Using Credit Rating for Stock Price Prediction with the Use of Machine Learning

COMP 4971C Independent Work

Supervised by **David Rossiter**

Jacob (Jun Seong) WOO

Abstract

This research focuses on studying the relationship between credit rating and stock prices of financial institutions worldwide. The scope of the study is limited to financial institutions within 29 developed countries around the world, and the study assumes that there is a strong correlation between credit rating and stock prices. Credit rating is a critical metric for any financial institution as it has a significant impact on its brand and reputation. Therefore, any changes in credit rating may affect how individuals and other corporates view these institutions, affecting their stock prices. With the help of machine learning, specifically the XGBoost model, the study is divided into two stages. The first stage focuses on deriving the essential indicators that significantly influence a financial institution's credit rating. The second stage takes a step further to use such indicators to predict the company's stock prices. As a result, the algorithm that takes advantage of the indicators from the first stage has the accuracy of 59% in predicting whether the stock price will go up, maintain its position, or go down.

Table of Contents

Table of Figures

1. Introduction

1.1 Background

The purpose of this report is to identify the relationship between credit rating and the stock price of financial institutions around the world. Many bankers, investors, and individuals have started being involved in the stock market. Some individuals have even entered the market as traders, especially after the global market's pandemic. The pandemic significantly dragged down each country's stock prices, providing new investment opportunities.

While these individuals have many industries to select, one industry lasting for the last few decades is the financial industry. It is also the industry that has become the ground for the stock market. The financial industry is mainly composed of banks or organizations that deal with money transactions. The term' financial institution' will be defined later in the report. Nevertheless, these investors all face common problems in making their decisions on investments:

1. They will have to perform a manual analysis of each company which may take hours and hours if done correctly.
2. It is required for these investors to continuously monitor the performance, such as credit rating, annual report, and stock prices, of each company. Monitoring credit rating alone can be a tremendous amount of work for a single individual.
3. Many of these decisions are based on personal experiences and intuition, exposing their thinking process to risks.

However, it turns out that the newest trend in machine learning can do a lot for these people to solve such problems.

The increase in usage of machine learning techniques in the financial industry is prevalent. Machine learning allows analysts to identify new patterns in existing data, create new forms of data for further analysis, and, most importantly, reduce human errors in decision-making and calculations. One of the applications of machine learning is credit rating prediction. Credit rating agencies are joining in this trend and taking advantage of machine learning in assessing each firm to decide between upgrading, downgrading, or maintaining the firm's current rating. Credit rating plays a massive role to all corporations, but it is even more critical to financial institutions.

1.2 Credit Rating

Credit rating agencies use both public and private information of a corporation to calculate the rating. Such information may involve factors from the quarterly or annual financial report, balance sheet, income statement, and statement of the company's cash flow. Usually, the balance sheet, income statement, and cash flow statement are all included within the company's annual report. The weighting of these factors, which differs from agency to agency, is unknown to the public. Each rating agency develops its system to perform a thorough company analysis. Many credit rating agencies exist in the global market; however, Moody's, S&P Global, and Fitch Ratings are the most widely known agencies. Individuals, investors, and corporates perceive this metric as critical in assessing each company's investment or lending assets. As mentioned previously, credit rating is regarded even more crucial to financial institutions. The rating can significantly impact its reputation and its relationships with its stakeholders.

Rating	Description	
AAA	Highest Credit Quality	Investment Grade
AA	Very High Credit Quality	
A	High Credit Quality	
BBB	Good Credit Quality	
BB	Speculative	
B	Highly Speculative	
CCC	Substantial Credit Risk	Non-Investment Grade
CC	Very High Levels of Credit Risk	
C	Near Default	
RD	Restricted Default	
D	Default	

Figure 1: Fitch Rating's Credit Rating Distribution

1.3 Financial Institutions

In this study, the term' financial institution' refers to any form of an organization regardless of its mission, assets, debts, scope, size, and geography, that is involved in any form of transactions limited to loans, borrowings, deposits, investments, and currency or cryptocurrency exchanges. Generally, financial institutions include companies in these sub-industries: commercial banking, investment banking, insurance companies, brokerage agencies, real estate development companies, asset management companies, and retail banks. Exceptional cases like digital banks may also fall into the scope of financial institutions.

1.4 XGBoost

XGBoost will be used as the primary strategy for this study. XGBoost (eXtreme Gradient Boosting) is a trending machine learning technique that focuses on effectiveness and speed by boosting the usage of decision tree algorithms. In more straightforward terms, it shares the roots with Gradient Boosting, which is explained below, but with more speed equipped with a time and cost-efficient algorithm. Its software library can only be incorporated mainly using Object-Oriented Programming (OOP) languages such as Python, Java, and C++. For this particular project, Python is used to implement this technology.

1.4.1 Gradient Boosting

Gradient Boosting is a technique in machine learning used to predict the output through classification and regression features. It uses multiple weak models to create the most suitable model for the project. Initially, the machine starts by oversimplifying the decision trees with all the weak models combined and calculating the prediction error. Then, this process is repeated repeatedly to reach an acceptable accuracy with minimal prediction error, which is significantly higher than the initial accuracy. Therefore, it is mainly used when the project's goal is focused on accuracy rather than speed.

1.4.2 Other Machine Learning Techniques

At the beginning of the study, XGBoost was nowhere close to being selected as the starting point. Other options included Linear Regression, Logistic Regression, Naïve Bayes, SVM (Support Vector Machine), Decision Tree, and Random Forest. At first, the Decision Tree technique seemed to be the one to build the prediction model. However, after seeing so many indicators, there was a big concern that each indicator may not contribute a lot to making the prediction. Moreover, one huge disadvantage of using a Decision Tree is that a minor change in the features may lead to a completely different outcome. However, this project required a technique that prioritizes accuracy more than other factors and a model that can consider multiple weak features to derive a final algorithm. In the end, XGBoost, the perfect fit for this study, was selected.

1.4.3 Libraries Used

The whole study was built on Jupyter Notebook using Python as the primary language. Here is the list of libraries used to build the final model: Pandas, Numpy, Os, and others, including Re and Warning. However, most of the functions come from Pandas library, mainly *sklearn* and XGBoost.

1.4.4 Process of Machine Learning

The machine learning technique used for this report will go through these four steps: data pre-processing, feature engineering, feature selection, and prediction. Therefore, the report will follow the same format as these steps.

1.5 Assumptions

For effective and easier data analysis, three major assumptions are made in the project.

1. As there are many types of credit ratings even under one agency, one assumption is made that different types of credit ratings issued by one agency can be classified as one specific type of credit rating. For example, 'Long-Term Credit Rating,' 'Bank's Financial Strength Rating,' and 'Insurance Financial Strength Rating' can be treated as one consolidated credit rating.
2. This study focuses on predicting whether a stock price will go up, down, or maintain its position. However, limited by the nature of credit rating, only quarterly and annual

data are available for use. Within the timeframe of a quarter or a year, it is nearly impossible for the stock price to be the same. Therefore, a second assumption is made that if the stock price changes are within 5% (2.5% below the original price or 2.5% above the original price), then it will be recognized as 'not having any significant changes in its price,' which in easier terms means that the stock price did not change.

3. To align with the purpose of this project, another assumption is made that credit rating is highly correlated with the stock prices of financial institutions. This assumption is considered the most critical and vulnerable assumption of this study. Without this assumption, the project loses its purpose and will not make sense. This assumption is based on the relationship between S&P 500 YTD stock returns of 2020 and credit rating, as shown in Figure #2 below. Most companies reported a decline in their stocks, which is highly due to the pandemic starting at the beginning of 2020. Yet, the trend is very noticeable. It is still effortless to see the rising stock prices and credit rating improvement. From this, we assume that we can apply the same direction to the relationship between credit rating and the stock prices of financial institutions.

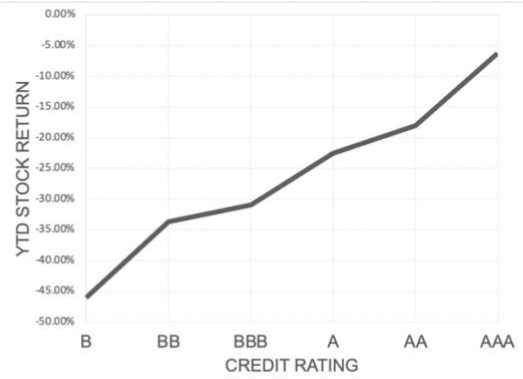

Figure 2: Relationship between Credit Rating and YTD Stock Return

2. Data Pre-Processing

2.1 Raw Data

Predicting credit rating and using such data to decide which stocks to buy require a lot of data. With so much data available in public, the CAMELS rating system has been used to identify the data needed to assess the financial institution. CAMELS stands for Capital adequacy, Assets, Management Capability, Earnings, Liquidity, and Sensitivity. It is a rating system that evaluates the strength of a financial institution through these 6 categories. Thus, many credit rating agencies use the score from the CAMELS system as a reference when analyzing the financial stability of a company.

Nonetheless, the rating derived from the CAMELS system should not be compared with the agency's credit rating as the outcome is delivered in a different format. In addition, the CAMELS system is only used in this study to limit infinitely many indicators in public information. All the data related to these categories can be found in a company's annual report. Here is the specific list of the data used for this study which also falls into the CAMELS system categories.

Raw Data Name	Time Period of Data	Number of Files Extracted	Source
Daily Closing Stock Prices	2006 January – 2021 June	12 Files	Eikon
Historical Issuer Rating	2001 March – 2021 June	5 Files	Eikon
Income Statement	1981 March – 2021 June	12 Files	Eikon
Balance Sheet	1981 March – 2021 June	12 Files	Eikon
Statement of Cash Flow	1981 March – 2021 June	12 Files	Eikon
Macroeconomic Indicators	1960 Jan – 2021 June	5 Files	World Bank

Figure 3: Table of Raw Data Used

Macroeconomic Indicators from Figure #3 include CAB (Current Account Balance), CPI (Consumer Price Index), Currency Exchange Rates, GDP (Gross Domestic Product), and PPP (Purchasing Power Parity).

2.2 Data Concatenation

For each set of data used, there were multiple files for each data. So, after reading the table and fixing the table format of all files in a consistent format, all the files were combined into one single file. For example, the 12 files of the Daily Closing Stock Prices have been compiled into a single Daily Closing Stock Prices file. When concatenating the files, the data before January 2006 was deleted due to the limited timeframe of Closing Stock Prices available.

2.3 Historical Issuer Rating Data Preparation

The scope of the credit rating used for this project is only limited to one agency: Fitch Rating Agency. Plus, one of the assumptions made was combining all types of credit ratings issued by the Fitch Rating Agency into one consolidated credit rating. This assumption means that even though some credit rating types may be different, they will be all treated equally. Thereby, it was essential to get rid of all the other ratings, such as domestic ratings and other rating agencies' ratings, and drop all the unused or unnecessary columns. So, for example, in Figure #4, the 'RIC,' the 'Rating Source Description,' and the 'Rating Source Description' columns would be removed.

Additionally, any companies that had the rating of WD or NR were also dropped because such rating means that the company has defaulted and no longer exists. The transformation is demonstrated below from Figure #4 to Figure #5. In the end, there was a total of 3,050 companies left with Fitch's ratings.

These criterias are not necessary as only Fitch ratings are used.

Ticker	RIC	Rating Source Description	Rating Scope Description	Issuer Rating	Date
TMB.BK	-	TRIS Rating Co Ltd	Domestic	BBB	30/11/2015
TMB.BK	-	Fitch Rating	Foreign	BB-	30/11/2015
2801.TW	-	Fitch Rating	Foreign	BB	25/9/2005
2801.TW	-	Moody's	Foreign	BB-	25/9/2005
2801.TW	-	Fitch	Foreign	A	27/9/2006

Problem: Same date, but different "Issuer Rating"

Figure 4: Historical Issuer Rating Before Preparation

Only Fitch Agency's ratings are used as "Issuer Rating"

Ticker	Issuer Rating	Date
TMB.BK	BBB	30/11/2015
TMB.BK	BB	30/02/2016
2801.TW	BB	25/9/2005
2801.TW	BBB	28/12/2005
2801.TW	A	27/9/2006

Date is in order, so it's easier to recognize the changes in ratings.

Figure 5: Historical Issuer Rating After Preparation

2.4 Null Value Imputation for Balance Sheet, Income Statement, and Statement of Cash Flow

2.4.1 Type Conversion

Most of the data stored in these files are either char or string types and thus may cause a problem in future usage, especially when testing the model. So, a massive conversion was done to convert these data into the correct data type. For example, for any quantitative numbers stored as a string, these were adjusted to a float data type, as many numbers of values went over the maximum value of the integer data type.

2.4.2 Balance Sheet Column Adjustment

A special adjustment has been made to the Balance Sheet compressed file. There were about 321 indicators in each company's balance sheet within each data set. Using all these indicators was impossible and unneeded, and some of these indicators were empty. So, from 321 indicators, the number of indicators was reduced to 27 indicators.

2.4.3 Null Value Imputation Preparation

For an easier process of replacing null values, any empty rows were dropped, and all infinity data or non-sense zeros, such as '0.0000000e + 00,' were replaced with 'NaN,' which stands for 'Not a Number.' Still, within this report, it represents null or rejected values and will be referred to by null values. This replacement makes it easier for loops to replace it with imputed values which will be discussed next.

2.4.4 Null Value Imputation Using Linear Interpolation

Linear interpolation is the most common and basic technique to replace null values. It uses the value before and after the null value to find the average between those two values. Linear interpolation is only applicable if the values are present before and after the null data, as shown in Figure #6. Since a value exists on both the top and bottom of the "NaN" value, linear interpolation is applicable. The equation from Figure #7 is used to impute the null or rejected value.

Return on Equity (ROE)
11%
NaN
15%

Figure 6: Linear Interpolation Requirement Example

$$y - y_1 = \frac{y_2 - y_1}{x_2 - x_1}(x - x_1)$$

Figure 7: Equation for Linear Interpolation

2.4.5 Null Value Imputation Using KNN Imputer

KNN Imputer, also known as k-Nearest Neighbor Imputer, is another applicable technique to replace the null values in the data. An assumption is made that its nearest neighbor can find similar values. For this case, the neighbor refers to other companies within the same country. Using this, a country-based selection of neighbors has been performed. The requirement for this imputation is that there are enough data to impute all columns. Look at Figure #8 as reference. With the green circle as the null value, it can make imputations based on red or blue triangles/rectangles around the null value. As some countries only possess a few banks, another imputation method is required.

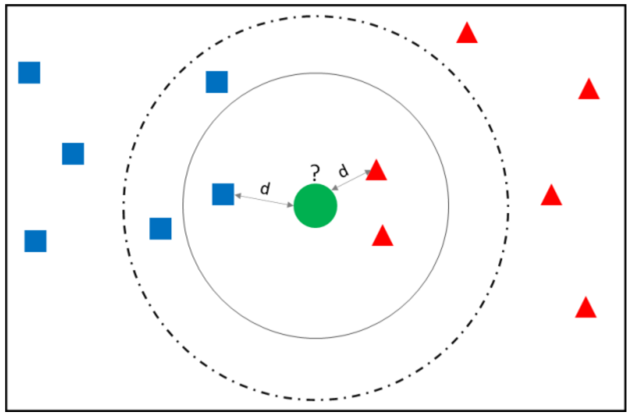

Figure 8: KNN Imputer Demonstration (Green is the Null Value)

2.4.6 Null Value Imputation Using Iterative Imputer

Iterative imputer is widely used in machine learning to fill in the missing data, specifically if the missing data requires a numeric value. This process focuses on using each indicator as a function of other indicators. In other words, the process allows previous values to predict the upcoming values. Most of the missing data not imputed by the previous two techniques have been assigned using this method. For the extreme cases, they were imputed with the global mean of the indicator.

2.5 Pre-Processing Stock Prices

Credit rating agencies release credit ratings either quarterly, biannually, or annually depending on the amount of information available to these agencies. Whether it's released once a year or four times a year, having the daily closing prices of each stock is not necessary. The solution to this is quite simple. While keeping the daily stock prices, additional indicators such as the average yearly/half-yearly/quarterly price change in percentage can be added for potential usage. As the project's final goal is to predict the stock price of a financial institution, it is also important to calculate the breakaway stocks. Breakaway stocks record the number of times the stock price change deviates at least two standard deviations away from the mean of each bank.

After adding these supplementary indicators, these can be merged into the final dataset. An additional action has also been taken on these stock prices to ensure a fair comparison between companies. The currency has all been changed to USD. The annual average currency exchange rate, included in the macroeconomic indicator data, was used to make the conversion.

2.6 Data Merging

After repeating the three techniques for Null Value Imputation for Balance Sheet, Income Statement, and Statement of Cash Flow, and formatting the Historical Issuer Rating, all these data were merged into a single file by companies' "Ticker." Additionally, macroeconomic indicators were merged into this file even if the company does not produce any macroeconomic metrics. Based on the "Ticker," macroeconomic indicators like GDP and PPP have been added. For example, in Figure #9, the company is from Taiwan based on the ticker's "TW" sign.

				Indicators from annual financial statements		
Ticker	Issuer Rating	Rating Date	Statement Issue Date	Additional Paid In Capital (USD)	Cash and Due From Banks (USD)	Cash and ST Investments (USD)
2801.TW	BB	2008-12-31	2008-12-31	4.153775e+10	2.089661e+11	2.814939e+11
2801.TW	BB	2009-12-31	2009-12-31	4.013532e+10	3.814991e+11	3.067101e+11
2801.TW	BB	2010-12-31	2010-12-31	5.41700e+10	3.921391e+11	2.939156e+11
2801.TW	BBB	2011-12-31	2011-12-31	5.227000e+10	3.503650e+11	2.942149e+11
2801.TW	BBB	2012-12-31	2012-12-31	5.932600e+10	4.643620e+11	2.837932e+11
2801.TW	BB	2013-12-31	2013-12-31	5.64500e+10	5.411410e+11	2.728146e+11
2801.TW	BB	2014-12-31	2014-12-31	5.79200e+10	6.693770e+11	2.883292e+11
2801.TW	B	2015-12-31	2015-12-31	5.311000e+10	7.385211e+11	3.000139e+11
2801.TW	BB	2016-12-31	2016-12-31	5.49100e+10	6.977301e+11	3.119392e+11

Figure 9: Dataset after Merging Historical Issuer Rating, Financial Statements, and Macroeconomic Indicators

Therefore, the GDP of Taiwan has been added to the data. These macroeconomic values will be later used during the next stage: Feature Engineering. The final data set looks like this, as shown in Figure #9; however, macroeconomic indicators will be displayed in the figures used in the next section as there are too many indicators.

2.7 Data Pre-Processing Summary

Data pre-processing is one of the hardest stages of this project involving imputing thousands of null values and ensuring each value assigned doesn't significantly affect the prediction model. Due to its complicatedness, here is the summarized version of this chapter from Figure #11 to 14.

Part A: Utilizing Available Data

Ticker	Year	Ratings	Net Profit	Return on Equity (ROE)
XX.T	2015	BB	JPY¥20B	N/A
XX.T	2016	N/A	N/A	13%
XX.T	2017	BBB	JPY¥30B	N/A
YY.T	2015	N/A	N/A	N/A

Financial Statements and Ratings

Ticker	Date	Share Price
XX.T	2015.01.04	JPY¥1500/share

Share Price Data

Country	Year	JPY:USD	GDP (USD)
Japan	2015	1:0.0091	$4.4 Trillion

Macroeconomic Indicators

Figure 10: Available Raw Data Format Before Transformation (Red values are null or rejected values)

Part B: Dropping Null Rows/Columns Across All Data and Applying Null Value Imputation Methods

Ticker	Year	Ratings	Net Profit	Return on Equity (ROE)
~~YY.T~~	~~2015~~	~~N/A~~	~~N/A~~	~~N/A~~

Drop Null Rows

Figure 11: One Type of Null Value Imputation (Dropping Null Rows/Columns)

Part C: Converting All Currency to USD Using Macroeconomic Indicator (Exchange Rate)

Ticker	Date	Share Price
XX.T	2015.01.04	USD$13.65/share

JPY Converted to USD

Figure 12: Demonstration of Converting Figure 9's Share Price to USD

Part D: Merging All the Prepared Data into One Dataset

Ticker	Year	Ratings	Net Profit	Return on Equity (ROE)
XX.T	2015	BB	JPY¥20B	11%
XX.T	2016	BB	JPY¥25B	13%
XX.T	2017	BBB	JPY¥30B	15%

N/A Values Filled Out

Ticker	XX.T
Date	2015.01.01
Rating	BB
Net Profit	USD$0.09B
Return on Equity (ROE)	10%
Share Price	USD$13.65/ share
GDP	$4.4 Trillion

Example of One Company

Figure 13: Final Data Format after Data Merging (Green values are the changed values)

3. Feature Engineering

3.1 Reading and Preparing Data

Before utilizing the pre-processed data to create the predictive model using XGBoost, more data preparation is required to minimize the prediction error. To begin with, encoding the credit ratings is required. For this project, each credit rating has been enumerated and quantified. As mentioned before, credit rating ranges from 'AAA' to 'D.' Therefore, the highest number was assigned to the highest credit rating, which was 11, and the lowest number was assigned to the lowest credit rating, which was 1. This method makes it easier to input this data into the model and create an understandable result.

Also, the size of each indicator seems to vary by a considerable difference. For example, the Total Assets of a company can be over millions of USD, but the same company's EPS (Earnings Per Share) can be less than 10. Comparing these two indicators for feature engineering will not be effective; therefore, all these numbers have been replaced by percentage change from the previous year.

After preparing the data, the final step is to separate the features and the target indicator. The final indicator is the probability of stock price going up, going down, or not having significant changes. The rest of the indicators have been sorted as the features used for feature selection. Subsequently, the data is split into test and train data.

3.2 Fitting Model

At the stage of training the model using the training data, signs of overfitting were noticed. The overfitting is most likely due to having too many features even after eliminating all the unnecessary ones. It only makes sense for the model to make a nearly accurate prediction if it considers all the features. Also, the nature of Gradient Boosting within XGBoost forces the machine to use all the elements regardless of how weak it is in contributing to prediction. The precision for the training model to predict the direction of stock price changes is shown below.

Stock Price Movement	Precision (%)
Going Down	94%
Neutral	89%
Going Up	98%
Average	94%

Precision of Using All 62 Indicators

Figure 14: Signs of Overfitting in Precision when Using All Indicators

Consequently, it was necessary to drop many features as all 62 indicators may not lead to a helpful conclusion.

3.3 Feature Importance

According to the trained model, the importance of each indicator is displayed by the weighting shown in Figure #16. Combining the weightings of all the indicators would lead to a sum of 100%. However, just by looking at the distribution of these weightings, there are a lot of repeated weightings. For example, the features from 13 to 15 all carry a weighting of 2.5%.

Although we can consider the difference to the thousandth decimal point, we cannot know which indicator is more important. These patterns can be noticed all over the chart, which is why the number of indicators had to be reduced while considering the highest accuracy. There was a total of 62 indicators used to make the prediction. The 22 indicators not shown in the figure above have been ignored. They only account for less than 1% and have already been dropped for the following feature selection.

In the next feature selection, these 40 features were used in the process repeatedly, one by one, until the highest accuracy was recorded. The model identified the features in which the accuracy improved when it was implemented in the model. As a result, the final 29 features were identified as significant indicators that have improved the accuracy of the model. These 29 indicators are listed below in Figure #17 with their respective weighting.

Indicators	Contributed Weighting
1. Total Earning Assets (Pct)	6.7%
2. Tier2 Cpaital (Abs)	6.5%
3. Cash to Assets Ratio (Pct)	3.3%
4. Purchasing Power Parity (PPP)	3.3%
5. Total Deposits (Abs)	3.2%
6. Return on Equity (ROE, Pct)	3.2%
7. Return on Assets (ROA, Pct)	2.8%
8. Tier1 Capital (Pct)	2.7%
9. Loan Loss Reserves Non Performing Loans (Pct)	2.6%
10. Consumer Price Index (CPI)	2.6%

Contributed Weighting of Each Indicator #1-10

Indicators	Contributed Weighting
11. Total Current Assets (Abs)	2.6%
12. Non Performing Loans to Gross Loans (Abs)	2.6%
13. Total Current Assets (Pct)	2.5%
14. Daily Stock Price Change	2.5%
15. Current Account Balance (CAB)	2.5%
16. Daily Stock Breakaway Down	2.4%
17.Total Loans (Pct)	2.3%
18. Capital Adequacy Ratio (Pct)	2.2%
19. Net Interest Margin (Abs)	2.1%
20. Debt to Equity Ratio (Pct)	2.1%

Contributed Weighting of Each Indicator #11-20

Indicators	Contributed Weighting
21. Liquidity Coverage Ratio (LCR, Pct)	2.0%
22. Net Income (Pct)	2.0%
23. Total Assets (Pct)	2.0%
24. Net Interest Margin (Pct)	2.0%
25. Core Tier1 Capital Abs)	1.8%
26. Net Income (Abs)	1.8%
27. Total Revenue (Pct)	1.8%
28. Non Performing Loans to Gross Loans (Pct)	1.7%
29. Total Deposits (Pct)	1.6%
30. Debt to Asset Ratio (Pct)	1.6%

Contributed Weighting of Each Indicator #21-30

Indicators	Contributed Weighting
31. Daily Stock Breakaway Up	1.5%
32. Core Tier1 Capital (Pct)	1.4%
33. Net Loans/Customer Deposits (Pct)	1.4%
34. Operating Margin (Pct)	1.4%
35. Gross Domestic Product (GDP)	1.4%
36. Operating Profit to Risk-Weighted Assets (Pct)	1.3%
37. Loan Loss Reserves Non Performing Loans (Abs)	1.3%
38. Return on Equity (ROE, Abs)	1.2%
39. Liquidity Coverage Ratio (LCR, Abs)	1.2%
40. Capital Adequancy Ratio (Abs)	1.1%

Contributed Weighting of Each Indicator #31-40

Figure 15: Weightings Distributed Over First 40 Indicators

Indicators		Contributed Weighting
1. Stock Price Average Daily Change in Stock Price		7.49%
2. Macroeconomic Consumer Price Index (CPI)		5.52%
3. Size Net Income	ΔYoY Change	5.22%
4. Macroeconomic Gross Domestic Product (GDP)		4.10%
5. Capitalization Tier 1 Capital	ΔYoY Change	4.02%
6. Capitalization Tier 2 Capital		4.01%
7. Asset Total Current Assets		3.97%
8. Macroeconomic Current Account Balance (CAB)		3.82%
9. Asset Quality Unreserved Non Performing Loans To Total Equity	ΔYoY Change	3.81%
10. Additional Ratios Total Liabilities		3.61%
11. Size Total Equity	ΔYoY Change	3.55%
12. Liquidity Liquidity Coverage Ratio (LCR)		3.50%
13. Capitalization Core Tier 1 Capital		3.43%
14. Macroeconomic Purchasing Power Parity (PPP)		3.43%
15. Earnings Net Interst Margin	ΔYoY Change	3.36%
16. Additional Ratios Operating Margin	ΔYoY Change	3.24%
17. Size Total Deposits	ΔYoY Change	3.14%
18. Liquidity Net Loans / Customer Deposits		3.09%
19. Earnings Return on Equity (ROE)	ΔYoY Change	3.07%
20. Earnings Return on Assets (ROA)	ΔYoY Change	3.06%
21. Size Total Loans	ΔYoY Change	3.00%
22. Earnings Return on Equity (ROE)		2.95%
23. Size Total Assets		2.83%
24. Asset Quality Non Performing Loans to Gross Loans Ratio	ΔYoY Change	2.62%
25. Stock Price Number of Breakaway Signals Down		2.37%
26. Asset Quality Loan Loss Reserves Non Performing Loans	ΔYoY Change	2.33%
27. Liquidity Liquidity Coverage Ratio	ΔYoY Change	1.95%
28. Capitalization Capital Adequacy Ratio	ΔYoY Change	1.91%
29. Earnings Operating Profit to Risk-Weighted Assets	ΔYoY Change	1.60%

Contributed Weighting of Top Indicators #1-29

Figure 16: Final Selection of Indicators with the Highest Precision

3.3.1 Analyzing the Features with High Weightings

The features with the highest weights can be classified into three separate categories: stock price, macroeconomic factors, and bank size.

To start, it's fascinating to see how stock prices, in general, of a financial institution can have a considerable impact in predicting stock prices. That's very similar to saying that your current body weight will significantly influence the probability of your body weight changing either up or down. The sum of weightings of Average Daily Change in Stock Price and the weightings of Number of Breakaway Signals contribute to approximately 10% of the weighting in predicting the stock prices. Although it may seem like it does not make sense, these indicators have shown to be quite accurate when indicating the stock price will go down. This phenomenon is demonstrated by Figure #18 below.

The chart below displays the relationship between the Average Daily Change in Stock Price (x-axis) and the percentage of the number of stocks with prices that went down, shown in blue (y-axis). At the very left, when the daily change in stock price was at its lowest (high negative), the proportion of the stocks with its prices going down was highest.

Figure 17: Impact of Average Daily Change in Stock Price on Percentage of Stock Price Movements

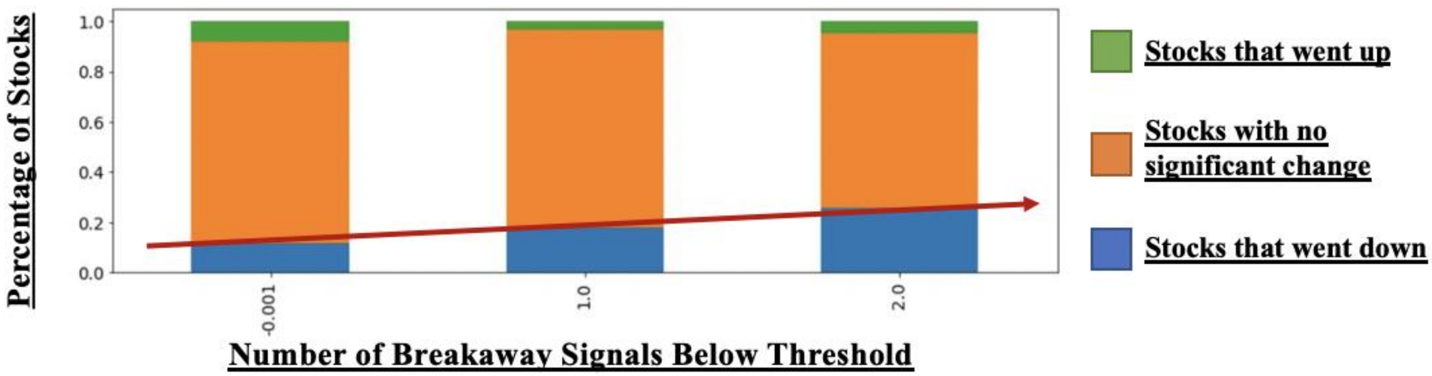

Figure 18: Impact of Number of Breakaway Signals Below Threshold on Percentage of Stock Price Movements

The chart above is another figure, Figure #19, displaying the relationship between the Number of Breakaway Signals below the threshold (x-axis) and the percentage of the number of stocks that have gone down in blue (y-axis). At the very right, at two breakaway signals meaning that the stock price has moved at least two standard deviations away from the mean, the proportion of the stocks that went down is at its highest.

Moving on, macroeconomic indicators are hard to ignore because a country's economy can have a massive impact on the stock prices regardless of the industry. The sum of GDP, PPP, CPI, and CAB's weightings accounts for more than 17% of the total weightings. This weighting is likely as financial institutions are very vulnerable to macroeconomic changes. Most of their performances depend on the interest rates and the economy's general health. From Figure #20 below, as the GDP or the PPP increases, the number of stocks going down decreases significantly. This situation is because financial institutions located in countries with relatively high GDP or PPP are backed by capital, therefore, have less tendency to affect the stock prices.

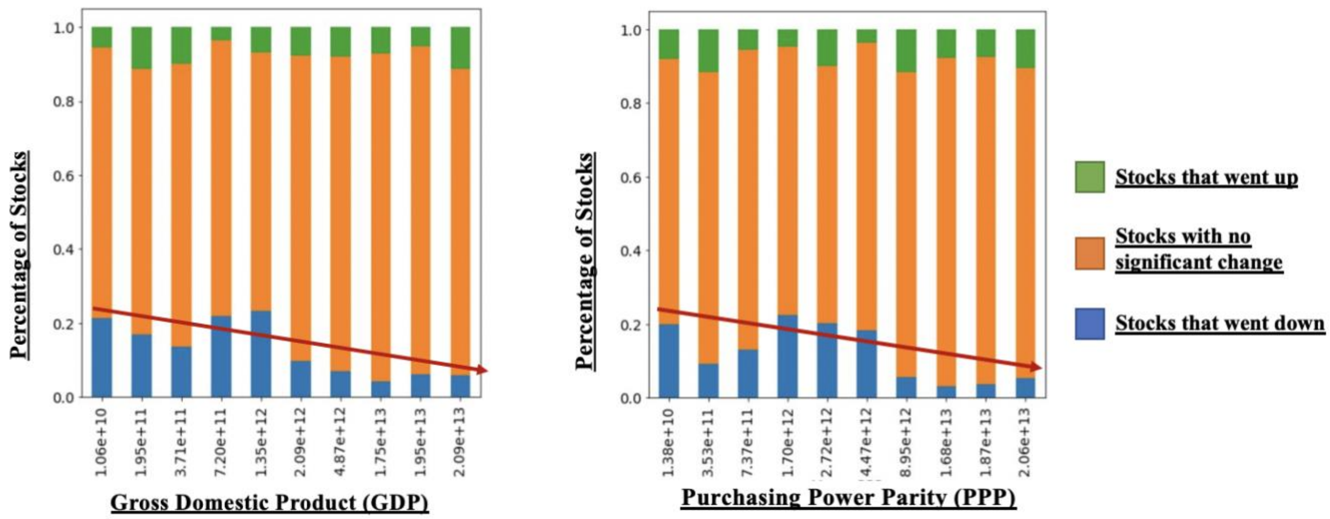

Figure 19: Impact of GDP and PPP on Percentage of Stock Price Movements

Finally, the bank size is also an essential factor that affects the probability. It turns out that indicators like change in Net Income, change in Total Equity, change in Total Deposits, and change in Total Loans show a negative correlation with the stock prices movement probability.

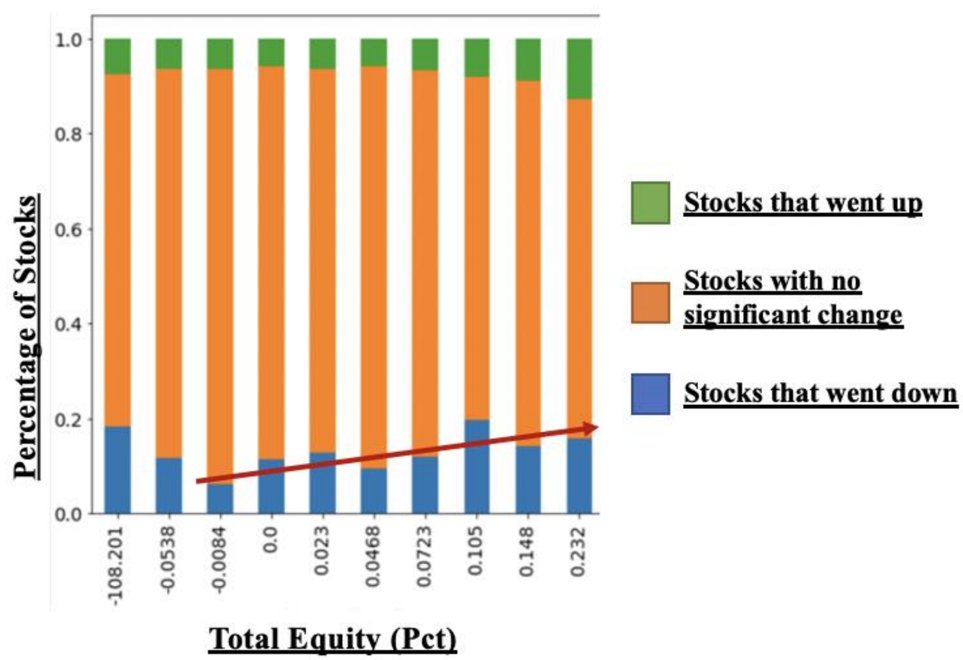

Figure 20: Impact of Total Equity on the Percentage of Stock Price Movements

When the Total Equity increases, the proportion of stock prices going down increases, as seen in Figure #21. Although it is hard to make a conclusion from such an increase, it is still possible to make an educated prediction that banks with significant changes in size metrics, even seemingly optimistic, are more prone to downgrades.

3.4 Fitting Model with the Best Features Plus Back-Testing

Using the XGBClassifer from XGBoost, the model gives us the model's accuracy in predicting the stocks using this weighting from predicting the credit rating migrations. It turns out the model is about 77% correct in predicting any credit rating migrations. Note that predicting credit rating and stock price is different. As the model for the stock price has been derived from the model for credit rating, it makes sense that the probability of accuracy for credit rating is higher than that of stock prices. The back-testing feature is not part of the model and must be tested manually using many loops. According to the result displayed in Figure #22, the model had an accuracy of 73% in predicting the stock price will go down, 57% in predicting the stock price will not have any significant changes, and 50% in predicting the stock price goes up.

Stock Price Movement	Precision (%)
Going Down	73%
Neutral	57%
Going Up	50%
Average	60%

Precision of Using 29 Best Indicators

Figure 21: Precision of the Model Using 29 Most Impactful Indicators

4. Discussion and Potential Future Works

4.1 Possible Error

Before considering the following potential study regarding the relationship between stock prices and credit rating, it is vital to go over the possible errors that may have affected the result of the study. As mentioned earlier, this study is based on the huge assumption that credit rating and stock prices are highly correlated. Therefore, it was possible to directly apply the weightings used to predict credit rating on predicting stock prices.

Another error comes from the fact that there is too little data to use machine learning to conclude. Usually, machine learning requires more data to produce a credible outcome. However, for this study, the process of data pre-processing reduced the amount of data significantly. As a result, about 5,000 financial institutions were cut down due to a lack of data.

4.2 Limitation

This strategy is only applicable to financial institutions' stock-related decisions until the subsequent credit ratings are released. However, due to the pandemic, the rating given in June of 2021 will likely not change significantly. Therefore, it is safe to assume that this strategy's validity will be extended until the end of the pandemic. After then, the users will have to input new data to derive new weightings and use those weightings to develop new algorithms.

4.3 Discussion

While the accuracy rate for the stock price predictions of the financial institution was meaningful, it may even be more meaningful to discuss the reasons behind these accuracy rates, especially for the accuracy rate for predicting stock prices that will go down. First, consider the data used and the model's highest weighted indicators. The data that was used here is from January 2006 to June 2021. It was the data of an annual report from financial institutions, including real estate and insurance companies, worldwide. Within the time frame, there was one financial crisis and one pandemic, which did cause a near-crisis impact on the stock market. Also, as mentioned before, three categories of data contributed the most to the model: stock prices, macroeconomic indicators, and the size of the bank.

Considering all these factors, it makes sense why the model performed better in predicting the stock prices going down. The biggest victim of the financial industry in 2008 were real estate, insurance, and central banks. Their stock prices plummeted, and even one of the biggest investment banks globally called the Lehman Brothers went down. Furthermore, major macroeconomic indicators were shaking. People were losing jobs and committing suicides, which accumulated huge volatility and instability in the global economy. Powerful government institutions like the Federal Reserve Bank were pulling extreme monetary policies like Quantitative Easing and negative interest rates. Similarly, in March of 2020, COVID-19 has officially begun its activity worldwide. Stock prices plunged as well as the macroeconomic indicators.

These data types contributed to more than 40% of the weightings of the indicators used for the model. As the global economy and the financial institutions were more unstable than stable in the past century, it only makes sense that the model is more accurate in predicting the falling stocks.

4.4 Conclusion

The result obtained from this study is more than significant and may apply to a real trading strategy. Having a strategy that is correct 76% in predicting the stock price will go down, 57% in predicting that there won't be significant changes, and 50% in predicting the stock price will go up is impressive, which is the same as predicting the probability of tossing a head in a coin flip. It may seem overwhelming, but if the assumption that a correlation between stock prices and credit rating is correct, this may become a powerful money-making strategy. Traders mainly interested in the financial industry may use this model. Still, they may need to perform some manual work in extracting the financial data from The World Bank and Eikon/Bloomberg Terminal of each financial institution.

4.5 Next Potential Research

Credit rating is not only given to publicly listed companies. It is also given to any form of traded assets, whether that's a commodity, ETFs, currency, etc. One of the traded assets that are more related to credit rating than companies' stock price is the bond price. Bond price is almost solely dependent on the credit rating. So, it would be an exciting project to study the relationship between bond prices and credit rating. There will not be any assumptions for this study, as it is already proven that bond prices are related to credit rating. So, the money-making strategy for this specific study is to calculate the credit rating of the bond before any agencies release it. It can lead to purchasing/selling decisions of the bonds before anybody else.