PORTFOLIO EVALUATION: INSIGHTS FOR EFFECTIVE DECISION-MAKING AT SREI EQUIPMENT FINANCE LTD

SUMMER INTERNSHIP PROJECT

Submitted to
Xavier Business School,
St. Xavier's University, Kolkata.

As Partial Fulfilment of the Requirements
for the MBA Degree

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Under the Supervision of
Prof Dr. Shuvendu Chakraborty

Submitted by
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CIN NO. 23-001-05-01-0043
MBA 2023-2025

DECLARATION

I, Atishya Ghosh, hereby declare that the internship report titled **“Portfolio Evaluation: Insights for Effective Decision Making”** at **Srei Equipment Finance Ltd** submitted by me, for the completion of my summer internship at Srei Equipment Finance Limited, is genuine and original work carried out by me under the guidance and supervision of industry guides Mr. Sandeep Kumar Ghosh (Chief Distribution Officer, Srei Equipment Finance Ltd) & Mr. Arnab Sett (Manager, Srei Equipment Finance Ltd) and faculty guide Dr. Shuvendu Chakraborty (Associate Professor, Xavier Business School).

I further declare that the content presented in this report contains my personal view points based on observations and research conducted during the internship period. All external sources of information used have been duly acknowledged and referenced.

I confirm that this internship report has not been submitted earlier for any academic or professional purpose. It has been solely prepared for the fulfilment of the requirements by the Xavier Business School for the summer internship program at Srei Equipment Finance Limited. I accept complete responsibility for the authenticity, accuracy, and integrity of the information included in this report. I recognize that any form of plagiarism or misrepresentation is a serious violation that may lead to disciplinary action.

Atishya Ghosh

INTERNSHIP COMPLETION CERTIFICATE

SREI

TRAINING COMPLETION CERTIFICATE

July 31, 2024

To Whomsoever It May Concern

This is to certify that **Ms.Atishya Ghosh** has successfully completed her internship with **Srei Equipment Finance Ltd** from **27th May, 2024 till 31st July, 2024** under the guidance of **Mr.Sandeep Kumar Ghosh** in **Sales & Marketing** department, **Head Office – Salt Lake**.

During the period of internship with us her performance was good. We found her hard-working with an aptitude for learning and ability to grasp diverse concepts quickly.

We wish her all the best for her future endeavors.

For **Srei Equipment Finance Limited,**

Swati

Swati Ghosh
Chief Manager – Human Resources

APPROVAL OF FACULTY GUIDE

This is to certify that Atishya Ghosh, roll no 43, a second-year student of Xavier Business School has successfully completed the project titled "PORTFOLIO EVALUATION: INSIGHTS FOR EFFECTIVE DECISION-MAKING" as partial fulfillment of the requirements for MBA, under my guidance. The student consulted with me regularly throughout the project, and I am pleased with their work and the manner in which they have applied my guidance. I also certify that the report presented is the original work of my student.

Dr. Shuvendu Chakraborty
Associate Professor
Xavier Business School
St. Xavier's University, Kolkata

Signature:

ACKNOWLEDGEMENT

I want to express my heartfelt gratitude to Srei Equipment Finance Limited and everyone involved in making my summer internship a success. I am especially thankful to **Mr. Sandeep Kumar Ghosh**, my mentor, for his invaluable guidance, support, and encouragement throughout my time there. I also extend my appreciation to **Mr. Arnab Sett**, my project guide, who dedicated his time to help me develop my project and articulate my findings. The warm welcome I received from the company allowed me to actively engage in a real-world project, giving me valuable hands-on experience and insights into the financing industry. Additionally, I want to thank my colleagues, whose camaraderie and willingness to share knowledge made my experience at Srei Equipment Finance Limited enjoyable and enriching.

I would like to express my sincere thanks to **Prof Dr. Shuvendu Chakraborty,** for guiding me in identifying a suitable project to meet requirements in addition to helping me with the analysis and results. His expertise, patience, and constructive feedback have been instrumental in shaping this project contributing to my overall learning experience.

I would also like to express my appreciation to my educational institution and faculty for giving me the opportunity to undertake this internship and for creating an environment that promotes learning and growth. Additionally, I want to thank my friends and family for their constant support, motivation, and understanding during this journey. Their encouragement helped me stay focused and determined as I navigated the challenges I encountered.

In conclusion, this internship has been a rewarding experience, and I am deeply thankful for the support and mentorship I received from everyone involved. The knowledge and skills I acquired during this time will undoubtedly have a lasting effect on my personal and professional growth.

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ABOUT SREI EQUIPMENT FINANCE LIMITED

SREI started operations in 1989 and identified infrastructure sector for its core business strategy[1]. In 1992 the initial public offering was made and prior to December 14, 2023 was listed on all major stock exchanges like BSE, NSE and CSE[1, 2]. SREI Infrastructure Finance Ltd (SIFL) is a premier non-banking financial institution (NBFI) in India. The company finances infrastructure equipment, infrastructure projects, infrastructure development and provides advisory services[3]. SREI Equipment Finance limited (SEFL) is a leading non-banking financing company in the organized equipment financing sector in India with a principal focus on financing infrastructure equipment. Their financial products and services include loans, leases, rentals and fee-based services[4]. SEFL is registered with the RBI as a systemically important non-deposit taking asset finance company[4]. SEFL operates across several business verticals encompassing Infrastructure Equipment Financing, Technology and Solutions Financing, Healthcare Equipment Financing, Agriculture and Farming Equipment Financing, Construction and Mining Equipment and Used Equipment Financing[4]. In 2008, a joint venture with BNP Paribas resulted in a 50-50 partnership forming SREI BNP Paribas[1]. In 2016, SEFL becomes 100 % subsidiary of SIFL[1].

SEFL’s unique business model provides equipment financing services covering ‘Equipment Life Cycle’ starting from procurement of equipment, their deployment, their maintenance and the shift to second life financing and exit stages[5]. It is the chief financier in the Construction, Mining and allied Equipment (CME) sector in India with customer base of more than 100,000 till date[6]. It was the market leader with dominant Market Share till FY 19[7]. Prior to October 2021, SREI was a Kanoria foundation entity[8]. The Reserve Bank of India (RBI) vide Press Release dated October 04, 2021, in exercise of the powers conferred under RBI Act superseded the Board of Directors of SREI owing to governance concerns and defaults by the Company in meeting payment obligations[9]. RBI appointed Mr. Rajneesh Sharma, Ex- Chief General Manager, Bank of Baroda as the Administrator of the Company in addition to a three-member advisory committee to assist Mr. Sharma[1]. SIFL and SEFL were admitted to Corporate Insolvency Resolution Process (CIRP) under Insolvency and Bankruptcy Code (IBC), 2016, vide National Company Law Tribunal (NCLT), Kolkata Bench Order dated October 8, 2021[1]. As per the IBC process, a Committee of Creditors (CoC) was formed for approving a Resolution Plan submitted by Resolution Applicants[10]. CoC approved the Resolution Plan submitted by National Asset Reconstruction Company Limited (NARCL)[1]. NCLT via its order dated 11th August, 2023 approved the Resolution Plan submitted by NARCL[1]. SREI current ownership includes NARCL and India Debt Resolution Company Limited (IDRCL). An Implementation and Monitoring Committee (IMC) has been set up to supervise the implementation of the Approved Resolution Plan and oversee the management of the affairs of the companies as per the terms of the Approved Resolution Plan.

NARCL took over the two companies on December 8, 2023[11]. Loans to SEFL & SREI Infrastructure Finance Ltd (SIFL), aggregating to about Rs. 33000 Crores was classified as NPA. NARCL has distributed ₹2,580 crore to creditors. The cash was distributed as part of the ₹3,180 crore upfront payment promised in the resolution plan[12]. In the future, NARCL will move for documentation, issuance of debentures and equity stake to lenders as promised in its resolution plan[13]. NARCL plans to retain only SIFL and SEFL will be wound up after recovering outstanding debts and pending court cases are settled[14]. According to the resolution plan, NARCL will cease all lending activities in SEFL. Most of the assets remain with SEFL due to previous restructuring[14]. Fresh lending activities will be conducted under SIFL[14].

EXECUTIVE SUMMARY

During my internship period at Srei equipment finance limited, I was asked to analyze the equipment portfolio of the company. An equipment portfolio analysis is vital for an equipment financing company such as Srei Equipment Finance Limited to ensure optimized financial performance, risk management, and strategic planning. This analysis provides a comprehensive evaluation of the current portfolio by equipment type, identifies opportunities for improvement, and helps align the company's operations with market demands and financial goals.

As part of my internship, I analysed new and used equipment portfolios using metrics Credit Exposure (outstanding debt) and Default Exposure (outstanding debt past 60 days overdue) as the primary measures of evaluation. The analysis encompasses a comprehensive business comparison, region-wise analysis, customer segment-wise analysis, asset type analysis and CIBIL Score analysis. A business comparison highlights the benefits of investing in new technology versus the utility of extending the life of existing assets. Regional analysis uncovers geographic trends and disparities in equipment investments. Some regions might exhibit high business but low default portfolio making it a desirable region for financing. Other regions might bring low business and also have high default portfolios, deeming them undesirable for financing. Understanding these regional dynamics with in depth analysis by equipment type (new vs used) aids in in tailoring financial strategies and resource allocation. Different customer segments exhibit varied exposure trends for new versus used equipment. We aimed to identify segments that have greater default exposure in order to provide information to help make financing decisions based on customer segment. Analysis of different asset types (e.g., Excavator, Backhoe Loader, Crane) reveals distinct patterns in new and used equipment exposure, debt levels, and default exposure. This differentiation aids in understanding market demand, debt management, and lifecycle management for various asset categories. CIBIL Score analysis can reveal a credit score cutoff below which financing is risky.

Conducting a thorough equipment portfolio analysis is essential for an equipment financing company to run a profitable, and competitive operation. By systematically evaluating the performance, risks, and alignment of the portfolio, the company can make strategic decisions that promote strategic growth, improve financial health, and mitigate potential risks. Frequent analysis and adjustment of the portfolio warrants sustained success and resilience in a dynamic market environment. Unfortunately, due to RBI undertakings under process, I am unable to present this research due to the confidential and private nature of the data analysed.

Thus, this study analyses the credit exposure data of two world bank organisations (open-source data from Kaggle similar to actual data analysed at Srei) - The International Bank for Reconstruction and Development (IBRD) and the International Development Association (IDA), which provides funding, policy guidance, and technical support to governments of developing countries[15]. IDA helps the world's poorest countries, while IBRD assists middle-income and creditworthy poorer countries[15]. The data tracks exposure amounts across different categories and counterparty ratings over specific time periods for the two organizations.

The data contains 5 columns – Organization, Period End Date, Category, Counterparty Rating and Amount in millions of US dollars. The Organization column contains IBRD or IDA as values indicating the organization involved in the financial transaction. The data contains a period column which indicates the end date of each financial period representing when the data was recorded. The Category column shows the financial asset being tracked. Counterparty rating is a scoring system used to predict the probability that a loan applicant, existing borrower, or in other words the counterparty will default or become delinquent. The rating follows an alphabetical scale where AAA rating indicates highest credibility ranging towards C ratings indicating progressively lower creditworthiness[16]. Amount column is the value of the exposure in millions of US dollars.

The study aims to complete a time series analysis of aggregate total exposure by counterparty rating and category to analyze exposure trends for these two features over different periods. We also aim to identify the association between Category and Counterparty rating and conduct an organization risk appetite assessment. The analysis results in **Comprehensive Risk Profiling**: From the above analysis, you get a wholistic picture of both the trends in exposure and the relationships between the different features, alongside an understanding of how two major organizations compare in their risk profiles. It also provides a path for **Actionable Insights for Portfolio Management**: The results help in identifying areas where risk is concentrated, either by time period, category, rating, or organization, allowing for better risk mitigation strategies.

INTRODUCTION

BACKGROUND

The Non-Banking Financial Companies (NBFC) sector plays a pivotal role in the global economy by providing essential financial services that support both personal and business financial needs. Portfolio analysis within this sector is crucial for managing risks, optimizing returns, and ensuring the financial stability and growth of institutions.

Key Concepts in Portfolio Analysis

There are a few terms relevant to portfolio analysis which are explained in detail below.

Overdue Payment (OD): An overdue payment is the amount not settled by the due date specified for a transaction[17].

Opening Overdue (OD): The balance of overdue debt at the beginning of a financial period. It is the amount that was past due and unpaid from the previous period. The Opening OD is the closing balance of overdue debt from the previous period.

Closing Overdue (OD): The balance of overdue debt at the end of a financial period. It shows the amount of debt that remains past due and unpaid at the close of the period. The Closing OD is established by taking the Opening OD and adjusting it for any new overdue amounts that emerged and any repayments made during the period.

Overdue (OD) Collected: The total amount of overdue debt that has been successfully collected during a specific financial period. This metric indicates the efficacy of the institution's efforts in recuperating overdue payments. Overdue Collected is the sum of all overdue payments received within the period.

Overdue (OD) Due: The total amount of debt that is past due and remains unpaid at a specific point in time. This metric is a measure of all the outstanding overdue balances that need to be collected. Overdue Due is the sum of all unpaid overdue amounts as of a particular date.

OD Since Days: It is the number of days an account or payment has been overdue. It measures the duration for which an outstanding debt has been unpaid past its due date. This metric is important for understanding the aging of overdue debts and for evaluating the severity of delinquency.

Days Past Due (DPD) Buckets: These are categories used to group overdue accounts based on the number of days they have been past due. These buckets aid in segmenting and analyzing overdue accounts to manage collection efforts and credit risk.

Future Principal Outstanding: Future Principal Outstanding denotes the amount of the principal portion of a loan or credit that remains unpaid. It represents the total amount that the borrower is still obligated to repay to the lender, excluding any interest or fees that may amass over time.

Repossession Overdue (OD): The total overdue debt that has led to the repossession of the collateral asset. It includes all overdue amounts that were not paid by the borrower, instigating the lender to repossess the asset.

Repossession Principal Outstanding: The total principal amount of the loan that remains unpaid when the asset is repossessed. It excludes any interest or fees amassed after the initiation of the repossession process.

Repossession Book Value: The Repossession Book Value is calculated by summing the Repossession Overdue and the Repossession Principal Outstanding. This combined value represents the total financial obligation that the repossessed asset is meant to cover.

Credit Exposure: Exposure is calculated by summing the Repossession Book Value, Closing Overdue, and Future Principal Outstanding. This combined value signifies the total financial risk or obligation that the lender faces with respect to the borrower. It is a measurement of the maximum potential loss to the lender if the borrower defaults on payment[24].

Default Exposure: Default Exposure is the amount of outstanding debt that is past due and is unpaid within a specified period, typically beyond 60 days.

Collectable Percentage: Collectable Percentage refers to the proportion of outstanding debt that a financial company expects to positively collect from borrowers within a specified period.

Portfolio analysis using Exposure and Default Exposure is essential for NBFCs like Srei, financing construction equipment. By segmenting the portfolio by geographical regions, customer segments, and asset types, NBFCs can gain valuable insights into the risk profile of their portfolio, enabling them to make knowledgeable strategic decisions, manage risks effectually, and ensure long-term financial stability. This comprehensive approach to portfolio analysis helps NBFCs in sustaining a balanced and profitable loan portfolio while supporting the growth and development of the construction sector in the case of Srei. Similarly, portfolio analysis of the two world bank organizations will help develop loan diversification and risk mitigation strategies for the two organizations.

OBJECTIVES OF THE STUDY

The key objectives are:

1. To evaluate the total exposure through segmentation based on criteria such as Fiscal Year, Category, Counterparty Rating and Organization.
2. To identify the association between asset categories and counterparty ratings with statistical analysis.
3. To assess organization risk appetite using statistical analysis.

SIGNIFICANCE OF THE STUDY

The benefits of this project include:

1) **Enhanced Decision-Making**: Data-driven insights from the analysis guide informed decisions regarding portfolio adjustments, investments, and divestments.

2) **Risk Mitigation**: Identifying and managing risks proactively reduces the likelihood of unexpected financial losses and operational disruptions.

3) **Strategic Growth:** Aligning the loan disbursement with profitable counterparty ratings (least exposure) aligns the organization for strategic growth.

4) **Operational Efficiency**: Efficiently managing financing of the different assets warrants operational efficiency and effectiveness.

LITERATURE REVIEW

There are research gaps in credit risk management in current academic and financial literature. These are four areas where more research can be conducted to gather actionable insights for portfolio and risk management.

1) While there is ample literature on credit risk, few studies have delved into how specific asset categories (e.g., Sovereigns, Corporates, Agencies) are impacted by credit exposure trends. A lot of these papers analyze default probabilities and not exposure[18]. Examples of existing literature on credit risk management include Modeling credit risk for SMEs: Evidence from the US market[18].

2) There is a gap in statistical testing to determine counterparty ratings and asset category associations. Consider the paper Determinants and impact of sovereign credit ratings[19]. This paper discusses sovereign credit ratings in detail but research such as this study lacks a statistical analysis of associations between ratings and asset category (Sovereign for example).

3) There is a lack of Comparative Studies Between Organizations on Credit Exposure measure. Coherent measures of risk as an academic paper is about different risk measures and The effect of credit risk management and bank-specific factors on the financial performance of the South Asian commercial banks encompasses all organizations as a whole in their analysis[20,21]. Other papers are organization specific. It is rare to find papers where organizations are compared or analysed on credit exposure management.

4) An underexplored area includes Time Series Analysis of Credit Exposure by Rating. Modelling Term Structure of Defaultable Bonds is a paper focusing on forecasting methods considering time in the analysis[22]. But specifically, a time series understanding of exposure trends for counterparty rating or asset category has not been conducted and can provide insights for loan disbursement policies.

5) Rethinking risk management is a paper that discusses risk management practices but does not delve deeply into operational efficiency in managing credit exposure across asset categories and ratings[23]. This study addresses the operational efficiency facet, predominantly in balancing exposure portfolios. The table below summarizes the research pertaining to Credit Exposure in detail.

Year	Author	Objectives	Methodology	Findings
2007	Altman, E. I., & Sabato, G.	Predict credit worthiness of an SME (small medium enterprise) using relevant financial measures.	• >2000 SME data • Logistic regression	Findings indicate managing credit risk for SME requires different models and procedures than larger corporations. Model uses EBITDA, Equity Book Value, Retained Earnings, Interest, Default Rates.
1996	Cantor, R., & Packer, F.	Analyze the determinants and impact of the sovereign credit ratings	• Correlation between determinant variable and rating • Multiple regression • Tests of statistical significance	Six factors appear to play an important role in determining a country's rating: per capita income, GDP growth, inflation, external debt, level of economic development, and default history. Rating announcements have a highly substantial impact on certain sovereign grades but a statistically insignificant effect on other types of sovereigns.
1999	Artzner, P., Delbaen, F., Eber, J. M., & Heath, D.	Study both market risks and nonmarket risks, without complete markets assumption, and discuss methods of measurement of these risks.	• SPAN (Standard Portfolio Analysis of Risk) • Quantile-based Value at Risk (VaR)	Provided Definition of Coherent Risk Measure. Authors introduced a new framework for evaluating risk.

2022	Siddique, A., Khan, M.A. and Khan, Z.	The study aims to capture the effect of credit risk management and bank-specific factors on South Asian commercial banks' financial performance (FP).	• 19 commercial banks data • Generalized method of moment (GMM)	The results indicated that non-performing loan (NPLs), cost-efficiency ratio (CER) and liquidity ratio (LR) have significantly negatively related to FP (Return on Asset and Return on Equity), while capital adequacy ratio (CAR) and average lending rate (ALR) have significantly positively related to the FP of the Asian commercial banks.
1999	Duffie, D., & Singleton, K. J.	This paper aims to identify a new approach to modeling term structures of bonds and other contingent claims that are subject to default risk.	• Reduced form approach • Empirical Estimation	The model shows how credit spreads (the difference between yields on defaultable and default-free bonds) are driven by the default intensity process.
1996	Stulz, R. M.	The main purpose of the paper is to critically examine traditional risk management approaches.	• Case Studies and Practical Examples of real companies such as GE and Merck	Traditional Risk Management is Incomplete. Firms should employ strategic risk management by focusing on risks that are critical to their business and that can threaten their long-term survival, such as financial distress risk. By managing these critical risks effectively, firms can increase their expected cash flows and enhance firm value.

Table 1: Literature Review of Research pertaining to Credit Exposure.

RESEARCH METHODOLOGY

Data Preparation and Analytics Steps for the summer internship project at Srei: Equipment Portfolio Analysis.

Creating the Master File for Analysis We started the research project by creating a master file to be used for the purpose of analysis. We first merged the year end closing debtors statements and the repossession stock accounting statements for the years 2016-2020 to create two files. We then merged the two files using “left merge” in python using the column ID in both files, a field which was created by concatenating contract number and reporting year. We merged several other files with this merged file using the same method to add several columns such as Collection Team, Region, Zone, CIBIL score and Asset Type. In addition to master file, we had two separate files- one containing business data and the other containing repossession information.

Feature Engineering with Python We created a field called Loan/Lease using the product column in the master file to indicate whether a product is loan, lease, bank guarantee or owned assets. For this, we converted the product value to a “string” and checked whether the string contained certain key words to assign a Loan/Lease category. We created a function to return whether a contract is co-lending or not using the product column. We assigned the returned values to a Remarks column. We created the field AIRR bucket using the AIRR column and the “pandas” library particularly the “pd.cut” function in it to bin the numerical AIRR data into discrete intervals. We created the financial year column which contains financial year of the contract based on commencement date using the “fiscalyear” library. We created a field DPD (Days Past Due) bucket using the Repo Status column which indicates whether a contract asset is repossessed and OD (Outstanding Due) Since Days column which provides the number of days that the payment was delayed. The contracts which were marked Repossessed in the Repo Status column were classified as Repossessed in the DPD bucket field and the remaining contracts were classified into categorical bins based on OD Since Days using the “pd.cut” function. We converted Business Category value to “string” and checked if it contained certain key words to assign equipment type values New, Used or Collateral. Repo Book Value column was created by summing the Repo OD (Repossession Outstanding) and Repo POS (Reposition Principal Outstanding) columns as per the definition in background. Similarly, Exposure column was created by adding the OD closing, Future Principal Outstanding and Repo Book

Value columns. The Exposure value represents any outstanding balance a contract owes the company. We created CIBIL bucket field which bins CIBIL scores into predetermined categories. We finally created a field called Consider with categories Yes or No. Certain Collection teams, Bank Guarantees, and Collateral equipment type for example were marked No in the Consider field amongst others. The purpose of this is to filter out contracts marked No from analysis. We exported the file as an excel file using "pyexcelerate" library which is memory efficient library for large files.

Data Analysis & Visualization We did a portfolio distribution analysis region wise year on year using the region, reporting year, equipment type and exposure values. We used pivot table in Excel for the analysis where Consider is the filter (only Yes selected for analysis), Equipment Type and Year as columns, Region as rows and summation of Exposure as values. Similar analysis was performed by switching the row values to DPD bucket, Customer Segment, Loan/Lease, CIBIL bucket and Asset Type. We calculated collectable % (outstanding collection %) region wise YoY by dividing the OD collected with the sum of Opening OD and OD Due. We calculated the default exposure (default contracts are those with OD Since Days> 60 and Repossessed contracts) for each region for new and used equipment as a % of the total portfolio of that region for disbursement years 2016-2019 in order to obtain first year and second year default. We calculated the default rate asset type wise for new and used equipment using a similar process. We represented our portfolio data as heat maps, box plots, bar plots, line plots and overlaying the portfolio values for each region on Map of India. These plots were created using excel, "matplotlib", "seaborn" and "geopandas" libraries in python and ggplot2 library in R.

Data Analysis Steps for World Bank Data For the open-source World Bank Data, the first two steps can be skipped as the data need not be merged with another data file and the data will be analyzed in its raw form. Credit Exposure is also already calculated. We will follow the same steps for data analysis and visualization. This study analyzed a portfolio distribution analysis year on year using the period, organization, category, counterparty rating and exposure values with pivot tables. A chi-square test was run to check for association between category and counterparty rating in R. Cross tabulation of these two variables was also performed in R for further analysis. We performed t-tests to analyze if both world bank organizations have similar loan portfolios using the exposure and organization variables. We represented our portfolio data as heat maps, bar charts, radar plots and box plots created in R using ggplot2.

DATA ANALYSIS AND FINDINGS

Aim 1. <u>To evaluate the total exposure through segmentation based on criteria such as Fiscal Year, Category, Counterparty Rating and Organization.</u>

(✓) Aim 1.1. <u>Determine Portfolio Distribution and trends YoY.</u>

Rationale & Approach: Year-over-Year (YoY) portfolio analysis using credit exposure as a measure is performed to evaluate how the portfolio's risk and opportunities changes as a function time. Credit exposure represents the potential risk a lender is taking by providing credit to a borrower. By analyzing how exposure changes YoY, one can assess whether the risk level of the portfolio is growing or shrinking. We utilized a box plot to visualize 5- point summary – min, first quartile, median, third quartile and max Exposure values for each fiscal year in figure 1. This analysis can help evaluate policies regarding allocation of resources, adjusting lending criteria or evaluating capital adequacy to manage loan portfolio.

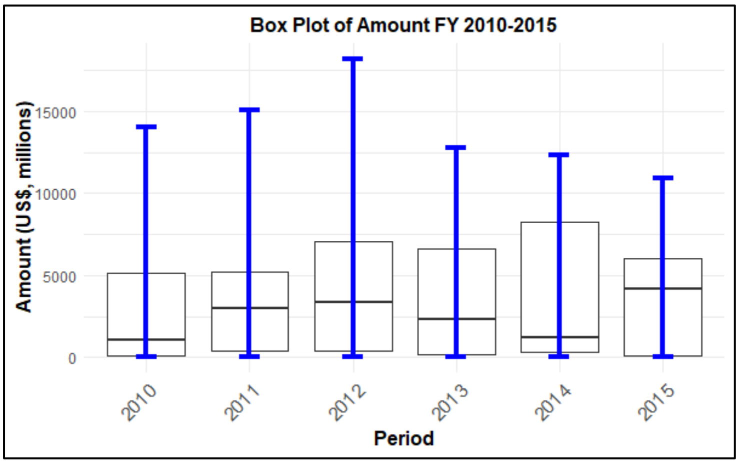

Figure 1. Box Plot of Amount FY 2010-2015.

Observations: The median exposure amount increased between the years 2010-2012 then showed a decreasing trend for the next two years but drastically increased in 2015. Maximum Exposure was observed in 2012.

Interpretation: Median Exposure is the middle point of the dataset, meaning half of the exposures are above this value and half are below. An increasing median informs us that more of the portfolio's exposures are moving towards higher values over time. After the financial crisis of 2008-2009, many countries reached out to World Bank for financial assistance for recovery. The World Bank likely lent more to support infrastructure development, poverty alleviation, and other projects with lax credit policies resulting in an increasing exposure trend. By 2013-2014, some countries may have begun stabilizing, reducing the need for loans and financial aid and might have paid their debts thereby decreasing the total exposure. The sharp increase in exposure in 2015 might have been caused by renewed demand for credit due to the collapse of oil price from June 2014 to Jan 2015.

(✓) Aim 1.2. <u>Determine Portfolio Distribution and trends for World Bank Organizations IBRD and IDA.</u>

Rationale & Approach: Performing a portfolio analysis using credit exposure as a measure for World Bank organizations like the International Development Association (IDA) and the International Bank for Reconstruction and Development (IBRD) is crucial for assessing the performance, risk, and impact of their lending activities. We compare total Exposure YoY for both organizations using a bar chart in figure 2 and how the exposure changes compared to the previous year that is quantify and visualize the growth or decrease in exposure with a line chart in figure 3. Raw data in Appendix 1.1. The formula for Growth is as follows:

$$\text{Growth} = \frac{\textit{Exposure in Current Period} - \textit{Exposure in previous Period}}{\textit{Exposure in Previous Period}} \times 100$$

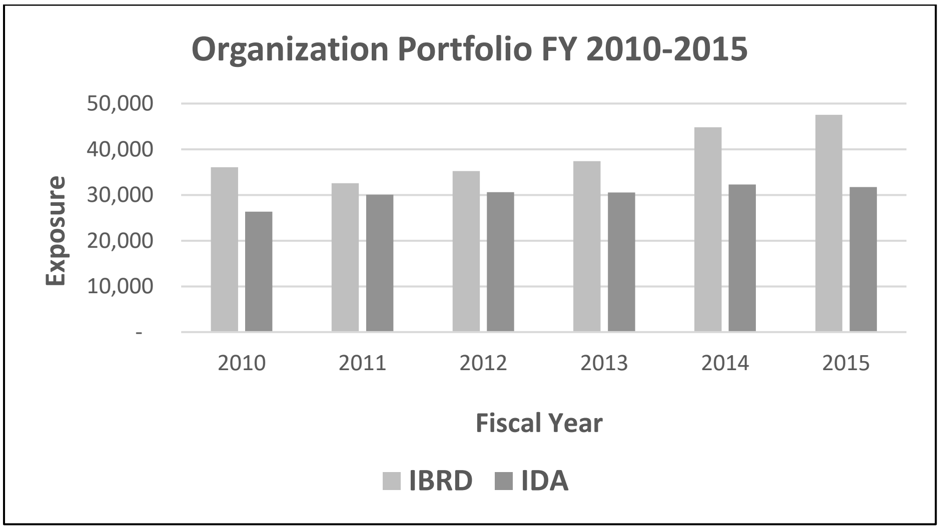

Figure 2: Bar Chart showing Total Exposure of Each Organization YoY.

Observations: IBRD consistently has a higher exposure than IDA every year.

Interpretation: IBRD primarily lends to more developed countries. Thus, it can provide larger loans without taking an excessive financial risk. IDA loans to poor countries and thus has a conservative approach in lending resulting in this exposure disparity.

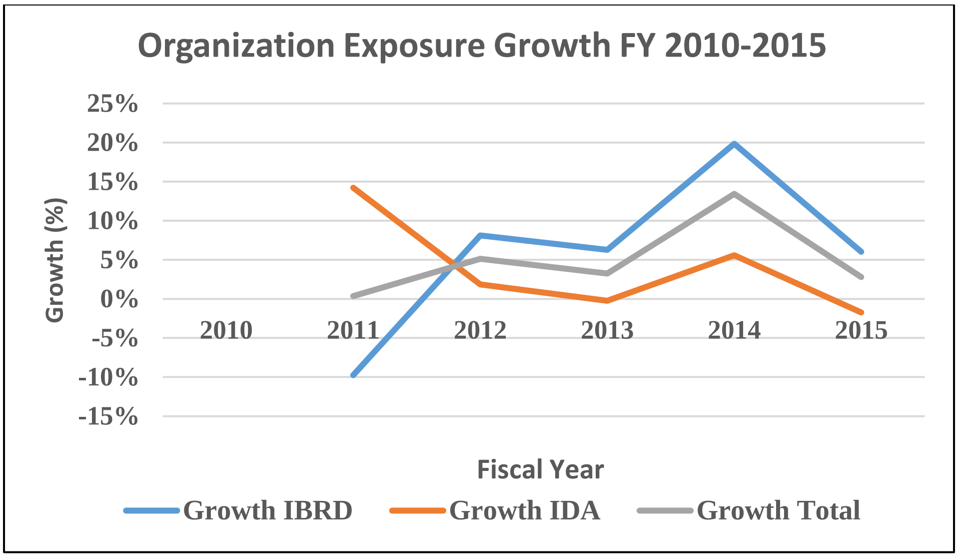

Figure 3: Line Chart showing Exposure Growth Fiscal Years (FY) 2010-2015.

Observation: IBRD exposure started at a high point in 2010, then declined significantly in 2011. IBRD exposure growth fluctuates through the years. IDA exposure started at a low point in 2010, then experienced a significant increase in 2011. IDA exposure shows a general decreasing trend except for a 5% rise in 2014.

Interpretation: The decline in IBRD lending activities in 2011 could be attributed to the global financial crisis of 2008, which led to a decrease in demand for loans from developed countries. Poorer countries were more affected by 2008 financial crisis. The increase in IDA lending in 2011 might indicate an alteration in the World Bank's focus towards providing assistance to the poorest countries. The stability/increase in IBRD lending in the following years suggests that developing countries began to recover from the financial crisis, leading to a renewed demand for loans with lax repayment policies due to confidence in the repayment abilities of the richer countries. IDA countries with small and fragile economies, may not have experienced the same level of growth during this period. Economic or political instability in some IDA countries limited their ability to take on significant levels of debt and as previously mentioned IDA has a conservative lending / structured financing approach with the poorer countries.

(✓) Aim 1.3. <u>Determine Portfolio Distribution and trends of World Bank based on Counterparty Rating.</u>

Rationale & Approach: Counterparty ratings reflect the creditworthiness of the borrowers, which directly impacts the level of risk the World Bank organizations are exposed to. By analyzing exposure distribution based on these ratings, the World Bank can better assess the overall risk profile of its lending portfolio. Very High exposure of low-rated institutions (e.g., countries facing political instability or economic downturns) might indicate a need for World Bank to adjust its lending practices. We visualize the distribution of Exposure for each rating with a box plot in figure 4. We use radar plot and heat map to visualize the portfolio distribution with the exposure measure YoY in figures 5 and 6. Raw Data available in Appendix 1.2.

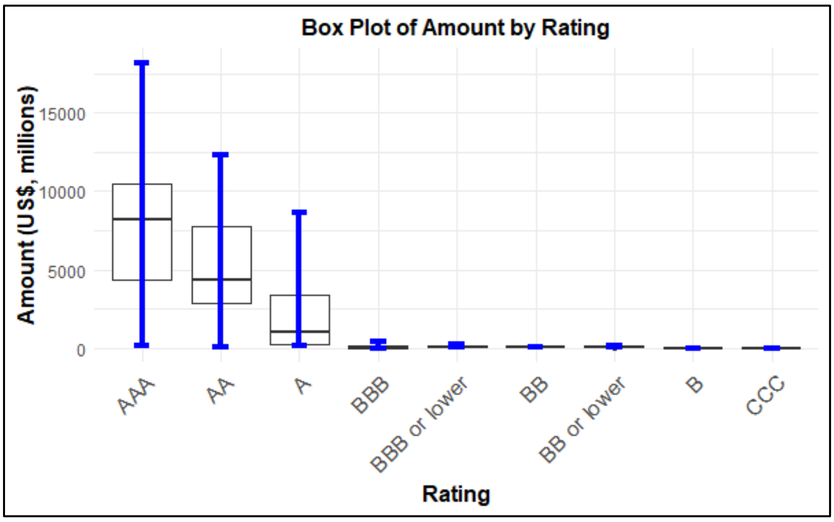

Figure 4: Box Plot of Exposure for each Rating.

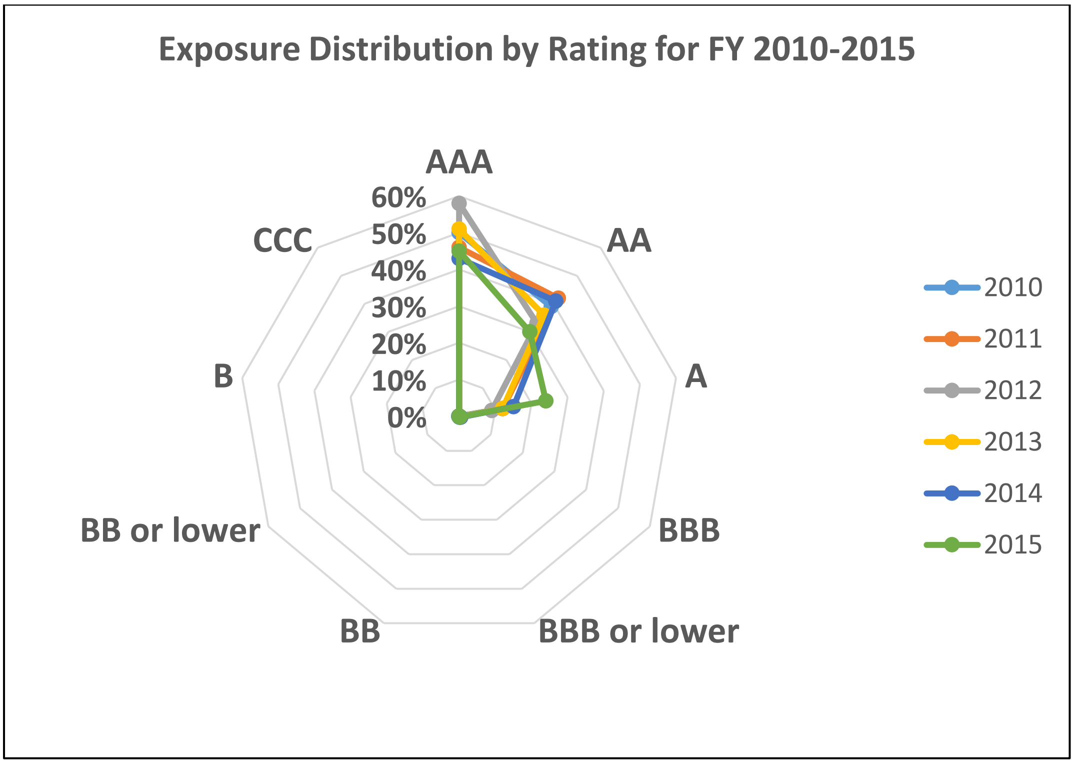

Figure 5: Star Chart of Exposure Distribution by Rating for FY 2010-2015.

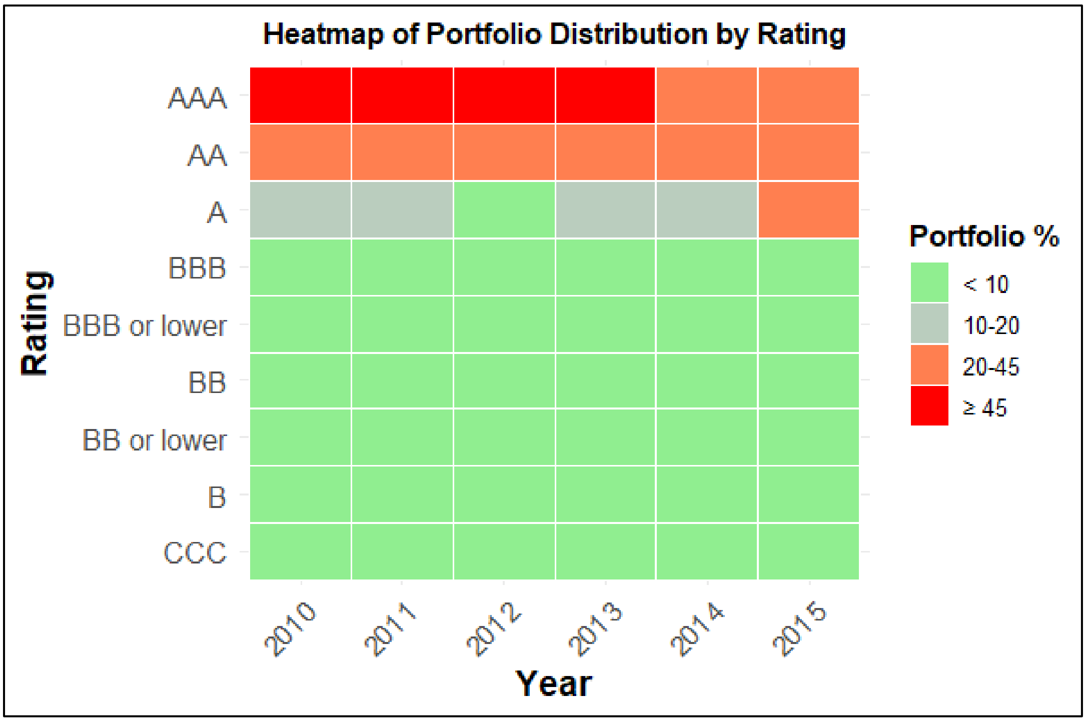

Figure 6: Heat Map of Portfolio (Exposure) Distribution by Rating for FY 2010-2015.

Observations: In figure 4, we observe that AAA rating has highest median exposure. We notice a general correlation between rating and exposure amount. In figure 5, we observe that AAA and AA categories have greater exposure % (Exposure of each rating as a proportion of whole) consistently every year while BBB and below categories have 0 Exposure every year. In figure 6, we get a better pictorial clarity on the exposure % for each rating for each fiscal year. A ratings have highest exposures (red boxes) while BBB and below categories have close to 0 exposure (green boxes).

Interpretation: AAA, AA, and A-rated institutions are considered low-risk. These ratings indicate that these countries or institutions are highly likely to meet their financial obligations and repay loans on time. The low default risk associated with these counterparties allows financial institutions like the World Bank to lend larger sums of money with greater confidence that they will recover the full amount, resulting in higher exposure. Astonishingly, Moderate rated institutions with BBB and BB ratings have the same exposure or portfolio has poorer ratings. Moderate-rated borrowers are perceived as too risky for large loans and simultaneously not needy enough to receive special concessional financing as poor countries. The data suggests low financial support for high-risk, low-income countries. While extremely high exposure for poorer ratings is undesirable, low exposure percent suggests lack of investment which increases inequality.

(✓) Aim 1.4. <u>Determine Portfolio Distribution and trends of World Bank based on Asset Category.</u>

Rationale & Approach: Analyzing credit exposure by asset category allows for a clearer understanding of the risk profiles associated with different types of borrowers. Categorizing credit exposure also helps the World Bank diversify its portfolio effectively. By understanding how much is allocated to each asset category, it can certify a balanced mix of investments. We use box plot to visualize exposure amount distribution for each category and a heat map for exposure % as a fraction of whole for each category YoY in figures 7 and 8. Raw Data in Appendix 1.3.

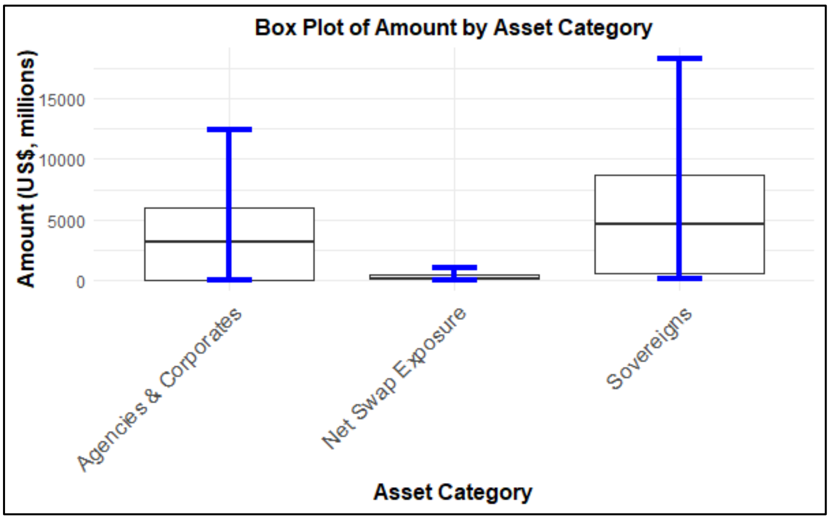

Figure 7: Box Plot of Exposure for each Asset Category.

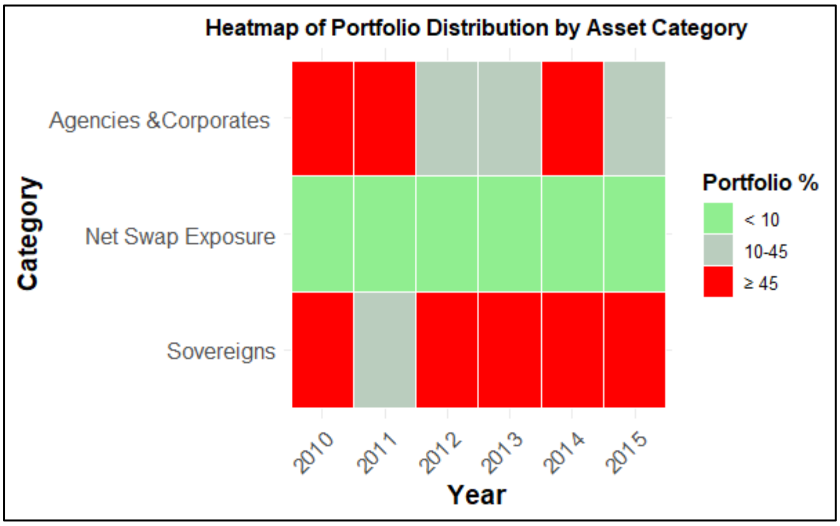

Figure 8: Heat Map of Portfolio (Exposure) Distribution by Category for FY 2010-2015.

Observations: From Figures 7, we observe Sovereigns have highest exposure, followed by Agencies & Corporates and Net Swaps have least Exposure. This trend is observed YoY in the heatmap in figure 8.

Interpretation: Sovereigns refer to the national governments that borrow from the World Bank. Net swap exposure refers to the financial exposure the World Bank faces due to the use of derivatives like interest rate swaps or currency swaps. These swaps help the World Bank manage interest rate risks and currency risks on its loans or bonds. Agencies & Corporates include state-owned institutions, large infrastructure projects or private sector companies that are involved in World Bank financed projects. Sovereigns are a lower risk because they are backed by national governments. They are perceived to have predictable repayment capabilities due to their taxing power and control over national budgets, which explains why loans are given to them freely. Corporates require financing for projects which can be substantial but generally not at the scale of sovereign borrowing. Corporates carry higher risks associated with business cycles & market dynamics. This may limit the amount of financing they receive compared to Sovereigns. Net swap exposures have much lower exposure because they do not represent direct financing requirements for development projects. Instead, they are financial instruments that help manage existing other risks associated with lending. The volume of net swaps is generally much lower than direct loans to sovereigns, or corporates. As a result, the Net swap exposure is comparatively minimal.

Aim 2. <u>To analyze the association between asset categories and counterparty ratings.</u>

(✓) Aim 2.1. <u>Determine frequency distribution of each category for each rating.</u>

Rationale & Approach: Using cross tabulation (column summation) we can tabulate frequency of each category for each rating. Understanding the frequency distribution helps identify which asset categories are concentrated in specific ratings, enabling better risk assessment and management and creating a diversified portfolio.

	Counterparty Rating								
Category	**AAA**	**AA**	**A**	**BBB**	**BBB or lower**	**BB**	**BB or lower**	**B**	**CCC**
Agencies & Corporates	48 %	40 %	44 %	60 %	50 %	100 %	88 %	100 %	100 %
Net Swap Exposure	4 %	20 %	22 %	10 %	0 %	0 %	12 %	0 %	0%
Sovereigns	48 %	40 %	33 %	30 %	50 %	0 %	0 %	0 %	0%

Table 2: Frequency Distribution of Category for each Counterparty Rating.

Observations: Sovereigns have higher ratings. Corporates and Agencies that have received funding have ratings that range across the entire scale. Net swap typically has higher ratings except for a small loan in the BB or lower category.

Interpretation: Sovereigns receiving loans from World Bank, generally have higher ratings because they represent entire countries that can generate revenue through taxation and control their economies. The World Bank's altruistic mission involves aiding development in countries with higher risk, which often involves lending to corporates with lower credit ratings. These borrowers may require concessional financing in spite of their weaker financial hold. The World Bank possibly has low exposure for lower ratings, as the purpose of swaps is to decrease risk rather than adopt additional risk.

(✓) Aim 2.2. <u>Association Analysis of Counterparty Rating and Asset Category.</u>

Rationale & Approach: Above we observed Sovereigns have higher ratings. The Chi-square test is a quantitative measure to check the association between asset categories and counterparty ratings. This is an objective way to confirm if the observed association is statistically significant or if it could have occurred by chance (Figure 9). This enables the World Bank to identify patterns such as whether Sovereigns consistently receive higher ratings compared to Corporates & Agencies.

Null Hypothesis: There exists no association between the variables Category and Counterparty Rating.

Alternate Hypothesis: There exists an association between the variables Category and Counterparty Rating.

```
        Pearson's Chi-squared test

data:  Category_Rating_Data
X-squared = 16.662, df = 16, p-value = 0.4078
```

Figure 9. Chi-Square Test Results for Category and Rating Data.

Observation: From figure 9 we observe,

- **Chi-square value (χ^2)** = 16.662
- **Degrees of freedom (df)** = 16
- **p-value** = 0.4078

Interpretation: df = (number of categories in variable 1-1) * (number of categories in variable 2-1) = (9-1) x (3-1) = 16. The Chi-square value signifies the difference between the observed frequencies in our data and the expected frequencies. If the chi-square calculated value is greater than the chi-square critical value determined using df and significance value (0.05 in our case), then we can reject the null hypothesis. Since it is less than the critical value 26.3, we cannot reject our null hypothesis. Additionally, since $p > 0.05$, we cannot reject the null hypothesis, indicating there is no statistically significant association between asset categories and counterparty ratings in this dataset.

Aim 3. Compare Organization Wise Risk Appetite.

(✓) Aim 3.1. Determine frequency distribution of each category for each rating for each organization.

Rationale & Approach: Analyzing the frequency distribution of each asset category for each rating within IDA and IBRD of the World Bank offers valuable insights into the credit risk profile and portfolio composition of both organizations. It helps compare the risk exposures across different asset classes for each organization and identify rating patterns characteristic of each organization. This aids in evaluating financial health, determining risk mitigation strategies, and allocating resources optimally. Additionally, it highlights differences in risk management approaches between IDA (focused on lower-income countries) and IBRD (lending to middle income nations), highlighting their individual tailored risk policies.

Organization = IBRD

	Counter Party Rating								
Category	**AAA**	**AA**	**A**	**BBB**	**BBB or lower**	**BB**	**BB or lower**	**B**	**CCC**
Agencies & Corporates	24 %	20 %	22 %	60 %	0 %	50 %	63 %	0 %	0 %
Net Swap Exposure	4 %	20 %	22 %	10 %	0 %	0 %	13 %	0 %	0 %
Sovereigns	24 %	20 %	19 %	30 %	0 %	0 %	0 %	0 %	0 %

Table 3: Frequency Distribution of Category for each Counterparty Rating for IBRD.

Organization = IDA

	Counter Party Rating								
Category	**AAA**	**AA**	**A**	**BBB**	**BBB or lower**	**BB**	**BB or lower**	**B**	**CCC**
Agencies & Corporates	24 %	20 %	22 %	0 %	50 %	50 %	25 %	100 %	100 %
Net Swap Exposure	0 %	20 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Sovereigns	24 %	20 %	15 %	0 %	50 %	0 %	0 %	0 %	0 %

Table 4: Frequency Distribution of Category for each Counterparty Rating for IDA.

Observations: We observe that Corporates and Sovereigns have equal portfolio for A ratings for both organizations. Sovereigns as already established why in aim 2 do not have portfolios for both organizations for lower ratings. Net Swap has higher portfolio in IBRD than IDA for higher ratings. IBRD has more corporate portfolio in moderate ratings. IBRD has no corporate portfolio in lower ratings B and CCC but IDA does.

Interpretation: IBRD primarily lends to middle-income and creditworthy lower-income countries. These countries generally have more stable economies. Thus, they have higher ratings and moderate credit ratings for the assets in IBRD's portfolio. IDA provides loans and grants to the world’s poorest and least creditworthy countries. They typically have higher risk due to their detrimental economic conditions. This explains why IDA might have some corporate portfolio holdings in lower ratings (B and CCC), as institutions in these countries face greater credit challenges such as poor credit history and are less likely to obtain higher ratings.

(✓) Aim 3.1. Perform two sample t-test to determine if there is a statistically segment difference in mean exposure between IBRD and IDA.

Rationale & Approach: Given that IBRD and IDA have different borrower characteristics—IBRD focuses on middle-income countries while IDA focuses on poor countries—comparing their exposure amounts can help assess if these differences in borrower traits lead to notable differences in how much financial exposure each institution takes on. The t-test evaluates whether any observed difference in means is due to random chance or is a reflection of a true underlying difference in financial exposure strategies. To run a two-sample t-test, we need to ensure the sample is drawn from a normally distributed population. Normality was checked using Shapiro-Wilk normality test, Lilliefors (Kolmogorov-Smirnov) normality test & Anderson-Darling normality tests in R to take the best out of 3 results. We also need to check whether the exposure variances in the two groups are statistically equal with levene test in R. Lastly, we perform the appropriate two sample t-test for equal or unequal variance if normally assumption is fulfilled.

Observation:

Normality test results for Exposure Amount Data for each Organization

Organization = IBRD

```
        Shapiro-Wilk normality test

data:  Amount[Organization == "IBRD"]
W = 0.82308, p-value = 2.318e-07
```

```
        Anderson-Darling normality test

data:  Amount[Organization == "IBRD"]
A = 4.715, p-value = 8.21e-12
```

```
        Lilliefors (Kolmogorov-Smirnov) normality test

data:  Amount[Organization == "IBRD"]
D = 0.26509, p-value = 2.21e-12
```

Organization = IDA

```
        Shapiro-Wilk normality test

data:  Amount[Organization == "IDA"]
W = 0.80857, p-value = 3.69e-06
```

```
        Anderson-Darling normality test

data:  Amount[Organization == "IDA"]
A = 2.9567, p-value = 1.492e-07
```

```
        Lilliefors (Kolmogorov-Smirnov) normality test

data:  Amount[Organization == "IDA"]
D = 0.22113, p-value = 7.932e-06
```

Figure 10. Normality tests for Exposure Amounts of IBRD and IDA.

In figure 10**,** we observe our sample is not drawn from a normally distributed population. Our null hypothesis for all three tests is that Sample comes from a normal distribution. Alternate hypothesis is Distribution is not normal. A low p-value for all the tests for both organizations suggests we should reject the null hypothesis. Thus, normality assumption does not hold.

Checking of Equality of Variance between the 2 organizations

```
Levene's Test for Homogeneity of Variance (center = median)
      Df F value Pr(>F)
group  1  0.0785 0.7798
```

Figure 11. Test Results for Homogeneity of Variance.

The test in figure 11 assumes for each organization, variance is equal as the null hypothesis. Since the p-value is 0.7798> 0.5, we cannot reject null hypothesis. Thus, we assume equal variance for both categories.

Two sample t-test to compare the 2 Organizations based on Credit Exposure

```
        Two Sample t-test

data:  Amount by Organization
t = -0.53738, df = 108, p-value = 0.5921
alternative hypothesis: true difference in means between group IBRD and group IDA is not equal to 0
95 percent confidence interval:
 -2058.658  1180.497
sample estimates:
mean in group IBRD  mean in group IDA 
          3594.631           4033.711 
```

Figure 12. Two sample t-test results for exposure differences between IBRD and IDA.

Interpretation: Since or normality assumption does not hold, ideally two-sample t-test cannot be conducted. But since our overall sample is large enough with comparable sample sizes for both organizations, relaxation can be given to this assumption. Two sample t-test with equal variance test assumes a null hypothesis that there is no difference between the means of the two populations being compared. Alternate hypothesis is there is a significant difference between IBRD Exposure and IDA Exposure. P-value>0.05 indicates null hypothesis holds and there is no true difference. This suggests the average amounts of financial budget (loans, credits, guarantees) for both organizations are similar, despite their different target countries. This could also happen if both organizations although serving different income groups, maintain comparable risk management practices or adjust their lending portfolios in ways such that overall exposure is balanced.

Note: All R codes for graphs and statistical analyses in aims 1-3 are available in Appendix 2.

CONCLUSIONS

KEY FINDINGS

The median exposure amount increased between the years 2010-2012 then showed a decreasing trend for the next two years but drastically increased in 2015. The variations in loan portfolio can be attributed to fluctuations in economic environments. IBRD consistently has a higher loan portfolio than IDA every year. IBRD exposure growth fluctuates through the years. IDA exposure shows a general decreasing trend. AAA and AA categories (higher counterparty ratings with low risk) have greater loan portfolio consistently every year while BBB and below categories have 0 Exposure every year. Sovereigns backed by national governments have highest loan portfolio, followed by Agencies & Corporates and Net Swaps have least portfolio. There exists no association between the variables Category and Counterparty Rating. There is no statistically significant difference between IBRD Exposure and IDA Exposure.

RECOMMENDATIONS

I believe IDA is doing a good job of managing its loan portfolio. Exposure has been stable YoY. It can improve its standing by reducing credit lines to extremely poor counterparty rated institutions with ratings such as CCC. IBRD has fluctuations in exposure which can be attributed to various economical factors and not specifically its management practices. For IBRD, I recommend maintaining a balance between corporate investments in A ratings and moderate ratings. Loans for moderate ratings can bring higher returns compared to loans for higher ratings because they are associated with more risk. In lending, there is typically a risk-return tradeoff: borrowers with moderate credit ratings (e.g., BBB or BB) are considered riskier than those with higher ratings (e.g., AAA or AA), so lenders can charge higher interest rates to compensate for the increased risk of default.

LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

Some limitations of the study include inconsistent data in some fields such as counterparty Rating. BB is a rating and so is BB or below. To be correct, the values should be BB and less than BB. Less than BB includes C categories but C categories are separately labelled. This inconsistency can arise if different employees have filled the database or if guidelines have changed through the years for rating assessment. We cannot account for this limitation as we do not have all the knowledge to correct for it. Additionally, the analysis period is only 2010-2015, it is difficult to assess and suggest recommendations to an organization for today's loan disbursement practices based on old historical data. Ideally this analysis should be repeated from 2000- 2024 to get an accurate picture of each organization's loan management practices.

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APPENDIX 1

Appendix 1.1

Organization wise Portfolio Distribution

US Million Dollars

Organization	2010	2011	2012	2013	2014	2015
IBRD	36,073	32,557	35,208	37,414	44,843	47,556
IDA	26,317	30,061	30,622	30,552	32,261	31,704
Total	**62,390**	**62,618**	**65,830**	**67,966**	**77,104**	**79,260**
Growth IBRD		**-10%**	**8%**	**6%**	**20%**	**6%**
Growth IDA		**14%**	**2%**	**0%**	**6%**	**-2%**
Growth Total		**0%**	**5%**	**3%**	**13%**	**3%**

%

Organization	2010	2011	2012	2013	2014	2015
IBRD	58%	52%	53%	55%	58%	60%
IDA	42%	48%	47%	45%	42%	40%

Appendix 1.2

Rating wise Portfolio Distribution

US Million Dollars

Rating	2010	2011	2012	2013	2014	2015
AAA	30,972	28,926	38,378	34,786	32,935	35,556
AA	24,055	26,437	21,552	24,275	31,891	24,005
A	7,343	7,226	5,807	8,488	11,544	19,282
BBB	4	4	4	296	410	233
BBB or lower				110	227	161
BB	12					
BB or lower		25	89	11	97	23
B	3					
CCC	1					
Total	**62,390**	**62,618**	**65,830**	**67,966**	**77,104**	**79,260**

%

	2010	2011	2012	2013	2014	2015
AAA	50%	46%	58%	51%	43%	45%
AA	39%	42%	33%	36%	41%	30%
A	12%	12%	9%	12%	15%	24%
BBB	0.00%	0.00%	0.00%	0.40%	0.50%	0.30%
BBB or lower	0.00%	0.00%	0.00%	0.20%	0.30%	0.20%
BB	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
BB or lower	0.00%	0.00%	0.10%	0.00%	0.10%	0.00%
B	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CCC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Appendix 1.3

Category Wise Portfolio Distribution

US Million Dollars

Category	2010	2011	2012	2013	2014	2015
Agencies & Corporates	29,175	34,665	28,445	30,763	38,805	34,669
Net Swap Exposure	827	1,179	727	579	672	192
Sovereigns	32,388	26,774	36,658	36,624	37,627	44,399
Total	**62,390**	**62,618**	**65,830**	**67,966**	**77,104**	**79,260**
Growth		**0%**	**5%**	**3%**	**13%**	**3%**

%

Category	2010	2011	2012	2013	2014	2015
Agencies &Corporates	47%	55%	43%	45%	50%	44%
Net Swap Exposure	1%	2%	1%	1%	1%	0.20%
Sovereigns	52%	43%	56%	54%	49%	56%

APPENDIX 2

R Code

Box Plot Code for plotting Amount for each FY

```
##Load Data
library(readxl)
df <- read.delim("C:/Users/ghosh/Desktop/Portfolio/Portfolio.csv", header = TRUE, sep =
",")

###Creating Box plot for Amount for each fiscal year
# Load necessary library
library(ggplot2)

# Assuming the data is loaded into a dataframe called 'df'
# Convert the Amount to numeric
df$Amount <- as.numeric(df$Amount)

# Ensure 'Period' is a factor for correct box plot behavior
df$Period <- as.factor(df$Period)

# Create the box plot with min/max lines
ggplot(df, aes(x = Period, y = Amount)) +
  geom_boxplot() +
  # Adding max and min lines
  stat_summary(fun.ymin = min, fun.ymax = max, geom = "errorbar", width = 0.2, color =
"blue", size = 1.5) +
  labs(title = "Box Plot of Amount FY 2010-2015", x = "Period", y = "Amount (US$,
millions)") +
  theme_minimal() +
  theme(plot.title = element_text(size = 12, hjust = 0.5, face = "bold"),
        axis.title.x = element_text(size = 12, face = "bold"),
        axis.title.y = element_text(size = 12, face = "bold"),
        axis.text.x = element_text(angle = 45, hjust = 1, size = 12))
```

Box plot for Amount by Category

```
# Load necessary library
library(ggplot2)

# Assuming the data is loaded into a dataframe called 'df'
# Convert the Amount to numeric
df$Amount <- as.numeric(df$Amount)
```

```
# Create the box plot with min/max lines
ggplot(df, aes(x = Category, y = Amount)) +
  geom_boxplot() +
  # Adding max and min lines
  stat_summary(fun.min = min, fun.max = max, geom = "errorbar", width = 0.2, color =
"blue", size = 1.5) +
  labs(title = "Box Plot of Amount by Asset Category", x = "Asset Category", y = "Amount
(US$, millions)") +
  theme_minimal() +
  theme(plot.title = element_text(size = 12, hjust = 0.5, face = "bold"),
        axis.title.x = element_text(size = 12, face = "bold"),
        axis.title.y = element_text(size = 12, face = "bold"),
        axis.text.x = element_text(angle = 45, hjust = 1, size = 12))
```

Box Plot for Amount by Rating

```
# Load necessary libraries
library(ggplot2)
library(forcats)

# Convert 'Amount' to numeric
df$Amount <- as.numeric(df$Amount)

# Reorder the 'CounterpartyRating' factor levels in the desired order
rating_levels <- c("AAA", "AA", "A", "BBB", "BBB or lower", "BB", "BB or lower", "B",
"CCC", NA)
df$CounterpartyRating <- factor(df$CounterpartyRating, levels = rating_levels)

# Replace NA in 'CounterpartyRating' with "CCC"
df$CounterpartyRating <- fct_explicit_na(df$CounterpartyRating, na_level = "CCC")

# Create the box plot with reordered x-axis
ggplot(df, aes(x = CounterpartyRating, y = Amount)) +
  geom_boxplot() +
  # Adding max and min lines
  stat_summary(fun.min = min, fun.max = max, geom = "errorbar", width = 0.2, color =
"blue", size = 1.5) +
  labs(title = "Box Plot of Amount by Rating", x = "Rating", y = "Amount (US$, millions)") +
  theme_minimal() +
  theme(plot.title = element_text(size = 12, hjust = 0.5, face = "bold"),
        axis.title.x = element_text(size = 12, face = "bold"),
        axis.title.y = element_text(size = 12, face = "bold"),
        axis.text.x = element_text(angle = 45, hjust = 1, size = 12))
```

Heat Map of Portfolio Distribution by Category

```
##Load Data
library(readxl)
df <- read.delim("C:/Users/ghosh/Desktop/Portfolio/Category.csv", header = TRUE, sep =
",")

###Destroy X function to remove X before Year in Column name as R automatically
incorporates an X
destroyX = function(es) {
  f = es
  for (col in c(1:ncol(f))){ #for each column in dataframe
    if (startsWith(colnames(f)[col], "X") == TRUE)  { #if starts with 'X' ..
      colnames(f)[col] <- substr(colnames(f)[col], 2, 100) #get rid of it
    }
  }
  assign(deparse(substitute(es)), f, inherits = TRUE) #assign corrected data to original name
}

df = destroyX(df)

# Reshape data to long format
df_long <- melt(df, id.vars = "Category", variable.name = "Year", value.name =
"Portfolio_Percent")

# Ensure the Year variable is a factor with levels in the correct order
df_long$Year <- factor(df_long$Year, levels = c("2010", "2011", "2012", "2013", "2014",
"2015"))

# Reorder the Category factor to reverse the order
df_long$Category <- factor(df_long$Category, levels = rev(unique(df_long$Category)))

# Define color palette based on efficiency thresholds
color_palette <- c("lightgreen", "#bacdbe", "red")
breaks <- c(-Inf, 9,  45, Inf)  # Define breaks for color categories
labels <- c("< 10",  "10-45", "⩾ 45")  # Labels for legend

# Cut Portfolio_Percent into categories and create a new column for fill color
df_long <- df_long %>%
  mutate(Efficiency_Category = cut(Portfolio_Percent, breaks = breaks, labels = labels,
include.lowest = TRUE, right = TRUE))
```

```
# Plotting the heat map with custom color categories
ggplot(df_long, aes(x = Year, y = Category, fill = Efficiency_Category)) +  # Use
Efficiency_Category instead of Portfolio_Percent
  geom_tile(color = "white") +
  scale_fill_manual(values = color_palette,
                    guide = guide_legend(title = "Portfolio %")) +
  labs(title = "Heatmap of Portfolio Distribution by Asset Category",
    x = "Year",
    y = "Category") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 12),
        axis.text.y = element_text(size = 12),
        axis.title.x = element_text(size = 14, face = "bold"),
        axis.title.y = element_text(size = 14, face = "bold"),
        plot.title = element_text(hjust = 0.5, size = 12, face = "bold"),
        legend.title = element_text(size = 12, face = "bold"),
        legend.text = element_text(size = 10))
```

Heat Map of Portfolio Distribution by Rating

```
##Loading Data
library(readxl)
df <- read.delim("C:/Users/ghosh/Desktop/Portfolio/HeatMap.csv", header = TRUE, sep =
",")

##Destroy X function
destroyX = function(es) {
  f = es
  for (col in c(1:ncol(f))){ #for each column in dataframe
    if (startsWith(colnames(f)[col], "X") == TRUE)  { #if starts with 'X' ..
      colnames(f)[col] <- substr(colnames(f)[col], 2, 100) #get rid of it
    }
  }
  assign(deparse(substitute(es)), f, inherits = TRUE) #assign corrected data to original name
}
df = destroyX(df)

# Reshape data to long format
df_long <- melt(df, id.vars = "Rating", variable.name = "Year", value.name =
"Portfolio_Percent")

# Ensure the Year variable is a factor with levels in the correct order
df_long$Year <- factor(df_long$Year, levels = c("2010", "2011", "2012", "2013", "2014",
"2015"))
```

```
# Reorder the Rating factor to match the desired order")
rating_levels <- c("CCC", "B", "BB or lower", "BB", "BBB or lower", "BBB", "A", "AA",
"AAA")
df_long$Rating <- factor(df_long$Rating, levels = rating_levels)

# Define color palette based on efficiency thresholds
color_palette <- c("lightgreen", "#bacdbe", "Coral", "red")
breaks <- c(-Inf, 9, 20, 45, Inf)  # Define breaks for color categories
labels <- c("< 10", "10-20", "20-45", "⩾ 45")  # Labels for legend

# Cut Portfolio_Percent into categories and create a new column for fill color
df_long <- df_long %>%
  mutate(Efficiency_Category = cut(Portfolio_Percent, breaks = breaks, labels = labels,
include.lowest = TRUE, right = TRUE))

# Plotting the heat map with custom color categories
ggplot(df_long, aes(x = Year, y = Rating, fill = Efficiency_Category)) +
  geom_tile(color = "white") +
  scale_fill_manual(values = color_palette,
                    guide = guide_legend(title = "Portfolio %")) +
  labs(title ="Heatmap of Portfolio Distribution by Rating",
    x = "Year",
    y = "Rating") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 12),
        axis.text.y = element_text(size = 12),
        axis.title.x = element_text(size = 14, face = "bold"),
        axis.title.y = element_text(size = 14, face = "bold"),
        plot.title = element_text(hjust = 0.5, size = 12, face = "bold"),
        legend.title = element_text(size = 12, face = "bold"),
        legend.text = element_text(size = 10))
```

Cross tabulation of Category and Rating

```
df <- read.delim("C:/Users/ghosh/Desktop/Portfolio/Portfolio.csv", header = TRUE, sep =
",")
attach(df)
crosstab = xtabs(~category+CounterpartyRating)
prop.table(crosstab,2)*100
```

Chi-Square test for Variables CounterpartyRating and Category

```
category = as.factor(Category)
CounterpartyRating = as.factor(CounterpartyRating)
Category_Rating_Data= table(category,CounterpartyRating)
chisq.test(Category_Rating_Data)
```

Counterparty Rating, Category and Organization Cross tabulation code

```
crosstab = xtabs(~category+CounterpartyRating+organization)
crosstab
prop.table(crosstab,2)*100
```

Normality test

```
library(readxl)
df <- read.delim("C:/Users/ghosh/Desktop/Portfolio/Portfolio.csv", header = TRUE, sep =
",")
attach(df)
shapiro.test(Amount[Organization == "IBRD"])
shapiro.test(Amount[Organization == "IDA"])
library(nortest)
ad.test(Amount[Organization == "IBRD"])
ad.test(Amount[Organization == "IDA"])
lillie.test(Amount[Organization == "IBRD"])
lillie.test(Amount[Organization == "IDA"])
```

Variance test

```
library(car)
leveneTest(Amount~Organization)
```

Two sample t-test

```
t.test(Amount~Organization,data = df, var.equal = TRUE)
```

AtishyaGhosh

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