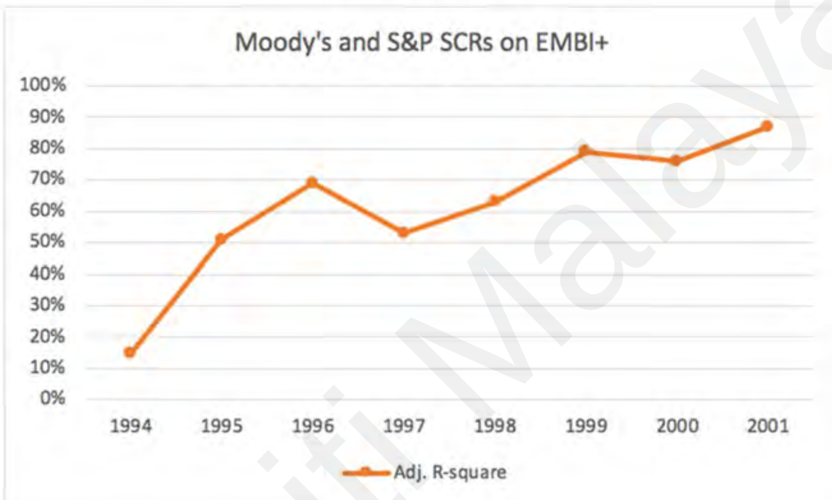
$$SBY_i = a + AvgSCR_i + e_i \quad \textit{2-9}$$

where SBY_i is the sovereign bond yields in natural log values, the $AvgSCR_i$ was the average ordinal scale of the SCRs issued by Moody's and S&P, GNP_i was the GNP per capita, GDP_i was the average GDP Growth, Inf_i was the average Inflation Rate, Fis_i was the average Fiscal Balance, CAB_i was the average Current Account Balance, ED_i was the External Debt, EDI_i was the Economic Development Indicator, and DHI_i was the Default History Indicator of the i sovereign. The a and e_i were the intercept and error term of the regression model.

The SCRs information value for SBYs price discovery was determined on the $Adjusted\ R^2$ derived from Equations 2-8 and 2-9 against the $Adjusted\ R^2$ derived from Equation 2-7, the baseline model. With $Adjusted\ R^2$ of 92% produced from Equation 2-8, and 91% from Equation 2-9, and compared to the baseline model's $Adjusted\ R^2$ of

86%, the researchers reported that SCRs transmitted superior information value on both counts: SCRs as an additional regressor and as a standalone regressor. The outcome of their research was consistent with Ederington et al. (1987) on corporate ratings information value.

Figure 2-6: SCRs Information Value on EMBI+ Sovereign Bond Yields



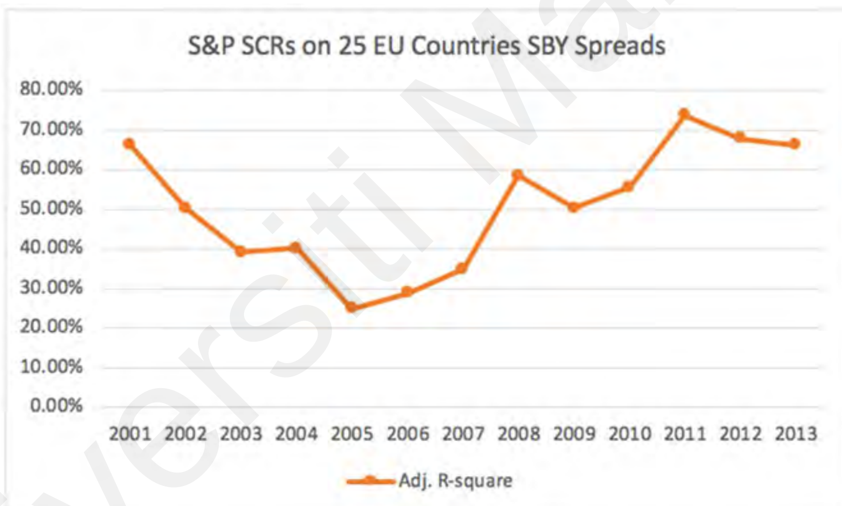
Note: The line chart is plotted by the author about Table 2 on page 9 from Sy (2002). The EMBI+ is produced by JPMorgan on bond indexes consist of Argentina, Brazil, Bulgaria, Colombia, Ecuador, South Korea, Mexico, Morocco, Panama, Peru, Philippines, Poland, Qatar, Russia, South Africa, Turkey, and Venezuela.

Another study by Sy (2002), with a sample of emerging countries (i.e., EMBI+[11]) constitutes of observations spanning from 1994 to 2001. The annual cross-sectional results as reconstructed in Figure 2-6 depicts the gradual improvement from 1994 at 15% to 2001 at 87% on SCRs information value in debts pricing. The researcher highlighted that the weak SCRs information value reported in 1994 was due to the infancy stage of

[11] The Emerging Market Bond Index Plus (EMBI+) sovereign spreads were produced by J.P. Morgan on countries such as Argentina, Brazil, Bulgaria, Colombia, Ecuador, South Korea, Mexico, Morocco, Panama, Peru, Philippines, Poland, Qatar, Russia, South Africa, Turkey, and Venezuela.

SCRs in the 1990s. As the number of emerging countries rated with SCRs increases substantially in the 2000s, the SCRs information value in debts pricing also strengthen. Another insight reported by the researcher was the sensitivity of SCRs information value towards external events. This sensitivity could be visually observed from the chart depicted in Figure 2-6. The line chart representing the $Adjusted\ R^2$ dipped in 1997 was due to the Asian financial crisis (AFC) and the dipped in 2000 was due to the millennium bug scare.

Figure 2-7: SCRs Information Value on 25 EU Countries on Sovereign Bond Yields



Note: The line chart is plotted by the author about Emilian-Constantin's (2015) empirical results reported in Table 5 on page 145.

From the European countries' perspective, Miricescu (2015) selected 25 European Union (EU) countries with observations spanning from 2001 to 2013 as the sample. Recognizing the potential weakness of ordinal scale transformed SCRs, the author adopted the logistic transformation method[12] advocated by Afonso, Sr, and Rother (2007). Their empirical outcomes of SCRs information value are depicted in Figure 2-7. As claimed by the researchers, the deterioration of SCRs information value in SBYs pricing as reported from 2002 to 2005 was due to a change in investors' risk appetite. Despite lower SCRs explanatory power at the range of 20% to 30%, the SCRs remained statistical significance.

In the context of SBYs determinants, the credit default risk is a designated component in SBYs pricing structure. When cross-referenced the set of SCRs determinants (see Table 2-6) with the set of SBYs determinants examined in previous studies (Ardagna, Caselli, & Lane, 2007; Attinasi, Checherita-Westphal, & Nickel, 2009; Hauner & Kumar, 2006; Kinoshita, 2006; Poghosyan, 2014; Sgherri & Zoli, 2009), the set of determinants are almost identical in both contexts. On SBYs studies that explicitly examined the SCRs as a proxy of credit default risk component, the works of Jaramillo and Tejada (2011), Afonso et al. (2013), Jaramillo and Weber (2013), and Miricescu (2015) reported that the SCRs were a significant determinant and produce the "above and beyond" information value in SBYs price discovery.

[12] $SCR_{LT,i}$ = ln (SCR_i/1 - SCR_i), where $SCR_{LT,i}$ is the logistic transformed SCR scale of country *I,* and SCR_i is derived from (2$SCR_{ordinal\ scale,i}$)/ (2n), and n = maximum number of ordinal scales on SCRs based on linear transformation.

2.4.2 Information Value on Sovereign Credit Default Swap Spreads (SCDSs)

Based on the paper commissioned by IDSA[13], Culp, Merwe, and Starkle (2016) furnished a compilation of studies regarding the derivatives. In specific, the sovereign credit default swap (SCDSs) is officially referred to as the single-name credit default swap derivative. It is a single name because a single reference entity is used to produce the derivative. In this case, the reference entity is the sovereign bond issued by a country. Due to this close relation between SBYs and SCDSs, it is a logical extension to study the SCRs information value on SCDSs.

Many previous studies on SCDSs were based on the structural model presented by Hull and White (2000) and Pan and Singleton (2008). For instance, the term structure of SCDSs constitutes of credit risk, non-credit risk, and systematic risk components are observed in earlier empirical studies (Badaoui, Carthart, & El-Jahel, 2013; Beber, Brandt, & Kavajecz, 2009; Culp et al., 2016; Longstaff, Pan, Pedersen, & Singleton, 2011). As reported in the work of Badaoui et al. (2013), the credit risk component alone accounted for 55.6%, and the non-credit risk component explained the remaining 44.3% of the spreads. Their findings regarding the influence of credit risk and non-credit risk components in SCDSs remained consistent as concurred by the empirical outcomes from the works of Beber et al. (2009) and Longstaff et al. (2011). In a more recent paper by Hsien-Yi and Sheng-Syan (2018), the Worldwide Governance Indicator from the World Bank was examined as a potential proxy of credit risk component. Their study produced empirical evidence to support the proxy's viability.

---

[13] International Swaps and Derivatives Association https://www.isda.org/

Besides the credit risk and non-credit risk components, the spreads of SCDSs are also susceptible to systematic risk or external events. As pointed by Longstaff et al. (2011) that the US financial market condition explained 1/3 of the SCDSs while credit risk and the non-credit risk components accounted for 2/3. The influence of systematic risk in SCDSs' spreads was echoed by Aizenman, Chinn, and Hutchison (2009), Dieckman and Plank (2012), Aizenman, Hutchison, and Jinjarak (2013), Eyssell, Fung, and Zhang (2013), and Kallestrup, Lando, and Murgoci (2016).

The SCRs information value in the pricing of SCDSs is evidenced. For instance, the effect of SCRs upgrades and downgrades in the pricing of SCDSs was empirically significant as reported in the works by Afonso, Furceri, and Gomes (2012), Blau and Roseman (2014), and Ismailescu and Phillips (2015). Although SCRs are ratings assigned on SBYs and not SCDSs, the close relation between SBYs and SCDSs suggests that SCRs information value is traceable in SCDSs. The role of SBYs in SCDSs price discovery and vice versa is substantiated from earlier studies (Alper, Forni, & Gerard, 2013; Ammer & Cai, 2007; Chan-Lau & Kim, 2004; Coudert & Gex, 2011; Fontana & Scheicher, 2010; Hassan, Ngene, & Yu, 2015; Li & Huang, 2011).

It is evident that the credit risk component in SCDSs' structure has a significant influence on the spreads. Although other variables were explored, the SCRs are the common proxy for the credit risk component. The SCRs were able to explain 56% of the spreads.

2.4.3 Commonality of Split Sovereign Credit Ratings (Split-SCRs)

It is common for countries seeking SCRs to have commissioned more than one credit rating agency. It is almost common for the countries rated by multiple CRAs to be assigned with varying SCR notches, or split-SCRs. Based on the recent list of rated countries, Moody's rated 144 countries[14], S&P rated 132 countries[15], and Fitch rated 120 countries[16]. When we cross-referenced the list of rated countries amongst these three CRAs, the total countries rated with SCRs are 159. Out of 159 rated countries, 103 countries or 65% of these countries are rated by all three leading CRAs, 16% are rated by two of the three CRAs, and the remaining 9% are rated by one of the three CRAs. The 159 countries rated by the three leading CRAs are compiled in Table 2-2.

Table 2-2: List of Countries Rated by Moody's, S&P and Fitch

Country	Moody's	S&P	Fitch	Country	Moody's	S&P	Fitch
Abu Dhabi	Aa2	AA	AA	Laos	Caa2		B-
Albania	B1	B+		Latvia	A3	A	A-
Andorra		BBB	BBB+	Lebanon	C	B-	RD
Angola	B3	B-	B-	Lesotho			B
Argentina	Ca	B	RD	Liechtenstein		AAA	
Armenia	Ba3		BB-	Lithuania	A3	A	A
Aruba		BBB+	BB	Luxembourg	Aaa	AAA	AAA
Australia	Aaa	AAA	AAA	Macao	Aa3		AA
Austria	Aa1	AA+	AA+	Macedonia		BB-	
Azerbaijan	Ba2	BB+	BB+	Malaysia	A3	A-	A-
Bahamas	Ba2	BB+		Maldives	B3		B
Bahrain	B2	B+	B+	Mali	B3		
Bangladesh	Ba3	BB-	BB-	Malta	A2	A-	A+
Barbados	Caa1	SD		Mauritius	Baa1		
Belarus	B3	B	B	Mexico	Baa1	BBB+	BBB-
Belgium	Aa3	AA	AA-	Moldova	B3		
Belize	Caa1	B-		Mongolia	B3	B	B
Benin	B2	B+	B	Montenegro	B1	B+	
Bermuda	A2	A+		Montserrat		BBB-	
Bolivia	B1	BB-	B+	Morocco	Ba1	BBB-	BBB-
Bosnia	B3	B		Mozambique	Caa2	SD	CCC
Botswana	A2	A-		Namibia	Ba2		BB
Brazil	Ba2	BB-	BB-	Netherlands	Aaa	AAA	AAA
Bulgaria	Baa2	BBB-	BBB	New Zealand	Aaa	AA	AA
Burkina Faso		B		Nicaragua	B3	B-	B-
Cambodia	B2			Niger	B3		
Cameroon	B2	B	B	Nigeria	B2	B	B
Canada	Aaa	AAA	AA+	North Macedonia			BB+
Cape Verde		B	B-	Norway	Aaa	AAA	AAA
Cayman Islands	Aa3			Oman	Ba3	BB	BB-
Chile	A1	A+	A	Pakistan	B3	B-	B-
China	A1	A+	A+	Panama	Baa1	BBB+	BBB

[14] www.moodys.com reported on August 21st 2020
[15] www.capitaliq.com reported on July 2nd 2019
[16] www.fitchratings.com as at August 22nd 2020

Country	Moody's	S&P	Fitch	Country	Moody's	S&P	Fitch
Colombia	Baa2	BBB-	BBB-	Papua New Guinea	B2	B	
Congo-Brazzaville		B-	CCC	Paraguay	Ba1	BB	BB+
Cook Islands		B+		Peru	A3	BBB+	BBB+
Costa Rica	B2	B+	B	Philippines	Baa2	BBB+	BBB
Cote d'Ivoire	Ba3		B+	Poland	A2	A-	A-
Croatia	Ba2	BBB-	BBB-	Portugal	Baa3	BBB	BBB
Cuba	Caa2	BBB+		Qatar	Aa3	AA-	AA-
Cyprus	Ba2	BBB-	BBB-	Republic, Congo	Caa2	CCC+	CCC
Czech Republic	Aa3	AA-	AA-	Romania	Baa3	BBB-	BBB-
DRC, Congo	Caa1			Russia	Baa3	BBB-	BBB
Denmark	Aaa	AAA	AAA	Rwanda	B2	B	B+
Dominican Republic	Ba3	BB-	BB-	San Marino			BB+
Ecuador	Caa3	B-	RD	Saudi Arabia	A1	A-	A
Egypt	B2	B	B+	Senegal	Ba3	B+	
El Salvador	B3	B-	B-	Serbia	Ba3	BB	BB+
Estonia	A1	AA-	AA-	Seychelles			B+
eSwatini	B3			Sharjah	Baa2	BBB+	
Ethiopia	B2	B	B	Singapore	Aaa	AAA	AAA
Fiji	Ba3	B+		Slovakia	A2	A+	A
Finland	Aa1	AA+	AA+	Slovenia	Baa1	AA-	A
France	Aa2	AA	AA	Solomon Islands	B3		
Gabon	Caa1		CCC	South Africa	Ba1	BB	BB
Georgia	Ba2	BB-	BB	Spain	Baa1	A-	A-
Germany	Aaa	AAA	AAA	Sri Lanka	B2	B	B-
Ghana	B3	B	B	Sint Maarten	Baa3		
Greece	B1	B+	BB	St. Vincent & the Grenadines	B3		
Guatemala	Ba1	BB-	BB-	Suriname	Caa3	B	CC
Guernsey		AA-	BB-	Sweden	Aaa	AAA	AAA
Honduras	B1	BB-		Switzerland	Aaa	AAA	AAA
Hong Kong	Aa3	AA+	AA-	Taiwan	Aa3	AA-	AA-
Hungary	Baa3	BBB	BBB	Tajikistan	B3	B-	
Iceland	A2	A	A	Tanzania	B2		
India	Baa3	BBB-	BBB-	Thailand	Baa1	BBB+	BBB+
Indonesia	Baa2	BBB	BBB	Togo	B3	B	
Iraq	Caa1	B-	B-	Trinidad and Tobago	Ba1	BBB+	
Ireland	A2	A+	A+	Tunisia	B2		B
Isle of Man	Aa2			Turkey	B1	B+	BB-
Israel	A1	AA-	A+	Uganda	B2	B	B+
Italy	Baa3	BBB	BBB-	Ukraine	B3	B-	B
Jamaica	B2	B	B+	United Arab Emirates	Aa2		
Japan	A1	A+	A	United Kingdom	Aa2	AA	AA-
Jersey		AA-		United States	Aaa	AA+	AAA
Jordan	B1	B+	BB-	Uzbekistan	B1	BB-	BB-
Kazakhstan	Baa3	BBB-	BBB	Uruguay	Baa2	BBB	BBB-
Kenya	B2	B+	B+	Venezuela	C	SD	
Korea	Aa2	AA	AA-	Vietnam	Ba3	BB	BB
Kuwait	Aa2	AA	AA	Zambia	Ca	B-	CC
Kyrgyz Republic	B2						

Note: Countries rated by Moody's are sourced from www.moodys.com reported on August 21st, 2020, countries rated by S&P are sourced from www.capitaliq.com reported on July 2nd, 2019, and countries rated by Fitch are sourced from www.fitchratings.com as of August 22nd, 2020.

Among the 103 multi-rated countries, only 33% are rated with the equivalent SCR notches by all three leading CRAs. The remaining 69 multi-rated countries are assigned with split-SCRs (i.e., 55 countries with 1 SCR notch different, 14 with at least 2 SCR notches different) from the three leading CRAs.

The samples employed in empirical studies have demonstrated the persistency of split-SCRs. For instance, the previous studies on split corporate credit ratings (Alsakka & Gwilym, 2010b; Cantor, Packer, & Cole, 1997; Ederington, 1986; Livingston, Naranjo, & Zhou, 2008; Morgan, 2002), and split-SCRs (Abad, Alsakka, & Gwilym, 2018; Alsakka & Gwilym, 2010a, 2013; Alsakka & Gwilym, 2009; Cantor & Packer, 1996; Cantor & Parker, 1995) have demonstrated the split-ratings as a going concern in the rating universe.

Initially, Cantor and Parker (1995) claimed that the occurrence of split-SCRs was due to the infancy stage of SCRs. Although SCRs can be traced back to the 1890s, the SCRs services only managed to reboot in the late 1970s and only gained significant traction in the early 1990s, when countries were tapping into the US liquidity boom. To participate in the "Yankee" bond market, participating countries must first be rated with SCRs. Therefore, there was some basis to relate the occurrence of split-SCRs to the infancy stage.

However, the work of Alsakka and Gwilym (2009) using a sample of 90 rated with observations spanning from 2000 to 2006 clearly dismissed the claim that split-SCRs only occurred in the early stage. In their study, the researchers reported 64% of SCRs issued by Moody's and S&P on the 90 countries disagree. Some of those disagreements reached 6 notches different (*i.e.,* Paraguay SCRs between Feb. 2003 to Mar. 2003 with 'B1' by Moody's and 'SD' by S&P, *etc.*). On a separate paper, Alsakka and Gwilym (2010b) expanded the number of CRAs from 3 to 6 for examination. Using a sample of 49 emerging countries with observations spanning from 2000 to 2008, the researchers reported that SCRs issued by Moody's and S&P continued to convey varying opinions on credit profiles among the 49 rated countries, 59% of these countries were issued with split-SCRs. The split-SCRs between Moody's and Fitch were at 58%, and between S&P and Fitch were at 35%. The SCRs from Capital Intelligence (CI), Japan Rating and Investment Information (JRII), and Japan Credit Rating Agency (JCR) also recorded 52% to 84% disagreement with SCRs issued by the three leading CRAs. The researchers claimed that the cause of split-SCRs was likely due to different SCRs methodologies and discretion exercised by respective CRAs. The statistics on split-SCRs by CRAs as reported by the above-stated studies are compiled in Table 2-3.

Table 2-3: Split-SCRs by CRAs and Researchers

Split SCRs between CRAs	**(Cantor & Parker, 1995)**	**(Alsakka & Gwilym, 2009)**	**(Alsakka & Gwilym, 2010b)**	**(Alsakka & Gwilym, 2010a)**
Moody's Vs. S&P	48%	64%	59%	51%
Moody's Vs. Fitch	n/a	n/a	58%	47%
Moody's Vs. JRII	n/a	n/a	71%	54%
Moody's Vs. JCR	n/a	n/a	84%	52%
Moody's Vs. CI	n/a	n/a	58%	n/a
S&P Vs. Fitch	n/a	n/a	35%	36%
S&P Vs. JRII	n/a	n/a	52%	44%
S&P Vs. JCR	n/a	n/a	71%	47%
S&P Vs. CI	n/a	n/a	52%	n/a
Fitch Vs. JRII	n/a	n/a	65%	51%
Fitch Vs. JCR	n/a	n/a	71%	52%
Fitch Vs. CI	n/a	n/a	54%	n/a

Note: The statistics on this table are compiled from multiple pieces of literature. The study by Cantor & Parker (1995) on split SCRs was based on the snap shot of SCRs issued by Moody's and S&P on 48 countries as of 9th June 1995. The paper by Alsakka & Gwilym (2009) was based on 90 countries with monthly SCRs observations spanning from January 2000 to May 2006. Although the paper also considered the SCRs from the listed CRAs but details were not provided on split SCRs on other pairs of CRAs, therefore 'n/a' is inserted. The split SCRs by Alsakka & Gwilym (2010b) were based on 49 emerging countries rated by Moody's, S&P, Fitch, Capital Intelligence (CI), Japan Rating and Investment Information (JRII), and Japan Credit Rating Agency (JCR) on annual SCRs spanning from the year 2000 to 2008. The research by Alsakka & Gwilym (2010a) was based SCRs issued by Moody's, S&P and Fitch from 10th August 1994 to 30th June 2009 on 84 to 97 countries (depending on country coverage by the respective CRA), and SCRs issued by JRII and JCR from 1st January 2000 to 30th June 2009 on 34 to 46 countries on daily data frequency.

The persistence occurrence of split-SCRs on rated countries is a dilemma for rated countries and institutional investors alike. For rated countries, government bond issuers would prefer the SCR notch that denotes better creditworthiness, therefore, allows them to borrow at a lower cost. On the other side, the institutional investors would consider the SCR notch that denotes a higher default rate, therefore, demand a higher risk premium to compensate for the additional default risk they assumed. In practice, a trade-off between the two SCR notches would be anticipated. With Fitch offering the third opinion, the trade-off on split-SCRs amongst the three leading CRAs becomes more complicated. For instance, Alsakka and Gwilym (2010a) claimed that there were dominant roles amongst these three leading CRAs. SCRs issued by Moody's was leading indicator on SCR upgrades while SCRs issued by S&P was leading indicator on SCR downgrades. SCRs issued by Fitch was reported to be neutral. Their findings implied that SCRs issued by Fitch were redundant as compared to SCRs issued by Moody and S&P in SCRs information value context.

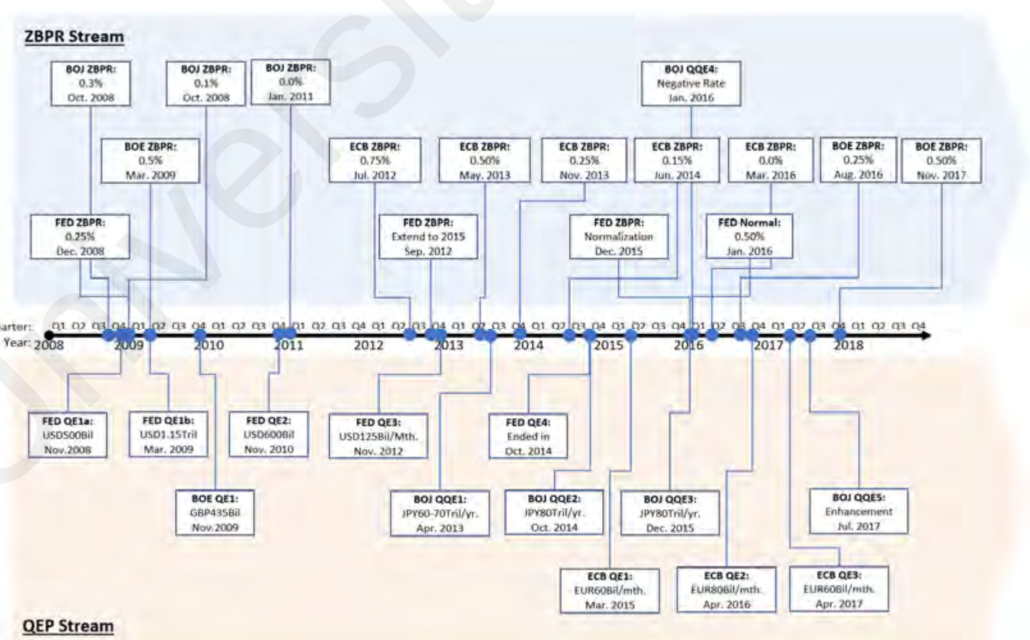
The occurrence of split-SCRs also has significant implications on economic growth as reported by Chen, Chen, Chang, and Yang (2016). As part of the robustness check procedure, the researchers found that split-SCRs demonstrated competing effects on economic growth. On a separate paper (2016), they claimed that both SCRs upgrades and downgrades events would lead to downward revision on the economic growth forecast of non-event countries, especially on countries rated in lower SCR notches.

2.5 Zero-Bound-Policy-Rate (ZBPR) and Quantitative Easing Programme (QEP)

The global financial crisis (GFC) in 2008 marked the beginning of a record low policy rates rolled out by four key Central Banks: US Federal Reserves (FED), Bank of England (BOE), European Central Bank (ECB), and Bank of Japan (BOJ).

Before the GFC, the policy rate of BOJ was already set at 0.5%, and it was lowered to 0.3% in October 2008. The FED also set the policy rate at 0.25% in December 2008 and maintained the same policy rate until December 2015. The BOE lowered the bank rate to 0.5% in March 2009, followed by ECB lowered its policy rate to 0.75% in July 2012. The policy rates set by these four key Central Banks are collectively referred to as the zero-bound-policy rate (ZBPR) in this thesis.

Figure 2-8: ZBPR and QEP Rollout by Four Key Central Banks Timeline



Note: The zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP) rollout timeline by four key Central Banks are compiled from sources: *Federal Reserve Board - Monetary Policy*, *Monetary policy | Bank of England*, *Monetary Policy (europa.eu)*, and *Outline of Monetary Policy: 日本銀行 Bank of Japan (boj.or.jp)*. The FED stands for US Federal Reserves, BOE stands for Bank of England, ECB stands for European Central Bank, and BOJ stands for Bank of Japan. The QEP rolled out by BOJ is known as the quantitative and qualitative easing programme (QQEP), which is an expansion of pre-existing QEP

Realizing with the ZBPR alone would be challenging to achieve the 2% inflation target, the de facto growth rate for developed economies, these four key Central Banks started to inject fresh liquidity through quantitative easing programme (QEP). The FED rolled out its first quantitative easing programme (QEP) in November 2008 with a USD500 billion budget to purchase financial assets. Briefly, in March 2009, the second tranche of QEP liquidity injection worth USD1.5 trillion was rolled out by the FED. In about the same period, the BOE also rolled out QEP with an initial budget of GBP75 billion. By 2018, the fresh liquidity injected by BOE through QEP aggregated to GBP435 billion. The BOJ renamed its QEP with the quantitative and qualitative easing programme (QQEP) in April 2013 and with new rounds of fresh liquidity injection worth JPY60 to 70 trillion budget per annum. In March 2015, the ECB rolled out its first QEP with a monthly budget of EUR60bil. The QEPs and QQEP are collectively referred to as the quantitative easing programme (QEP) in this thesis. The ZBPR and QEP announcements by the four key Central Banks are mapped in a single timeline as depicted in Figure 2-8.

Although the ZBPR and QEP are inbound focused, the global spillover will be inevitable, given that the currencies of these four key Central Banks are international reserves and trade currencies. Moreover, the QEP has injected an aggregate of USD12 trillion of fresh liquidity. When the financial market is spoiled with abundance liquidity at relatively cheap borrowing cost, the occurrence of "flight-to-yield" would be common and rationally motivated. According to a report[17], Fitch commented that ZBPR and QEP could have both positive and negative results on rated countries. The negative results emphasized mainly the after effect of ZBPR and QEP. In addition, Moody's raised the concern that the QEP may be effective for developed economies to stabilize domestic

[17] https://finance.yahoo.com/news/fitch-quantitative-easing-support-sovereign-100116259.html

debt markets and liquidity, the exit plans on ZBPR and QEP do present significant risks on recovery and debts serviceability[18]. The ZBPR normalization and QEP tapering would present a significant negative impact on countries with weak economic fundamentals, especially the emerging countries, A recent study by Curcuru, Kamin, Li, and Rodriquez (2018) provides evidence on ZBPR and QEP spill over to other countries, with significant influence in price discovery. Their event study claimed that ZBPR and QEP rolled out by FED spilt over to Germany, Canada, United Kingdom, South Korea, Mexico, and Brazil.

2.6 Concluding Remarks

The SCR notches (e.g., Aaa/AAA. Aa1/AA+, Aa2/AA, Aa3/AA-, etc.) are having a similar monotonous feature of KMV EDF credit risk rankings. For example, the Aaa/AAA-rated countries by official definition are having the lowest default risk, therefore are at the furthest milestone from the default region. Countries rated with Aa1 or AA+ are inferior to those rated Aaa or AAA, but superior to those rated with Aa2 or AA. Therefore, Aa1/AA+ rated countries are one milestone closer to the default region as compared to Aaa/AAA-rated countries, and so on. Those rated with SD, RD, or D by S&P or Fitch are already in the default region. In the context of sovereign debts, the default distance is not measured by $A(V,t)$ and $D(V,t)$. The SCR notches can be comprehended as the default milestones, a viable substitute for default distance in the Merton model.

[18] https://finance.yahoo.com/news/moodys-emerging-markets-quantitative-easing-044006183.html

There are few distinct observations we could gather from the empirical studies of the determinants of SCRs. First, the set of determinants could be easily expanded but those that proven statistically significant are principal component variables and are almost identical to the original set of determinants employed by Cantor and Packer (1996). Second, the ordered response model (OPM) is indeed a more appropriate method as compared to the linear method for estimating the predictive power of selected determinants of SCRs. On that note, the empirical results using cross-section methods (Afonso, 2003; Cantor & Packer, 1996; Rowland, 2004) with 80% to 90% goodness of fit could have overstated the predictive power of the selected determinants. Although the same set of determinants estimated with the ordered response models produced a lower predictive power, in the range of 40% to 50%, the results are more reliable given the method is equipped with the right econometric (Wooldridge, 2002). Third, despite the variance in predictive power, the majority of principal component variables remain robust as significant determinants of SCRs when estimated with both the linear method and ordered response method. The final observation on the determinants of SCRs is that potentially time-varying as demonstrated by Reusens and Croux (2017) on multi-year and single-year models.

On SBYs, the SCRs determinants are equally effective as SBYs determinants. Previous studies have proven that SCRs as additional determinant did covey the “above and beyond” information value of SCRs, and the SCRs as standalone determinant was equally effective in explaining SBYs. However, the SCRs information value in SBYs price discovery is sensitive to external events. The SCRs explanatory power could weaken significantly during negative external events (e.g., 1997 Asia financial crisis, 2000 millennium bug, etc), but SCRs information value remained significant in SBYs price discovery.

In addition, the lineage of SCDSs to SBYs making the SCDSs an ideal substitute for SBYs as the dependent variable. The lineage is the basis that SCRs information value is transmissible from SBYs to SCDSs. This relationship is established in empirical studies. The use of SCRs as a proxy of credit risk component in explaining the spreads of SCDSs is also substantiated with empirical evidence.

The studies of split-SCRs information value on debts price discovery are rather interesting. On one hand, the split-SCRs are proxied by an average ordinal scaled SCRs in debts price discovery. On the other hand, the split-SCRs are treated as lead and lag indicators to predict SCRs upgrades and downgrades amongst the three leading CRAs. While the latter branch of study on split-SCRs is well covered empirically, the former will be examined further in this thesis.

Regarding the ZBPR and QEP, the concerted effort from four key Central Banks: the US Federal Reserves, Bank of England, European Central Bank, and Bank of Japan, presented both opportunities and threats to SCRs rated countries. In recent studies, there is evidence of ZBPR and QEP spillover (Curcuru et al., 2018; Kinateder & Wagner, 2017). The studies furnished by Miricescu (2015) and Reusens and Croux (2017) did examine the SCRs with the effects of ZBPR and QEP embedded in their respective samples. In other words, the potential effects of ZBPR and QEP on SCRs and SCRs information value are real and have not been addressed.

This thesis is motivated by the potential effect of ZBPR and QEP on SCRs, a research gap with broad implications. This thesis will revisit the determinants of SCRs, the SCRs information value, and split-SCRs information in debt price discovery using a sample where the effects of ZBPR and QEP are embedded.

CHAPTER 3: SOVEREIGN CREDIT RATINGS (SCRs) SYNTHESIS

3.1 Introduction

It is essential to first establish the credit rating agencies (CRAs) that countries would commission for sovereign credit ratings (SCRs) and that SCRs are widely accepted by institutional investors. In accordance with the NRSRO[19], there are ten registered CRAs by US Securities Commissions. The most sought-after CRAs are Moody's, S&P, and Fitch. These three CRAs are with 99% combined market share on government bonds issuance ratings.

The SCRs issued by Moody's are technically known as sovereign bond ratings (SBRs) in the form of alpha-numeric (i.e., Aaa, Aa1, Aa2, Aa3, etc.), and with scales of 21 notches. The SCRs issued by S&P are known as sovereign ratings (SRs) in the form of alpha-symbol (i.e., AAA, AA+, AA, AA-, etc.), and with scales of 23 notches. Finally, the SCRs issued by Fitch are known as sovereign issuer default ratings (IDRs), also in the alpha-symbol form like S&P but only with scales of 21 notches.

The sovereign credit rating methodology of these three leading CRAs is the key to understand the similarities and differences on the assigned SCRs. Apparently, all three leading CRAs take in quantitative and qualitative inputs for assessments. The quantitative inputs consist of mainly economic variables. The qualitative inputs are indicators on the rated countries furnished by third parties (i.e., IMF, World Bank, etc.), and the CRA's internally derived indicators. All three CRAs also obtain privilege information through non-disclosure-agreement from the rated country to facilitate their assessment on

[19] Annual Report on Nationally Recognized Statistical Rating Organization (NRSRO), December 2018.

creditworthiness. Both publicly obtained information and non-disclosure-agreement obtained information will be assessed by designated analysts following the framework dictated in the sovereign credit rating methodology of respective CRAs.

In the nutshell, Moody's, and S&P leverage on pre-established mapping tables while Fitch adopts regression-derived weightage in formulating the baseline SCR. Upon establishing the baseline SCRs, the assigned analysts will present the baseline SCR notches to the rating committee for deliberation. The rating committee would then decide on the final SCR notch. The final SCR notch will first be conveyed to the rated country and subsequently disseminated to the public via official channels.

This synthesis reveals that SCRs issued by Moody's, S&P, and Fitch could be summarized as a function of publicly available information (PAI), non-disclosure-agreement obtained information (NDAI), and sovereign credit rating methodology (SCRM) components. The assignment of the final SCR is not the end of the rating process. SCRs surveillance will be conducted in a periodical manner by respective CRAs to determine whether the current credit profile matches the rated credit profile. If current and rated credit profiles are matched, the assigned SCR notch will be maintained. Otherwise, the upgrade or downgrade on the assigned SCR notch is to be anticipated. As revealed from this synthesis, the change of rated countries' credit profiles is one of the factors considered by CRAs when deciding on upgrade or downgrade. The other two factors are the migration rates and default rates among the cohorts (i.e., the cluster of Aaa/AAA, Aa/AA, A/A, etc.). These three factors are key measurements in the Through-the-Cycle (TTC) philosophy observed by respective CRAs in the SCRs determination process.

The change on the assigned SCR notch generated new information value in debts price discovery. The pricing of SCRs information value follows the risk-reward pricing convention advocated by Merton (1973) and Kealhofer and Bohn (1993). With 65% of rated countries that are multi-rated by all three leading CRAs (see Table 2-2), the persistency of split-SCRs complicates the SCRs information value in debts price discovery. The causes of varying opinions on rated countries' creditworthiness amongst these three leading CRAs could be traced back to the NDAI and SCRM components. These two components are also the source of "above and beyond" information value, and the essence of SCRs.

In the following sections of this chapter, the synthesis will furnish an overview of SCR notches and official definitions on SCRs issued by Moody's, S&P, and Fitch. A summary of a thorough review of proprietary rating methodologies of the three leading CRAs will be reported in the subsequent section. The concept of SCRs function conceived from this synthesis and its relation to SCRs determinants studies are discussed in the section follows suit. The SCRs default milestones and the relevance of SCRs information value are elaborated in conjunction with the applicable economic theories. The synthesis will also touch on the causes of split-SCRs before concluding.

3.2 SCRs Notches and Definitions

As briefly stated earlier in the introduction section, the SCRs issued by Moody's are technically known as the sovereign bond ratings (SBRs), which consists of 21 notches in the form of alpha-numeric (i.e., Aaa, Aa1, Aa2, Aa3, etc.). Whereas the SCRs issued by S&P are known as the sovereign ratings (SRs) that consist of 23 notches, and the sovereign issuer default ratings (IDRs) issued by Fitch consist of 21 notches. Both SRs and IDRs are issued in the form of alpha-symbol (i.e., AAA, AA+, AA, AA-, etc.). Although the number of notches and the formats are different amongst the three leading

CRAs, the official definitions of SBR, SR, and IDR notches are almost the (Emery, 2017; FitchRatings, 2017; Ratings, 2016).

For instance, the SBR notch of Aaa issued by Moody's is equivalent to SR notch of AAA issued by S&P and IDR notch of AAA issued by Fitch. Countries rated with Aaa or AAA are denoted as having the highest creditworthiness by respective CRAs. Whereas countries rated with Aa1 or AA+ are also having the same credit quality profile, which is inferior to Aaa/AAA-rated countries but superior to those rated with Aa2 or AA. The next notch down the hierarchy is Aa3 or AA-, followed by A1 or A+, and so on. The list of SBR, SR, and IDR notches and official risk ranking definitions are compiled in Table 3-1.

Table 3-1: SBR, SR, and IDR Notches and Official Definitions from Moody's, S&P, and Fitch

No	Moody's Long-Term Rating Scale		S&P Long-Term Issuer Credit Ratings		Fitch Long-Term Issuer Default Ratings	
1	Aaa	Obligations rated Aaa are judged to be the highest quality, subject to the lowest level of credit risk	AAA	An obligor rated 'AAA' has an extremely strong capacity to meet its financial commitment. 'AAA' is the highest issuer credit rating assigned by S&P Global Ratings	AAA	Highest credit quality. 'AAA' ratings denote the lowest expectation of default risk. They are assigned only in cases of exceptionally strong capacity for payment of financial commitments. This capacity is highly unlikely to be adversely affected by foreseeable events.
2 3 4	Aa1 Aa2 Aa3	Obligations rated Aa1 – Aa3 are judged to be high quality, subject to very low credit risk.	AA+ AA AA-	An obligor rated 'AA' has a very strong capacity to meet its financial commitments. It differs from the highest-rated obligors only to a small degree.	AA+ AA AA-	Very high credit quality. 'AA' ratings denote expectations of very low default risk. They indicate a very strong capacity for payment of financial commitments. This capacity is not significantly vulnerable to foreseeable events.

No	Moody's Long-Term Rating Scale		S&P Long-Term Issuer Credit Ratings		Fitch Long-Term Issuer Default Ratings	
5 6 7	A1 A2 A3	Obligations rated A1 – A2 are judged to be upper-medium grades and subject to low credit risk.	A+ A A-	An obligor rated 'A' has a strong capacity to meet its financial commitments but is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories.	A+ A A-	High credit quality. 'A' rating denotes expectations of low default risk. The capacity for payment of financial commitments is considered strong. This capacity may, nevertheless, be more vulnerable to adverse business or economic conditions than is the case for higher ratings.
8 9 10	Baa1 Baa2 Baa3	Obligations rated Baa1-Baa3 are judged to be medium grades and subject to moderate credit risk, and as such may possess certain speculative characteristics	BBB+ BBB BBB-	An obligor rated 'BBB' has adequate capacity to meet its financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.	BBB+ BBB BBB-	Good credit quality. 'BBB' ratings indicate that expectations of default risk are currently low. The capacity for payment of financial commitments is considered adequate, but adverse business or economic conditions are more likely to impair this capacity.
11 12 13	Ba1 Ba2 Ba3	Obligations rated Ba1-Ba3 are judged to be speculative and subject to substantial credit risk	BB+ BB BB-	An obligor rated 'BB' is less vulnerable in the near term than other lower-rated obligors. However, it faces major ongoing uncertainties and exposure to adverse business, financial, or economic conditions which could lead to the obligor's inadequate capacity to meet its financial commitments.	BB+ BB BB-	Speculative. 'BB' ratings indicate an elevated vulnerability to default risk, particularly in the event of adverse changes in business or economic conditions over time; however, business or financial flexibility exists that supports the servicing of financial commitments.
14 15 16	B1 B2 B3	Obligations rated B1-B3 are considered speculative and subject to high credit risk	B+ B B-	An obligor rated 'B' is more vulnerable than the obligor rated 'BB', but the obligor currently has the capacity to meet its financial commitments. Adverse business, financial, or	B+ B B-	Highly speculative. 'B' ratings indicate that material default risk is present, but a limited margin of safety remains. Financial commitments are

No	Moody's Long-Term Rating Scale		S&P Long-Term Issuer Credit Ratings		Fitch Long-Term Issuer Default Ratings	
				economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.		currently being met; however, capacity for continued payment is vulnerable to deterioration in the business and economic environment.
17 18 19	Caa1 Caa2 Caa3	Obligations rated Caa1-Caa3 are judged to be speculative of poor standing and subject to very high credit risk	CCC+ CCC CCC-	An obligor rated 'CCC' is currently vulnerable, and is dependent upon favourable business, financial, and economic conditions to meet its financial commitments.	CCC	Substantial credit risk. Default is a real possibility.
20	Ca	Obligations rated Ca are highly speculative and are likely in, or very near, default, with some prospect of recovery of principal and interest	CC	An obligor rated 'CC' is currently highly vulnerable. The 'CC' rating is used when a default has not yet occurred, but S&P Global Ratings expects default to be a virtual certainty, regardless of the anticipated time to default.	CC	Very high levels of credit risk. Default of some kind appears probable.
21	C	Obligations rated C are the lowest rated and are typically in default, with little prospect for recovery of principal or interest	R	An obligor rated 'R' is under regulatory supervision owing to its financial condition. During the pendency of the regulatory supervision, the regulators may have the power to favour one class of obligations over others or pay some obligations and not others.	C	Near default A default or default-like process has begun, or the issuer is in a standstill, or for a closed funding vehicle, payment capacity is irrevocably impaired. Conditions that are indicative of a 'C' category rating for an issuer include: 1. the issuer has entered into a grace or cure period following non-payment of a material financial obligation; 2. the issuer has entered into a temporary negotiated waiver or standstill

No	Moody's Long-Term Rating Scale		S&P Long-Term Issuer Credit Ratings		Fitch Long-Term Issuer Default Ratings	
						agreement following a payment default on a material financial obligation; 3. the formal announcement by the issuer or their agent of a distressed debt exchange; 4. a closed financing vehicle where payment capacity is irrevocably impaired such that it is not expected to pay interest and/or principal in full during the life of the transaction, but where no payment default is imminent
22			SD	An obligor rated 'SD' (selective default) or 'D' is in default on one or more of its financial obligations including rated and unrated financial obligations but excluding hybrid instruments classified as regulatory capital or in non-payment according to terms. An obligor is considered in default unless S&P Global Ratings believes that such payments will be made within five business days of the due date in the absence of a stated grace period or within the earlier of the stated grace period or 30 calendar days. A 'D' rating is assigned when S&P Global Ratings believes that the default will be a general default	RD	Restricted default. 'RD' ratings indicate an issuer that in Fitch's opinion has experienced: 1. an uncured payment default on a bond, loan, or other material financial obligation, but 2. has not entered into bankruptcy filings, administration, receivership, liquidation, or other formal winding-up procedure, and 3. has not otherwise ceased operating. This would include: i. the selective payment default on a specific class or currency of debt; ii. the uncured expiry of any applicable grace period, cure period or default forbearance period following a

No	Moody's Long-Term Rating Scale	S&P Long-Term Issuer Credit Ratings		Fitch Long-Term Issuer Default Ratings	
			and that the obligor will fail to pay all or substantially all its obligations as they come due. An 'SD' rating is assigned when S&P Global Ratings believes that the obligor has selectively defaulted on a specific issue or class of obligations but it will continue to meet its payment obligations on other issues or classes of obligations in a timely manner. An obligor's rating is lowered to 'D' or 'SD' if it is conducting a distressed exchange offer.		payment default on a bank loan, capital markets security or other material financial obligation; ii. the extension of multiple waivers or forbearance periods upon a payment default on one or more material financial obligations, either in series or in parallel; ordinary execution of a distressed debt exchange on one or more material financial obligations.
23		D		D	Default. 'D' ratings indicate an issuer that in Fitch's opinion has entered into bankruptcy filings, administration, receivership, liquidation, or other formal winding-up procedure or that has otherwise ceased business.
24		NR	An issuer designated 'NR' is not rated	NR	An issuer designated 'NR' is not rated

Note: Moody's Long-Term Rating Scale and definitions are referred to Global Long-Term Rating Scale table on page 6 Rating Symbols and Definition were released in July 2017 and sourced from Moody's Investors Services. The numeric scales of 1 to 3 indicate the upper bound, median, and lower bound to the respective ranking. I.e., Aa1 is of superior quality compared to Aa2 and Aa3 within the Aa range. S&P Long-Term Issuer Credit Ratings and definitions are referred to as S&P Global Ratings Definitions in Table 3 page 6 released in August 2016 and sourced from www.standardandpoors.com/ratingsdirect. The + and – signs indicate the relative strength within the rating range, like Moody's numeric indicators. Fitch Long-Term Issuer Default Ratings and definitions are referred to as Rating Definitions from pages 18 to 19 sourced from Fitch Ratings in March 2017.

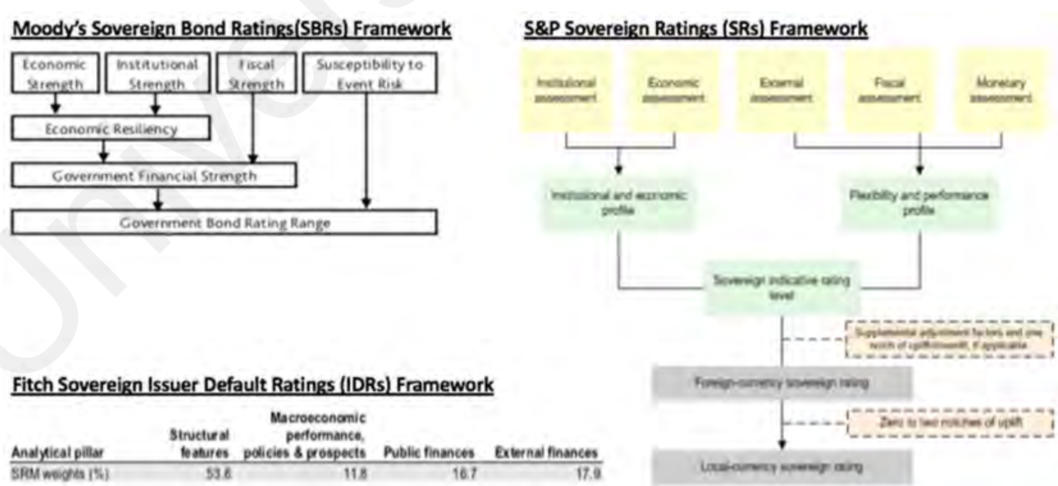
From the list, it becomes obvious that Moody's SBR notches stop at "near default" or the tagging of "C". The SRs by S&P and IDRs by Fitch do rate defaulted countries with the tagging of "SD" that denotes selective default, "R" denotes under regulatory supervision, "RD" denotes restricted default, and "D" denotes default in general. The SRs, S&P, and IDRs are collectively referred to as the SCRs from here onwards. It is interesting to take note that the classification of investment grade and speculative grade categories is not originated from any of the three leading CRAs. The classification of investment-grade versus speculative-grade assets is adopted by the financial industry as one of the criteria for asset allocation. The former category consists of SCR notches from Aaa/AAA to Baa3/BBB-, and those rated below Baa3/BBB- are grouped in the latter category.

3.3 Sovereign Credit Rating Methodology

Although the SCRs issued by the three leading CRAs are having almost identical notches and definitions on credit profiles, the rating methods employed by Moody's, S&P, and Fitch are not the same. As per Hornung et al. (2016), Moody's uses predefined mapping matric tables in assessing the economic, institutional, fiscal, and eternal susceptibility factors in determining the SBR notches. The S&P also uses the predefined mapping matric tables method in assessing the economic, institutional, fiscal, monetary, and external susceptibility factors in determining the SR notches (Kraemer et al., 2017). On the other hand, Fitch's approach appeared to be more statistically inclined. The weightage on the structural, macroeconomic performance and policies, fiscal, and external finances factors are statistically derived to determine the IDR notches (Stringer et al., 2016).

Despite different rating methodologies, the input variables in determining the SBRs, SRs, and IDRs or SCRs, in a collective term, could be harmonized into four key factors: economic, institution, fiscal, and susceptibility to external events. As depicted in Figure 3-1, the economic strength factor in Moody's SBRs, the economic assessment factor in S&P's SRs, and the structural features and part of macroeconomic performance, policies, and prospect factors in Fitch's IDRs are assessing the same economic strength of the rated countries. The assessment of economic strength is to determine the rated country's ability to service its debts. The institution factor in this context is referring to the government of a rated country. The assessment focuses on the institution's efficiency in rolling out sound policies that translate to sustainable economic performance. This institution factor is assessed under the institutional strength factor in Moody's SBRs, institutional assessment factor in S&P's SRs, and part of macroeconomic performance, policies, and prospect factor in Fitch's IDRs. As the term indicates that the fiscal factor assessment focuses on the incomes and expenses of the government or institution. In the nutshell, the emphasis of this assessment is to determine whether the institution could service and/or repay its debts through tax revenues, new debts, or a mixture of both. This factor is carried out under the fiscal strength factor in Moody's SBRs, fiscal assessment and monetary assessment factors in S&P's SRs, and public finances and part of external finances factors in Fitch's IDRs.

Figure 3-1: Moody's SBRs S&P SRs and Fitch IDRs Overview



Note: This Moody's SBRs framework is sourced from Hornung et al. (2016) on exhibit 3, page 4, the S&P SRs framework is sourced from Kraemer et al. (2017) on page 2, and the Fitch sovereign IDRs framework is sourced from Stringer et al. (2016) on page 6.

On the susceptibility to external events factor, the emphasis of this assessment is to gauge the rated countries' ability and capacity in mitigating external shocks (e.g., Asian financial crisis in 1997, Dot Com bubble in 2000, U.S. Sub-primes crisis in 2008, European debts crisis in 2010, etc.). The assigned SCR notch of a rated country would be maintained if the economic, institution and fiscal fundamentals factors are sustainable. Otherwise, the creditworthiness profile of a rated country would be lowered in anticipation of negative effects on the other three factors due to external events. This assessment is carried out under the susceptibility to the external risk factor in Moody's SBRs, the external assessment factor in S&P's SRs, and the macroeconomic performance, policies, and prospects factor in Fitch's IDRs.

3.3.1 Input Variables of the Key Factors

Under the respective sovereign credit rating methodologies (Hornung et al., 2016; Kraemer et al., 2017; Stringer et al., 2016), all three leading CRAs rely on quantitative and qualitative inputs to assess the strength of the four key factors before the credit profile of a given country is determined. The quantitative inputs of the key factors are summarized below.

Economic factor – this factor is considered under economic strength (ES) factor in Moody's SBRs, external assessment (ExA) factor in S&P's SRs, and the structural features (SF) and part of macroeconomic performance, policies, and prospects (MPPP) factors in Fitch's IDRs. The inputs to this factor by respective CRAs under the broad classification of Economic Factor are presented in Table 3-2.

Table 3-2: Economic Factor Variables

No	Moody's SBRs ES	S&P SRs EA	Fitch IDRs SF and MPPP
1	Real GDP growth	Real GDP per capita growth	Real GDP Growth
2	Real GDP growth volatility	Real GDP per capita growth volatility	Real GDP growth volatility
3	Nominal GDP	Nominal GDP	Nominal GDP
4	GDP per capita	GDP per capita	GDP per capita
5	WEF Global Competitiveness Index		Consumer Price Index / Inflation

Note: The quantitative variables under Moody's are references from Hornung et al. (2016) on Economic Strength from page 8 to 13, the quantitative variables under S&P' are referred from Kraemer et al. (2017) on pages 6 to 7, and the quantitative variables under Fitch are referred from Stringer et al. (2016) on page 13 to 20. The listed variables are non-exhaustive as compared to all inputs considered by the three leading CRAs on this key factor.

The nominal GDP is meant to differentiate the countries based on their respective economic share of global GDP. The rationale is that countries with higher GDP are better equipped to withstand external shocks. The GDP per capita is employed as a proxy for government revenue. Countries with high GDP per capita provide a greater threshold for additional tax revenue when needed. The real GDP growth and growth volatility are key determinants of forward-looking assessment. For instance, countries with high real GDP growth volatility indicate that the current real GDP growth is not sustainable. Countries with high volatility on real GDP growth are likely to experience greater GDP contraction when unfavourable external events occurred. The global competitiveness index from World Economic Forum is a relative measure to compare the economic strength among the rated countries.

The qualitative aspect of the economic factor revolves around the quality of GDP growth. If the GDP growth was debts induced, the growth is usually not sustainable and would be volatile against the credit boom-bust cycle. Countries with debts induced GDP growth would be weighted lower on the strength of the economic factor. The other aspect of adjustment is the level of economic concentration (e.g., commodity-exporting sovereigns, etc.). The GDP of countries with a high concentration in specific industries or commodities is dynamic due to the cyclical nature of certain industries and sensitivity to the global economic growth trajectory.

Institution factor – this factor is assessed under institutional strength (IS) factor in Moody's SBRs, Institutional assessment (IA) factor in S&P's SRs, and the structural features (SF) and part of macroeconomic performance, policies, and prospects (MPPP) factors in Fitch's IDRs. The inputs to this factor by respective CRAs under the classification of Institution Factor are compiled in Table 3-3.

Table 3-3: Institution Factor Variables

No	Moody's SBRs IS	S&P SRs IA	Fitch IDRs SF and MPPP
1	WGI – Government Effectiveness	WGI – Government Effectiveness	WGI – Government Effectiveness
2	WGI – Rule of Law	WGI – Rule of Law	WGI – Rule of Law
3	WGI – Control of Corruption	WGI – Control of Corruption	WGI – Control of Corruption
4	Inflation Level	Transparency and free flow of information	WGI – Voice and Accountability
5	Inflation Volatility	Check and Balance	WGI – Regulatory Quality
6			WGI – Political Stability and Absence of Violence

Note: The quantitative variables under Moody's are referred from Hornung et al. (2016) on pages 8 to 13, the quantitative variables under S&P' are referred from Kraemer et al. (2017) on pages 4 to 6, and the quantitative variables under Fitch are referred from Stringer et al. (2016) on page 13 to 17. The listed variables are non-exhaustive as compared to all inputs considered by the three leading CRAs on this key factor.

In this factor, all three CRAs rely on inputs mainly sourced from Worldwide Governance Indicators (WGI). The WGI is a social project commissioned by World Bank. For instance, the WGI – Government Effectiveness Indicator furnished under this project encompasses the policy planning, implementation, and level of independence in carrying out planning and implementation. The indicator measures the government's effectiveness in implementing sound policies that promote economic growth and social welfare. The WGI – Rule of Law Indicator measures the judicial system of the country regarding the contract, property rights, crimes enforcement by the rule of law, and the impartiality of the judicial system. The WGI – Control of Corruption Indicator is employed to ensure policies are planned and implemented for the greater good of the country and the welfare of the people. The WGI – Voice and Accountability Indicator reflects the civil rights of the country. For instance, the government is elected by the citizen, the citizen is free to express, to congregate, and to have access to media. The WGI – Regulatory Quality Indicator measures the efficiency of the government in making sound policies to promote development in the private sector. The WGI – Political Stability and Absence of Violence Indicator measures the likelihood of political instability and politic-motivated violence in a country. Besides these qualitative WGI-indicators, the conventional quantitative variable, inflation, is assessed by CRAs to determine the government's effectiveness.

Table 3-4: Fiscal Factor Variables

No	Moody's SBRs FS	S&P SRs FA and MA	Fitch IDRs PF and EF
1	General government debt/GDP	General government debt/GDP	Gross government debt/GDP
2	General government interest payments/Government revenue	General government interest payments/Government revenue	General government interest payments/Government revenue
3	General government foreign currency debt/ General government debt	General government foreign currency debt/ General government debt	General government foreign currency debt/ General government debt
4	General government debt/Government revenue	Net general government debt/GDP	General government fiscal balance/GDP
5	General government interest payments/GDP	Inflation rate	External interest service/Current external receipts
6	Debt Trend	Inflation volatility	Current account balance + Foreign direct investment/ GDP

Note: The quantitative variables under Moody's are references from Hornung et al. (2016) on pages 17 to 21, the quantitative variables under S&P' are referred from Kraemer et al. (2017) on pages 10 to 13, and the quantitative variables under Fitch are referred from Stringer et al. (2016) on page 21 to 24. The listed variables are non-exhaustive as compared to all inputs considered by the three leading CRAs on this key factor.

Fiscal factor – this factor is considered under fiscal strength (FS) factor in Moody's SBRs, fiscal assessment (FA) and monetary assessment (MA) factors in S&P SBs, and the public finances (PF) and part of external finances (EF) factors in Fitch's IDRs. The inputs to this factor by respective CRAs under the classification of Fiscal factor are compiled in Table 3-4.

The inputs to this factor are quantitative-centric and measured in ratios of many variations. The core nominators of these ratios mainly focus on general government debt and general government interest payments.

The general government debt (GGD) over the gross domestic product (GDP) and GGD over the government revenue (GR) are relative yardsticks on a rated country's debt burden. The denominator of the latter yardstick employed by Moody's SBRs is to measure the government's ability to raise revenue as means to service and to sustain the debt stock. The net general government debt (NGGD) over GDP adopted by S&P is the indicator of the excessive debt burden that potentially raises the debt sustainability issues. The key emphasis on a country's maximum debt burden is affordability, which is measured via general government interest payments (GGIP) over GR or GDP. The general government foreign currency debt (GGFCD) over the GGD ratio is to determine the debt burden's structure. Countries with a higher proportion of GGFCD are more vulnerable to exchange rate dynamics. These two ratios are consistently measured by all three leading CRAs.

On the qualitative aspect, any negative development observable from fiscal balance and/or debt trend would motivate respective CRA to take the pre-emptive measure by lowering the creditworthiness of the rated country. For instance, developing countries are usually faced with fiscal constraints in funding their respective infrastructure projects. It is common for developing countries to fund fiscal projects through debts, which in retrospect increases the debt burden and debt interest payment ratio. In the case of developed countries, the ageing population is a growing fiscal challenge. A significant portion of the fiscal budget of developed countries is allocated to fund healthcare and healthcare-related programmes.

Besides fiscal challenges, Moody's has included debt trends as part of qualitative variables on the fiscal factor. Both S&P and Fitch also assessed debt trends, but in the contexts of policies and government accomplishments. The debt trend is changes of GGD/GDP ratio over time. The upward trajectory means the debt burden of the country had expanded, and vice versa. The debt burden ratio is also a proxy to measure the country's fiscal performance. In addition, S&P's SRs leverages inflation rate and inflation rate volatility to determine the effectiveness of the government in implementing sound fiscal and monetary policies.

Susceptibility to External Events factor – this factor is considered under susceptible to external risk events (SER) factor in Moody's SBRs, external assessment (ExA) factor in S&P's SRs, and the external finances (EF) macroeconomic performance, policies, and prospects (MPPP) factors in Fitch's IDRs. Unlike the previous 3 key factors, the emphasis of this factor is to evaluate the negative impact of the external events on the economic, institution, and fiscal factors.

The two main negative external events under Moody's consideration are banking crises and foreign exchange crises. These two categories of events could trigger the following developments. The political risks encompass domestic political risk and GDP per capita. The geopolitical is another form of political risk that could emerge due to escalation of tension with neighbouring countries that led to the military expedition. The government liquidity risk focuses on the government borrowing requirements relative to GDP or debt/GDP and debt trend. If the debt structure consists of a high proportion of nonresident versus residents, this means higher reliance on external funding. This translates to funding stress where external funding is critical to meet the borrowing requirement. The contingent liability of the government (i.e., the off-balance-sheet commitments) which is not reported in fiscal account also contributes to funding stress. The proxies to measure sovereign contingent liability are the explicit government guarantees, contractual commitment to pay, and official support extended to government-linked companies (GLC) and financial systems (i.e., banking, capital markets, etc.). The size of the banking system matters. The domestic deposit capacity is a good proxy for domestic liquidity capacity that the government could leverage on for additional funding. On external shocks, the current account balance and foreign direct investment are critical indicators. Positive FDI and/or foreign reserves provide additional coffer to meet current account deficit and buffer to absorb negative effect on exchange rate. The foreign reserves over import coverage ratio is another key indicator to assess the degree of susceptibility to external events. S&P SRs leverages the Inflation rate and volatility to measure the effectiveness of rated countries in overcoming the negative external events.

The exchange rate regime emphasized by S&P is to determine whether the sovereign's currency is categorized as reserves currency or actively traded currencies. Countries that are not in those categories have less flexibility on monetary policy. On the monetary policy credibility, the measurement focuses on the Central Bank's performance in achieving price stability mandate. The performance of the Central Bank is assessed on its capacity to make policies independently, track records in sustaining price stability, and crises management performance. In the event of financial stress, Central Bank must be able to exercise the role of last resort lender to the financial system. Hence, a well-developed financial system and capital market are essential components to boost the country's monetary flexibility. This means the size of the capital market is equally important as compared to the domestic banking system. Both domestic banking systems and the capital market provide the critical pool of funds for government debts denominated in local currency. Sound and robust domestic capital market enhance the Central Bank's ability to steward the economy through bank reserves, policy rates, monetary injection. If the government borrowings are leaning heavily on foreign currency denominated debts, it means the Central bank has very limited flexibility over its monetary policy.

Another aspect to be considered is the implementation of monetary policy under unions setup (e.g., European Central Bank, etc.). For instance, countries that are a member of a monetary union has no control of its exchange rate. Hence the assessment will focus on strength of fiscal and economic developments, and the monetary factor is considered weak given its rigidity.

Countries with currencies that are accepted as international reserves currency or are actively traded are less vulnerable to liquidity shocks based on Fitch's assessment. However, countries that do not possess the domestic currency advantage could leverage the foreign reserves and sovereign net foreign assets (SNFA). The SNFA is derived from the international reserves reported by the Central Bank plus the foreign assets of the government or sovereign wealth fund minus general government and central bank foreign currency debts. Countries with a high level of economic concentration (i.e., petroleum exporting countries, etc.) or rely on a single counterpart country are considered to have a higher default probability when experiencing negative external shocks. The foreign currency reserves would be the mitigating factor for these countries. The coffer from foreign currency reserves could mitigate the exchange rate disparity and import settlements.

The current account and foreign direct investment (FDI) are assessments made on foreign injections either via debts or equity basis. For instance, the debts injection is considered risky, when the current account has been in deficit. The expanded debt burden will expose the country to short-term shocks and liquidity mismatch. On the other hand, the FDI is considered a positive external injection as compared to debts injections.

3.3.2Mapping Matrices and Scales Overview

With the qualitative and quantitative inputs, the CRA will assess and assign weight to the predefined factors. The weightage of individual inputs and factors for Moody's and S&P are based on predefined mapping matrices tables. Fitch adopted an econometric approach in determining the weightage of factors instead of individual inputs as shown in Figure 3-1.

Moody's SBRs – in accordance to Hornung et al. (2016), the four factors in Moody's SBRs are assessed in a two-dimension matrix table where each factor is assigned a scale following the 15 scales mapping table as depicted in Figure 3-2. The score range and mid-point are the cut-off points of the 15 scales used to guide appointed analysts in determining the relative strength or weakness of the inputs for the factor. By definitions, the VH+ denotes as "Very High Plus" or highest strength, followed by VH denotes as "Very High" strength, intuitively M stands for "Mid", L stands for "Low", and VL- stands for "Very Low Minus", which is the weakest category of the scales.

Figure 3-2: Moody's SBRs Mapping Scale

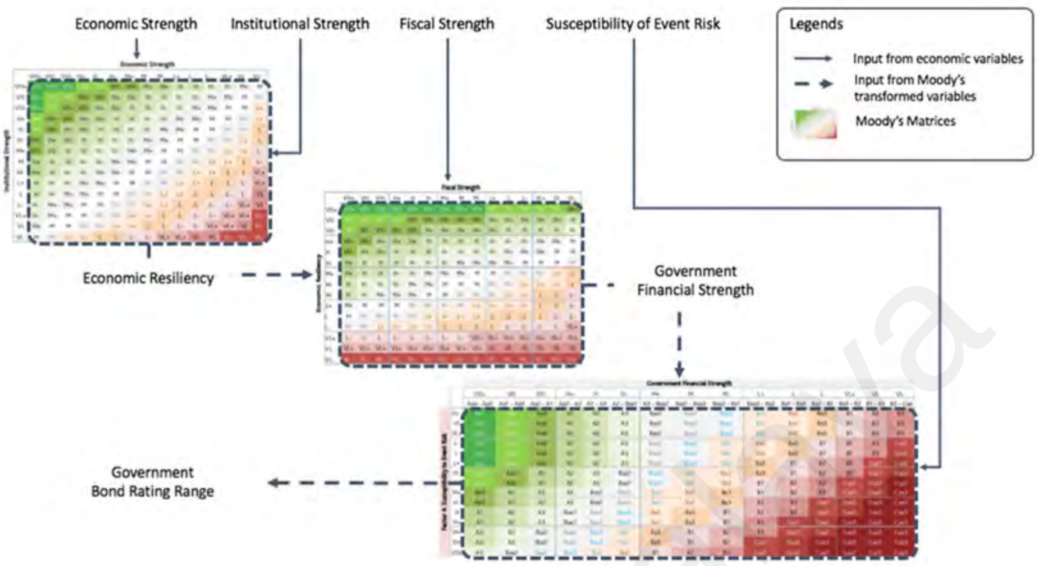
EXHIBIT 2

Category	VH+	VH	VH-	H+	H	H-	M+	M	M-	L+	L	L-	VL+	VL	VL-
Score Range	100 - 85	85 - 80	80 - 75	75 - 70	70 - 65	65 - 60	60 - 55	55 - 50	50 - 45	45 - 40	40 - 35	35 - 30	30 - 25	25 - 20	20 - 1
Mid-Point	92.5	82.5	77.5	72.5	67.5	62.5	57.5	52.5	47.5	42.5	37.5	32.5	27.5	22.5	10.5

* The ranges include the lower number but exclude the higher number, except that the VH+ range is from (and including) 85 to (and including) 100

Note: This exhibit 2 is sourced from Hornung et al. (2016) on 4.

Figure 3-3: Moody's SBRs Mapping Iterations



Note: This diagram is visualised based on exhibits 3, 4, 5, and 6 from Hornung et al. (2016) on pages 4, 5, and 6.

Once the scales on economic strength (ES) and institutional strength (IS) factors are established, the strength of these two factors would be combined using the two-dimension matrix mapping table to form the economic resilience factor. The strength (i.e., VH+, VH, VH-, etc.) of the economic resilience factor would then be mapped against the fiscal strength (FS) factor using another two-dimension matrix mapping table to determine the strength of government financial strength factor using the same scales depicted on Figure 3-2. The determined strength of the government financial strength factor will be mapped against the susceptibility to event risk (SER) factor using the third two-dimension matric mapping table to produce the government bond rating range or the indicative SCR notch. This three-level mapping iteration on SBRs is summarized in Figure 3-3.

Figure 3-4: S&P SRs Indicative Rating Levels Mapping Table

Table 2
Indicative Rating Levels From The Combination Of The Institutional And Economic Profile With The Flexibility And Performance Profile

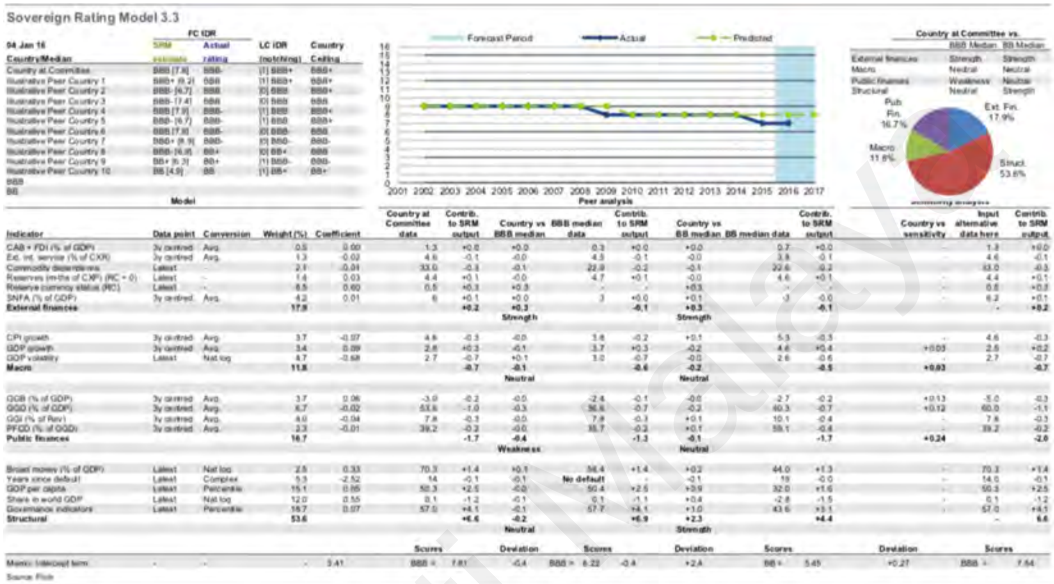
		Institutional and economic profile										
Flexibility and performance profile	Category	Superior	Extremely strong	Very strong	Strong	Moderately strong	Intermediate	Moderately weak	Weak	Very weak	Extremely weak	Poor
Category	Assess-ment	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6
Extremely strong	1 to 1.7	aaa	aaa	aaa	aa+	aa	a+	a	a-	bbb+	N/A	N/A
Very strong	1.8 to 2.2	aaa	aaa	aa+	aa	aa-	a	a-	bbb+	bbb	bb+	bb-
Strong	2.3 to 2.7	aaa	aa+	aa	aa-	a	a-	bbb+	bbb	bb+	bb	b+
Moderately strong	2.8 to 3.2	aa+	aa	aa-	a+	a-	bbb	bbb-	bb+	bb	bb-	b+
Intermediate	3.3 to 3.7	aa	aa-	a+	a	bbb+	bbb-	bb+	bb	bb-	b+	b
Moderately weak	3.8 to 4.2	aa-	a+	a	bbb+	bbb	bb+	bb	bb-	b+	b	b
Weak	4.3 to 4.7	a	a-	bbb+	bbb	bb+	bb	bb-	b+	b	b-	b-
Very weak	4.8 to 5.2	N/A	bbb	bbb-	bb+	bb	bb-	b+	b	b	b-	b-
Extremely weak	5.3 to 6	N/A	bb+	bb	bb-	b+	b	b	b-	b-	'b-' and below	'b-' and below

Assigning 'CCC+', 'CCC', 'CCC-', and 'CC' ratings is based on "Criteria For Assigning 'CCC+', 'CCC', 'CCC-', And 'CC' Ratings," Oct. 1, 2012.

Note: This table is sourced from Kraemer et al. (2017) on page 3.

S&P SRs – in accordance to Kraemer et al. (2017), S&P SRs also uses similar predefined mapping scales and matric tables approach in deriving SCRs. However, the mapping scales set by S&P are rather dynamic among the key assessment factors. For instance, the institutional assessment (IA) and economic assessment (EA) factors, there are eleven scales from "superior" category to "poor" category. Whereas the external assessment (ExA), fiscal assessment (FA), and monetary assessment (MA) factors are weighted in nine scales from the "extremely strong" category to the "extremely weak" category. The strength of each key assessment factor is established using the predefined scales and is mapped using the two-dimension matric table to establish the economic and institutional profile. The three-dimensional mapping table is employed to establish the flexibility and performance profile. These two profiles will then be mapped using the third two-dimensional matric table to establish the indicative rating levels or the indicative SCR notch. The abstract of the two-dimensional matric table on indicative rating levels is depicted in Figure 3-4.

Figure 3-5: Fitch IDR Dashboard



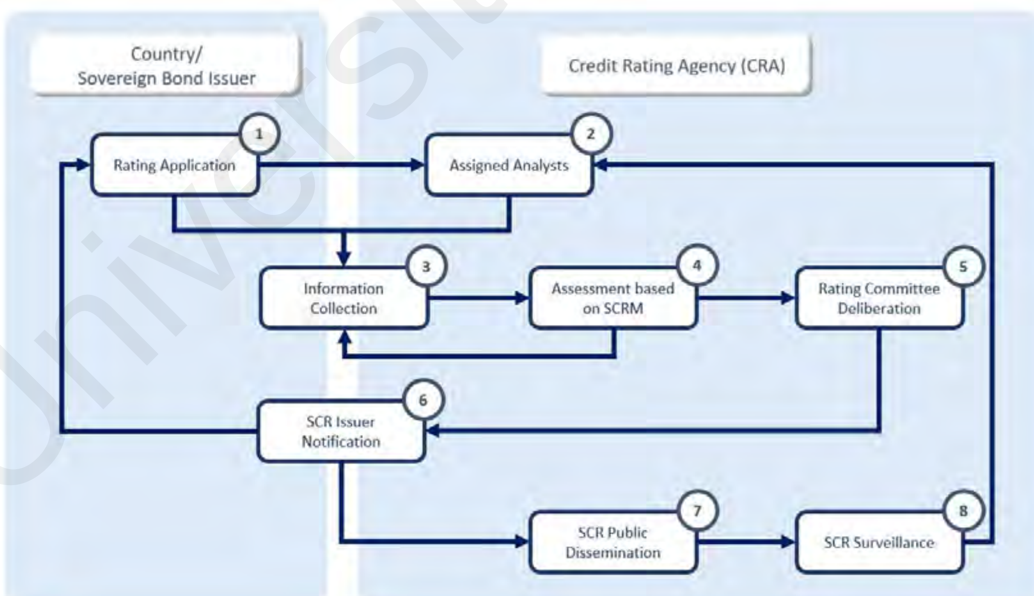
Note: Fitch IDR Dashboard is sourced from Stringer et al. (2016) on page30.

Fitch's IDRs – based on Stringer et al. (2016), the indicative SCR notch is derived using the ordinary least square method. The model consists of 18 variables representing the four key factors. The estimated coefficients of the 18 variables are weighted, and the overall strength of these variables is aligned against the predefined weightage of each key factor in the model. For instance, the structural features (SF) factor carries the highest weight at 54%, followed by the external finances (EF) factor at 18%, the public finances (PF) factor at 17%, and the macroeconomic performance, policies, and prospects (MPP) factor at 12%. The output of each key factor on the country under assessment will be compared against the median strength of each factor associated with the SCR cluster. The strength of each key factor will then be adjusted according to the median strength of the respective factors. The adjusted strength of each key factor will be aggregated, and the aggregated strength of all four key factors will determine the indicative SCR notch. An overview of Fitch's IDRs processes is depicted in Figure 3-5.

3.3.3 An Overview of SCR End-to-End Processes

What is described in subsection 3.3.2 only reflects the scientific approach on SCRs issuance, and the outcome of the scientific approach is the indicative SCR notch. The rating process is incomplete. The indicative SCR notch will undergo the art approach before the final SCR notch is communicated to the rated country and disseminated publicly. This is best comprehended through a visual representation of the end-to-end process of SCRs as depicted in Figure 3-6.

Figure 3-6: An Overview of a Typical SCRs Rating Process



Note: The diagram is a typical SCRs rating process conceptualized through harmonizing the rating processes of Moody's (Services, 2017), S&P (Ratings, 2017), and Fitch (FitchRatings, 2016).

The typical rating process begins with a government applying to the credit rating agency (CRA) for sovereign credit rating. Upon receiving the complete application, the CRA will initiate the engagement by assigning a lead analyst and supporting analyst to engage with the country. The assigned analysts will engage their counterparts to gather the required information (see Subsection 3.3.1). Once the information is gathered and determined sufficient, the assigned analysts will proceed with the assessment based on respective methodology (see Subsection 3.3.2). It is common for the assigned analysts to engage their counterparts again for clarification, or additional information. Therefore, the loop between steps 3 and 4 is formed (see Figure 3-6).

Upon finalizing the indicative SCR notch for the country in step 4, the appointed analysts will present the materials together with the indicative SCR notch to the rating committee for deliberation. In step 5, the rating committee could either endorses the indicative SCR notch or assign a different SCR notch as the rating committee deemed fit. Their discretion to assign different SCR notch is confined within the allowed thresholds (i.e., 2 to 3 notches from indicative SCR notch) as provisioned in the respective rating methodologies (Hornung et al., 2016; Kraemer et al., 2017; Stringer et al., 2016).

The rating committee endorsed SCR notch will disclose to the country through the appointed analysts. Within a given grace period, the country could either agree to the assigned SCR notch or appeal for a better SCR notch. For the latter, the country must provide additional material information for consideration. However, the decision to change or maintain the assigned SCR notch is rested with the rating committee.

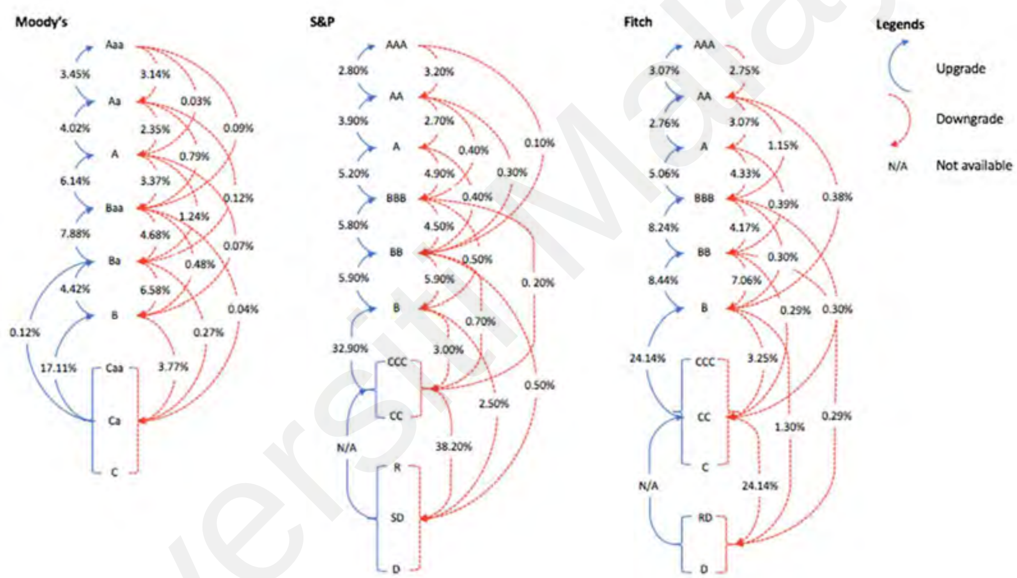
Once the assigned SCR notch is agreed upon by the country, it will be disseminated through official channels. Subsequently, the periodical surveillance process will begin, typically 12 months after the SCR notch is announced. From step 8 onwards, the entire rating process as depicted in Figure 3-6 will be repeated. However, the emphasis for the designated analysts is to determine whether the current credit profile of the rated country matches the credit profile of the assigned SCR notch. There are three possible outcomes at the end of the surveillance process. The designated analysts would either propose an upgrade, downgrade, or status quo to the rating committee for deliberation. The respective CRAs uses the credit outlook and credit watchlist reports to inform the stakeholders of potential changes on the assigned SCRs. The difference between credit outlook and credit watchlist is that the former focuses on upgrades and downgrades in near future (i.e., 12 to 24 months), while the latter focuses mainly on downgrades within 6 to 12 months.

3.3.4 SCRs Default Rates, Migration Rates, and Through-the-Cycle Philosophy

The periodical surveillance is a critical process for the CRAs to maintain the SCRs' stability. The term "stability" is measured about the change frequency and the number of notches changed on an assigned SCR in predefined timeframes. All three leading CRAs track SCRs' stability through a 12-month migration rate as depicted in Figure 3-7. From the diagrams, all three leading CRAs exercised greater discipline on SCRs upgrades than SCRs downgrades. The SCRs upgrades are moving up the hierarchy in a single-notch change. The SCRs downgrades are dynamic, in a multiple-notch change. However, as suggested by the reported migrate rates (i.e., Moody's Aaa to Baa at 0.09%, S&P AAA to BB at 0.10%, Fitch AA to B at 0.38%, etc.), the multiple notch downgrades are isolated cases.

Having stated that, the occurrence of multiple-notch downgrades reflects the consequence of a trade-off between rating accuracy versus stability as pointed out by Cantor and Mann (2006). The means new information that suggested a lower SCR notch, but the information is being processed gradually, in favour of stability, before the actual change on the assigned SCR notch is materialized. As Kiff, Kisser, and Schumacher (2013) pointed out that as long as the new information stays within the thresholds of stress scenario, the preference on rating stability (i.e., Through-the-Cycle) only resorted to a negligible loss of rating accuracy (i.e., Point-in-Time). For rated countries with material new information that goes beyond the thresholds, the consequent on losing rating accuracy is apparent (Kiff et al., 2013; Loeffler, 2004; Slapnik & Loncarski, 2021).

Figure 3-7: SCRs 12-Month Migration Rates Overview

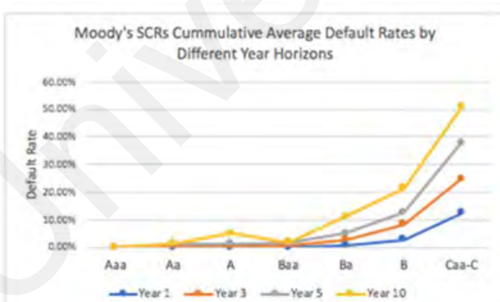


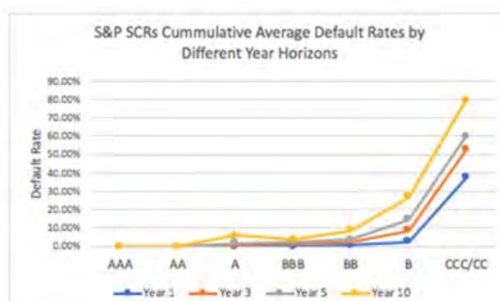
Note: The SCR migration diagrams are conceptualized from data sourced from Moody's Sovereign Default and Recovery Rates 1983 -2016, S&P's 2016 Annual Sovereign Defaults and Rating Transition, and Fitch's Global Sovereign 2016 Transition and Default Studies. Although all three diagrams are based on a 12-month migration window, the data points vary among the three CRAs. Moody's 12-month migration rates are the 12-month average from the dataset from 1983 to 2016, S&P's 12-month transition rates are the 12-month average from a dataset from 1975 to 2016, and Fitch's 12-month average transition rates are based on a dataset from 1995 to 2016.

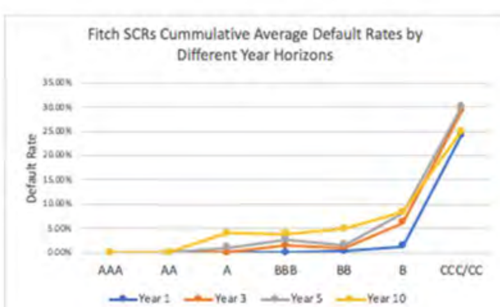
Maintaining SCRs' stability is only one part of the Through-the-Cycle (TTC) philosophy, the art of timely migration among rated countries is the second part of the philosophy. The migration timing is critical for maintaining the monotonous feature of SCRs, the rank-order default rates by SCR notches as depicted in Figure 3-8.

The default rate is derived from the actual number of countries that defaulted over the total number of countries with the same SCR notch or cohort. In accordance with the official definition (Liu, Duggar, & Ou, 2017; Needham & Stringer, 2017; Ratings, 2016), the definition of default is when a rated country failed to service and/or repay its debts as per original terms. The term cohort is about the group of countries rated in the same alphabetical SCR notches (i.e., Aaa/AAA, Aa/AA, A/A, etc.), or SCRs in broad ordinal scales. For instance, when Greece defaulted in 2010, the country was rated with A/A. It means Greece defaulted within the cohort of A/A-rated countries. Assuming there were 10 countries rated with A/A, inclusive of Greece in 2010, the number of A/A cohort is 10. The default rate for the A/A cohort would be 1 over 10, or 10%. The blip on the A/A cohort revealed on the 10-year horizon line chart as depicted in Figure 3-8 is caused by Greece's default. If the respective CRAs managed to downgrade or migrate Greece from the A/A cohort into Baa/BBB or even Ba/BB cohort, the disruption to the rank-order default rates in association with SCRs notches could have been avoided.

Figure 3-8: SCRs Cumulative Average Default Rates by Moody's, S&P, and Fitch







Note:
The lines charts are plotted on data sourced from Moody's Sovereign Default and Recovery Rates 1983 -2016, S&P's 2016 Annual Sovereign Defaults and Rating Transition, and Fitch's Global Sovereign 2016 Transition and Default Studies. The cummulative average default rates from Moody's are based on dataset from 1983 to 2016, S&P from 1975 to 2016, and Fitch 1995 to 2016.

Maintaining the rank-order default rates is equally essential in achieving SCRs stability. This is because the cut-off points between investment grade (i.e., Aaa/AAA to Baa3/BBB-) and speculative-grade (i.e., Ba1/BB+ and lower) categories are based on the ran-order default rates. Although the occurrence of Greece's default had disrupted the monotonous trend, the line charts tagged with 1-year, 3-year, and 5-year horizons as depicted in Figure 3-8 suggest that the A/A-rated default was an isolated case. This means the rank-order default rates and monotonous features of SCRs remain intact. This also explains why the migration rates on SCRs downgrades are dynamic as compared to SCR upgrades CRAs (see Figure 3-7).

In summary, the three leading CRAs rely on periodical surveillance processes to maintain the rank-order default rates and monotonous features of SCRs ranking, and SCRs' stability. SCRs upgrades and downgrades are essential steps for respective CRAs to manage the cohort bases and measure the default rates. While the CRAs are in favour of TTC over PIT philosophy, the credit outlook and credit watchlist are added communication tools for the respective CRAs to reflect upon PIT information. It is important to note that credit outlook and credit watchlist announcements have no immediate effect on the assigned SCRs.

3.4 SCRs Function and the SCRs Determinants Studies

By comparing the similarities and differences of SCRs and the rating methodologies amongst the three leading CRAs, the SCRs could be comprehended as a function of publicly available information (PAI), non-disclosure-agreement obtained information (NDAI), and the proprietary sovereign credit rating methodology (SCRM) components. The SCRs function is expressed as follows:

$$SCR = f(PAI, NDAI, SCRM) \qquad 3\text{-}1$$

The PAI component constitutes inputs to the 4 key factors: economic, institution, fiscal, and susceptibility to external events. The inputs are predominantly economic fundamentals and are sourced from countries seeking SCRs and third parties such as the World Bank and International Monetary Fund. The economic fundamentals assessed for the issuance of SCRs are quite identical amongst the three leading CRAs (see Subsection 3.3.1).

The NDAI component consists of privileged information about the country seeking SCR. The pieces of information are either provided by the government or sourced from reliable third parties (i.e., Non-Government Organizations, etc.). As the term suggested, the information is obtained on the basis of non-disclosure therefore not observable (Hornung et al., 2016; Kraemer et al., 2017; Stringer et al., 2016).

The SCRM component represents the proprietary rating methodology (see Section 3.3). This component is the source of the forward-looking opinion of the respective CRAs on rated countries' creditworthiness, and the essence of SCRs.

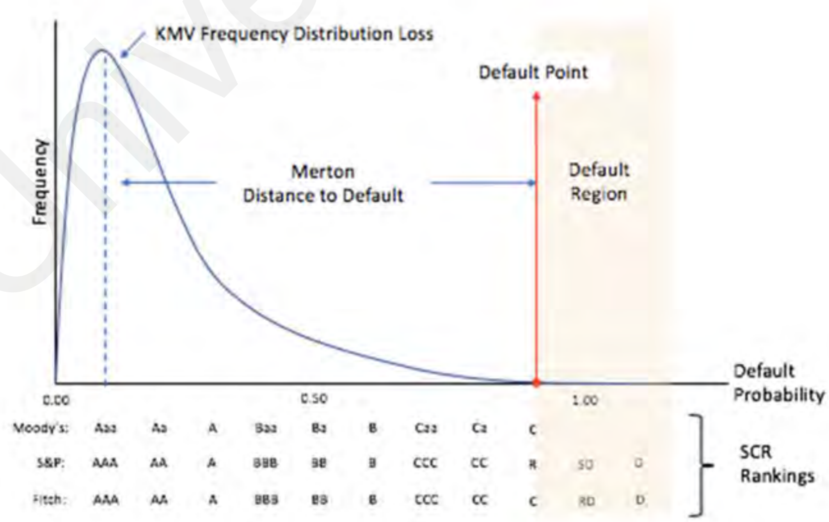
Equipped with these new insights, it is apparent that earlier studies on SCRs determinants only examined the inputs of PAI component (Afonso, 2003; Afonso et al., 2009; Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Bissondoyal-Bheenick et al., 2006; Cantor & Packer, 1996; Mellios & Paget-Blanc, 2006; Reusens & Croux, 2017; Rowland, 2004). It is also obvious that the challenges faced by these researchers on the NDAI, which is not observable, and the SCRM, which was not available at that time. Hence, the NDAI and SCRM components are never examined. In this thesis, an attempt will be carried out to quantify the NDAI and SCRM components for the first time. Using the newly conceived

SCRs function as the building blocks, the NDAI and SCRM influence on assigned SCRs will be measured.

3.5 SCRs Default Milestones and the SCRs Information Value

The SCRs' default rates are derived differently as compared to the default point advocated by Merton (1973). The monotonous feature of SCRs and the associated rank-order default rates could be comprehended as the SCRs' default milestones. For instance, Aaa/AAA-rated countries are profiled as having the highest credit quality or near-zero default risk, therefore are at the furthest milestone from the default point. Those rated Aa1/AA+ are inferior to Aaa/AAA hence are one milestone closer to the default milestone, and so on. Drawing the same aspiration from Kealhofer and Bohn (1993), the SCRs default milestone is a viable substitute for the default distance advocated by Merton (1973). This can be visualized on the diagram depicted in Figure 3-9.

Figure 3-9: SCRs Distance to Default Resemblance



Note: This chart is illustrated by the author based on the concept of sovereign credit rating rankings and definitions sourced from Emery (2017), Ratings (2016), and FitchRatings (2017) being treated as default milestones as a substitute for the KMV model on Frequency distribution loss (Kealhofer & Bohn, 1993), and the default distance from Merton (1973).

In doing so, the main structure of the Merton model is preserved and the SCRs information value will follow the same risk-reward pricing convention. Earlier studies on SCRs information value in price discovery were conducted on the assumption that SCR notches are good proxies on credit risk premium that follows the same risk-reward pricing convention (Afonso, 2003; Cantor & Packer, 1996; Miricescu, 2015; Sy, 2002).

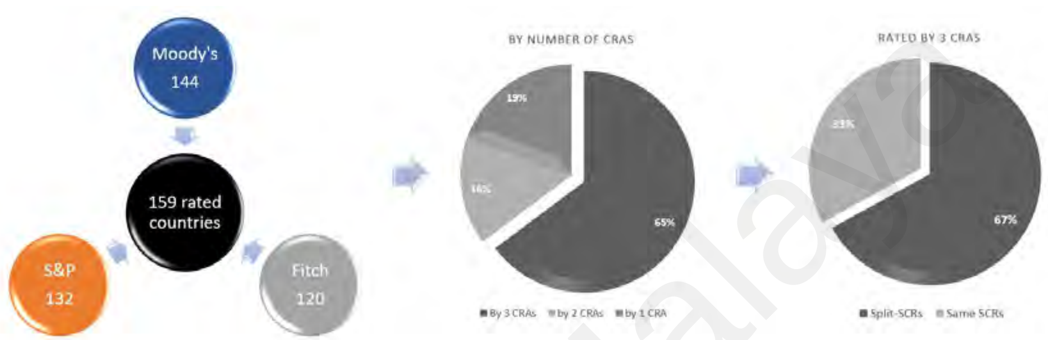
As demonstrated in the works of Cantor and Packer (1996), Jaramillo and Tejada (2011), Afonso et al. (2013), Jaramillo and Weber (2013), and Miricescu (2015), the SCRs information value can be measured in "above and beyond" and standalone estimation setups. In the "above and beyond" estimation setup, the SCRs are regressed with the set of SCRs determinants or baseline regressors in explaining sovereign bond yields (SBYs). The additional explanatory power contributed by SCRs regressor is the "above and beyond" information value. The statistical significance of SCRs regressor in explaining SBYs is the proof the "above and beyond" information value of SCRs. If the SCRs regressor is excluded from the model in explaining SBYs, the SCRs determinants should be interpreted simply as the SBYs determinants (Ardagna et al., 2007; Attinasi et al., 2009; Hauner & Kumar, 2006; Kinoshita, 2006; Poghosyan, 2014; Sgherri & Zoli, 2009). This is because the information on NDAI and SCRM components are not represented by the SCRs determinants, which are only proxies of PAI component. In other words, SCRs determinants cannot be construed as complete proxy of SCRs. For standalone SCRs, all three components represented on the assigned SCRs.

3.6 Split-SCRs: Dilemmas and Potential Causes

Based on the latest list of rated countries, Moody's rated 144 countries, S&P rated 132 countries, and Fitch rated 120 countries. Among the total 159 rated countries, 65% of these countries are rated by all three leading CRAs (see Table 2-2 in Subsection 2.4.3).

Among the 103 multi-rated countries, 67% are rated with varying SCR notches or split-SCRs. An overview of the number of split-SCRs by rated countries is depicted in Figure 3-10.

Figure 3-10: Overview on rated countries and countries rated with split-SCRs



Note: These charts are plotted based on the list of countries rated by Moody's on August 21st, 2020, rated by S&P on July 2nd, 2020, and rated by Fitch on August 22nd, 2020.

The persistency of split-SCRs raises two contentions. The first contention is the cause of split-SCRs, and the second contention is how the market value the information of split-SCRs. The work of Alsakka and Gwilym (2009) has suggested that split-SCRs were the outcome of the proprietary rating methodology of respective CRAs. Indeed, their suggestion is in sync with our hypothesis. As revealed earlier, the causes of split-SCRs and the factors that make the respective CRAs unique could be narrowed down to NDAI and SCRM components (see Subsection 3.4). Moreover, the persistency of split-SCRs is essential for the three leading CRAs to remain relevant. In other words, there is no economic incentive for the three leading CRAs to work towards issuing the same forward-looking opinions on the same rated countries' creditworthiness.

Regarding the split-SCRs information value in pricing, earlier studies either selected SCRs from one of the three leading CRAs or treated SCRs from all three leading CRAs the same by adopting the average approach (Badaoui et al., 2013; Cantor & Packer, 1996;

Reusens & Croux, 2017; Rowland, 2004). In doing so, researchers were assuming that SCRs issued by either one of the three leading CRAs are the same and with equal information value in price discovery.

The equality assumption amongst the three leading CRAs does not reflect the reality that SCRs issued amongst these CRAs for the same countries are at least 67% different. Since the multi-rated countries are rated with varying risk profiles, the equality assumption on split-SCRs information value in price discovery could be challenged. Under such circumstances, the empirical results could have suffered from omission bias, if SCRs issued by one of the three leading was used, or misspecification, if the average SCRs of all three leading CRAs were used.

3.7 Conclusion

This SCRs synthesis is performed on the proprietary rating methodologies of the three leading CRAs: Moody's, S&P, and Fitch. The synthesis encompasses the SCRs notches and official definitions, the input variables, the rating methodology, rating processes and procedures, the rating committee's discretion, the surveillance process, and the discussion on Through-the-Cycle (TTC) philosophy.

Although SCRs issued by Moody's are in the alpha-numeric form and SCRs issued by S&P and Fitch are in the alpha-symbol form, the SCRs notches are relatable and have an almost identical definition on associated risk profiles. For instance, the Aaa and AAA-rated countries are having the same credit profile. Moreover, the economic fundamentals of the rated countries assessed by all three leading CRAs are the same in the majority.

These similarities amongst the three leading CRAs might create a wrong impression that the SCRs issued by them are no different. However, the synthesis has revealed that the

SCRs issued by these three CRAs are indeed different. Although the economic variables considered under the PAI component are almost identical among them, the SCRM component is unique amongst these three leading CRAs. With the concept of SCRs function, the essence of SCRs or forward-looking opinion of respective CRAs on rated countries' creditworthiness is formulated within the NDAI and SCRM components.

This synthesis also revealed the limitation in earlier studies, where only the PAI component was examined. The significance of the "above and beyond" information value of SCRs in price discovery provides evidence that the essence of SCRs is indeed not represented by the PAI component. Moreover, the NDAI and SCRM components are also the causes of split-SCRs. Countries assigned with varying credit profiles will lead to pricing dilemmas. Under such circumstances, the institutional investors and sovereign bond issuers would need to negotiate among the assigned SCR notches to price the risk premium. This highlighted the importance of NDAI and SCRM components in making inferences on SCRs determinants and SCRs information value in price discovery studies. In addition, the concerted effort of four key Central Banks on ZBPR and QEP implementations since 2008 could have affected the ways SCRs are determined, and the pricing of SCRs information value.

CHAPTER 4: METHODOLOGY

4.1 Introduction

The empirical research design and approaches are outlined in this methodology chapter. First, the theoretical framework guided by Shannon's information theory is elaborated in the immediate Section 4.2. In Section 4.3, the research questions and objectives are discussed in detail. The specific econometric models selected to address the research questions and objectives are described in Section 4.4. Finally, the data selection, considerations, and sources are detailed in Section 4.5.

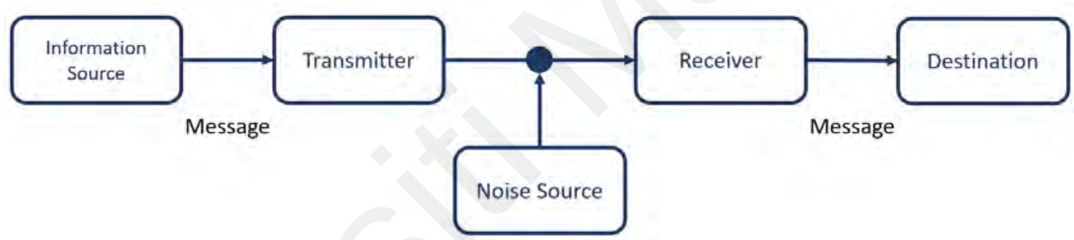
4.2 Theoretical Framework

The theoretical framework for this thesis is guided by the information theory advocated by Shannon (1948), and the research design is inspired by the works of Ederington et al. (1987) on corporate ratings and Cantor and Packer (1996) on SCRs.

Based on pieces of literature reviewed for this thesis, all were conducted on the anchoring assumption that SCRs are a relevant proxy on credit default risk and in debts pricing. This means there is no precedent on SCRs irrelevancy study. To address this limitation, there are two options that this thesis can adopt to proceed. The first option, the study could explore a new research approach in the context of SCRs irrelevancy study. The second option, the study could adapt proven approaches on SCRs studies with transposed inferences on SCRs relevancy determination. In option 1, it will be a herculean undertaking for this thesis to proceed with too many unknowns. The second option provides the needed references and broad research framework that enable us to focus on the research objectives. Hence, the second option is chosen.

The information theory championed by Shannon (1948) presents the comprehensive framework to research SCRs determination and SCRs information value in pricing discovery. The theory was originally conceived from the telegram that involves the technicality and mechanism of the electrical transmission of messages. Although the information theory seems dated, the schema of the communication system (see Figure 4-1) remains relevant in the broad context of information transmission. The five schemes of information theory can be adapted to study SCRs determinants and SCRs information value in price discovery.

Figure 4-1: Diagram of a General Communication System by the Information Theory



Note: Refurnished from Shannon (1948)

On the **Information Source** scheme, the theory explains that the source of the message could be from a radio, telephone, or television, and that could be simplified in the function of x and y coordinates and time dimension (*i.e.,* $f(x, y, t)$). In the context of sovereign credit ratings (SCRs), the quantitative and qualitative inputs considered by credit rating agencies (CRAs) could be sourced from publicly available information and non-disclosure-agreement obtained information (Hornung et al., 2016; Kraemer et al., 2017; Stringer et al., 2016). The publicly available information (PAI) and non-disclosure-agreement obtained information (NDAI) are the information source of SCRs (see Chapter 3). As the term indicated that NDAI is not observable, therefore only the PAI component in SCRs function could be examined. The inputs to four key factors of the PAI component are detailed in Subsection 3.3.1, and the economic variables selected as proxies of the PAI component are discussed in Section 4.5.

Next, the scheme of **Transmitter** is the mechanism to convert the information sources into a message that could be received and understood by the intended receiver from the other end. For instance, the electrical current on telephone transmission, the dots, dashes, and spaces on telegraph transmission are all transpired within the transmitter scheme. In the context of SCRs, the PAI and NDAI components are input to the proprietary sovereign credit rating methodology (SCRM) component. Hence, the SCRM component is the transmitter employed by respective CRAs to convert the PAI and NDAI information into SCR notches, the message.

As described in the information theory, the **Receiver** is simply the inverse operation of the **Transmitter**. The encoded message must be decoded so that the original message could be understood by the recipients. For SCRs, the alpha-numeric SCRs (i.e. Aaa, Aa1, Aa2, Aa3, etc.) issued by Moody's and alpha-symbol SCRs (i.e. AAA, AA+, AA, AA-, etc.) issued by S&P and Fitch are consistent risk ranking methods with homogenous definitions (Emery, 2017; FitchRatings, 2017; Ratings, 2016). These SCRs notches and their associated risk ranking definitions are widely understood and fully integrated into the global financial system (*i.e.* Basel Accord, Investment Grade Category, *etc.*).

The **Destination** scheme is where the decoded message is received or processed. For SCRs, the stakeholders in the destination scheme are the rated countries, institutional investors, speculators, other competing CRAs, and scholars on researching the subject, such as this. The conveyed SCR notches are used mainly on asset allocation and pricing of credit risk premium.

The potential technical glitches that undermine the clarity of the intended message are classified as the **Noise Source**. This scheme is also applicable in the context of SCRs. It is common for multi-rated countries to be assigned with varying SCR notches from competing CRAs, or the split-SCRs (see Section 3.6). Countries rated with split-SCRs are equivalent to having multiple credit profiles. It means the credit profiles of these countries are ambiguous, and that causes dilemmas between the rated countries on borrowing costs and institutional investors on expected yields.

4.2.1Information Source, Transmitter, and the SCRs Determinants

Based on existing studies, the transmission between Information Source and Transmitter schemes of SCRs is studied in the context of SCRs determinants (Afonso, 2003; Afonso et al., 2009; Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Cantor & Packer, 1995; Canuto, Santos, & Porto, 2012; Mellios & Paget-Blanc, 2006; Reusens & Croux, 2017; Rowland, 2004). Empirically, a set of economic variables is selected as proxies of SCRs determinants, the information source, to predict the assigned SCRs, the message. The empirical method, the transmitter, will produce the estimated coefficients of the determinants. The t-test is used to determine the statistical significance of the variables, and the model's predictive power is measured on the prediction accuracy between predicted SCR notches versus the actual assigned SCR notches.

4.2.2Receiver, Destination, and the SCRs information Value

The SCRs notches or risk profiles of the rated countries are used as criteria on assets allocation and as a proxy for pricing of credit risk premium. Empirically, the SCRs information value in pricing discovery is commonly examined using the sovereign bond yields (SBYs), the instruments that are rated with SCRs as the dependent variable, and the SCRs as the main regressor (Afonso, 2003; Cantor & Packer, 1996; Csonto & Ivaschenko, 2013; Jaramillo & Tejada, 2011; Jaramillo & Weber, 2013; Miricescu, 2015; Sy, 2002). The sovereign credit default swap spreads (SCDSs) are also a common dependent variable to study SCRs information value (Afonso et al., 2012; Blau & Roseman, 2014; Ismailescu & Phillips, 2015). This is because the reference entity of SCDSs is the SBYs, and the lineage between them is empirically proven (Alper et al., 2013; Ammer & Cai, 2007; Chan-Lau & Kim, 2004; Coudert & Gex, 2011; Fontana & Scheicher, 2010; Hassan et al., 2015; Li & Huang, 2011). Irrespective of whether the SBYs or SCDSs are used, the pricing of SCRs information value transpired in the financial market, the **Destination** scheme.

4.2.3Noise Source and the Split-SCRs Message

Countries rated by more than one CRAs are often being rated with varying SCR notches or split-SCRs (see Section 3.6). This causes the risk profile of the multi-rated countries with split-SCRs to be fuzzy. Since split-SCRs are a going concern amongst the three leading CRAs in the rating universe, the occurrence of split-SCRs is anticipated as the standard **Noise Source** in Shannon's information theory.

Empirical studies on split-SCRs are conducted on two streams: forward and backward. In the forward stream, researchers proceed with the presumption that SCRs issued by Moody's, S&P, and Fitch are weighted equally, and have the same information value in pricing. The researchers would choose SCRs from one of the three leading CRAs as a proxy for the other two CRAs, or convert SCRs from all three leading CRAs into a single issuer's SCRs using the average approach (Badaoui et al., 2013; Cantor & Packer, 1996; Reusens & Croux, 2017; Rowland, 2004). In the backward stream, the works of Alsakka and Gwilym (2009), Alsakka and Gwilym (2010b), and Alsakka and Gwilym (2010a) explored the potential split-SCRs feedbacks, the **Noise Source,** back to SCRs by respective CRAs, the **Transmitter**.

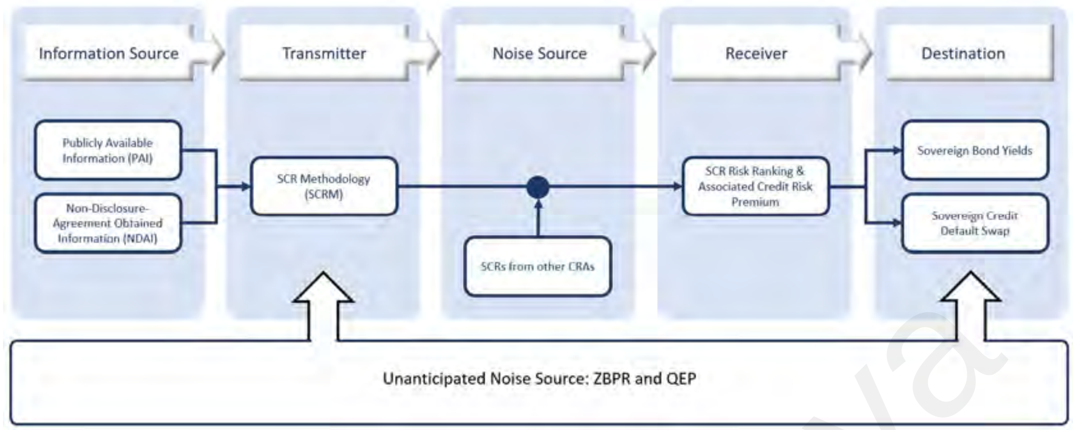
4.2.4 Emergence of Unanticipated Noise Source: Zero-Bound-Policy-Rate and Quantitative Easing Programme

The concerted effort from four key Central Banks in keeping the policy rate at zero bound or ZBPR, and injecting fresh liquidity through QEP (see Section 2.5) that managed to steer the global economy from recession is not without consequence. When the financial market is spoiled with cheap and abundant liquidity, countries can afford to borrow more and roll over matured debts with new debts at a lower cost. As the result, the risk of sovereign default disappeared, especially for investment-grade rated countries, and the SCRs also become negligible.

These interventions are unprecedented in scale and duration, therefore, the potential joint effect of ZBPR and QEP on SCRs is classified as the **Unanticipated Noise Source**. The joint effect of ZBPR and QEP is anticipated to disrupt the transmission at the **Transmitter** and **Destination** schemes of information theory.

In summary, the information theory advocated by Shannon (1948) remains pertinent and is adapted as the theoretical framework for studying the SCRs determinants and SCRs information value in pricing discovery. By incorporating points highlighted in Subsection 4.2.1, 4.2.2, 4.2.3, and 4.2.4, the theoretical framework for this thesis is summarized in the diagram depicted in Figure 4-2.

Figure 4-2: Theoretical Framework for Studying Determinants and Information Value of SCRs in the Presence of Unanticipated Noise Source



Note: The Schema of Shannon's Information Theory depicted in Figure 4-1 is adapted where the SCRs components and the unanticipated noise source on ZBPR and QEP are populated in respective schemes.

4.3 Research Questions and Objectives

The theoretical framework depicted in Figure 4-2 provides a clear path in addressing the main question: "Are SCRs relevant on debts price discovery when ZBPR and QEP were in effect?". The answer to the question comes in three parts. The three research questions for the three-part answer are restated in Table 4-1 for ease of reference.

Table 4-1: Research Questions and Objectives

No	Research Questions	Research Objectives
1	Do CRAs interpret the economic variables of the countries seeking SCRs similarly?	To determine the economic variables that explain the SCRs issued by different CRAs.
2	Do SCRs convey information value on debts pricing?	To examine if SCRs produce "above and beyond" information value on debts pricing.
3	How do split-SCRs contribute to the SCRs information value on debts pricing?	To determine the role of split-SCRs on SCRs information value for debts pricing.

Note: Restated from Table 1-1.

Research Question 1 – this research question focuses on assessing the significant determinants in predicting SCRs issued by respective CRAs. The empirical results are derived from the sample where the joint effect of ZBPR and QEP are embedded. Based on the theoretical framework, this empirical study will transpire between the **Information Source** and **Transmitter** schemes. In addition to SCRs determination examination, the study will also assess the variability amongst the selected CRAs on SCRs issuance. With the concept of SCRs function, the influence of NDAI and SCRM components on SCRs by CRAs will be measured for the first time.

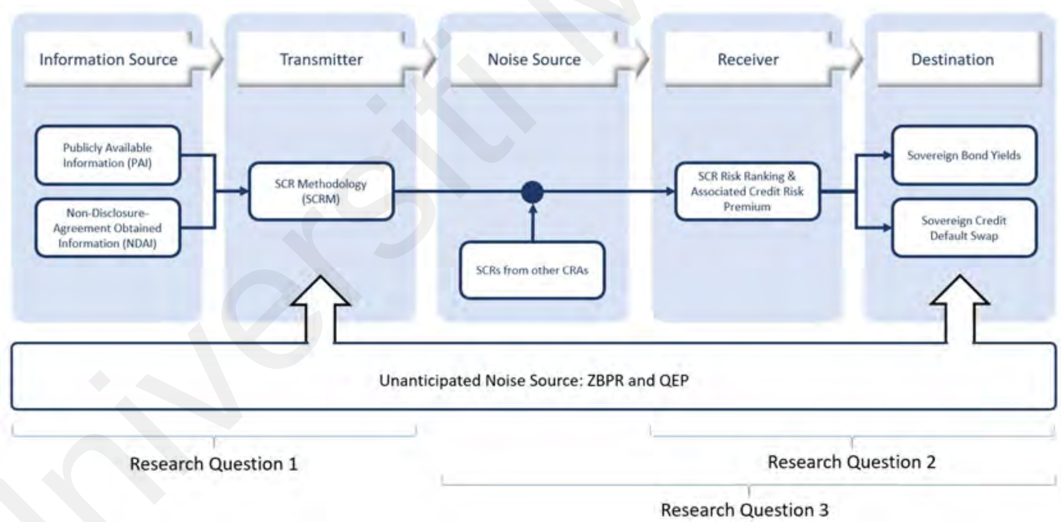
Research Question 2 – the empirical study on this research question focuses on the information value of SCRs in the pricing of sovereign bond yields. For this research question, the SCRs by respective CRAs are assumed to convey noise-free SCRs information value. In other words, the effect of split-SCRs is not examined in this empirical study. However, the joint effect of ZBPR and QEP, the **Unanticipated Noise Source,** is assumed to have been reflected in the yields. The study on SCRs information value in sovereign bond yields (SBYs) price discovery will transpire the **Receiver** and **Destination** schemes.

Research Question 3 – this research question focuses on the split-SCRs information value, the anticipated **Noise Source**. With a similar assumption regarding the **Unanticipated Noise Source**, this empirical study will transpire in the **Noise Source, Receiver,** and **Destination** schemes**.** The sovereign credit default swap spreads (SCDSs) will replace SBYs as the dependent variable. The SCRs issued by all three leading CRAs will be examined as standalone SCRs by CRAs, the pairing SCRs of any two CRAs, and the average SCRs of all three CRAs, the vector of SCRs.

Main Question – the empirical findings from research questions 1, 2, and 3 will subsume as the collective answer to the main question. The first part of the answer from research question 1 is to find out whether the SCRs issuance by any of the three CRAs was compromised due to the influence of ZBPR and QEP. The second part of the answer from research question 2 focuses on whether SCRs information value remains significant in SBYs price discovery when ZBPR and QEP were in effect. On research question 3, the ambiguity caused by split-SCRs on the SCRs information value is examined. The empirical study will also examine the potential complementary role amongst the CRAs on SCRs information value in pricing the SCDSs when ZBPR and QEP were in effect.

The three research questions on the theoretical framework are summarized on the diagram presented in Figure 4-3.

Figure 4-3: Theoretical Framework and the Four Research Questions



Note: This diagram is an extension from Figure 4-2, where schemes applicable to the three research questions are demarcated.

4.4 Empirical Methods

The empirical research approach closely resembles the works of Ederington et al. (1987) and Cantor and Packer (1996) that encompasses the full schema of information theory as depicted in Figure 4-3. However, the dated econometric models (i.e., cross-sectional method) are substituted with more advanced. The following subsections describe the specific econometric models.

4.4.1 Ordered Response Models

The ordered response model (OPM) as advocated by Wooldridge (2002) is the most appropriate econometric method to study the sovereign credit ratings (SCRs), given its discreet and rank order characteristics. It is evident from the transition observed from previous studies on SCRs determinants, the ordinary least square (OLS) methods (Afonso, 2003; Cantor & Packer, 1996; Rowland, 2004) is phased out, and OPM is adopted instead (Afonso et al., 2009; Afonso et al., 2011; Bissondoyal-Bheenick et al., 2006; Mellios & Paget-Blanc, 2006; Reusens & Croux, 2017). The OPM consists of two main branches: namely the ordered probit model (OPM) and the ordered logit model (OLM). The main difference between OPM and OLM is the distribution method. The former assumes normal distribution whereas the latter assumes the logistic distribution[20]. The latent variable of OPM is expressed on Equation 4-1, in the panel data format.

$$y_{it}^* = \beta x_{it} + v_{it} \qquad 4\text{-}1$$

[20] The OPM equation is $G(z) \equiv \Phi(z) \int_{\infty}^{z} \emptyset\,(v)dv$, where $\emptyset(z)$ is the standard normal density, and $\emptyset(z) = (2\pi)^{-1/2} \exp\,({-z^2}/{2})$. The OLM equation is $G(z) = \Lambda(z) \equiv {\exp\,(z)}/{[1 + \exp\,(z)]}$ (Wooldridge, 2002).

where y_{it}^* is predicted using linear explanatory variables of x_{it}, β denotes the coefficient of x_{it}, and v_{it} denotes the error term. The observed y_{it} is determined by the predicted y_{it}^* using the following rules:

$$y_{it}^* = \begin{cases} 0 & if\ y_{it}^* \leq \gamma_1 \\ 1 & if\ \gamma_1 < y_{it}^* \leq \gamma_2 \\ 2 & if\ \gamma_2 < y_{it}^* \leq \gamma_3 \\ \ldots & \\ \mathrm{M} & if\ \gamma_m < y_{it}^* \end{cases}$$

Although the category representing y_{it}^* is arbitrary, the order specification must be observed so that $y_{it}^* < y_{jt}^*$ implies $y_{it} < y_{jt}$. The γ_n is the threshold value, which is estimated along the coefficients using the maximum log-likelihood function.[21]

The OPM empirical model is specified by substituting the y_{it}^* with $SCRs_{it}^*$ as the prediction for actual $SCRs_{it}$, and x_{it} with $SCRsDet_{it}$, the explanatory variables of short-term and long-term determinants. For category ranking, the broad ordinal scales (see Table 3-4) are redefined where Baa/BBB as 1, A/A as 2, Aa/AA as 3, and Aaa/AAA as 4. The latent variable model as expressed in Equation 4-1 is modified to accommodate the above-stated specification. The modified latent variable model is expressed in Equation 4-2, and with the following observed rules on using $SCRs_{it}^*$ to determine $SCRs_{it}$.

[21] $l(\beta,\gamma) = \sum_{i=1}^{N}\sum_{j=0}^{M} \log(\Pr(y_i = j|\, x_i,\beta,\gamma)) \cdot l(y_i = j)$, where $l(.)$ is an indicator function which take the value of 1 if the argument is true, otherwise 0 if the argument is false.

$$SCRs_{it}^{*} = \beta SCRsDet_{it} + v_{it} \qquad 4\text{-}2$$

$$SCRs_{it}^{*} = \begin{cases} 1 & if\ SCRs_{it}^{*} \leq \gamma_1 \\ 2 & if\ \gamma_1 < SCRs_{it}^{*} \leq \gamma_2 \\ 3 & if\ \gamma_2 < SCRs_{it}^{*} \leq \gamma_3 \\ 4 & if\ \gamma_3 < SCRs_{it}^{*} \end{cases}$$

Both OPM and OLM methods will be used to estimate Equation 4-2 on SCRs issued by Moody's, S&P, and Fitch. The selected economic variables, the regressors, will take the form of short-term determinants and long-term determinants. Both sets of regressors will be examined.

The predicted $SCRs_{it}$ are compared against the actual assigned $SCRs_{it}$ to derive the prediction accuracy. The number of predicted $SCRs_{it}$ matches actual $SCRs_{it}$ with no variation will be the measurement of the model prediction accuracy. The number of predicted $SCRs_{it}$ matches actual $SCRs_{it}$ but with variation will also be reported in 4 categories: >=2, 1, -1, and <=-2. This reporting method is consistent with earlier studies (Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Bissondoyal-Bheenick et al., 2006; Hill, Brooks, & Faff, 2010).

4.4.2 The Weightage of SCRs Determinants and the "Above and Beyond" Information Value of SCRs

In Chapter 3, the SCRs synthesis enables the SCRs to be conceptualized as a function of publicly available information (PAI), non-disclosure-agreement obtained information (NDAI), and the proprietary sovereign credit rating methodology (SCRM), or $SCRs = f(PAI, NDAI, SCRM)$. With the aid of SCRs function, the synthesis also revealed that most studies on SCRs determinants only examined the PAI component-related variables as determinants to predict SCRs. This indicates that the SCRs determinants reported on earlier studies, including the OPM specified early (see Subsection 4.4.1), cannot be construed as a complete proxy of SCRs. This is because the NDAI and SCRM components have never been quantified.

By converting the SCRs function into the weighted SCRs function, the NDAI and SCRM components could be therefore be accounted for. The relationship is as follows:

$$w_i(SCRs) = w_i(PAI) + w_i(NDAI) + w_i(SCRM) \qquad \textit{4-3}$$

where $w_i(PAI)$ is the weightage given by CRA_i to the PAI component when deciding on the SCR notch, $w_i(NDAI)$ is the weightage for the NDAI component, and $w_i(SCRM)$ is the weightage for SCRM components. Since the weight of the three components adds up to one as expressed below.

$$w_i(PAI) + w_i(NDAI) + w_i(SCRM) = 1 \qquad \textit{4-4}$$

where $w_i(PAI)$ can be observed from the model prediction accuracy on assigned SCRs that are explained by the PAI component. The $w_i(PAI)$ therefore could be obtained from the predictive power analysis as described in Subsection 4.4.1. Given both NDAI and SCRM components are not observable, this constraint means only the sum of the weightage on NDAI and SCRM components could be accounted for using the equation 4-5.

$$w_i(NDAI) + w_i(SCRM) = 1 - w_i(PAI) \quad 4\text{-}5$$

The weight of NDAI and SCRM components is the key differentiator amongst the three leading CRAs. These two components are the source of the "above and beyond" information value of SCRs, the causes that lead to the persistency of split-SCRs, and ultimately the essence of SCRs. Hence, Equation 4-5 that emphasizes the NDAI and SCRM components could complement Equation 4-2 that only tackle the PAI component of SCRs.

4.4.3 Panel Fixed Effect and Random Effect Models

On research question 2, the SCRs information value on sovereign bond yields (SBYs) will be estimated using panel fixed effect (FE) and panel random effect (RE). Given that the presence of individual effect and heteroscedastic errors are commonly anticipated in cross-sectional data, the SBYs will be converted into natural logarithm values as the solution to overcome these potential errors. In the case of the time-invariant component of an individual effect, the panel fixed effect (FE) estimator and the panel random effect (RE) estimators are considered. The equations on panel FE and panel RE estimators are expressed on Equations 4-6 and 4-7 respectively.

$$y_{it} = \beta_1 x_{it} + \alpha_i + v_{it} \quad 4\text{-}6$$

$$y_{it} = \beta_1 x_{it} + \alpha + c_i + u_{it} \quad 4\text{-}7$$

where y_{it} is the dependent variable, x_{it} are the explanatory variables, α_i is the individual effect, and v_{it} is the composite error term in the panel FE estimator. On the panel RE estimator, the y_{it} and x_{it} remain the same, the α is the common intercept, c_i is the unobserved random factor, and u_{it} is the idiosyncratic error term.

To examine the SCRs information value in SBYs pricing, the empirical regression is conducted in three parts. The first part of the empirical regression is to establish the explanatory power of SCRs determinants which are denoted as $SCRsDet_{it}$, which are the baseline regressors. In the second part of the empirical regression, the SCRs by individual CRA denoted as $SCRs_{it}$, will be introduced as an additional regressor. The $SCRs_{it}$ is meant to measure the "above and beyond" information value of SCRs. The third part of the empirical regression, the $SCRs_{it}$ will maintain as the sole regressor without the $SCRsDet_{it}$. The purpose of dropping $SCRsDet_{it}$ is to remove the potential confounding effect on $SCRs_{it}$.

Hence, by replacing y_{it} with $log\,SBY_{it}$, the explained variable, and x_{it} with $SCRsDet_{it}$ and/or $SCRs_{it}$, the panel FE regression expressed on Equation 4-8 provides the baseline model, Equation 4-9 is specified to measure "above and beyond" information value of SCRs on SBYs, and Equation 4-10 is specified to measure the standalone SCRs information value on SBYs.

$$log\,SBY_{it} = \beta_1\, SCRsDet_{it} + \alpha_i + v_{it} \qquad \textit{4-8}$$

$$log\,SBY_{it} = \beta_1\, SCRsDet_{it} + \beta_2 SCRs_{it} + \alpha_i + v_{it} \qquad \textit{4-9}$$

$$log\,SBY_{it} = \beta_1\, SCRs_{it} + \alpha_i + v_{it} \qquad \textit{4-10}$$

where $SCRsDet_{it}$ represents the two sets of short-term and long-term determinants and the $SCRs_{it}$ represents the vector of SCRs: Moody's, S&P, and Fitch. Both panel FE and panel RE estimators will be conducted, the selection of appropriateness between the two models will be determined through the Hausman test.

This three-part empirical approach is inspired by earlier studies (Afonso et al., 2012; Cantor & Packer, 1996; Ederington et al., 1987; Jaramillo & Tejada, 2011; Miricescu, 2015). By adopting the same empirical approach, the estimates from this empirical study could compare and make references to reported estimates and findings. The emphasis of this empirical study is on the statistical significance of the regressors and the model explanatory power.

The validation is through hypothesis testing on the estimated coefficients with the typical 5% significance level. The sign of the estimated coefficients for $SCRs_{it}$ is anticipated to be negative, to reflect the risk-reward pricing convention (Afonso, 2003; Cantor & Packer, 1996; Canuto et al., 2012; Jaramillo & Tejada, 2011; Miricescu, 2015; Rowland, 2004). Otherwise, the positive sign of the estimated coefficient of $SCRs_{it}$ will invalidate the significance of the regressor.

The next assessment is on the model explanatory power. Using the $SCRsDet_{it}$ as the baseline regressors, the estimated coefficient of $SCRs_{it}$ that is significant at the 5% level and with the anticipated negative sign should elevate the model explanatory power in the pricing of SBYs. This means the "above and beyond" information value of SCRs is significant in the pricing of SBYs. The same assessment criteria are also applicable to the standalone $SCRs_{it}$ regressor estimates.

4.4.4Information Value Transmission

Based on empirical estimates from Chapter 5, the SCRs, irrespective of CRAs, are rendered irrelevant in the pricing of SBYs. This means the SBYs are not viable as the dependent variable for examining the occurrence of split-SCRs on SCRs information value in debts pricing. The sovereign credit default swaps (SCDSs) are the obvious substitute for SBYs. This is because the SCDSs, the single name derivative, are derived from SBYs, the reference entity. This strong lineage between SCDSs and SBYs suggests that the SCRs information value in SBYs pricing should be transmittable to SCDSs. Therefore, the SCDSs should be a viable dependent variable to study the split-SCRs information value.

However, a few quick preliminary validations are necessary before finalizing the SCDSs as the substitute for SBYs. First, the proof of Granger causality from SBYs to SCDSs must be established. This is to establish that the SCRs information value on SBYs is indeed transmittable to SCDSs through the Granger causal relation. Second, the proof of SCRs information value in SCDSs price discovery. This proof is validated through the t-test on estimated coefficients of SCRs at significant at 5% level and with the anticipated negative sign. The empirical results are expected to be consistent on SCRs issued by all selected CRAs. These two tests are elaborated as follows.

Granger Causality – by default, the SCDSs must be correlated with SBYs given the fact that the former are derivatives of SBYs, which is the reference entity to SCDSs (Culp et al., 2016). To validate this relationship between SBYs and SCDSs, the panel VAR method is adopted to examine the Granger causality relation between the two. The results presented in Chapter 7 show that SBYs Granger causes SCDSs, therefore the assumption on SCRs information value transmission from SBYs to SCDSs could be established.

Panel FE and RE – with an established Granger causality relationship between SBYs and SCDSs, the next step is to examine the relevancy of SCRs information value in SCDSs pricing. This preliminary validation is performed on SCRs issued by the selected CRAs using Equation 4-10. All specifications are kept the same, only the dependent variable $log\,SBY_{it}$ is substituted with SCDSs in natural logarithmic value or $log\,SCDSSs_{it}$. The estimated β_1 is subjected to the same assessment criteria: 5% significance level, the anticipated negative sign, and the empirical outcome must be consistent on SCRs issued by all selected CRAs. The results presented in Chapter 7 shows that SCRs information value is statistically significant and with the expected negative sign in explaining SCDSs. This means the examination of split-SCRs information value can proceed with SCDSs as the dependent variable.

4.4.5Spearman Rank Order Correlation

Among the 159 rated countries, 65% of these countries are rated by all three leading CRAs. About 62% of these multi-rated countries are rated with varying SCR notches or split-SCRs (see Table 2-2 in Chapter 2). The persistency of split-SCRs indicates that SCRs from competing CRAs cannot be treated as the same. On the other hand, the alpha-numeric SCRs (i.e., Aaa, Aa1, Aa2, Aa3, etc.) issued by Moody's, and alpha-symbol SCRs (i.e., AAA, AA+, AA, AA-, etc.) issued by S&P and Fitch respectively are closely homogenous by definitions. This means countries rated with Aaa by Moody's and those rated with AAA by S&P, and/or Fitch are having identical credit profiles. In the context of SCR notches, especially in the form of ordinal scaled SCRs, this indicates that the SCRs amongst the three leading CRAs are highly correlated.

Both conditions present econometric challenges. Empirical studies that excluded SCRs from any one of the three leading CRAs might suffer from omission and/or selection bias. Empirical studies that included SCRs from all three leading CRAs potentially succumbed to multicollinearity issues. While the omission bias is almost certain if SCRs from any one of the three leading CRAs are excluded, as suggested by split-SCRs persistency amongst these CRAs. The multicollinearity issue if presented could be overcome.

First, the level of correlation on SCRs amongst the CRAs can be established using the Spearman rank-order correlation method, which is ideal for discreet and rank-ordered characteristics of SCRs. The correlation coefficient or r_s (*rho*) indicates the strength of correlation amongst the $SCRs_{it}$. If r_s is closer to 1 or perfect correlation, this suggests that $SCRs_{it}$ may be diverse based on contemporary opinions but these opinions are aligned in the long run. It means regressing SCRs with perfect correlation amongst these CRAs will lead to multicollinearity issues. This method was adopted by Scholtens (1999) and Sy (2002) for the same purpose.

4.4.6Dynamic Panel Models

The Spearman rank-order correlation results reported in Chapter 7 show that SCRs issued by Moody's, S&P, and Fitch are indeed closely correlated. This means regressing SCRs issued by all three leading CRAs will lead to multicollinearity issues. To overcome this issue, the average approach commonly employed in earlier studies is adopted to handle SCRs issued by these CRAs. The SCRs issued by the three leading CRAs will be combined in pairs of any two of three leading CRAs, and the SCRs pair of all three CRAs. The standalone SCRs by respective CRAs, the paired SCRs will form the vector of SCRs for examination.

The vector of SCRs will first be examined using panel FE and RE methods on Equation 4-10. The regressor $\mathrm{SCRs}_{\mathrm{it}}$ represents the vector of SCRs in the estimator. Since the SCDSs term structure consists of credit risk and non-credit risk components (Culp et al., 2016; Hull & White, 2000; Pan & Singleton, 2008), the non-credit risk component is not specified in Equation 4-10. Therefore, the SCDSs in lagged term is employed as the proxy for non-credit risk component, this approach is consistent with earlier studies (Aizenman et al., 2009; Aizenman et al., 2013; Dieckman & Plank, 2012; Eyssell et al., 2013;

Longstaff et al., 2011). However, including the dependent variable as a regressor will lead to endogeneity issues, and rendered the panel FE and RE methods inappropriate.

As advocated by Hayashi (2000) and Wooldridge (2002), the generalized method of moments (GMM) is the solution to overcome the endogeneity issue. The second part of the empirical regression on research question 3 will be conducted using the GMM method. The specification for GMM or dynamic model is expressed in Equation 4-11.

$$y_{it} = \beta_1 y_{it-1} + \beta_2 x_{it} + v_{it} \tag{4-11}$$

where y_{it} denotes as the dependent variable, y_{it-1} denotes the endogenous variable, x_{it} denotes the vector of independent variables, v_{it} denotes the composite error term, and β_n denotes the estimated coefficients. By substituting y_{it} with $SCDSs_{it}$, $\mathrm{y}_{\mathrm{it-1}}$ with $SCDSs_{it-1}$, and x_{it} with $SCRs_{it}$, the vector of SCRs, the regression equation is stated in Equation 4-12.

$$SCDSs_{it} = \beta_1 SCDSs_{it-1} + \beta_2 SCRs_{it} + v_{it} \tag{4-12}$$

The individual effect is denoted as α_i is dropped from the equation because it is already handled through the first differencing transformation method as explained by Arellano and Bond (1991), thereafter known as the first differencing generalized method of moments (FD-GMM). Alternatively, the α_i is also addressed through forward orthogonal deviation transformation method, or the FOD-GMM championed by Arellano and Bover (1995). Both FD-GMM and FOD-GMM follow the two-step estimations. Although the FOD-GMM is proven to be more efficient as compared to FD-GMM (Arellano & Bover, 1995; Hayakawa, 2009; Hsiao & Zhou, 2017), both FD-GMM and FOD-GMM will be carried out for comparison and robustness test purposes.

4.5 Data

Based on the Nationally Recognized Statistical Rating Organization (NRSRO) report[22], there are ten listed credit rating agencies (CRAs) certified by US Securities Commission. Out of the ten CRAs, Moody's, S&P, and Fitch accounted for a combined 99% of sovereign credit ratings (SCRs) on government securities as shown in Figure 4-4. This means these three leading CRAs are the subjects of this thesis.

Figure 4-4: Number of Outstanding Credit Ratings by Rating Category

Chart 1: Number of Outstanding Credit Ratings as of December 31, 2017 by Rating Category*

NRSRO	Financial Institutions	Insurance Companies	Corporate Issuers	Asset-Backed Securities	Government Securities	Total Ratings
A.M. Best	N/R	7,191	1,079	5	N/R	8,275
DBRS	12,730	164	2,938	14,951	18,865	49,648
EJR	9,446	864	6,420	N/R	N/R	16,730
Fitch	39,189	3,261	18,933	29,108	205,674	296,165
HR Ratings	560	N/R	184	N/R	374	1,118
JCR	839	59	2,464	N/R	440	3,802
KBRA	838	32	0	8,110	72	9,052
Moody's	36,631	2,484	28,635	59,320	598,614	725,684
Morningstar	44	N/R	297	2,530	N/R	2,871
S&P	57,091	6,496	51,213	43,760	920,306	1,078,866
Total	**157,368**	**20,551**	**112,163**	**157,784**	**1,744,345**	**2,192,211**

* N/R indicates that the NRSRO was not registered in the applicable rating category as of the reporting date.
Source: NRSRO annual certifications for the 2017 calendar year, Item 7A on Form NRSRO

Note: The chart is extracted from the NRSRO 2018 Annual Report.

[22] Annual Report on Nationally Recognized Statistical Rating Organization (NRSRO) December 2018

Based on the current list of rated countries, Moody's rated 144 countries, S&P rated 132 countries, and Fitch rated 120 countries. Countries rated by all three leading CRAs are the target sample for this empirical study (see Table 2-2 in Subsection 2.4.3). This condition is essential for variability amongst the CRAs to be compared and measured. Since the potential influence of zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP) on SCRs is the motivation of this thesis, the condition imposed on the classes of assets that can be purchased through QEP becomes the second data selection criteria. This means only countries rated by all three leading CRAs and within the investment-grade category are selected.

The third data selection criterion focuses on dependent variables: SCRs, SBYs, and the SCDSs. On SCRs, only investment grade (i.e., Aaa/AAA to Baa3/BBB-) countries rated by all three leading CRAs are selected. These multi-rated countries must have data on both SBYs and SCDSs and are tracked on the Bloomberg platform. The rationale of these conditions is that SBYs and SCDSs tracked on Bloomberg are actively traded therefore provide the assurance that information on SCRs, ZBPR, and QEP are efficiently transmitted and priced in. The SBYs and SCDSs with 5-year maturity are selected in consideration of having the highest liquidity over other durations.

On independent variables, the economic variables must be publicly available data and are sourced from independent third parties: World Bank and International Monetary Fund. The emphasis of this selection criterion is to exclude CRA-related variables that were proven potent in earlier studies but would also lead to obvious data selection bias.

Lastly, the observation window is defined as per the duration when the ZBPR and QEP were in effect. For instance, the data points on dependent and independent variables will be gathered from the year 2008, when ZBPR and QEP first rolled out, to the year 2017, when QEP tapering kicked in.

4.5.1Countries in the Sample of Study

Guided by the data selection criterion, countries that are rated by all three leading CRAs, with both SBYs and SCDSs of 5-year maturity, and are actively tracked in the Bloomberg platform summed up to 40 countries. Among the 40 countries, 8 speculative-grade rated countries are dropped from the list. The remaining 32 investment grade multi-rated countries are listed in Table 4-2.

Table 4-2: List of 32 Cross-Sectional Investment Grade Rated Countries

Australia	Finland	Lithuania	Slovenia
Austria	France	Malaysia	South Korea
Belgium	Germany	Mexico	Spain
Bulgaria	HK	Netherlands	Sweden
Chile	Ireland	Norway	Switzerland
China	Israel	New Zealand	Thailand
Czech	Italy	Poland	United Kingdoms
Denmark	Japan	Slovakia	United States

Note: The list of cross-sectional sovereigns is based on data selection criteria defined in Section 3.5 and data availability (i.e., SBY, SCDSS, and SCRs from the three leading CRAs from Bloomberg)

4.5.2Dependent Variables

The dependent variables are SCRs issued by Moody's, S&P, and Fitch, and both SBYs and SCDSs with 5-year maturity of the 32 countries listed in Table 4-2.

On SCRs, the alpha-numeric SCRs (i.e., Aaa, Aa1, Aa2, Aa2, etc.) issued by Moody's and the alpha-symbol SCRs (i.e., AAA, AA+, AA, AA-, etc.) issued by S&P and Fitch respectively on the same 32 countries are sourced from Bloomberg. These SCRs are first harmonized based on official definitions (Emery, 2017; FitchRatings, 2017; Ratings, 2016), then transformed into ordinal scales following the standard convention adopted in earlier studies (Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Cantor & Packer, 1996; Canuto et al., 2012; Hill et al., 2010; Mellios & Paget-Blanc, 2006; Reusens & Croux, 2017). For this thesis, both fine and broad ordinal scales are considered and are defined in Table 4-3. To be specific, research question 1 will employ the broad ordinal scaled SCRs as dependent variables, on research question 2 both broad scaled SCRs and fine-scaled SCRs will be examined as independent variables, and research question 3 will employ only the fine-scaled SCRs as independent variables.

Table 4-3: Harmonized and Transformed Ordinal Scales of SCRs

Generalized Description	Moody's	S&P	Fitch	Fine Scale	Broad Scale
		Investment Grade			
Highest credit quality	Aaa	AAA	AAA	21	8
Very high credit quality	Aa1	AA+	AA+	20	7
	Aa2	AA	AA	19	7
	Aa3	AA-	AA-	18	7
High credit quality	A1	A+	A+	17	6
	A2	A	A	16	6
	A3	A-	A-	15	6
Good credit quality	Baa1	BBB+	BBB+	14	5
	Baa2	BBB	BBB	13	5
	Baa3	BBB-	BBB-	12	5
		Speculative Grade			
Speculative	Ba1	BB+	BB+	11	4
	Ba2	BB	BB	10	4
	Ba3	BB-	BB-	9	4
Highly speculative	B1	B+	B+	8	3
	B2	B	B	7	3
	B3	B-	B-	6	3
Substantial credit risk	Caa1	CCC+		5	2
	Caa2	CCC	CCC	4	2
	Caa3	CCC-		3	2
Very high level of credit risk	Ca	CC	CC	2	1
/ Near default	C		C	1	1
Default		SD	RD	1	1
		D	D	1	1

Note: The exact description could be slightly different when referring to specific SCR methodology, but the underlying risk profile could be harmonized and converted to ordinal scales as defined above. Moody's does not provide a rating on defaulted countries. **Source:** Bloomberg

On SBYs and SCDSs, the former is directly rated with SCRs and the latter is linked to SCRs through SBYs. The direct and indirect lineages to SCRs make them ideal instruments to study SCRs' information value. These two dependent variables are also sourced from Bloomberg. The quarterly data points on these variables are gathered from 2008 to 2017 as observations. On research question 2, the empirical regression will be based on an annual data point, where the quarter 4 data point will be treated as an annual data point. On research question 3, the empirical regression will proceed with the quarterly data points.

Due to some missing data points from SBYs and SCDSs, the total workable observations of the 32 selected countries summed up to 1117. The descriptive statistics on SCRs, SBYs, and SCDSs are compiled in Table 4-4.

Table 4-4: Descriptive Statistics of Dependent Variables

	Moody's SCR	S&P SCR	Fitch SCR	SBYs	SCDSs
Mean	18.077	18.016	17.959	2.164	93.360
Median	19.000	19.000	19.000	2.003	68.290
Maximum	21.000	21.000	21.000	12.673	753.950
Minimum	11.000	11.000	12.000	-1.099	7.000
Std. Dev.	2.992	2.869	2.876	1.778	90.171
Skewness	-0.592	-0.527	-0.423	0.649	2.903
Kurtosis	2.051	2.002	1.820	3.684	15.123
Observations	1280	1280	1280	1129	1252

Note: The observations are gathered from the list of 32 countries presented in Table 4-2 on quarterly internal spanning Q1 2008 to Q4 2017, predominantly from Bloomberg. The descriptive statistics on dependent variables are presented on an individual basis. This information will be useful in subsequent chapters when the workable common observations are different due to missing data points. For instance, the data points on SBYs and SCDSs which are less compared to SCRs by CRAs.

4.5.3Independent Variables

The independent variables are identified through cross-referencing the SCRs determinants reported significant from earlier studies (see Chapter 2) with inputs of key factors employed by Moody’s, S&P, and Fitch (see Chapter 3).

Although new economic variables were introduced and examined over time by researchers (Afonso et al., 2012; Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Bissondoyal-Bheenick et al., 2006; Cantor & Packer, 1996; Hill et al., 2010; Mellios & Paget-Blanc, 2006), the economic variables that proven statistically significant as SCRs determinants did not deviate much from the set of principal component variables reported by Afonso et al. (2011), and closely resembling the initial set of economic variables: GDP

Growth, Inflation Rate, Fiscal Balance, Current Account Balance, External Debts, Economic Development Indicator, and Default History, employed by Cantor and Packer (1996). This suggests that the three leading CRAs have been consistently relying on the same set of economic variables to determine SCR notches for assignment.

When these empirical determinants of SCRs are cross-referenced with the inputs to the four key factors: economic, institution, fiscal, and susceptible to external events (see Chapter 3), these empirical determinants indeed match the core inputs (i.e., the nominator of ratios). However, these empirical determinants of SCRs only represent to publicly available information (PAI) component. The non-disclosure-agreement obtained information (NDAI) and sovereign credit rating methodology (SCRM) components are not represented. Due to both NDAI and SCRM components are not observable, this study will continue to leverage empirical determinants of SCRs that matched with inputs to the PAI component as independent variables. The eight selected economic variables are elaborated as per the following.

Economic Variables – the gross development product (GDP) appeared to be the base in measuring a country's repayment ability. The two key variables consistently employed and proven significant by earlier researchers are GDP Growth Rate and GDP Per Capita. Both variables contribute positively to a country's creditworthiness. The former is attributed to the size of the economy and the latter to productivity.

Institution Variables – this refers to the government in promoting economic growth and social welfare. While the CRAs employed almost the complete set of WDIs furnished by the World Bank, the Government Effectiveness Indicator (GEI) is the only commonly employed variable in earlier studies. The other variable is the inflation rate that is assessed in the context of fiscal and monetary policies. A higher GEI conveys a positive correlation, while a higher inflation rate conveys a negative correlation on SCR notches assigned by all three leading CRAs.

Fiscal Variables – once the size of the economy and the government's efficiency in maintaining robust economic growth is established, the next assessment is to determine whether the GDP growth is revenue-funded or debt-funded. Hence, the deficit from Fiscal Balance indicates a debt-funded, while surplus means a revenue-funded economy. While fiscal surplus may not necessarily lower the overall debt, the fiscal deficit will most certainly require the government to borrow more. This leads to an increase in the country's debts burden.

The next consideration is the aggregated government borrowing relative to GDP, the common proxy is Debt to GDP. The size of external debt or debt denominated in the foreign currency relative to debts stock is another core variable in measuring fiscal strength. An increase in external debts proportion indicates weakness in domestic funding capacity. This will lower the government's flexibility on fiscal and monetary policies. Hence, an increase in Fiscal Balance presents a positive correlation of the fiscal position, while an increase in Debt to GDP and External Debt to GDP presents a negative correlation on SCRs. Due to data availability, only the Debt to GDP is selected for this study.

Susceptibility to External Events Variables – variables considered in this factor although dynamic, but the main emphasis revolves around the variables in the economic, institution, and fiscal factors. For this paper, the emphasis is predominantly on liquidity variables and not external event variables (*i.e.,* geopolitical risks, exchange rate risk). The rationale behind this exclusion is because the external events are beyond the control of any country. For instance, the occurrence of negative external events presents a cluster effect (*i.e.,* Asia financial crisis 1997/1998, US Subprime crisis 2008/2009, European

Debt Crisis 2010). On liquidity variables, the selected variables are Reserve to GDP and Financial Development Index. Both proxies are selected to reflect the country's ability to absorb the expansion in government borrowing, and the domestic banking system to provide the local funding. An increase in these two variables should present a positive correlation to a country's SCR ranking.

Excluded Common Variables – the Default History, a dummy variable commonly employed in earlier studies is not included in this study. This is because the selected 32 countries have not defaulted, and are not listed on the default lists from Moody's or S&P, the two CRAs with the longest sovereign rating track records[23]. Therefore, the exclusion of Default History is to avoid unnecessary loss in the degree of freedom. The other common and significant variable is the External Debt. This variable is not selected due to inconsistency in measurement and availability. For instance, the External Debt data employed by Afonso *et al* (2011) was only limited to non-industrial countries. The Foreign Debt to GDP employed by Bissondoyal-Bheenick (2005) was sourced from Moody's. Mellios and Paget-Blanc (2006) used the External Debt to Current External Receipt as a proxy on External Debt. Due to data constraints on countries rated with Aa3/AA- and above, Hill, Brooks and Faff (2010) had improvised with a dummy variable, countries with no data on External Debt were tagged with 0.

Since the variables are only available in annual data points, the data points for the observation window spanning from the year 2008 to 2017 will sum up to 320

---

[23] https://www.moodys.com/Pages/Sovereign-Default-Research.aspx?stop_mobi=yes
https://www.spratings.com/documents/20184/774196/2018AnnualSovereignDefaultAndRatingTransitionStudy.pdf
https://www.fitchratings.com/site/re/10074863

observations. The descriptive statistics of the selected independent variables are presented in Table 4-5.

Drawing inspiration from the work of Afonso et al. (2011) on short-term and long-term SCRs determinants, and the Through-the-Cycle (TTC) philosophy on SCRs ratings (Cantor & Mann, 2006; Kiff et al., 2013; Loeffler, 2004), the eight selected economic variables will take the form of short-term determinants, in contemporary value, and the long-term determinants, in 3-year simple arithmetic average value. The estimates from long-term determinants would enable analyses that are not overly perturbed by annual fluctuations when making longer-term inferences. In other words, the short-term determinants represent the Point-in-Time (PIT), and the long-term determinants represent the TTC.

Table 4-5: Descriptive Statistics of Independent Variables

	GDP Growth Rate	GDP Per Capita	Govt. Effect. Ind.	Inflation	Debt to GDP	Fiscal Bal.	Fin. Dev. Ind.	Res. To GDP
Mean	1.986	35958.270	84.908	1.877	59.544	-2.714	0.651	17.819
Median	2.087	38333.330	88.462	1.766	47.176	-2.618	0.680	10.186
Maximum	25.163	103059.200	100.000	12.349	236.335	18.684	0.981	126.257
Minimum	-14.814	3468.304	52.404	-4.478	0.055	-32.030	0.256	0.000
Std. Dev.	3.185	21283.570	12.253	1.819	41.047	4.665	0.179	23.441
Skewness	0.463	0.528	-0.777	1.172	1.984	-0.502	-0.451	2.562
Kurtosis	13.968	3.078	2.530	7.891	8.750	10.014	2.294	10.627
Observations	320	320	320	320	320	320	320	320

Note: The 320 observations are gathered from the list of 32 countries presented in Table 4-2 on annual internal, spanning 2008 to 2017, and sourced from World Bank and International Monetary Fund Reports. Govt. Effect. Ind. is Government Effectiveness Indicator; Fiscal Bal. is Fiscal Balance; Fin. Dev. Ind. is Financial Development Indicator; and Res. To GDP is the Reserves to GDP.

4.5.4Data Sources

The descriptions and sources of selected variables are presented in Table 4-6.

Table 4-6: Selected Variables, Description, and Data Source

No	Variables	Description	Source
1	Sovereign Credit Ratings (SCRs)	Long-Term Foreign-Currency ratings issued by Moody's, S&P, and Fitch	Bloomberg
2	Sovereign Bond Yields (SBYs)	Government bond yields with a 5-year maturity	Bloomberg
3	Sovereign Credit Default Swap Spreads (SCDSs)	Single name derivative on government bond with a 5-year maturity	Bloomberg
4	GDP Growth Rate	GDP Growth % (Annual) from World Development Indicators	World Bank
5	GDP Per Capita	GDP Per Capita in USD from World Development Indicators	World Bank
6	Government Effective Index	Government Effectiveness from Worldwide Governance Indicators	World Bank
7	Inflation	Average consumer price index	International Monetary Fund
8	Debt to GDP	Gross Debt to GDP Ratio from Historical Public Debt Dataset	International Monetary Fund
9	Fiscal Balance	Revenue exclusive of grant (% to GDP) minus General Government Final Consumption Expenditure (% to GDP) from World Development Indicators	World Bank
10	Financial Development Index	Financial Market Index from Financial Development Index Dataset	International Monetary Fund
11	Reserves to GDP	Total reserves inclusive of gold in USD over Gross Domestic Product (GDP) in USD from World Development Indicators	World Bank
12	Moody's SCRs	These are *SCRs* issued by Moody's converted into ordinal scale based on convention defined in Table 3.4	Derived
13	S&P SCRs	These are *SCRs* issued by S&P converted into ordinal scale based on convention defined in Table 3.4	Derived
14	Fitch SCRs	These are *SCRs* issued by Fitch and converted into ordinal scale based on convention defined in Table 3.4	Derived
15	Log_SBYs2	These are *SBYs* transformed into natural logarithm form at base plus 2 to address negative observations and the potential heteroscedasticity issue common to cross-sectional data	Derived
16	Log_SCDSs	These are *SCDSs* transformed into natural logarithm form to address the potential heteroscedasticity issue common to cross-sectional data	Derived

CHAPTER 5: SOVEREIGN CREDIT RATINGS (SCRs) DETERMINANTS

5.1 Introduction

In Chapter 3, the sovereign credit ratings (SCRs) synthesis has provided the much-needed insights about SCRs issued by the three leading credit rating agencies (CRAs): Moody's, S&P, and Fitch. The synthesis also contributes to the concept of SCRs function, which is vital to measure the essence of SCRs. In this chapter, the three components of SCRs function: publicly available information (PAI), non-disclosure-agreement obtained information (NDAI), and sovereign credit rating methodology (SCRM), are put to test empirically.

Based on the work of Cantor and Packer (1996), the researchers leveraged the Moody's and S&P commentary on variables leading to SCRs upgrades and downgrades to select the set of economic variables. Indeed, the selected economic variables were able to explain over 90% of SCRs in the sample of 48 countries. Using a similar research setup and the cross-sectional regression method, Afonso (2003) and Rowland (2004) examined new variables as potential SCRs determinants.

Subsequently, the question emerged on the suitability of the cross-sectional regression method to study the discrete nature of SCRs. As pointed out by Wooldridge (2002), the ordered response model (OPM) is almost a tailored-econometric method for studying the monotonous and discrete characteristics of SCRs. The work of Bissondoyal-Bheenick (2005) was the earliest adopter of the OPM. With relatively the same set of SCRs determinants, the OPM predicted SCRs issued by S&P with 40% accuracy and 42% on SCRs issued by Fitch. With an expanded set of SCRs determinants and sample size, the ordered response model adopted by Afonso et al. (2009) predicted the SCRs issued by Moody's with 47% accuracy, and 45% accuracy on SCRs issued by S&P and Fitch, respectively. In a follow-up paper (2011), the researchers expanded the set of SCRs determinants further. The expanded set of determinants consist of the principal component variables and non-principal variables. The set of determinants is reclassified into short-term and long-term determinants. The empirical results generated by the OPM reported the model's prediction accuracies of 47% on SCRs issued by Moody's, 46% on S&P, and 44% on Fitch. The statistically significant and consistent determinants were mainly the principal component variables. Further investigation revealed that the principal component variables were almost an identical set of economic variables employed by Cantor and Packer (1996).

In this empirical study, the statistically proven economic variables as SCRs determinants in earlier studies (see Chapter 2) will be matched against the inputs to the 4 key factors: economic, institution, fiscal, and susceptibility to external events (see Chapter 3). The economic variables that fulfilled the selection criteria are selected for this empirical examination (see Section 4.5). The ordered probit model (OPM) and ordered logit model (OLM) as defined in Section 4.4.6 are adopted to regress the sample of 32 investment-grade rated countries. The sample consists of the annual data point on observations spanning from 2008 to 2017, the duration when zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP) was effective.

In the subsequent sections, the dataset and empirical methodology that are applicable for this empirical study will be recapped briefly from Chapter 4, the empirical estimates will be presented next, and followed by the analysis and discussion. Finally, the findings are summarized in the concluding section.

5.2 Data and the Empirical Model

The dependent variable for this empirical study is the alpha-numeric SCRs (i.e., Aaa, Aa1, Aa2, Aa3, etc.) issued by Moody's and the alpha-symbol SCRs (i.e., AAA, AA+, AA, AA-, etc. issued by S&P and Fitch respectively for the 32 investment-grade rated countries (see Table 4-2). Since the economic variables are mainly available on an annual interval, the yearly data point from 2008 to 2017 is used for this study. The SCRs by CRAs recorded in Q4 of each year are used as the annual data points. Collectively, these SCRs are converted into ordinal scales following the convention defined in Table 4-3. For this empirical examination, the broad scaled SCRs are selected due to equitable representation of the sample among the SCR notches. The study focuses on investment-grade rated countries, therefore, the broad-scale for Aaa/AAA-rated countries will be reassigned with 4, followed by Aa/AA with 3, A/A with 2, and Baa/BBB with 1.

The eight selected economic variables representing the 4 key factors (i.e., economic, institution, fiscal, and susceptibility to external events) are elaborated in Section 4.5.3 of Chapter 4. The following table provides a quick overview of the eight selected economic variables by respective key factors:

Key Factor	Economic Variables
Economic:	GDP Growth and GDP Per Capita
Institution:	Government Effectiveness Indicator and Inflation
Fiscal:	Fiscal Balance and Debt to GDP
Susceptibility to External Events:	Reserve to GDP and Financial Development Indicator.

Following the rationales presented in earlier studies (Afonso et al., 2009; Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Cantor & Packer, 1996), these eight independent variables are reclassified into short-term determinants with contemporary value and long-term determinants with the 3-year average value.

Both short-term and long-term determinants are subjected to the order probit model (OPM) and the order logit model (OLM) to derive the predictor power over SCRs issued by Moody', S&P, and Fitch respectively (see Chapter 4 and Section 10.3.1 in Chapter 10). The predictive power of the models are compared amongst the three leading CRAs and against the predictive power of models researched by Mellios and Paget-Blanc (2006), Afonso et al. (2009), Afonso et al. (2011), and Reusens and Croux (2017).

5.3 Empirical Results

The estimates from the eight-determinant OPM and OLM models are presented in this section.

5.3.1Short-Term Estimates

Among the eight short-term determinants, four determinants: GDP Per Capita, Government Effectiveness Indicator, Debt to GDP, and Financial Development Indicator, are significant at 5% level in explaining SCRs issued by all three CRAs. The Fiscal Balance is also significant for SCRs issued by all three CRAs, but not all are significant at the 5% level. The Reserves to GDP is significant at 5% level for SCRs issued by Moody's and Fitch, but not SCRs issued by S&P. The GDP Growth Rate is significant at 10% for SCRs issued by Moody's based on the ST-OPM model, and significant at 5% level for SCRs issued by Fitch based on both models. The reported significant determinants remain robust when fine ordinal scaled SCRs of all three CRAs are examined[24].

The estimates generated from OPM and OLM based on short-term determinants are compiled in Table 5-1.

Table 5-1: Estimates using Short-Term Determinants

	Moody's SCRs		**S&P SCRs**		**Fitch SCRs**	
	ST-OPM	**ST-OLM**	**ST-OPM**	**ST-OLM**	**ST-OPM**	**ST-OLM**
GDP Growth Rate	-0.038	-0.035	-0.024	-0.056	-0.057*	-0.097*
	(0.021)	(0.046)	(0.022)	(0.043)	(0.023)	(0.046)
GDP Per Capita	0.035**	0.069**	0.036**	0.063**	0.050**	0.096**
	(0.008)	(0.015)	(0.008)	(0.015)	(0.009)	(0.017)
Gov. Effect. Ind.	0.038**	0.076**	0.062**	0.121**	0.049**	0.083**
	(0.010)	(0.019)	(0.011)	(0.020)	(0.011)	(0.021)
Inflation	0.047	0.081	0.061	0.105	0.021	0.035
	(0.038)	(0.066)	(0.040)	(0.071)	(0.043)	(0.075)
Debt to GDP	-0.012**	-0.020**	-0.010**	-0.017**	-0.011**	-0.020**
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)
Fiscal Bal.	0.055**	0.068	0.049*	0.070*	0.070**	0.098*
	(0.019)	(0.037)	(0.019)	(0.034)	(0.022)	(0.044)
Fin. Dev. Ind.	2.029**	3.464**	1.561**	2.600**	2.243**	4.468**
	(0.508)	(0.911)	(0.513)	(0.926)	(0.538)	(0.999)
Res. To GDP	-0.012**	-0.025**	-0.002	-0.005	-0.013**	-0.025**
	(0.003)	(0.006)	(0.004)	(0.007)	(0.003)	(0.006)
Pseudo R^2	**0.333**	**0.358**	**0.391**	**0.395**	**0.450**	**0.463**
Cut-Off						
1	1.420	2.811	2.617	5.329		
2	2.925	6.072	4.943	9.466	4.025	7.124
3	4.139	8.374	6.312	12.016	5.927	10.757
4	5.328	10.613	7.864	14.795	7.331	13.349
Log likelihood	-298	-287	-272	-271	-238	-233
Observations	320	320	320	320	320	320

Note: ST-OPM = short-term ordered probit model, ST-OLM = short-term ordered logit model. The Cut-Off is the fitted linear index for the four categories (i.e., 4 = Aaa/AAA, 3 = Aa1 to Aa3 / AA+ to AA-, 2 = A1 to A3 / A+ to A-, and 1 = Baa1 to Baa3 to BBB+ to BBB-). Govt. Effect. Ind. is Government Effectiveness Indicator; Fiscal Bal. is Fiscal Balance; Fin. Dev. Ind. is Financial Development Indicator; and Res. To GDP is the Reserves to GDP. The estimation is based on Equation 4-2 in Section 4.4.1. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

[24] Fine ordinal scaled SCRs follow the convention defined in Table 4-3. For full results, refer to Appendix 4, Table A4-1.

5.3.2 Long-Term Estimates

The OPM and OLM regressions performed on Equation 4-2 are repeated using the long-term determinants. The estimates are compiled in Table 5-2.

Table 5-2: Estimates using Long-Term Determinants

	Moody's SCRs		**S&P SCRs**		**Fitch SCRs**	
	ST-OPM	**ST-OLM**	**ST-OPM**	**ST-OLM**	**ST-OPM**	**ST-OLM**
GDP Growth Rate	0.018 (0.031)	0.126 (0.069)	0.006 (0.032)	0.022 (0.069)	-0.013 (0.032)	0.028 (0.072)
GDP Per Capita	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)
Gov. Effect. Ind.	0.037** (0.010)	0.072** (0.019)	0.056** (0.011)	0.106** (0.020)	0.048** (0.011)	0.077** (0.021)
Inflation	0.106 (0.054)	0.157 (0.095)	0.104 (0.057)	0.173 (0.102)	0.091 (0.065)	0.116 (0.115)
Debt to GDP	-0.009** (0.002)	-0.017** (0.004)	-0.008** (0.002)	-0.014** (0.004)	-0.008** (0.002)	-0.016** (0.004)
Fiscal Bal.	0.109** (0.022)	0.136** (0.044)	0.104** (0.023)	0.170** (0.043)	0.137** (0.027)	0.199** (0.056)
Fin. Dev. Ind.	1.695** (0.525)	2.973** (0.932)	1.260** (0.530)	2.119** (0.961)	2.054** (0.554)	4.159** (1.034)
Res. To GDP	-0.014** (0.004)	-0.030** (0.006)	-0.001 (0.004)	-0.006 (0.008)	-0.016** (0.004)	-0.031** (0.007)
Pseudo R^2	**0.356**	**0.377**	**0.414**	**0.413**	**0.470**	**0.476**
			Cut-Off			
1	1.257	2.535	1.990	4.025		
2	2.963	6.158	4.577	8.580	4.124	6.975
3	4.244	8.550	6.017	11.178	6.153	10.711
4	5.457	10.830	7.625	14.023	7.607	13.347
Log likelihood	-288	-278	-262	-262	-230	-227
Observations	320	320	320	320	320	320

Note: LT-OPM = long-term ordered probit model, LT-OLM = long-term ordered logit model. The Cut-Off is the fitted linear index for the four categories (i.e., 4 = Aaa/AAA, 3 = Aa1 to Aa3 / AA+ to AA-, 2 = A1 to A3 / A+ to A-, and 1 = Baa1 to Baa3 to BBB+ to BBB-). Govt. Effect. Ind. is Government Effectiveness Indicator; Fiscal Bal. is Fiscal Balance; Fin. Dev. Ind. is Financial Development Indicator; and Res. To GDP is the Reserves to GDP. The estimation is based on Equation 4-2 in Section 4.4.1. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Among the eight short-term determinants, five determinants: GDP Per Capita, Government Effectiveness Indicator, Debt to GDP, Fiscal Balance, and Financial Development Indicator, are significant at 5% level, and the results are unanimous for SCRs issued by all three CRAs. The Reserves to GDP is significant at a 5% level for

SCRs issued by Moody's and Fitch, but not SCRs issued by S&P. The GDP Growth Rate and Inflation are not significant at 5% level for SCRs issued by all three leading CRAs.

When these long-term determinants are regressed using the fine ordinal scaled SCRs of all three CRAs, the results remain robust[25]. The GDP Growth Rate and Inflation continue to be insignificant at 5% level for SCRS issued by all three CRAs, and the Reserves to GDP is only significant at 5% level for SCRs issued by Moody's and Fitch.

5.3.3SCRs Determinants Predictive Power

The prediction powers of short-term and long-term determinants are measured using the estimated cut-off intervals presented in Table 5-5, and Table 5-6, respectively. The estimated SCRs are categorized according to the cut-off intervals to establish the predicted SCR notches. The prediction accuracy is derived by the number of predicted SCRs notches that matches the actual assigned SCRs notches, with zero variation between the predicted and actual SCR notches. The prediction powers of the respective models for SCRs by CRAs are compiled in Table 5-3.

Based on Table 5-3, the percentage of SCR notches correctly predicted by the OPM and OLM models are in the range of 61% to 75%. For SCRs issued by Moody's and Fitch, the estimates generated from OLM provides better predictive power than OPM. However, the gain in the predictive power is marginal. For SCRs issued by S&P, the predictive powers of OPM and OLM are equally effective. On short-term determinants versus long-term determinants, there is no significant gain on the predictive power between OPM and

[25] Fine ordinal scaled SCRs follow the convention defined in Table 4-3. For full results, refer to Appendix 4, Table A4-1.

OLM models for SCRs issued by Moody's. There is a negligible loss of 1% on the LT-OLM model as compared to ST-OPM, ST-OLM, and LT-OLM models in predicting SCRs issued by S&P. On SCRs issued by Fitch, the long-term determinants contributed to a significant enhancement in predictive power with an additional 11% over short-term determinants in both OPM and OLM models. As part of the robustness test, the same models are regressed using the fine ordinal scaled SCRs issued by all three CRAs. Collectively, the models able to predict the SCRs with zero notch error at 50% range prediction accuracy. For predicted SCRs with plus/minus 1 notch error, the models' prediction accuracy reached the 70% range[26].

Table 5-3: ORM Prediction Accuracy Comparison Summary

	Methods	**Obs.**	**Number of Predicted SCRs Notches Matching Actual SCR Notches by Variation in Notches**					**% Correctly Predicted**
			<=-2	**-1**	**0**	**1**	**>=2**	
Moody's SCRs	ST-OPM	320	16	51	213	33	7	67%
	ST-OLM	320	17	41	226	28	8	71%
	LT-OPM	320	11	56	213	33	7	67%
	LT-OLM	320	12	46	227	29	6	71%
S&P SCRs	ST-OPM	320	8	58	200	47	7	63%
	ST-OLM	320	8	56	203	46	7	63%
	LT-OPM	320	3	61	201	48	7	63%
	LT-OLM	320	3	64	199	47	7	62%
Fitch SCRs	ST-OPM	320	2	33	196	71	18	61%
	ST-OLM	320	2	34	204	67	13	64%
	LT-OPM	320	3	39	231	47	0	72%
	LT-OLM	320	5	36	239	40	0	75%

Note: ST-OPM = short-term ordered probit model, ST-OLM = short-term ordered logit model, LT-OPM = long-term ordered probit model, LT-OLM = long-term ordered logit model. The % correctly predicted is derived from the number of predicted SCR_{it} matching actual assigned SCR_{it} with the number of 0 variations over the total observation of 320. For instance, the 67% accuracy on Moody's SCRs from ST-OPM is derived from 213 predicted SCR_{it} with numbers of 0 variations over 320. The numbers of predicted SCR_{it} under variation 1 and >=2 indicate the predicted SCR_{it} are of higher SCR notches as compared to actual assigned SCR_{it}, and vice versa on numbers of predicted SCR_{it} under variation -1 and <=-2.

[26] Fine ordinal scaled SCRs follow the convention defined in Table 4-3. For full results, refer to Appendix 4, Table A4-1.

5.3.4SCRs Function: The Components Weightage

Despite the commendable predictive power of the eight-determinants models for SCRs issued by all three leading CRAs, the models' specifications only represented the publicly available information (PAI) component. The other two components: non-disclosure-agreement obtained information (NDAI) and sovereign credit rating methodology (SCRM) components, of the SCRs function, are not specified in the model.

In previous studies, the NDAI and SCRM components were accounted for in the context of the "above and beyond" information value of SCRs (Afonso et al., 2013; Cantor & Packer, 1996; Jaramillo & Tejada, 2011; Miricescu, 2015). As revealed in Chapter 3, the NDAI and SCRM components are the essence of SCRs, the source of forward-looking opinions of respective CRAs on rated countries' creditworthiness, and the cause of split-SCRs persistency. This means the influence of NDAI and SCRM components in SCRs determination is essential to gain a complete appreciation of SCRs issued by all three leading CRAs.

Table 5-4: NDAI and SCRM Component Weightage by CRAs

	Methods	Weight of Selected SCR Determinants / PAI Component	Weight of NDAI and SCRM Components
Moody's SCRs	ST-OPM	67%	33%
	ST-OLM	71%	29%
	LT-OPM	67%	33%
	LT-OLM	71%	29%
S&P SCRs	ST-OPM	63%	37%
	ST-OLM	63%	37%
	LT-OPM	63%	37%
	LT-OLM	62%	38%
Fitch SCRs	ST-OPM	61%	39%
	ST-OLM	64%	36%
	LT-OPM	72%	28%
	LT-OLM	75%	25%

Note: ST-OPM = short-term ordered probit model, ST-OLM = short-term ordered logit model, LT-OPM = long-term ordered probit model, LT-OLM = long-term ordered logit model. The Weight of Selected SCR Determinants / PAI Component populated from the % correctly predicted reported in Table 5-3. The Weight of NDAI and SCRM Components is derived using Equation 4-5 defined in Section 4.4.2 of Chapter 4.

Although the inputs to the NDAI component and the proprietary nature of the SCRM component rendered both components not observable, the SCRs synthesis has presented a method to quantify the influence of NDAI and SCRM components on SCRs determination (see Chapter 3). Based on the rationales presented on the weight SCRs function, the weight of NDAI and SCRM components can be derived using Equation 4-5, as defined in Section 4.4.2. The results of the derivation are presented in Table 5-4.

By holding on to the assumption that the eight determinants are an effective and consistent representation of the PAI component for SCRs issued by all three leading CRAs, the derived weight of NDAI and SCRM components ranging from 25% to 39%. Irrespective of whether short-term or long-term determinants are used, and OPM versus OLM methods, the NDAI and SCRM components have 31% influence on SCRs issued by Moody's and 37% on SCRs issued by S&P. In the case of SCRs issued by Fitch, the weight of NDAI and SCRM components based on long-term determinants is about 27%. Collectively, the NDAI and SCRM components exerted 1/3 of the influence on SCRs determination amongst the three leading CRAs.

5.4 Discussion

It should be noted that the eight selected economic variables: GDP Growth Rate, GDP Per Capita, Government Effectiveness Index, Inflation, Debt-to-GDP, Fiscal Balance, Financial Development Index, and Reserves to GDP, do not deviate much from the se t of economic variables employed by Cantor and Packer (1996) or the principal component variables examined by Afonso et al. (2009) in predicting SCRs issued by Moody's, S&P, and Fitch. Moreover, the eight selected economic variables are inputs to the 4 key factors: economic, institution, fiscal, and susceptibility to external events, assessed by all three leading CRAs (see Chapter 4). With 32 investment-grade countries rated by all three leading CRAs and observations spanning from 2008 to 2017, the sample in this study allows the empirical estimates to be assessed in the context of SCRs variability amongst Moody's, S&P, and Fitch when ZBPR and QEP were in effect.

Among these eight selected economic variables, the GDP Per Capita, Government Effectiveness Indicator, Debt to GDP, Fiscal Balance, and Financial Development Indicator are significant determinants of SCRs, irrespective of whether short-term or long-term determinants are used. The statistical significance of these five determinants in predicting SCRs are unanimous on all three leading CRAs. Moreover, the four key factors of SCRs determination are equitably represented with the eight selected economic variables, and the five significant and robust determinants provide the empirical evidence on the claim.

Moreover, the GDP Growth Rate that is significant at 10% level for SCRs issued by Moody's, at 5% significant on SCRs issued Fitch, but not on SCRs issued by S&P in short-term context, and insignificant on SCRs issued by all three leading CRAs in the long-term context are signs of variability amongst these CRAs. The SCRs determinant variability could also be observed from Inflation and Reserves to GDP. The former is not significant as a short-term determinant but is significant as a long-term determinant only for SCRs issued by Moody's and S&P at a 10% significant level, respectively. The Reserves to GDP is statistically significant as short-term and long-term determinants only for SCRs issued by Moody's and Fitch, but not SCRs issued by S&P.

Despite the highlighted SCRs determinant variabilities amongst the CRAs, the eight-determinant OPM and OLM models continue to provide better predictive power for SCRs issued by all three leading CRAs, with models' prediction accuracy in the range of 61% to 75% as compared to 50% range reported in earlier studies (Afonso et al., 2009; Afonso et al., 2011; Reusens & Croux, 2017). When broad ordinal scaled SCRs are substituted with fine ordinal scaled SCRs, the eight determinants and the models' predictive power remain robust in predicting SCRs issued by all three leading CRAs.

For SCRs issued by Moody's, the OLM model has better predictive power as compared to the OPM model, irrespective of whether short-term or long-term determinants are used. The OLM model can predict SCRs issued by Moody's at 71% accuracy, which is 5% higher as compared to the OPM model. Both OPM and OLM methods, regardless of whether short-term or long-term determinants are used, can predict SCRs issued by S&P with consistent accuracy at 63%. For SCRs issued by Fitch, the long-term determinants produced greater prediction power with an 11% gain in accuracy as compared to short-term determinants, irrespective of whether OPM or OLM are used.

The SCRs determinant variability amongst these three leading CRAs as discussed earlier is potentially motivated by the non-disclosure-agreement obtained information (NDAI) and the proprietary sovereign credit rating model (SCRM) components. Similar to previous studies (Afonso, 2003; Afonso et al., 2009; Afonso et al., 2011; Bissondoyal-Bheenick, 2005; Bissondoyal-Bheenick et al., 2006; Cantor & Packer, 1996; Reusens & Croux, 2017; Rowland, 2004), the NDAI and SCRM components are not represented in these eight-determinant models. This means the eight-determinant models are incomplete therefore cannot be construed as a complete proxy of SCRs.

To account for NDAI and SCRM components, the weighted SCRs function provides the equation to determine the influence of these two components in the assigned SCRs. For SCRs issued by Moody's, the influence of NDAI and SCRM components is weighted at an average of 31%. For SCRs issued by S&P and Fitch, these two components exerted influence at an average of 37% and 32%, respectively. By assuming the PAI component is comprehensively represented by the eight selected economic variables, and the sample is properly controlled for (see Section 4.5), the influence of NDAI and SCRM in SCRs issued by all three leading CRAs is about 1/3. This 1/3 influence of NDAI and SCRM components is the essence of SCRs, the forward-looking opinions of CRAs on rated countries' creditworthiness, the source of the "above and beyond" information value of SCRs, and the cause of split-SCRs persistence amongst these three leading CRAs.

Regarding the effects of ZBPR and QEP on SCRs determination, there is no evidence to suggest that the issuance of SCRs was compromised when ZBPR and QEP were in effect. The empirical estimates show that all 4 key factors proxied by the eight determinants are reasonably represented. The eight-determinant models have robust predictive power for SCRs issued by Moody's, S&P and Fitch. Moreover, most of the selected economic variables that were proven statistical significance as determinants of SCRs in previous studies, are re-examined and continue to be significant determinants in this empirical study.

5.5 Conclusion

This empirical study is aimed to examine whether the three leading credit rating agencies (CRAs) measure the economic fundamentals differently of countries seeking sovereign credit ratings (SCRs) when the zero-bound-policy rate (ZBPR) and the quantitative easing programme (QEP) were in effect. This study also serves as an extension of Chapter 3 on SCRs synthesis, where the three components of SCRs function are measured.

With these aims, the economic variables proven in previous studies as significant determinants of SCRs are cross-referenced against the inputs of four key factors assessed by Moody's, S&P, and Fitch in SCRs determination. The eight economic variables that match the list of examined and proven economic variables in previous studies and the list of inputs to the four key factors are selected. Among these eight selected economic variables, five are statistically significant and consistent in predicting SCRs issued by all three leading CRAs. These five economic variables are the GDP Per Capita, Government Effectiveness Index, Debt-to-GDP, Fiscal Balance, and Financial Development Index. The sixth significant economic variable is the Reserves to GDP, but this determinant is only significant for SCRs issued by Moody's and Fitch.

Since the majority of eight selected economic variables were proven significant in previous studies and remain significant in predicting for SCRs issued by all three leading CRAs in this empirical study, there is evidence to suggest that SCRs issuance was compromised when ZBPR and QEP were in effect.

Although the eight-determinant models provide better predictive power as compared to models from previous studies, like previous models, the eight determinants only represent the publicly available information (PAI) component. The non-disclosure-agreement obtained information (NDAI) and sovereign credit rating methodology (SCRM) components are not specified in the eight-determinants models. These two components are the essences of SCRs, the forward-looking opinions of respective CRAs on rated countries' creditworthiness profiles, the sources of the "above and beyond" information value of SCRs, and the causes of split-SCRs persistency. With the weighted SCRs function, the NDAI and SCRM components are measured for the first time. Collectively, these two components exerted 1/3 of the influence on the assigned SCRs. The weight of NDAI and SCRM components should enrich the discussion regarding CRAs' preference for SCRs stability (i.e., Through-the-Cycle philosophy) at the expense of SCRs' accuracy (i.e., Point-in-Time philosophy).

In summary, the empirical estimates show the eight selected economic variables are good proxies of the 4 key factors: economic, institution, fiscal, and susceptibility to external events, assessed by all three leading CRAs in SCRs determination. Despite the effort to ensure the selected economic variables are indeed assessed by all three leading CRAs, there are signs of variability in assessment on the selected economic variables amongst the three leading CRAs. However, their differences do not jeopardy the OPM and OLM models' predictive power for the assigned SCRs. The eight-determinant models produce significantly higher predictive accuracy, in a range of 61% to 75%, as compared to the previous models in earlier studies, are a 50% range. The results of variability are reflected in the persistent split-SCRs amongst these CRAs, and the causes of variability could be traced back to the NDAI and SCRM components. These two components explain 1/3 of assigned SCRs, are the forward-looking opinions of respective CRA on creditworthiness, the sources of the "above and beyond" information value of SCRs in price discovery.

Since the majority of the selected economic variables were significant determinants of SCRs proven in previous studies, and remain significant in predicting SCRs issued by all three leading CRAs, hence there is no evidence to suggest that SCRs issuance was compromised when ZBPR and QEP were in effect. Moreover, the empirical results are robust on both broad-ordinal scaled SCRs and fine-ordinal scaled SCRs of all three leading CRAs.

CHAPTER 6: SOVEREIGN CREDIT RATINGS (SCRs) INFORMATION VALUE FOR DEBT PRICING

6.1 Introduction

Since the 1980s, sovereign credit ratings (SCRs) have gained market acceptance globally, and the influence of credit rating agencies (CRAs) through SCRs issuance has attracted some negative attentions. The concern on CRAs' influence became mainstream based on the article furnished by Friedman (1996). In the article, he commented that Moody's could do a lot of damage by downgrading a country's SCR notch. This is because the upgrade and downgrade of the assigned SCR notch change the credit profile of the rated country, which in retrospect affects the borrowing cost of the country.

The alpha-numeric SCR notches issued by Moody's and alpha-symbol SCRs notches issued by S&P and Fitch, respectively, could be comprehended as the default milestones, which are equivalent to the default distance advocated by Merton (1973). This means the SCR notches can be used for the pricing of credit risk premia. For instance, the Aaa/AAA-rated countries (see Table 3-1 in Chapter 3) are having the highest credit quality thus are furthest from the default point and able to borrow at the lowest cost. Countries rated with Aa1/AA+ are inferior to those rated with Aaa/AAA, therefore these countries are borrowing at a relatively higher cost, and so on.

Fast forward to recent incidents such as the US subprime crisis in 2008 and the European debts crisis in 2010, the three leading CRAs were summoned to explain their involvements and actions that could have potentially exacerbated the crises[27]. In their

[27] ESMA Report on CRA Market Share Calculation: https://www.esma.europa.eu/sites/default/files/library/esma33-9 340_cra_market_share_calculation_2019.pdf

concluding remark to the enquiry committee, all three leading CRAs have maintained their independence in forming the forward-looking opinions of rated countries' creditworthiness, and the SCRs are issued consistently following their respective proprietary methodologies.

Since SCRs issued by these three leading CRAs and the market acceptance are unperturbed by the negative incidents, and the empirical outcome from Chapter 5 do resonate well with the concluding remark, the chapter will proceed to examine the SCRs information value in debts price discovery. Although the evidence on SCRs information value in debts price discovery is well established, the potential effects of zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP) in SCRs information value have not been examined. This research gap is the emphasis in this chapter.

The structure of this chapter is as follows. In the immediate section, the applicable dataset and the empirical methods are recapped briefly from Chapter 4. Section 6.3 will cover the empirical estimates, followed by the discussion in Section 6.4. The concluding remarks are presented in Section 6.5.

6.2 Data and Models

The observations are gathered from 2008 to 2017 to reflect the entire duration when zero-bound-policy-rate (ZBPR) and quantitative easing programme (QEP) were in effect. The annual data points are used in this chapter. The sample constitutes of 32 investment-grade rated countries (see Table 4-2), the dependent variable is sovereign bond yields (SBYs), and the eight selected economic variables of SCRs and SCRs issued by Moody's, S&P, and Fitch are the independent variables (see Section 4.5.3 in Chapter 4).

The SBYs are selected as the dependent variable for this empirical study because the financial instrument has a direct association with the assigned SCRs[28]. The SBYs are converted into the natural logarithm value, the common approach to address the potential heteroscedasticity present in cross-sectional data (Cantor & Packer, 1996; Ederington et al., 1987; Miricescu, 2015). However, due to the persistency of negative value in SBYs, even at base plus 1, the log *SBYs* with base plus 2 will be used. On missing SBY observations from the source, the total number of workable annual observations summed up to 292. The descriptive statistics of *SBYs* and *log SBYs Base+2* are presented in Table 6-1.

Table 6-1: SBYs and Log SBYs Descriptive Statistics

	SBYs	**Log_SBYs Base+2**
Mean	2.063	0.568
Median	1.941	0.596
Maximum	7.583	0.982
Minimum	-0.756	0.095
Std. Dev.	1.725	0.193
Skewness	0.549	-0.211
Kurtosis	2.757	2.110
Observations	292	292

Source: The observations are gathered from the list of 32 countries presented in Table 4-2 on annual internal spanning 2008 to 2017, predominantly from Bloomberg. The total observations on SBYs are less than 320 due to missing data points. Due to some data points of SBYs are with a negative value, therefore the logarithm transformation on SBYs base plus 2 is adopted.

Regarding the independent variables, the eight economic variables are the GDP Growth Rate, GDP Per Capita, Government Effectiveness Index, Inflation, Debt-to-GDP, Fiscal Balance, Financial Development Index, and Reserves to GDP. These eight economic

[28] Since 2008, the US FED rate had been set 0.25% until 2016 when normalization started. Hence, there will be negligible different when spreads or actual yields is used. Second, the rate is not driven by market force. Third, US is no longer tripled Aaa/AAA rated countries, S&P downgraded US from AAA to AA cluster. Moreover, some studies that focused on European countries used German Bund instead of US Treasury bill as proxy on risk free rate.

variables are the same set of variables referred to as the SCRs determinants in Chapter 5 and are repurposed as the baseline regressors for this study. In similar setups, the baseline regressors will take the forms of short-term determinants in contemporary value and long-term determinants in 3-year average value. In addition, the alpha-numeric and alpha-symbol SCRs of the sample countries are key regressors to study SCRs information value. The SCRs will be converted into ordinal scales following the convention commonly practised in previous studies (Afonso, 2003; Afonso et al., 2011; Alsakka & Gwilym, 2010a, 2010b; Bissondoyal-Bheenick, 2005; Cantor & Packer, 1996; Reusens & Croux, 2017). Both broad ordinal scales and fine ordinal scales (see Table 4-3 in Chapter 4) will be examined in this study.

The panel models described in Section 4.4.3 are adopted for this empirical study. A series of panel fixed effect (FE) and panel random effect (RE) regressions will be conducted on Equations 4-8, 4-9, and 4-10. The Hausman test will also be conducted the determine the appropriateness between panel FE and RE.

As reported in the works of Chen, Chen, Yang, et al. (2016) and Chen, Chen, Chang, et al. (2016) and Hsien-Yi and Sheng-Syan (2018), regressing baseline regressors together with the SCRs regressor may lead to the endogeneity issue that causes the inference to be biased. To control the feedback effect between the baseline regressors and the SCRs regressor, the baseline regressors in Equation 4-9 are replaced with the SBYs in the lagged term. The dynamic panel model as described in Section 4.4.6 is adopted to address the endogeneity issue that continues to be present in the modified equation.

6.3 Empirical Results

The panel models and dynamic panel model estimates derived from Equation 4-8, 4-9, 4-10, and modified Equation 4-9 are reported in this section.

6.3.1 Panel Estimates: The Baseline and SCRs Regressors

The panel fixed effect (FE) and random effect (RE) models estimates based on short-term determinants are reported in Table 6-2, and those with long-term determinants are reported in Table 6-3. Both tables are organized in a similar format, Panel A reports the estimates using the eight selected economic variables, the baseline regressors. Results reported from panel B to panel G are estimates derived using Equation 4-9, which consists of the baseline regressors and SCRs regressor. For instance, estimates reported under Panel B and C are derived using baseline regressors and SCRs issued by Moody's. For SCRs, the fine ordinal scaled SCRs is employed in Panel B and broad ordinal scaled SCRs is employed in Panel C. Based on the same arrangement, results under Panel D and E are derived using baseline regressors and SCRs issued by S&P. For results reported under Panel F and G, the SCRs are issued by Fitch.

Between the panel FE and RE models, the Hausman test is conducted to facilitate the selection of the appropriate panel model, and estimates from the model will be used for discussion in the subsequent section. The Hausman test results are reported in Tables 6-2 and 6-3, accordingly.

Table 6-2: Panel Model Estimates based on Short-Term Determinants

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
			Fixed Effect (FE)				
GDP Growth Rate	-0.026**	-0.027**	-0.026**	-0.026**	-0.027**	-0.026**	-0.026**
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
GDP Per Capita	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov. Effect. Ind.	0.009	0.009	0.009	0.009	0.010	0.010	0.010
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Inflation	0.064**	0.063**	0.063**	0.065**	0.066**	0.066**	0.065**
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Debt to GDP	-0.005**	-0.006**	-0.006*	-0.003	-0.003	-0.004	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fiscal Bal.	-0.035**	-0.035**	-0.035**	-0.033**	-0.035**	-0.034**	-0.034**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Fin. Dev. Ind.	0.847	0.947	0.918	0.810	0.786	0.788	0.809
	(0.595)	(0.604)	(0.612)	(0.592)	(0.598)	(0.598)	(0.599)
Res. to GDP	-0.008	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**	-0.008**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Moody's SCRs BS		-0.043					
		(0.045)					
Moody's SCRs FS			-0.010				
			(0.020)				
S&P SCRs BS				0.089			
				(0.046)			
S&P SCRs FS					0.022		
					(0.022)		
Fitch SCRs BS						0.053	
						(0.051)	
Fitch SCRs FS							0.014
							(0.023)
Adj. R^2	**0.645**	**0.645**	**0.644**	**0.649**	**0.645**	**0.645**	**0.644**
			Random Effect (RE)				
GDP Growth Rate	-0.024**	-0.025**	-0.025**	-0.024**	-0.024**	-0.024**	-0.024**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
GDP Per Capita	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov. Effect. Ind.	-0.003	-0.002	-0.002	-0.004	-0.003	-0.003	-0.002
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Inflation	0.062**	0.062**	0.062**	0.061**	0.062**	0.062**	0.062**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Debt to GDP	-0.005**	-0.006**	-0.006**	-0.005**	-0.005**	-0.005**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fiscal Bal.	-0.025**	-0.025**	-0.024**	-0.023**	-0.02**	-0.024**	-0.024**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Fin. Dev. Ind.	0.382	0.485	0.467	0.316	0.394	0.378	0.417
	(0.307)	(0.305)	(0.293)	(0.293)	(0.290)	(0.296)	(0.291)
Res. to GDP	-0.006**	-0.007**	-0.006**	-0.006**	-0.006**	-0.006**	-0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Moody's SCRs BS		-0.043					
		(0.034)					
Moody's SCRs FS			-0.014				
			(0.014)				
S&P SCRs BS				0.045			
				(0.038)			
S&P SCRs FS					-0.003		
					(0.016)		
Fitch SCRs BS						0.002	

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
						(0.040)	
Fitch SCRs FS							-0.008
							(0.017)
Adj. R^2	**0.315**	**0.313**	**0.308**	**0.312**	**0.306**	**0.307**	**0.306**
				Hausman Test			
Chi^2	24.686**	30.567**	36.219**	35.255**	37.201**	35.076**	36.386**

Note: The dataset consists of all 32 cross-sectional countries with a total of 292 observations spanning from 2008 to 2017. The sources of the covariates are from World Bank (WB) and International Monetary Fund (IMF). Govt. Effect. Ind. = Government Effectiveness Index, Fiscal Bal. = Fiscal Balance, Fin. Dev. Ind. = Financial Development Index, and Res. To GDP = Reserves to GDP. Moody's SCRs, S&P SCRs, and Fitch SCRs (source: Bloomberg and Thomson Reuter) are ordinal scale transformed on the convention as defined in Table 3.2. FS is the fine-scale whereas BS is the broad-scale of SCRs issued by the three CRAs. The dependent variable is the natural log of SBY base plus 2. The estimations are based on Equations 4-8 and 4-9 in Section 4.4.3. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Table 6-3: Panel Model Estimates based on Long-Term Determinants

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
				Fixed Effect (FE)			
GDP Growth Rate	-0.034**	-0.033**	-0.033**	-0.033**	-0.034**	-0.034**	-0.034**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
GDP Per Capita	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov. Effect. Ind.	0.002	0.002	0.001	0.003	0.003	0.002	0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Inflation	0.114**	0.112**	0.111**	0.115**	0.116**	0.116**	0.116**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Debt to GDP	-0.007**	-0.008**	-0.009**	-0.005**	-0.006**	-0.006**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fiscal Bal.	-0.012	-0.011	-0.011	-0.014	-0.013	-0.013	-0.012
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Fin. Dev. Ind.	1.510*	1.616**	1.676**	1.497*	1.467*	1.480*	1.462*
	(0.612)	(0.615)	(0.623)	(0.609)	(0.615)	(0.614)	(0.617)
Res. to GDP	-0.010**	-0.010**	-0.010**	-0.010**	-0.010**	-0.010**	-0.010**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Moody's SCRs BS		-0.059					
		(0.042)					
Moody's SCRs FS			-0.024				
			(0.018)				
S&P SCRs BS				0.079			
				(0.042)			
S&P SCRs FS					0.016		
					(0.020)		
Fitch SCRs BS						0.037	
						(0.047)	
Fitch SCRs FS							0.015
							(0.022)
Adj. R^2	**0.694**	**0.695**	**0.695**	**0.697**	**0.693**	**0.693**	**0.693**
				Random Effect (RE)			
GDP Growth Rate	-0.034**	-0.033**	-0.034**	-0.033**	-0.033**	-0.033**	-0.033**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
GDP Per Capita	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gov. Effect. Ind.	-0.005	-0.004	-0.004	-0.006	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Inflation	0.114**	0.115**	0.116**	0.113**	0.115**	0.115**	0.115**

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Debt to GDP	-0.008**	-0.006**	-0.006**	-0.005**	-0.005**	-0.005**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fiscal Bal.	-0.005	-0.004	-0.003	-0.006	-0.005	-0.005	-0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Fin. Dev. Ind.	0.818**	0.864**	0.846**	0.708*	0.753**	0.743*	0.754**
	(0.305)	(0.299)	(0.287)	(0.290)	(0.285)	(0.295)	(0.290)
Res. to GDP	-0.007**	-0.008**	-0.008**	-0.007**	-0.007**	-0.007**	-0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Moody's SCRs BS		-0.032					
		(0.033)					
Moody's SCRs FS			-0.013				
			(0.013)				
S&P SCRs BS				0.055			
				(0.036)			
S&P SCRs FS					0.004		
					(0.016)		
Fitch SCRs BS						0.021	
						(0.039)	
Fitch SCRs FS							0.004
							(0.016)
Adj. R^2	**0.410**	**0.405**	**0.401**	**0.407**	**0.399**	**0.402**	**0.400**
			Hausman Test				
Chi^2	21.107**	29.100**	35.037**	30.107**	33.749**	29.916**	32.448**

Note: The dataset consists of all 32 cross-sectional countries with a total of 292 observations spanning from 2008 to 2017. The sources of the covariates are from World Bank (WB) and International Monetary Fund (IMF). Govt. Effect. Ind. = Government Effectiveness Index, Fiscal Bal. = Fiscal Balance, Fin. Dev. Ind. = Financial Development Index, and Res. To GDP = Reserves to GDP. Moody's SCRs, S&P SCRs, and Fitch SCRs (source: Bloomberg and Thomson Reuter) are ordinal scale transformed on the convention as defined in Table 3.2. FS is the fine-scale whereas BS is the broad-scale of SCRs issued by the three CRAs. The dependent variable is the natural log of SBY base plus 2. The estimations are based on Equations 4-8 and 4-9 in Section 4.4.3. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Regressions based on short-term determinants (see Table 6-2), the results under Panel A show that 6 out of 8 determinants are significant at 5% level and with the expected signs. These six significant short-term determinants are GDP Growth Rate, GDP Per Capita, Inflation, Debt to GDP, Fiscal Balance, and Reserves to GDP. These six determinants remain significant in explaining SBYs even when SCRs by CRAs are introduced individually as the SCRs regressor. However, the majority of the estimated coefficients of SCRs regressors do not have the expected negative sign. In cases where the estimated coefficients of SCRs are with the negative sign, they are not significant. These results are reported under Panel B to Panel G. The results remain fairly consistent, irrespective of whether fine-scaled SCRs or broad scaled SCRs are used. The explanatory power of the models mainly concentrated within the baseline regressors at 64.5%.

Regressions based on long-term determinants (see Table 6-3), the results under Panel A show that five determinants are significant: GDP Growth Rate, Inflation, Debt to GDP, Financial Development Indicator, and Reserves to GDP. These five baseline regressors remain significant when the SCRs regressor by respective CRAs is added for estimation. The use of fine ordinal scaled SCRs and broad ordinal scaled SCRs do not change the outcome on the estimated coefficients of SCRs. The estimated coefficients of SCRs are mostly significant without the negative sign. These results can be observed from Panel B to G. Regarding the models' explanatory power, the long-term determinants models provide marginally higher explanatory power at 69.4 as compared to the short-determinants models at 64.5%.

To check if the results remain robust, the fixed effect models are re-estimated by fixing both the cross-section and period effects (Appendix 4, Table A4-2). The fixed cross-section and period model produces greater models' explanatory power at above 80% as compared to 64% for short-term determinants models and 69% for long-term determinants models, where the period is not fixed. Despite the increase in explanatory power, the SCRs, irrespective of CRAs, remain irrelevant. The fixed effect models are also re-estimated with cross-section fixed effects and White cross-section robust standard errors (Appendix 4, Table A4-3) and White period robust standard errors (Appendix 4, Table A4-4). The estimates with both White robust standard errors did not change the outcome of this study, the findings on SCRs being rendered irrelevant remain robust and unanimous for SCRs issued by all three leading CRAs.

6.3.2Panel Estimates: The Standalone SCRs Regressor

When the SCRs regressor is estimated with the baseline regressors (see Equation 4.9), the possibility of confounding effect among these regressors is high. Since the baseline regressors are also significant determinants of SCRs (see Chapter 5). To eliminate the potential confounding effect, the baseline regressors are dropped and only the SCRs regressor is maintained. This is expressed in Equation 4.10 (see Section 4.4.3 in Chapter 4.

Table 6-4: Panel Model Estimates based on Standalone SCRs Regressor

	Panel H	Panel I	Panel J	Panel K	Panel L	Panel M
			Fixed Effect (FE)			
Moody's SCRs BS	-0.007 (0.026)					
Moody's SCRs FS		-0.003 (0.011)				
S&P SCRs BS			0.055 (0.030)			
S&P SCRs FS				0.007 (0.013)		
Fitch SCRs BS					0.025 (0.031)	
Fitch SCRs FS						0.010 (0.013)
Adj. R^2	**0.778**	**0.778**	**0.781**	**0.778**	**0.779**	**0.778**
			Random Effect (RE)			
Moody's SCRs BS	0.055 (0.031)					
Moody's SCRs FS		0.023 (0.012)				
S&P SCRs BS			0.096** (0.034)			
S&P SCRs FS				0.024 (0.014)		
Fitch SCRs BS					0.079* (0.034)	
Fitch SCRs FS						0.025 (0.014)
Adj. R^2	**0.007**	**0.008**	**0.022**	**0.006**	**0.014**	**0.007**
			Hausman Test			
Chi^2	11.123**	15.701**	21.865**	19.416**	21.082**	22.350**

Note: The dataset consists of all 32 cross-sectional countries with a total of 292 observations spanning from 2008 to 2017. Moody's SCRs, S&P SCRs, and Fitch SCRs (source: Bloomberg and Thomson Reuter) are ordinal scale transformed on the convention as defined in Table 3.2. FS is the fine-scale whereas BS is the broad-scale of SCRs issued by the three CRAs. The dependent variable is the natural log of SBY base plus 2. The estimation is based on Equation 4-10 in Section 4.4.3. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

The same series of panel FE and RE models and Hausman test are performed, and the estimates are compiled in Table 6-4. The results under Panel H and I are based on SCRs issued by Moody's, Panel J and K are based on SCRs issued by S&P, and Panel L and M are based on SCRs issued by Fitch.

The Hausman test results have rejected the panel RE models as the appropriate model, therefore the estimates from panel FE models will be used for analysis. The panel FE estimates show that all estimated coefficients of SCRs, irrespective of whether broad or fine ordinal scaled SCRs are used, are insignificant at the 5% level.

The FE models for all panels are re-estimated by fixing both the cross-section and period effects (Appendix 4, Table A4-5). The findings on SCRs issued by all three CRAs being rendered irrelevant remain robust. The model is also re-estimated with cross-section fixed effects and White cross-section robust standard errors, and White period robust standard errors (Appendix 4, Table A4-6). The SCRs, irrespective of CRAs, remain irrelevant.

6.3.3Dynamic Panel Model Estimates

Regressing baseline regressors together with the SCRs regressor, the estimates may suffer from confounding effects. Dropping the baseline regressors, as in the case of Equation 4-10, may cause the model to be underspecified. To address these two issues, the baseline regressors are substituted with the SBYs in a lagged term. The endogeneity issue presented by lagged SBYs is overcome using the generalized method of moments (GMM). The first difference generalized method of moments (FD-GMM) and forward orthogonal deviation generalized method of moments (FOD-GMM) are conducted on Equation 4-11 (see Section 4.4.6. in Chapter 4). The empirical results of FD-GMM and FOD-GMM are compiled in Table 6-5.

Table 6-5: Dynamic Panel Model Estimates

	Panel N	Panel O	Panel P	Panel Q	Panel R	Panel S
Periods:	8					
Cross-Sections:	32					
Dependent Variable:	log(SBYs Base+2)					
Instrument Variable:	log(SBYs Base+2(-1))					
First Difference (FD) Transformation						
log(SBYs Base+2(-1))	0.659**	0.591**	0.593**	0.627**	0.589**	0.527**
	(0.014)	(0.009)	(0.007)	(0.003)	(0.008)	(0.009)
Moody's SCRs BS	0.330**					
	(0.000)					
Moody's SCRs FS		0.171**				
		(0.009)				
S&P SCRs BS			0.408**			
			(0.022)			
S&P SCRs FS				0.185**		
				(0.013)		
Fitch SCRs BS					0.382**	
					(0.100)	
Fitch SCRs FS						0.275**
						(0.005)
SSR	21.056	21.918	19.974	20.499	20.894	22.124
Instrument Rank	32	32	32	32	32	32
J-Stat	31.791	30.695	31.963	31.633	31.720	31.869
Arellano-Bond Serial Correlation Test						
AR(1)	-3.373**	-3.106**	-3.411**	-3.335**	NA	-2.900**
AR(2)	2.037*	2.084*	1.593	2.235*	NA	1.858
Forward Orthogonal Deviation (FOD) Transformation						
log(SBYs Base+2(-1))	0.726**	0.670**	0.682**	0.710**	0.654**	0.627**
	(0.007)	(0.006)	(0.007)	(0.002)	(0.007)	(0.008)
Moody's SCRs BS	0.358**					
	(0.019)					
Moody's SCRs FS		0.171**				
		(0.005)				
S&P SCRs BS			0.404**			
			(0.029)			
S&P SCRs FS				0.178**		
				(0.014)		
Fitch SCRs BS					0.406**	
					(0.053)	
Fitch SCRs FS						0.258**
						(0.007)
SSR	13.148	14.477	11.920	11.820	12.860	17.858
Instrument Rank	32	32	32	32	32	32
J-Stat	31.675	31.360	31.933	31.837	31.675	31.835

Note: Due to the first differencing and orthogonal deviations transformation in GMM, the workable observations sum up 215 spanning from 2008 to 2017. Moody's SCRs, S&P SCRs, and Fitch SCRs (source: Bloomberg and Thomson Reuter) are ordinal scale transformed on the convention as defined in table 3.2. FS is the fine-scale whereas BS is the broad-scale of SCRs issued by the three CRAs. The dependent variable is the natural log of SBY base plus 2. Coef. = coefficient, Std. Error = standard error, p-Value = probability value, SSR = sum squared residuals and J-Stat. = J statistic. The J-Stat. is meant to determine the status of identification by Sargan statistics. AR = Autocorrelation, (1) indicates first order and (2) the second-order tests. The estimation is based on Equation 4-11 in Section 4.4.6. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

The results show that irrespective of whether the broad or fine ordinal scaled SCRs are used, all estimated coefficients of SCRs do not have the expected negative sign. Although the estimated coefficients of SCRs are significant at 5% level. The positive sign invalidates the statistical significance of the estimates. Although the autocorrelation test at second-order or AR(2) indicated that serial correlation is present in FD-GMM estimates, the outcomes on the estimated coefficient of SCRs issued by all three leading CRAs remain robust as concurred with FOD-GMM estimates.

6.4 Discussion

The discussion will be based on estimates from panel FE models as reported in Tables 6-2, 6-3, and 6-4. This is because the null hypothesis that favours the panel random effect model is rejected following the Hausman test, and the results are unanimous on all panels. On the dynamic panel model estimates, the discussion will focus on estimates generated by FOD-GMM instead of FD-GMM. This is because the serial correlation persisted in FD-GMM estimates.

6.4.1 Short-Term and Long-Term Determinants on Explaining SBYs Pricing

The short-term and long-term determinants of SCRs in Chapter 5 are repurposed as the baseline regressors in explaining sovereign bond yields (SBYs). The baseline regressors' estimates reported under Panel A in both Table 6-2 and 6-3 show that the eight SCRs determinants are equally effective as SBYs determinants with 64% and 69% explanatory power, respectively.

On the short-term determinants, six out of eight determinants are significant in explaining SBYs. Comparing these six significant determinants of SBYs with significant determinants of SCRs, the variation of emphasis begins to reveal. For instance, the Government Effectiveness Indicator and Financial Development Indicator are significant determinants in predicting SCRs but are insignificant in SBYs price discovery. The Government Effectiveness Indicator is an input to assess the institution factor and the Financial Development Indicator is an input to assess the susceptibility to external events factor based on the respective sovereign credit rating methodology (see Chapters 3 and 5).

The variation regarding the sign of the estimated coefficients also provides a new revelation. In particular, the positive sign is reported on the estimated coefficient of GDP Per Capita and the negative sign on the estimated coefficient of Debt to GDP in explaining SBYs. While there are intuitive for the GDP Per Capita to be positive and the Debt to GDP to be negative concerning SCRs determination (see Chapter 3 and Section 4.5.3 of Chapter 4), but they are counter-intuitive in SBYs price discovery. The GDP Per Capita with positive relation to SBYs suggests that positive productivity growth would lead to an increase in borrowing costs. On the other hand, the negative relation between Debt to GDP and SBYs suggests that the debt stock expansion would lead to lower borrowing costs.

The sign and significance level of the estimated coefficients of SBYs short-term determinants reported in Tables 6-2 and 6-3 and the estimated coefficients of SCRs short-term determinants reported in Table 5-2 are summarized in Table 6-6.

Regarding the long-term determinants, five out of eight determinants are significant at a 5% level in explaining SBYs. The variation of emphasis between the SBYs price discovery and the SCRs determination on long-term determinants persisted. For instance, the anomaly observed on the sign of the estimated coefficient of Debt to GDP, in the context of short-term determinants, persisted in the context of long-term determinants. On the plus side, the anomaly observed on the estimated coefficients of GDP Per Capita becomes irrelevant due to statistical insignificant. The other variation is observable on the estimated coefficient of the Financial Development Indicator. The positive sign of this determinant in explaining SBYs suggests that countries with better developed financial systems would have to borrow at a higher cost.

Table 6-6: Significance and Sign Comparison on Short-Term Determinants on SCRs and SBYs

Dependent Variable:		Moody's SCRs		S&P SCRs		Fitch SCRs		SBYs
	Model:	OPM	OLM	OPM	OLM	OPM	OLM	FE
GDP Growth Rate	Significant	No	No	No	No	Yes	Yes	Yes
	Sign	-	-	-	-	-	-	-
GDP Per Capita	Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	+	+	+	+	+	+	+
Gov. Effect. Ind.	Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	+	+	+	+	+	+	+
Inflation	Significant	No	No	No	No	No	No	No
	Sign	+	+	+	+	+	+	+
Debt to GDP	Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	-	-	-	-	-	-	-
Fiscal Bal.	Significant	Yes	No	Yes	Yes	Yes	Yes	Yes
	Sign	+	+	+	+	+	+	+
Fin. Dev. Ind.	Significant	Yes	Yes	Yes	Yes	Yes	Yes	No
	Sign	+	+	+	+	+	+	+
Res. to GDP	Significant	Yes	Yes	No	No	Yes	Yes	Yes
	Sign	-	-	-	-	-	-	-

Note: The row labelled as 'Significant' refers to whether the estimated coefficients are significant, where Yes denotes significance at 5% level, and No denotes not significant. The Sign denotes the positive and negative signs of the estimated coefficients. The referenced results on OPM and OLM are from Table 5-1 in Chapter 5, and FE is from Table 6-2. Moody's SCRs, S&P SCRs, and Fitch SCRs (source: Bloomberg and Thomson Reuter) are ordinal scale transformed on convention defined in Table 3.2. FS is the fine-scale whereas BS is the broad-scale of SCRs issued by the three CRAs.

The sign and significance level of the estimated coefficients of SBYs long-term determinants reported in Tables 6-2 and 6-3 and the estimated coefficients of SCRs short-term determinants reported in Table 5-3 are summarized in Table 6-7 for ease of reference.

Table 6-7: Significance and Sign Comparison on Long-Term Determinants on SCRs and SBYs

	Dependent Variable:	Moody's SCRs		S&P SCRs		Fitch SCRs		SBYs
	Model:	**OPM**	**OLM**	**OPM**	**OLM**	**OPM**	**OLM**	**FE**
GDP Growth Rate	Significant	No	No	No	No	No	No	Yes
	Sign	+	+	+	+	-	+	-
GDP Per Capita	Significant	Yes	Yes	Yes	Yes	Yes	Yes	No
	Sign	+	+	+	+	+	+	+
Gov. Effect. Ind.	Significant	Yes	Yes	Yes	Yes	Yes	Yes	No
	Sign	+	+	+	+	+	+	+
Inflation	Significant	No	No	No	No	No	No	Yes
	Sign	+	+	+	+	+	+	+
Debt to GDP	Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	-	-	-	-	-	-	-
Fiscal Bal.	Significant	Yes	Yes	Yes	Yes	Yes	Yes	No
	Sign	+	+	+	+	+	+	-
Fin. Dev. Ind.	Significant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	+	+	+	+	+	+	+
Res. to GDP	Significant	Yes	Yes	No	No	Yes	Yes	Yes
	Sign	-	-	-	-	-	-	-

Note: The row labelled as 'Significant' refers to whether the estimated coefficients are significant, where Yes denotes significance at 5% level, and No denotes not significant. The Sign denotes the positive and negative signs of the estimated coefficients. The referenced results on OPM and OLM are from Table 5-2 in Chapter 5, and FE is from Table 6-3. Govt. Effect. Ind. = Government Effectiveness Index, Fiscal Bal. = Fiscal Balance, Fin. Dev. Ind. = Financial Development Index, and Res. To GDP = Reserves to GDP

Among the highlighted determinants with the anomaly, the effect of GDP Per Capita is negligible given that the strength of estimated coefficients (i.e., short-term, and long-term) is near zero. The Fiscal Balance is reported as a significant short-term determinant but insignificant as a long-term determinant in explaining SBYs. This variation could be explained that the occurrence of the fiscal surplus was contemporary and cyclical in trajectory in the long run. The remaining and key anomaly among the selected determinants is the Debt to GDP. The negative sign of the estimated coefficients indicated that an increase in debt stock leads to a decrease in borrowing costs. We conjectured that this anomaly between Debt to GDP and SBYs could be fuelled by the zero-bound-policy rate (ZBPR) and quantitative easing programme (QEP).

Between the short-term and long-term determinants models, the latter have better models' explanatory power for SBYs at an average of 69% as compared to 65% from the former. By assuming the short-term determinants as proxies for Point-in-Time (PIT) and long-term determinants for Through-the-Cycle (TTC) as defined by Kiff et al. (2013), the 5% additional explanatory power on long-term determinants indicated that the financial market's preference towards stability in price discovery. This indication echoes the same argument presented by Cantor and Mann (2006).

6.4.2SCRs Information Value on SBYs Pricing

Regarding the "above and beyond" information value of SCRs, the Panel B to G estimates presented in Table 6-2 and 6-3 derived using Equation 4-9 is consistent with the approach adopted in previous studies (Afonso et al., 2013; Cantor & Packer, 1996; Jaramillo & Tejada, 2011; Jaramillo & Weber, 2013; Miricescu, 2015). The criteria of assessment are the estimated coefficient of SCRs must be significant at least at the 5% level and with the expected negative sign (see Section 4.4.3), otherwise, the SCRs estimate will be considered irrelevant in SBYs pricing.

The panel FE estimates show that the estimated coefficients of SCRs are statistically insignificant. The results are unanimous for SCRs issued by all three leading CRAs, regardless of whether broad ordinal scaled SCRs or fine ordinal scaled SCRs are used and the short-term or long-term determinants are used as the baseline regressors. This means the information on the creditworthiness of the rated countries as conveyed through SCR notches was not reflected in SBYs pricing.

Referring to the panel FE estimates derived using SCRs as the standalone regressor, where the potential confounding effects of baseline regressors are controlled for, all the estimated coefficients of SCRs are statistically insignificant in explaining SBYs.

Separately, the short-term and long-term determinants are substituted with the lagged SBYs as the baseline regressor, and the generalized method of moments (GMM) is adopted to address the endogeneity issue presented by the endogenous regressor. The results from FOD-GMM show that all estimated coefficients of SCRs are significant at the 5% level but are not with the expected negative sign. The positive sign on FOD-GMM estimates means the SCRs information value did not price following the risk-reward pricing convention, therefore the SCRs information value was irrelevant in SBYs pricing.

Table 6-8: Significance and Sign Comparison on SCRs as additional Regressor and Standalone Regressor

		Moody's		S&P		Fitch	
		SCRs BS	**SCRs FS**	**SCRs BS**	**SCRs FS**	**SCRs BS**	**SCRs FS**
Short-Term *plus* SCRs	Significant	No	No	No	No	No	No
	Sign	-	-	+	+	+	+
Long-Term *plus* SCRs	Significant	No	No	No	No	No	No
	Sign	-	-	+	+	+	+
Standalone SCRs	Significant	No	No	No	No	No	No
	Sign	-	-	+	+	+	+
FD-GMM	Significant	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	+	+	+	+	+	+
FOD-GMM	Significant	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	+	+	+	+	+	+

Note: The row labelled as 'Significant' refers to whether the estimated coefficients are significant, where Yes denotes significance at 5% level, and No denotes not significant. The Sign denotes the positive and negative signs of the estimated coefficients. The referenced results on Short-Term Determinants *plus* SCRs are sourced from Table 6-2, Long-Term Determinants *plus* SCRs from Table 6-3, Standalone SCRs from Table 6-4, and both FD-GMM and GOD-GMM are from Table 6-5.

Although the baseline regressors remain statistically significant in explaining SBYs, the NDAI and SCRM components are not represented (see Chapter 3). Therefore, the explanatory power based on baseline regressors cannot be equated as the proxy of SCRs. This means the SCRs information value was irrelevant in SBYs pricing, and the findings are robust.

The sign and significance level of the estimated coefficients of SCRs reported under Panel B to G in Tables 6-2 and 6-3, Panel H to M in Table 6-4, and Panel N to S in Table 6-5 are summarised in Table 6-8 for ease of reference.

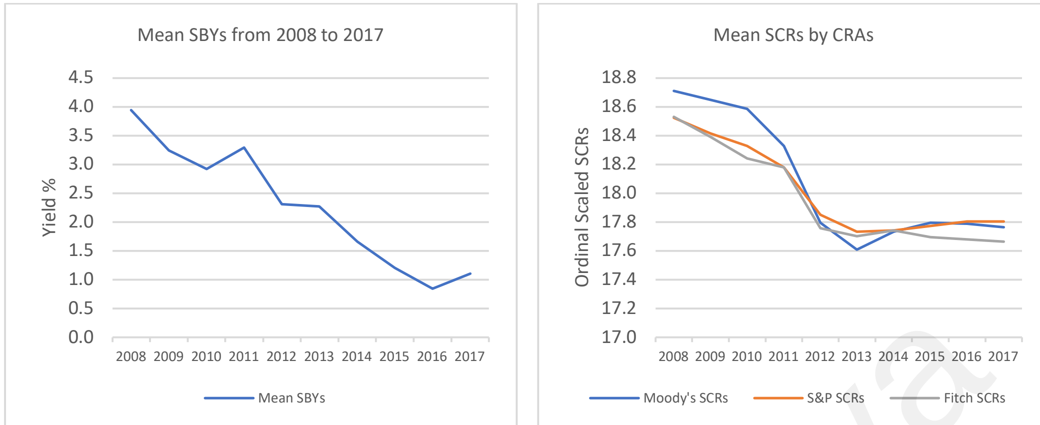
6.4.3SBYs Price Discovery: When ZBPR and QEP were in Effect

The positive sign on estimated coefficients of Debt to GDP reported in Tables 6-2 and 6-3 is the evidence to support the conjecture that SCRs information value was rendered irrelevant in SBYs pricing when the zero-bound-policy rate (ZBPR) and the quantitative easing programme (QEP) were in effect.

The positive sign on estimated coefficients of Debt to GDP to SBYs means an increase in borrowing leads to a lower borrowing cost. Based on the capital assets pricing model by Fama (1969), the borrowing cost or expected yield is the result of a risk-free rate plus risk premia. The proxy for the risk-free rate is the policy rate, and the risk premia are the differences derived between the market expected returns of the asset and the risk-free rate. The risk premia consist of the credit default premium and the market premium on credit condition or liquidity premium.

On that note, the downward trend of mean SBYs since 2008, as depicted in Figure 6-1, could be contributed by the policy rate, risk premia or the combination of the risk-free rate and risk premia. Given that the credit default premium of risk premia is proxied by SCRs, and mean SCRs by three leading CRAs of the sample were also worsen since 2008, the decrease in SBYs cannot be contributed by the credit risk premium. This is because the drop in mean SCRs should have contributed to higher expected yields, following the risk-reward pricing convention.

Figure 6-1: Mean SBYs and Mean SCRs by CRAs Annual Trend from 2008 to 2017

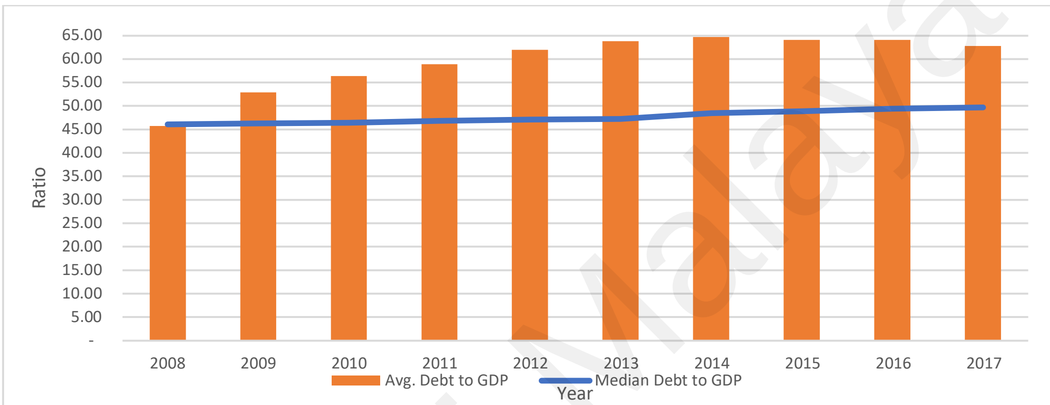


Note: The mean SBYs are derived using a simple arithmetic method of averaging from quarter datapoints from 2008 to 2017 of 32 cross-section countries. The mean SCRs are derived from SCRs issued by Moody's, S&P, and Fitch in the form of fine ordinal scales as defined in Table 3-4.

The remaining components that contributed to the mean SBYs downward trend are the risk-free rate and the liquidity risk premium. Since the US Treasury Bill is commonly used as a proxy of the risk-free rate, and the FED has lowered its policy rate from 4% to 0.25%, the ZBPR, since 2008, and maintained the ZBPR until the end of 2015. It is therefore a given that ZBPR, in the context of the risk-free rate, has contributed to the contraction of mean SBYs.

With regards to QEP contribution to mean SBYs contraction, this could be observed from the average Debt to GDP of the sample as depicted in Figure 6-2. The average Debt to GDP peaked in 2014 from about 45% in 2008 to 65% in 2014 does explain the dropped in mean SCRs by CRAs (see Figure 6-1). This is because the increase in debt stock also lower the debt serviceability ratio, which in retrospect causes the sovereign default probability to increase. The dropped in mean SCRs by CRAs mean the assigned SCR notches were downgraded to reflect the worsened credit profiles. With over a 40% increase in credit demand from 2008 to 2014, the expected yields should have increased or at least halted the mean SBYs to converge towards the ZBPR. However, the positive sign on estimated coefficients of Debt to GDP indicated that more borrowing leads to lower yields. This positive relation between Debt to GDP and SBYs is only possible when credit supply is greater than credit demand. Hence, the aggregate of USD12 trillion fresh liquidity injected through QEP is the driver that caused the mean SBYs to contract and converge towards the ZBPR.

Figure 6-2: Average Debt to GDP from 2008 to 2017

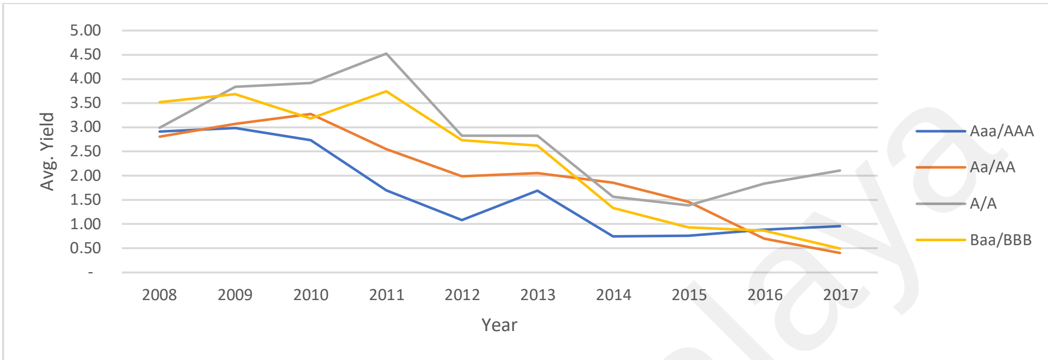


Note: The average Debt to GDP bar is the Debt to GDP ratio of the 32 selected countries is derived in simple arithmetic average by year. The median Debt to GDP line is the median Debt to Ratio of the same 32 selected countries by year.

The joint effect of ZBPR and QEP on the SBYs as observed in this sample is consistent with the observation highlighted by Kinateder and Wagner (2017) and D. Malliaropulos and P. Migiakis (2018). Under such a credit conducive environment, new debts issuance and refinance matured debts would face little or no constraint, especially for investment-grade rated countries. This means the sovereign default risk as conveyed through SCR notches become negligible or irrelevant. The SCRs information value irrelevancy in SBYs pricing is shown in Figure 6-3. The monotonous feature of SCRs in the pricing discipline is no longer observed. For instance, the average borrowing cost of Baa/BBB rated countries was lower compared to A/A rated countries from 2009 to 2017. The anomaly is also observable among Aa/AA, A/A, and Baa/BBB rated countries in 2014 and 2015, and between Aaa/AAA and Aa/AA rated countries in 2016 and 2017. The

SBYs converged towards ZBPR, fuelled by QEP, explain the positive sign on the significant coefficients of SCRs estimated from the FOD-GMM (see Table 6-8).

Figure 6-3: Mean SBYs Trends of 32 Countries by SCR Notches from 2008 to 2017



Note: The mean SBYs are the SBYs of the 32 selected countries grouped by SCR notches and derived in simple arithmetic average by year. The Aaa/AAA constitutes of the mean SCR ordinal scale of 21 issued by all three CRAs, the Aa/AA constitutes of mean SCR ordinal scales of 18 to 20, and A/A constitutes of 15 to17 ordinal scales, and Baa/BBB consists of 12 to 14 ordinal scales. See Section 4.3 of Chapter 4 on ordinal scale convention.

6.5 Conclusion

This empirical study focuses on the sovereign credit ratings (SCRs) information value in sovereign bond yields (SBYs) price discovery when the zero-bound-policy-rate (ZBPR) and quantitative easing programme (QEP) was in effect. The eight economic variables selected as SCRs determinants in Chapter 5 are repurposed as the baseline regressors in explaining SBYs. The SCRs by CRAs are introduced as the additional regressor to the models to measure the “above and beyond” information value of SCRs. In addition, the SCRs by CRAs are examined as the standalone regressor to measure SCRs information value in SBYs price discovery.

The empirical results show that the “above and beyond” information value of SCRs was not reflected in SBYs pricing. The estimated coefficients of SCRs issued by all three CRAs, the determinant to measure the “above and beyond” information value of SCRs, are statistically insignificant. Even after controlling the potential confounding of baseline regressors, the estimated coefficients of SCRs remain statistically insignificant. The results remain robust with estimates derived using dynamic panel models. The positive sign of the estimated coefficients of SCRs shows that SCRs information value was disregarded in SBYs pricing. The empirical findings are unanimous on SCRs issued by all three leading CRAs, irrespective of whether the broad ordinal scaled SCRs or fine ordinal scaled SCRs are used in the study.

Further scrutiny conducted on the sample reveals the traces of ZBPR and QEP affecting the SBYs. Due to ZBPR and QEP influence, the SCRs information value was disregarded in SBYs pricing. The 44% jumped in average debt stock of the sample and yet the mean SBYs contracted from about 4% in 2008 to 1% range in 2017 provide the strongest traces of joint effect from the ZBPR and QEP. The mean SBYs by SCR notches also revealed that the monotonous feature in risk pricing was disregarded when ZBPR and QEP were in effect.

In conclusion, this study on SCRs information value in SBYs pricing when ZBPR and QEP were in effect show that the SCRs information value was indeed disregarded and rendered irrelevant. Although the baseline regressors are equally effective in explaining SBYs, the essence of SCRs is not represented in the model, therefore, cannot be construed as the proxy of SCRs. Even after controlling the potential confounding effects presented in baseline regressors, and the handling of endogeneity issue with the instrumental variable in generalized method of moments, the research outcome on SCRs information value irrelevancy remains robust. The traces of ZBPR and QEP rendered SCRs information value irrelevant are revealed in mean SCRs by CRAs and average Debt to GDP of the sample of 32 investment-grade rated countries.

CHAPTER 7: EFFECT AND COMPLEMENTARY ROLE OF SPLIT-SCRs ON DEBT PRICING

7.1 Introduction

It is common for a rated country to seek a 2nd or even 3rd opinion on its' creditworthiness from competing credit rating agencies (CRAs). Although there are more than a handful of US SEC certified CRAs, the go-to CRAs are Moody's, S&P, and Fitch. By the NRSRO report[29], these three CRAs have a combined market share of 99% in rating government debts. It is also common for countries rated by more than one of the three leading CRAs to be assigned with varying sovereign credit rating notches or split-SCRs. Based on the latest list of rated countries (see Section 2.4.3 of Chapter 2), 65% of the total 159 rated countries are rated by all three CRAs: Moody's, S&P, and Fitch. Amongst this 65% multi-rated countries, 55 countries are rated with one SCR notch different, and another 14 countries are rated with at least two notches different.

In other words, 67% of countries rated by all three CRAs are having split-SCRs. Countries rated with split-SCRs are equivalent to having multiple creditworthiness profiles, which is a dilemma to the rated countries and institutional investors. On one hand, the rated countries would argue in favour of the SCR notch that conveys a better credit profile, therefore, led to lower borrowing costs. On the other hand, the institutional investors would lean on a lower SCR notch and press for a higher expected risk premium to compensate for the higher default risk. The dilemma of split-SCRs would have amplified if the SCR notches fall in between the investment-grade category (i.e., Aaa/AAA to Baa/BBB) and the speculative-grade category (i.e., Ba/BB and lower). This is because

[29] Based on annual report on Nationally Recognized Statistical Rating Organizations dated December 2016 from U.S. Securities and Exchange Commission.

the speculative-grade rated countries do not have the same access to funds as compared to investment-grade rated countries.

In this chapter, the empirical study will focus on the dilemma of split-SCRs of investment-grade rated countries in debts price discovery. By studying the split-SCRs in the context of information theory (Shannon, 1948), the varying SCR notches issued by competing CRAs could be treated as the noise source that causes ambiguity to the message regarding the creditworthiness profile of rated countries. In practice, the agreed debt pricing would be a trade-off between a higher SCR notch versus a lower SCR notch. The application of this trade-off is straightforward when there are only two varying SCR notches from two competing CRAs. The trade-off becomes complicated when there are more than two varying SCR notches.

In earlier studies (Badaoui et al., 2013; Cantor & Packer, 1996; Reusens & Croux, 2017; Rowland, 2004), the average approach was adopted to address the split-SCRs. The presumption in the average approach is that the financial market weighs SCRs information values issued by Moody's, S&P, and Fitch equally. The equality presumption may be far from the actual market practice. The point of contention is not the approach but the presumption of equality on SCRs information value amongst the three leading CRAs, and the presumption that all SCRs issued by competing CRAs were priced evenly. This chapter is aimed to address this research gap by examining how the financial market weighs the SCRs information value in the presence of split-SCRs issued by three competing CRAs, and whether they are indeed priced in evenly.

The structure of this chapter is as follows. The next section describes data and empirical models adopted for this study. The empirical estimates are reported in Section 7.3. The ensuing section focuses on the analysis and discussion. This chapter will then be concluded with a summary of empirical findings and inferences.

7.2 Data and Models

The empirical study on split-SCRs information value will employ the sovereign credit default swap spreads (SCDSs) as the dependent variable. This is because the sovereign credit ratings (SCRs) information value was irrelevant in sovereign bond yields (SBYs) price discovery (see Chapter 6). The SCDSs lineage to SBYs, their reference entities, enables the transmission of SCRs information value from SBYs to SCDSs. Therefore, the SCDSs are selected as the viable alternative to SBYs.

While the lineage to SBYs is the reason the SCDSs are selected, the lineage is also the cause of concern. Given the SCDSs is the derivative instrument of SBYs, the SCRs information value could also become irrelevant in SCDSs price discovery. To address this specific concern, a few preliminary tests are carried out as follows.

7.2.1 Granger Causality Study

To ensure that SCDSs are indeed viable substitutes for SBYs, the panel VAR method on Granger causality is conducted for quick validation. The estimate presented in Table 7-1 shows that the null hypothesis is rejected at the 5% significant level. This means that SBYs Granger causes SCDSs. The SCDSs as viable substitutes for SBYs as the dependent variable for this study is validated.

Table 7-1: Granger Causality Test Result

Chi^2 statistic = 85.228**
H_0: SBYs do not Granger cause SCDSs

Note: Setting log_SBYs+2 of 32 selected countries as dependent variable and log_SCDSs of the same set of countries as the independent variable with 2 lags. p-Value = probability value. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

7.2.2SCRs Information Value on SCDSs Price Discovery Study

The next preliminary test is to determine whether SCRs exert significant information value in the pricing of SCDSs. Equation 4-10 (i.e., $y_{it} = \alpha + x_{CRAit} + v_{it}$) as specified in Section 4.4.3 in Chapter 4 is adapted with a small modification, by substituting y_{it} with SCDSs. The Hausman test rejected the null hypothesis that the random effect panel model is the appropriate model, hence, the estimates generated from fixed effect are used for validation. The estimates are presented in Table 7-2, and the results show that the estimated coefficients of SCRs of all three leading credit rating agencies (CRAs) are significant at the 5% level and with the expected negative sign in SCDSs price discovery.

Table 7-2: Panel Estimates of SCRs Information Value on SCDSs

	Fixed Effect (FE)	**Random Effect (RE)**	**Hausman Test Result**	
Explained Variable: *Log_SCDSs*				
Moody's SCRs	-0.042**	-0.113**	Chi^2	82.582**
	(0.012)	(0.009)		
$\boldsymbol{Adj.R^2}$	**0.542**	**0.103**		
S&P SCRs	-0.052**	-0.131**	Chi^2	50.862**
	(0.015)	(0.011)		
$\boldsymbol{Adj.R^2}$	**0.542**	**0.099**		
Fitch SCRs	-0.031*	-0.127**	Chi^2	68.316**
	(0.016)	(0.011)		
$\boldsymbol{Adj.R^2}$	**0.539**	**0.096**		

Note: The data points on SCRs by CRAs from Q1 2008 to Q4 2017 of 32 selected countries listed in Table 4-2 summed up to 1280 observations. Due to 28 missing data points on SCDSs, the total common observations were reduced to 1252. SCRs and SCDSs are sourced from Bloomberg. The estimation is based on the equation 4-10 in Section 4.4.3. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

7.2.3SCRs Pairing Consideration

It is established in Chapter 4 that the SCRs issued by three leading CRAs could be expressed as a function of publicly available information (PAI), non-disclosure-agreement obtained information (NDAI), and sovereign credit rating methodology (SCRM) components. In Chapter 5, the PAI component is empirically examined and the weight of NDAI and SCRM components is quantified for the first time. The NDAI and SCRM components are the essences of SCRs and the source of split-SCRs.

Despite their differences in contributing to split-SCRs, the alpha-numeric SCRs (i.e., Aaa, Aa1, Aa2, Aa3, etc.) and alpha-symbol SCRs (i.e., AAA, AA+, AA, AA-, etc.) are homogenous by the official definition on creditworthiness ranking (see Section 3.2 in Chapter 3). Once these SCR notches are converted into ordinal scales (see Table 4-3 in Section 4.5.2), it becomes even more difficult to differentiate the SCR's issuers. For instance, the Aaa issued by Moody's and AAA issued by S&P and Fitch will be assigned with 8 in broad ordinal scales or 21 in fine ordinal scales. This suggests that SCRs issued amongst the three leading CRAs are highly correlated in the econometric expedition.

To establish the SCRs correlation empirically, the Spearman rank-order correlation test (see Section 4.4.5 of Chapter 4) is adopted, and the results are summarized in Table 7-3. The results show that SCRs issued amongst the three leading CRAs are indeed highly correlated with correlation coefficients ranging from 94% to 96%. This means regressing on SCRs issued by any two or all three CRAs in the same estimator will lead to a multicollinearity issue.

Table 7-3: Spearman Rank Order Correlation on SCRs amongst Moody's, S&P, and Fitch

Observations		Moody's SCR	S&P SCR	Fitch SCR
2008 – 2017	**Moody's SCR**	-	0.94	0.96
	S&P SCR	0.94	-	0.96
	Fitch SCR	0.96	0.96	-

Note: The data points on SCRs by CRAs from Q1 2008 to Q4 2017 of 32 selected countries listed in Table 4-2 summed up to 1280 observations. Since the SCDSs are not part of this regression there is no loss of data points, the total common observations maintained at 1280. SCRs are sourced from Bloomberg.

On the other hand, it is also flaw to assume that SCRs from one of the three CRAs to be equitable to SCRs issued by the other two CRAs based on near-perfect correlation. By doing so, the estimates may succumb to the potential of selection bias. This is because 67% of multi-rated countries are assigned with split-SCRs, which mean the SCRs amongst these CRAs are different.

To tackle both multicollinearity and selection bias issues, the SCRs issued amongst the three CRAs are paired using the same arithmetic average approach employed in previous studies (Afonso et al., 2011; Alsakka & Gwilym, 2010a; Cantor & Packer, 1996). Unlike those studies, this study will examine the pairing of SCRs issued by any two of the three CRAs and the pairing of SCRs issued by all three CRAs in SCDSs price discovery. The vector of SCRs is summarized in Table 7-4.

Table 7-4: Vector of SCRs

SCRs Pairs	Description
Moody's SCRs	The alpha-numeric SCRs issued by Moody's in the form of fine ordinal scale
S&P SCRs	The alpha-symbol SCRs issued by S&P in the form of fine ordinal scale
Fitch SCRs	The alpha-symbol SCRs issued by Fitch in the form of fine ordinal scale
Moody's_S&P SCRs	This is derived from the average of SCRs issued by Moody's and S&P in the form of fine ordinal scales
Moody's_Fitch SCRs	This is derived from the average of SCRs issued by Moody's and Fitch in the form of fine ordinal scales
S&P_Fitch SCRs	This is derived from the average of SCRs issued by S&P and Fitch in the form of fine ordinal scales
Average SCRs	This is derived from the average of SCRs issued by the three CRAs in the form of fine ordinal scales

Note: The SCR ordinal scale transformation on both alpha-numeric and alpha-symbol SCRs is based on the fine-scale convention defined in Table 4-3 in Chapter 4.

It is important to highlight that this empirical study focuses on the assigned SCR notches instead of the SCR notches in transition such as those reported in credit outlook or credit watchlist. Undeniably, the inclusion of credit outlook and watchlist increases the dynamics of ordinal scales of SCRs that stimulate more pricing activities as reported in earlier studies (Binici & Hutchison, 2018; Sy, 2002; Vu, Alsakka, & Gwilym, 2015). Based on the SCRs synthesis (see Chapter 3), the default rates and the migration rate are measured by SCR cohorts. The SCR cohorts are the broad SCR notches (i.e., Aaa/AAA, Aa/AA, A/A, Baa/BBB, etc.). The modifiers (i.e., 1, 2, and 3 adopted by Moody's, and the "+" and "-" adopted by S&P and Fitch) are stability mechanisms added by respective CRAs to smoothen the migration rate.

The credit outlook and credit watchlist are the latest addition for CRAs to provide the financial market with SCRs surveillance updates. Indeed, the likelihood of rated countries listed in the credit watchlist being downgraded was high as compared to those listed in the credit outlook. However, the occurrence of actual SCR downgrades in those countries was not immediate. Those listed in the credit outlook will have a grace period of 12 to 24 months as compared to those listed in the credit watchlist are with a shorter grade period of 6 to 12 months before the assigned SCR notches are changed: downgraded or upgraded. Since SCRs upgrades and downgrades are not the emphases of this empirical study, we reckon it is not necessary to increase the dynamic of SCRs scales and inherent the speculative noises in the sample. The adoption of fine ordinal scaled SCRs should suffice to serve the purpose of this study.

7.2.4Data and Models

Without the data constraint of economic variables that are only available annually, this empirical study will employ quarterly data from Q1 2008 to Q4 2017 for the same sample of 32 countries listed in Table 4-2. The descriptive statistics of the dataset are presented in Table 7-5.

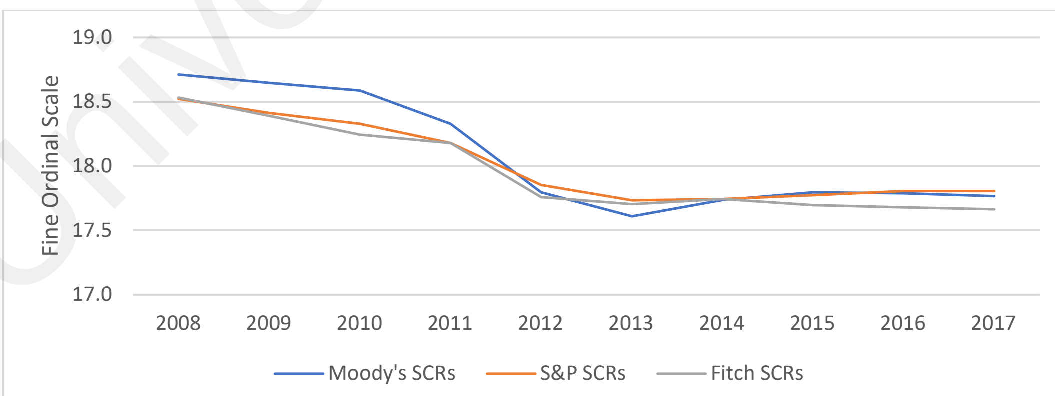
Table 7-5: Descriptive Statistics of Dependent and Independent Variables

	SCDSs	Log_ SCDSs	Moody's SCRs	S&P SCRs	Fitch SCRs	Moody's_ S&P SCRs	Moody's_ Fitch SCRs	S&P_ Fitch SCRs	Avg. SCRs
Mean	93.36	4.20	18.06	18.01	17.95	18.03	18.00	17.98	18.00
Median	68.29	4.22	19.00	19.00	18.00	18.50	18.50	18.50	18.67
Maximum	753.95	6.63	21.00	21.00	21.00	21.00	21.00	21.00	21.00
Minimum	7.00	1.95	11.00	11.00	12.00	12.00	12.00	11.50	12.00
Std. Dev.	90.17	0.82	3.00	2.87	2.88	2.90	2.91	2.86	2.88
Skewness	2.90	0.12	-0.59	-0.53	-0.42	-0.52	-0.47	-0.46	-0.48
Kurtosis	15.12	2.70	2.04	2.01	1.82	1.87	1.82	1.88	1.83
Obs.	1252	1252	1252	1252	1252	1252	1252	1252	1252

Note: The observations are gathered from the list of 32 countries presented in Table 4-2 on quarterly internal spanning Q1 2008 to Q4 2017, predominantly from Bloomberg. Due to missing data points on SCDSs, the total common observations for this empirical study are 1252. Std. Dev = Standard Deviation, Avg. SCRs = Average SCRs, and Obs. = Observation

The empirical regression will be performed on the full dataset and subsequently on two sub-periods. Sub-period1 constitutes of observations from Q1 2008 to Q4 2011, and sub-period2 covers observations spanning from Q1 2012 to Q4 2017. The cut-off point between the two sub-periods is determined by the divergence and convergence of SCRs amongst the three leading CRAs. These can be observed from the mean SCRs trends by CRAs as depicted in Figure 7-1.

Figure 7-1: Mean SCRs Notch by CRAs



Note: The mean SCR notch is the average SCRs of the 32 selected countries defined in Table 4-2 in Chapter 4. The SCRs are converted into fine ordinal scale following the convention defined in Table 4-3 in Chapter 4.

Our view on SCRs divergence and convergence is consistent with earlier studies where divergence leads to greater ambiguity and convergence leads to greater clarity in SCRs information value (Abad et al., 2018; Cantor et al., 1997; Hill et al., 2010; Vu et al., 2015). Assessing in the context of information theory, the split-SCRs with greater divergence amongst the CRAs contribute to mixed messages. Whereas the convergence of split-SCRs contributes to greater clarity on the transmitted message. Hence, sub-period1 will examine the split-SCRs information value with greater ambiguity in explaining SCDSs. For split-SCRs in sub-period2, the converged SCRs information value should carry greater weight in explaining SCDSs pricing.

The full dataset and two sub-periods will be regressed using panel models as specified in Equation 4-10 (see Section 4.4.3) is adopted with some modifications. The dependent variable is substituted with the SCDSs, and the independent variables constitute the vector of standalone SCRs by CRAs and paired SCRs as listed in Table 7-4. The Hausman test will also be conducted to determine the appropriateness of these two models.

To account for the non-credit risk component in SCDSs structure, the SCDSs in lagged term is used as the proxy for the component, following the same practice adopted in earlier studies (Aizenman et al., 2009; Aizenman et al., 2013; Dieckman & Plank, 2012; Eyssell et al., 2013; Longstaff et al., 2011). With lagged SCDSs as the additional regressor, the panel models are not appropriate to handle the endogenous variable. Therefore, the generalized method of moments (GMM) is adopted to overcome the endogeneity issue presented by the lagged SCDSs. The dynamic panel model specified in Equations 4-12 (see Section 4.4.6 in Chapter 4) will be estimated. Specifically, the GMM settings will follow the first differencing generalized method of moments (FD-GMM) advocated by Arellano and Bond (1991) and the forward orthogonal deviation generalized method of moments (FOD-GMM) advocated by Arellano and Bover (1995).

Both FD-GMM and FOD-GMM will be performed on the full dataset and the two sub-periods.

7.3 Empirical Results

The setup of this empirical study is to examine the going concern of split-SCRs, the **noise source**, on SCRs information value, the **message**, in the pricing of SCDSs, the **destination**, under the information theory advocated by Shannon (1948). The empirical estimates consist of three parts. In the first part, the estimates are derived from the full dataset. The estimates from divergence split-SCRs or sub-period1 are the second part, and the last part is focusing on estimates derived from sub-period2. The results are presented in the following sub-sections.

7.3.1 Full Dataset Estimates

Estimates derived from the full dataset are presented as follows. The fixed effect and random effect estimates are reported in Table 7-6. The estimates derived using the first differencing generalized method of moments (FD-GMM) are reported in Table 7-7. The forward orthogonal deviation generalized method of moments (FOD-GMM) are compiled in Table 7-8.

The estimated coefficients of SCRs by respective CRAs are reported under panel A to panel C, and the paired SCRs are reported under panel D to panel G. All estimated coefficients of SCRs derived using panel fixed effect (FE) and random effect (RE) are significant at 5% level and with the expected negative sign. This means the SCRs information value in SCDSs price discovery was significant and the results are unanimous on SCRs by CRAs and the paired SCRs. Between panel FE and panel RE models, the

Hausman test results have ruled out panel RE as the appropriate panel model. Therefore, the estimates from panel FE models will be used in the discussion. The panel FE models' explanatory powers are at 54% on all panels. This suggests that none of the three leading CRAs demonstrated superior SCRs information value over the others.

The robustness of the results is checked further. The panel FE estimated coefficients of SCRs on all panels remain robust with control imposed on time-variant variables (see Appendix 4, Table A4-7). When White Cross-Section robust standard errors are used, all the estimated coefficients of SCRs are with the expected negative sign but statistically insignificant (see Appendix 4, Table A4-8). With White Period robust standard errors, there are mixed results (see Appendix 4, Table A4-9). This means the Panel FE estimates on the full dataset are not robust due to heteroscedasticity.

The FD-GMM estimated coefficients of SCRs are most significant at the 5% level (Table 7.7). However, the estimated coefficients of SCRs are not with the expected negative sign, which renders them irrelevant. This is because the positive sign is not aligned with the risk-reward pricing convention (see Section 2.2 in Chapter 2). Moreover, the Arellano-Bond serial correlation test shows that estimates could be biased due to negative serial correlation as reported in Table 7-7. Although the estimated coefficients of SCRs remain consistent and not bias, the statistical significance in AR(2) indicated that the standard errors of the coefficients are biased.

When cross-referenced with estimates from FOD-GMM as reported in Table 7-8, the estimated coefficients of SCRs by CRAs and paired SCRs are all significant at a 5% level but do not have the expected negative sign. Since FOD-GMM is more efficient compared with FD-GMM (Arellano & Bover, 1995; Hayakawa, 2009; Hsiao & Zhou, 2017), and the results are qualitatively similar, both FD-GMM and FOD-GMM estimates indicate that SCRs information value is irrelevant in SCDSs price discovery.

Table 7-6: Panel Estimates on Full Dataset

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
			Fixed Effect (FE)				
Moody's SCRs	-0.042**						
	(0.012)						
S&P SCRs		-0.052**					
		(0.015)					
Fitch SCRs			-0.031**				
			(0.016)				
Moody's_S&P SCRs				-0.050**			
				(0.014)			
Moody's_Fitch SCRs					-0.041**		
					(0.014)		
S&P_Fitch SCRs						-0.045**	
						(0.016)	
Average SCRs							-0.046**
							(0.015)
$Adj.R^2$	**0.542**	**0.542**	**0.539**	**0.542**	**0.540**	**0.540**	**0.541**
			Random Effect (RE)				
Moody's SCRs	-0.113**						
	(0.009)						
S&P SCRs		-0.131**					
		(0.011)					
Fitch SCRs			-0.127**				
			(0.011)				
Moody's_S&P SCRs				-0.132**			
				(0.010)			
Moody's_Fitch SCRs					-0.127**		
					(0.010)		
S&P_Fitch SCRs						-0.135**	
						(0.011)	
Average SCRs							-0.134**
							(0.010)
$Adj.R^2$	**0.103**	**0.099**	**0.096**	**0.118**	**0.113**	**0.105**	**0.117**
			Hausman Test				
Chi^2	82.582**	50.862**	68.316**	67.753**	76.537**	57.780**	67.059**

Note: On vector of SCRs, please refers to Table 7-4 for description. Coef. = coefficient, Std. Error = standard error, p-Value = probability value. Full-dataset constitutes of observations from Q12008 to Q42017 of 32 selected countries listed in Table 4-2. The estimation is based on the equation 4-10 in Section 4.4.3. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Table 7-7: FD-GMM Estimates on Full Dataset

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
Periods:		38					
Cross-Sections:		32					
Dependent Variable:		log(SCDSs)					
Instrument Variable:		log(SCDSs(-2))					
First Difference Transformation							
log(SCDSs(-1))	0.831**	0.829**	0.824**	0.824**	0.829**	0.828**	0.827**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
Moody's SCRs	0.069*						
	(0.032)						
S&P SCRs		0.075					
		(0.060)					
Fitch SCRs			0.085**				
			(0.008)				
Moody's_S&P SCRs				0.085**			
				(0.008)			
Moody's_Fitch SCRs					0.095		
					(0.070)		
S&P_Fitch SCRs						0.081**	
						(0.024)	
Average SCRs							0.087**
							(0.017)
SSR	192.086	192.822	191.974	191.974	192.066	191.923	192.232
Instrument Rank	32	32	32	32	32	32	32
J-Stat	31.890	31.957	31.97239	31.972	31.859	31.888	31.964
Arellano-Bond Serial Correlation Test							
AR(1)	-5.160**	-5.181**	-5.191**	-5.146**	-5.175**	-5.189**	-5.177**
AR(2)	-4.094**	-4.086**	-4.083**	-4.067**	-4.099**	-4.077**	-4.091**

Note: Total observation is 1186 on all panels. Coef. = coefficient, Std. Error = standard error, p-Value = probability value, SSR = sum squared residuals and J-Stat. = J statistic. The J-Stat. and p-Value on J-Stat. are meant to determine the status of identification by the Sargan statistics. AR = Autocorrelation, (1) indicates first order and (2) the second-order tests. The estimation is based on the equation 4-12 in Section 4.4.6. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Table 7-8: FOD-GMM Estimates on Full Dataset

	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
Periods:	38						
Cross-Sections:	32						
Dependent Variable:	log(SCDSs)						
Instrument Variable:	log(SCDSs(-2))						
Forward Orthogonal Deviation Transformation							
log(SCDSs(-1))	0.829**	0.827**	0.822**	0.828**	0.826**	0.824**	0.826**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Moody's SCRs	0.061**						
	(0.002)						
S&P SCRs		0.076**					
		(0.005)					
Fitch SCRs			0.085**				
			(0.004)				
Moody's_S&P SCRs				0.074**			
				(0.003)			
Moody's_Fitch SCRs					0.075**		
					(0.003)		
S&P_Fitch SCRs						0.086**	
						(0.004)	
Average SCRs							0.080**
							(0.004)
SSR	117.863	117.879	118.051	117.989	118.084	118.032	118.081
Instrument Rank	32	32	32	32	32	32	32
J-Stat	31.939	31.924	31.912	31.949	31.937	31.931	31.942

Note: Total observation is consistent at 1186 on all panels. Coef. = coefficient, Std. Error = standard error, p-Value = probability value, SSR = sum squared residuals and J-Stat. = J statistic. The J-Stat. and p-Value on J-Stat. are meant to determine the status of identification by the Sargan statistics. The estimation is based on the equation 4-12 in Section 4.4.6. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

7.3.2Sub-period 1 Estimates

The panel FE and RE estimates based on divergence split-SCRs or sub-period1 are reported in Table 7-9. The Hausman test results have rejected the panel RE model as the most appropriate method for all panels, except Panel H. Despite this exception, the estimated coefficients of SCRs by CRAs and paired SCRs are significant at a 5% level and are with the expected negative sign. When the control is imposed on the time-variant variable, the results remain robust (see Appendix 4, Table A4-7). In addition, when White Cross-Section and Period robust standard errors are used individually, the panel FE estimated coefficients of SCRs remain robust on all SCRs by CRAs and paired SCRs (see Appendix 4, A4-8, and A4-9).

Table 7-9: Panel Estimates on Sub-period 1

	Panel H	Panel I	Panel J	Panel K	Panel L	Panel M	Panel N
Fixed Effect (FE)							
Moody's SCRs	-0.243**						
	(0.032)						
S&P SCRs		-0.307**					
		(0.043)					
Fitch SCRs			-0.288**				
			(0.045)				
Moody's_S&P SCRs				-0.298**			
				(0.038)			
Moody's_Fitch SCRs					-0.291**		
					(0.039)		
S&P_Fitch SCRs						-0.325**	
						(0.046)	
Average SCRs							-0.314**
							(0.041)
$Adj.R^2$	**0.550**	**0.543**	**0.534**	**0.552**	**0.548**	**0.543**	**0.550**
Random Effect (RE)							
Moody's SCRs	-0.207**						
	(0.019)						
S&P SCRs		-0.214**					
		(0.020)					
Fitch SCRs			-0.204**				
			(0.020)				
Moody's_S&P SCRs				-0.219**			
				(0.020)			
Moody's_Fitch SCRs					-0.213**		
					(0.020)		
S&P_Fitch SCRs						-0.214**	
						(0.020)	
Average SCRs							-0.218**
							(0.020)
$Adj.R^2$	**0.192**	**0.194**	**0.172**	**0.202**	**0.189**	**0.188**	**0.195**
Hausman Test							
Chi^2	2.083	5.817*	4.528*	5.886*	5.507**	7.339**	7.242**

Note: On vector of SCRs, please refers to Table 7-4 for description. Coef. = coefficient, Std. Error = standard error, p-Value = probability value. Full-dataset constitutes of observations from Q12008 to Q42017 of 32 selected countries listed in Table 4-2. The estimation is based on the equation 4-10 in Section 4.4.3. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Regarding FD-GMM estimates, all the estimated coefficients of SCRs are significant at a 5% level and have the expected negative sign as reported in Table 7-10. However, the second-order autocorrelation test continues to report serial correlation in the errors. This means inference based on FD-GMM estimates could be biased due to negative serial correlation.

Table 7-10: FD-GMM Estimates on Sub-Period 1

	Panel H	Panel I	Panel J	Panel K	Panel L	Panel M	Panel N
Periods:		14					
Cross-Sections:		32					
Dependent Variable:		log(SCDSs)					
Instrument Variable:		log(SCDSs(-2))					
First Difference Transformation							
log(SCDSs(-1))	0.525**	0.555**	0.519**	0.530**	0.509**	0.530**	0.517**
	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)	(0.003)	(0.007)
Moody's SCRs	-0.242**						
	(0.026)						
S&P SCRs		-0.161**					
		(0.054)					
Fitch SCRs			-0.404**				
			(0.005)				
Moody's_S&P SCRs				-0.247**			
				(0.039)			
Moody's_Fitch SCRs					-0.402**		
					(0.021)		
S&P_Fitch SCRs						-0.320**	
						(0.023)	
Average SCRs							-0.355**
							(0.016)
SSR	105.555	102.823	104.319	103.202	106.139	102.230	103.473
Instrument Rank	32	32	32	32	32	32	32
J-Stat	31.732	31.915	31.964	31.745	31.917	31.999	31.931
Arellano-Bond Serial Correlation Test							
AR(1)	-4.032**	-4.279**	-4.081**	-4.183**	-3.977**	-4.060**	-4.011**
AR(2)	-3.049**	-3.205**	-3.203**	-3.163**	-3.183**	-3.245**	-3.215**

Note: Total observation is consistent at 418 on all panels. Coef. = coefficient, Std. Error = standard error, p-Value = probability value, SSR = sum squared residuals and J-Stat. = J statistic. The J-Stat. and p-Value on J-Stat. are meant to determine the status of identification by the Sargan statistic. AR = Autocorrelation, (1) indicates first order and (2) the second-order tests. The estimation is based on the equation 4-12 in Section 4.4.6. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

The FOD-GMM estimates reported in Table 7-11 show that the outcome on estimated coefficients of SCRs generated from FD-GMM remains robust. All estimated coefficients of SCRs produced by FOD-GMM are also significant at a 5% level and with the expected negative sign.

Since the FD-GMM regression method is ruled out due to serial correlation findings, the remaining elimination process is to select the estimates between the panel FE and FOD-GMM for further analysis and discussion. The estimates produced by FOD-GMM are preferred because the model is better specified, the serial correlation is neutralized through its transformation method, and the endogeneity issue is also handled.

Table 7-11: FOD-GMM Estimates on Sub-period 1

	Panel H	Panel I	Panel J	Panel K	Panel L	Panel M	Panel N
Periods:	14						
Cross-Sections:	32						
Dependent Variable:	log(SCDSs)						
Instrument Variable:	log(SCDSs(-2))						
Forward Orthogonal Deviation Transformation							
log(SCDSs(-1))	0.549**	0.581**	0.558**	0.556**	0.538**	0.563**	0.548**
	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Moody's SCRs	-0.254**						
	(0.016)						
S&P SCRs		-0.139**					
		(0.010)					
Fitch SCRs			-0.342**				
			(0.027)				
Moody's_S&P SCRs				-0.256**			
				(0.014)			
Moody's_Fitch SCRs					-0.386**		
					(0.032)		
S&P_Fitch SCRs						-0.281**	
						(0.018)	
Average SCRs							-0.337**
							(0.022)
SSR	80.058	72.196	81.831	76.667	88.100	76.667	81.228
Instrument Rank	32	32	32	32	32	32	32
J-Stat	31.946	31.950	31.869	31.895	31.924	31.886	31.864

Note: Total observation is consistent at 418 on all panels. Coef. = coefficient, Std. Error = standard error, p-Value = probability value, SSR = sum squared residuals and J-Stat. = J statistic. The J-Stat. and p-Value on J-Stat. are meant to determine the status of identification by the Sargan statistics. The estimation is based on the equation 4-12 in Section 4.4.6. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

7.3.3Sub-period 2 Estimates

With converged split-SCRs or sub-period2, the panel FE and RE estimates are reported in Table 7-12. The Hausman test results continue to endorse panel FE as the most appropriate panel model. Based on the panel FE estimates, only estimates from Panel P and Panel R are significant at a 5% level and with the expected negative sign. The SCRs regressor in Panel P is issued by, and the SCRs regressor in Panel R is the paired SCRs issued by Moody's and S&P.

When the control is imposed on time-variant variables, most of the panel FE estimates are significant at 5% level and with the negative sign, except the estimates under Panels C and D. The SCRs regressor in Panel C are issued by Fitch, and the estimated coefficient of SCRs is with positive sign and statistically insignificant. The SCRs regressor in Panel D is the paired SCRs issued by Moody's and Fitch, and the estimated coefficient of SCRs is with the expected negative sign but only significant at 10% level (see Appendix, Table 4-7).

When the panel FE models are regressed with White Cross-Section and Period robust standard errors, respectively, the estimates coefficients of SCRs of all panels are statistically insignificant (see Appendix, Table A4- 8, and A4- 9). This means the panel FE estimates are not robust.

Based on Table 7-13, the FD-GMM estimates of sub-period 2 show that all estimated coefficients of SCRs are significant at a 5% level but are not with the expected negative sign. Without the expected negative sign, the estimated coefficients of SCRs even though significant are considered irrelevant due to the violation of the risk-reward pricing convention (see Section 2.2 in Chapter 2). Moreover, the FD-GMM estimates continue to exhibit second-order serial correlation in standard errors. This means the estimates are inconsistent for inferences.

Table 7-12: Panel Estimates on Sub-period 2

	Panel O	Panel P	Panel Q	Panel R	Panel S	Panel T	Panel U
				Fixed Effect (FE)			
Moody's SCRs	-0.055 (0.031)						
S&P SCRs		-0.062* (0.029)					
Fitch SCRs			0.049 (0.038)				
Moody's_S&P SCRs				-0.071* (0.034)			
Moody's_Fitch SCRs					-0.016 (0.038)		
S&P_Fitch SCRs						-0.025 (0.037)	
Average SCRs							-0.043 (0.037)
$Adj. R^2$	**0.663**	**0.663**	**0.662**	**0.663**	**0.661**	**0.661**	**0.662**
				Random Effect (RE)			
Moody's SCRs	-0.169** (0.013)						
S&P SCRs		-0.172** (0.014)					
Fitch SCRs			-0.180** (0.013)				
Moody's_S&P SCRs				-0.184** (0.013)			
Moody's_Fitch SCRs					-0.184** (0.012)		
S&P_Fitch SCRs						-0.185** (0.013)	
Average SCRs							-0.188** (0.013)
$Adj. R^2$	**0.182**	**0.165**	**0.199**	**0.212**	**0.220**	**0.198**	**0.222**
				Hausman Test			
Chi^2	16.371**	18.055**	40.224**	13.248**	22.331**	21.595**	17.041**

Note: On vector of SCRs, please refers to Table 7-4 for description. Coef. = coefficient, Std. Error = standard error, p-Value = probability value. Full-dataset constitutes of observations from Q12008 to Q42017 of 32 selected countries listed in Table 4-2. The estimation is based on the equation 4-10 in Section 4.4.3. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Table 7-13: FD-GMM Estimates on Sub-period 2

	Panel O	Panel P	Panel Q	Panel R	Panel S	Panel T	Panel U
Periods:	24						
Cross-Sections:	32						
Dependent Variable:	log(SCDSs)						
Instrument Variable:	log(SCDSs(-2))						
First Difference Transformation							
log(SCDSs(-1))	0.874**	0.871**	0.867**	0.873**	0.871**	0.870**	0.871**
	(0.012)	(0.015)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
Moody's SCRs	0.038**						
	(0.012)						
S&P SCRs		0.031**					
		(0.011)					
Fitch SCRs			0.058**				
			(0.005)				
Moody's_S&P SCRs				0.040**			
				(0.011)			
Moody's_Fitch SCRs					0.052**		
					(0.008)		
S&P_Fitch SCRs						0.049**	
						(0.008)	
Average SCRs							0.049**
							(0.009)
SSR	64.112	64.046	63.721	64.070	63.906	63.935	63.969
Instrument Rank	32	32	32	32	32	32	32
J-Stat	31.846	31.811	31.842	31.822	31.840	31.832	31.831
Arellano-Bond Serial Correlation Test							
AR(1)	-5.188**	-5.190**	-5.177**	-5.188**	-5.181**	-5.189**	-5.186**
AR(2)	-2.999**	-3.031**	-3.036**	-3.024**	-3.019**	-3.045**	-3.033**

Note: Total observation is consistent at 768 on all panels. Coef. = coefficient, Std. Error = standard error, p-Value = probability value, SSR = sum squared residuals and J-Stat. = J statistic. The J-Stat. and p-Value on J-Stat. are meant to determine the status of identification by the Sargan statistics. AR = Autocorrelation, (1) indicates first order and (2) the second-order tests. The estimation is based on the equation 4-12 in Section 4.4.6. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Table 7-14: FOD-GMM Estimates on Sub-period 2

	Panel O	Panel P	Panel Q	Panel R	Panel S	Panel T	Panel U
Periods:	24						
Cross-Sections:	32						
Dependent Variable:	log(SCDSs)						
Instrument Variable:	log(SCDSs(-2))						
Forward Orthogonal Deviation Transformation							
log(SCDSs(-1))	0.877**	0.876**	0.871**	0.876**	0.874**	0.873**	0.874**
	(0.000)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Moody's SCRs	0.033**						
	(0.003)						
S&P SCRs		0.026**					
		(0.003)					
Fitch SCRs			0.057**				
			(0.000)				
Moody's_S&P SCRs				0.034**			
				(0.003)			
Moody's_Fitch SCRs					0.048**		
					(0.001)		
S&P_Fitch SCRs						0.045**	
						(0.001)	
Average SCRs							0.045**
							(0.001)
SSR	30.417	30.508	30.348	30.435	30.341	30.411	30.384
Instrument Rank	33	32	32	32	32	32	32
J-Stat	25.812	30.823	31.057	31.026	30.908	30.842	30.884

Note: Total observation is consistent at 768 on all panels. Coef. = coefficient, Std. Error = standard error, p-Value = probability value, SSR = sum squared residuals and J-Stat. = J statistic. The J-Stat. and p-Value on J-Stat. are meant to determine the status of identification by the Sargan statistics. The estimation is based on the equation 4-12 in Section 4.4.6. The standard errors are presented in parentheses, and * indicates 5% and ** indicates 1% significance levels.

Not all are lost, the FOD-GMM estimates as reported in Table 7-14 also show that the estimated coefficients of SCRs of all panels are significant at 5% level and without the expected negative sign. Given that the empirical model is better specified in the dynamic panel model as compared to the panel FE model, and FOD-GMM has better econometric properties as compared to FD-GMM, this means the FOD-GMM estimates are more efficient.

7.4 Discussion

Although the Hausman test results indicated that panel FE models are better suited as compared to panel RE models on full and two sub-periods, only panel FE estimates derived from sub-period1 are consistent. When the same three datasets are regressed using the dynamic panel models, where the non-credit risk component is specified, the results also show that only estimated coefficients of SCRs by CRAs and paired SCRs from sub-period1 are significant at 5% level and with the expected negative sign. The discussions are elaborated as follows.

7.4.1 Full Dataset

The panel FE estimates reported in Table 7-6, FD-GMM estimates in Table 7-7, and FOD-GMM estimates in Table 7-8 are summarized in Table 7-15 for ease of reference.

Referring to Table 7-15, all panel FE estimated coefficients of SCRs are significant at 5% level and with the expected negative sign. The 54% adjusted R^2 on all panels indicates that SCRs by CRAs and paired SCRs conveying the same information value in explaining SCDSs. When cross-referencing with estimates from FD-GMM and FOD-GMM[30], not all estimated coefficients are significant at the 5% level or with the expected negative sign. On FD-GMM estimates, there are mixtures of significant and insignificant estimates among the SCRs regressors. However, all estimates are without the expected negative

[30] Given the dynamic panel model is better specified as compared to panel FE model, the estimates from GMM, especially estimates from FOD-GMM, are more reliable. This is because both the endogeneity and serial correlation issues are addressed using the method.

sign. The estimates from FOD-GMM show that all estimated coefficients are significant at a 5% level and without the expected negative sign. The positive sign on estimated coefficients of SCRs means the SCRs information value is not priced accordingly, which invalidate the significance of the SCRs regressor in SCDSs price discovery.

Table 7-15: Significance and Sign Comparison on Standalone SCRs and Paired SCRs - Full Dataset

		Panel	**FD-GMM**	**FOD-GMM**
Moody's SCRs	Significant	Yes	Yes	Yes
	Sign	-	+	+
	$\boldsymbol{Adj.R^2}$/SSR	54%	192	118
S&P SCRs	Significant	Yes	No	Yes
	Sign	-	+	+
	$\boldsymbol{Adj.R^2}$/SSR	54%	193	118
Fitch SCRs	Significant	Yes	Yes	Yes
	Sign	-	+	+
	$\boldsymbol{Adj.R^2}$/SSR	54%	192	118
Moody's_S&P SCRs	Significant	Yes	Yes	Yes
	Sign	-	+	+
	$\boldsymbol{Adj.R^2}$/SSR	54%	192	118
Moody's _Fitch SCRs	Significant	Yes	No	Yes
	Sign	-	+	+
	$\boldsymbol{Adj.R^2}$/SSR	54%	192	118
S&P_Fitch SCRs	Significant	Yes	Yes	Yes
	Sign	-	+	+
	$\boldsymbol{Adj.R^2}$/SSR	54%	192	118
Avg._SCRs	Significant	Yes	Yes	Yes
	Sign	-	+	+
	$\boldsymbol{Adj.R^2}$/SSR	54%	192	118

Note: The row labelled as 'Significant' refers to whether the estimated coefficients are significant, where Yes denotes significance at 5% level, and No denotes not significant. The * indicates that the estimate is significant at the 10% level. The Sign denotes the positive and negative signs of the estimated coefficients. The $Adj.R^2$ = adjusted R-squared on panel model, the SSR = sum of squared residuals on FD-GMM and FOD-GMM. The results on the fixed effect panel are sourced from Table 7-6, results from FD-GMM are sourced from Table 7-7, and those on FOD-GMM are sourced from Table 7-8.

The results from panel FE could be due to under specification, where the non-credit risk component is not specified. In the dynamic panel models, where the non-credit risk component is specified, the sign of estimated coefficients of SCRs changed from negative sign on the panel FE estimates to positive sign on FD-GMM and FOD-GMM estimates.

Given the FOD-GMM has better econometric properties as compared to FD-GMM, and the estimator is better specified as compared to the panel FE model, the FOD-GMM estimates are more efficient. This means the SCRs by CRAs and paired SCRs were irrelevant in SCDSs pricing.

7.4.2Divergence and Convergence of SCRs Amongst CRAs

In sub-period1, where split-SCRs amongst the three leading CRAs were more apparent, the estimates produced by panel FE, FD-GMM, and FOD-GMM are consistent. All estimated coefficients of SCRs are significant at a 5% level and with the expected negative sign. This means the SCRs by CRAs and paired SCRs were relevant and significant in SCDSs price discovery, even though the message on rated countries' creditworthiness was lack clarity.

With regards to estimates from sub-period2, where the SCRs information value had greater clarity due to convergence of forward-looking opinions amongst the three leading CRAs on rated countries' creditworthiness, the results are mixed between panel FE estimates and estimates derived from FD-GMM and FOD-GMM. Although all panel FE estimates are with the expected negative sign, they are statistically insignificant. Whereas the estimates from FD-GMM and FOD-GMM are statistically significant but are not with the expected negative sign. Despite these technical differences in estimates, the outcome is unanimous. All estimated coefficients of SCRs by CRAs and paired SCRs were disregarded in SCDSs pricing from 2012 onwards, even though the message on SCRs information value had greater clarity.

The sign and significance of the estimates from sub-period1 and sub-period2 are summarized in Table 7-16 for ease of reference.

Table 7-16: Significance and Sign Comparison on Standalone SCRs and Paired SCRs on Sub-periods

		Sub-period1: SCRs Divergence			Sub-period2: SCRs Convergence		
		Panel	**FD-GMM**	**FOD-GMM**	**Panel**	**FD-GMM**	**FOD-GMM**
Moody's SCRs	Significant	Yes**	Yes	Yes	No	Yes	Yes
	Sign	-	-	-	-	+	+
	$Adj.R^2$/SSR	55%	106	80	66%	64	30
S&P SCRs	Significant	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	-	-	-	-	+	+
	$Adj.R^2$/SSR	54%	103	72	66%	64	31
Fitch SCRs	Significant	Yes	Yes	Yes	No	Yes	Yes
	Sign	-	-	-	+	+	+
	$Adj.R^2$/SSR	53%	104	82	66%	64	30
Moody's_S&P SCRs	Significant	Yes	Yes	Yes	Yes	Yes	Yes
	Sign	-	-	-	-	+	+
	$Adj.R^2$/SSR	55%	103	77	66%	64	30
Moody's _Fitch SCRs	Significant	Yes	Yes	Yes	No	Yes	Yes
	Sign	-	-	-	-	+	+
	$Adj.R^2$/SSR	55%	106	88	66%	64	30
S&P_Fitch SCRs	Significant	Yes	Yes	Yes	No	Yes	Yes
	Sign	-	-	-	-	+	+
	$Adj.R^2$/SSR	54%	102	77	66%	64	30
Avg._SCRs	Significant	Yes	Yes	Yes	No	Yes	Yes
	Sign	-	-	-	-	+	+
	$Adj.R^2$/SSR	55%	103	81	66%	64	30

Note: The row labelled as 'Significant' refers to whether the estimated coefficients are significant, where Yes denotes significance at 5% level, and No denotes not significant. The * indicates that the estimate is significant at a 10% level. The ** indicates Hausman test recommended random effect estimates but fixed effect estimates are reported here because the estimated coefficient is also significant and with the same negative sign and for ease of comparison among fixed effect estimates of all other models. The Sign denotes the positive and negative signs of the estimated coefficients. The $Adj.R^2$ = adjusted R-squared on panel model, the SSR = sum of squared residuals on FD-GMM and FOD-GMM. Under Sub-period1 Group, the results under the Panel column are results from fixed effect panel sourced from Table 7-9, results from FD-GMM are sourced from Table 7-10, and those on FOD-GMM are sourced from Table 7-11. Under Sub-period1 Group, the results under the Panel column are results from fixed effect panel sourced from Table 7-12, results from FD-GMM are sourced from Table 7-13, and those on FOD-GMM are sourced from Table 7-14 The results on fixed effect panel sourced from Table 7-9, results from FD-GMM are sourced from Table 7-10, and those on FOD-GMM are sourced from Table 7-11.

While SCRs information value was still significant and relevant in explaining SCDSs, which was from Q1 2008 to Q4 2011, the differences observed on models' explanatory power are negligible (see Table 7-9, 7-10, and 7-11). This means there is no strong evidence to support the claim of dominant SCRs amongst the three leading CRAs. However, the strength of the estimated coefficients of SCRs suggests that the financial market does price the SCRs information value by respective CRAs differently.

Based on FOD-GMM estimates in sub-period1 (see Table 7-11), the SCRs issued by Fitch had the highest influence on SCDSs pricing at -34.2%, followed by SCRs issued by Moody's at -25.4%, and SCRs issued by S&P had the least at -13.9%. When cross-referencing with paired SCRs, the pairing of SCRs issued by Moody's and Fitch has the highest influence among the SCRs by CRAs and paired SCRs at -38.6%. The strengths of the rest of the paired SCRs are above the strength of SCRs issued by Moody's but below the strength of SCRs issued by Fitch.

Few revelations can be deduced from this empirical experiment on the vector of SCRs. First, the empirical results concur that the financial market does not rely on a single CRA for SCRs information value in pricing. Second, it is a flaw to assume that the SCRs information value amongst the three leading CRAs is priced evenly, which is indicated in the strength of estimated coefficients among the SCRs regressors. Third, it is evident that the pairing of SCRs issued by Moody's and Fitch conveys the optimal SCRs information value and produces the highest complemented influence on SCDSs pricing.

This means the selection of SCRs by CRAs matters for studying SCRs information value in price discovery. Moreover, not all paired SCRs produce the highest complemented information value, some paired SCRs cannibalise and lead to lower SCRs information value (i.e., the pairing of SCRs issued by all three leading CRAs).

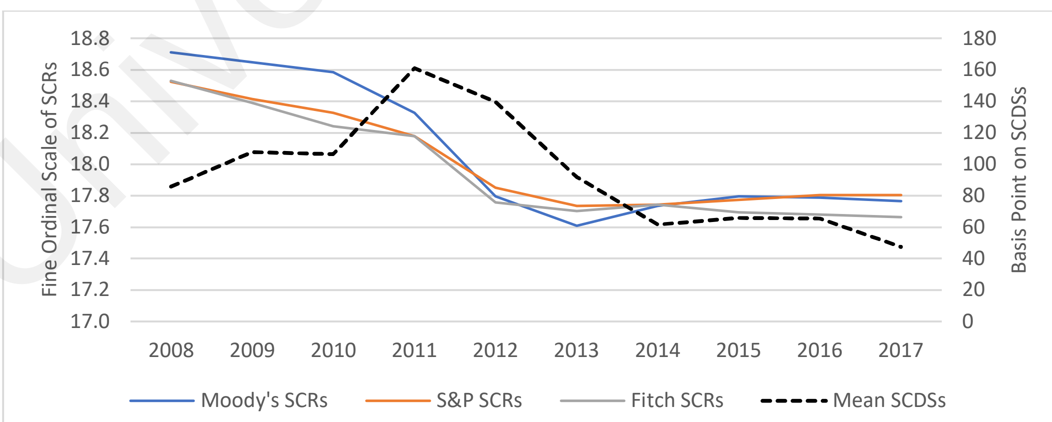
For estimates derived from sub-period2, all estimated coefficients of SCRs produced by FOD-GMM are with the positive sign, therefore, rendered SCRs information value irrelevant in SCDSs price discovery. Even if the condition on the estimates to have an expected negative sign for SCRs information value to be relevant is relaxed, the strength of the estimated coefficients of SCRs, regardless of CRAs, is significantly weakened. At 3 to 6% as compared to at least 33% and above in previous studies (Badaoui et al., 2013; Beber et al., 2009; Longstaff et al., 2011), the strength of the estimated coefficients of

SCRs would have suggested the same outcome. The SCRs information value is irrelevant in SCDSs price discovery since 2012.

7.4.3 SCRs Information Value on SCDSs Price Discovery When ZBPR & QEP in Effect

Given SCRs information value is the common proxy for the credit risk component in SCDSs' structure and the SCRs information value was disregarded since 2012, this means the remaining determinant of SCDSs pricing must be the non-credit risk component. The non-credit risk component is proxied by lagged SCDSs. The estimated coefficients of lagged SCDSs as reported in Table 7-14 are significant at a 5% level. The strength of estimated coefficients of lagged SCDSs with over 87% influence on SCDSs pricing supports this hypothesis. The hypothesis also reflected on the interaction between the mean SCDSs and mean SCRs by CRAs as depicted in Figure 7-2.

Figure 7-2: Mean SCRs Notch Trend from 2008 to 2017 issued by Moody's, S&P, and Fitch Versus Mean SCDSs



Note: The mean SCR notch is the average SCRs of the 32 selected countries defined in Table 4-2 in Chapter 4. The SCRs are converted into fine ordinal scale following the convention defined in Table 4-3 in Chapter4. The mean SCDSs of the same 32 selected countries are based on quarterly observations spanning from Q1 2008 to Q4 2017.

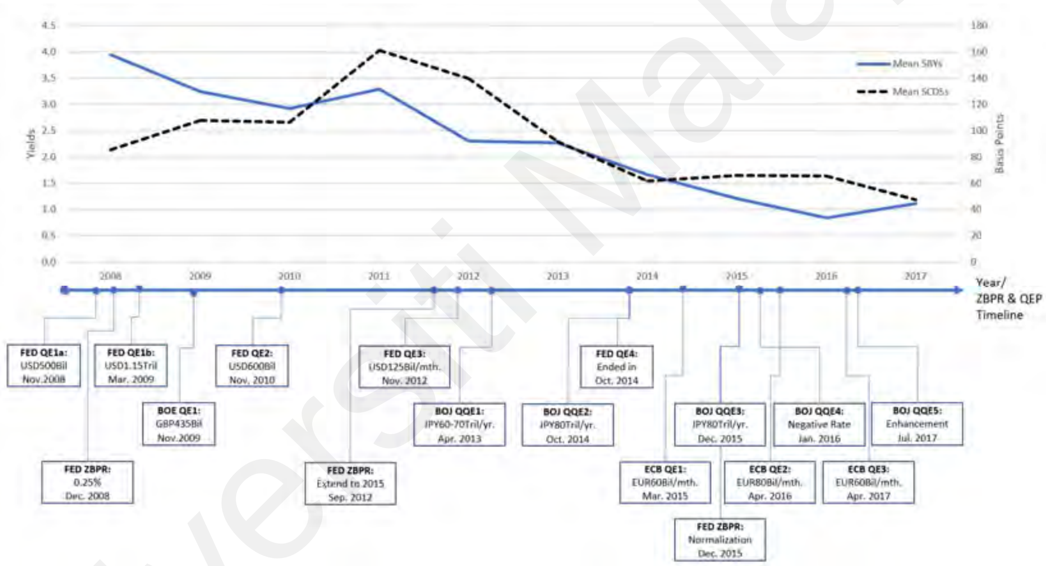
In sub-period1, which transpired from Q1 2008 to Q4 2011, the mean SCDSs had increased from 80 basis points (bps) in 2008 to 160 bps in 2011. The increase in mean spreads was expected given that the mean SCRs by all CRAs had lowered from above 18.5, which is equivalent to Aa2/AA, in 2008 to below 18.5 or Aa3/AA-. The increase in mean SCDSs was due to additional compensation for the worsened risk profile of the sample. This explains why the expected coefficients of SCRs in sub-period1 are significant at a 5% level and with the expected negative sign. The SCRs information value was relevant in SCDSs price discovery because the risk-reward pricing discipline was observed.

After 2011, the mean SCDSs changed course and started to contract while the mean SCRs stayed in the range of Aa3/AA-. The mean SCDSs had contracted from the peak of 160 basis points (bps) in 2011 to about 50bps in 2017. Given that the credit profile of the sample remained status quo, the mean SCDSs downward trajectory must be motivated by the non-credit risk component. This explains why the estimated coefficients of SCRs in sub-period2 are with the positive sign and deemed irrelevant in SCDSs pricing.

Regarding the non-credit risk component, the common determinants are risk appetite and liquidity risk. The S&P volatility index (S&P VIX) is commonly used as the proxy for risk appetite. A quick check, the S&P VIX was subdued from the height of 60 points less than 25 points throughout the same window of observation. When S&P VIX is low, this indicates that the financial market is operating in low volatility or low risk-averse environment. It became apparent that the liquidity risk became negligible when QEP was in effect. With the aggregate of USD12 trillion fresh liquidity injected through QEP, there was plenty of liquidity to go around.

Hence, we conjectured that ZBPR and QEP are the causes to mean SCDSs contraction. The announcement to keep ZBPR until the end of 2015 made by the US Federal Reserves in 2012 was the trigger point. The announcement was a sign of conviction to maintain the ZBPR and to continue the injection of fresh liquidity through QEP. This became clear then that hedging risk premia through SCDSs were futile. The mean SCDSs trajectory changed course and since moving in tandem with the mean SBYs as depicted in Figure 7-3. As a result, the SCRs information value became irrelevant and was disregarded in SCDSs pricing since 2012.

Figure 7-3: Mean SBYs and Mean SCDSs Trends overlayed with ZBPR and QEP Timeline



Note: The mean SCDSs is the average SCDSs of the same 32 selected countries based on quarterly observations spanning from Q1 2008 to Q4 2017. The mean SBYs are the average SBYs of the same 32 selected countries based on quarterly observations spanning from Q1 2008 to Q4 2017. The FED = US Federal Reserves, BOE = Bank of England, BOJ = Bank of Japan, ECB = European Central Bank, QEP = Quantitative Easing Program, QQEP = the BOJ version of QEP, and ZBPR = Zero Bound Policy Rate. The QEP and ZBPR timelines are sourced from https://www.reuters.com/article/us-usa-fed-banlancesheet/fed-announces-plan-to-end-balance-sheet-runoff-in-september-idUSKCN1R12QA, https://www.forbes/sites/greatspeculations/2015/11/16/quantitatives-easing-in-focus-the-u-s-experience/#e1e23528d539 on FED QEP and ZBPR, https:www.bankofengland.co.uk/monetary-policy/quantitative-easing on BOE QEP, https://www.ecb.europe.eu/mopo/implement/omt/html/index.en.html on ECB QEP, and https://www.boj.or.jp/en/mopo/outline.qqe,htm/ on BOJ QQEP.

7.5 Conclusion

Based on the list of 159 rated countries, 64% of these countries are rated by all three leading credit rating agencies (CRAs). Among these 103 multi-rated countries, 67% of them are rated with varying SCR notches or split-SCRs. In fact, the occurrence of split-SCRs has been a going concern in the SCRs universe.

In earlier studies, the SCRs issued by competing CRAs were assumed to carry equal information weight in debts pricing. Based on this assumption, the simple arithmetic average approach was adopted to handle SCRs issued by more than one CRA. The average approach is also a simple solution to overcome the multicollinearity issue presented by highly correlated SCRs amongst the three leading CRAs. The point of contention is not the average approach but rather on the presumption that SCRs issued by competing CRAs are having the same information value and are priced evenly.

The setup of this empirical study is to examine the SCRs information value in the context of SCRs by CRAs and paired SCRs in SCDSs price discovery. On SCRs by CRAs, the objective is to examine how the financial market weighs the SCRs information by respective CRAs on SCDSs price discovery. The estimates from SCRs by CRAs will also serve as the baseline for examining the paired SCRs estimates. The vector of SCRs by CRAs and paired SCRs are regressed using panel FE, FD-GMM, and FOD-GMM models using the full dataset when ZBPR and QEP were in effect. The full dataset is recategorized into two sub-periods. In sub-period1, where the divergence of SCRs amongst the CRAs was apparent, and in sub-period2 where the forward-looking opinions on rated countries' creditworthiness amongst the CRAs converged.

The empirical results from sub-period1 show that there is indeed some variation of SCRs explanatory powers amongst the three leading CRAs, but the differences are negligible. Therefore, there is no strong evidence to suggest superiority amongst these three leading

CRAs. However, the effect of SCRs information value in pricing SCDSs reveals that the financial market did price the SCRs by CRAs differently. Amongst the three leading CRAs, SCRs issued by Fitch had the highest influence and SCRs issued by S&P had the least influence in SCDSs price discovery. The empirical study also revealed that the financial market did not rely on SCRs issued by single nor all three leading CRAs. The paring of SCRs issued by Moody's and Fitch is optimal, and the paired SCRs conveys the highest influence in SCDSs price discovery. This means the presumption of equality amongst these three CRAs is flawed, and the selection of SCRs by CRAs matters.

Unfortunately, the pricing effect of the optimal paired SCRs cannot be validated in sub-period2, where SCRs information value was greater in clarity due to convergence. This is because the SCRs information value, irrespective of CRAs, was disregarded in SCDSs price discovery.

Further sample scrutinization reveals that the pricing of SCDSs from 2012 onwards was dominated by the non-credit risk component. When the SCDSs peaked in 2011 and then changed the trajectory, the SCDSs contracted by 110 bps and settled at 50 bps in 2017. As conjectured, the trigger point was the conviction to keep the ZBPR until the end of 2015 and to continue with QEP announced by the US Federal Reserves in 2012. Since then, the SCRs information value, irrespectively of CRAs, had been disregarded in SCDSs price discovery.

CHAPTER 8: CONCLUSION

8.1 Introduction

This thesis begins with the general enquiry on the potential effect of zero-bound-policy-rate (ZBPR) and quantitative easing programme (QEP) on sovereign credit ratings (SCRs) issuance and the SCRs information value in debts pricing. While existing pieces of literature regarding SCRs determinants, SCRs information value, and split-SCRs information value are extensive, we have yet to come across any literature that studies the potential effect of ZBPR and QEP on SCRs, or the likelihood of SCRs becomes irrelevant. This thesis could be the first to have done so.

In Chapter 2, the SCRs and the SCRs related literature are reviewed and recorded. This literature review is an essential step in empirical research. The reviewed pieces of literature have been instrumental in shaping the research questions, approach, econometric methods, and drawing inferences.

With access to proprietary rating methodologies that are made accessible by respective credit rating agencies (CRAs)[31], the SCRs synthesis elaborated in Chapter 3 reveals greater insights about SCRs that was otherwise categorized as a "black box" in earlier studies. The SCRs issued by the three leading CRAs: Moody's, S&P, and Fitch could be simplified as a function of publicly available information (PAI), non-disclosure-agreement obtained information (NDAI), and the proprietary sovereign credit rating methodology (SCRM) components. These three components are key to understand the similarities and differences amongst the three leading CRAs in SCRs determination.

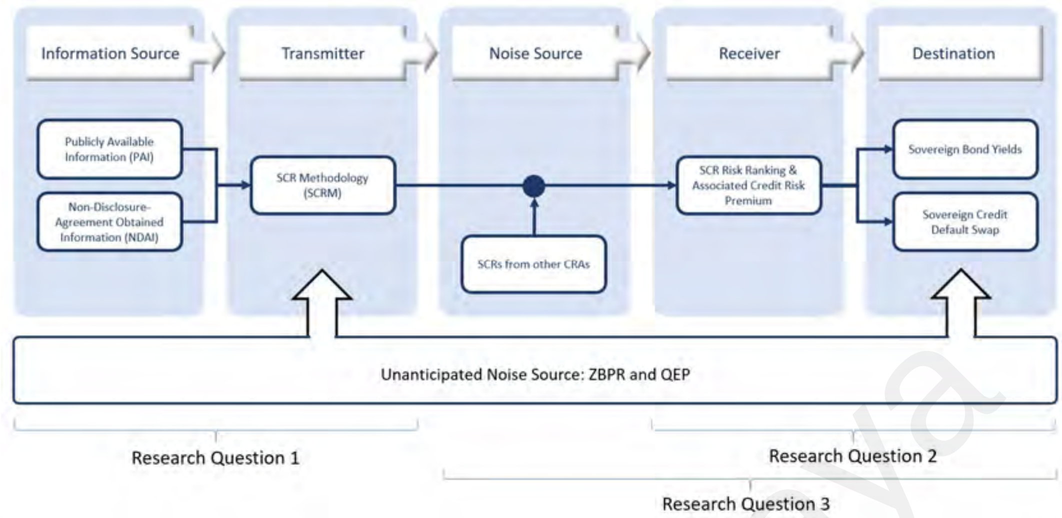
[31] Credit to Dodd Frank Acts in the US and ESMA empowered by ECB on regulatory reform imposed upon credit rating agencies

In Chapter 4, equipped with these new insights from SCRs synthesis, and the knowledge gained from previous studies on the subject, the information theory advocated by Shannon (1948) is adapted to guide and structure the theoretical research framework. In addition, the econometric methods streamlined to tackle specific research questions, data selection criteria, and sample for the study are described in this chapter. This chapter elaborates how the main question: "Are SCRs relevant on debts pricing when ZBPR and QEP were in effect?" is answered.

The answer to the main question consists of three parts or three research questions. Using the schema of information theory as the building blocks, these three research questions are mapped into applicable schemes so that SCRs, the message, is examined consistently and structurally.

On that note, research question 1 focuses on SCRs determinants that transpire between "Information Source" and "Transmitter" schemes. The SCRs information value in debts pricing that transpires between "Receiver" and "Destination" schemes is the emphasis of research question 2. With split-SCRs information value, the message will flow through the "Noise Source" scheme, where the varying SCRs notches are processed before the message is transmitted to the "Receiver", and eventually priced at the "Destination" scheme. The potential effect of ZBPR and QEP, as conjectured, would intercept at "Transmitter" and "Destination" schemes, and cause additional ambiguity to the message. These intercepts caused by ZBPR and QEP are classified as "Unanticipated Noise Source", an addition to the original schema of information theory. These are summarized in Figure 8-1.

Figure 8-1: Theoretical Research Framework and the 4 Research Questions



The structure of this chapter is as follows. The empirical findings of the three research questions are summarized in Section 8.2, followed by contributions of this study are described in Section 8.3, and the potential implications are listed in Section 8. Finally, the limitations are highlighted in Section 8.5.

8.2 Summary of Findings

With a sample of 32 countries that are rated by all three leading CRAs. These investment-grade rated countries are within the assets purchasing radar of QEP. The sample allows "A to A" comparison amongst the CRAs. Moreover, the selected economic variables are cross-referenced with inputs to the PAI component. This is to ensure that the four key input factors of SCRs are reasonably represented by the selected economic variables. The selected economic variables are further categorized into short-term determinants and long-term determinants. These two categories are proxies to assess Point-in-Time (PIT) and Through-the-Cycle (TTC) philosophies in the determination of SCRs. The data points for the sample are gathered from 2008 to 2017. The observation window demarcates the beginning and ending of ZBPR and QEP measures in response to the global financial crisis (GFC). Hence, the effects of ZBPR and QEP are embedded in the selected observations.

In Chapter 5, the eight selected economic variables: GDP Growth Rate, GDP Per Capita, Government Effectiveness Indicator, Inflation, Debt-to-GDP, Fiscal Balance, Financial Development Indicator, and Reserves to GDP, demonstrated equitable representation of the four key factors assessed by all three leading CRAs. Among these eight selected economic variables, four are statistically significant as short-term determinants and five are statistically significant as long-term determinants. The results are consistent on SCRs issued by all three leading CRAs, and remain robust in both ordered probit and ordered logit estimates. Between the short-term and long-term determinants, the latter model has higher predictive power on SCRs issued by Fitch. The ordered logit model is better suited to predict SCRs issued by Moody's and Fitch. The effects of short-term versus long-term determinants, and ordered probit versus ordered logit models are neutral on SCRs issued by S&P. On average, the eight-determinant models can predict SCRs issued by all three leading CRAs with 67% accuracy. The predictive power is significantly higher with a 17% gain in accuracy as compared to the 50% range reported in previous studies (Afonso et al., 2009; Afonso et al., 2011; Mellios & Paget-Blanc, 2006; Reusens & Croux, 2017).

Despite the promising predictor power, this eight-determinant model only represents the PAI component, therefore cannot be construed as a complete proxy of SCRs. This is because the NDAI and SCRM components are not accounted for in the models. For apparent reasons, the NDAI and SCRM components are derived separately using the weighted SCRs function. On average, the weight of NDAI and SCRM components of SCRs is about 1/3. Although proportionally lower compared to the PAI component, the NDAI and SCRM components are the essence of forward-looking opinions of CRAs' on rated countries' creditworthiness, the source of "above and beyond" information value of SCRs, and the causes of split-SCRs.

To conclude in the context of research question 1, the empirical results show that SCRs determination amongst the three leading CRAs had been consistent when ZBPR and QEP were in effect. The majority of the eight selected economic variables are also principal component variables examined in previous studies. Since these selected economic variables are proven significant in previous studies and continue to be significant in this study, this suggests continuity and consistency in SCRs determination exercised by all three leading CRAs. There are indeed some variations of emphasis on the selected economic variables amongst the CRAs, these variations are results of proprietary rating methodology and discretion adopted in respective rating processes. Hence, there is no evidence to suggest that the SCRs determination process was compromised when the ZBPR and QEP were in effect.

In Chapter 6, the eight selected economic variables are repurposed as baseline regressors to examine the SCRs information value in sovereign bond yields (SBYs) price discovery. The empirical results show that the eight selected economic variables are also effective as the determinants of SBYs and with considerable explanatory power at a range of 65% to 69%.

When SCRs by CRAs are introduced as the additional regressor to measure the "above and beyond" information value of SCRs, all estimated coefficients of SCRs are statistically insignificant. The use of short-term and long-term determinants as baseline regressors did not change the empirical outcome. This indicates the SCRs information value, irrespective of CRAs, was disregarded in SBYs pricing. The models are re-estimated by fixing both cross-section and period, cross-section fixed with White cross-section standard error, and cross-section fixed with White period standard error, the results remain robust.

Separately, the potential confounding effect of baseline regressors on the SCRs regressor are addressed using the streamlined model, where baseline regressors are dropped, and the dynamic panel model, where the baseline regressors are substituted with the endogenous variable. All estimated coefficients of SCRs from these two models are either statistically significant but are not with the expected negative sign, or insignificant and with the negative sign. In both cases, they lead to the same conclusion that is the SCRs information value was irrelevant in SBYs pricing.

Further scrutinization of the sample reveals that the pricing of SBYs did not follow the risk-reward pricing convention. Since the default risk pricing discipline was not observed, the SCRs information value became negligible therefore disregarded. Based on CAPM structure, the investigation also reveals the traces of ZBPR influence on the risk-free rate and QEP influence on liquidity risk in risk premia that contributed to SBYs downward trajectory, from an average of 4% in 2008 to less than 1% in 2017. To conclude in accordance to research question 2, since 2008 the SCRs information value was disregarded and rendered irrelevant in SBYs price discovery when ZBPR and QEP were in effect.

In Chapter 7, the sovereign credit default swap spreads (SCDSs), the derivatives of SBYs, are selected as the dependent variable to study the split-SCRs information value. A series of panel and dynamic panel regressions are conducted on the combination of the vector of SCRs by CRAs and paired and three datasets: full, sub-period1 and sub-period2. The empirical results presented mixed outcomes on split-SCRs information value in SCDSs price discovery.

Based on the forward orthogonal deviation generalized method of moments (FOD-GMM), all estimated coefficients of SCRs by CRAs and paired SCRs derived from the full dataset are irrelevant in SCDSs price discovery. When cross-referenced with estimates from sub-period1, from Q1 2008 to Q4 2011, and sub-period2, from Q1 2012 to Q4 2017, the results are mixed.

In sub-period1 when the divergence of forward-looking opinions amongst the three leading CRAs was apparent, all estimated SCRs by CRAs and paired SCRs are significant and with the expected negative sign. There are variations reported on the models' explanatory power amongst the CRAs, however, the magnitude of variations is negligible to suggest the existence of dominant SCRs amongst the three leading CRAs. This means SCRs issued by all three leading CRAs are equally recognized and accepted in price discovery. With regards to the strength of price adjustment, the SCRs issued by Fitch had the highest influence and SCRs issued by S&P had the least influence on SCDSs pricing amongst the three CRAs. The study reveals that the pairing of SCRs issued by Moody's and Fitch had the highest influence on SCDSs pricing, as compared to SCRs by CRAs and the rest of the paired SCRs. The influence of the optimal paired SCRs in SCDSs pricing is evident that the financial market does not rely on just one CRA nor all the three leading CRAs on SCRs information value. This means the selection of SCRs by CRAs matters on empirical outcomes.

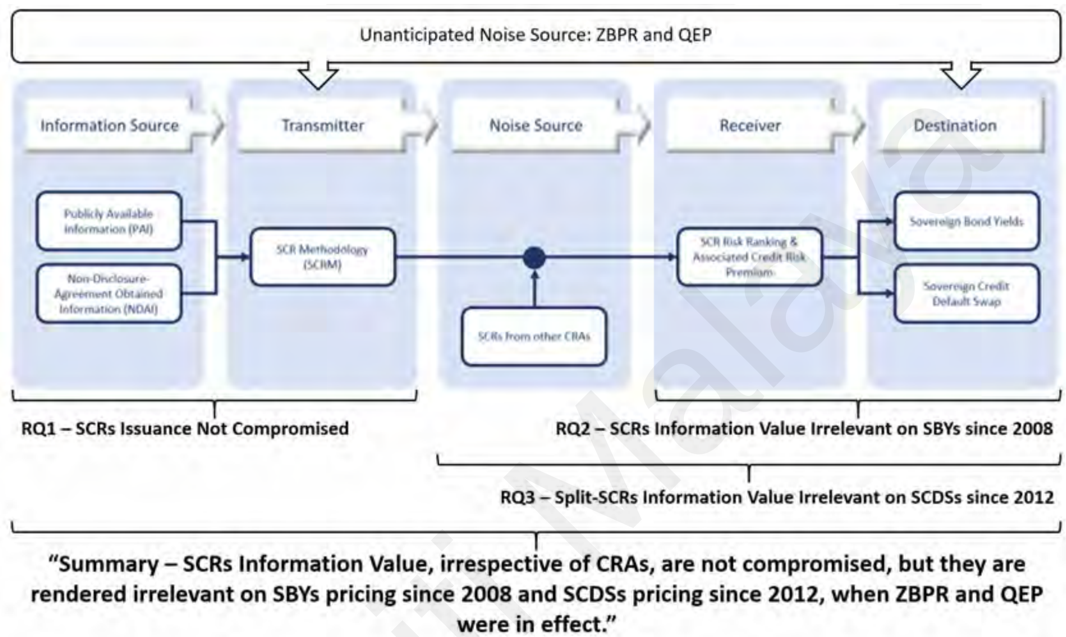
In sub-period2 where split-SCRs amongst the three CRAs converged since Q1 2012, the FOD-GMM estimates on SCRs by CRAs and paired SCRs are rendered irrelevant due to the positive sign. This is because the positive sign violated the risk-reward pricing convention, therefore, indicates that the SCRs information value had been disregarded in SCDSs pricing. Unfortunately, this means the optimal paired SCRs cannot be validated when the forward-looking opinions of the three leading CRAs converged.

Given SCRs are the common proxy of credit risk component in SCDS structure, and the SCRs were disregarded, hence the SCDSs trajectory must be motivated by non-credit risk component. With ample fresh liquidity injected into the financial market through the QEP, the liquidity risk in the non-credit risk component should have contracted and contributed to the SCDSs downward trend. As conjectured, the trigger point to ditch hedging credit risk with SCDSs was the announcement made by the US Federal Reserves in 2012 to keep ZBPR until the end of 2015 and the continuation of QEP.

To sum up in specific to research question 3, the empirical results on split-SCRs information in SCDSs pricing are mixed. When split-SCRs information value was significant and relevant in SCDSs price discovery, the pairing of SCRs issued by Moody's and Fitch had the highest influence on SCDSs pricing. From 2012 onwards, although the split-SCRs amongst the three leading CRAs converged and conveyed the assigned credit profiles in greater clarity, the SCRs information value was disregarded and rendered irrelevant in SCDSs pricing. The results are unanimous on SCRs issued by Moody's, S&P, and Fitch.

This brings us back to the main question of whether SCRs were relevant when ZBPR and QEP were in effect. The answer comes in three parts. First, as demonstrated in Chapter 5, the SCRs determination is not compromised. This means the SCRs issued by Moody's, S&P, and Fitch and SCRs information value continue to be reliable in debts pricing. Second, the SCRs information value is used to price SBYs. The empirical results are consistent and robust on SCRs issued by all three leading CRAs, the SCRs information value was disregarded in SBYs pricing since 2008. Third, the empirical results show that split-SCRs information value was still significant and relevant in SCDSs price discovery from 2008 to 2011. From 2012 onwards, even with spit-SCRs information value of greater clarity, SCRs issued by all three leading CRAs had been rendered irrelevant in SCDSs pricing. The empirical outcomes to the three-part answer are summarized in the diagram presented in Figure 8-2.

Figure 8-2: Empirical Outcomes Summary



8.3 Contribution of Study

The contributions of this study are described in this section.

8.3.1 Concept of SCRs function

With insights from the proprietary rating methodology of Moody's, S&P, and Fitch, the concept of SCRs function (i.e., $SCRs = f(PAI, NDAI, SCRM)$) is conceived. The SCRs function enables the NDAI and SCRM components to be quantified for the first time. The NDAI and SCRM components are the essence of SCRs, the source of the "above and beyond" information value of SCRs, and the cause of split-SCRs persistency.

The weight of NDAI and SCRM components are quantified using Equation 4-5 (see Section 4.4.2). On average, the NDAI and SCRM components contribute to an average of 1/3 information content of SCRs amongst the three leading CRAs. This 1/3 information content of SCRs would be the new research paradigm on SCRs determinants and SCRs information value studies. Therefore, it is worthy for researchers to go beyond the PAI component, and focus on the potential proxies of NDAI and SCRM components. The concept of the SCRs function presented in this thesis can be adapted for future research.

8.3.2SCRs Relevancy and the Unchained Anchoring Effect

The SCRs, especially those issued by Moody's, S&P, and Fitch, are fully integrated into the global financial system. This could be the reason that previous studies proceeded with the presumption of SCRs were reliable and relevant proxies of credit risk. This presumption could be explained by the anchoring effect advocated by Sherif, Taub, and Hovland (1958).

Like earlier researchers, this study did proceed with the same presumption that SCRs must be reliable and relevant on debts pricing and conjectured that SCRs information value would deteriorate during the period when the ZBPR and QEP were in effect. Although the SCRs issuance was not compromised, the empirical results show that the SCRs information was disregarded in SBYs price discovery since 2008, and in SCDSs price discovery from 2012 onwards.

This means future research on SCRs cannot proceed with the anchoring assumption. Moreover, the empirical results also suggest researchers reassess the suitability of spreads from SBYs and SCDSs as proxies for credit risk premia.

8.3.3Findings on Potential Selection and/or Omission Bias

In Chapter 7, the study examines whether SCRs by respective CRAs, the pairing of SCRs from two leading CRAs, and the average SCRs issued by all three leading CRAs will lead to greater model's explanatory power and influence on SCDSs pricing. However, the outcome of this experiment can only be observed from sub-period1 estimates.

Although the empirical results indicate that the differences among the vector of SCRs on the models' explanatory power are negligible, the pairing of SCRs issued by Moody's and Fitch had the highest influence on SCDSs pricing. This suggests that the selection of SCRs by CRAs matters in empirical studies. The empirical results derived from full-dataset and the two sub-periods also reveal the sensitivity of observation's window on empirical outcomes. The empirical results suggest that sample with a long observation timeframe (e.g., 10 years), the effect of selection/omission bias on an empirical outcome is subdued. This highlights that future research on SCRs must conduct due diligence on SCRs and sample selection.

8.4 Implications of Study

The implications of this study are described in this section.

8.4.1Implication on Countries Seeking or Rated with SCRs

The main motivation of countries seeking SCRs is to market foreign currency-denominated debts. Countries rated with SCR notches that signify better creditworthiness profile could borrow at a lower cost as compared to those rated with lower credit quality. When the financial market is spoiled with abundant liquidity offered at a relatively cheap rate, there is little incentive for rated countries to work towards better SCRs notches. The only prevailing incentive for the rated countries is to stay within the investment-grade category.

Under ZBPR and QEP environment, countries are exposed to two possible scenarios. In the first scenario where ZBPR and QEP are assumed to continue indefinitely. Investment-grade rated countries could afford more debts and be able to roll over matured debts with new debts at lower cost with little constraint. On the other hand, speculative-grade rated countries are also benefited under such conditions, due to "flight-to-yields". The foreseeable consequences are that the probability of default would continue to be undermined that rendered the SCRs information value relevancy, debt stock expanded considerably, and the debts serviceability ratio would hinge on ZBPR and QEP trajectories.

In the second scenario where ZBPR is to be normalized, and QEP moves into tapering mode. When the market condition resumes normalcy, countries that have overstretched their debt capacity are pressured to adopt austerity measures. If the market normalcy happens too quickly, SCRs downgrades would be inevitable, followed by a cluster of sovereign defaults were to be anticipated. The likelihood of sovereign default is already indicated on the Debt to GDP of the sample of 32 investment-grade rated countries. The average Debt to GDP of these countries increased by more than 44%, from about 45% in 2008 to above about 65% since 2014.

In other words, the SCRs may be irrelevant in debts pricing when ZBPR and QEP are in effect, but it is not indefinitely. It is advisable for countries to adopt prudent measures in building the needed coffer when ZBPR and QEP remain in effect and strife for better credit profiles. Both recommendations if adopted will bear fruits when scenario 2 kicks in.

8.4.2 The CRAs

Although the empirical results from Chapter 5 provide no evidence that SCRs issuance amongst the three leading CRAs is compromised, the debt stocks of the sample indeed expanded significantly when the ZBPR and QEP were in effect. For instance, the average Debt-to-GDP ratio of the sample of 32 investment-grade rated countries has expanded by approximately 40%, from about 45% in 2008 to about 63% in 2017. The current Debt-to-GDP ratio, in our opinion, is not sustainable, and the likelihood of systematic risk is materializing. Although some countries may have better fundamentals to weather the inversed effect of ZBPR and QEP, the spillover between event and non-event countries is inevitable. This observation is consistent with the study by Chen, Chen, Yang, et al. (2016), and Chen, Chen, Chang, et al. (2016).

Given majority of SCR cohorts are heavily indebted, this will be a significant challenge for respective CRAs to juggle between migration rates and default rates. This is because the inevitable SCR downgrades as per existing rating metrics could potentially lead to series of sovereign defaults. If the respective CRAs opted to observe further rather than initiates the downgrade, this decision could undermine the model stability. If another investment-grade rated country was to default, it would create a chain-effect that undermine the monotonous feature of SCRs notches. This means sovereign default could happen in any cohort. It is a catch-22 situation, CRAs must tread carefully in trying to balance both risks. The risk of ZBPR and QEP on SCRs are real and must be accounted for in the rating parameters.

8.5 Limitations of Study

The limitations of this study are described in this section.

8.5.1Speculative Grade Rated Countries' Debts

The study focused exclusively on investment-grade rated countries due to the considerations described in Chapter 4. This means the empirical outcome on SCRs information value irrelevancy in SBYs and SCDSs pricing when ZBPR and QEP were in effect only applicable on investment-grade rated debts. In other words, the effect of ZBPR and QEP on speculative graded rated SCRs is not examined.

Although the QEP focuses on investment-grade assets, the evidence on QEP spill over and ZBPR motivated "Flight-to-Yields" suggests that speculative graded rated assets are not completely side-lined. Hence, the study of SCR information value in speculative-grade rated debts pricing is worthy to pursue in a separate study.

8.5.2ZBPR and QEP Spill-Over

The zero-bound-policy rate (ZBPR) and the quantitative easing programme (QEP) are not exclusively rolled out by the US Federal Reserves (FED). The Bank of England (BOE) and European Central Bank (ECB) also rolled out similar measures of ZBPR and QEP. The Bank of Japan (BOJ) upgraded its existing QEP to the quantitative and qualitative easing programme (QQEP) and set the policy rate at near-zero (see Section 2.5). The concerted effort of these four Central Banks on ZBPR and QEP is assumed to be embedded in SBYs and SCDSs pricing, and not empirical examined in this paper.

The works of Curcuru et al. (2018), Kinateder and Wagner (2017), D. Malliaropulos and P. Migiakis (2018), and D. Malliaropulos and P. M. Migiakis (2018) do support our conjecture on the ZBPR and QEP spill over to other countries. However, their studies mainly focused on QEP spillover from FED. Hence, the collective effect of ZBPR and

QEP that rolled out by four key Central Banks is not examined, and will be a worthy for future research.

8.5.3 Regulatory Reform on CRAs

The US subprime mortgage crisis in 2008 had paved the way for Dodd-Frank Act to be adopted in 2010, under the Securities Exchange Act of 1934. The SEC's Office of Credit Ratings (OCR) is set up under this provision of the Securities Exchange Act of 1934 to regulate credit rating agencies (CRAs) registered as nationally recognized statistical rating organizations (NRSRO) as per the Credit Rating Agency Reform Act of 2006. The OCR has broad mandates of oversight on NRSRO registered CRAs, but with limitations. As highlighted by Jessica Kane, the Director of OCR, the OCR is not allowed to dictate the rating parameters, methodology, and procedures of the respective CRAs on SCRs issuance[32].

In 2009, European Parliament passed the "CRA Regulation" into law and empowered the European Securities and Markets Authority (ESMA), the counterpart of the US SEC, to regulate CRAs. Similarly, CRAs are required to register, pay the fee, and disclose the rating methodology used and fee charges to ESMA. Unlike OCR, the term "regulatory technical standards" employed by ESMA to assess credit rating methodologies is rather fluid. Hence, it is not clear whether ESMA could dictate the rating parameters used by CRAs in determining the SCRs notches on European countries.

[32] Speech by Jessica Kane on "The SEC's Office of Credit Ratings and NRSRO Regulation: Past, Present, and Future", 24 February 2020. https://www.sec.gov/news/speech/speech-jessica-kane-2020-02-24

For instance, recent studies such as the work of Reusens and Croux (2017) examined and reported the "Eurozone Membership Indicator" to be a significant determinant of the European rated countries. However, this indicator is not part of the rating inputs as per respective proprietary rating methodologies (Hornung et al., 2016; Kraemer et al., 2017; Stringer et al., 2016). Moreover, the terms "credit scores" and "credit ratings" as defined by ESMA could also be the cause of split-SCRs. While the empirical results from Chapter 5 do not indicate such influence, In March of 2021, Moody's was issued a fine amounting to EUD3.7million by ESMA, due to shareholders' conflict of interest[33].

The regulations imposed upon CRAs and the recent regulatory events suggest that OCR and ESMA have the tools to exert influence on how CRAs operate and potentially on how SCR notches are determined. Although it is not the emphasis of this thesis, it is worthy to study SCRs determination in the perspective of regulatory influence on a separate paper.

[33] See press release on "ESMA fines Moody's €3.7 million for conflicts of interest failures" , 30 March 2021. https://www.esma.europa.eu/press-news/esma-news/esma-fines-moody%E2%80%99s-%E2%82%AC37-million-conflicts-interest-failures

REFERENCES

Abad, P., Alsakka, R., & Gwilym, O. a. (2018). The influence of rating levels and rating convergence on the spillover effects of sovereign credit actions. *Journal of International Money and Finance, 85*(40 - 57). doi:https://doi.org/10.1016/j.jimonfin.2018.03.005

Afonso, A. (2003). Understanding the determinants of sovereign debt ratings: Evidence for the two leading agencies. *Journal of Economics and Finance, 27*(1), 56 - 74. doi:https://doi.org/10.1007/BF02751590

Afonso, A., Arghyrou, M., & Kontonikas, A. (2013). The determinants of sovereign bond yield spreads in the EMU. *ISEG Economics Working Paper No.36/2012/DE/UECE*.

Afonso, A., Furceri, D., & Gomes, P. (2012). Sovereign credit ratings and financial markets linkages: Application to European data. *Journal of International Money and Finance, 31*(3), 606-638. doi:https://doi.org/10.1016/j.jimonfin.2012.01.016

Afonso, A., Gomes, P., & Rother, P. (2009). Ordered response models for sovereign debt ratings. *Applied Economics Letters, 16*(8), 769 - 773. doi:https://doi.org/10.2139/ssrn.943418

Afonso, A., Gomes, P., & Rother, P. (2011). Short- and long-run determinants of sovereign debt credit ratings. *International Journal of Finance & Economics, 16*(1), 1 - 15. doi:https://doi.org/10.1002/ijfe.416

Afonso, A., Sr, P. M. G., & Rother, P. (2007). What 'Hides' behind sovereign debt ratings? *ECB Working Paper, No.711*, 1 - 65.

Aizenman, J., Chinn, M., & Hutchison, M. (2009). Understanding global liquidity in a volatile world. *Review of International Economics, 17*(4), 651 - 654. doi: https://doi.org/10.1111/j.1467-9396.2009.00839.x

Aizenman, J., Hutchison, M., & Jinjarak, Y. (2013). What is the risk of European sovereign debt defaults? Fiscal space, CDS spreads and market pricing of risk. *Journal of International Money and Finance, 34*, 37 - 59. doi:https://doi.org/10.1016/j.jimonfin.2012.11.011

Alper, C. E., Forni, L., & Gerard, M. (2013). Pricing of sovereign credit risk: Evidence from advanced economies during the financial crisis. *International Finance, 16*(2), 161 - 188.

Alsakka, R., & Gwilym, O. (2010a). Leads and lags in sovereign credit ratings. *Journal of Banking and Finance, 34*(11), 2614 - 2626. doi:https://doi.org/10.1016/j.jbankfin.2010.05.001

Alsakka, R., & Gwilym, O. (2010b). Split sovereign ratings and rating migrations in emerging economies. *Emerging Market Review, 11*, 79 - 97. doi:https://doi.org/10.1016/j.ememar.2009.11.005

Alsakka, R., & Gwilym, O. (2013). Rating agencies' signals during the European sovereign debt crisis: Market impact and spillovers. *Journal of Economic Behaviour and Organization, 85*, 144 - 162. doi:https://doi.org/10.1016/j.jebo.2011.12.007

Alsakka, R., & Gwilym, O. a. (2009). Heterogeneity of sovereign rating migrations in emerging countries. *Emerging Market Review, 10*(2), 151 - 165. doi:https://doi.org/10.1016/j.ememar.2008.12.001

Ammer, J., & Cai, F. (2007). Sovereign CDS and bond pricing dynamics in emerging markets: Does the cheapest-to-deliver option matter? *Journal of International Financial Markets, Institutions and Money, 21*(3), 369 - 387. doi:https://doi.org/10.1016/j.intfin.2011.01.001

Ardagna, S., Caselli, F., & Lane, T. (2007). Fiscal discipline and the cost of public debt service: some estimates for OECD countries. *The B.E. Journal of Macroeconomics, 7*(1), 1 - 33. doi:http://dx.doi.org/10.2202/1935-1690.1417

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277 - 297. doi:https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*, 29 - 51. doi:https://doi.org/10.1016/0304-4076(94)01642-D

Attinasi, M. G., Checherita-Westphal, C. D., & Nickel, C. (2009). What explains the surge in euro area sovereign spreads during the financial crisis od 2007-2009? *ECB Working Paper No. 1131*.

Badaoui, S., Carthart, L., & El-Jahel, L. (2013). Do sovereign credit default swaps represent a clean measure of sovereign default risk? A factor model approach. *Journal of Banking and Finance, 37*(7), 2392 - 2407. doi:https://doi.org/10.1016/j.jbankfin.2013.01.038

Barrios, S., Iversen, P., Lewandowska, M., & Setzer, R. (2009). Determinants of intra-euro area government bond spreads during the financial crisis. *European Commission Economic Paper 388*.

Beber, A., Brandt, M. W., & Kavajecz, K. A. (2009). Flight-to-quality or flight-to-liquidity? Evidence from Euro-Area bond market. *The Review of Financial Studies, 22*(3), 925 - 957. doi:https://doi.org/10.1093/rfs/hhm088

Berndt, A., & Obreja, L. (2010). Decomposing European CDS returns. *Review of Finance, 14*(2), 189 - 233. doi:https://doi.org/10.1093/rof/rfq004

Binici, M., & Hutchison, M. (2018). Do credit rating agencies provide valuable information in market valuation of sovereign default risk? *Journal of International Money and Finance, 85*, 58 - 75. doi:https://doi.org/10.1016/j.jimonfin.2018.04.001

Bissondoyal-Bheenick, E. (2005). An analysis of the determinants of sovereign ratings. *Global Finance Journal*(15), 251 - 280. doi:https://doi.org/10.1016/j.gfj.2004.03.004

Bissondoyal-Bheenick, E., Brooks, R., & Yip, A. Y. N. (2006). Determinants of sovereign ratings: A comparison of case-based reasoning and ordered probit approaches. *Global Finance Journal*(17), 136 - 154. doi:https://doi.org/10.1016/j.gfj.2006.06.001

Black, F., & Cox, J. C. (1976). Valuing corporate securities: Some effects of bond indenture provisions *The Journal of Finance, 16*(2), 351 to 367. doi:https://doi.org/10.1111/j.1540-6261.1976.tb01891.x

Blau, B. M., & Roseman, B. (2014). The reaction of European credit default swap spreads to the U.S. credit rating downgrade. *International Review of Economics & Finance, 34*, 131 - 141. doi:https://doi.org/10.1016/j.iref.2014.07.009

Cantor, R., & Mann, C. (2006). *Analyzing the tradeoff between ratings accuracy and stability*. Retrieved from https://ssrn.com/abstract=996019

Cantor, R., & Packer, F. (1995). The credit rating industry. *The Journal of Fixed Income Winter, 5*(3), 10 - 34. doi:DOI: https://doi.org/10.3905/jfi.1995.408153

Cantor, R., & Packer, F. (1996). Determinants and impact of sovereign credit ratings. *Economic Policy Review, 2*(2), 37 - 53. doi:http://dx.doi.org/10.2139/ssrn.1028774

Cantor, R., Packer, F., & Cole, K. (1997). Split ratings and the pricing of credit risk. *Journal of Fixed Income, 7*(3), 72 - 82. doi:https://doi.org/10.3905/jfi.1997.408217

Cantor, R., & Parker, F. (1995). *Sovereign credit ratings*. Retrieved from NY, United States of America: https://ssrn.com/abstract=1001511

Canuto, O., Santos, P. F. P. D., & Porto, P. C. D. S. (2012). Macroeconomics and sovereign risk ratings. *Journal of International Commerce, Economics and Policy, 3*(2), 1 - 25. doi:https://doi.org/10.1142/S1793993312500111

Chan-Lau, J. A., & Kim, Y. S. (2004). Equities prices, credit default swaps, and bond spreads in emerging markets. *IMF Working Paper WP/04/27*.

Chen, S.-S., Chen, H.-Y., Chang, C.-C., & Yang, S.-L. (2016). The relation between sovereign credit rating revisions and economic growth. *Journal of Banking & Finance, 64*, 90 - 100. doi:https://doi.org/10.1016/j.jbankfin.2015.10.012

Chen, S.-S., Chen, H.-Y., Yang, S.-L., & Chang, C.-C. (2016). Output spillovers from changes in sovereign credit ratings. *Journal of International Money and Finance, 63*, 48 - 63. doi:https://doi.org/10.1016/j.jimonfin.2016.01.007

Codogno, L., Favero, C., & Missale, A. (2003). Yield spreads on EMU government bonds. *Economic Policy, 18*(37), 503 - 532. doi:https://doi.org/10.1111/1468-0327.00114_1

Coudert, V., & Gex, M. (2011). Credit default swap and bond markets: Which leads the others? *Financial Stability Review, Banque de France, 14*, 161 - 167.

Crosbie, P., & Bohn, J. (2003). *Modeling default risk*. Retrieved from https://www.moodysanalytics.com/quantitative-research
Csonto, B., & Ivaschenko, I. (2013). Determinants of sovereign bond spreads in emerging markets: Local fundamentals and global factors vs. ever-changing misalignments. *IMF Working Paper WP/13/164*.
Culp, C. L., Merwe, A. v. d., & Starkle, B. J. (2016). *Single-name credit default swaps: A review of the empirical academic literature*. Retrieved from https://ssrn.com/abstract=2851264
Curcuru, S. E., Kamin, S. B., Li, C., & Rodriquez, M. (2018). International spillovers of monetary policy: Conventional policy vs. quantitative easing. *International Finance Discussion Papers 1234*. doi:https://doi.org/10.17016/IFDP.2018.1234
Dieckman, S., & Plank, T. (2012). Default risks of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance, European Finance Association, 16*(4), 903 - 934. doi:https://doi.org/10.1093/rof/rfr015
Duffie, D., & Singleton, K. J. (1997). An econometric model of the term structure of interest rate swap yields. *The Journal of Finance, 52*(4), 1287 - 1321. doi:https://doi.org/10.2307/2329437
Ederington, L. H. (1986). Why split ratings occur. *Financial Management, 15*(1), 37 - 47. doi:https://doi.org/10.2307/3665276
Ederington, L. H., Yawitz, J. B., & Roberts, B. E. (1987). The informational content of bond ratings. *The Journal of Financial Research, 10*(3), 211 - 226. doi:https://doi.org/10.1111/j.1475-6803.1987.tb00492.x
Edwards, S. (1985). The pricing of bonds and bank loans in international markets: An empirical analysis of developing countries' foreign borrowing. *National Bureau of Economic Research Working Paper No.1689*. doi:https://doi.org/10.1016/0014-2921(86)90009-7
Emery, K. (2017). Rating symbols and definitions. Retrieved from https://www.moodys.com
Eyssell, T., Fung, H.-G., & Zhang, G. (2013). Determinants and price discovery of China sovereign credit default swaps. *China Economic Review, 24*, 1 - 15. doi:https://doi.org/10.1016/j.chieco.2012.09.003
Fama, E. F. (1969). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383 - 417. doi:https://doi.org/10.2307/2325486
Favero, C., & Missale, A. (2012). Sovereign spreads in the eurozone: Which prospects for a Eurobond? *Economic Policy, 27*(70), 231 - 273.
FitchRatings. (2016). The rating process. Retrieved from https://www.fitchratings.com
FitchRatings. (2017). Rating definitions. Retrieved from https://www.fitchratings.com
Fontana, A., & Scheicher, M. (2010). An analysis of Euro area sovereign CDS and their relation with government bonds. *Journal of Banking & Finance, 62*, 126 -140. doi:https://doi.org/10.1016/j.jbankfin.2015.10.010
Friedman, T. L. (1996, February 22 1995). Foreign affairs; Don't mess with Moody's. *The New York Times*. Retrieved from https://www.nytimes.com/1995/02/22/opinion/foreign-affairs-don-t-mess-with-moody-s.html
Hassan, M. K., Ngene, G. M., & Yu, J.-S. (2015). Credit default swaps and sovereign debt markets. *Economic Systems, 39*, 240 - 252. doi:https://doi.org/10.1016/j.ecosys.2014.07.002
Hauner, D., & Kumar, M. S. (2006). Fiscal policy and interest rates: How sustainable is the "new economy"? *IMF Working Paper WP/06/112*.
Hayakawa, K. (2009). First difference or forward orthogonal deviation - Which transformation should be used in dynamic panel data models?: A simulation study. *Economic Bulletin, 29*(2), 2008 - 2017.
Hayashi, F. (2000). *Econometrics*. 41 William Street, Princeton, New Jersey 08540: Princeton University Press.
Hill, P., Brooks, R., & Faff, R. (2010). Variations in sovereign credit quality assessments across rating agencies. *Journal of Banking and Finance, 34*(6), 1327 - 1343. doi:https://doi.org/10.1016/j.jbankfin.2009.11.028
Hornung, D., Robinson, M., Lemay, Y., Wilson, A., Leos, M., Diron, M., & Sheth, A. (2016). Rating methodology: Sovereign bond Ratings. Retrieved from https://www.moodys.com

Hsiao, C., & Zhou, Q. (2017). First difference or forward demeaning: Implications for the method of moments estimators. *Econometric Reviews, 36*(6-9), 883 - 897. doi:https://doi.org/10.1080/07474938.2017.1307594

Hsien-Yi, C., & Sheng-Syan, C. (2018). Quality of government institutions and spreads on sovereign credit default swaps. *Journal of International Money and Finance, 87*, 82 - 95. doi:https://doi.org/10.1016/j.jimonfin.2018.05.008

Hull, J. C., & White, A. (2000). Valuing credit default swaps I: No counterparty default risk. *The Journal of Derivaties, 8*(1). doi:https://doi.org/10.3905/jod.2000.319115

Ismailescu, L., & Phillips, B. (2015). Credit default swaps and the market for sovereign debt. *Journal of Banking and Finance, 52*, 43 - 61. doi:https://doi.org/10.1016/j.jbankfin.2014.10.015

Jaramillo, L., & Tejada, C. M. (2011). Sovereign credit ratings and spreads in emerging markets: Does investment grade matter? *IMF Working Paper WP/11/44*.

Jaramillo, L., & Weber, A. (2013). Bond yields in emerging economies: It matters what state you are in. *Emerging Markets Review, 17*, 169 - 185. doi:https://doi.org/10.1016/j.ememar.2013.09.003

Jarrow, R. A., & Turnbull, S. M. (1995). Pricing derivatives on financial securities subject to credit risk. *The Journal of Finance, 50*(1), 53 - 85. doi:https://doi.org/10.2307/2329239

Kallestrup, R., Lando, D., & Murgoci, A. (2016). FInancial sector linkages and the dynamics of bank and sovereign credit spreads. *Journal of Empirical Finance, 38*, 374 - 393. doi:https://doi.org/10.1016/j.jempfin.2016.01.004

Kealhofer, S., & Bohn, J. R. (1993). *Portfolio management of default risk*. Retrieved from https://www.moodysanalytics.com/quantitative-research

Kiff, J., Kisser, M., & Schumacher, L. (2013). Rating Through-the-Cycle: What does the concept imply for rating stability and accuracy? *IMF Working Paper WP/13/64*.

Kinateder, H., & Wagner, N. (2017). Quantitative easing and the pricing of EMU sovereign debt. *The Quarterly Review of Economics and Finance, 66*, 1 - 12. doi:https://doi.org/10.1016/j.qref.2017.04.013

Kinoshita, N. (2006). Government debt and long-term interest rates. *IMF Working Paper WP/06/63*.

Kraemer, M., Esters, C., Briozzo, S., Tan, K., Dianous, B. D., Montmaur, V., . . . Puccia, M. (2017). Criteria | Governments | Sovereigns: Sovereign rating methodology. Retrieved from https://www.standardandpoors.com

Lando, D. (1998). On cox processes and credit risky securities. *Review of Derivatives Research, 2*(2), 99 - 120. doi:https://doi.org/10.1007/BF01531332

Laubach, T. (2009). New evidence on the interest rate effects of budget deficits and debt. *Journal of the European Economic Association, 7*(4), 858 - 885.

Li, N., & Huang, A. (2011). Price discovery between sovereign credit default swaps and bond yield spreads of emerging markets. *Journal of Emerging Market Finance, 10*(2), 197 - 225.

Liu, Y., Duggar, E. H., & Ou, S. (2017). Sovereign default and recovery rates, 1983-2016. Retrieved from https://www.moodys.com

Livingston, M., Naranjo, A., & Zhou, L. (2008). Split bond ratings and rating migration. *Journal of Banking and Finance, 32*(8), 1613 - 1624. doi:https://doi.org/10.1016/j.jbankfin.2007.11.019

Loeffler, G. (2004). An anatomy of rating through the cycle. *Journal of Banking & Finance, 28*(3), 695 - 720. doi:https://doi.org/10.1016/S0378-4266(03)00041-4

Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics, 3*(2), 75 - 103. doi:https://doi.org/10.3386/w13658

Malliaropulos, D., & Migiakis, P. (2018). The re-pricing of sovereign risks following the global financial crisis. *Journal of Empirical Finance, 49*, 39 - 56. doi:https://doi.org/10.1016/j.jempfin.2018.09.003

Malliaropulos, D., & Migiakis, P. M. (2018). Quantitative easing and sovereign bond yields: A global perspective. *Bank of Greece Working Paper No. 253*.

Mellios, C., & Paget-Blanc, E. (2006). Which factors determine sovereign credit ratings? *The European Journal of Finance, 12*(4), 361 - 377. doi:https://doi.org/10.1080/13518470500377406

Merton, R. C. (1973). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance, 29*(2), 449 - 470. doi:https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

Miricescu, E.-C. (2015). The correlation of sovereign rating and bonds' interest rate in EU member states. *Transylvanian Review of Administrative Sciences, 45*, 136 - 148. doi:https://www.rtsa.ro/tras/index.php/tras/article/download/442/431

Mody, A. (2009). From Bear Sterns to Anglo Irish: How eurozone sovereign spreads related to financial sector vulnerability. *IMF Working Paper WP/09/108*.

Morgan, D. P. (2002). Rating banks: Risk and uncertainty in an opaque industry. *The American Economic Review, 92*(4), 874 - 888.

Nazeran, P., & Dwyer, D. (2015). *Credit risk modeling of public firms: EDF9*. Retrieved from https://www.moodysanalytics.com/quantitative-research

Needham, C. L., & Stringer, T. (2017). Global Sovereign 2016 Transition and Default Study. Retrieved from https://www.fitchratings.com/site/search?request=&content=entity&filter=4294288074

Pan, J., & Singleton, K. J. (2008). Default and recovery implicit in the term structure of sovereign CDS spreads. *The Journal of Finance, 63*(5), 2345 - 2384. doi: https://doi.org/10.1111/j.1540-6261.2008.01399.x

Poghosyan, T. (2014). Long-run and short-run determinants of sovereign bond yields in advanced economies. *Economic Systems, 38*(1), 100 - 114. doi:https://doi.org/10.1016/j.ecosys.2013.07.008

Ratings, S. P. G. (2016). S&P global ratings definitions. Retrieved from https://www.standardandpoors.com

Ratings, S. P. G. (2017). General description of the credit rating process as of July 25, 2017. Retrieved from https://www.standardandpoors.com

Remolona, E., Scatigna, M., & Wu, E. (2008). The dynamic pricing of sovereign risk in emerging markets: Fundamentals and risk aversion. *Journal of Fixed Income, 17*(4), 57 - 71. doi: https://doi.org/10.3905/jfi.2008.705542

Remolona, E. M., Scatigna, M., & Wu, E. (2007). Interpreting sovereign spreads. *BIS Quarterly Review*(March), 27 - 39.

Reusens, P., & Croux, C. (2017). Sovereign credit rating determinants: A comparison before and after the European debt crisis. *Journal of Banking and Finance, 77*, 108 - 221. doi:https://doi.org/10.1016/j.jbankfin.2017.01.006

Rowland, P. (2004). Determinants of spread, credit ratings and creditworthiness for emerging market sovereign debt: A follow-up study using pooled data analysis. *Banco de la Replublica de Colombia, Borradores de Economia*. doi:https://doi.org/10.32468/be.296

Schlafer, T., & Uhrig-Homburg, M. (2014). Is recovery risk priced? *Journal of Banking & Finance, 40*, 257 - 270. doi:https://doi.org/10.1016/j.jbankfin.2013.11.033

Schneider, P., Sogner, L., & Veza, T. (2010). The economic role of jumps and recovery rates in the market for corporate default risk. *Journal of Financial and Quantitative Analysis, 45*(6), 1517 - 1547.

Scholtens, B. (1999). On the comovement of bond yield spreads and country risk ratings. *Journal of Fixed Income*, 99 - 103. doi:https://doi.org/10.3905/jfi.1999.319248

Services, M. s. I. (2017). How to get rated: Moody's Process. Retrieved from https://www.moodys.com

Sgherri, S., & Zoli, E. (2009). Euro area sovereign risk during the crisis. *IMF Working Paper WP/09/222*.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal, 27*, 379 - 423. doi: https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Sherif, M., Taub, D., & Hovland, C. I. (1958). Assimilation and contrast effects of anchoring stimuli of judgments. *Journal of Experimental Psychology, 55*(2), 150 - 155. doi:https://doi.org/10.1037/h0048784

Slapnik, U., & Loncarski, I. (2021). On the information content of sovereign credit rating reports: Improving the predictability of rating transitions. *Journal of International Financial Markets, Institutions and Money, 73*, 101344. doi:https://doi.org/10.1016/j.intfin.2021.101344

Stringer, T., McCormack, J., Parker, E., Gamble, P., Colquhoun, A., & Shearman, R. (2016). Sovereign rating criteria. Retrieved from www.fitchratings.com

Sy, A. N. R. (2002). Emerging market bond spreads and sovereign credit ratings: Reconciling market views with economic fundamentals. *Emerging Market Review, 3*, 380 - 408 doi:https://doi.org/10.1016/S1566-0141(02)00043-2

Vasicek, O. (1977). An equilibrium characterization of the term structure. *Journal of Financial Economics, 5*(2), 177 -188. doi:https://doi.org/10.1016/0304-405X(77)90016-2

Vu, H., Alsakka, R., & Gwilym, O. a. (2015). The credit signals that matter most for sovereign bond spreads with split rating. *Journal of International Money and Finance, 53*, 174 - 191. doi:https://doi.org/10.1016/j.jimonfin.2015.01.005

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: MIT Press.