A STUDY OF FACTORS IMPACTING SOVEREIGN CREDIT RATINGS

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I can't change the direction of the wind, but I can adjust my sails to always reach my destination.

Jimmy Dean

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CANDIDATE'S DECLARATION

I Abhinav Goel hereby certify that the work which is being presented in the thesis entitled, "A Study of Factors Impacting Sovereign Credit Ratings" in partial fulfillment of the requirements for the award of the Degree of Doctor in Philosophy, submitted in the Delhi School of Management, Delhi Technological University is an authentic record of my own work carried out during the period from Jan 2020 to Jun 2025 under the supervision of Dr. Archana Singh.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Candidate's Signature

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CERTIFICATE BY THE SUPERVISOR

Certified that Abhinav Goel (Enrollment No.: 2K19/PHDDSM/503) has carried out their research work presented in this thesis entitled "A Study of Factors Impacting Sovereign Credit Ratings," for the award of Doctor of Philosophy from the Delhi School of Management, Delhi Technological University, under my guidance and supervision. The thesis embodies results of original work, and studies are carried out by the student herself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

Dr. Archana Singh
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Delhi Technological University,
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Place and Date:

This thesis is dedicated to my wife-my biggest pillar of support, my parents, children, sisters, and my teachers

*For their endless love,
support and encouragement*

A STUDY OF FACTORS IMPACTING SOVEREIGN CREDIT RATINGS

ABHINAV GOEL

ABSTRACT

Sovereign Credit Ratings are independent opinions of a sovereign's ability to repay its debt obligations in a timely manner. Ability is a synthesis of capacity and willingness to repay. While the capacity to pay is generally determined through analysis of quantitative macroeconomic data, the willingness to pay is analyzed through study of various qualitative variables. (Ozturk, 2016)

SCRs influence a sovereign’s access to and cost of international debt funds. SCRs can also influence flow of money into the economy, including foreign direct investment (FDI). SCRs also impacts availability and cost of borrowing for corporates and banks within the country through concepts like country ceiling. SCRs help international investors to choose and optimally price credit risk, while lending to sovereigns and corporate & banking entities domiciled within the sovereign.

A study of the methodologies of the three large credit rating agencies (CRAs – S&P, Moody’s & Fitch) shows that they evaluate both quantitative and qualitative factors to arrive at their sovereign credit rating decisions. However, most existing academic studies analyses only quantitative factors, without considering the CRA methodologies. While there is largely a consensus on which quantitative variables are important for determining SCR, a similar consensus on qualitative variables has not been achieved. Also, there is substantial literature which establishes the link between banking sector risk and sovereign credit risk in general but work on the qualitative aspects of banking sector risk which contribute to build-up of NPLs is limited.

Overall, this work finds gaps in previous research on the issues of selection of variables impacting SCR; impact of qualitative variables individually and as a group on sovereign credit ratings; consistency in application of rating criteria across nation-groups; and qualitative aspects of banking sector risks. This work proposes to address some of these gaps, especially in the context of India. All these gaps offer a vital opportunity for researchers to make a significant contribution to the related research stream. While we will do an international study on the quantitative and qualitative factors impacting SCR, we have laid special emphasis on

comparison of India across nation groups.

This first work analyses the impact of qualitative factor “rule of law” on the sovereign credit rating. Thorough analysis has been done on the complete developed dataset using linear regression, R squared value and the correlation coefficient. The results indicate a positive linkage, having 82% positive correlation between the “Rule of Law” percentile ranking of a country and its sovereign credit rating across various income groups and regions. The finding suggests that countries striving for higher sovereign credit ratings should consider ways to improve their world standing on qualitative variables like the ‘Rule of Law” and not only concentrate on improving macroeconomic factors. While this paper studies only one variable, there are many other qualitative variables which could be important in determining sovereign credit ratings, which can subject of future research.

For further analysis, two different datasets were developed which comprises of 55 countries from all income groups and geographical locations with SCR obtained from two major CRA’s for a period of 10 years. In these two different datasets, various factors were replaced by their contemporary factors along with the data source. This was done to perform correlation analysis on these datasets individually to assess the importance of different parameters and to predict the sovereign credit rating using extra tree classifier. An important outcome is that all factors with low correlation are quantitative in nature while qualitative factors have high-moderate correlation with SCR. This indicates that the qualitative (socio-political) factors, individually and as a group, are more important in determining SCR than quantitative (economic) factors.

Comparative analysis of results for these 2 datasets indicates the importance of the qualitative factors remains the same in determining SCR irrespective of its data source. This also finds the possibility of a bias in favor of “high-income” nations while assigning SCR. Moreover, banking sector factors appear to have moderate correlation with SCR. The results analysis reflects that given the importance of qualitative factors in determination of sovereign credit ratings; sovereigns particularly developing/low-middle income might be better placed by focusing on socio-political reforms instead of focusing only on economic factors.

The third task analyses data related to NPLs and other banking performance parameters taken from institutions like RBI and World Bank. The findings of this work reveal that bank ownership in India is a major factor impacting levels of stressed assets with PSBs having relatively worse asset quality than private and foreign banks operating in India. Moreover, quality of regulatory system plays a key role in timely stress recognition and maintaining the health of a country’s banking system.

The fourth task analyses the evolution of the stressed assets resolution framework in India from 1985 to 2020 and its impact on the recovery rate, recovery time and amounts recovered. It shows that a pro-creditor stance to resolution has worked better in India than a pro-debtor stance. Though time to recovery has improved substantially, most cases under IBC are breaching the timeline stipulated under law. In an international context, post-IBC, India has made substantial improvement in recovery rates, which are now much higher than developing country peers and moving towards developed countries standards. Also, the time to recovery has substantially reduced and is now closer to developing country peers though still poor compared to developed countries. Indian cost of recovery has meanwhile remained stagnant and in the middle of the stack in the comparison.

LIST OF PUBLICATIONS

Journal Papers

- Abhinav Goel and Archana Singh, “Impact of Economic and Socio-Political Risk Factors on Sovereign Credit Ratings” *Information, Processing and Management*, Elsevier. **(SSCI, ABDC indexed – ‘B’, Impact Factor – 7.4)**
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- Abhinav Goel and Archana Singh, “Stressed Asset Resolution Framework in India: Has a pro-creditor stance made a difference?” *International Journal of Business Information Systems*, Inderscience. **(ABDC indexed – ‘C’)**
- Abhinav Goel and Archana Singh, “Are Sovereign Credit Ratings Impacted by Institutional Quality?” *International Journal of Economics and Accounting*, Inderscience. **(ABDC indexed – ‘C’)**

Conference Papers

- Abhinav Goel and Archana Singh, “Linkages of Rule of Law and Sovereign Credit Ratings – a Data Driven Approach,” *International Conference on Data Analytics and Computing (ICDAC) 2022*, Wenzhou Kean University, China, May 2022 (Springer, Scopus Indexed)
- Abhinav Goel and Archana Singh, “Bank Ownership and Stressed Assets in India: A Critical Study,” *12th Conference on Excellence in Research and Education* (CERE), IIM Indore, June 2022 (Allied Publishers)

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BDT	Bagged Decision Tree
CRA	Credit Rating Agency
CPI	Consumer Price Inflation
EFW	Economic Freedom of the World Report
EIU	Economist Intelligence Unit
EDA	Exploratory Data Analysis
GBM	Gradient Boosting Machine
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GoI	Government of India
HDI	Human Development Index
IMF	International Monetary Fund
MLP	Multi-Layer Perceptron
ML	Machine Learning
NPL	Non-Performing Loans
OEC	Observatory of Economic Complexity
RF	Random Forest
SCR	Sovereign Credit Rating
S & P	Standard & Poor’s
SVM	Support Vector Machines
SOTA	State of the art Work
UN	United Nations

WEF	World Economic Forum
WGI	Worldwide Governance Indicators
WB	World Bank

CHAPTER 1

INTRODUCTION

1.1 Sovereign Credit Ratings

Sovereign Credit Ratings are a forward-looking assessment of a sovereign's capacity and willingness to repay its debt obligations on a timely basis (Fitch, S&P). While the capacity to pay is generally determined through analysis of quantitative macroeconomic data, the willingness to pay is analyzed through study of various qualitative variables (Fitch 2022, Ozturk 2016).

Sovereign credit ratings (SCR) are important from a national and international perspective as they not only enable governments to borrow from the international financial markets, they also influence the cost of borrowing. The sovereign rating also impacts availability and cost of borrowing for corporates and banks within the country through issues like country ceiling. Sovereign ratings could also influence the quantum of capital flows into the country, including foreign direct investment. SCR help international investors to choose and optimally price credit risk, while lending to sovereigns and corporate & banking entities domiciled within the sovereign.

A study of the methodologies of the three large credit rating agencies (CRAs – S&P, Moody's & Fitch) shows that they evaluate both quantitative and qualitative factors to arrive at their sovereign credit rating decisions. Moody's explains that its approach to assessing sovereign credit includes "qualitative and quantitative factors" and that qualitative factors are "informed by quantitative information." S&P states that "both quantitative factors and qualitative considerations form the basis for these forward-looking assessments." Fitch states that its "approach to sovereign credit risk analysis is a synthesis of quantitative analysis and qualitative judgements that capture the willingness as well as the capacity of the sovereign to meet its debt obligations".

However, most literature about sovereign ratings has focused on certain quantitative measures while relatively less relevance has been attached to qualitative factors (Soudis, 2017). Moreover, earlier research has concentrated on variables that were considered significant to sovereign ratings on theoretical basis, rather than being empirically chosen (Choy et al., 2020).

Post the global financial crisis (GFC) of 2008, banking sector risks have attracted greater attention for its linkages with sovereign credit risk. An important lesson from the GFC of 2008 was that a tight linkage can exist between the banking sector, the economy and therefore sovereign credit risk (Krueger, 2013). There is a two-way link between banking sector risk and sovereign credit risk as a distressed financial sector induces government bailouts, whose cost increases sovereign credit risk (Acharya et al., 2014). And increased sovereign credit risk, in turn, weakens the financial sector by eroding the value of its government support and bond holdings (Acharya et al., 2014).

It is therefore important to study the factors impacting SCR given its impact on the availability and cost of borrowing for banks and corporates domiciled within a country and the two-way relationship between banking sector risk and sovereign credit risk. Higher sovereign risk could lead to a weak banking sector which cannot properly support the growth of the corporate sector in a country.

1.2 Overview of Sovereign Credit Rating Methodologies of CRAs

The top three CRAs (Moody's, S&P and Fitch) dominate the credit rating industry (Hung et al., 2021) and account for around 95% of the international rating business (https://corporatefinanceinstitute.com/resources/fixed-income/rating-agency/). For its reporting, the SEC, USA classifies Fitch, Moody's, and S&P as "larger NRSROs" or nationally recognized statistical rating organizations (the legal term for CRAs). As per the SEC 2020 report (https://www.sec.gov/files/2020-annual-report-on-nrsros.pdf), the three "larger NRSROs" accounted for 93.3%-94.4%) of revenue between 2019-2016 period.

Given the domination of these three CRA's, we have studied the methodologies of only these large NRSROs (CRA) as defined by SEC (USA). Methodologies of the three CRAs suggest that sovereign ratings are analyzed from the perspective of four to five broad pillars. These broad pillars are analyzed by each CRA in a unique mix along with variables relating to every pillar. However, there is commonality in the pillars which broadly represent the following: institutional assessment, economic assessment, external assessment, fiscal assessment, and monetary assessment. Other rating considerations like susceptibility to event risk can form an overlay to these pillars. From the study of the rating methodologies from the three large CRAs, we conclude that there are significant similarities in the broad rating pillars as well as sub factors within these pillars. Some of the common appearing qualitative factors have been marked in bold in the Key Rating Pillar tables (Table 1.1-Table 1.3) of the three CRAs presented below.

Table 1.1: Key Rating Pillars – Moody's

Economic strength	Institutional and Governance Strength	Fiscal strength	Susceptibility to event risk
Average real GDP growth	**Quality of Legislative and Executive Institutions**	Govt debt/GDP	**Domestic Political and Geopolitical Risk**
Volatility in real GDP Growth	**Strength of Civil Society and Judiciary**	Govt debt/Revenue	Ease of Access to Funding
GDP per capita (PPP, US$)	Fiscal Policy Effectiveness	Govt interest cost/ Revenue	**Risk of Banking Sector Credit Event** Total domestic bank assets/GDP
Nominal GDP (US$ bn)	Monetary and Macroeconomic **Policy Effectiveness (including banking regulation effectiveness)**	Govt interest cost/ GDP	External vulnerability indicator (EVI) (Current account balance + FDI inflows)/ GDP
	Government Default History	Debt Trend Govt forex debt/ total debt Other non-financial public sector debt/ GDP Public sector financial assets/Debt	

Moody's is using various qualitative factors in measuring "institutional and governance strength" as well as "event risk." Banking sector risks are included in "event risk" as well as in "institutional and governance strength" under policy effectiveness.

Table 1.2: Key Rating Pillars – S&P

Economic assessment	Institutional assessment	Fiscal assessment	External assessment	Monetary assessment
GDP per capita	**Policy effectiveness track record**	Fiscal performance and flexibility including Net Govt Debt/GDP	External indebtedness	Exchange rate regime
Real per capita GDP trend growth	**Policy stability track record**	Debt burden including Interest/ Govt Revenue	FX reserves position	Credibility of monetary policy including inflation
GDP projections	**Policy predictability track record**	Debt structure and funding access **Banking Sector Risks Risks of contingent liabilities**	External Liquidity	
Economic diversity and volatility	**Stability of political institutions**	Long-term fiscal trend and vulnerabilities including availability	Currency Status in international transactions	

		of liquid financial assets, **future spending pressure (UN HDI)**		
	Transparency and accountability			
	Sovereign debt payment culture **External security/ war risks**			

Table 1.3: Key Rating Pillars – Fitch

Structural features	**Macroeconomic performance policies and prospects**	**Public finances**	**External finances**
Governance indicators GDP per capital Share in world GDP Years since default Broad money supply	Real GDP growth volatility Inflation Real GDP Growth	Gross government debt/GDP Government interest (% of revenue) General government fiscal balance/GDP Foreign-currency government debt/GGD	Reserve-currency flexibility Sovereign net foreign assets (% of GDP) Commodity dependence FX reserves (months of CXP) External interest service (% of CXR) Current account balance + FDI (% of GDP)
Qualitative Overlay			
Structural features	Macroeconomic performance policies and prospects	Public finances	External Finances
Political stability **Financial sector risks (including Banking Sector Risks)** Other structural factors	**Macroeconomic policy credibility & flexibility** GDP growth outlook (five years) Macroeconomic stability	Fiscal financing flexibility Public debt sustainability Fiscal structure	External financing flexibility External debt sustainability **Vulnerability to shocks**

`S&P is using various qualitative factors in its “institutional assessment” as well as “fiscal assessment”. Banking sector risks are also included in “fiscal assessment.” Whereas, Fitch is using various qualitative factors extensively in its assessment of “structural features” and to some extent in the assessment of “macroeconomic policies” and “external finances”. Banking sector risks are also included in financial sector risks under “structural features”.

In general, rating agencies arrive at a sovereign credit rating through assessment of quantitative as well as qualitative factors which are then, in a process of weighting and consideration of potential adjustments, combined into a single rating score (Figure 1.1). These factors are embedded in the rating pillars described earlier.

While quantitative factors reflecting ‘ability to pay’ are more observable and easier to link with sovereign risk, qualitative factors reflecting ‘willingness to pay’ are unobservable, but can be a good measure to approximate a sovereign credit risk (Ozturk, 2016). Qualitative factors can be a “proxy for many intangible and difficult-to-measure factors that enhance debt tolerance” (Fitch).

The approach of these three CRAs is summarized as follows:

- Moody’s explains that its approach to assessing sovereign credit includes “qualitative and quantitative factors” and that qualitative factors are “informed by quantitative information” (Moody’s, 2016).
- S&P states that “both quantitative factors and qualitative considerations form the basis for these forward-looking assessments” (How We Rate Sovereigns, 2019).
- Fitch states that its “approach to sovereign credit risk analysis is a synthesis of quantitative analysis and qualitative judgements that capture the willingness as well as the capacity of the sovereign to meet its debt obligations” (Fitch 2022, n.d.).

A study of the sovereign rating methodologies of the three major international CRAs shows that they use several quantitative factors like GDP growth, GDP per capita, government fiscal balance, current account balance, Debt/GDP and inflation to determine SCRs.

The CRAs also place significant reliance on qualitative factors like political stability (Fitch), financial sector risks (Fitch), strength of civil society and judiciary (Moody’s), quality of legislative and executive institutions (Moody’s), monetary and macroeconomic effectiveness (Moody’s), transparency and accountability of institutions, data and processes (S&P). Most of these measures come under different heads and nomenclatures in the rating methodologies of the three CRAs, e.g., banking sector risk (Moody’s), domestic and geopolitical risk (Moody's), Governance quality including rule of law, control of corruption, voice and accountability (Fitch).

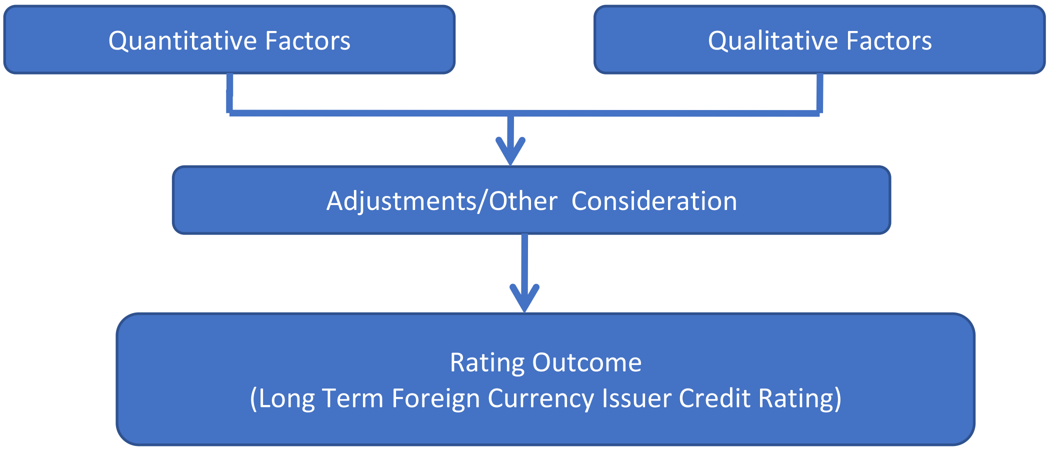

Figure 1.1 – Sovereign Credit Rating Framework (Author's Interpretation)

Banking sector risks are also considered important determinants of SCR. S&P for instance refers to contingent liabilities and their potential impact on sovereign ratings. Bank NPLs are key among these liabilities that have the potential to affect a government's fiscal profile (S&P). While there is a link between banking sector risk and sovereign credit risk, the former is not yet popular in existing literature on models of sovereign ratings (Choy et al. 2020).

Institutions and governance provide a strong indication of a government's willingness to repay its debt (Moody's) and are therefore considered important by CRAs. However, these qualitative factors have not received adequate attention in literature related to sovereign credit risk as there is insufficient utilization of rating agencies' methodology papers in assisting with the selection of variable (Choy et al., 2020).

1.3 Rationale of the Work

All countries strive to improve or maintain their sovereign credit ratings. This is particularly true for developing/ low-middle income countries or countries with low SCRs. While there is a broad consensus on the significance of quantitative factors, the role of qualitative factors is still debated. It is important to understand which factors have a significant role in determination of these ratings. Given the important influence of qualitative factors, it might be better for sovereigns to focus on institutional reforms rather than focus on solely on macroeconomic factors (Soudis, 2017).

India is one of the largest and fastest growing major economies in the world, but has the lowest investment grade rating ('BBB-'), which has effectively remained at the same level over the past one and a half decades. Therefore, factors which influence SCR need greater attention.

In the years following the GFC, banking sector risks came up prominently as one of the key risks impacting sovereign risk. Most countries which defaulted or came close to default like Ireland, Greece, Italy, Portugal and Spain saw banking sector risks exacerbating sovereign risks significantly. In the case of Spanish banking sector recapitalization of 2012, additional debt issued to finance the recapitalization increased sovereign default risk, and translated in lower sovereign bond prices (Kwaak & Wijnbergen, 2017). Incidentally, despite economic growth, India's banking asset quality has been among the worst in major economies over the past decade.

As per a recent media report, in 2020 the government of India prepared an internal report on qualitative factors impacting India's credit rating as it worried that they may lead to a downgrade of India's SCR. This shows that the subject is under consideration at the highest levels in India and our work could provide useful inputs for not only India but several other countries with low scores on qualitative factors. https://indianexpress.com/article/india/worried-india-rating-may-turn-junk-govt-pushed-narrative-management-strategy-7907161/ (Accessed on 10th May 2022 and 18th May 2025).

There are two ways in which the sovereign credit risks impact business environment within a country:

a) Sovereign credit risks impact the access and cost of funds for corporates and banks within a country and therefore it has direct impact on the business environment.
b) Given the two-way linkage of banking sector and sovereign credit risks (Acharya et al., 2014), there are clear implications of sovereign risks on the banking sector and the business environment. A weak banking sector cannot properly support the growth of the corporate sector in a country.

Hence, further research needs to be done on how sovereign credit ratings are determined in practice, focusing on qualitative aspects including banking sector risks in addition to a quantitative analysis of the determinants of sovereign ratings.

1.4 Research Gaps

After a study of the CRA sovereign rating methodologies and existing academic literature on the subject, the following gaps are identified:

a) CRA methodologies consider both quantitative factors and qualitative factors prominently while determining SCR. However, most existing academic studies have laid greater emphasis on quantitative factors. This shows that there is inadequate use of CRA methodologies in choosing variables for research in this area (Choy et al., 2020; Literature Review Analysis).
b) While some researchers have found certain qualitative factors to be important, their relative degree of importance as a group in determining sovereign credit ratings has not been widely researched (Literature Review Analysis).
c) While there is largely a consensus on which quantitative variables are important for determining SCR, a similar consensus on qualitative variables has not been achieved. There is a need to find which qualitative variables have important influence of determination of sovereign credit ratings (Soudis, 2017; Literature Review Analysis).
d) While some research has been done on the consistency of application of factors determining SCR across countries, such research with focus on India is sparse. Given that India is one of the largest and fastest growing major economies in the world, but has the lowest investment grade rating, this issue needs greater attention (Literature Review Analysis).
e) While there is substantial literature which establishes the link between banking sector risk and sovereign credit risk in general but work on the qualitative aspects of banking sector risk which contribute to build-up of NPLs is limited (Brůha and Kočenda, 2018), especially in the context of India (Literature Review Analysis).
f) Quicker NPL resolutions with higher recovery rate would reduce banking sector risks, ultimately impacting sovereign risk as well. Studies in this area have been sparse in India, and have mostly focused on a single regulation. There is a need to study the evolution of the Indian legal framework for NPL resolution in a holistic manner along with its impact on NPL reduction (Literature Review Analysis).

Overall, this work finds gaps in previous research on the issues of selection of variables impacting SCR; impact of qualitative variables on sovereign credit ratings; consistency in application of rating criteria; and qualitative aspects of banking sector risks. This work proposes to address some of these gaps, especially in the context of India.

All these gaps offer a vital opportunity for researchers to make a significant contribution to the related research stream. While we will do an international study on the quantitative and qualitative factors impacting SCR, we will lay special emphasis on comparison of India with other countries across income/development and regions.

1.5 Research Objectives

The primary goal of this research was to analyse the factors affecting SCR given its impact on the availability and cost of borrowing for banks and corporates domiciled within a country. This also analyses the relationship between banking sector risk and sovereign credit risk. Also, the research focuses on developing a model for prediction of SCR. The methodologies used, its application, research findings, and accomplishments for each of the research goals are listed below in this segment:

Research Objective 1:

- To analyze the methodologies adopted by the three large credit rating agencies for assigning sovereign credit ratings

Research Objective 2:

- To analyze the impact of various quantitative and qualitative factors on the overall sovereign credit ratings assigned

Research Objective 3:

- To examine the impact of qualitative banking sector factors on NPL creation in India.

Research Objective 4:

- To examine the impact of legal framework on resolution and reduction of NPLs in India

Research Objective 5:

- To develop a model for prediction of sovereign credit ratings.

1.6 Research Contribution

This research has focused on four tasks. The first task involves development of a vast dataset of Sovereign Credit rating which comprises of credit ratings along with various qualitative and quantitative indicators for 55 countries for 10 years from 2011 to 2020. Ratings assigned to each country independently by Moody's and Fitch (one at a time) at the end of each calendar year, have been considered the target/dependent variable. Data from Moody's, and Fitch credit rating agencies have been considered and a total of 17 quantitative & 9 qualitative factors for dataset 1; 17 quantitative & 7 qualitative factors for dataset 2 have been considered. Therefore, this dataset can be used for varied kind of analysis ranging from weight of parameters in determination of sovereign rating, relation between parameters, presence of biasness in sovereign rating, training a model for predicting a country's sovereign credit rating etc.

The second work examines various aspects related to SCR including the relative importance of quantitative variables versus qualitative variables as determinants of SCR; possibility of a developed country bias in SCR; and relative importance of banking sector risks as determinant of SCR. This uses the dataset developed in the first work and then replacing few variables alongwith their respective data sources to create a second dataset. Correlation analysis indicates that all factors with low correlation are quantitative in nature while qualitative factors have high-moderate correlation with SCR. This indicates that that the qualitative (socio-political) factors, individually and as a group, are more important in determining SCR than quantitative (economic) factors. Further result analysis indicates the importance of the qualitative factors remains the same in determining SCR irrespective of its data source. This also finds the possibility of a bias in favor of "high-income" nations while assigning SCR.

The third work analyses the impact of stressed assets resolution framework on the recovery rate, recovery time and amounts recovered by banks in India using data from RBI and World Bank. This work also analyzes various laws and schemes issued by the GoI and the RBI. While this shows some improvement in terms of recovery rates, these remained far below international standards till the introduction of IBC in 2016. Besides the recovery rate, given that some very large stressed assets have been resolved under IBC, the absolute amount of debt recovered is substantially more than that recovered through other mechanisms It shows that a pro-creditor stance to resolution has worked better in India than a pro-debtor stance. In an international context, post-IBC, India has made substantial improvement in recovery rates, which are now much higher than developing country peers and moving towards developed countries standards. Also, the time to recovery has substantially reduced and is now closer to developing country peers though still poor compared to developed countries.

The fourth work compares Indian Non-Performing Loans (NPLs) in an international context. This analyses data related to NPLs and other banking performance parameters taken from institutions like RBI and World Bank. The considered data ranges pertain to Indian banking from FY07-FY20 on 'loans subject to restructuring and restructured loans' across the three categories of banks – PSBs, Private Banks and Foreign Banks. The findings reveal that bank ownership in India is a major factor impacting levels of stressed assets with PSBs having relatively worse asset quality than private and foreign banks operating in India. Moreover, quality of regulatory system plays a key role in timely stress recognition and maintaining the health of a country's banking system. This work concludes that PSBs need to strengthen their credit appraisal systems, which could include inculcating best practices from international banks. This could help bring Indian banking NPL levels down to levels of other large developed and developing countries.

This fifth work analyses the impact of qualitative factor "rule of law" on the sovereign credit rating. For a thorough analysis, initially a dataset is developed that comprises of parametric values for "rule of law" and the sovereign rating which is converted to ordinal values. Thorough analysis has been done on the complete developed dataset using linear regression, R squared value and the correlation coefficient. The results indicate a positive linkage, having 82% positive correlation between the "Rule of Law" percentile ranking of a country and its sovereign credit rating across various income groups and regions. The finding suggests that countries striving for higher sovereign credit ratings should consider ways to improve their world standing on qualitative variables like the 'Rule of Law" and not only concentrate on improving macroeconomic factors. This paves the way for analysis of other qualitative variables which could be important in determining sovereign credit ratings.

1.7 Organization of the Thesis

The thesis comprises seven chapters followed by conclusions and future scope and a bibliography. The thesis is organized as following:

Chapter 1: Introduction

This chapter will cover the motivation and purpose of the outlined research topic. It will also contain the main idea for the development of the thesis.

Chapter 2: Literature Review

In this chapter, a detailed literature review of the CRA methodologies and the importance of qualitative and quantitative factors in assigning the SCR is presented. This chapter also highlights the significant link between banking sector risk and sovereign credit risk. This seeks to identify the determinants of SCR, deriving factors largely from macroeconomics and the socio-political perspective, and from rating agencies methodologies as well as previous research. This is followed by discussion of the current limitations of the existing studies, chapter summary and contribution of the present research to the field.

Chapter 3: Development of Dataset for Sovereign Credit Rating

This chapter contributes to the development of a vast dataset comprising of SCR and the various qualitative and quantitative variables. Such dataset has been used in the current work to predict the SCR or analyzing the impact of various factors on the sovereign rating. This chapter details the utilized methodology to prepare the dataset, its processing, and rationale behind the duration considered, countries considered for the dataset development.

Chapter 4: Does Qualitative factor "Rule of Law" impact SCR

This chapter analyzes the role of qualitative factors in the determination of SCR for a country. While there could be various qualitative factors impacting SCR, this chapter focuses on a specific institutional factor, namely "Rule of Law" and analyzes its linkage with the assigned SCR. Regression analysis has been used on the developed dataset for sixty countries covering all the continents/regions across the globe for a period of five years (2016-2020).

Chapter 5: Impact of Economic and Socio-Political Risk Factors on Sovereign Credit Ratings

This chapter uses developed dataset to predict the SCR or analysing the impact of various factors on the SCR. This also analyses the importance of quantitative and qualitative variables in determining SCR. This work also explores the linkages of banking sector risks with SCR and the presence of any developed nation bias for evaluating SCR. Further, machine learning pipeline, correlation analysis and various plots have also been implemented to the developed dataset for corroborating the results.

Chapter 6: Bank Ownership and Stressed Assets in India: A Critical Study

Examining the impact of some qualitative factors on banking sector risks in India, this chapter contributes to finding the impact of bank ownership on stressed assets in the Indian Banking Sector and the importance of the regulatory system for timely stress recognition. The work further compares Indian Non-Performing Loans (NPLs) in an international context. The present work also suggests measures to lower the Indian NPL levels which can be achieved if PSBs strengthen their credit appraisal systems, which could include inculcating best practices from international banks. Further, the regulatory framework needs be tight regarding stress recognition, using forbearance sparingly.

Chapter 7: Regulatory Framework for Stressed Asset Resolution in Indian Banking: Is the Evolution making an Impact?

Timely recognition of stressed assets is imperative for effective resolution, Hence, continuing from Chapter 6, this chapter discusses another qualitative factor i.e. examining the impact of the legal framework on resolution and reduction of NPLs in India. This chapter also discusses the evolution of various laws and schemes issued by the Government of India and the Reserve Bank of India (RBI) from 1985 to 2020 along with the secondary data from RBI and World Bank. The present chapter classifies the laws and schemes related to NPLs into three categories: Initial Laws (enacted in the 1980s-1990s); Intermediate laws and schemes (enacted in the 2000s); and Recent laws and schemes (enacted in the 2010s). This contributes to research in the area of financial regulation in two ways. Firstly, it critically analyses the evolution of the Indian stressed assets resolution framework in a holistic manner with pros and cons of each law and scheme. The effect of the laws on recovery rate and absolute amounts recovered has been compiled and analyzed.

Chapter 8: Conclusion and Future Directions

This chapter will contain the summary of all the analysis, observations and contributions of the results obtained in each objective. Also, the future directions in this field are sketched in this section.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

CRAs clearly use both qualitative and quantitative factors to assign sovereign credit ratings, even though the exact weightages are not disclosed. However, academic literature has focussed largely on quantitative factors impacting SCRs. Literature on qualitative factors impacting SCR is relatively less. Some researchers have also found inconsistencies in the application of these factors across various country-groups (like developed vs developing) while assigning SCRs. Moreover, post the global financial crisis, banking risk has emerged as a prominent risk impacting sovereign risk. Researchers have also concluded a two-way linkage between banking sector risk and sovereign risk.

While the most obvious impact of sovereign ratings is on the cost of borrowing for the rated government, the impact of SCR also extends deeply to the economy in general, the banking sector and thereon to corporate access to capital, as well as investment activities. This chapter, therefore, covers the existing studies on various aspects of SCR that have examined the impact of quantitative and qualitative factors on SCRs; the linkages between banking sector risks and sovereign credit risks; and certain qualitative factors that impact banking sector risks. To present it systematically, an attempt was made to classify and organize the entire literature into five broad themes.

a) The first broad theme covers studies that have either focussed on quantitative factors or found quantitative factors to be largely impacting SCRs.
b) The second theme covers studies that have specifically analysed the impact of qualitative factors on SCRs and found them to be important or otherwise.
c) The third theme covers studies that they focused on finding whether application of CRA methodologies is consistent across various country-groups or whether a home-bias exists in favour of the country where a CRA is domiciled; or bias towards certain nation groups.
d) The fourth theme covers studies that have analysed inter-linkages between banking sector and sovereign risks.

e) The fifth theme covers studies that have focused on some qualitative factors impacting banking sector risks, and hence eventually sovereign credit risk. These factors could include bank ownership, banking regulation and stressed asset resolution.

2.2 Quantitative/Macroeconomic factors

There is a large body of literature which has found quantitative/ macroeconomic variables to be principal determinants of SCR. Some of these studies also found few qualitative variables to be important but those are much lesser in comparison. Among the initial works on the determinants of sovereign credit ratings is of that Cantor & Packer (1996) who studied 8 variables which were mostly quantitative. Some of the most commonly occurring quantitative variables in these studies include GDP growth, GDP per capita, fiscal balance, current account balance, international reserves/imports, inflation, external debt and Debt/GDP.

Some researchers while studying both kinds of factors have concluded that quantitative factors are the primary determinants of SCR. Haque et al (1998) find that creditworthiness appears to be determined primarily by economic variables and not so much by political variables. Bennell et al (2006) do not explicitly include political indicators in their study based on previous research indicating that although both political instability and economic variables are taken into account in evaluating country creditworthiness, these perceptions are largely reflected in a country's economic performance anyway.

Some researchers have also concluded that moving beyond quantitative variables to any subjective elements can bias the rating in the wrong direction and that objective parameters have prediction power both in the short & long term, unlike subjective parameters which don't work as well in the long term (Vernazza & Nielsen, 2015). Table 2.1 below presents a summary of some of the important research studying the determinants of SCR, which either focussed on quantitative factors or found those to be of primary importance.

While most research in this theme has found quantitative factors to be dominant, some qualitative factors (like political stability, corruption legal environment and government effectiveness) have been found to be contributing, though relatively much less. This does not seem to be in consonance with CRA methodologies which are seemingly placing more emphasis on qualitative factors. Overall, a significant body of literature exists on quantitative factors impacting SCR with certain quantitative factors having gained consensus.

Table 2.1: Important Research studying Quantitative determinants of SCR

Reference	Model	Type of date study; sample size (no. of countries)	Period	CRA	Variable studied
Cantor and Packer (1996)	OLS	Cross-section; 49	1995	Moody's and S & P	8 variables; GNP per capita, GDP growth, inflation, external debt-to exports ratio, fiscal balance, current account balance, economic development and default history.
Afonso (2003)	OLS	Cross-section; 81	2001	Moody's and S&P	8 variables; GDP per capita, inflation, developed nation status, external debt-to-exports ratio, development status default history, fiscal balance and current account balance.
Bissoondoyal-Bheenick (2005)	Ordered probit	Panel;95	1995-1999	Moody's and S&P	10 variables; GNP per capita inflation, fiscal balance, governance debt, real exchanges rate, foreign reserves, current account balance, net exports, unemployment rate and unit labour cost.
Gaillard (2012)	OLS and ordered probit	Cross-section; 95	2006	Moody's	8 variables: GDP per capita inflation current account balance, government debt external debt foreign reserves, government effectiveness, and default history.
Reusens and Croux (2017)	Ordered probit	Panel; 90	2002-2015	Fitch, Moody's and S&P	10 variables: GDP per capita, government debt, GDP growth, inflation, financial balance, external debt, current account, economic development, Eurozone membership, and default history.
D'Rosari et al (2018)	ANN	16 Latin American countries	1992-2003	S&P & Moody's	17 variables: GDP per capita, GDP growth, inflation, external debt/GDP, fiscal balance, current account balance, polity, election year, president's ideology (including economic reforms) etc.

2.3 Qualitative Factors

Besides quantitative factors, CRAs use several qualitative factors while determining sovereign credit ratings. Some researchers have found qualitative factors to be important in determining SCRs while acknowledging that they more difficult to measure as they are unobservable (Ozturk,2016).

An important question which arises is that which qualitative factors can influence timely debt repayment by a sovereign. While researchers acknowledge the importance of qualitative factors in general, there is lack of consensus around which of these are more important (Soudis, 2017), unlike quantitative factors where there is a consensus on a core set of parameters.

Researchers have found different qualitative factors to be important for determining SCRs. Choy et al (2020) find that regulatory quality and rule of law are two variables which are important determinants of SCR. Ozturk (2014) asserts that government ineffectiveness and poor regulatory quality were the two main factors that explained the low ratings for developing countries. Lawson & Roychoudhury (2010) found that the economic freedom index and cost of borrowing of a country are linked. Biglaiser & Staats (2012) find that rule of law, strong and independent courts, and protection of property rights have significant positive effects on bond ratings. Connolly (2007) concluded that corruption downgrades the creditworthiness of sovereign bonds. The worldwide governance indicators (WGI) published by the World Bank have been specifically found by some researchers to be significant explanatory factors in SCRs (Vu et al., 2017; Ozturk, 2016).

Some researchers even conclude that qualitative factors might be more important than quantitative ones in determining SCR (Soudis, 2017). Vu et al. (2017) found that political risk played a greater role in explaining split ratings among CRAs than quantitative indicators. Basu et al. (2013) found that following the global financial crisis of 2008, CRAs give lesser importance to cyclical variables such as GDP volatility, and have more stress on structural factors such as the rule of law.

If qualitative factors have a substantial role to play in the assignment of these ratings, then countries which strive to improve sovereign ratings must prioritise and improve socio-political institutions and other qualitative factors (Choy et al. 2020). Montes et al. (2016) found that besides the traditional macroeconomic variables, adoption of inflation targeting, financial openness, democracy, law and order, and less corruption are important to improve the sovereign ratings.

While many authors have found qualitative factors to be important while determining SCR, many studies have been contradictory. Benito et al. (2015) had mixed results and found that transparency plays a role at the time of crisis, but in normal times core economic indicators are more important determinants of sovereign cost of funds. Archer et al. (2007) conclude that political factors have little effect on SCR while quantitative factors like trade, inflation, growth, and bond default strongly affect SCR. Mellios & Paget-Blanc (2006) conclude that SCR are mostly influenced by quantifiable factors.

From the literature review we can conclude that the 'willingness to repay' is the more difficult part to assess while assigning SCRs as it is not directly measurable and therefore can only be proxied through qualitative factors. Scholars have used various measures as proxy like corruption, rule of law, political stability and judicial independence. However, the number of papers focusing on political determinant of ratings is not as voluminous as their more economic oriented counterparts (Soudis, 2017).

CRAs have clearly mentioned use of factors like World Bank's World Governance Indicators (Fitch) and UN Human Development Index (S&P). However, due to lack of transparency in the methodologies of CRAs, there is no certainty of the relative weight of variables used and how much of variation they cause in the SCR (Soudis, 2017).

In summary, besides quantitative factors, many authors have found qualitative factors to be important for determining SCR; however, some studies have contradictory findings as to their importance. Another issue is that researchers have found different qualitative factors to be important from a SCR perspective; there is no broad consensus on the matter. Moreover, the relative degree of importance of qualitative factors as a group has not been widely researched. CRAs also do not clearly state the weightage they give to various factors, including qualitative ones. It is therefore imperative to research the relative degree of importance of qualitative factors as a group in determining SCRs along with which of these specific factors are important.

2.4 Treatment for different countries or regions

Within the broad theme of treatment for different countries or regions, there are three sub-themes as given below:

a) Whether the application of various variables for determining SCR is consistent across countries or groups of countries.

b) Whether there is a "home-bias" towards the country where the CRA is headquartered or towards culturally-similar countries.
c) Whether there is a bias towards a specific rated sovereign.

Bissoondoyal-Bheenick (2005) found the weighting of variables for high-rated countries is different to those of low-rated countries. Karakaş et al. (2011) concludes that the consistency of credit ratings differs by favouring developed countries. Ozturk (2014) links lower rating of developing countries with their relatively poor institutional quality. Gultekin-Karakas et al (2011) conclude that developed countries tend to receive a higher rating compared to developing countries regardless of what their fundamentals would suggest.

Tennant et al. (2020) conclude that there is statistical bias against poor countries whenever their fundamentals change. Botha and Pretorius (2020) find that the determinants of sovereign credit ratings differ between African regions and income groups. Mutize & Nkhalamba (2020) conclude that macroeconomic factors are relatively less important in determining country's risk profile in Africa than in other developing and developed countries.

Ke Chen et al. (2011) found in the case of China that while earlier ratings may have been underestimated, recent Chinese sovereign credit ratings were not. Stolbov, Mikhail. (2016) concludes that in the case of Russia, the role of domestic factors in determining sovereign credit risk was limited relative to global risk factors.

Yalta & Yalta (2018) found a strong home country bias towards the United States, while there seem to be no special biases against individual groups of countries. Fuchs & Gehring (2013) conclude that countries culturally more similar to the CRA home-country, and countries to which home-country banks have a larger risk exposure receive higher ratings than justified by their economic and political fundamentals. Moor et al. (2017) concludes that the rated sovereign's lobbying effort or its familiarity from a United States point of view make a difference to the SCR.

On the whole, some researchers have found that SCRs seem to differ for countries with similar macroeconomic variables or do not improve commensurately for some countries despite improvement in macroeconomic fundamentals. Scholarship has explained some of these seeming inconsistencies with the differences in institutional quality or data quality (which is also eventually linked to institutional quality). This also ties-in with some of the inferences drawn in the literature review on the impact of qualitive factors, especially that of institutional quality, on SCRs. The proposed work will build on this theme and while analysing the various determinants of SCRs, we will also study if their application if consistent across country-groups, with special reference to India.

2.5 Linkages of banking sector risks and sovereign credit risk

The significant link between banking sector and sovereign risk was highlighted during the global financial crisis of 2008 where many countries faced downgrades due to weaknesses in their banking sectors. There is some literature which establishes the link between banking sector risk and sovereign credit risk, though much less than that related to hard quantifiable macroeconomic measures (Brůha and Kočenda , 2018). This is perhaps because banking sector risks are both quantitative (like NPL/Gross Loans) and qualitative (regulatory quality, bank ownership etc).

There is a two-way link between banking sector risk and sovereign credit risk as a distressed financial sector induces government bailouts, whose cost increases sovereign credit risk. Increased sovereign credit risk, in turn, weakens the financial sector by eroding the value of its government guarantees and bond holdings (Acharya et al., 2014). There is two-way relationship between non-performing loans and sovereign ratings over and above the impact of macroeconomic and financial determinants (Boumparis et al., 2019). Another channel of transmission of the banking sector risk to sovereign risk is through the corporate credit. There is a private sector debt threshold beyond which further credit expansion can exacerbate sovereign risk (Brůha and Kočenda, 2018).

Important banks are vital to countries and when they become seriously troubled, a cost-effective solution might be to bail them out because bankruptcy would exert costly and damaging effects on the economy (Gerlach et al., 2010). However, funds for a rescue package increase government indebtedness and consequently sovereign default risk increases (Campolongo et al., 2011; Reichlin, 2014). Kwaak & Wijnbergen (2017) found that additional sovereign debt issued to finance the recapitalization of Spanish banking sector in 2012 increased sovereign default risk, and translated in lower sovereign bond prices.

One of the most important lessons from the GFC of 2008 was that a close link can exist between the banking sector and the macroeconomy (Krueger, 2013). Martínez et al. (2016) found that that the aggregate prudential ratios of banking soundness impact sovereign risk; specifically, a high NPLs lead to a deterioration in sovereign ratings. Choy et al (2020) conclude that banking sector variables like non-performing loans over gross loans (NPL ratio) and loans-to-deposits ratio (LD ratio) also influence sovereign credit ratings, while Brůha and Kočenda (2018) found capital adequacy ratio to have linkage with sovereign credit rating.

The above findings are supportive of the link between banking sector risk and sovereign credit risk which could be two-way. Fitch, Moody's and S&P also incorporate banking sector credit risks within their assessment of sovereign ratings.

Given the general acceptance of the two-way link between banking sector risk and sovereign risk, it is imperative to study some qualitive and quantitative aspects which could influence banking sector risks and hence sovereign risks. This is important as sovereign downgrades can to lead to a vicious cycle of banking rating downgrades which in turn lead to a reduction in lending supply and impact the entire corporate sector.

2.6. Qualitative Factors impacting Banking Sector Risks

Literature has concluded there is a link between banking sector risk and sovereign risk which could be two-way. A similar two-way link has been found specifically between NPLs and sovereign risk. Branching from this theme of literature, there are various sub-topics on qualitative factors which could impact creation or resolution of NPLs in the banking system of a country:

a) the link between bank ownership and NPLs.
b) impact of banking regulation and supervision on NPLs
c) impact of regulatory framework on resolution and eventual reduction in NPLs

2.6.1 Linkages between bank ownership, banking regulation and NPLs

Both academic literature and CRA methodologies include NPLs and quality of banking regulation as part of banking sector risks while analysing sovereign credit risk. Our focus in the proposed work will be on India while providing an international context.

The present section provides a brief literature review on the relation of bank ownership and stressed assets both in the Indian and global context. Cull et al. (2017) conclude that state-owned banks appear to have a higher fraction of NPLs loans than privately-owned banks. Gonzalez-Garcia and Grigoli (2013) find that a larger presence of state-owned banks in the banking system is associated with larger fiscal deficits, and higher NPLs. Agarwala and Agarwala (2019) found that the growth rate of NPLs in Indian private banks is moderate when compared to PSBs. Lee and Lu (2015) found that increased government ownership is related to poorer levels of bank efficiency.

Kane (2009) concluded that a faulty regulatory structure was the most significant contributor to the GFC of 2008. Samet *et al.* (2018) argued that enhanced bank regulation and oversight would bring market discipline to PSBs, reducing their tendency for excessive risk-taking. Lee and Lu (2015) found that bank fragility is reduced as a result of better regulation, as indicated by lower NPL levels. Krueger (2013) concludes that for crisis prevention, a key lesson is the importance of regulation and supervision in preventing the build-up of NPLs; it was the potential collapse of the banking systems that led to the heavy sovereign debt burdens of European nations like Iceland and Ireland.

However, some studies have reached contradictory conclusions on the aspects of bank ownership, banking regulations and NPLs. Barth *et al.* (2004) found that there is no significant relationship between government ownership and bank performance. In a study of Chinese commercial banks, Liu *et al.* (2020) found that concentration of ownership with the government decreases credit risk for banks. Rajeev and Mahesh (2010) found that PSBs have been as successful in reducing NPLs as private banks; the authors also concluded that self-monitoring has been sufficient to reduce NPLs.

On presence of foreign banks, Ozili (2019) concluded that NPLs rise in tandem with increased financial development, which manifests itself in the form of increased foreign bank presence. On the other hand, Brůha and Kočenda (2018) conclude that foreign bank penetration and a more diversified structure of the banking industry, inducing competition are linked to lower sovereign risk.

While identifying a two-way relationship between non-performing loans and sovereign ratings, Boumparis et al. (2019) suggest that future research could also focus on the potential role of state-owned versus private banks in NPLs in the banking system. It is therefore imperative to analyse the entire Indian banking sector and study aspects of bank ownership and regulatory framework in a holistic manner including their impact on NPL creation.

2.6.2 Impact of NPL resolution framework on the level of NPLs and Banking Sector Risks

Both academic literature and CRA methodologies include NPLs and quality of banking regulation as part of banking sector risks while analysing sovereign credit risk. The level of NPLs in a country's banking system depends not only on the pace of NPL creation but also on the efficiency of NPL resolution. The below section provides literature review on the sub-theme of NPL resolution.

Literature on the stressed asset resolution framework in India is sparse and most studies are focussed on particular laws and do not present a comprehensive picture. While we propose to study this sub-theme in the Indian context, a global perspective will be provided in this section to provide a broader perspective of issue in hand.

Zwieten (2015)points that the application of SICA by the Indian legal system was extremely pro-debtor, favouring shareholders and employees at the cost of lenders. Ravi (2015) argued that the Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interests Act (SARFAESI) may have provided some relief to banks and secured creditors, at the expense of a well-organized insolvency process that maintains value and benefits all stakeholders. Shikha, N. and Shahi (2021) studied data pertaining to 1189 companies under IBC as on March 2020 and found that 224 were resolved companies (19%) while 965 were liquidated (81%). While the liquidation rate was high, the recovery rate under IBC is also significantly higher than the previous laws.

Developed countries have also faced several challenges in stressed asset resolution and the laws there have evolved over a period of time (Baudino, P. and Yun, 2017). Bougatef (2016) concluded that bankruptcy regulations were beneficial in lowering NPLs. Giesecke et al. (2011) found that pro-creditor bankruptcy regimes exhibit low default rates while pro-debtor regimes exhibit higher default rates.

Most studies in India have focussed on one or few legislations or schemes in the area of stressed assets resolution. There is a need to study the evolution of the Indian stressed assets resolution framework in a holistic manner with pros and cons of each law and their effect on recovery rate and absolute amounts recovered. This perspective is particularly important as there are two-way linkages between banking sector risk and sovereign credit risk. Also, there is a need to analyse the improvement in recoveries due to changes in the stressed asset resolution framework in India when compared to other developing and developed nations over a period of time.

2.7 Conclusion and Future Scope

The present chapter gives an overview about the various qualitative and quantitative factors that are important and are considered by the credit rating agencies to evaluate the SCR. This also studies about the different treatment given to different countries while determining its SCR. The link between banking sector risk and sovereign credit risk as also been analysed here. This chapter also gives a global perspective on stressed asset resolution framework in India.

CHAPTER 3

DEVELOPMENT OF SOVEREIGN CREDIT RATING DATASET

3.1 Introduction

Sovereign credit rating assesses the creditworthiness of a sovereign entity or nation. Credit rating agencies such as Standard & Poor's (S&P), Moody's and Fitch evaluate a country's economic parameters and political environment to assign a rating to it. The sovereign credit rating typically impacts the access and cost of funding in the global bond markets.

For a thorough understanding of the SCR, a vast dataset is required which can help in the analysis of the sovereign credit rating achieved by any sovereign and the various parameters that influence the rating. Literature and thorough research indicate that no such dataset is available in public domain. Thus, the first and foremost requirement to achieve the research objectives is to develop such a dataset. However, development of dataset involves several decisions like the rating agency, time period to be included, countries, various qualitative and quantitative variables, conversion of rating to ordinal numbers, source of this collated data. This chapter discusses about the development of two separate consolidated datasets and provide an in-depth reasoning for the decisions taken.

3.2 Decisions for the dataset

3.2.1 Rating Agencies

The top three CRAs (Moody's, S&P and Fitch) dominate the credit rating industry (Hung et al., 2021) and account for around 95% of the international rating business (https://corporatefinanceinstitute.com/resources/fixed-income/rating-agency/). For its reporting, the SEC, USA classifies Fitch, Moody's, and S&P as "larger NRSROs" or nationally recognized statistical rating organizations (the legal term for CRAs). As per the SEC 2020 report (https://www.sec.gov/files/2020-annual-report-on-nrsros.pdf), the three "larger NRSROs" accounted for 93.3%-94.4%) of revenue between 2019-2016 period.

From the above it can be concluded that the top three CRAs dominate the market and literature has found high degree of correlation between the results of these three CRAs. Literature reveals that while the rating techniques and timings of the agencies may differ slightly, there is a high degree of correlation between the three large agencies' assessments [Choy et al. (2020), Basu et al. (2013), and Afonso (2003)]. Thus, the present work analyses the linkage between various variables and the ratings assigned by two (Moody's and Fitch) of these three CRAs as representative, for verification or validation of the results.

3.2.2 Timeline

To draw any conclusion from the developed dataset, it is essential that data should be considered over a broad period, should have lot of variations like developing nations, developed nations etc. With small data of 2-year to 3-year data, conclusive results cannot be obtained; a predictive model will also be not very accurate. For better generalization, accurate prediction of SCR using ML, efforts have been done to develop dataset for 20 years, however, due to unavailability of several parameters for all the countries in the public domain, the dataset was finally considered for 10 years only 2011- 2020, as for this period most of the parametric values were available from the reliable sources like IMF, World Bank etc.

3.2.3 Countries

To create a diversified set of countries covering various regions of the world across income levels, the top 20 countries in "high income", "upper middle income" and "lower middle income" categories as classified by the World Bank were chosen. The developed dataset in present work cover countries from almost all regions of the world – "North America, East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, South Asia, East Asia & Pacific, Sub-Saharan Africa, Middle East & North Africa" as classified by the World Bank.

Table 3.1: List of Countries in the Final Dataset

S.No.	Country Name	Income Group	Region
1	United States	High Income Top 20	North America
2	Japan		East Asia & Pacific
3	Germany		Europe & Central Asia
4	United Kingdom		Europe & Central Asia
5	France		Europe & Central Asia
6	Italy		Europe & Central Asia
7	Canada		North America
8	Korea, Rep.		East Asia & Pacific
9	Australia		East Asia & Pacific

10	Spain		Europe & Central Asia
11	Netherlands		Europe & Central Asia
12	Switzerland		Europe & Central Asia
13	Saudi Arabia		Middle East & North Africa
14	Poland		Europe & Central Asia
15	Sweden		Europe & Central Asia
16	Belgium		Europe & Central Asia
17	Austria		Europe & Central Asia
18	Ireland		Europe & Central Asia
19	Israel		Middle East & North Africa
20	Norway		Europe & Central Asia
21	China	Upper middle income Top 20	East Asia & Pacific
22	Russian Federation		Europe & Central Asia
23	Brazil		Latin America & Caribbean
24	Mexico		Latin America & Caribbean
25	Turkey		Europe & Central Asia
26	Thailand		East Asia & Pacific
27	Argentina		Latin America & Caribbean
28	Malaysia		East Asia & Pacific
29	South Africa		Sub-Saharan Africa
30	Colombia		Latin America & Caribbean
31	Romania		Europe & Central Asia
32	Peru		Latin America & Caribbean
33	Kazakhstan		Europe & Central Asia
34	Iraq		Middle East & North Africa
35	Cuba*		Latin America & Caribbean
36	Ecuador		Latin America & Caribbean
37	Dominican Republic		Latin America & Caribbean
38	Guatemala		Latin America & Caribbean
39	Bulgaria		Europe & Central Asia
40	Costa Rica		Latin America & Caribbean
41	India	Lower middle income Top 20	South Asia
42	Indonesia		East Asia & Pacific
43	Nigeria		Sub-Saharan Africa
44	Egypt, Arab Rep.		Middle East & North Africa
45	Philippines		East Asia & Pacific
46	Bangladesh		South Asia
47	Vietnam		East Asia & Pacific
48	Pakistan		South Asia

49	Iran, Islamic Rep.*		Middle East & North Africa
50	Ukraine		Europe & Central Asia
51	Algeria*		Middle East & North Africa
52	Morocco		Middle East & North Africa
53	Kenya		Sub-Saharan Africa
54	Sri Lanka		South Asia
55	Myanmar*		East Asia & Pacific
56	Ghana		Sub-Saharan Africa
57	Tanzania*		Sub-Saharan Africa
58	Cote d'Ivoire		Sub-Saharan Africa
59	Uzbekistan		Europe & Central Asia
60	Angola		Sub-Saharan Africa

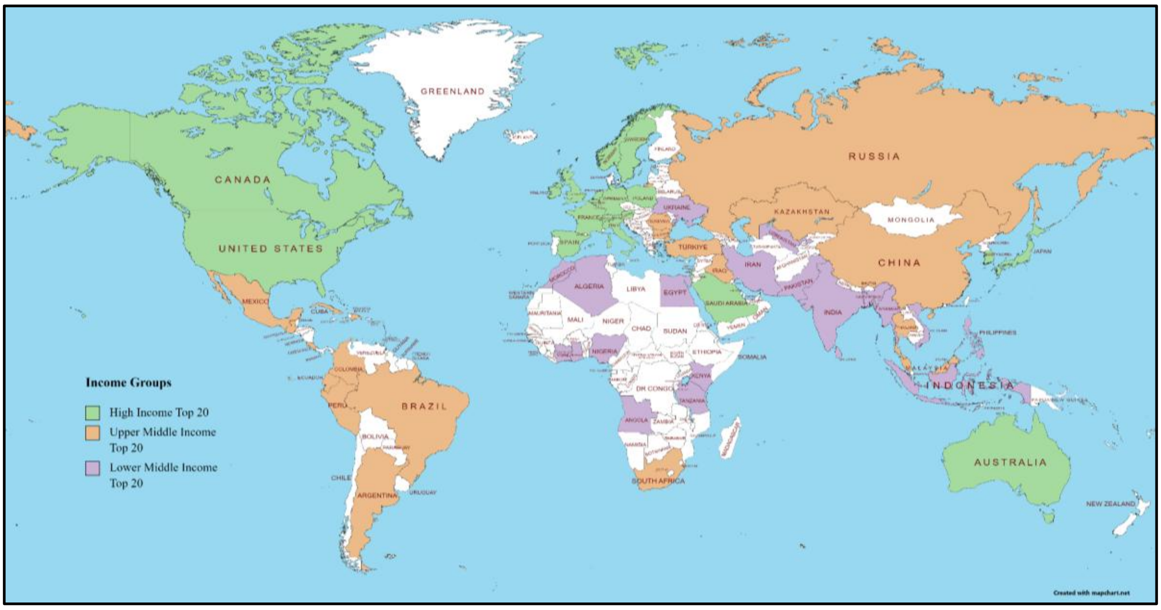

Figure 3.1. Representation of 55 countries considered in the development of dataset 1 and 2 with High Income (Top 20), Upper Middle Income (Top 20), and Lower middle income (Top 20).

Out of the 60 countries thus chosen, data was insufficient for 5 countries - one from the "upper middle income" category (Cuba) and four from the "lower middle income" category (Iran, Algeria, Myanmar, Tanzania). Hence, the final developed data set comprises 55 countries. This list includes all the 'High Income Top 20' countries, 19 countries from the 'Upper Middle-Income Top 20' and 16 countries from the 'Lower Middle-Income Top 20' bracket. A depiction of the spread of these 55 countries is indicated in Table 3.1 and shown geographically in Figure 3.1.

3.2.4 Qualitative & Quantitative Parameters

While most academic literature found quantitative factors to be more important in determining SCR, the methodologies of CRAs seem to place significant reliance on qualitative factors as well. Hence both quantitative and qualitative factors have been chosen for the current work. We have considered 32 factors (independent variables) put together in the two datasets. Among these 32 factors, 17 are quantitative and the remaining 15 are qualitative. The details regarding the qualitative and quantitative independent variables have been mentioned below. Most of these factors have been selected after a study of previous literature and CRA methodologies while some have been introduced by the authors. Hence these factors are derived not only from academic literature but also from practice. In the process, the authors introduce some qualitative variables hitherto not used in SCR literature. A short description of the qualitative and quantitative variables is given in Table 3.2 and Table 3.3, respectively.

Literature suggests that CRAs are overly reliant on some sources for qualitative information like the World Bank WGI (Ozturk, 2016; Thomas, 2010; Vu et al., 2017). To examine whether this concern regarding over-reliance is correct and it tilts the outcome to a certain direction, we have created 2 sets of data. The first set contains various quantitative factors and qualitative factors. The qualitative factors for this set are primarily from the World Bank with some from the UN, OEC and WEF. The second set contains the same quantitative factors while replacing qualitative factors from the World Bank with those from other sources like Transparency International, EIU, EFW and Heritage Foundation. The factors in dataset 1 which are replaced by their contemporary factors in dataset 2 are given in Table 3.4. The rationale for replacing the factors is tabulated in Table 3.5.

For example, Control of Corruption in dataset 1 is replaced by Corruption Perception Index in dataset 2. This has been done because both the factors primarily measure the same risk but their nomenclature and the source are different. Control of Corruption measure of World Bank indicates “extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.”
While, Corruption Perception Index of Transparency International defines corruption as an "abuse of entrusted power for private gain.” Their formal explanation indicates that they are pointing to the same risk. Likewise, the similarity between all the original factors and the ones with which they are replaced has been tabulated in Table 3.5.

The dataset 1 has 17 quantitative indicators and 9 qualitative factors while dataset 2 has

17 quantitative indicators and 7 qualitative factors (Table 3.6). Whereas, their unit and data source alongwith the previous use of these parameters is indicated in Table 3.7-3.9.

Table 3.2: Qualitative macroeconomic factors in Final Dataset 1 & 2

Sr. No.	Qualitative Independent Variable	Description
1.	**Rule of Law**	Gauges adherence to societal rules, including contract enforcement, property rights, police, and courts. (Percentile Rank)
2.	**Regulatory Quality**	Reflects perceptions of government effectiveness in formulating and implementing policies for private sector development. (Percentile Rank)
3.	**Control of Corruption**	Measures the extent to which public power is used for private gain, encompassing various forms of corruption and state “capture” by elites. (Percentile Rank)
4.	**Government Effectiveness**	Reflects perceptions of public service quality, civil service independence, policy formulation and implementation, and government commitment credibility. (Percentile Rank)
5.	**Political Stability and Absence of Violence/Terrorism**	Gauges perceptions of the likelihood of political instability, politically-motivated violence, and terrorism. (Percentile Rank)
6.	**Voice & Accountability**	Measures citizens' participation in government selection, along with freedom of expression, association, and media. (Percentile Rank)
7.	**Human Development Index**	A composite index measuring average achievement in three basic dimensions of human development - a long and healthy life, knowledge and a decent standard of living. (Higher the better)
8.	**Corruption Perception Index**	Ranks countries based on perceived levels of public sector corruption, defined as the “abuse of entrusted power for private gain.” (Scale ranging from 0 to 100 i.e. highly corrupt to very clean)
9.	**Legal System and Property Rights**	Emphasizes the role of the legal system in economic freedom. Key components include the rule of law, security of property rights, an independent judiciary, and effective law enforcement, collectively assessing the government's protective functions. (Higher the better)
10.	**Regulation**	Regulation assesses how regulations impede market entry and hinder voluntary exchange, diminishing economic freedom. Its components specifically target regulatory constraints affecting exchange in credit, labor, and product markets. (Higher the better
11.	**Democracy Index**	Offers a global snapshot of democracy by utilizing five categories—electoral process and pluralism, functioning of government, political participation, political culture, and civil liberties—to classify each country as “full democracy”, “flawed democracy”, “hybrid regime”, or “authoritarian regime” based on scores within these indicators. (Higher the score, more the democracy)
12.	**Index of Economic Freedom**	Assesses jurisdictions based on trade freedom, tax burden, and judicial effectiveness, with weighted factors contributing to an overall score. It ranks countries from “free” to “repressed”. (Higher score to lower score)

13.	**Economic Complexity Index**	Measure of an economy's capacity. Proven to predict key macroeconomic outcomes, including income, economic growth, income inequality, and greenhouse gas emissions. Utilizes diverse data sources such as trade, employment, stock market, and patent data.
14.	**Soundness of Banks**	Corresponds to responses to the question "In your country, how do you assess the soundness of banks?" on a scale from 1 (extremely low—potential need for recapitalization) to 7 (extremely high—banks generally healthy with sound balance sheets).
15.	**Global Competitiveness Index**	A comprehensive index capturing both microeconomic and macroeconomic foundations of national competitiveness. It assesses competitiveness as the combination of institutions, policies, and factors determining a country's productivity level.

Both the datasets have distinct qualitative factors except one factor, 'soundness of banks.' Some of the qualitative factors used in dataset 2 were either less used or not used at all earlier. A glimpse of the dataset for all the 55 countries for the Sovereign rating and the quantitative factors is indicated in Table 3.10 and Table 3.11, respectively. The indicated data is only for the year 2020, while data has been developed for 10-year data (2011-2020). Due to space constraints, the complete data is not being given here, only indicative data is represented; the entire dataset will be released soon on an open-source platform.

Table 3.3: Quantitative macroeconomic factors in Final Dataset 1 & 2

Sr. No.	Quantitative Independent Variable	Description
1.	**GDP Growth (%)**	Annual percentage growth rate of Gross Domestic Product at constant loc currency values, aggregated at constant 2015 prices and expressed in U.S. dollar GDP includes gross value added by resident producers, product taxes, ar excludes subsidies. Depreciation of assets and depletion of natural resources a not deducted in the calculation.
2.	**GDP (USD)**	Sum of gross value added, product taxes, and minus subsidies, calculated without deductions for asset depreciation or natural resource depletion. Figures are in current U.S. dollars, converted using official or alternative exchange rates.
3.	**GDP per capita**	GDP is expressed in current U.S. dollars per person. Data are derived by first converting GDP in national currency to U.S. dollars and then dividing it by total population.
4.	**CPI**	Measures changes in prices of goods and services used by households, calculated as weighted averages of percentage price changes for a specified consumer "basket." Widely used to index pensions and other payments, and as a proxy for general inflation in monetary policy.
5.	**Fiscal Balance**	The cyclically adjusted balance for the general government, accounting for nonstructural elements beyond the economic cycle, such as temporary financial sector movements and one-off revenue or expenditure items. This value is

		generally negative.
6.	**Current Balance**	Represents all transactions, excluding financial and capital items, including goods, services, income, and current transfers in the balance of payments (BOP) between an economy and the rest of the world.
7.	**Debt/GDP**	Encompasses all future payment obligations of a debtor to a creditor, including SDRs, currency, deposits, debt securities, loans, insurance, pensions, and other accounts payable. Excludes equity, investment fund shares, financial derivatives, and employee stock options.
8.	**Govt Rev/GDP**	Comprises taxes, social contributions, grants receivable, and other income. It contributes to the government's net worth, the difference between assets and liabilities. Transactions altering the balance sheet composition, like asset sales or incurring liabilities, don't impact net worth.
9.	**Unemployment Rate**	Can be defined by national, ILO harmonized, or OECD harmonized definitions. The OECD harmonized rate is the percentage of unemployed persons in the labor force. ILO defines unemployed as those not working but willing and able to work, available, and actively seeking employment.
10.	**NPL/ Gross Loans**	The ratio of the value of nonperforming loans to the total value of the loan portfolio. Nonperforming loans are recorded at their gross value on the balance sheet, encompassing the entire loan amount rather than just the overdue portion.
11.	**Bank Capital to Assets Ratio**	The ratio of bank capital and reserves to total assets, where capital includes tier 1 capital and total regulatory capital. Capital and reserves consist of funds from owners, retained earnings, reserves, provisions, and valuation adjustments. Total assets encompass all non-financial and financial assets.
12.	**Money Supply (% GDP)**	The sum of currency outside banks, demand deposits excluding those of the central government, time, savings, and foreign currency deposits of resident sectors (excluding the central government), bank and traveler's checks, other securities like certificates of deposit and commercial paper.
13.	**Interest (% of Rev.)**	Interest payments include interest payments on government debt--including long-term bonds, long-term loans, and other debt instruments--to domestic and foreign residents.
14.	**Total reserves (Months of imports)**	Includes monetary gold, special drawing rights, IMF members' reserves held by the IMF, and foreign exchange under the control of monetary authorities. Presented as reserves relative to the number of months of goods and services imports they could cover.
15.	**Real Effective Exchange Rate**	The nominal effective exchange rate (a measure of the value of a currency against a weighted average of several foreign currencies) divided by a price deflator or index of costs.
16.	**Tax Revenue (% of GDP)**	Refers to compulsory transfers to the central government for public purposes. Certain compulsory transfers such as fines, penalties, and most social security contributions are excluded. Refunds and corrections of erroneously collected tax revenue are treated as negative revenue.
17.	**Trade (% of GDP)**	Sum of exports and imports of goods and services measured as a share of gross domestic product.

Table 3.4 Replacement of variables between Set 1 and Set 2

Factor (Set 1)	Source	Replaced by (Set 2)	Source
Rule of Law	WB	Legal System and Property Rights	EFW; Fraser Institute
Regulatory Quality	WB	Regulation	EFW; Fraser Institute
Control of Corruption	WB	Corruption Perception Index	Transparency International
Govt Effectiveness	WB	Index of Economic Freedom	Heritage Foundation
Political Stability and Absence of Violence	WB	Democracy Index	EIU
Voice & Accountability	WB	Democracy Index	EIU
Economic Complexity Index	OEC	Global Competitiveness Index	WEF
Human Development Index	UN	Global Competitiveness Index	WEF
Soundness of Banks	WEF	Soundness of Banks	WEF

Table 3.5 Rationale for change of factors

Set 1 Qualitative Variable Definition	Set 2 Replacement Qualitative Variable Definition
Rule of Law measure of World Bank indicates "extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence"	**Legal System and Property Rights** measure of EFW indicates "rule of law, security of property rights, an independent and unbiased judiciary, and impartial and effective enforcement of the law"
Regulatory Quality measure of World Bank indicates "ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development"	**Regulation** parameter of EFW measures "how regulations that restrict entry into markets and interfere with the freedom to engage in voluntary exchange reduce economic freedom". It focuses on "regulatory restraints that limit the freedom of exchange in credit, labor, and product markets"
Control of Corruption measure of World Bank indicates "extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests"	**Corruption Perception Index** of Transparency International defines corruption as an "abuse of entrusted power for private gain"
Govt Effectiveness measure of World Bank indicates "quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies"	Index of Economic Freedom of Heritage Foundation indicates "extent and effectiveness of government activity in twelve areas that are known to have a significant impact on levels of economic growth and prosperity"
Political Stability and Absence of Violence measure of World Bank indicates "likelihood of political instability and/or politically-motivated violence, including terrorism"	Research shows that democracies are likely to be more politically stable (Tusalem ,2015, Feng,1997). Drawing upon this conclusion, nations ranked higher on the Democracy Index should be politically more stable. Therefore, the **Democracy Index** has been used as a replacement for Political Stability and

	Absence of Violence indicator Democracy Index of EIU is "based on five categories: electoral process and pluralism, functioning of government, political participation, political culture, and civil liberties."
Voice & Accountability measure of World Bank indicates "extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media."	**Democracy Index** of EIU is "based on five categories: electoral process and pluralism, functioning of government, political participation, political culture, and civil liberties".
Economic Complexity Index (ECI) of The Observatory of Economic Complexity indicates "the productive capabilities of large economic systems" including countries. ECI "explains the knowledge accumulated in a population and that is expressed in the economic activities present in the country. Higher economic complexity as compared to country's income level drives economic development".	**Global Competitiveness Index** of WEF "assesses the ability of countries to provide high levels of prosperity to their citizens which in turn depends on how productively a country uses available resources". The GCI "measures the set of institutions, policies, and factors that set the sustainable current and medium-term levels of economic prosperity".
Human Development Index (HDI) of United Nations measures "average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living". The underlying thought is that nations with higher levels of human development should become developed over a period of time.	Though there is no direct replacement for HDI as a variable, this work uses **GCI** as a proxy as two of the twelve pillars of competitiveness used by GCI include "Good health and primary education" and "Higher education and training" The GCI works with the thought that "human capital is a key driver of economic prosperity and productivity. It can be developed by ensuring individuals are able to sustain good health, and they are in possession of in-demand skills and capabilities".
The **Soundness of banks** indicator is the same in both sets, i.e., not replaced.	The **Soundness of banks** indicator is the same in both sets, i.e., not replaced.

3.2.5 Source of Data

The various qualitative and quantitative factors considered in Dataset 1 and Dataset 2 have been indicated in the previous section along with their description and the rationale for replacement. The value for these factors has been taken from the well-established international sources like World Bank, United Nations, World Economic Forum etc. The replacement has been done to address the concern of certain researchers regarding over-reliance on the Worldwide Governance Indicators (WGI) published by the World Bank (Ozturk, 2016; Thomas, 2010; Vu et al., 2017). Rating agencies like Fitch explicitly state their use of WB WGI for assigning SCR (Fitch 2022, n.d.).

Table 3.6: Independent Variables and Years of Data considered for the dataset samples

SAMPLE 1 (2011-2020)		SAMPLE 2 (2011-2020)
Rule of Law		Corruption Perception Index
Reg Quality		Legal System and Property Rights
Control of Corruption		Regulation
Govt Eff		Democracy Index
Pol Stab		Index of Economic Freedom
Voice & Acc		Soundness of Banks
HDI		Global Competitive Index
Economic Complexity Index		GDP Growth (%)
Soundness of Banks		GDP(USD)
GDP Growth (%)		GDP per capita
GDP(USD)		CPI
GDP per capita		Fiscal Bal
CPI		Current bal
Fiscal Bal		Debt/GDP
Current bal		Govt Rev/GDP
Debt/GDP		Unemployment Rate
Govt Rev/GDP		NPL/ Gross Loans
Unemployment Rate		Bank Capital to Assets Ratio
NPL/ Gross Loans		Money Supply (% GDP)
Bank Capital to Assets Ratio		Interest (% of Rev.)
Money Supply (% GDP)		Total reserves (Months of imports)
Interest (% of Rev.)		Real Eff Exc Rate
Total reserves (Months of imports)		Trade (% of GDP)
Real Eff Exc Rate		**Total variables = 23**
Trade (% of GDP)		**Total years of data = 10**
Total variables = 25		
Total years of data = 10		

NOTES:
1. The names of independent variables discussed were abbreviated to form column names, for brevity.
2. The color orange signifies qualitative independent variables.
3. The color green signifies quantitative independent variables.

Table 3.7 – Details of Quantitative Factors in the developed dataset (common for Set 1 and Set 2)
*IMF nomenclature is General government structural balance

S. No.	Name	Units	Source	Earlier Used in
1	GDP Growth (%)	Percent change	IMF	(Afonso et al., 2011; Borio & Packer, 2004; Cantor & Packer, 1996; Fitch 2022, n.d.; Moody's, 2016)
2	GDP(USD)	USD	IMF	(Borio & Packer, 2004; Moody's, 2016)
3	GDP per capita	USD	IMF	(Afonso, 2003; Gaillard, 2011; How We Rate Sovereigns, 2019; Moody's, 2016)
4	CPI	Percent change	IMF	(Afonso et al., 2011; Bozic & Magazzino, 2013; Cantor & Packer, 1996; Fitch 2022, n.d.)
5	Fiscal Balance*	Percent of GDP	IMF	(Cantor & Packer, 1996; Fitch 2022, n.d.; Reusens & Croux, 2017)
6	Current Account Balance	Percent of GDP	IMF	(Afonso et al., 2011; Cantor & Packer, 1996; Fitch 2022, n.d.; Moody's, 2016; Reusens & Croux, 2017)
7	Debt/GDP	Percent of GDP	IMF	(Boumparis et al., 2019; Fitch 2022, n.d.; How We Rate Sovereigns, 2019; Moody's, 2016)
8	Govt Revenue/GDP	Percent of GDP	IMF	(Canuto et al., 2012)
9	Unemployment Rate	Percent of total labor force	IMF	(Bissoondoyal-Bheenick, 2005)
10	NPL/ Gross Loans	Percent	World Bank	(Choy et al., 2021)
11	Bank Capital to Risk Weighted Assets	Percent	IMF	(Brůha & Kočenda, 2018)
12	Money Supply (% GDP)	Percent	World Bank	(Fitch 2022, n.d.)
13	Interest (% of Rev.)	Percent of Revenue	World Bank	(Fitch 2022, n.d.; How We Rate Sovereigns, 2019; Moody's, 2016)
14	Total reserves (Months of imports)	As Months of Import	World Bank	(Fitch 2022, n.d.)
15	Real Effective Exchange Rate (REER)	Indexed Value (2010=100)	World Bank	(Bissoondoyal-Bheenick, 2005; Choy et al., 2021; Mellios & Paget-Blanc, 2006)
16	Tax Revenue (% of GDP)	Percent of GDP	World Bank	(Mellios & Paget-Blanc, 2006)
17	Trade (% of GDP)	Percent of GDP	World Bank	(Archer et al., 2007; Biglaiser & Staats, 2012; Canuto et al., 2012; Mellios & Paget-Blanc, 2006)

Table 3.8 – Details of Qualitative Factors in the developed dataset 1

S.No.	Name	Units	Source	Earlier Used in
1	Rule of Law	Percentile Rank	World Bank	(Choy et al., 2021; Fitch 2022, n.d.; Ozturk, 2016; Vu et al., 2017)
2	Regulatory Quality	Percentile Rank	World Bank	(Choy et al., 2021; Fitch 2022, n.d.; Ozturk, 2016; Vu et al., 2017)
3	Control of Corruption	Percentile Rank	World Bank	(Choy et al., 2021; Fitch 2022, n.d.; Ozturk, 2016; Vu et al., 2017)
4	Govt Effectiveness	Percentile Rank	World Bank	(Choy et al., 2021; Fitch 2022, n.d.; Ozturk, 2016; Vu et al., 2017)
5	Political Stability and Absence of Violence	Percentile Rank	World Bank	(Choy et al., 2021; Fitch 2022, n.d.; Ozturk, 2016; Vu et al., 2017)
6	Voice & Accountability	Percentile Rank	World Bank	(Choy et al., 2021; Fitch 2022, n.d.; Ozturk, 2016; Vu et al., 2017)
7	Human Development Index	Index Value	United Nations	(How We Rate Sovereigns, 2019)
8	Economic Complexity Index	Index Value	The Observatory of Economic Complexity	(Moody's, 2016)
9	Soundness of Banks	Value (1-7; best being 7)	World Economic Forum	*Selected by Authors*

Table 3.9 – Details of Qualitative Factors in the developed dataset 2

S.No.	Name	Units	Source	Earlier Used in
1	Corruption Perception Index	Index Value	Transparency International	(Connolly, 2007; Mellios & Paget-Blanc, 2006)
2	Legal System and Property Rights	Rating Score	Economic Freedom of the World (EFW); Fraser Institute	(Biglaiser & Staats, 2012; Roychoudhury & Lawson, 2010)
3	Regulation	Rating Score	Economic Freedom of the World (EFW); Fraser Institute	(Roychoudhury & Lawson, 2010)
4	Democracy Index	Index Value (0-10; best is 10)	Economist Intelligence Unit (EIU)	*Selected by Authors*
5	Index of Economic Freedom	Index Value	Heritage Foundation	(Soudis, 2017b)
6	Soundness of Banks	Value (1-7; best being 7)	World Economic Forum	*Selected by Authors*
7	Global Competitiveness Index	Index Value	World Economic Forum	*Selected by Authors*

3.2.6 Conversion of Rating to Ordinal Number

A 22-point scale has been devised to convert the ratings from their original letter notation to an ordinal numeric notation in line with existing literature (Afonso, 2003; Connolly, 2007). For example, a Fitch rating of 'AAA' corresponds to 22 as per the scale and a rating of 'D' corresponds to 1. On the other hand, a Moody's rating of 'Aaa' corresponds to 22 and a rating of 'C' corresponds to 2 on our 22-point scale. A representation of this conversion for the year 2020 is indicated below in Table 3.10. Likewise the obtained SCR for all the 55 countries by both Moody's and Fitch has been converted to ordinal numbers for the complete period 2011-2020.

Table 3.10 – Details of Sovereign rating achieved and converted to 22 point scale for the year 2020

Country Name	Income Group	Region	Moody's	Moody's No.	Fitch	Fitch No.
United States	High Income Top 20	North America	Aaa	22	AAA	22
Japan		East Asia & Pacific	A1	18	A	17
Germany		Europe & Central Asia	Aaa	22	AAA	22
United Kingdom		Europe & Central Asia	Aa3	19	AA-	19
France		Europe & Central Asia	Aa2	20	AA	20
Italy		Europe & Central Asia	Baa3	13	BBB-	13
Canada		North America	Aaa	22	AA+	21
Korea, Rep.		East Asia & Pacific	Aa2	20	AA-	19
Australia		East Asia & Pacific	Aaa	22	AAA	22
Spain		Europe & Central Asia	Baa1	15	A-	16
Netherlands		Europe & Central Asia	Aaa	22	AAA	22
Switzerland		Europe & Central Asia	Aaa	22	AAA	22
Saudi Arabia		Middle East & North Africa	A1	18	A	17
Poland		Europe & Central Asia	A2	17	A-	16
Sweden		Europe & Central Asia	Aaa	22	AAA	22
Belgium		Europe & Central Asia	Aa3	19	AA-	19
Austria		Europe & Central Asia	Aa1	21	AA+	21
Ireland		Europe & Central Asia	A2	17	A+	18
Israel		Middle East & North Africa	A1	18	A+	18
Norway		Europe & Central Asia	Aaa	22	AAA	22
China	Upper middle income Top 20	East Asia & Pacific	A1	18	A+	18
Russian Federation		Europe & Central Asia	Baa3	13	BBB	14
Brazil		Latin America & Caribbean	Ba2	11	BB-	10
Mexico		Latin America & Caribbean	Baa1	15	BBB-	13
Turkey		Europe & Central Asia	B2	8	BB-	10
Thailand		East Asia & Pacific	Baa1	15	BBB+	15

Argentina		Latin America & Caribbean	Ca	3	CCC	5
Malaysia		East Asia & Pacific	A3	16	BBB+	15
South Africa		Sub-Saharan Africa	Ba2	11	BB-	10
Colombia		Latin America & Caribbean	Baa2	14	BBB-	13
Romania		Europe & Central Asia	Baa3	13	BBB-	13
Peru		Latin America & Caribbean	A3	16	BBB+	15
Kazakhstan		Europe & Central Asia	Baa3	13	BBB	14
Iraq		Middle East & North Africa	Caa1	6	B-	7
Ecuador		Latin America & Caribbean	Caa3	4	B-	7
Dominican Republic		Latin America & Caribbean	Ba3	10	BB-	10
Guatemala		Latin America & Caribbean	Ba1	12	BB-	10
Bulgaria		Europe & Central Asia	Baa1	15	BBB	14
Costa Rica		Latin America & Caribbean	B2	8	B	8
India	Lower middle income Top 20	South Asia	Baa3	13	BBB-	13
Indonesia		East Asia & Pacific	Baa2	14	BBB	14
Nigeria		Sub-Saharan Africa	B2	8	B	8
Egypt, Arab Rep.		Middle East & North Africa	B2	8	B+	9
Philippines		East Asia & Pacific	Baa2	14	BBB	14
Bangladesh		South Asia	Ba3	10	BB-	10
Vietnam		East Asia & Pacific	Ba3	10	BB	11
Pakistan		South Asia	B3	7	B-	7
Ukraine		Europe & Central Asia	B3	7	B	8
Morocco		Middle East & North Africa	Ba1	12	BB+	12
Kenya		Sub-Saharan Africa	B2	8	B+	9
Sri Lanka		South Asia	Caa1	6	CCC	5
Ghana		Sub-Saharan Africa	B3	7	B	8
Cote d'Ivoire		Sub-Saharan Africa	Ba3	10	B+	9
Uzbekistan		Europe & Central Asia	B1	9	BB-	10
Angola		Sub-Saharan Africa	Caa1	6	CCC	5

3.4 Glimpse of the Developed Dataset

Considering various decisions and the available parametric values, the final developed dataset comprises of data for 55 countries from different regions of the World. In this dataset, there are 20 countries from High-Income group, 19 from Upper Middle-Income and 16 from Lower middle-income groups. The data has been considered for 10 years (2011-2020). 17 quantitative variables and 11 qualitative variables has been considered. Data has been collated from the sources like IMF, Fitch, Moody, World Bank, United Nation, The Observatory of

Economic Complexity, World Economic Forum, Transparency International etc. A detailed list of the parameters alongwith their source has been indicated in Table 3.7 - Table 3.9.

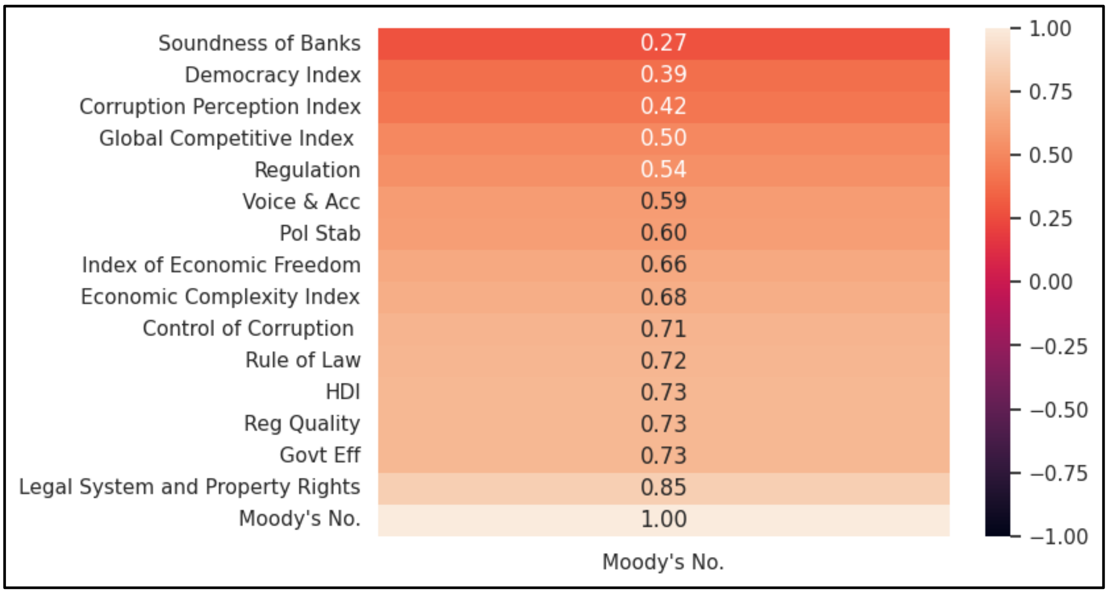

Figure 3.2: Correlation Heatmap - Qualitative independent variables vs Moody's rating.

For the final developed dataset, correlation heatmap was made between the various qualitative and quantitative parameters with the Moody's and Fitch rating. Figure 3.2 and Figure 3.3 indicate the correlation heatmap of qualitative variables with Fitch and Moody's while Figure 3.4 and Figure 3.5 indicate the correlation heatmap of quantitative variables with Fitch and Moody's.

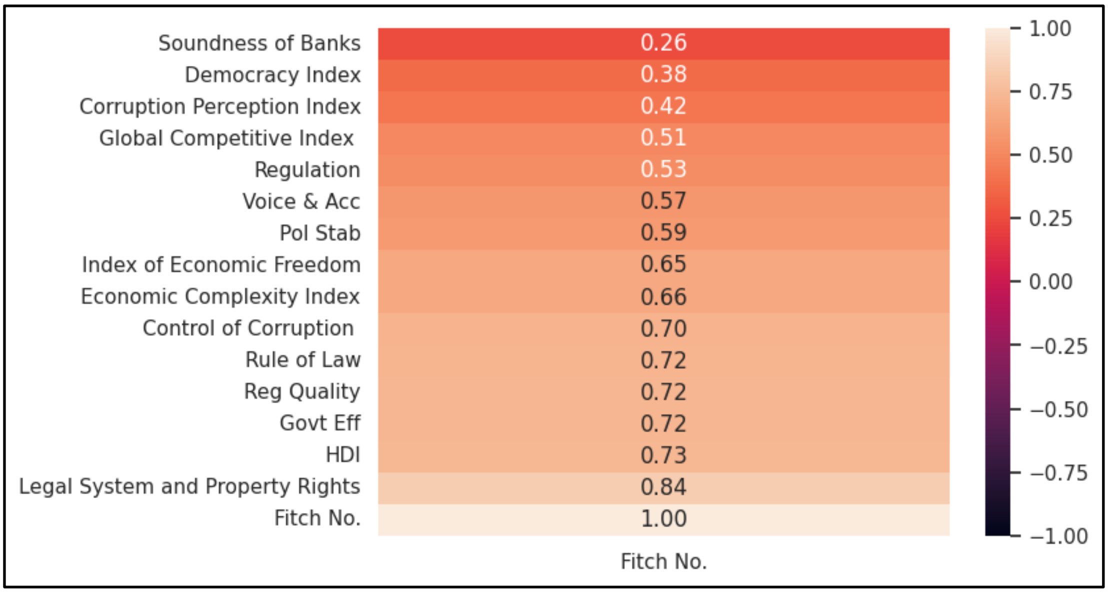

Figure 3.3: Correlation Heatmap - Qualitative independent variables vs Fitch rating.

This heatmap, plotted using Python's Seaborn library, represents the correlation of 15 quantitative factors with Moody's and Fitch Number, an ordinal number given to each Rating (refer Table 3.10). For this set of variables, no variable shows negative correlation. The lighter the color on the heatmap, the more positive is the correlation of the independent variable with rating. The heatmap has been sorted in the ascending order from top to bottom. For Moody's rating, soundness of banks has the lowest correlation value (27%), compared to Legal System and Property Rights with the highest correlation value (85%).

While for Fitch, Soundness of banks has the lowest correlation value (26%), compared to Legal System and Property Rights with the highest correlation value (84%). For both Moody's and Fitch rating, 12 out of the 15 variables have more than 50% correlation with the rating, indicating the influence of subjective factors on a country's sovereign credit rating.

Similarly, heatmap has been plotted for quantitative variables for both Fitch and Moody's rating. This heatmap, plotted using Python's Seaborn library, represents the correlation of 17 quantitative factors with both Moody's and Fitch Number, an ordinal number given to each Rating (refer Table 3.10). The lighter the color on the heatmap, the more positive is the correlation of the independent variable with the rating. The heatmap has been sorted in the ascending order from top to bottom.

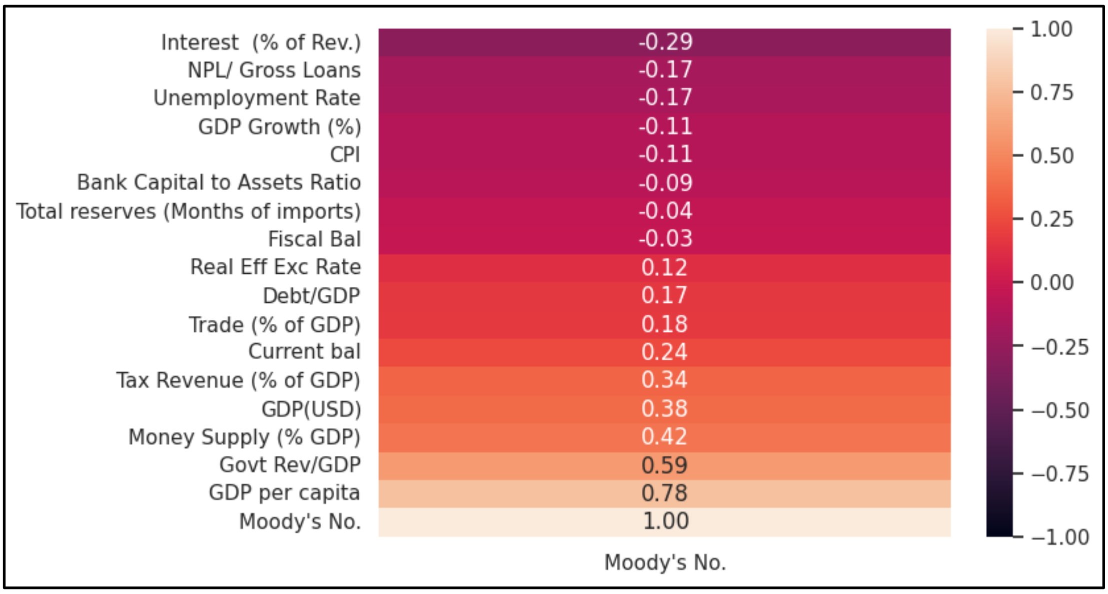

Figure 3.4: Correlation Heatmap - Quantitative independent variables vs Moody's rating

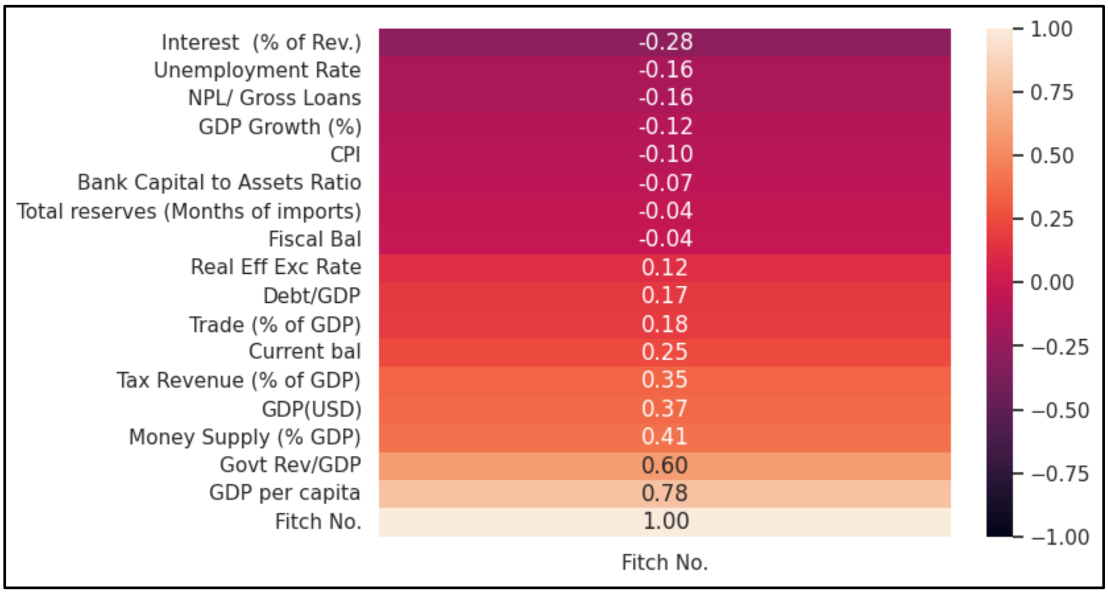

Figure 3.5: Correlation Heatmap - Quantitative independent variables vs Fitch rating.

For Moody's data, this set of variables, 8 variables show negative correlation. Interest (% of Revenue) shows the maximum negative correlation with a value of -29%. Fiscal Balance has the lowest correlation value (-3%), compared to GDP per capita with the highest correlation value (78%). While for Fitch data, this set of variables, 8 variables show negative correlation Interest (% of Revenue) shows the maximum negative correlation with a value of -28%. Fiscal Balance and Total Reserves (Months of imports) have the lowest correlation value (-4%), compared to GDP per capita with the highest correlation value (78%). Only 3 out of the 17 variables have more than 50% correlation with rating (both Fitch and Moody's), indicating that objective factors are collectively used during calculation of a country's sovereign credit rating and not individually.

Table 3.11 – Quantitative Parametric values for 55 countries for the year 2020

Country Name	Rule of Law	Reg Quality	Control of Corruption	Govt Eff	Pol Stab	Voice & Acc	Economic Complexity Index
United States	88.462	87.500	82.692	87.019	46.226	72.947	1.556
Japan	90.865	89.423	90.385	93.269	87.264	79.710	2.185
Germany	91.346	93.269	95.192	88.942	68.868	94.203	1.881
United Kingdom	89.904	92.308	94.231	89.423	61.321	89.372	1.425
France	87.981	85.577	84.615	86.538	56.604	82.609	1.342
Italy	60.577	68.269	69.231	67.308	59.906	82.126	1.297
Canada	92.788	94.231	91.827	94.231	90.094	96.135	0.930
Korea, Rep.	84.615	81.250	75.962	89.904	62.736	71.981	1.875
Australia	92.308	98.077	93.750	93.750	73.113	93.237	-0.311
Spain	78.365	73.558	76.442	77.885	58.019	80.676	0.762
Netherlands	94.712	96.635	96.154	97.596	74.057	98.068	1.132

Switzerland	97.596	93.750	97.115	99.519	93.396	98.551	1.989
Saudi Arabia	60.096	61.538	62.981	58.654	22.642	5.314	0.859
Poland	69.231	76.442	73.077	66.346	63.208	66.667	1.028
Sweden	96.635	95.192	98.077	95.673	85.377	97.101	1.586
Belgium	88.942	88.942	89.904	83.654	64.623	90.821	1.334
Austria	97.115	90.865	90.865	94.712	74.528	95.652	1.519
Ireland	90.385	91.827	91.346	90.865	83.019	95.169	1.341
Israel	82.212	87.019	70.673	83.173	18.396	68.599	1.161
Norway	99.519	95.673	97.596	98.558	94.340	100.000	0.710
China	52.885	50.000	52.885	72.596	37.736	4.831	0.965
Russian Federation	22.596	36.058	19.231	54.808	20.755	19.807	0.499
Brazil	48.077	46.154	43.750	36.538	32.075	56.522	0.439
Mexico	26.923	54.808	21.635	46.154	17.925	44.928	1.147
Turkey	40.385	51.923	44.231	52.404	11.792	23.672	0.580
Thailand	57.692	58.654	38.462	63.462	24.528	26.087	0.911
Argentina	34.615	31.731	50.000	43.269	48.585	65.700	0.087
Malaysia	73.077	74.038	62.500	82.212	50.943	40.097	1.023
South Africa	49.519	59.615	59.135	62.981	40.566	70.048	0.086
Colombia	33.654	63.462	47.596	55.288	22.170	52.657	0.137
Romania	64.423	64.423	54.808	42.788	63.679	65.217	1.005
Peru	41.346	70.192	33.654	42.308	38.679	54.589	-0.683
Kazakhstan	38.462	57.692	39.904	60.096	39.151	15.942	-0.245
Iraq	3.846	8.654	9.135	9.615	1.415	20.773	-0.692
Ecuador	32.212	17.308	32.212	37.019	34.434	46.377	-1.015
Dominican Republic	45.192	51.442	26.923	40.385	52.358	55.072	-0.131
Guatemala	13.942	44.712	13.942	25.481	31.132	35.266	-0.396
Bulgaria	51.442	69.712	46.154	50.481	60.849	56.039	0.518
Costa Rica	70.192	66.346	77.404	64.904	71.698	87.440	0.177
India	54.327	47.596	46.635	66.827	16.981	53.140	0.556
Indonesia	41.827	55.288	38.942	65.385	28.302	52.174	-0.093
Nigeria	21.154	13.942	13.462	12.981	4.717	32.367	-1.648
Egypt, Arab Rep.	39.904	25.481	22.596	32.212	11.321	7.729	-0.166
Philippines	31.731	53.365	34.135	56.250	18.868	41.063	0.576
Bangladesh	30.769	16.346	16.827	20.192	16.038	26.570	-1.191
Vietnam	48.558	46.635	42.308	61.538	44.811	12.077	-0.057
Pakistan	25.481	24.038	22.115	31.731	5.189	23.188	-0.712
Ukraine	27.404	40.865	23.558	38.942	12.264	51.691	0.501
Morocco	50.962	48.558	42.788	52.885	35.377	30.435	-0.504
Kenya	31.250	35.577	21.154	39.423	14.151	35.749	-0.472
Sri Lanka	53.365	44.231	45.673	50.962	45.283	43.961	-0.515
Ghana	53.846	52.404	50.481	46.635	51.887	64.734	-1.319
Cote d'Ivoire	29.808	41.827	32.692	34.615	15.094	33.816	-1.173
Uzbekistan	13.462	15.385	15.865	34.135	30.189	6.763	-0.566
Angola	16.827	15.865	18.269	11.058	26.887	25.604	-1.287

A glimpse of the dataset is indicated in Table 3.11 above and the Table 3.10. The data has been indicated for the year 2020 only. The complete dataset cannot be put here due to shortage of space. The complete dataset has 25 columns, 55 rows for 1 year, making a data matrix of 1375 cells. For a 10-year period, this totals to 13,750 entries (i.e. thirteen thousand seven hundred and fifty cell matrix).

Lot of analysis can be done using such a huge dataset. This dataset can help to determine the relative importance of various qualitative and quantitative factors in sovereign credit rating method. This can also be used to train a model that will predict a country's sovereign credit rating as per Moody's ratings and Fitch ratings individually, given the values of the various qualitative and quantitative indicators. The next few chapters discusses and the presents the performed analysis and the conclusion drawn from the analysis. It also helps to do reverse engineering, i.e., what are the precautions or steps any Government can take today to improve upon their future Sovereign ratings.

3.5 Conclusion and Future Scope

The present work develops two datasets covering 55 countries and compiles the data for 10 years (2011-2020) in terms of SCR obtained from Moody's and Fitch, and the values for various quantitative and qualitative factors. These countries cover various income groups as defined by the world bank and all geographical regions of the world. The dataset comprises of 18,700 data points obtained from 32 independent variables; 17 are quantitative and 15 qualitative. Some qualitative factors are also introduced which were not used earlier in SCR literature The data has been collated from World Bank, International Monetary Fund, United Nations etc. This dataset can be used for various kind of analysis related to SCR like finding whether qualitative factors, individually and as a group, are more important in determining SCR than quantitative factors, presence of bias towards high-income nations, importance of banking parameters in determination of SCR etc. Analysis using this dataset will provide a more holistic picture of the determinants of SCR. Since CRA methodologies keep evolving with time, future researchers can reexamine the various contemporary factors used for determining SCR.

CHAPTER 4

DOES QUALITATIVE FACTOR "RULE OF LAW" IMPACT SCR?

4.1 Introduction

Sovereign ratings are among the most important indicators used in the international financial market to reduce information asymmetry (Poor's 2011). They relate to the future creditworthiness of the debt issuers, *i.e.,* the risk taken by foreign investors in the process of acquiring debt securities of an issuer. In sovereign ratings, debt issuers are sovereign states and the ratings are done by three main international Credit Rating Agencies (CRAs), namely, Standard and Poor's Ratings Services (S&P), Fitch and Moody's Investors Service, which are independent organizations. These ratings provided by CRAs are of importance for any nation as it can impact their bonds issuances and costs thereof. The greater the risk which investors assume when acquiring some bond from a sovereign government, the lower the government's ability to make this acquisition attractive and thus attract foreign investors (Moody's Investor Service, 2016). Therefore, higher is the reward paid to investors to compensate them for assuming this risk (Basu et al. 2013, Seetharaman et al., 2014).

Table 4.1 Depiction of various macroeconomic parameters in sovereign rating

	Name of the Factor	Measured w.r.t
	Quantitative Factors	
1)	GDP per capita	
2)	Broad Money Supply	(% of GDP)
3)	Interest/General Govt. Revenue	
4)	Real GDP Growth	
5)	Consumer Price Inflation	
6)	Gross General Govt. Debt	(% of GDP)
7)	General Govt. Budget Balance	(% of GDP)
8)	Current Account Balance plus net FDI	(% of GDP)
9)	External Liquidity & External Indebted indicators	
	Qualitative Factors	
1)	Quality of Institutions	
2)	Strength of Civil Society & Judiciary	
3)	Policy Effectiveness including Banking Regulations	
4)	Domestic Political & Geopolitical Risks	
5)	Financial Sector/Banking Sector Risks	

In the last two decades, importance of sovereign ratings has grown manifold. Sovereign rating is the result of analysis of various quantitative and qualitative indices (see Table 4.1) which are directly impacted by the numerous economic and political risks (Poor's 2011, Moody's Investor Service, 2016). Specifically, the sovereign ratings involve judgment of various macroeconomic variables, as well as their prediction of the future (Moody's Investor Service, 2016). Literature reveals that lot of research has been done in past two decades to learn about how various economic variables influence the rating, but such research is based on a limited dataset that either comprises of developed, developing or emerging countries.

Also, the research is primarily focused towards the impact of quantitative variables on sovereign rating; the qualitative variables have not been analyzed thoroughly (Cantor & Packer, 1996; Afonso, 2003; D'Rosario & Hsieh, 2020). It is expected that a better research-based understanding of the relationship between sovereign ratings and the qualitative macroeconomic indices may have important policy implications. The present work analyzes the impact of qualitative variable "rule of law" on the sovereign rating. To analyze such a relationship, initially a dataset has been developed from World Bank classification of countries into high income, upper middle income, and lower middle income. For all these countries, data has been compiled for a five-year period from World Bank and Moody's rating. Regression has been then applied on the developed dataset to find out the correlation between the dependent variable (sovereign rating) and the independent variable ("rule of law"). The results have been thoroughly analyzed that indicates a positive correlation between the two variables.

The present chapter is organized as follows: Section 2 discusses the relevant literature in which the impact of various indices has been studied on the sovereign credit rating. Section 3 gives a detailed discussion and methodology for the dataset developed for the present work. Section 4 describes the methodology and the indices studied for analyzing the impact of qualitative parameter on sovereign credit rating. In Section 5, the results analysis has been presented in detail followed by concluding remarks in section 6.

4.2 Related Works

The present section discusses the relevant literature review wherein the impact of various parameters on sovereign credit rating has been explored. The study of the methodologies of the three large international credit rating agencies (Moody's, S&P and Fitch) reveals that both qualitative and quantitative factors are important in determining the SCR (Moody's 2019; Fitch Ratings, 2022; S&P, 2017). Besides quantitative factors, CRAs place significant reliance on qualitative factors like institutional & governance strength (Moody's 2019), structural features including governance indicators & political stability (Fitch Ratings, 2022), and institutional assessment (S&P, 2017). Methodologies of the three CRAs show that sovereign ratings are examined from four to five broad pillars and the aforesaid measures form a broad pillar in their methodology. Though the three CRAs give significant importance to qualitative factors; most of the previous research on sovereign ratings has focused on some quantitative macroeconomic measures only. This may be due to the fact that quantitative factors are relatively easier to quantify and research. However, gradually the importance of qualitative factors was realized and researchers started looking at how qualitative factors could be used, especially where they are informed by quantitative information - like in the case of scores or indices. Still, challenges remain in quantifying qualitative factors given their nature. Thus, analysis on qualitative factors is relatively less in existing literature.

Fuchs & Gehring believe that the economic and political features of rated countries have long been used to explain sovereign ratings (Fuchs & Gehring, 2013). Among the initial works on the determinants of sovereign credit ratings is of Cantor & Packer who studied eight variables which were mostly quantitative including, GDP growth, per capita GNP, government fiscal balance, current account balance and inflation (Cantor & Packer, 1996).

Afonso *et al.* (Afonso et al., 2003) studied the effect of eight variables on sovereign ratings, which were mostly quantitative variables and include external debt-to-exports ratio, per capita GDP, inflation, government fiscal balance and current account balance. Another study covered ten variables which were mostly quantitative including government debt, foreign exchange reserves, real exchange rate, net exports, unit labor cost and unemployment rate (Bissoondoyal-Bheenick, 2005). Afonso *et al.* (Afonso, 2011) later studied the influence of twelve variables which were again quantitative including GDP growth, government debt, external debt and others covered in previous literature.

Choy *et al.* (Choy et al., 2020) argued that rather than being chosen empirically, earlier research has concentrated on variables that were considered significant to sovereign ratings on theoretical basis. Amstad & Packer (2015) concluded that following the financial crisis of 2007, some criteria have become more significant for CRAs, highlighting the need to examine the drivers of sovereign ratings academically at regular intervals rather than relying on previous studies.

Qian & Strahan (2007) found private lending contracts reflect variations in creditor protection and contract enforcement laws, with better enforcement reflecting in long tenure loans and lower interest rates. Butler and Fauver (2006) find that the legal environment and sovereign credit ratings have a mutually reinforcing relationship. Similarly, it is observed that credit ratings are bolstered by legal protection and effective institutions, leading to lending with reduced credit risk premia (Bae and Goyal, 2009).

Montes *et al*. (2016) argued that while there is lot of research on the factors that influence sovereign ratings; there is a scarcity of literature that focuses only on developing countries. The authors took a sample of 40 developing countries for a twenty-year period (1994 – 2013); however, the sample does not include India.

It is assumed that the rating criteria of a credit rating agency will be same irrespective of the nations' region or category like developing, developed or emerging. Thus, a work/study done for developing nations should also give the same relationship between obtained credit rating and parameter for the developed nation as well. However, it is observed that most of the previous research on this subject has been done either on developed countries, developing countries or emerging countries separately, or on a large bunch of unclassified nations (Moor et al., 2017). Research has also been done regionally like Asia, Africa, Baltic nations or Latin American (Moor et al., 2017). Also, most of such analysis is focused around the quantitative parameters only, without analyzing the impact of qualitative parameters on the sovereign credit rating.

The present work thus proposes to analyze the linkage of macroeconomic qualitative parameters on the obtained sovereign credit rating. For the present work, countries from different income groups (high, upper middle and lower middle- as classified by World Bank) will be included in the dataset. This will make the dataset covering the developed, developing, and emerging nations instead of taking either one of them and limiting the efficacy of the work.

4.3 Method for Dataset Development

The present work focuses on analyzing the impact of qualitative factors on the sovereign credit rating for a mix of high income, upper middle-income, and lower middle-income nations irrespective of their geographical position, as detailed in Chapter 3. Considering the said objective in mind, the dataset has been carefully compiled. The qualitative parameter chosen for the present work is "rule of law," which is defined as follows: "Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank (https://databank.worldbank.org/source/worldwide-governance-indicators, 2022).” To summarize, “rule of law” helps determine the “willingness to pay” rather than the “capacity to pay.”

The percentile ranking on the “Rule of Law” variable has been taken from the World Bank’s Worldwide Governance Indicators (WGI) for various countries (https://databank.worldbank.org/source/worldwide-governance-indicators, 2022). The selection of the countries has been done on the income level classification (high, upper middle and lower middle) as given by the World Bank. Though the complete dataset comprises of 60 countries, a subset of dataset which comprises of 15 countries have been presented here due to scarcity of space. For giving equal representation to each income group, top five countries from each group have been presented below from the main dataset. This also ensures that analysis is being done among the largest entities from each income group, and not the largest versus the smallest.

Table 4.2 Subset of the developed dataset for 15 countries (Data Source- World Bank & Moody’s Ratings)

Country Name	GDP (current USD) USD bn-2020	Year	Sovereign Credit Rating	Ordinal Rating	“Rule of Law”: Percentile Rank
United States	20,953	2016	Aaa	22	91.346
		2017	Aaa	22	91.827
		2018	Aaa	22	89.904
		2019	Aaa	22	89.904
		2020	Aaa	22	89.462
United Kingdom	2,760	2016	Aa1	21	92.308
		2017	Aa2	20	92.788
		2018	Aa2	20	91.827
		2019	Aa2	20	91.827
		2020	Aa3	19	89.904
France	2621	2016	Aa2	20	88.462
		2017	Aa2	20	89.423
		2018	Aa2	20	88.942
		2019	Aa2	20	89.423
		2020	Aa2	20	87.981
Japan	5,058	2016	A1	18	88.942
		2017	A1	18	89.904
		2018	A1	18	90.385
		2019	A1	18	90.385
		2020	A1	18	90.865
Germany	3,846	2016	Aaa	22	91.827
		2017	Aaa	22	91.346

		2018	Aaa	22	91.346
		2019	Aaa	22	92.308
		2020	Aaa	22	91.346
China	14,723	2016	Aa3	19	41.346
		2017	A1	18	44.231
		2018	A1	18	48.077
		2019	A1	18	45.192
		2020	A1	18	52.885
Russian Federation	1,483	2016	Ba1	12	21.635
		2017	Ba1	12	22.596
		2018	Ba1	12	22.115
		2019	Ba3	13	25
		2020	Ba3	13	22.596
Brazil	1,445	2016	Ba2	11	49.038
		2017	Ba2	11	46.154
		2018	Ba2	11	44.712
		2019	Ba2	11	47.596
		2020	Ba2	11	48.077
Mexico	1,074	2016	A3	16	31.731
		2017	A3	16	31.731
		2018	A3	16	28.846
		2019	A3	16	27.404
		2020	Baa1	15	26.923
Turkey	720	2016	Ba1	12	46.635
		2017	Ba1	12	45.192
		2018	Ba3	10	42.308
		2019	B1	9	44.712
		2020	B2	8	40.385
India	2,660	2016	Baa3	13	53.365
		2017	Baa2	14	53.365
		2018	Baa2	14	55.288
		2019	Baa2	14	52.404
		2020	Baa3	13	54.327
Indonesia	1,058	2016	Baa3	13	40.385
		2017	Baa3	13	40.865
		2018	Baa2	14	42.788
		2019	Baa2	14	42.308
		2020	Baa2	14	41.827
Nigeria	432	2016	B1	9	15.385
		2017	B2	8	18.75
		2018	B2	8	18.269
		2019	B2	8	18.75
		2020	B2	8	21.154
Egypt, Arab Rep.	365	2016	B3	7	32.692
		2017	B3	7	32.692
		2018	B3	7	37.019

		2019	B2	8	37.981
		2020	B2	8	39.904
Philippines	361	2016	Baa2	14	39.423
		2017	Baa2	14	36.538
		2018	Baa2	14	34.135
		2019	Baa2	14	34.135
		2020	Baa2	14	31.731

Literature reveals that while the rating techniques and timings of the agencies may differ slightly, there is a high degree of correlation between the three agencies' assessments (Basu et al. 2013; Afonso, 2003; Choy et al., 2020). Thus, the present work analyses the linkage between “rule of law” and long-term foreign currency ratings from one large international CRA, Moody’s (Moody’s Sovereign Credit Ratings, 2022).

The abovementioned data has been compiled for 5 years period (2016-2020). All the ratings are as outstanding on year end from 2016 to 2020. Data has been taken till 2020 as this is the latest year for which all requisite data is available. The conversion of the ordinal rating scales (AAA/Aaa to D) used by international rating agencies into numbers in a linear manner (22 to 1) has been done by well-established methods (Afonso, 2003; Mutize and Nkhalamba, 2020).

For all the selected top 20 countries, from each income category, rule of law percentile ranks has been compiled along with the assigned sovereign credit rating and its corresponding ordinal rating. Though dataset has been created for 60 countries for the analysis purpose, only a part of dataset comprising of 15 countries have been indicated here in Table 4.2. These 15 countries consist of 5 countries from each of the income group.

4.4 Proposed Methodology

Sovereign Credit Ratings (SCR) are important from a national and international perspective as they not only enable governments to borrow from the international financial markets, but they also influence the cost of borrowing. SCR also influence the quantum of capital flows into the country, including foreign direct investment. Given the extensive impact of sovereign credit ratings on various economic aspects, it is imperative to analyze the variables which could impact it.

The methodology of the three CRAs show that importance is given to qualitative variables as they can impact quantitative variables like growth, fiscal balance and inflation and eventually impact even the capacity to pay (Moody’s 2019; Fitch Ratings, 2022; S&P, 2017).

For the present work, “rule of law” has been chosen as the qualitative variable for study.

To analyze the impact of “rule of law” on the sovereign rating, the dataset has been developed, as explained in the previous section. In this developed dataset, linear regression is used to model the relationship between the sovereign credit rating and the “rule of law,” wherein the former is a dependent variable and the latter is the explanatory or independent variable. For applying the regression, data has been taken for 60 countries (across the globe) for a period of five years (2016-2020). The data for these 60 countries is initially plotted year wise i.e., 2016, followed by 2017 and so on. Lastly, a consolidated scatter plot for all the five years and 60 countries are plotted in one single plot to analyze the relationship between the dependent and independent variable. A linear regression line is also plotted in the form of

$$y = ax + b \qquad (1)$$

where y is the dependent variable, x is the explanatory variable, slope of the line is a and $b$is the intercept.

The fitting of data around the regression line is then measured using a statistical measure, R-squared, also known as the coefficient of determination. R-Squared is also defined as a statistical measure of fit which indicates that to what extent an independent variable can explain the variation of a dependent variable. It is expressed by following equation

$$R^2 = 1- (Unexplained\ Variation/Total\ Variation) \qquad (2)$$

The value of R-squared is always between 0 to 1, where 0 indicates that the model is not able to explain any variation in the response variable around its mean and 1 indicates that the model completely explains all the variation in the response variable around its mean. Usually, the larger the R^2 value, better is the fitting of the regression model into the observations.

To analyze the importance of qualitative parameter “rule of law” on sovereign credit rating, the present work thus derives the regression equation between the two for a larger dataset and duration. The fitness of the regression line is measured using the statistical parameter R squared. The obtained results have been discussed in the next section.

4.5 Result Analysis and Discussion

As per the methodology explained in the previous section, results were obtained and thoroughly analyzed. The obtained results are analyzed using scatter plot and the R squared value. The obtained scatter plots for the year 2016, 2017, 2018, 2019 and 2020 are indicated in Figure 4.1.

It can be observed that the points are confined towards the regression line and not scattered in the entire region. This pattern is followed for all the five years. A consolidated scatter plot for the entire 5-year duration is plotted and is indicated in Figure 4.2. There also, the points are confined around the regression line only.

The independent regression equations and the R squared value obtained for each year and the entire duration (2016-2020) is indicated in Table 4.3. It can be observed that all the regression equations and the R squared values are approximately same, which indicates that the impact of "rule of law" on sovereign credit rating remains approximately same for all the years. A higher R squared value reflects that higher variance of the dependent variable "sovereign credit rating" is being explained by the variance of the independent variable, "rule of law."

(a)

(b)

(c)

(d)

(e)

Figure 4.1 Regression plot for 60 countries for the year (a) 2016, (b) 2017, (c) 2018, (d) 2019, (e) 2020.

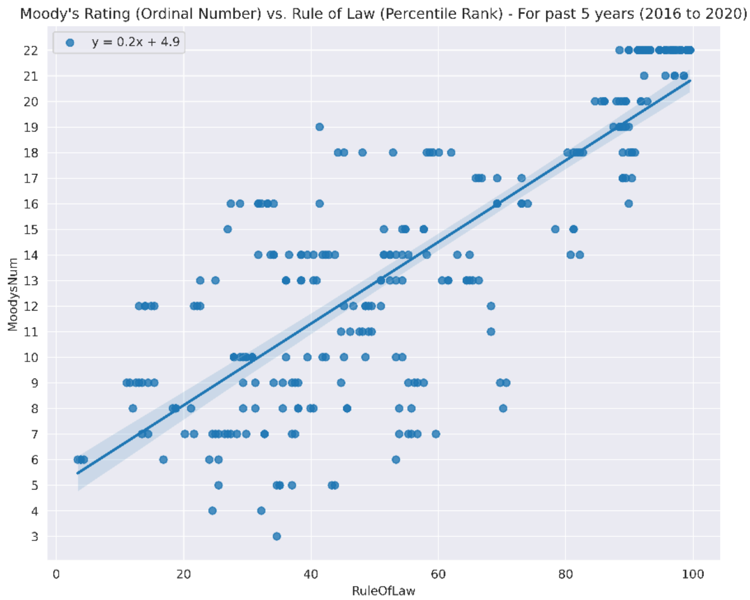

Figure 4.2 Regression plot for 60 countries for the period 2016- 2020.

It can be seen that the consolidated R squared error for the chosen 5-year duration is 0.8233. This indicates 82% positive correlation between Rule of Law and Moody's sovereign credit rating, i.e., higher the Rule of Law Percentile Rank, higher will be the Moody's sovereign credit rating (ordinal number). This show that sovereign credit ratings, and therefore cost and availability of international funds, can be improved by strengthening the "rule of law."

Table 4.3 Regression equation and the R squared value

S. No.	Year	Equation obtained	R squared value
1	2016	y = 0.2x + 5.2	0.8325
2	2017	y = 0.2x + 5.2	0.8344
3	2018	y = 0.2x + 5.0	0.8270
4	2019	y = 0.2x + 5.0	0.8162
5	2020	y = 0.2x + 4.3	0.8106
6	Consolidated for a period of 2016-2020	y = 0.2x + 4.9	0.8233

4.6 Conclusion

This work analyses the impact of qualitative factor "rule of law" on the sovereign credit rating. For a thorough analysis, initially a dataset is developed that comprises of parametric values for "rule of law" and the sovereign rating which is converted to ordinal values. The dataset has been developed for duration of 5 years for a total of 60 countries across income groups around the globe. The data has been taken from World Bank and the Moody's credit rating agency. Thorough analysis has been done on the complete developed dataset using linear regression, R squared value and the correlation coefficient. The results indicate a positive linkage, having 82% positive correlation between the “Rule of Law” percentile ranking of a country and its sovereign credit rating across various income groups and regions. The finding suggests that countries striving for higher sovereign credit ratings should consider ways to improve their world standing on qualitative variables like the ‘Rule of Law” and not only concentrate on improving macroeconomic factors. While this paper studies only one variable, there are many other qualitative variables which could be important in determining sovereign credit ratings, which can subject of future research. This conclusion is supported by the findings of the economics Nobel prize winners, “Societies with a poor rule of law and institutions that exploit the population do not generate growth or change for the better.” (https://www.nobelprize.org/prizes/economic-sciences/2024/press-release/)

CHAPTER 5

IMPACT OF ECONOMIC AND SOCIO-POLITICAL RISK FACTORS ON SOVEREIGN CREDIT RATINGS

5.1 Introduction

Sovereign Credit Ratings (SCRs) are opinions on a sovereign's "capacity" and "willingness" to pay interest and principal on its debt within committed timelines (Fitch 2022, n.d.; How We Rate Sovereigns, 2019). While the 'capacity to pay' is generally determined through analysis of quantitative (economic) data, the 'willingness to pay' is the more difficult part to assess as it is not directly measurable and therefore is proxied through qualitative (socio-political) factors (Soudis, 2017a).

From national and international perspective, sovereign credit ratings are significant as they influence the access and cost of borrowing for sovereigns as well as corporates and banks within the sovereign (Mora, 2006). These sovereign credit ratings also influence the quantum of capital flows into the country (Converse & Mallucci, 2019; De et al., 2021).

While there are differences in the way various Credit Rating Agencies (CRAs) assess SCR, there are several commonalities in the broad pillars and specific factors that they use. A study of the methodologies of the three large CRAs (Fitch 2022, n.d.; How We Rate Sovereigns, 2019; Moody's 2013, n.d.) shows that they evaluate both quantitative (economic) and qualitative (socio-political) factors to arrive at their sovereign credit rating decisions.

Though the approach indicates that both quantitative and qualitative factors are taken into consideration while evaluating the SCR; most of the literature has focused only on certain quantitative measures giving relatively less importance to qualitative factors (Choy et al., 2021; Soudis, 2017b; Ul Haque et al., 1998). These quantitative factors are "economic" indicators like "GDP per capita" and "Debt/GDP" among others.

Qualitative factors are researched less but several such factors are being used by the CRAs for determining the SCR (Fitch 2022, n.d.; How We Rate Sovereigns, 2019; Moody's, 2016). These qualitative factors are "socio-political" in nature and include World Bank's Worldwide Governance Indicators (Fitch 2022, n.d.), UN Human Development Index (How We Rate Sovereigns, 2019) and Economic Complexity Index (Moody's, 2016). However, due to lack of transparency in the methodologies of CRAs, there is no certainty of the relative weight of variables used and how much of variation they cause in the SCR (Ben Hmiden et al., 2024; Bonsall et al., 2017; Soudis, 2017b).

Some researchers have concluded that research on qualitative factors impacting SCR relies heavily on the Worldwide Governance Indicators (WGI) published by the World Bank (Ozturk, 2016; Thomas, 2010; Vu et al., 2017). Rating agencies like Fitch explicitly state their use of WB WGI for assigning SCR (Fitch 2022, n.d.).

The various other qualitative factors explored by the researchers include Corruption Perception Index, Index of Economic Freedom and various factors from the Economic Freedom of the World report (Biglaiser & Staats, 2012; Connolly, 2007; Mellios & Paget-Blanc, 2006; Roychoudhury & Lawson, 2010; Soudis, 2017b).

While researchers acknowledge the importance of qualitative factors in general, there is lack of consensus around which of these are more important (Soudis, 2017b), unlike quantitative factors where there is a consensus on a core set of parameters.

Further, researchers have found that SCRs seem to differ for countries with similar macroeconomic variables or do not improve commensurately for some countries despite improvement in macroeconomic fundamentals (Gültekin-Karakaş et al., 2011; Mutize & Nkhalamba, 2020). This chapter explains some of these seeming inconsistencies with the differences in institutional quality or data quality (Ozturk, 2014). Literature reveals that weight assigned to variables is different for high-rated countries in contrast to those of low-rated countries, favouring the developed countries by differing the consistency of credit ratings (Bissoondoyal-Bheenick, 2005; Gültekin-Karakaş et al., 2011; Ozturk, 2014; Singhal et al., 2024; Tennant et al., 2020).

Post the Global Financial Crisis (GFC) of 2008, banking sector risks have attracted greater attention for its linkages with sovereign credit risk. An important lesson from the GFC was that a tight linkage can exist between the banking sector, the economy and therefore sovereign credit risk (Kladakis & Skouralis, 2022; Krueger, 2013). There is a two-way link between banking sector risk and sovereign credit risk (Acharya et al., 2014; Krystyniak & Staneva, 2024). This is because a distressed financial sector can require government bailout, which increases the sovereign credit risk. An increased sovereign credit risk can weaken the financial sector by impacting economic activity as well as value of government bond holdings (Campolongo et al., 2012; Gerlach et al., 2010; Reichlin, 2014). The two-way relationship between non-performing loans and sovereign ratings can be over and above the impact of financial and macroeconomic determinants (Boumparis et al., 2019).

The above findings are supportive of the link between banking sector risk and sovereign credit risk which could be two-way. Fitch, Moody's and S&P (Fitch 2022, n.d.; How We Rate Sovereigns, 2019; Moody’s, 2016) also consider banking sector credit risks during the assessment of sovereign ratings.

Overall, the literature review suggests there is debate on the relative importance of quantitative versus qualitative factors in determining SCR with arguments on both sides. Also, there are some concerns regarding over-reliance on qualitative data from certain sources like WGI as well regarding a developed country bias in assigning SCR. Further, while banking sector risks are considered to have linkages with sovereign risk, the study in this respect is limited (Brůha & Kočenda, 2018).

For this work, “economic” factors are referred to as quantitative factors while “socio-political” factors are referred to as qualitative factors. This chapter examines various aspects related to SCR including the relative importance of quantitative variables versus qualitative variables as determinants of SCR; possibility of a developed country bias in SCR; and relative importance of banking sector risks as determinant of SCR.

To investigate this, two different datasets have been created and have been discussed well in Chapter 3. To summarize, the dataset comprises of 10-year SCR for 55 countries across the globe. These countries belong to “high income”, “upper middle income” and “lower middle income” categories as classified by the World Bank. The dataset comprises of the dependent variables and the independent variables, where the former depicts the SCR assigned to a country by Fitch and Moody’s and the latter comprises of various quantitative and qualitative parametric values that are possible determinants of SCR.

In the first dataset there are 17 quantitative (source: WB & IMF) and 9 qualitative variables (source: WB, UN, The Observatory of Economic Complexity and World Economic Forum). In the second dataset, the quantitative parameters remain the same and the qualitative parameters are replaced by alternative qualitative parameters (Table 3.4 and Table 3.5) (source: Transparency International, Economic Freedom of the World Report (EFW) of the Fraser Institute, Economist Intelligence Unit (EIU), Heritage Foundation and World Economic Forum). In both the datasets, the quantitative factors remain same and qualitative factors are different from each other, barring one banking factor, which is ‘soundness of banks.’

The present chapter fulfils the following four objectives:

1) To analyze the importance of quantitative and qualitative variables in determining SCR.
2) Linkages of banking sector risks with SCR and the presence of any developed nation bias for evaluating SCR.

3) Applying machine learning pipeline, correlation analysis and various plots to the developed dataset to corroborate the results

The remainder of the chapter is organized as follows. Section 5.2 presents the proposed methodology for sovereign rating prediction. Section 5.3 thoroughly discusses the analysis, findings of the present work followed by comparison with existing work in the same Section. Section 5.4 finally concludes the present work.

5.2 Dataset Details

Sovereign credit rating assesses the creditworthiness of a sovereign entity or nation. Credit rating agencies such as Standard & Poor's (S&P), Moody's and Fitch evaluate a country's economic parameters and political environment to assign a rating to it. The sovereign credit rating typically impacts the access and cost of funding in the global bond markets.

To determine the relative importance of various qualitative and quantitative factors in sovereign credit rating method, two separate consolidated datasets have been created. This dataset contains the credit ratings along with various qualitative and quantitative indicators for 55 countries for 10 years from 2011 to 2020. Ratings assigned to each country independently by Moody's and Fitch (one at a time) at the end of each calendar year, have been considered the target/dependent variable. Therefore, this dataset can be used to train a model that will predict a country's sovereign credit rating as per Moody's ratings and Fitch ratings individually, given the values of the various qualitative and quantitative indicators. The broad dataset details are as follows:

- Rating Agencies considered – Moddy's, Fitch
- Period – 10 years (2011 to 2020)
- Factors Considered - 17 quantitative & 9 qualitative for dataset 1; 17 quantitative & 7 qualitative for dataset 2
- Source of Data – International Monetary Fund (IMF), World Bank (WB), United Nations (UN), The Observatory of Economic Complexity (OEC), World Economic Forum (WEF), Economist Intelligence Unit (EIU), Economic Freedom of the World (EFW), Transparency International, Heritage Foundation
- Countries Considered – 55 Countries, the top 20 countries in "high income", "upper middle income" and "lower middle income" categories as classified by the World Bank. However, data for 5 low income and upper middle-income group were not completely available, which were then dropped; thus making the dataset for 55 countries.

A glimpse of the dataset for all the 55 countries for the Sovereign rating and the qualitative factors is indicated in the previous chapter. The same has been graphically depicted as Figure 5.1 and Figure 5.2, respectively. The indicated data is only for the year 2020, while for the analysis 10-year data (2011-2020) has been considered. Due to space constraints, the complete data is not being given here, only indicative data is represented; the entire dataset will be released soon on an open-source platform.

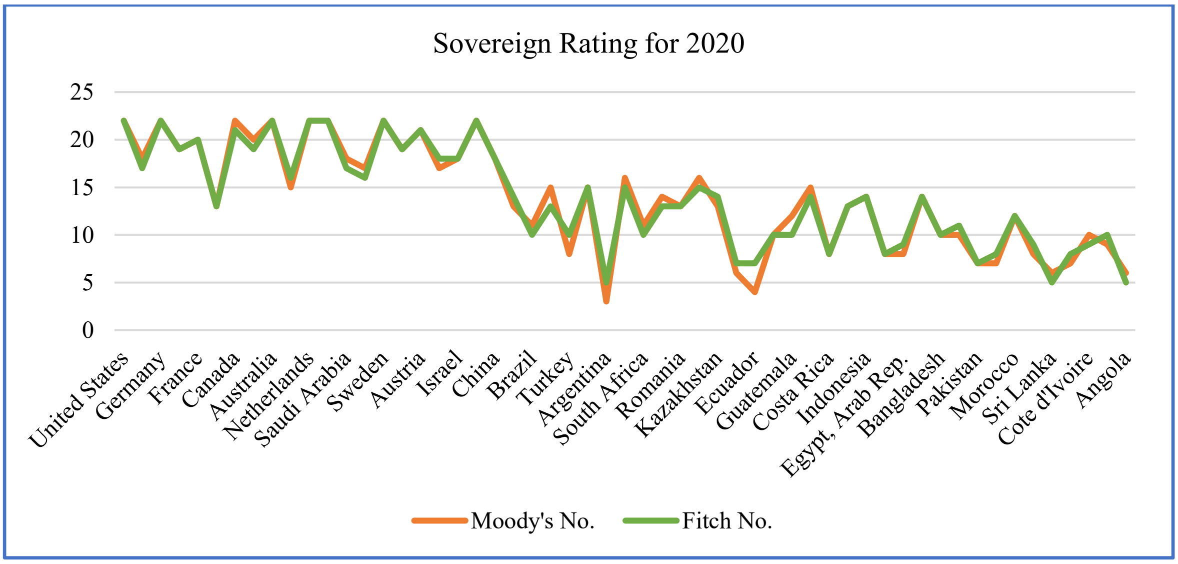

Figure 5.1 Sovereign rating achieved and converted to 22 point scale for the year 2020

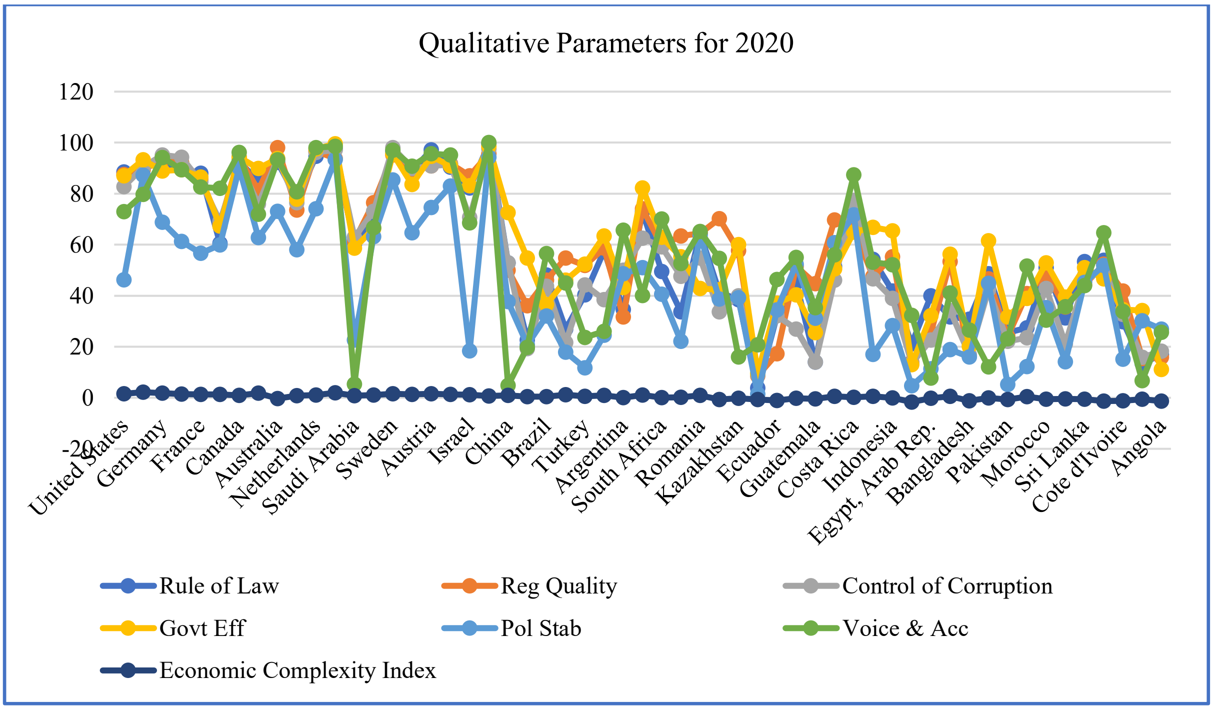

Figure 5.2 Quantitative Parameters for the year 2020

5.3 Proposed Methodology

With the integration of machine learning applications, the developed datasets were utilized to predict a country's sovereign credit rating as per Moody's ratings and Fitch ratings individually, given the values of the various quantitative and qualitative factors. Figure 5.3 illustrates the methodology followed to automatically predict a country's sovereign credit rating as per Moody's ratings and Fitch ratings individually. After developing two datasets as mentioned in the previous chapter and summarized in the section above, both the datasets were subjected to various Exploratory Data Analysis (EDA), which analyses and visualizes data to understand its main characteristics, uncover patterns, and gain insights before applying machine learning algorithms. Missing values were identified and were handled using linear interpolation method.

Detailed correlation analysis was performed to calculate correlation coefficients between different qualitative & quantitative variables to understand their relationships and dependencies. After EDA, the developed dataset 1 and 2 were individually considered and split into training and testing datasets. Three different split ratios namely random split, 80% training - 20% testing, 70% training - 30% testing split were considered for each dataset to analyze the impact of the proportions of the features in different years on the performance and generalization of the machine learning model.

For each of the split data, an extra-tree based machine learning pipeline was trained and tested. The best evaluation metrics were reported for the optimum splitting method. Then hyper-parameter tuning of the extra tree model was done to obtain the optimum hyper-parameters. In this, three hyper-parameters namely number of trees, number of features, and number of samples per split were considered for analysis. Whisker plots were visualized to analyze their variation with accuracy values obtained after variation of each hyper-parameter. Figure 5.6 illustrates the achieved plots for both dataset 1 and 2.

Extra tree classifiers are a type of ensemble classifiers which combine the principles of bagging and random feature selection (Geurts, 2006; He et al., 2022). Extra tree classifier builds multiple decision trees using random subsets of features and aggregates their predictions to make final classifications. This reduces variance of the model, making it less prone to over-fitting and improved accuracy. The choice of Extra Trees Classifier is motivated by the fewer requirement of computational resources in comparison to other classifiers like Support Vector Machines (SVM) or Gradient Boosting Machines (GBM). They are not only robust to noisy data, work efficiently on high dimensional features, but also provide good bias-variance trade-off by randomly selecting features and thresholds.

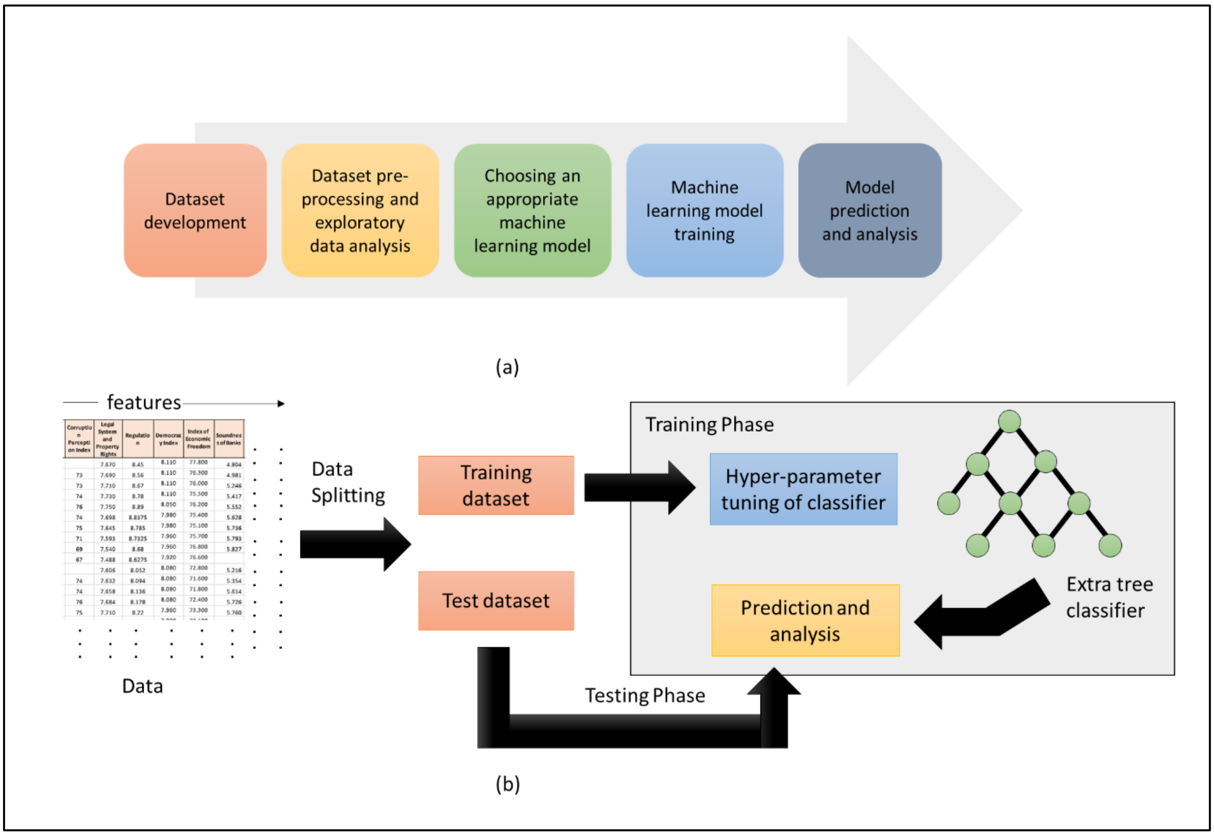

Figure 5.3 (a) Proposed methodology to automatically predict a country's sovereign credit rating as per Moody's ratings and Fitch ratings individually. (b) Methodology followed to obtain optimum hyper-parameters for the Extra-tree classifier.

In the area of determinants of SCR, most literature has used two main econometric approaches: linear regression methods and ordered response models (Parrado-Martínez et al., 2016); OLS and ordered probit (Bennell et al., 2006) have been the most commonly used methodologies. Since CRA rating assignment is a non-linear process, Artificial Neural Networks (ANN), Machine Learning (ML) models have proven to give better performance as compared to the deterministic systems like linear ordered probit, regressions etc. (Bennell et al., 2006; Choy et al., 2021). This is due to the fact that ML, ANN based methods have superior functioning in the absence of a precise theoretical model to underpin the relationships in the data (Bennell et al., 2006). However, literature focused on using ANN, ML techniques to ascertain determinants of SCR is sparse and has mostly focused on quantitative variables only. This paves the way for analyzing the contribution of qualitative factors using the ANN, and ML based techniques.

5.4 Result Analysis

The present work develops two datasets of 55 countries each for a period of 10 years (2011-2020). The common variables include the sovereign rating obtained by the respective country from two independent credit rating agencies and 17 quantitative variables. The distinct features are the qualitative variables along with their different data sources. Correlation analysis was done on these datasets individually and extra tree classifier was then implemented to assess the (i) importance of qualitative variables, quantitative variables, (ii) presence of bias for high income countries and (iii) linkage between sovereign rating risk and the banking sector risks. The thorough analysis has been segregated into different subsections for ease of understanding and is discussed below:

5.4.1 Correlation Analysis for Dataset 1

The correlation plot for various qualitative and quantitative variables has been analyzed for both Fitch and Moody's. From the plots (Figure 5.4), it can be observed that qualitative variables have relatively higher correlation than the quantitative ones. For instance, the qualitative variable, voice and accountability has the lowest correlation varying from 0.63 for both Moody's and Fitch, while government effectiveness and regulatory quality have the highest correlation of 0.86 for Moody's and 0.87 for Fitch. Other qualitative indicators like HDI and Economic Complexity Index also have high correlation of 0.75 & 0.74 for Moody's and 0.77 & 0.74 for Fitch, respectively.

In contrast to these qualitative variables, most quantitative variables have relatively lower correlation barring GDP per capita which is 0.79 for Moody's and 0.81 for Fitch. While Government Revenue/GDP and CPI have moderate correlation (0.59 & 0.53 for Moody's and 0.62 and 0.53 for Fitch), some of the most often quoted variables like Debt/GDP, Fiscal Balance, Total Reserves (months of imports) have much lower correlation (0.17, 0.19 & 0.08 for Moody's and 0.19, 0.18 and 0.05 for Fitch). The complete results are presented in Table 5.1. An important outcome to note is that all factors with low correlation are quantitative in nature. In fact, very few quantitative factors exhibited high or even medium level of correlation with the ratings. This indicates that the qualitative variables are relatively more important determinants of SCR than the qualitative ones.

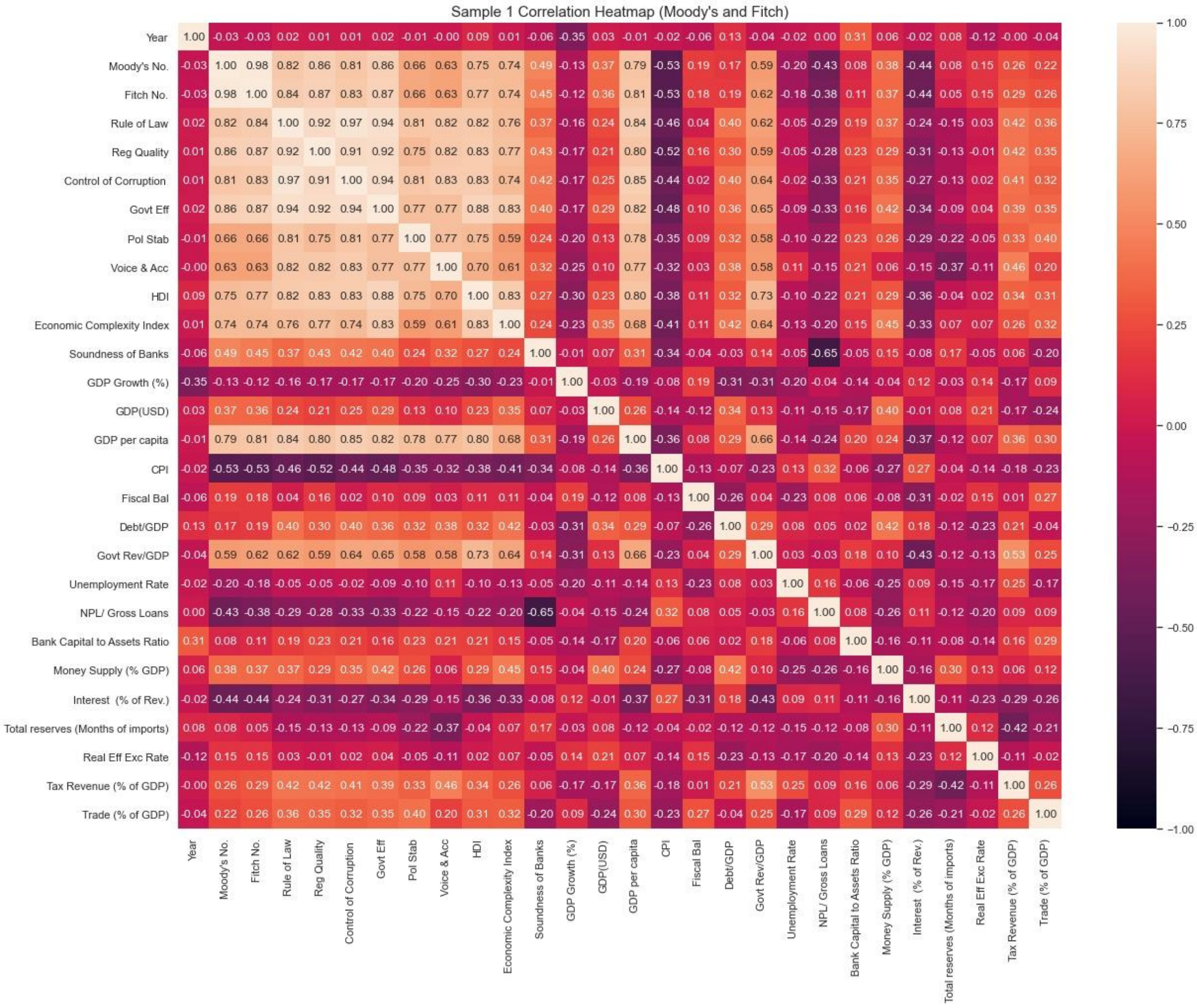

Figure 5.4 Correlogram Analysis for Dataset 1.

5.4.2 Correlation Analysis for Dataset 2

Researchers have concluded that research on qualitative factors impacting SCR relies heavily on certain sources like the WB WGI (Bennell et al., 2006; Ozturk, 2016; Vu et al., 2017). Rating agencies like Fitch explicitly state their use of WB WGI for assigning SCR (Fitch 2022, n.d.).

To examine whether the qualitative factors would still be important if the WB WGI and other factors used by CRAs are replaced with similar indices from other sources, we replace the qualitative factors in dataset1 with those in dataset 2 as depicted in Table 3.4 of Chapter 3. All the WB WGI indicators are replaced with alternative indicators. The non-WB WGI indicators were also replaced except the Soundness of Banks indicator, which was retained to examine the impact of banking indicators as a separate sub-category.

Table 5.1 Correlation Values for qualitative and quantitative factors with the SCR

Type of Parameter	Parameter	Moody's	Fitch
Qualitative Factors	Rule Of Law	0.82	0.84
	Control Of Corruption	0.81	0.83
	Government Effectiveness	0.86	0.86
	Regulatory Quality	0.87	0.87
	HDI	0.75	0.74
	Economic Complexity Index	0.77	0.74
Quantitative Factors	NPL/Gross Loans	0.43	0.38
	Interest As % Of Revenue	0.44	0.44
	GDP Per Capita	0.79	0.81
	Money Supply	0.38	0.37
	Government Revenue/GDP	0.59	0.62
	CPI	0.53	0.53
	Fiscal Balance	0.19	0.18
	Debt/GDP	0.17	0.19
	Unemployment Rate	0.20	0.18
	Bank Capital to Asset Ratio	0.08	0.11
	Total Reserves (as Months of Import)	0.08	0.05
	REER	0.15	0.15
	Tax Revenue as % of GDP	0.26	0.29
	Trade as % of GDP	0.22	0.26
	Debt/GDP	0.17	0.19
	Fiscal Balance	0.19	0.18
	Total Reserves (Months of Imports)	0.08	0.05

Since the purpose of creating Set 2 is to examine whether qualitative factors would still be important if these indicators are replaced with similar indices from other sources, the quantitative factors have been kept the same in Set 2. Therefore, the correlation of the quantitative factors to the SCR would remain the same and the analysis here will focus on the replaced qualitative factors.

The correlation plot for dataset 2 is indicated in Figure 5.5. Just like previous case of dataset 1, it can be observed that qualitative variables still have relatively higher correlation than the quantitative ones for dataset 2, i.e. when both the qualitative factors and their data source has been changed. For instance, the replaced indices like "democracy index" have the lowest correlation (0.59 for Moody's and 0.58 for Fitch), while the factor "legal system and property rights" have the highest correlation (0.82 for Moody's and 0.84 for Fitch). Other qualitative indicators like "corruption perception index", "index of economic freedom", "regulation" and "global competitiveness index" also have high correlation of 0.78, 0.80 0.69 & 0.74 for

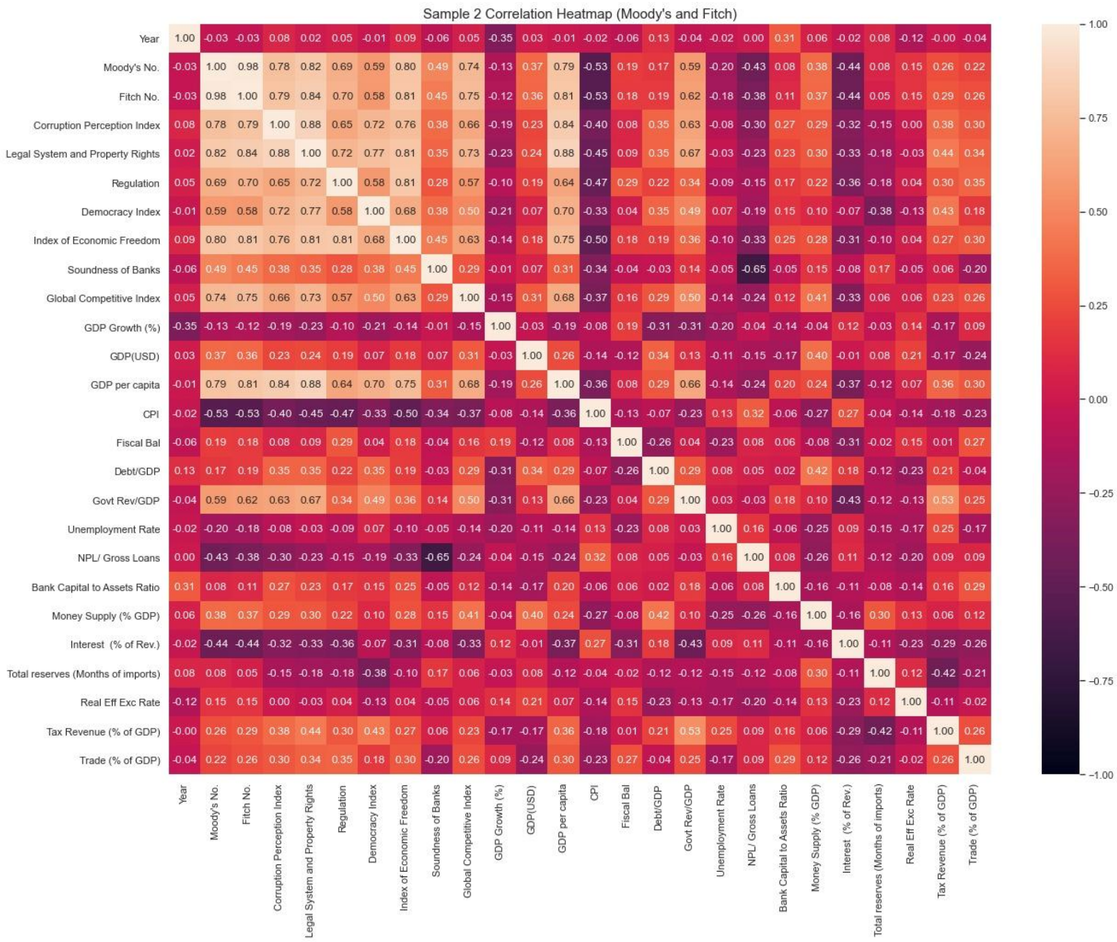

Figure 5.5 Correlogram Analysis for Dataset 2.

Moody's and 0.79, 0.81, 0.70 & 0.75 for Fitch, respectively. In contrast, the correlation of quantitative factors remains relatively lower and is not being repeated for sake of brevity.

5.4.3 Analysis for Banking Sector Factors

Post the Global Financial Crisis (GFC) of 2008, banking sector risks have attracted greater attention for its linkages with sovereign credit risk (Amstad & Packer, 2015). One of the objectives of this study is to determine the relative importance of banking sector factors as a sub-category within the overall factors impacting sovereign ratings.

The study has given mixed results as far as banking sector factors are concerned. Three banking sector factors have been taken for the purpose of this study. The study shows moderate correlation for the chosen qualitative factor in this sub-category – "Soundness of Banks" (0.49 and 0.45 for Moody's & Fitch respectively) and for one of the quantitative factors "NPL/Gross Loans" (0.43 and 0.38 for Moody's & Fitch respectively). However, for the other banking sector quantitative factor – "bank capital to asset ratio" – the correlation with SCR is low (0.08

and 0.11 for Moody’s & Fitch respectively). Overall, the banking sector factors appear to have moderate correlation with SCR.

While banking sector risks have attracted greater attention for the linkages with sovereign credit risk particularly, post GFC. This study finds that overall banking sector factors appear to have moderate correlation with SCR. As per our findings, the qualitative factors are far more important in determination of SCR than banking factors, irrespective of data sources.

5.4.4 High-Income/ Developed Country bias in SCR

The present work finds the possibility of a high-income country (defined on basis of ‘per capita income’ by World Bank) or developed country bias in assigned SCRs as “GDP per capita” emerges as the only quantitative variable with a high correlation with SCR (0.79 and 0.81 for Moody’s & Fitch respectively). Interestingly, “GDP growth rate” has low and negative correlation with SCR (-0.13 & -0.12 for Moody’s & Fitch respectively). A possible explanation for this result is that higher SCR are mostly secured by developed, rich nations which have reached levels of development from which growth remains relatively low. This is in line with the findings of Robert Solow, the 1987 Economics Nobel Prize winner. In his 1956 seminal paper, Solow suggested, “As per capita GDP goes up, people save more, and therefore there is more money to invest and more capital available per worker. This makes capital less productive. Rich economies, which are, in general, capital abundant tend to grow more slowly because new investment is not as productive.” (Duflo, 2019)

Another possible explanation for this scenario is a higher reliance on qualitative factors on which typically high-income nations tend to score higher, thus indirectly giving the appearance of a high-income nation bias in SCR. The high correlation of “GDP per capita” with most of chosen qualitative factors supports this possibility (Figure 5.4 & Figure 5.5). For instance, GDP per capita and the World Bank WGI have correlation varying from 0.77 (voice and accountability; lowest) to 0.85 (control of corruption; highest). GDP per capita also has high correlation of 0.80 and 0.68 with other qualitative indicators also, like HDI and Economic Complexity Index. Overall, it appears that “GDP per capita,” the chosen qualitative factors and the assigned SCR are highly correlated.

It is also possible that high-income and other good levels of other macroeconomic factors are achieved by Sovereigns with high instuitional quality [9,10,11]. The methodology of the three CRAs show that importance is given to qualitative variables as they can impact quantitative variables like growth, fiscal balance and inflation and eventually impact even the capacity to pay. [9,10,11]. This conclusion is corroborated by the work of 2024 economics Nobel prize winners for demonstrating the importance of societal instuition's for a country's prosperity. Societies with a poor rule of law and institutions that exploit the population do not generate growth or change for the better (https://www.nobelprize.org/prizes/economic-sciences/2024/press-release/). Jakob Svensson, Chair of the Committee for the Prize in Economic Sciences stated that "Reducing the vast differences in income between countries is one of our time's greatest challenges. The laureates have demonstrated the importance of societal institutions for achieving this." This is another way of saying that a strong and inclusive instuitional framework eventually leads to increased national prosperity or high per capita income.

So, we reiterate what appears to be a high-income nation bias in SCR is basically a reflection of strong instuitional framework in these countries. And, therefore, high per capita income and a strong instuitonal framework are basically the two sides of the same coin.

This possible bias for "high-income" nations could also be the reason why "lower middle income" nations like India end up receiving relatively low SCR despite high GDP growth rates. In the whole rating process, the chances of securing high SCR are greater for "high-income" nations rather than for "high-growth" nations.

5.4.5 Extra Tree Classifier Result Analysis

After analyzing the correlation of various quantitative and qualitative factors with SCR, the second step in the current work is to assess the predictive ability of these parameters, i.e., to assess with how much accuracy can we use these factors to predict SCR for a given year(s). We developed a machine learning based pipeline to fulfil this objective. Extra-tree classifier was utilized to automatically predict ratings as per Moody's and Fitch. No. of analysis were done to obtain optimum model performance and prediction accuracies. At first, different dataset split ratios were considered. Then hyper-parameter tuning was done for extra-tree classifier. The analysis has been discussed below.

Table 5.2 shows the achieved prediction accuracy values for different split ratios. It can be noticed that the prediction accuracy is almost similar for both Moody's and Fitch in the two datasets. The best model performance was achieved at random split with a prediction accuracy of up to 0.75-0.76 without hyper-parameter tuning.

Hyper-parameter tuning is a crucial part of machine-learning based pipelines. They play a major role in deciding the performance of the model, help in overcoming over-fitting and under-fitting of the model, and lead to improved computational efficiency.

Table 5.2 Achieved prediction accuracy values after the application of extra trees classifier for the developed dataset 1 and 2 with different training and test ratios. The reported values have been reported without hyper-parameter tuning.

Train –Test Split ratio	**Dataset 1**		**Dataset 2**	
	Moody's	**Fitch**	**Moody's**	**Fitch**
Random split	0.76	0.75	0.75	0.75
70:30 split Train: 2011-17 Test: 2018-2020	0.68	0.68	0.67	0.66
80:20 split Train: 2011-18 Test: 2019-2020	0.75	0.67	0.76	0.7

In extra-tree classifier, there are three main hyper-parameters namely number of trees, number of features, and minimum number of samples per split. The number of trees and features refer to the amount of trees and features required in the extra-tree structure to produce optimum performance. The minimum number of samples per split refer to the number of times a split is required while training the samples for extra-tree classifier.

Generally, the number of trees is increased till the model reaches its stabilized state and produces an optimum prediction accuracy on test dataset. The number of features required are estimated by finding the square root of the no. of input features. In case of the number of minimum number of samples per split, smaller number is able to achieve deeper and more specialized tree which may enhance the performance of the extra-tree classifier for un-seen data.

In the current work, a wide range of numbers (10, 50, 100, 500, 1000, 2500, and 5000) were considered to check the variation of number of trees w.r.t prediction accuracy values. The range considered for number of features and minimum number of samples per split were from 1-20 and 2-5, respectively. The whisker plots depicted through Figure 5.6 show the distribution of accuracy values for each varied hyper-parameter for both the datasets. A general trend was noticed for both the datasets during hyper-parameter tuning.

Fig. 5.4 comprises of 12 box plot panels, organized into four columns and three rows. These panels visualize the performance of an Extra Trees Classifier model under different parameter settings and configurations. These box plots reflect the model performance with respect to the change in the number of trees (first row), number of features (second row) and minimum samples per split (third row) for the Extra Trees Classifier.

In the first row, i.e. number of trees tested are 10, 50, 100, 500, 1000, 2500, and 5000, as indicated on the x-axis; y-axis indicates the accuracy scores. Fig. 7(a) indicates accuracy obtained for Moody's dataset 1 with slight variations across different numbers of trees, 7(b) exhibits similar trend for Moody's dataset 2, indicating consistency. Fig. 7(c) and Fig. 7(d) indicates the trend for Fitch dataset. For fitch dataset also, similar observations have been made. This indicates that irrespective of the Fitch or Moody dataset, the accuracy tends to stabilize with increasing the number of trees.

It can be noticed from Figure 5.6 that the accuracy values of extra-tree classifier rise and stays flat after about 500 number of trees. A value between 13 to 20 no. of features generated a stable model performance in the two datasets. Hence, a larger value i.e., 20 was considered for final analysis as the mean will be larger and result into a smaller standard deviation in prediction accuracy. Similarly, a value of 2-3 per split produced improved model performance in the two datasets.

The second row shows the model performance with respect to the change in number of features used at each split, ranging from 1 to 20. X-axis indicates the number of features (1 to 20) while the y-axis indicates the accuracy scores. Fig. 5.6(e) and Fig. 5.6 (f) indicates the result for Moody's dataset 1 and 2, respectively. While Fig. 5.6 (g) and Fig. 5.6 (h) indicates the result for Fitch dataset 1 and 2, respectively. From the plots, it can be observed that, as the number of features increases, accuracy improves initially but plateaus beyond a certain point.

The third row shows the model performance (y-axis) by varying the minimum number of samples required to split an internal node ranging from 2 to 5 (x-axis). Fig. 5.6 (i) and Fig. 5.6 (j) indicates the obtained results for Moody's dataset 1 and 2 respectively, while Fig. 5.6 (k) and Fig. 5.6 (l) indicates for Fitch dataset 1 and 2, respectively. All the plots indicate how different minimum samples per split values affect the model accuracy. Consistency can be observed with slight variations.

Statistically, in all the plots, the green triangles represent the mean accuracy scores, while the central lines within the boxes indicate the median values. Panels in the first row show that increasing the number of trees generally leads to a more stable and consistent central tendency (median).

The height of the boxes represents the interquartile range (IQR), indicating the spread of the middle 50% of the data. Wider boxes in the second row suggest greater variability in accuracy scores as the number of features increases. The third row shows moderate variability across different minimum samples per split values.

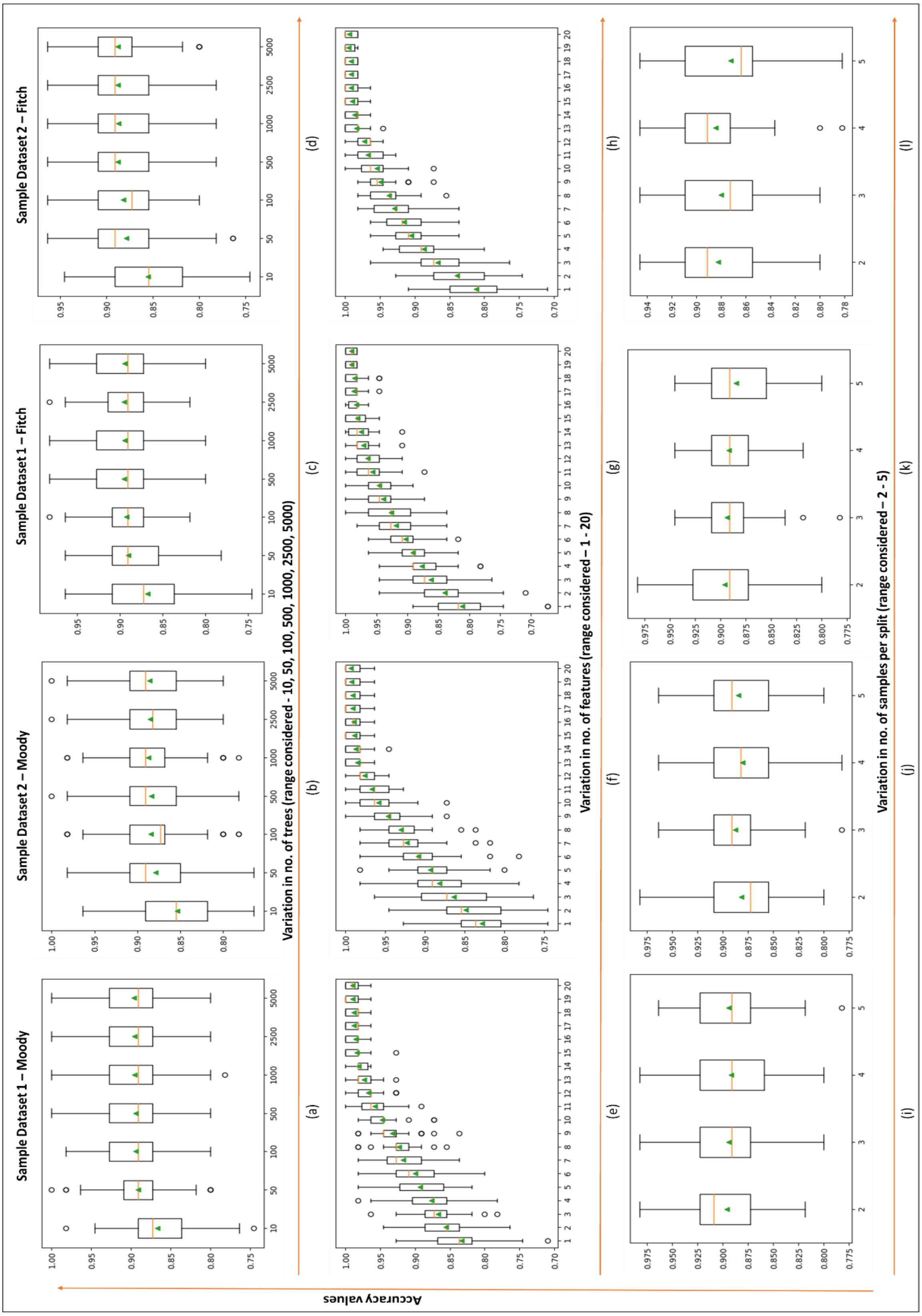

Figure 5.6 Achieved whisker plots to depict the distribution of accuracy values for each varied hyper-parameter for both the datasets.

Individual points outside the whiskers are considered outliers, showing extreme accuracy values. Outliers are more prevalent in the second and third rows, indicating some experimental runs significantly deviated from the norm. The figure visually summarizes the effects of varying key parameters (number of trees, number of features, and minimum samples per split) on the accuracy of the Extra Trees Classifier model. The box plots reveal that increasing the number of trees stabilizes model performance, while increasing the number of features improves accuracy up to a point before plateauing. The minimum samples per split parameter shows moderate impact on accuracy. These insights can guide parameter tuning for optimizing model performance.

Table 5.3 Achieved evaluation metrics for the optimum hyper-parameters (no. of features =20, sample split=2, and no. of trees=500) of Extra-tree classifier for the two developed datasets. The reported results have been averaged for all the classes.

Dataset S. No.	Rating (s)	Prediction accuracy	Average Precision	Average Recall	Average F1-score
Dataset 1	Moody	0.97	0.96	0.95	0.95
	Fitch	0.95	0.94	0.93	0.92
Dataset 2	Moody	0.98	0.98	0.98	0.98
	Fitch	0.96	0.96	0.95	0.95

Based on the achieved whisker plots, the final analysis was done on number of features =20, sample split=2, and number of trees=500. Table 5.3 shows the achieved evaluation metrics for the two datasets. The prediction accuracy, average precision, average recall, and F1-score ranges between 0.95-0.92 for the two datasets. The achieved results indicate the efficacy of the proposed methodology.

5.4.6 Comparative Analysis

The present section compares the obtained results with state-of-the-art methods. An extensive literature review reveals that not much of work has been done on Sovereign credit rating (Bennell et al., 2006; da Silva et al., 2019). Most of the literature revolves around the corporate credit rating (Golbayani, Florescu, et al., 2020a; Peng, 2021). Further, there is no standard dataset available for the sovereign credit rating analysis. Thus, a fair comparison with state of the art work is not possible, the closest possible comparison is given below and also tabulated in Table 5.4.

However, the authors discuss somewhat related work to give an idea of overall perspective of ML classifiers on credit rating data. Parisa et al. (Golbayani, Wang, et al., 2020) have analyzed the performance of four different neural network architectures (MLP, CNN, CNN2D, LSTM) for predicting the corporate credit rating, issued by S&P. The authors have analyzed the companies for financial, energy, and healthcare sectors in US. Further, the authors also implemented four different machine learning techniques for corporate credit rating in three different fields of financial, energy, and healthcare sectors in US. Considering all the three fields and four different classifiers, the minimum accuracy achieved in 25.49% and the maximum achieved is 88.88% (Golbayani, Florescu, et al., 2020b).

Table 5.4 Comparative Analysis Table

Work	**Credit Rating**	**Technique Used**	**Accuracy Achieved**
Bennel 2006 et al. (Bennell et al., 2006)	Sovereign Credit Rating	Regression model and Ordered Probit	96.7% 90%
D'Rosario and Hsieh (D'Rosario & Hsieh, 2018)	Sovereign Credit Rating	Multi-Layer Neural Network	75.5%
Ramon et al. (da Silva et al., 2019)	Sovereign Credit Rating	ML Classifier	Max. – 98.28% Min. – 78.52%
Parisa et al. (Golbayani, Wang, et al., 2020)	Corporate Credit Rating	BDT, RF, MLP and SVM	Max. - 88.88% Min – 25.49%
Proposed Method	Sovereign Credit Rating	Extra Tree classifier	**Moody's - 97%-98%** **Fitch - 95%-96%**

Bennel 2006 et al. (Bennell et al., 2006) have employed - regression model and ordered probit to classify the Sovereign credit rating. The best-case accuracy achieved is after three notches, where 96.7% ratings are correctly classified by regression based neural network model and approximately 90% by the other ordered probit. The authors conclude that the ANN models dominate the ordered probit approach in terms of accuracy. The proposed method of correlation study followed by the Extra Tree classifier however gives a prediction accuracy of 97%-98% for Moody's and 95%-96% for Fitch even when the qualitative parameters are changed, keeping the quantitative parameters same. Ramon et al. (da Silva et al., 2019) used machine learning classifier to predict the sovereign rating on a dataset which is highly imbalanced where 57.94% is the developing countries data, 31.77% as fully-developed economies and 10.28% as economies in transition. The PCA classifier gives 78.52% accuracy, however with lot of data reduction using K-means clustering the accuracy increased to 98.28%. Similarly, D'Rosario and Hsieh (D'Rosario & Hsieh, 2018) employed multi-layer neural network for estimation of Sovereign rating on a dataset of 18 variables and achieved a test accuracy of 75.5%.

In contrast to the state of the art work, the present work however has a balanced dataset wherein top 20 countries have been taken from all three categories on countries (except 5 countries for which data was not available). The dataset comprises of both quantitative and qualitative variables. The quantitative variables are 17 in number while the qualitative variables are 9 in one dataset and 7 in the other dataset. The present work not only predicts the sovereign rating but has also analyzed the importance of qualitative and quantitative variables along with their data sources. Further, with a balanced dataset without using any clustering of dimensionality reduction technique, the proposed classifier gives a maximum accuracy of 98%. This proves the efficacy of the proposed work over SOTA work.

5.5 Conclusion

Sovereign credit ratings help international investors price the risk of lending to sovereigns and entities domiciled within that sovereign, thereby impacting cost and availability of capital flows into an economy. The present work develops two datasets of 55 countries each for a period of 10 years (2011-2020). The common variables include the sovereign rating obtained by the respective country from two independent credit rating agencies and 17 quantitative variables. The distinct features are the qualitative variables along with their different data sources. Correlation analysis was done on these datasets individually to assess the importance of different parameters and extra tree classifier was then implemented to predict the sovereign credit rating. An important outcome is that all factors with low correlation are quantitative in nature while qualitative factors have high-moderate correlation with SCR. This indicates that that the qualitative (socio-political) factors, individually and as a group, are more important in determining SCR than quantitative (economic) factors. Comparative analysis of results for these 2 datasets indicates the importance of the qualitative factors remains the same in determining SCR irrespective of its data source. Further, the present work finds the possibility of a bias in favor of "high-income" nations while assigning SCR. Moreover, banking sector factors appear to have moderate correlation with SCR. The results analysis reflects that given the importance of qualitative factors in determination of sovereign credit ratings; sovereigns particularly developing/low-middle income might be better placed by focusing on socio-political reforms instead of focusing only on economic factors. In Future, the impact of specific qualitative factors on SCR can be studied in detail to indicate that what factors can be worked on by the sovereign to improve the credit rating.

CHAPTER 6

BANK OWNERSHIP AND STRESSED ASSETS IN INDIA: A CRITICAL STUDY

6.1 Introduction

High level of stressed assets negatively impacts the long-term performance of the banking sector in a country and thereby availability of capital to support economic growth. Therefore, banking sector risk is considered an important factor impacting macroeconomic stability and the sovereign credit rating. While there could be many factors impacting level of stressed assets, the purpose of this chapter is to specifically analyze the impact of bank ownership on stressed assets in the Indian Banking Sector and the importance of the regulatory system for timely stress recognition.

There are linkages between banking sector risk and sovereign credit risk (Acharya et al. 2012, 2014) and economic growth. An analysis of the sovereign rating methodologies of the three major international credit rating agencies (S&P Global Ratings 2017; Moody's 2019; and Fitch Ratings 2022) also indicate that banking sector risks /financial sector risks are included in the factors impacting sovereign credit ratings. This implies that persistence of high NPLs or higher banking sector risks impact sovereign credit ratings, which in turn impact the access to capital as well as borrowing cost of sovereigns and entities domiciled within a sovereign (Ntsalaze et al. 2016).

Given the severe impact that persistently high NPL levels can have on a nation's access to capital, cost of capital and economic growth, it is important to study the various factors which could impact the NPL levels. While there could be many factors impacting level of NPLs (or broadly speaking stressed assets), the purpose of the current work is to specifically analyze the impact of bank ownership on stressed assets in the Indian Banking Sector and the importance of the regulatory system for timely stress recognition.

While most previous literature on the Indian banking sector has focused on one or few banks or bank groups, the present work analyses the sector to look at important differences among all bank groups. Further, the work compares Indian Non-Performing Loans (NPLs) in an international context.

The Indian banking sector has one of the highest levels of NPLs or the worst banking asset quality among major developing and developed economies of the world, as indicated in Figure 6.1. While NPLs have been high in the Indian banking sectors for the past several decades, the situation appeared much better during the high growth years of the 2000s and even after the Global Financial Crisis (GFC) of 2008. This study, *inter alai*, analyses whether this appearance was deceptive.

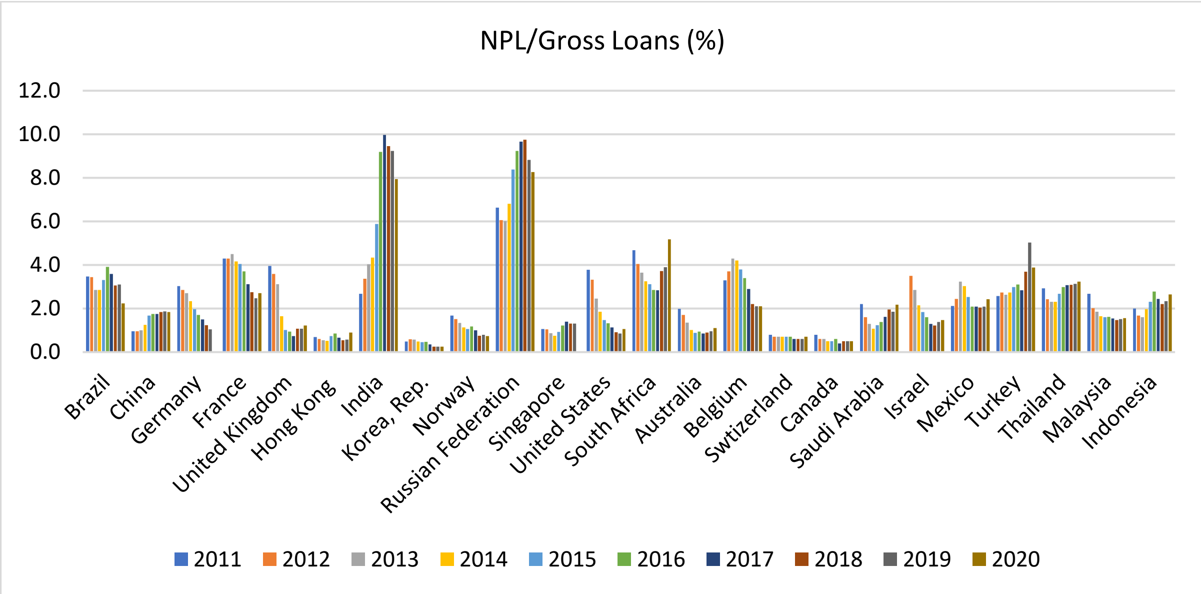

Figure 6.1: Bank NPL to Total Gross Loan (%), (Source: - World Bank)

The Reserve Bank of India (RBI) mandated the Asset Quality Review (AQR) in 2015 which highlighted the issue of NPAs in India. Following the AQR, the reported Gross NPA levels across all Scheduled Commercial Banks (SCBs) increased to 7.48% in FY16 (10.7% for PSBs) from 2.26% in FY08 (2.06% for PSBs). While for some preceding years, bank ownership and NPLs appeared to have been detached issues, greater regulatory oversight brought forward a very different picture. This work analyses the impact of bank ownership on NPLs, *i.e.*, has the trend of NPLs varied between different bank groups (based on ownership). The work also analyses the role played by the regulatory system in timely stress recognition. For this analysis, the following taxonomy has been adopted:

(i) Stressed assets are those loans which are either subject to restructuring, or are restructured or recognized as Non-Performing Asset (NPA) as per RBI guidelines. An NPA is a loan on which interest and/ or instalment of principal remain overdue for a period of more than 90 days.

(ii) The terms NPL and NPA have been used interchangeably in the current work, given the varied usage in the international and Indian contexts.

(iii) Bank ownership is divided in three broad groups as used by the RBI- PSBs; private sector banks and foreign banks.

The remainder of this chapter is organized as follows. Section 2 presents the literature review, while Section 3 presents the objectives of the study. Section 4 presents data and methodology. Section 5 presents the analysis and findings followed by conclusion and recommendations in Section 6.

6.2 Related Works

The present section provides a brief literature review on the relation of bank ownership and stressed assets both in the Indian and global context. Clarke et al. (2005) argued that PSBs are likely to suffer political pressure. Agarwala and Agarwala (2019) found that the growth rate of NPLs in Indian private banks is moderate when compared to PSBs. Shleifer and Vishny (1994) argued that PSBs may be unable to resist government intervention, but private banks may be able adopt more cautious lending practices. Shirley and Nellis (1991) argued that due to a lack of performance incentives and budget constraints, PSBs are forced to take on more risk.

Ghosh (2018) provides evidence to suggest that during crisis moments, Indian banks, particularly PSBs, boosted lending to hazardous, low-profit enterprises at low costs. Chavan and Gambacorta (2019) found that in the case of Indian banks, there is a procyclical risk-taking response to credit expansion. Lokare (2014) also found pro-cyclicality in the context of lending in the Indian banking sector.

Kane (2009) concluded that a faulty regulatory structure was the most significant contributor to the GFC of 2008. Samet *et al.* (2018) argued that enhanced bank regulation and oversight would bring market discipline to PSBs, reducing their tendency for excessive risk-taking. Lee and Lu (2015) found that bank fragility is reduced because of higher capital regulatory requirements, as indicated by lower NPL levels. The authors also found that increased government ownership is related to poorer levels of bank efficiency in their study of banks from 53 nations.

However, some studies have reached contradictory conclusions. Barth *et al.* (2004) found that regulatory policies that promote private supervision are linked to improved bank development and performance. However, when other aspects of bank supervision are controlled, no significant relationships between government ownership and bank performance are identified. In a study of Chinese commercial banks, Liu *et al.* (2020) found that concentration of ownership with the government decreases credit risk for banks. Rajeev and Mahesh (2010) found that PSBs have been as successful in reducing NPLs as private banks. The authors also concluded that self-monitoring has been sufficient to reduce NPLs. Ozili (2019) concluded that NPLs rise in tandem with increased financial development, which manifests itself in the form of increased foreign bank presence.

While most previous literature has focused on one or few banks or bank groups, there is a need to analyze the entire Indian banking sector and look at important differences amongst bank groups and identify improvement areas. Indian banking NPLs need to be examined both in domestic and international context. There is also a need to study aspects of bank ownership and regulatory framework in a holistic manner.

The present work, thus, aims to perform a thorough and systematic analysis to examine whether the extent of NPLs has varied depending on bank ownership in India. Analysis has also been done to examine the impact of the regulatory framework in recognizing stressed assets in India. This also critically evaluates the NPLs in the Indian banking system in a global context. Based on the analysis, the present work concludes by recommendations for improving the health of the Indian banking system.

6.3 Data & Methodology

The present work focuses on analyzing data related to NPLs and other banking performance parameters. Secondary data has been taken from institutions like RBI and World Bank. The key findings have been arrived at through a trend analysis of panel data from FY07-FY20. This period starts the year just preceding the GFC and upto FY20, which was the last year before full covid impact on corporate results and NPLs was felt. This period therefore captures the years of turmoil caused in the aftermath of the GFC, following restructuring of loans, recognition of several of these loans as NPA and finally the start of NPA resolution process and ends before the full impact of Covid-19 started.

The present work provides analysis of Indian banking data (Figure 6.2) from FY07-FY20 on 'loans subject to restructuring and restructured loans' across the three categories of banks – PSBs, Private Banks and Foreign Banks. In Figure 6.3, the present work provides analysis of Indian banking data from FY07-FY20 on the ratio of 'Loans subject to restructuring and restructured loans/Gross Advances' across the same three categories of banks. A comparison of the Gross NPA ratio from FY07-FY20 across the three categories of banks is presented in

Figure 6.4.

In the international context, Figure 6.1, also depicted as Table 6.1 provides an analysis of panel data on NPL Ratio comparing India with a sample of other developing and developed countries over the last decade (2011-2020).

6.4 Analysis & Findings

This section presents the extent of the NPL problem in the domestic and international context. In the domestic context, detailed analysis is performed for the Restructured Assets (RAs) and NPLs post the GFC.

6.4.1 Extent of the NPL Problem

After the GFC of 2008, NPLs in the Indian banking sector did not shoot significantly. Regulatory forbearance following the GFC was provided more to tackle the liquidity issues faced by Indian corporates rather than solvency issues. However, it was used by banks to avoid recognition of stressed assets. A lot of these loans were restructured assets which were essentially weak in nature but not recognized as NPLs.

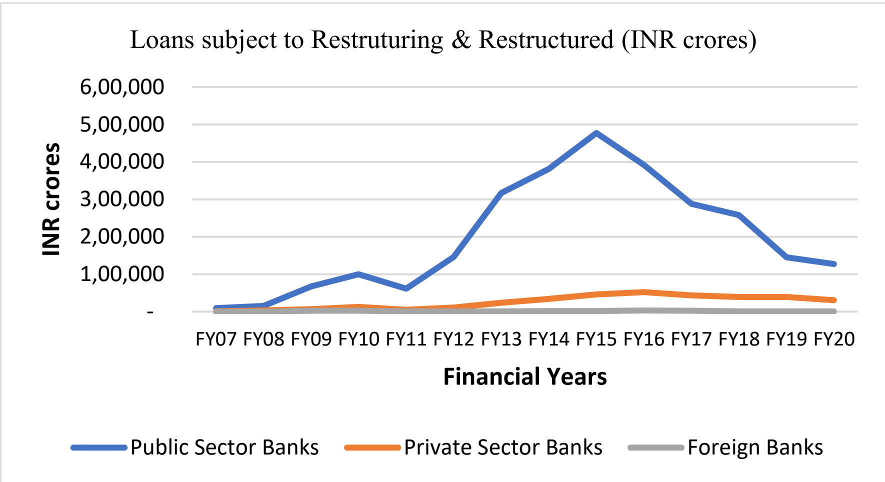

Figure 6.2: - Loans subject to Restructuring and Restructured Loans (Source: - *dbie.rbi.org.in)*

The variation of 'loans subject to restructuring and loans restructured' for the period FY07-FY20 is indicated in Figure 6.2. It can be observed that for PSB, the loans started rising sharply after FY08. The figure also increased for private sector banks, albeit at a much lower rate initially, followed by a sharper rate after FY13. For foreign banks, there was an increase in FY09 and FY10, after which the figure moderated. While the figure peaked for all banks in FY15-FY16 period, the peak for PSBs was the steepest, signifying the worst asset quality in this group.

The ‘loans subject to restructuring and loans restructured’ during a particular financial year is also illustrated as a percentage of gross advances in Figure 6.3. Since the gross advances provided by PSBs are much higher as compared to private or foreign peers, it is important to also make the comparison of ‘loans subject to restructuring and loans restructured’ as a percentage of gross advances to adjust for the higher gross advance base of PSBs (60% of total banking sector advances in FY20; and 73% in FY08).

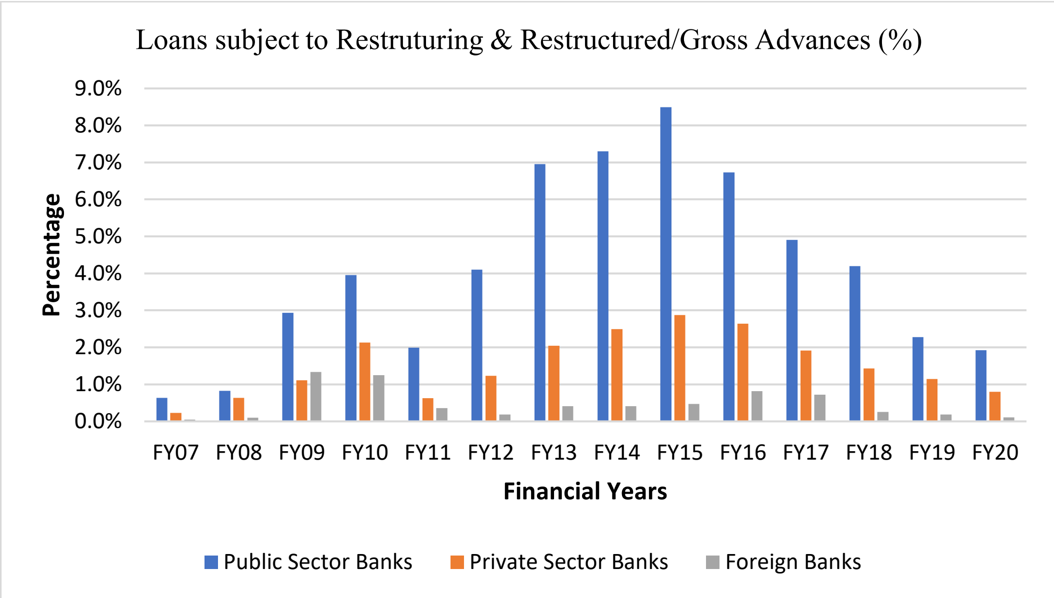

Figure 6.3: - Loans subject to Restructuring and Restructured Loans/Gross Advances (Source: dbie.rbi.org.in)

This ratio peaked at 8.5% for PSBs in FY15, at 2.9% for private banks in FY15 and at 0.8% for foreign banks in FY16 signifying the drastic difference in the performance of banks, with PSBs being the worst. This peak also signifies the huge amount of “Restructured Assets” that had built in the banking system, a large part of which had to be later recognized as NPAs, thus pushing up Gross NPA% significantly FY16 onwards. Following the AQR mandated in 2015, a large part of these RAs had to be recognized as NPAs, thus pushing up Gross NPA% significantly FY16 onwards (Figure 6.4), especially for the PSBs.

It can be observed from Figure 6.4 that contrary to general perception, PSBs were showing lower NPA levels than private banks till FY11 and the difference was not too stark till FY13. However, post AQR, FY16 onwards the difference between PSBs and other banks became stark, with PSB Gross NPA ratio moving steadily ahead of the other two bank categories. This shows that the problem was not created in FY16, rather it was recognized from there on.

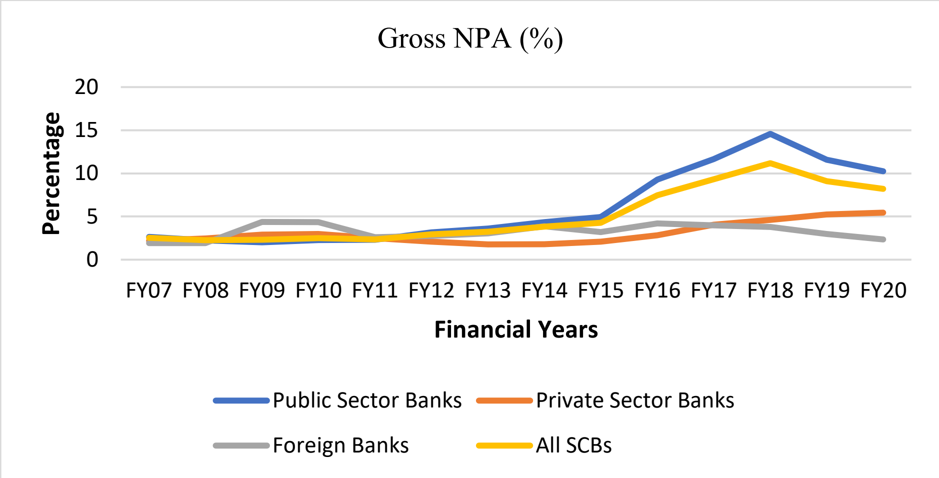

Figure 6.4: Gross NPAs (Source: dbie.rbi.org.in)

Also, Figure 6.4 depicts that foreign banks have the most consistent NPA recognition during the period, indicating either more robust stress recognition processes or better credit appraisal skills. The banking system NPA ratio moved in tandem with the PSB NPA ratio, underpinning the dominance of PSB in gross advances (c. 60% in FY20 vs 73% in FY08) and their higher share in NPAs. While the NPA problem ostensibly exploded in FY16, the signs were quite apparent post the GFC in the form of RAs. Regulatory forbearance in-effect became a tool for procrastinating the problem of recognizing asset quality.

6.4.2 Indian NPLs in the Global Context

When compared in an international context against a mix of developed and developing countries (Figure 6.1), Indian banking NPLs appear to be clearly standing out apart from Russia. A common understanding is that developing nations have higher NPLs than developed nations. While this is broadly correct, the point of concern for India is that its NPLs are much higher than even other comparable developing nations. Also, a disproportionately significant part of the stressed assets – whether in the form of RAs or NPLs – have origin in PSBs in India. In a way, the inefficiency of PSBs in managing their credit risk is largely reflected in India' poor standing in NPLs globally.

Another important point which can be deduced from this analysis is that in the early part of the last decade (2010-2014), Indian banking NPL Ratio was lower than many countries including France, UK, and USA. This appearance of a relatively healthier banking sector was however deceptive as the Indian banking NPL Ratio far surpassed other nations 2016 onwards as the RBI mandated AQR forced banks to recognize NPLs.

Table 6.1: Bank NPL to Total Gross Loan (%), Source: World Bank

Country Name	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Brazil	3.5	3.4	2.9	2.9	3.3	3.9	3.6	3.1	3.1	2.2
China	1.0	1.0	1.0	1.2	1.7	1.7	1.7	1.8	1.9	1.8
Germany	3.0	2.9	2.7	2.3	2.0	1.7	1.5	1.2	1.1	-
France	4.3	4.3	4.5	4.2	4.0	3.7	3.1	2.7	2.5	2.7
United Kingdom	4.0	3.6	3.1	1.7	1.0	0.9	0.7	1.1	1.1	1.2
Hong Kong	0.7	0.6	0.5	0.5	0.7	0.9	0.7	0.5	0.6	0.9
India	2.7	3.4	4.0	4.3	5.9	9.2	10.0	9.5	9.2	7.9
Korea, Rep.	0.5	0.6	0.6	0.5	0.5	0.5	0.4	0.3	0.3	0.2
Norway	1.7	1.5	1.3	1.1	1.1	1.2	1.0	0.7	0.8	0.7
Russian Federation	6.6	6.1	6.0	6.8	8.4	9.2	9.7	9.7	8.8	8.3
Singapore	1.1	1.0	0.9	0.8	0.9	1.2	1.4	1.3	1.3	-
United States	3.8	3.3	2.5	1.9	1.5	1.3	1.1	0.9	0.9	1.1
South Africa	4.7	4.0	3.6	3.2	3.1	2.9	2.8	3.7	3.9	5.2
Australia	2.0	1.7	1.4	1.0	0.9	0.9	0.9	0.9	1.0	1.1
Belgium	3.3	3.7	4.3	4.2	3.8	3.4	2.9	2.2	2.1	2.1
Switzerland	0.8	0.7	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.7
Canada	0.8	0.6	0.6	0.5	0.5	0.6	0.4	0.5	0.5	0.5
Saudia Arabia	2.2	1.6	1.3	1.1	1.2	1.4	1.6	2.0	1.9	2.2
Israel	-	3.5	2.9	2.2	1.8	1.6	1.3	1.2	1.4	1.5
Mexico	2.1	2.4	3.2	3.0	2.5	2.1	2.1	2.1	2.1	2.4
Turkey	2.6	2.7	2.6	2.7	3.0	3.1	2.8	3.7	5.0	3.9
Thailand	2.9	2.4	2.3	2.3	2.7	3.0	3.1	3.1	3.1	3.2
Malaysia	2.7	2.0	1.8	1.6	1.6	1.6	1.6	1.5	1.5	1.6
Indonesia	2.0	1.7	1.6	2.0	2.3	2.8	2.4	2.2	2.3	2.6

It is pertinent to mention that given that NPL norms are not globally standardized, no comparison on this subject is completely like-to-like. However, the use of World Bank data provides the best possible comparison in this context.

6.4.3 Summary of Analysis and Recommendations

The thorough and systematic analysis done during the current works indicates that bank ownership in India is a major factor impacting levels of banking NPAs. The problem of NPAs though prevalent in the entire Indian banking system, is more acute in the PSBs. Further, the quality of regulatory system is a key determinant in timely recognition of stressed assets; and resolution is not effective without proper recognition of stressed assets. It is also observed that, Indian banking NPLs are substantially higher when compared to key developed and developing economies in an international context.

Based on the key findings of the current, work, few measures can be taken to improve upon the Indian Banking System.

1. Given the continuing dominance of PSB in gross advances (approximately 60% in FY20 vs 73% in FY08) and their higher share in NPAs, strengthening the credit appraisal systems of PSBs is imperative to improving the health of the Indian banking system.
2. RBI needs to maintain a tight regulatory regime to ensure that Indian NPA levels are brought down to standards of comparable economies. Regulatory forbearance should be sparingly used.
3. Given the better performance of foreign banks as a group in India, global best practices regarding credit appraisal, monitoring and stress recognition can be studied and adopted by Indian banks.
4. In the international context, steps need to be taken to improve the asset quality of the Indian banking system to bring NPLs to standards of comparable economies. This could also contribute in improving macroeconomic stability and sovereign rating.
5. Technology can be used to provide quick and even real-time monitoring of loan accounts, aggregating data across lenders, so that the banking system can be strengthened. The Central Repository of Information on Large Credits (CRILC) is an example of such a system in the preliminary stages.

6.5 Conclusion

The present work analyses data related to NPLs and other banking performance parameters taken from institutions like RBI and World Bank. The findings of this work reveal that bank ownership in India is a major factor impacting levels of stressed assets with PSBs having relatively worse asset quality than private and foreign banks operating in India. Moreover, quality of regulatory system plays a key role in timely stress recognition and maintaining the health of a country's banking system. The present work concludes that PSBs need to strengthen their credit appraisal systems, which could include inculcating best practices from international banks. This could help bring Indian banking NPL levels down to levels of other large developed and developing countries. Further, the regulatory framework needs to be tight regarding stress recognition, using forbearance sparingly.

CHAPTER 7

REGULATORY FRAMEWORK FOR STRESSED ASSET RESOLUTION IN INDIAN BANKING: IS THE EVOLUTION MAKING AN IMPACT?

7.1 Introduction

The Indian banking sector has one of the highest levels of NPLs or in other words one of the worst 'banking asset quality' among major developing and developed economies of the world (Figure 7.1: World Bank). NPL is not a new issue for the Indian banking sector- the problem was big enough even in the 1980s to warrant the introduction of the SICA (Jain, 2015).

Law after law was introduced from the 1980s to the 2010s as not only did the problem of NPL persist in India, but also because managements of defaulting companies found ways of delaying the recovery process, leading to low recovery rates and high recovery periods. In the process, substantial amount of capital remained stuck in unproductive assets, thus constraining economic growth.

Moreover, there are linkages between banking and sovereign credit risks (Acharya et al., 2014, 2012; Farhi & Tirole, 2018). An analysis of the sovereign rating methodologies of the three major international credit rating agencies (Fitch Ratings, 2022; Moody's, 2019; S&P Global Rating's, 2017) also confirms that banking sector risks/financial sector risks are included in the factors impacting sovereign credit ratings. This means that persistence of high NPLs or higher banking sector risks impact sovereign credit ratings, which in turn impact the borrowing cost of sovereigns and entities domiciled within a sovereign (Ntsalaze et al., 2017) as well as access to both international debt and equity capital (Kim & Wu, 2011). It is therefore important to study various aspects of Indian banking sector risks including whether the evolution in the Indian stressed asset resolution framework has produced materially better results in recovery and some of the possible improvement areas going forward.

The present work traces the evolution of the Indian stressed asset resolution framework since the 1980s till 2020. While laws like SICA (1985), RDDBFI (1993) and SARFAESI (2002) did bring temporary relief in the tedious debt recovery process, the benefits were soon squandered as defaulting managements found loopholes in the processes. The Global Financial Crisis (GFC) of 2008 led to a surge in NPLs globally, but regulatory forbearance in India suppressed the actual NPL situation for many years.

The issue of NPLs again came into focus after RBI's Asset Quality Review (AQR) introduced in 2015, following which the reported Gross NPL levels across all Scheduled Commercial Banks (SCBs) shot up to 7.48% in FY16 (9.27% for public sector banks-PSBs) from 4.27% in FY15 (4.96% for PSBs) and 2.26% in FY08 (2.23% for PSBs) (https://rbi.org.in) In the backdrop of this rise in NPLs and the absence of a formal bankruptcy law in the country, the RBI introduced various schemes like SDR, 5:25 and S4A. Eventually, with the introduction of IBC (2016) stressed asset resolution gathered some pace. IBC has seen its own set of challenges and various amendments in a short span of time. However, it is the first pro-creditor law for the stressed asset resolution in India and has shown some hitherto unseen results in the Indian stressed asset market. In a similar experience in the Middle East and North Africa (MENA) region, Ghosh (Ghosh, 2023a) found that bankruptcy law reforms lead to a significant reduction in banking NPLs.

A pro-creditor regime is one where the balance of control is towards creditors rather than defaulting managements or shareholders. In the Indian context, IBC can be considered the first pro-creditor legislation for resolution of stressed assets. After the introduction of IBC, there has been a mindset shift among borrowers who cannot take default lightly and shareholders who cannot take ownership for granted (The Financial Express, 2020).

In the present work, the terms NPL and NPA have been used interchangeably, given the varied usage in the international and Indian contexts. For the purpose of this work, stressed assets refer to those loans which have been subjected to restructuring or resolution under any specific law or RBI scheme; or are recognized as NPA (as per RBI guidelines). As per extant RBI guidelines, an NPA is a loan on which interest and/or instalment of principal remain overdue for a period of more than 90 days.

The present work classifies the laws and schemes related to NPLs into three categories: Initial Laws (enacted in the 1980s-1990s); Intermediate laws and schemes (enacted in the 2000s); and Recent laws and schemes (enacted in the 2010s). With the careful analysis of the evolution of resolution framework and the data from RBI (https://rbi.org.in) & World Bank (https://data.worldbank.org/, www.doingbusiness.org), the present work analyses if there is an impact of this evolution on recovery rate, amounts recovered and time to recovery for Indian lenders in the domestic context and the international context. Based on the observations, the present work also suggests few modifications for improving the Indian stressed assets resolution framework.

This chapter contributes to research in the area of financial regulation in two ways.

Firstly, it critically analyses the evolution of the Indian stressed assets resolution framework in a holistic manner with pros and cons of each law and scheme (Table 7.1). The effect of the laws on recovery rate and absolute amounts recovered has been compiled and analyzed (Figure 7.2 and Figure 7.3). This is unlike most previous studies in India that have focused on one or few legislations or schemes in this area. Secondly, the present work evaluates Indian NPLs in a global context (Figure 7.4 and Figure 7.5) in contrast to most previous studies on India which have focused only on the domestic market without a global context.

This chapter is organized as follows: Section 7.2 presents the literature review. Data and methodology have been discussed in Section 7.3. Section 7.4 presents the analysis and findings followed by the conclusion, result and recommendations in Section 7.5.

7.2 Related Works

Literature on the stressed asset resolution framework in India is sparse and most studies are focused on particular laws and do not present a comprehensive picture. While most authors have pointed out lacunae in the laws studied by them, some have highlighted the positives as well. Though this study is in the Indian context, a global perspective has also been provided to provide a broader perspective of the issue in hand.

Van Zwieten (Zwieten, 2014) points that many provisions of the SICA in India were interpreted in such a manner by the courts that protected companies which should have been liquidated. For many of these companies even the BIFR had recommended liquidation. The application of SICA by the Indian legal system was extremely pro-debtor, favoring shareholders and employees at the cost of lenders.

Ravi (Ravi, 2015) argued that SARFAESI may have provided some relief to secured creditors, at the cost of formal bankruptcy process which maximizes overall value for all stakeholders. According to the author, a formal bankruptcy law is an opportunity to change this by increasing the scope of the legislation from merely debt recovery. Pandya (Pandya, 2015) argues that for non-core assets, the use of the SARFAESI Act, 2002 has been fair, but a free hand should not be given to lenders for security enforcement in core assets.

Shikha and Shahi (Shikha, 2021) studied data pertaining to 1189 companies under IBC as on March 2020 and found that 224 were resolved companies (19%) while 965 were liquidated (81%). While the liquidation rate was high, the recovery rate under IBC is also significantly higher than the previous laws. The authors also found that among the 1,497 ongoing cases as of September 2019, 57% of the ongoing cases had crossed 180 days' timeline and 35% had crossed 270 days signifying a high proportion of cases breaching the stipulated timelines under the law (Shikha, 2021).

Globally, bankruptcy laws provide two broad options- liquidation and reorganization – and selection between these options can have long term impact on borrowing costs, capital structure and productivity (Corbae & D'Erasmo, 2021). Legal reforms in Denmark providing more creditor empowerment in reorganization led to a sharp decline in liquidations (Agrawal et al., 2022). On the contrary, Closset et al conclude that creditors may be negatively impacted by bankruptcy law reforms favouring restructuring (Closset et al., 2023).

Iheme (Iheme, 2020) found that the Indian IBC is nearly a copy of the English Insolvency Act 1986 and has some features that are incompatible with local conditions in terms of loan access and business rescue. Iheme (Iheme, 2020) suggested that some of these flaws may stem from the IBC's unjust categorization of creditors as either "operational" or "financial". Datta (Datta, 2018) cites potential issues leading to wealth transfer problems and value destruction from the IBC process. The author suggests that some of the core legislative design choices made by Indian lawmakers need to be revisited. Using inventory and trade receivable accruals, insiders in India control earnings downward before filing for bankruptcy (Gopalan et al., 2017). According to the authors, a slew of robustness tests show that trade receivable accrual is not just a result of bad performance. Mohan and Raj (Ram Mohan & Raj, 2022) argue that ineligibilities for incumbent managements from participating in the corporate resolution under IBC are stringent and can be relaxed.

Despite its shortcomings, IBC helped reduce debt levels and borrowing costs at the firm level (Ghosh, 2023b) and helped increase period of debt maturity (Singh et al., 2021). However, an impact of higher recovery for secured creditors under IBC is that secured debt has increased for weaker firms more than that for relatively stronger firms (Singh et al., 2023).

In an overall Indian stressed asset recovery framework context, Rangoonwala (Rangoonwala, 2019) found that most financial laws in India have light penalties leading to willful defaults. Sengupta et al. (Sengupta et al., 2016) concluded that when policymakers use a piecemeal approach, focusing on one aspect of a complicated problem at a time, they are more likely to achieve inefficient results on the overall goal.

A close observation of the issue on a global level indicates that it is not only developing countries like India that face challenges in stressed asset resolution; developed countries have also faced several challenges in stressed asset resolution and the laws there have evolved over a period. Baudino and Yun (Baudino & Yun, 2017) also stated that the European financial crisis may have been exacerbated by fundamental flaws in the country's legal and judicial systems. The authors quote examples of several developed countries that took the learnings from crisis to reform their laws, to improve NPL resolution. Many countries have made the insolvency process easier to implement or added new tools like pre-insolvency proceedings (Baudino & Yun, 2017). D'Apice et al. conclude that strengthening contract enforcement eventually helps bring significant and lasting reduction in banks NPLs (D'Apice et al., 2023).

Bougatef (Bougatef, 2016) found a substantial positive association between corruption and non-performing loans in a sample of 22 developing market economies. The author also discovered that bankruptcy and collateral regulations were beneficial in lowering the impact of corruption on the loan portfolio. Giesecke et al. (Giesecke et al., 2011) found that changes in bankruptcy law and the average level of defaults in the United States have some long-term parallels. Low default rates are evident in times with significant penalties placed on debtors and management, which implies default rates are largely commensurate with the level of debtor protection provided during the various legal regimes. That is, pro-creditor bankruptcy regimes exhibit low default rates while pro-debtor regimes exhibit higher default rates. Quality of entity management during the corporate insolvency resolution process is also important and bankruptcy is initiated more often in countries where such management is efficient (Stef, 2022).

Most studies in India have focused on one or few legislations or schemes in the area of stressed assets resolution. There is a need to study the evolution of the Indian stressed assets resolution framework in a holistic manner with pros and cons of each law and their effect on recovery rate and absolute amounts recovered. This perspective is particularly important as there are linkages between banking and sovereign credit risks (Choy et al., 2021). Acharya et al. (Acharya et al., 2014, 2012) explain that among other things, through exposure to government securities in their balance sheets, banks are even more exposed to sovereign credit risk. Farhi & Tirole (Farhi & Tirole, 2018) suggested that banking and sovereign credit risks are interchangeable. An analysis of the sovereign rating methodologies of the three major international credit rating agencies (Fitch Ratings, 2022; Moody's, 2019; S&P Global Rating's, 2017) shows that banking sector risks /financial sector risks are included in the factors impacting sovereign credit ratings.

While there are many global studies about debt recovery, few studies have attempted to study Indian NPLs in a global context, which this study purports to do. This chapter analyses the improvement in recoveries due to changes in the stressed asset resolution framework in India when compared to other major developing and developed nations. The present work also analyses if the evolution of the resolution framework has improved recovery rates based on a comparison of different laws in India. Based on the observations, the present work also suggests few modifications for improving the Indian stressed assets resolution framework.

7.3 Data and Methodology

The present work focuses on analyzing all relevant stressed assets resolution laws and schemes introduced from 1985 till 2016, and their impact till 2020. The years indicate the year of introduction of the first major debt resolution law in India, i.e., SICA (1985) till the introduction of the latest debt resolution law, i.e., IBC (2016). For a thorough qualitative analysis, various laws & schemes issued by the GoI and the RBI in the above-mentioned time frame have been selected as the cases for study. The key features, purpose, benefits, and challenges of all these laws and schemes have been analyzed and tabulated (Table 7.1).

For the present work, secondary data has been taken from institutions like the RBI and World Bank. The present work provides a trend analysis of Indian time-series data (Figure 7.2 & Figure 7.3) from FY15-FY20 (RBI, 2020). This period starts from the year just preceding the introduction of IBC and up to FY20, which was the last year before full covid impact on corporate results and NPLs was felt. The following year, i.e., FY21, recorded a severe impact on corporate results as well as recovery efforts of lenders given the extraordinary pandemic conditions.

In the national context, variables analyzed in this study include recovery rate and amounts recovered. These variables have been studied for Lok Adalats, DRT, SARFEASI and IBC. The source of aforesaid data is RBI. In the international context, cross-section data (Figure 7.4 & Figure 7.5) and panel data (Figure 7.1) has been compiled and analyzed while comparing India with a sample of other developing and developed countries in this work. For international comparisons, variables like the gross NPLs as percentage of gross loans; recovery rate, cost and time to recovery have been used. The source of this data is the World Bank.

7.4 Analysis and Findings

The present section critically analyses various laws and schemes which have been broadly categorized into three categories. The key features, purpose, benefits and eventually the challenges that led to the development of the subsequent law have been pointed out. For a clear picture, the analysis has been compiled in a tabular manner, however the details have been discussed in the subsequent subsections. The section also presents analysis of Indian and international data on various parameters like NPL percentage, recovery rate, cost and time to recovery using various graphs.

7.4.1 Indian NPL Issue in an International Context

Indian NPLs are among the highest in the world among major economies as indicated in Figure 7.1. In comparison with other developed and developing countries, barring Russia, NPLs in the Indian banking system far exceed those in any other country, consistently for a large part of the last decade.

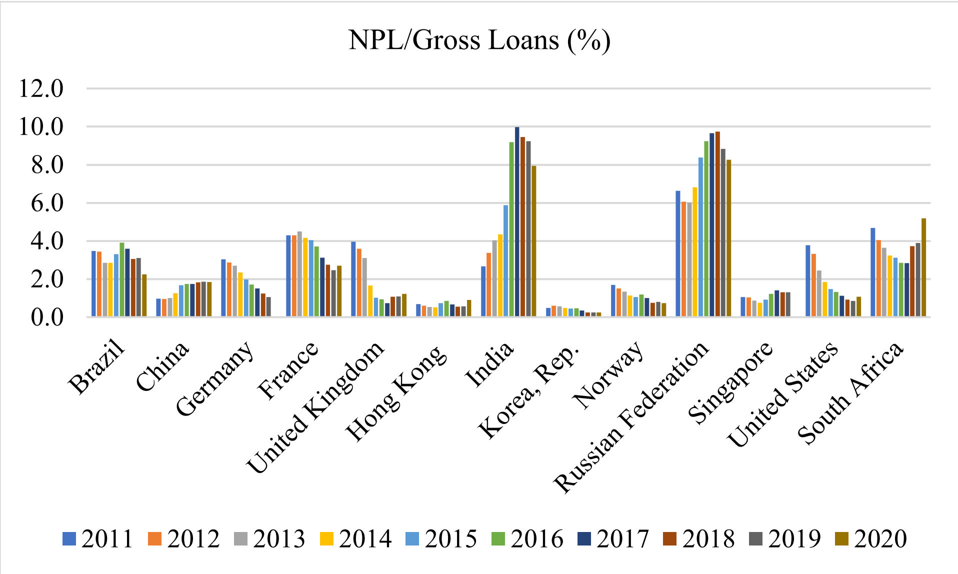

Figure 7.1: Bank NPL to Total Gross Loan (%), Source: World Bank

Since there is no standardization of NPL recognition norms across the world; cross-country NPL data is not strictly comparable. However, given that this data is from the World Bank, the above graph provides the best possible comparison on the matter.

7.4.2 Laws and Schemes to tackle stressed assets

The problem of NPLs is quite old in the Indian economy; various laws and schemes have been brought over decades to tackle the problem. 'Laws' are those that have been passed by acts of the Parliament, whereas 'schemes' are introduced by RBI from time to time by exercising its powers as the banking regulator. In the present work, the laws and schemes related to NPLs have been broadly put into three categories:

- Initial Laws- 1980s-1990s
- Intermediate laws and schemes – 2000s
- Recent laws and schemes – 2010s

The various laws and schemes covered in these broad categories along with their pros and cons are briefly described in Table 7.1.

Table 7.1: Summary of Laws and Schemes for Stressed Assets Recovery in India (1985-2016)

Law/Scheme	Year	Key Features	Purpose	Benefits	Challenges
Sick Industrial Companies (Special Provisions) Act (SICA)	1985	For industrial units which had existed for at least five years. Accumulated losses had to be equal to or more than the net worth.	Fasten revival of companies believed to be viable while closing those believed to be unviable.	First law intending to release capital out of non-productive assets.	Misused by borrowers to avoid obligations and secure concessions from lenders. Cases were heard in Civil Courts, leading to long pendency.
Lok Adalat (under the Legal Services Authorities Act)	1987	Alternative dispute redressal mechanism targeting an amicable compromise for cases pending in courts or at a pre-litigation stage.	Used primarily for small loans.	Help banks settle loans by way of compromise between the lender and the borrower, thereby reducing load on courts.	Low recovery rate as most parties try to fight instead of reaching a compromise
Recovery of Debts Due to Banks and Financial Institutions Act (RDDBFI)	1993	Replaced civil courts for recovery proceedings by forming Debt Recovery Tribunals (DRTs) and Debt Recovery Appellate Tribunals (DRATs).	Reduce burden on civil courts by establishing specialised tribunals for speedy recovery of NPLs.	Temporary relief to lenders by hastening recovery process.	Pendency at DRTs became much higher than planned as: Lower courts continued to play a role due to the limited judicial powers granted to DRT and DRAT. SICA reduced the effectiveness of DRTs as it continued to be in force and could be used while an application was filed with DRT, thus stalling recovery proceedings.
Corporate Debt Restructuring scheme (CDR)	2001	Voluntary, non-statutory scheme allowing banks to restructure the debt (more than INR 100 million) of corporate firms. Majority of lenders - 75% (by value) and 60% (by numbers) - could decide on restructuring	Restructuring of loans to otherwise viable firms to minimize losses to all parties and ensure efficient use of resources.	Provided banks a mechanism where debt to viable companies could be restructured instead of participating in lengthy court proceedings.	Long drawn process given a complex three tier structure. Some companies took considerable concessions only to fail again. Banks used the mechanism to avoid adequate provisioning.
Securitisation	2002	The first asset	Three purposes –	It provided an	Securitization, as a

and Reconstruction of Financial Assets and Enforcement of Security Interests Act (SARFAESI)		reconstruction company (ARC) of the country, ARCIL was set up under this act. Subsequently, many other ARCs have been established. Allowed enforcement of security without approaching a court or a tribunal.	securitization of financial assets; reconstruction of financial assets; or enforcement of security interest of lenders.	option to the lenders to securitize and reconstruct their stressed assets with the aid of ARCs, or to enforce security without intervention of any court or tribunal.	concept, did not work well with heterogeneous assets like corporate loans. Enforcement of security interest worked with small borrowers but not with large ones who could stall proceedings in various ways.
Joint Lending Forum (JLF) and Corrective Action Plan (CAP)	2014	Established the Central Repository of Information on Large Credits (CRILC) platform, which requires all lenders to notify the status of all accounts with an aggregate exposure (AE) of more than INR 50 million. Introduced three categories of Special Mention Accounts (SMA).	Facilitate identification of stress and revive a company well before time of it becoming an NPL	Helped identify stress well in time. Three options were provided under the corrective action plan (CAP) – Rectification, Restructuring or Recovery.	This provided a starting point by identifying stress but lacked adequate tools to achieve the options under CAP. Options were later provided by RBI through various schemes.
5:25 Flexible Restructuring Scheme	2014	Projects in the infrastructure and core industries were eligible under the scheme. Change in the amortization schedule was allowed provided that the Net Present Value (NPV) remained unchanged.	Help banks manage their asset liability mismatch (ALM). Due to their funding profile, banks typically restrict lending to a maximum of 10-12 years, as against higher economic life of an infrastructure assets.	Lenders were able to set longer amortisation periods up to 25 years based on the economic life and fundamental sustainability of the loan, with periodic refinancing every 5 years under the scheme.	Not very successful as borrowers kept looking for concessions whereas the scheme did not allow change in NPV.
Strategic Debt Restructuring (SDR)	2015	Provided an option to the JLF, at time of initial restructuring, to incorporate terms for conversion of debt to equity, if milestones were	In restructurings in India, despite lender sacrifices, many borrowers continued to be in stress due to managerial inefficiencies.	Lenders could become majority shareholders so that they could bring in new management by selling their	Finding a new owner for a stressed asset and that too within a short time-frame of 18 months was difficult. SDR required creating fresh documentation, for

		not met.	This scheme provided an option to change the inefficient management.	equity	which the existing shareholders did not easily agree.
Scheme for Sustainable Structuring of Stressed Assets (S4A)	2016	Limited to borrowers who had commenced commercial operations and where the determined sustainable debt (including accrued interest) was at least 50% of total debt.	Address limitations of earlier schemes by introducing greater flexibility. For instance, under 5:25, banks could not take haircut. Under SDR, banks needed to find a new buyer after conversion to equity within 18 months,	S4A provided banks sufficient period to find a new buyer, if required or adequate time for the company to turnaround or even take a haircut during restructuring.	Filtered out many companies especially those at project stage. Also, it did not allow rescheduling of original tenure or restructuring with better interest rates. Banks had a major issue with this scheme at it required substantial provisioning.
Insolvency and Bankruptcy Code, (IBC)	2016	A financial creditor or operational creditor can initiate the Insolvency Resolution Process (IRP); voluntary bankruptcy process is also allowed. The revival plan can include fresh finance, asset sale, haircuts, management change etc. Liquidation is also an option if revival is not possible.	To provide a formal insolvency regime which was lacking in the country till then.	Creditors can seek reorganization more actively rather than just suits for recovery or debt restructuring. First pro-creditor resolution regime led to higher recovery rates than previous laws and schemes. Introduced statutory timeline for resolution.	Timeline for resolution exceeded in most cases. High incidence of liquidation rather than resolution. Some large cases have seen very low recoveries (less than 10%), drawing criticism of the implementation of the law.

Source: Authors' Compilation

7.4.2.1 Initial Laws

The initial laws primarily include three acts – SICA, Lok Adalat and the RDDBFI Act. The following sub-sections give a brief overview of these acts.

a) Sick Industrial Companies (Special Provisions) Act, 1985 (SICA)

For an industrial company to be covered under SICA, it had to comply with two key conditions along with various other conditions. These two conditions are as follows:

- Unit existed for at least five years
- Accumulated losses should be equal to or exceed the net worth of the company/unit

The purpose of SICA was to fasten revival of companies believed to be viable while closing those believed to be unviable. This would have helped revive potentially productive assets and release capital out of non-productive assets to the extent possible so that it might be deployed elsewhere more productively. However, weak corporate governance practices which led to a lot of industrial sickness in the first place also led to misuse of the provisions of this law. The sole purpose of filing a sickness declaration for some companies was to avoid debt repayments and secure concessions from lenders. Matters related to SICA were heard in the civil courts of the country. The generally slow Indian legal procedure coupled with frivolous arguments by borrowers meant long pendency of cases in civil courts. Cases also increased as some company founders tried to misuse the law by gaining undue concessions from lenders under SICA.

b) Lok Adalat (under the Legal Services Authorities Act, 1987)

Lok Adalat is an alternative dispute redressal mechanism, where an amicable compromise is targeted for cases pending in courts or at a pre-litigation stage. The Legal Services Authorities Act, 1987 provides a statutory status to Lok Adalats which largely help banks settle loans by way of compromise between the lender and the borrower. Lok Adalats are used primarily for small loans - this can be gauged from the fact that in FY20, over 5.6 million cases were referred to them with amount involved of INR 67,8 billion; in contrast only 1953 cases were referred under IBC with amount involved of INR 2,325 billion. Recovery rates from Lok Adalats have been low, ranging between 3.2% and 6.2% between FY15 and FY20.The focus of Lok Adalats is on compromise and if none is reached, the case goes to the court. The key reason for low recoveries through this system is that most parties try to fight instead of reaching a compromise.

c) Recovery of Debts Due to Banks and Financial Institutions Act, 1993 (RDDBFI)

Given the significant pendency of SICA related cases in the civil courts, the RDDBFI Act was introduced to establish tribunals for speedy recovery of NPLs. The Act replaced civil courts for recovery proceedings by forming Debt Recovery Tribunals (DRTs) and Debt Recovery Appellate Tribunals (DRATs). This provided temporary relief to lenders but soon the tribunals were clogged with cases. The maximum number of cases to be pending at any DRT at any given time, according to the Deshpande Committee Report, was to be around 800 whereas the actual average pendency was around 2000 (CUTS International, 2016).

There were other issues too with the DRT process which limited its effectiveness. While the DRT process was intended to relieve pressure on lower courts, the lower courts continued to play a role in practice due to the limited judicial powers granted to DRT and DRAT. For instance, the DRTs and DRATs do not have jurisdiction over issues like property succession rights, KYC monitoring and implementation, which require intervention of civil courts, thus, delay in cases was experienced (Phadnis & Prabhala, 2016).

Moreover, SICA reduced the effectiveness of DRTs as it continued to be in force and could be used while an application was filed with DRT, thus stalling recovery proceedings. RDDBFI Act permitted that DRTs were used in addition to, and not in place of the SICA. Borrowers often blocked processes by filing claims against lenders in civil courts. Matters in DRTs also got stuck on things like state dues, workmen dues, and claims concerning unsecured assets. It became clear that some other mechanism would have to be evolved to contain the rising NPL burden.

7.4.2.2 Intermediate laws & schemes

The intermediate laws & schemes primarily include the CDR scheme and the SARFAESI act, introduced in 2001 and 2002, respectively. The following sub-sections give a brief overview of these schemes and acts.

a) Corporate Debt Restructuring scheme, 2001(CDR)

CDR was a voluntary, non-statutory scheme introduced by RBI in 2001, which allowed multiple banking or consortium of lenders to restructure the debt (more than INR 100 million) of corporate firms. The rationale was to allow restructuring of loans to otherwise viable firms to minimize losses to all parties and ensure efficient use of resources.

Debtor Creditor Agreement (DCA) and Inter Creditor Agreement (ICA) formed the cornerstone of the mechanism in which approvals required a supermajority of 75% lenders (by value) and 60% (by numbers). There was a complex three tier structure of Standing Forum, Empowered Group and CDR Cell. Ultimately it proved to be a long-drawn process whereby some companies took considerable concessions only to fail again.

Also, it was observed that many assets restructured under CDR were severely stressed and should have been subjected to advance capital provisioning. By not doing so, CDR served as the starting point for under-provisioning and excessive risk taking by banks. This led to initiation of a process which was repeated in the forbearance period after the global financial crisis (GFC) of 2008.

b) *Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interests Act, 2002 (SARFAESI)*

SARFAESI Act had three purposes – securitisation of financial assets; reconstruction of financial assets; or enforcement of security interest of lenders. The first asset reconstruction company (ARC) of the country, ARCIL was set up under this act. The Act's objective was to provide an option to the lenders that helps in securitisation and reconstruction of their stressed assets with the aid of ARCs, or to let them enforce security without intervention of any court or tribunal.

Recoveries through SARFAESI remained muted as it suffered from several limitations. Firstly, securitisation, as a concept, works better with a pool of homogenous assets and not assets like corporate loans which exhibit substantial heterogeneity. Secondly, enforcement of security interest worked with small borrowers but not with large ones, who could use their resources to delay the process legally or play off one banker against another by choosing to repay one but strategically default on the other.

7.4.2.3 Recent laws and schemes

After the 2008 GFC, the RBI allowed a special regulatory treatment for restructured assets whereby the lender was not required to downgrade the asset quality. The forbearance was not intended for solvency issues but was to help the borrowers and lenders tide over the GFC induced liquidity shock. This led to not only an increase in restructured assets during this period but also excessive lending, especially between 2009-2012, in sectors like steel, power, telecom, construction and infrastructure. After certain extensions, RBI announced withdrawal of forbearance from end of FY15. The process of tightening prudential norms related to asset classification and income recognition started and was accompanied by the asset quality review (AQR) introduced in 2015. In the absence of an insolvency law, several schemes with insolvency law-like features were also introduced by RBI to provide a mechanism for resolving stressed assets. These schemes introduced before the IBC have been discussed below, followed by a detailed discussion on IBC:

a) Joint Lending Forum (JLF) and Corrective Action Plan (CAP), 2014

The main purpose of the JLF and CAP mechanism was to facilitate lenders in identifying the stress and revive a company well before time of it becoming an NPL. To give early warning indications, the RBI established the Central Repository of Information on Large Credits (CRILC) platform, which requires all lenders to notify the status of all accounts with an aggregate exposure (AE) of more than INR 50 million. As a result, banks must create three subcategories under the Special Mention Account (SMA) category to identify incipient stress in accounts before they become NPAs. The SMA subcategories (SMA 0, 1, 2) are largely based on number of days of delay in debt servicing.

When a lender classifies an account as SMA 2 and the AE exceeds INR 1 billion, bankers are required to construct a JLF. They can, however, create JLF even if the first two requirements are not met. JLF develops a CAP to find an early and realistic solution to protect the economic worth of the underlying assets and the lenders' loans.

Three options were provided under CAP – Rectification, Restructuring or Recovery. Rectification involved a promise from the borrower to correct the books, including the possibility of obtaining additional equity investors, without affecting the loan terms. Only if restructuring appeared to be feasible was it to be implemented. JLF could carry out restructuring without involving CDR Cell. If the first two options weren't viable, the recovery process could begin.

The main contribution of this mechanism was the implementation of CRILC and SMA systems which helped to improve early warning signs. Subsequently, RBI provided various tools to lenders to achieve the above-mentioned options under CAP, which are explained below.

b) 5:25 Flexible Structuring Scheme, 2014

A perennial problem with the Indian banking industry is its asset-liability mismatch (ALM), particularly while financing long-gestation projects. Due to the asset-liability mismatches, banks restrict funding to a maximum of 10-12 years, as against higher economic life of the asset, say 25 years. This means higher than viable repayment burden on projects as based on their cash-flows, thus leading to stress.

This scheme was created to help banks manage their ALM mismatches. Lenders were able to set longer amortisation periods up to 25 years based on the economic life and fundamental sustainability of the loan, with periodic refinancing every 5 years under the scheme. Projects in the infrastructure and core industries were eligible under the scheme. As per a key condition of the scheme, the Net Present Value (NPV) of the loan was to remain unchanged even after change in the amortization schedule. This became the biggest challenge in the success of the scheme as borrowers kept looking for concessions. Clearly, the intent of RBI was to provide a remedy for ALM to lenders and ease repayment burden to borrowers and not change the economic reward for lenders for their risk-taking.

c) Strategic Debt Restructuring scheme, 2015 (SDR)

With the long history of restructuring in India under various laws and schemes, it was experienced that despite lender sacrifices, borrowers continued to be in stress due to managerial inefficiencies. SDR provided an option to the JLF, at time of initial restructuring, to incorporate terms for conversion of debt to equity, if milestones were not met. Decision to convert loans into equity was to be taken by 75% of lenders (by value) and 60% of lenders (by numbers). With this, lenders were to become majority shareholders (51% or above) so that they could bring in new management by selling their equity within 18 months of becoming shareholders.

SDR suffered from many limitations, the principal being the problem of finding a new owner within a short time-frame, which was a major roadblock as it was not easy to find buyers for stressed assets. Further, SDR required creating fresh documentation, for which the existing shareholders did not easily agree. Borrowers also obstructed the process of converting debt into equity within the stipulated 210 days.

d) Scheme for Sustainable Structuring of Stressed Assets, 2016 (S4A)

S4A scheme was limited to borrowers who had commenced commercial operations and where the determined sustainable debt (including accrued interest) was at least 50% of total debt. It tried to address the limitations of the earlier schemes while introducing greater flexibility in the stressed asset resolution framework. For instance, under 5:25, banks could not take haircut after restructuring, however, under S4A, banks were allowed to do so. Under SDR, banks needed to find a new buyer after conversion to equity within about 18 months, but S4A provided banks sufficient period to find a new buyer, if required or adequate time for the company to turnaround.

Like other schemes S4A had its limitations like filtering out many companies especially those at project stage. Also, it did not allow rescheduling of original tenure or restructuring with better interest rates. It did not allow factoring in possible incremental cash flows during the process of making a resolution plan. Banks also had a major issue with this scheme at it required substantial provisioning.

e) *Insolvency and Bankruptcy Code, 2016 (IBC)*

The schemes introduced by RBI between 2014-16 were meant to create a resolution framework in the absence of a formal insolvency and bankruptcy law. The lack of a formal insolvency regime was finally overcome with the introduction of the IBC in 2016.

A financial creditor or operational creditor can initiate the Insolvency Resolution Process (IRP); voluntary bankruptcy process is also allowed. Under IBC, creditors can seek reorganization more actively rather than just filing cases for recovery or debt restructuring. Upon admission of a case under IBC, management control is taken over by a resolution professional (RP) who operates the business as a 'going concern' under directions of the committee of creditors (CoC).

The revival plans can include fresh finance, asset sale, haircuts, management change etc. Liquidation can be undertaken under various conditions like (i) if recommended by the CoC, or (ii) if no resolution plan is submitted at the national company law tribunal (NCLT) or (iii) if the NCLT rejects resolution or (iv) if the debtor contravenes the decided plan. However, under the spirit of the code, the adjudicating authority would mostly ensure that the due process of law is followed, leaving the actual solution to the professional wisdom of the CoC.

The biggest change that IBC has brought to the Indian stressed asset resolution framework is that the control has shifted from defaulting management to its creditors. It is therefore the first 'pro-creditor' legislation in the Indian context.

However, IBC also has not been insulated from delays which have been a plague of the Indian judicial system. Under the initial IBC rules, the CoC had to decide on revival plan or liquidation within 180 days, which was further extendable by 90 days. Many cases continued to extend beyond the defined timelines. An amendment in 2019 increased the total time available for resolution to 330 days from 270 days.

Literature indicates that as of September 2019, 57% of the ongoing cases had crossed 180 days' timeline and 35% had crossed 270 days (Shikha, 2021). The authors found that 64% delay is caused in the process of taking approval for the resolution plan. The authors didn't find any correlation between the delay and debt size, which is contrary to perception of even resolution professionals (RPs) dealing with such cases.

An analysis of the available data shows that the key reasons for such delay include inadequate staff capacity at NCLT, difficulty in marketing stressed assets to prospective buyers, non-cooperation by corporate debtors and improper documentation systems of companies. A report of The Times of India stated that a Parliamentary Standing Committee in 2021 has noted that against the sanctioned strength of 62 members in NCLT the actual strength was only 28 (*NCLT Members' Absence May Affect IBC Reform - Times of India.* , 2021). Inadequate staffing has contributed to high case pendency at NCLT; as per a report of The Economic Times, 21,259 cases were pending before NCLT all over the country as at end December 2020 while more than 2270 cases were filed in the first 9 months of FY21 (The Economic Times, 2021).

Further, for every one case resolved under IBC, four cases end up in liquidation (Shikha, 2021). Though the recovery rate under IBC is higher compared to previous laws, the high rate of liquidation is a matter of concern. The authors also found that in case of non-cooperation by the corporate debtor, only 3% RPs took legal action even while law has provision for such action. Developed jurisdictions like Singapore, United Kingdom, and Hong Kong, under their insolvency laws severely penalize non-cooperation of the corporate debtor with the RP.

7.4.3 Comparison of Recoveries Pre and Post IBC

The limited experience from IBC has shown that it has much superior recovery rates (Figure 7.2) when compared to some of the earlier mechanisms. The data indicates that Lok Adalats have the lowest recovery rates while DRTs have fared a little better.

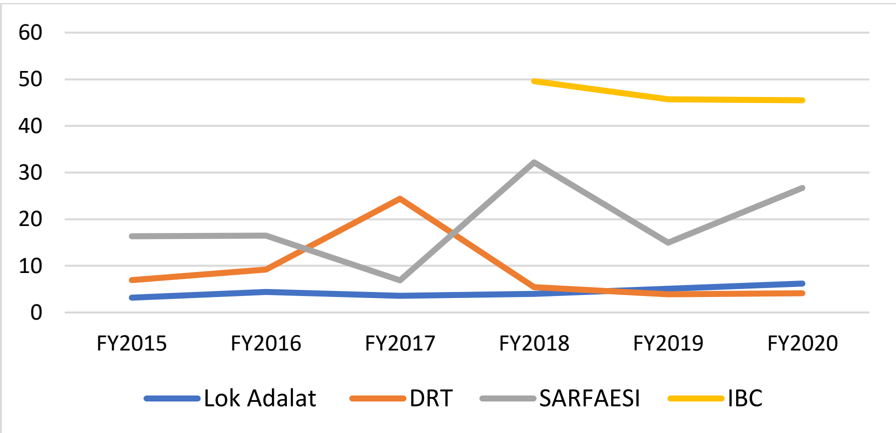

Figure 7.2: Recovery Rate (%) under Various Laws (data source: (RBI, 2020))

Further, SARFAESI has shown better recoveries than the former two mechanisms but IBC has created a paradigm shift in the India stressed assets recovery space by introducing a pro-creditor framework for the first time.

Another important aspect where IBC has made an impact is the amount of debt recovered from the process. Since some very large stressed assets have been resolved under IBC, the amount of debt recovered is substantially more than that recovered through other mechanisms, as indicated in Figure 7.3. IBC has had a major contribution in recoveries from FY19, soon after the law was introduced in FY17 (Figure 7.3).

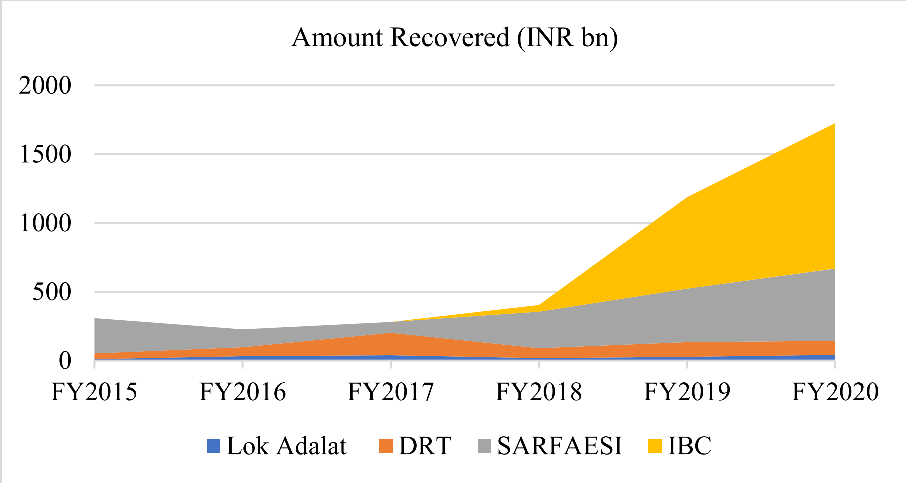

Figure 7.3: Amount Recovered under Various Laws (data source: (RBI, 2020))

Data shows that recoveries in India from resolving insolvencies have improved substantially post the introduction of IBC when put in an international context (Figure 7.4 and Figure 7.5). A comparison of pre and post IBC for a mix of developed and developing countries is discussed here on and indicated in Figure 7.4 and Figure 7.5. As per June 2017 World Bank data, Indian recovery rate was the lowest in this comparison while the time for resolution was by far the worst, even by developing country standards (Figure 7.4). Since IBC was introduced in 2016, it can be safely assumed that not many cases would have been resolved by the time this data was compiled; hence the 2017 data is reflective of the pre-IBC regime. India's Resolving Insolvency Rank was 103 in the world as per World Bank's Ease of Doing Business rankings at that time.

Analysis reveals that post IBC, India has made substantial improvement in recovery rates, which are now much higher than developing country peers and reaching close to developed countries (Figure 7.5). However, it is important to note that this is the average rate and, in some cases, recoveries have been less than even five percent. The time to recovery has reduced substantially post IBC and is closer to developing country peers though still higher than developed countries. Indian cost of recovery has meanwhile remained stagnant and in the middle of the stack. India's Resolving Insolvency Rank had improved to 52 in the world as per World Bank's Ease of Doing Business rankings in 2019.

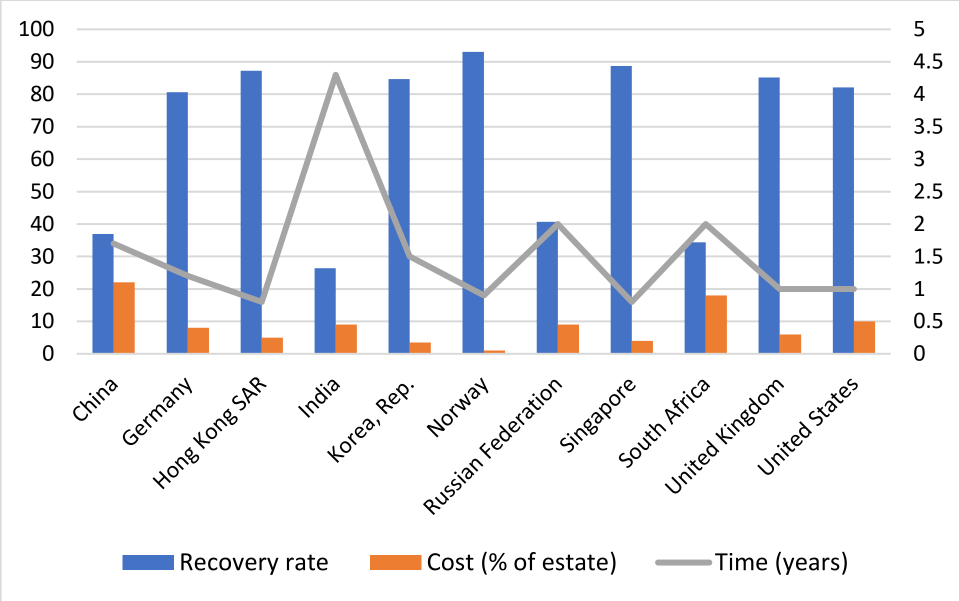

Figure 7.4: International Comparison: Recovery Rate, Cost & Time, 2017 (data source: www.doingbusiness.org)

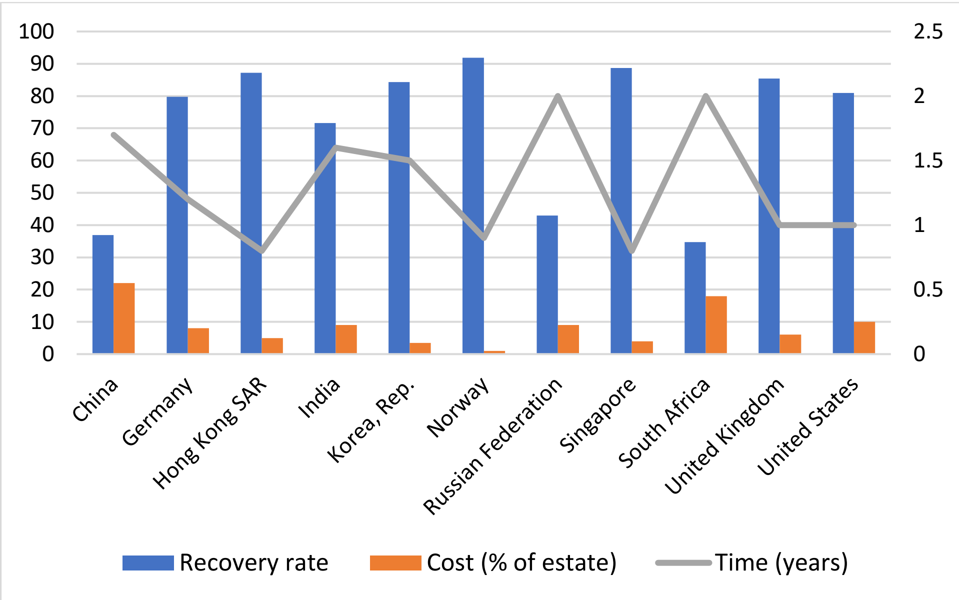

Figure 7.5: International Comparison: Recovery Rate, Cost & Time, 2019 (data source: www.doingbusiness.org)

While the introduction of IBC has improved recovery rates in India, the law is still a recent one. As the law matures, it would be interesting to analyze if it also helps reduce the incidence of NPL in the Indian financial system through a change in the mindset of Indian business founders and managements towards borrowing and repayment.

7.5 Results & Conclusion

The present chapter analyses the evolution of the stressed assets resolution framework in India from 1985 to 2020 and its impact on the recovery rate, recovery time and amounts recovered. For a thorough analysis, data from RBI and World Bank are considered along with various laws and schemes issued by the GoI and the RBI. The results from the aforesaid analysis are summarized below.

Indian stressed asset resolution framework witnessed a slew of laws and schemes from 1985, with every new law or scheme attempting to improve upon the shortcomings of the previous ones. While some improvement was achieved in terms of recovery rates, these remained far below international standards till the introduction of IBC in 2016. Also, while IBC is making substantial improvement in the recovery rate over previous laws, it is important to note that this is the average rate and, in certain cases, recoveries have been in low single digits.

Besides the recovery rate, given that some very large stressed assets have been resolved under IBC, the absolute amount of debt recovered is substantially more than that recovered through other mechanisms It shows that a pro-creditor stance to resolution has worked better in India than a pro-debtor stance. Though time to recovery has improved substantially, most cases under IBC are breaching the timeline stipulated under law.

In an international context, post-IBC, India has made substantial improvement in recovery rates, which are now much higher than developing country peers and moving towards developed countries standards. Also, the time to recovery has substantially reduced and is now closer to developing country peers though still poor compared to developed countries. Indian cost of recovery has meanwhile remained stagnant and in the middle of the stack in the comparison.

Further, an analysis of the data and results indicates that the challenges in the legal system which cause delays need to be ironed out and the tribunals need to be adequately staffed to ensure that the systematic gains that have been achieved can continue in the right direction. Also, non-cooperation by the corporate debtor needs to be severely penalized under the law. These changes can help in improving upon the gains achieved from IBC in recovery rate and timelines and eventually reduce Indian banking sector risks.

CHAPTER 8

CONCLUSION, FUTURE SCOPE, AND SOCIAL IMPACT

In this thesis, we addressed tasks namely (a) impact of various qualitative and quantitative factors on the SCRs to ascertain this impact of various aforesaid factors on the SCR; a detailed dataset was created comprising of 55 countries across income categories and geographical areas around the world for a period of 10 years. Data on 42 unique factors was collected for these countries from various reputed international sources, (b) examining banking risk factors in-depth including qualitative banking risk factors. Given the relationship between banking sector risk and sovereign credit risk, found in previous literature as well as CRA rating methodologies. This thesis has specifically studied two qualitative risk factors *w.r.t.* the Indian banking sector (i) impact of bank ownership on stressed asset creation (ii) regulatory framework and its impact on resolution/recovery of stressed assets.

8.1 Summary of the Work Done in the Thesis

This work analyses the impact of qualitative factor "rule of law" on the sovereign credit rating. Thorough analysis has been done on the complete developed dataset using linear regression, R squared value and the correlation coefficient. The results indicate a positive linkage, having 82% positive correlation between the "Rule of Law" percentile ranking of a country and its sovereign credit rating across various income groups and regions. The finding suggests that countries striving for higher sovereign credit ratings should consider ways to improve their world standing on qualitative variables like the 'Rule of Law" and not only concentrate on improving macroeconomic factors. While this work studies only one variable, there are many other qualitative variables which could be important in determining sovereign credit ratings, which can subject of future research.

For the analysis, two different datasets were developed which comprises of 55 countries from all income groups and geographical locations with SCR obtained from two major CRA's for a period of 10 years. In these two different datasets, various factors were replaced by their contemporary factors along with the data source. This was done to perform correlation analysis on these datasets individually to assess the importance of different parameters and to predict the sovereign credit rating using extra tree classifier. An important outcome is that all factors with low correlation are quantitative in nature while qualitative factors have high-moderate correlation with SCR. This indicates that the qualitative (socio-political) factors, individually and as a group, are more important in determining SCR than quantitative (economic) factors.

Comparative analysis of results for these 2 datasets indicates the importance of the qualitative factors remains the same in determining SCR irrespective of its data source. This also finds the possibility of a bias in favor of "high-income" nations while assigning SCR. Moreover, banking sector factors appear to have moderate correlation with SCR. The results analysis reflects that given the importance of qualitative factors in determination of sovereign credit ratings; sovereigns particularly developing/low-middle income might be better placed by focusing on socio-political reforms instead of focusing only on economic factors.

The third task analyses data related to NPLs and other banking performance parameters taken from institutions like RBI and World Bank. The findings of this work reveal that bank ownership in India is a major factor impacting levels of stressed assets with PSBs having relatively worse asset quality than private and foreign banks operating in India. Moreover, quality of regulatory system plays a key role in timely stress recognition and maintaining the health of a country's banking system.

The fourth task analyses the evolution of the stressed assets resolution framework in India from 1985 to 2020 and its impact on the recovery rate, recovery time and amounts recovered. It shows that a pro-creditor stance to resolution has worked better in India than a pro-debtor stance. Though time to recovery has improved substantially, most cases under IBC are breaching the timeline stipulated under law. In an international context, post-IBC, India has made substantial improvement in recovery rates, which are now much higher than developing country peers and moving towards developed countries standards. Also, the time to recovery has substantially reduced and is now closer to developing country peers though still poor compared to developed countries. Indian cost of recovery has meanwhile remained stagnant and in the middle of the stack in the comparison.

8.2 Future Scope/Directions and Social Impact

This dataset can be used for varied kind of analysis ranging from weight of parameters in determination of sovereign rating, relation between parameters, presence of bias in sovereign rating, training a model for predicting a country's sovereign credit rating etc.

- Prioritization of instuitional factor for reform - Qualitative factors individually can be studied to find their importance in determination of SCR. This can give direction to Sovereigns to which instuitional factors to prioritize for improvement in SCR.
- Pre vs Post GFC Analysis - Given the increased focus on banking risk as a factor determining SCR, post the GFC, a study specifically focused on relative importance of various factors imparting SCR pre vs post GFC can be done.
- Revaluation of Factors - Since CRA methodologies keep evolving with time, future researchers can reexamine the various contemporary factors used for determining SCR.
- Social Impact - Importance of SCR for the economy cannot be undermined given its impact on access and cost of international funds. As per media reports, GoI is specifically studying qualitative factors impacting India's credit rating. Additionally, separate unit has been formed under the Niti Aayog to see India's ranking on various qualitative factors. Hence this research can be useful input to the Indian thinktanks looking at prospects of qualitative rankings and their impact on India. If the GoI decides to focus more attentively on socio political reforms rather than only macroeconomic factors, then this can indirectly have a social impact not only in India but also in similar developing countries.

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LIST OF PUBLICATIONS

Journal Papers

1. Abhinav Goel and Archana Singh, “Impact of Economic and Socio-Political Risk Factors on Sovereign Credit Ratings” *Information, Processing and Management*, Elsevier. **(SSCI, ABDC indexed – ‘B’, Impact Factor – 7.4)**
2. Abhinav Goel and Archana Singh, “Bank Ownership and Asset Quality in Indian Banking: Is there a Link?” *International Journal of Economics and Accounting, Inderscience*. **(ABDC indexed – ‘C’)**
3. Abhinav Goel and Archana Singh, “Stressed Asset Resolution Framework in India: Has a pro-creditor stance made a difference?” *International Journal of Business Information Systems*, Inderscience. **(ABDC indexed – ‘C’)**
4. Abhinav Goel and Archana Singh, “Are Sovereign Credit Ratings Impacted by Institutional Quality?” *International Journal of Economics and Accounting*, Inderscience. **(ABDC indexed – ‘C’)**

Conference Papers

1. Abhinav Goel and Archana Singh, “Linkages of Rule of Law and Sovereign Credit Ratings – a Data Driven Approach,” *International Conference on Data Analytics and Computing (ICDAC) 2022*, Wenzhou Kean University, China, May 2022 (Springer, Scopus Indexed)
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