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The Impact of Bank Stability Metrics on Distance-from-Default

- Faysal Ahmad Khan*
- Imran Mahmud**

Abstract

The study aims to determine whether bank stability metrics can predict the default risk of listed banks in Bangladesh. To achieve this, a sample of 29 banks (7 Shariah-based banks and 22 conventional banks) from 2010 to 2023 is used. As a proxy for default risk, ROA based Altman's Z score and Merton's distance to default (DTD) were used. For bank stability ratios, Non-performing Loan to Equity (NPLE), Return on Equity (ROE), Liquidity Coverage Ratio (LCR), and Capital Adequacy Ratio (CRAR) were taken. Age, GDP growth, and a dummy for COVID were taken as control variables. Random effect model was tested to interpret the results across all models. The impact of stability metrics differs depending on the proxies taken in the study, as evidenced by the endogeneity and robustness test; however, it was found that capital adequacy, asset quality and profitability significantly impact bank's default risk for all models, respectively. Additionally, shariah-based banks are more sensitive to asset quality and profitability, where changes in these factors have a heightened effect on default risk. Conventional banks tend to be more sensitive to capital adequacy suggesting that capital adequacy management is critical for these banks' default risk.

Keywords: Z-score, Metron's Distance to Default, Default Risk, Random Effect Model, Conventional Banks, Shariah-based Banks, Endogeneity Test
JEL Classification: C23, C36, G21, G32, G33, G41

1. Introduction

Following the devastating effects of the global financial crisis on financial systems around the world, maintaining financial stability has emerged as a key priority of central banks' regulatory responsibilities globally. Bangladesh is not an exception. The "Financial Stability Assessment Report (FSAR)" published by the central bank of Bangladesh raise the concern as well that reveals a mixed landscape with both positive trends and concerning issues. The June 2024 quarterly issue of FASR shows that profitability has shown a slight improvement. Total assets grew to approximately BDT 25,462 billion. However, there has been a decline in asset quality, with the Non-performing Loan (NPL) ratio increasing

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*Faysal Ahmad Khan is an Assistant Professor, Email: faysalfindu@gmail.com; and Imran Mahmud is a lecturer, Email:imran.mahmud.bicm@gmail.com; Institute of Capital Market (BICM), Dhaka. The views expressed in this article are the authors' own.

significantly. The provision maintenance ratio also dropped, indicating potential weaknesses in the bank's ability to absorb losses. Capital adequacy has weakened slightly, with the Capital to Risk-Weighted Assets Ratio (CRAR) falling to 10.64 percent and the Tier-1 capital ratio to 7.61 percent. While most banks still meet the regulatory capital requirements, these reductions highlight diminishing buffers against losses. Liquidity measures remain compliant with regulatory benchmarks, and stress tests indicate moderate resilience to economic shocks, though credit risk is a notable concern. An increase in NPLs and defaults from key borrowers may threaten to push the CRAR below the minimum regulatory threshold of 10 percent, reflecting the sector's vulnerability to credit risks. Total defaulted loans in Bangladesh's banking sector stood at around Tk 1.45 lakh crore by the end of 2023, up from the previous year (Bangladesh Bank, 2023). NPLs have risen due to weak corporate governance, political interference, and poor risk management practices, making the sector more vulnerable to financial instability and default risk (The Business Standard, 2023).

In South Asia, the banking sector is under stress. In India, NPLs as a percentage of total loans went up from 7.5 percent in 2019 to 8.3 percent in 2022 (Reuters, 2022). Pakistan has seen similar trends, inflation rose to 24.5 percent in 2022, which added to the economic pressure on borrowers (Dawn, 2024). At the close of 2023, Pakistan's banking sector experienced a notable increase in Non-performing Loans (NPLs). The total NPLs rose by approximately 7.6 percent, escalating from PKR 924.04 billion in December 2022 to PKR 994.82 billion by December 2023. These are compounded by structural issues like high unemployment and fiscal deficits, leading to tighter credit conditions and slower economic growth (Dawn, 2023).

Recent evaluations have also pointed out persistent difficulties within the banking sector of Bangladesh. An analysis by S&P Global Ratings in August 2024 noted that the volatile political climate in Bangladesh has intensified the banking industry's weaknesses, including insufficient liquidity, limited capital buffers, and declining asset quality (S&P Global Ratings, 2024, August 14). Moreover, Fitch Ratings downgraded Bangladesh's Long-Term Foreign-Currency Issuer Default Rating to 'B+' from 'BB-' in May 2024, citing worries about the nation's financial stability (Fitch Ratings, 2024). These events highlight the need for close observation of financial stability indicators like NPL ratios and capital adequacy ratios to understand their influence on banks' default risks.

Given these conditions, it is crucial to analyze how various financial stability metrics affect the default risk of banks in Bangladesh. Gaining insights into the relationships among profitability, asset quality, capital adequacy, and liquidity can inform efforts to enhance the sector's resilience and ensure a stable financial environment.

The overall objective of this study is to understand the effects of the financial stability indicators on the default risk of listed banks of Bangladesh, either partially or entirely and to provide suggestions to policymakers on ensuring financial stability in the banking sector.

To the best of our knowledge, there exists a research gap in this area. Firstly, while previous studies have explored the relationship between financial stability indicators and the profitability of the banking industry, no research has specifically examined the impact of these ratios on the default risk of banks. Secondly, no studies have differentiated the impact of stability indicators on the default risk between conventional banks and shariah-based banks. No studies have used multiple definitions of default risk to make the relationship between the predictor variables on default risks.

Additionally, this study employs a panel data approach, which has been absent in similar previous research (Anwarul et al., 2012; Rafiq, 2016). It also covers a more extensive time frame, analyzing data from 29 listed conventional and sharia-based banks from 2010 to 2023. This study aims to fill the existing literature gap by determining whether the stability ratios of the banks’ financial conditions have any impact on the default probability of these banks using the Distance to Default (DTD) and Distance from Default (DFD) models. This aspect is notably absent in other studies conducted on the banking sector of Bangladesh.

2. Literature Review

2.1 Predicting Default Probability of Banks

One of the most important metrics for evaluating default risk in banks is the probability of credit default, which gauges the possibility that a borrower will not fulfill their loan commitments. The likelihood of credit default has demonstrated significant patterns in industrialized economies such as the United States. According to a study by Altman and Kishore (1995), regulatory changes, better risk management, and a rebounding economy all contributed to the chance of decline after the 2008 financial crisis. For instance, the probability of a credit default for US investment-grade corporate bonds was roughly 2.5 percent in 2010 and dropped to about 0.5 percent by 2017, indicating a more stable market. Similarly, Japan has seen a decline in the likelihood of credit default, which Ohashi et al. (2004) attribute to a low-interest rate environment and decisive government intervention.

Altman and Saunders (1997), the first seminal paper, contended subjective analysis where various characteristics of borrowers, known as 4 “Cs”, are used to judge the credit granting decisions. With the move towards more objective-based assessment of default risk, credit scoring model and multivariate model like the linear model, logit model, probit model, and the discriminant model were being used. Altman and Saunders (1997) used the logit model, akin to the components of the extant CAMEL model used by bank examiners to assess the strength of banks. They also introduced a separate class of models that impute the implied probabilities of default using the yield spread of term structure of interest rate of corporate risky securities.

Coats & Fant, (1993) and Trippi & Turban (1992) used the neural network approach that identified hidden correlations between predicted variables as additional explanatory variables in predicting the non-linear function of bankruptcy.

The mostly used model of prediction of bankruptcy is the option pricing models that were proposed by Black and Scholes (1973), Merton (1974), and Hull and White (1995). According to the model, the likelihood of a default depends on the initial value of assets relative to its total interest-bearing liabilities and the company's volatility in the value of assets. The model assumes that the equity holders' value is a call option on the company's book value of assets, where the company's debt represents the strike price. The input of these models - specifically the value of assets and the volatility of the value of assets- are easily estimable for publicly traded firms with adequate data on stock return. The option pricing model expresses that defaults occur when the market value of a company's asset falls below its outstanding short-term debt obligations. This model used by Merton (1974) denoted that the model value expresses how many standard deviations asset values (A) are above debt (B) and the percentage of units that went bankrupt in a one-year time with that many standard deviations of asset values above B. He named the value as Distance to Default (DTD). Bharat and Shumway (2008) tested the model accuracy of Merton (1974) and argued that the DTD model can be a good predictor of forecasting bankruptcy.

A recent study by Giordana & Schumacher (2017) conducted a study on the impact of Basel-III standards on a bank's default risk using the Z score as the indicator of default risk where the Z score represents the distance from default (DFD). A higher DFD reflects a lower probability of default and greater financial stability. Sagatbekovich et al. (2021) also used the Z score model to explore the effect of regulatory norms on the performance of the banking industry. They argued that the Z score could be a better measure of DFD than Merton's DTD when market data used in DTD is not suitable for its unavailability or unreliability. They also pointed out that since banks are highly regulated and accounting data is standardized and publicly available, the Z score can be a good measure of default risk.

2.2 Default risk and firm stability studies conducted on the banking industry

Sundararajan et al. (2002) described the indicators of financial soundness, including capital adequacy, asset quality, profitability, and banks' liquidity. Indicators of Financial Soundness (FSIs) are measurements used to evaluate the stability and resilience of markets, financial institutions, and associated corporate and household units. FSIs include aggregated information about financial institutions and indicators of the marketplaces in which they operate.

Using quarterly data from 2005 to 2019, Maulana et al. (2023) examined 80 Indonesian banks, concentrating on variables that affect default probability, such as the Common Equity Tier-1 (CET-1) ratio, the inefficiency ratio, and the deposit ratio. The study uses the copula approach to investigate the impact of macro-financial indicators on default likelihood, including policy rate, real exchange rate, economic growth, and unemployment. The findings show that macroeconomic factors similarly lower default likelihood, but the CET1 ratio, inefficiency ratio, and deposit ratio have a negative impact. The report emphasizes how crucial deposit and capital management practices are in reducing banks' propensity for taking on unnecessary risk.

Nicolas et al. (2021) analyzes European banks' default risk determinants, examining the impact of bank-specific and macroeconomic variables over 2004-2013. Key findings indicate that bank size, profitability, asset quality, liquidity, and macroeconomic conditions significantly influence default risk.

Jabra et al. (2017) focused on institutional variables like statutory liquidity ratio (SLR), macroeconomic variables like GDP, and stability indicators like capital adequacy, asset quality, management quality, earnings, and liquidity. It also analyzed data from 280 European commercial banks between 2000 and 2019. The study divided the data into pre- and during-crisis eras to evaluate the impact of the financial crisis. It looked at the factors that lead to bank default using panel data and the binomial Logit model. The results showed that institutional, macroeconomic, and stability variables all impacted bank default, underscoring the important roles that these variables play in predicting bank default. This thorough approach shed light on the intricate interactions between institutional, macroeconomic, and financial issues that affect bank failure in the European banking system.

Several studies have investigated the relationship between the Capital Adequacy Ratio (CAR) and bank default probability. Sood (2016) examined US bank holding firms during the years 2003–2009 and found that a Tier 1 capital ratio of less than 6 percent was associated with meaningful bank failure. Karugu et al. (2018) studied Kenyan commercial banks and concluded that CAR is a highly consistent indicator of financial difficulty. Fiordelisi and Mare (2013) found that adequate capital lowers the likelihood of default, suggesting that larger capital buffers offer more absorbency for losses. Additionally, Sang (2021) found that the banks' default probability of Vietnamese commercial banks is negatively correlated with CAR. Obadire (2022) analyzed the effect of banking regulation, Basel III, on the stability of African banks. The results demonstrated that, contrary to the general consensus surrounding the Basel III Accord, the minimum capital requirement, CAR, and capital buffer premium had a negligible and negative relationship with the stability of banks in the African context. At the same time, the LCR stood out as having a substantial positive relationship with the stability of the banks.

Buchdadi et al. (2020) discovered that both bad loans and capital adequacy significantly impact the financial distress of rural banks. Meanwhile, Saputra et al. (2020) found that capital adequacy has a positive effect on bank stability in Indonesia, while credit risk and liquidity have a negative effect. Hossain et al. (2017) studied the resilience of banks in the BRICS economies and found that CAR is strong in boosting banks' resilience. Finally, Aroghene (2023) studied Nigerian banks and found a positive but insignificant effect of CAR on bank stability. Another study by Aroghene and Ikeora (2022) yielded similar results, showing an insignificant effect of CAR on bank stability as measured by the z-score.

A study conducted by Ejoh et al. (2014) examined how asset quality and liquidity impact the default risk of Nigerian banks. Their findings revealed a negative correlation between asset quality and liquidity. This suggests that as the credit risk, or the occurrence of bad loans, increases, the bank's loan portfolio (asset) is negatively affected, leading to a rise in bank illiquidity. Furthermore, the likelihood of a bank default is influenced by both asset quality and liquidity risk.

Amollo (2015) studied the relationship between earning quality and profitability of commercial banks in Kenya. The study found that at a 95 percent confidence level, the study discovered that profit rates significantly improve the financial performance of Kenyan commercial banks. It was also discovered that there was a linear link between the profit rates and the profitability of default, with better profitability resulting from higher profit rates.

The relationship between the probability of default and the effectiveness of bank management has been the subject of numerous studies. Cost-effectiveness and problem loans have been linked by Berger and DeYoung (1997), suggesting that banks with higher levels of efficiency had a lower likelihood of experiencing financial difficulties. In a similar vein, Altunbas et al. (2007) found that lower risk and a lower likelihood of default are linked to increased managerial efficiency in European banks. Mester (1996) provided evidence in support of this by highlighting how risk preferences affect management effectiveness and the probability of bank failure. Goddard et al. (2004) discovered that efficient management practices contribute to lower default risk. Fiordelisi and Marques-Ibanez (2013) highlighted the role of management efficiency in mitigating systemic bank default risk, while Wheelock and Wilson (2000) underscored the critical role of management efficiency in reducing the likelihood of default in their study of U.S. bank failures and acquisitions. Finally, Said and Tumin (2011) demonstrated the significance of financial ratios reflecting management efficiency for bank performance and stability in their comparative analysis of banks in Malaysia and China. These studies collectively affirm the significant role of higher management efficiency in lowering the probability of bank defaults and ensuring financial stability.

To the best of authors' knowledge, no study has been conducted on all banks (conventional and shariah) in Bangladesh that examines the impact of Capital adequacy, liquidity, profitability, and asset quality on the distance from default (DFD) and differentiate the results between conventional and shariah-based banks. Therefore, this study has addressed this gap and employed the necessary techniques to obtain the objective of the research. Additionally, the study aims to incorporate measures of the DTD to check the robustness of the hypotheses.

3. Hypothesis

Based on the above literature, the study aims to determine the relationship between DFD and bank stability metrics. Bank stability metrics are identified as the *capital adequacy, liquidity, profitability, and asset quality* of the banks based on the study of Sundararajan et al (2002). The hypotheses are developed based on the study of Podpiera & Ötker (2010). The alternate hypotheses for this study are as follows:

H_1: There is a significant relationship between Capital adequacy and DFD of banks

H_2: There is a significant relationship between Asset quality and DFD of banks

H_3: There is a significant relationship between Liquidity and DFD of banks

H_4: There is a significant relationship between Profitability and DFD of banks

4. Methodology

4.1 Data

In the study, secondary data has been utilized to carry out a panel data analysis to delve into the relationship between bank stability metrics and the DFD of banks. Data on banking attributes and stability indicating information were retrieved from the Dhaka Stock Exchange (DSE) website, published annual reports, and company websites. The DSE had 32 banks listed as of 2023. This study thus only looks at 29 of these institutions for a balanced panel; including other three banks would have disturbed the estimation process parameter and eligibility criteria (Baltagi, 2005). Among them, twenty-two banks were scheduled commercial banks, and seven banks were shariah-compliant banks. The time frame when data are collected was extended from 2010 through July to 2023, excluding the period between 1994 and 2009 because of significant date fragmentation.

4.2 Variables

The study incorporates one dependent variable and four independent variables, including a few control variables. The definition of dependent and independent variables is as follows:

4.2.1 Dependent variable: The study's key dependent variable is Altman's z-score, a gauge of the bank's distance from default (DFD). According to Altman (1968), a higher Z score means a bank has more equity relative to its assets and earnings volatility, reflecting a better distance from default. A lower Z score thus means a proximity to default. Bandyopadhyay (2005), Giordana & Schumacher (2017) and Kaliyev & Nurmakhanova (2020) use the following estimation for the z-score:

$$\text{Z-score} = \frac{\left(\frac{Equity}{Total\ assets}\right)+ROA}{sd(ROA)}$$

Whereas Return on Assets (ROA) is determined by dividing net profit after taxes by the entire amount of assets. The standard deviation of return on assets serves as the equation's denominator. Equity serves as a safety net against financial loss. The bank's ability to make a profit on its whole asset base is shown by its Return on Assets (ROA). According to the equation, banks with higher profitability and equity-to-asset ratios will have higher z scores, eventually showing that they are more resilient and have a lower default risk.

Merton (1974) formulated the Distance to Default (DTD) formula that measures how far the firm's assets is away from the threshold default value of debt in terms of standard deviations. The formula was also tested for the robustness of the hypotheses. The formula can be written as follows:

$$\text{DTD}=\frac{ln(MVE)+[E\ (ROA)-Var\frac{(A)}{2}]}{Std\ (A)}$$

Whereas MVE is the market value of equity calculated by deducting the market value of assets from the company's total debt. E(ROA) is the expected average return on assets. Var (A) is the variance of assets of the company over the sample period. Std (A) is the standard deviation of assets of the company over the sample period.

4.2.2 Independent variables: *Capital Adequacy* is the first factor. The term "capital adequacy" describes the level of capital that is anticipated to be maintained in proportion to the risks to protect the financial institution's debt holders and absorb any potential losses. Following the papers of Altan et al. (2014), Wanke et al. (2016), and Karim et al. (2018), the Capital Adequacy Ratio has been employed as a proxy variable for the analysis.

The second factor to consider is the bank's asset quality. The quality of an asset is determined by whether it is uncollectable or whether its true value is less than what the bank reports on its balance sheet. In line with the research of Sahut and Mili (2011), Altan et al. (2014), Lahrech et al. (2014), and Alqahtani et al. (2017), NPLs to Equity were used for the study.

Return on equity (ROE) has been used to measure profitability, according to the works of Wanke et al. (2016), Alqahtani et al. (2017), and Karim et al. (2018).

Liquidity is the last thing to be tested. LCR is used to determine liquidity in accordance with the Basel-III requirements and assess a bank’s ability to meet its short-term obligations. It estimates the ratio of a bank's highly liquid asset holdings to its anticipated net cash withdrawals over a given time frame, usually 30 days.

Three control variables were included in the analysis. The age of the bank's history from its founding was the first control variable following the study of Berger et al. (2012). A dummy variable that represented COVID-19 was also employed as a control variable because of theorized connections between it and the bank's performance (Imran, 2023). Finally, GDP, a macroeconomic component, was also incorporated into the analysis as a control variable.

Table 1: Operational Definition of Variables

Measures	Operational Variables	Concepts	Formula	Expected sign	References
Dependent	Z score	Distance from Default (DFD)	[(Equity/Assets)]/sd(ROA)		(Kaliyev & Nurmakhanova, 2020)
Independent variables	Capital Adequacy (CA)	Capital Adequacy Ratio (CRAR)	Total Regulatory Capital/ Risk weighted Asset	(+)	Altan et al., (2014); Wanke et al., (2016) and Karim et al., (2018)
	Asset Quality (AQ)	NPLs to Total Equity (NPLE)	NPLs/Total Equity	(-)	Sahut and Mili (2011); Altan et al., (2014); Lahrech et al., (2014) and Alqahtani et al., (2017)
	Profitability (P)	Return on Assets (ROE)	Net Profit/Total Equity	(+)	Wanke et al., (2016); Alqahtani et al. (2017) and Karim et al., (2018)
	Liquidity (L)	Liquidity Coverage Ratio (LCR)	(High-Quality Liquid Assets)/(Net Cash Outflows)	(+)	(Amara & Mabrouki 2019)
Control variable	COVID	Binary variable having 1 for COVID years otherwise 0 (COVID)		(-)	Elnahass et al. (2021)
	AGE	Years of operation since its inception (AGE)		(+)	DeYoung & Hasan (1998)
	GDP	GDP Growth Rate of Respective Year (GDPGR)		(+/-)	Demirguc et al (1998)

4.3 Model of the Study

To develop the baseline model of the study, the study followed the methodology of Sundararajan et al (2002) and Podpiera & Ötker (2010). Accordingly, the model equation of the study is:

$$\text{Z-score}_{it} = \alpha + \sum_{j=1}^{4} Bj\ Stability\ Indicators_{ijt} + \sum_{k=1}^{3} \delta_k Control_{ikt} + \epsilon_{it}$$

Where;

Z-score$_{it}$ is the Z-score of bank i at time t, representing the distance from default, α is the intercept, βj are the coefficients for the Stability Indicators parameters, δ_k are the coefficients for the control variables, Stability Indicators $_{ijt}$ represents the four parameters: CA, AQ, P, L for bank i at time t. Control$_{ikt}$ represents the three control variables for bank i at time t: CV1$_{it}$, CV2$_{it}$, and CV3$_{it}$ (GDP growth, age, COVID 19), ϵ_{it} is the error term for bank i at time t.

5. Empirical Results

5.1 Descriptive Statistics

The dataset comprises 406 observations from 29 scheduled banks in Bangladesh. Table-2 shows the mean, standard deviation, minimum and maximum values as part of the descriptive statistics. The analysis of descriptive analysis gives us the guidelines for testing the dataset against the assumptions of normal distributions and getting the optimum regression model.

Table 2: Descriptive Statistics

Variable	Observation	Mean	Std. Dev.	Min	Max
CRAR	406	0.13	0.02	0.03	0.19
LCR	406	1.68	1.18	0.42	1.90
NPLE	406	0.56	0.69	0.03	7.37
ROE	406	0.11	0.08	-0.78	0.36
AGE	406	24	8.53	9.00	47.00
GDPGR	406	0.06	0.01	0.03	0.08
COVID	406	0.14	0.35	0.00	1.00
DFD (z score)	406	18.20	8.64	0.64	48.40
Merton’s DTD	406	23.61	0.84	20.61	26.90

Source: Author’s calculation

Table-2 shows that the banks overall have a Z-score (average of 18.2 and SD = 8.64), indicating a lower probability of default and a greater distance to default in the banking industry. The non-performing loan ratio (mean of 0.56, SD of 0.69) ranged considerably in terms of problems with asset quality. The financial profitability of lending activities is steady with a net interest margin. The liquidity of the banking sector, with an average liquidity coverage ratio of 168 percent, shows a stable 30-day safety margin for the banks in difficult times. The average bank age was 23 years with a mix of mature and somewhat newer banks. CRAR suggests sufficient capital buffers with a mean of 13 percent. Finally, 75 percent of banks are conventional, and the rest of the banks are shariah-based.

5.2 Diagnostic Test

The study conducted several tests and ultimately determined that the most appropriate model was being used in order to satisfy the assumptions of the underlying panel data analysis.

Normality test: The study included the Shapiro-Wilk Test for Normality to determine whether the selected variables had a normal distribution. P-value, which is less than 5 percent, shows that the test results show that none of the study's variables have a normal distribution. However, the study uses appropriate model which is robust to violations of normality assumptions.

Table 3: Shapiro Wilk Normality Test

Variable	Observation	z	Prob>z
DFD (zscore)	406	4.45	0.000
DTD	406	6.55	0.000
NPLE	406	11.93	0.000
CRAR	406	4.54	0.000
LCR	406	11.43	0.000
ROE	406	10.72	0.000
AGE	406	5.44	0.000
COVID	406	4.75	0.000
GDPGR	406	9.08	0.000

Multicollinearity Test: Since none of the explanatory variables have a correlation coefficient higher than 0.80, the Pearson Correlation Coefficient finding clearly shows that none exhibit multicollinearity problems. The Variance Inflation Factor (VIF) was another tool utilized in the study to verify multicollinearity. The test indicates that the mean VIF is 1.41. Its value of less than 10 suggests that multicollinearity is not present.

Table 4: Pearson Correlation Matrix

VAR_COVAR	CRAR	LCR	NPLE	ROA	GDPGR	AGE	COVID
CRAR	1						
LCR	-0.0713	1					
NPLE	-0.4111	0.1538	1				
ROA	0.1698	-0.0011	-0.4916	1			
GDPGR	0.0343	-0.076	0.0635	-0.0445	1		
AGE	0.096	0.1898	0.2687	-0.2477	0.0426	1	
COVID	0.2635	0.0928	0.0459	-0.0713	-0.4794	0.1928	1

Table 5: Variance Inflation Factor (VIF) Test

Variable	VIF	1/VIF
NPLE	1.72	0.581341
COVID	1.59	0.629622
CRAR	1.47	0.680215
GDPGR	1.42	0.70233
ROA	1.36	0.73321
AGE	1.22	0.817985
LCR	1.08	0.930129
Mean VIF	1.41	

Heteroskedasticity Test: Utilizing the Breusch-Pagan/Cook-Weisberg test, the study verified the heteroskedasticity. The Chi-square value is 28.78.13 and p-value is close to 0.000. Therefore, the data exhibits the presence of heteroskedasticity.

Table 6: Breusch-Pagan/Cook-Weisberg Test for Heteroskedasticity

Model	chi2	Prob>chi2	Presence of Heteroscedasticity
DFD	28.78	0.0000	Yes

Autocorrelation Test: The Wooldridge test has been performed to check autocorrelation for this model. The F-value is 0.437, and the p-value is 0.52. Considering a 10 percent significance level, the test suggests that there is no first-order autocorrelation in the dataset.

Table 7: Wooldridge Test for Autocorrelation in Panel Data

Model	F value	Prob>F	Presence of Autocorrelation
DFD	0.437	0.5203	No first order autocorrelation

Cross-sectional Dependency: The study performed Friedman's methods to check the cross-sectional dependence among the panel data set. The Friedman's Value is 11.708, and P-value is 0.55 which suggests no presence of cross-sectional dependence at 5 percent significance level.

Table 8: Pesaran's Test of Cross-Sectional Independence

Model	Friedman's Value	P-Value	Presence of Cross-Sectional Dependence
DFD	11.708	0.5517	No

Hausman Test: The study explored the Hausman test while deciding between the Fixed Effects Model and the Random Effect Model. Based on the Hausman test, where the P-value is close to 0.000, the study used the Random Effect Model.

Table 9: Hausman Test

Model	chi^2	Prob > chi^2	Decision
DFD	74.86	0.000	Random Effect Model (RE)

Since the data exhibits heteroskedasticity but no first-order autocorrelation and cross-sectional dependence, the Random Effects (RE) model can be an effective decision. Additionally, the Hausman test confirmed that RE is preferable to Fixed Effects (FE), suggesting that individual-specific effects are uncorrelated with explanatory variables. Since heterogeneity was present, RE accommodates variation across banks while allowing for generalizable insights into the banking sector's default risk.

5.3 Baseline Model and Sub-Sample Analysis: Conventional vs. Shariah Banks

The study conducted the baseline model, whereby all the listed banks were regressed against the DFD (z score). Sub-sample analysis helps to identify potential heterogeneity in regression and the overall generalization of the results (Angrist & Pischke, 2009). Gujarati and Porter (2009) expressed that sub-sample analysis helps detect patterns and biases hidden in the full sample to check the external validity of the dataset. To check for the robustness of the study and whether the result of baseline regression holds among the conventional and shariah-based banks, the study also covers the result of the two sub-sample models.

Table 10: Result of Baseline and Sub-Sample Models

	Model 1: All Banks	**Model 2: Conventional Banks**	**Model 3: Shariah-based Banks**
Variables	**Coef**	**Coef.**	**Coef.**
CRAR	55.14*** (12.71)	63.77*** (15.14)	85.27*** (24.84)
NPLE	-2.52*** (0.54)	-0.87 (0.60)	-5.81*** (1.62)
ROE	5.06** (2.51)	7.35*** (2.16)	25.47*** (7.98)
LCR	-0.12 (0.25)	0.05 (0.32)	-1.40*** (0.38)
Control Variables			
Age	-0.09 (0.33)	-0.84*** (0.14)	-0.51*** (0.18)
GDP	-1744.65* (980.76)	-28.96 (25.54)	-4.38 (33.19)
COVID	15.86 (10.18)	0.03 (1.24)	-0.29 (1.37)
Constant	20.50*** (5.70)	33.76*** (6.32)	27.95*** (6.45)
Firm Effect	YES	YES	YES
Year Effect	YES	YES	YES
Overall R-Square	88.01%	88.79%	92.78%
Prob>Chi2	0.00	0.00	0.00
Total Observation	406	308	98

Source: Author's Analysis Using STATA (Version 14.2)
Note: Here *** Means Significant at 1% Level; ** Means Significant at 5% level; *Means Significant at 10% Level; Values in () are Standard Errors

From Table-10, it was found that for all banks, higher Capital Adequacy (CA) was associated with a higher DFD (Z score), as indicated by a positive and significant coefficient of CRAR. Asset Quality (AQ) exhibits a significant negative relationship with the Z score, indicating that higher NPLE increases default risk by reducing the distance from default. The Profitability (P) of the banks, as expressed by ROE, has a significant positive impact on the Z score, implying that higher profitability decreases default risk. Liquidity (L) of the banks, as expressed by LCR, is found to have an insignificant relationship with the Z score. The study also revealed a negative coefficient for the age of banks, indicating that newer banks have lower default risk, whereas older banks are prone to high default risk, as evidenced by lower DFD.

For conventional banks, CRAR maintains a positive and significant relationship with the Z score, reinforcing that higher CAR lowers default risk. NPLE remains insignificantly negative, indicating increased default risk with higher NPLE. The profitability of the commercial banks has a significant positive impact on the Z score, implying that higher profitability decreases default risk. Age continues to show significant effects, with older banks having higher default risk and higher market valuation reducing default risk.

In the case of Shariah-based banks, the study found a positive and highly significant relationship between default risk and both CAR and ROE, along with the age of banks having a negative and highly significant impact on default risk. The result also reinforces a negative relationship between distance from default and LCR and NPLE.

Moreover, the model displayed high explanatory power, with R-squared values of 88.01 percent for all banks, 88.79 percent for conventional banks, and 92.78 percent for Shariah-based banks. Overall, shariah-based banks are more sensitive to asset quality and profitability, where changes in these factors have a heightened effect on default risk. Conventional banks tend to be more sensitive to capital adequacy suggesting that capital adequacy management is critical for these banks' default risk.

5.4 Endogeneity Tests

Regression analysis can lead to inconsistent estimation of coefficients if endogeneity is present in the dataset. Three primary sources of endogeneity- omitted variable bias, measurement error, and reverse causality- can be a critical concern (Gujarati & Porter, 2009; Angrist & Pischke, 2009). To show that the result of the study holds water in the issue of endogeneity, an omitted variable bias test and measurement error test have been conducted.

5.4.1 Omitted Variable Bias Test

According to Wooldridge (2010), when a relevant variable that has a significant influence on the dependent variable is left out of the model, it can cause biased coefficients capturing the effect of the missing variables. In the banking literature, Norden and Weber (2010) argued that excessive credit growth may lower the lending quality, thereby heightening default risk. Conversely, Laeven and Levine (2009) postulated that well-managed asset growth can reduce default risk by invoking economies of scale. According to Lipton and Lorsch (1992), a larger board size may cause incoordination and diluted accountability potentially elevating higher default risk. Following these arguments, the study included asset growth and board size as omitted variables to test the baseline model.

Table 11: Result of Baseline and Omitted Variable Bias based Models

VARIABLES	(1)	(2)	(3)	(4)
	Baseline	**Asset Growth**	**Board Size**	**Combined**
CRAR	55.14***	69.52***	69.97***	69.58***
	(12.707)	(4.537)	(4.581)	(4.538)
NPLE	-2.52***	-0.598	-0.657	-0.647*
	(0.543)	(-1.351)	(-1.474)	(-1.447)
ROE	5.06**	1.295	1.411	1.287
	(2.514)	(0.485)	(0.534)	(0.482)
LCR	-0.13	-0.184	-0.199	-0.199
	(0.250)	(-0.713)	(-0.770)	(-0.768)
COVID	15.86	-9.502**	-9.155**	-9.301**
	(10.184)	(-2.055)	(-1.985)	(-2.007)
AGE	-0.09	-0.0832	-0.104	-0.0932
	(0.334)	(-0.238)	(-0.298)	(-0.266)
GDPGR	-1744.65*	-64.55	-66.57	-64.89
	(980.75)	(-0.730)	(-0.754)	(-0.733)
ASSETGROWTH		-0.813		-1.088
		(-0.277)		(-0.368)
BSIZE			0.0726	0.0766
			(0.776)	(0.813)
CONSTANT	119.63***	23.37*	22.45*	22.18*
	(45.844)	(1.901)	(1.818)	(1.790)

VARIABLES	(1) Baseline	(2) Asset Growth	(3) Board Size	(4) Combined
Observations	406	406	406	406
Firm RE	Yes	Yes	Yes	Yes
Firm Cluster	No	No	No	No
seasonal adjustment	No	No	No	No
R2 within	0.868	0.860	0.860	0.860
R2 overall	0.880	0.872	0.872	0.872
Wald chi2	2626.73	2433	2437	2431
Prob > chi2	0.00	0.00	0.00	0.00
z-statistics in parentheses and *** p<0.01, ** p<0.05, * p<0.1				

Source: Author's analysis using STATA

From Table-11, it can be observed that the inclusion of asset growth and board size in the baseline model has a notable shift in the significance and directional impact of financial stability metrics (CRAR, NPLE, ROE, and LCR). For CRAR, the positive and significant relationship observed in the baseline model becomes even stronger when asset growth and board size are included, with the combined model maintaining this upward trend. For Asset quality (NPLE), the negative and significant impact in the baseline model loses its impact in terms of lower coefficient value, though the directional relationship holds. Regarding profitability (ROE), its positive and moderately significant association in the baseline becomes insignificant across the asset growth, board size, and combined models. It suggests that the baseline relationship may have been partially driven by these omitted factors. Finally, liquidity (LCR) remains statistically insignificant across all models, suggesting neither of these two omitted factors affects its relationship within the model framework. Overall, the result shows that even after accounting for these two omitted variables, the result of the baseline model still holds its significance and direction arguing that the model does not suffer from endogeneity up to a level.

5.4.2 Measurement Error Test

Where the explanatory variables are measured inaccurately or the variables are defined inaccurately, it will lead to measurement error and can cause the coefficients to be biased (Angrist & Pischke, 2009). This measurement error is a common source of endogeneity in regression analysis. To tackle this problem, alternative definitions of the stability indicators are used in the study.

The alternate predictor variables used to test measurement error are given in Table-12.

Table 12: Operational Definition of Alternate Variables

Name of Predictor	Baseline Variable Used	Alternate Variable Used	Measurement of Alternate Variable	References
Capital Adequacy (CA)	Capital to Risk-Weighted Assets Ratio (CRAR)	Equity to Total Assets (ETA)	Total Equity / Total Assets	Berger & Bouwman (2013)
Asset Quality (AQ)	Non-Performing Loans to Equity (NPL/Equity)	Non-Performing Loans to Total Loans (NPLL)	Non-Performing Loans / Total Loans	Ghosh (2015); Louzis et al. (2012)
Profitability (P)	Return on Equity (ROE)	Net Interest Over Equity (INOE)	(Interest Income - Interest Expense) / Average Equity	Demirgüç-Kunt & Huizinga (2010); Imran (2023)
Liquidity (L)	Liquidity Coverage Ratio (LCR)	Loan to Deposit Ratio (LTD)	Total Loans / Total Deposits	Altan et al. (2014); Vodová (2011).

To determine whether the outcome of the baseline predictor factors also aligns with alternate variables, the study performs a panel regression for each of these alternate variables. The results are shown in Table-13.

Table 13: Result of Alternate Variables based Models

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	ETA	**NPLL**	**INOE**	**LTD**	**Combined**
ETA	1.078				0.847
	(0.397)				(0.313)
NPLE	-0.433		0.624	0.615	
	(-1.115)		(1.471)	(1.403)	
ROE	0.222	-2.429		-1.138	
	(0.0822)	(-0.953)		(-0.433)	
LCR	-0.127	-0.159	-0.0495		
	(-0.480)	(-0.615)	(-0.183)		
CRAR		59.57***	67.55***	69.14***	
		(4.526)	(4.471)	(4.555)	
NPLL		-0.884			-0.338

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
	ETA	NPLL	INOE	LTD	Combined
		(-0.476)			(-0.177)
INOE			-1.510		-1.666*
			(-1.557)		(-1.763)
LTD				-0.674**	-0.698**
				(-1.962)	(-1.964)
COVID	12.32	18.25*	19.21*	18.79*	13.30
	(1.145)	(1.730)	(1.831)	(1.785)	(1.252)
AGE	-0.0884	-0.0848	-0.0908	-0.0937	-0.0703
	(-0.247)	(-0.243)	(-0.262)	(-0.271)	(-0.198)
GDPGR	-1,373	-1,980*	-2,075**	-2,045**	-1,481
	(-1.328)	(-1.949)	(-2.055)	(-2.019)	(-1.450)
Constant	103.2**	131.0***	135.2***	133.8***	109.1**
	(2.132)	(2.760)	(2.871)	(2.827)	(2.290)
Observations	406	406	406	406	406
Number of groups	29	29	29	29	29
Firm Effect	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes
R2 within	0.392	0.423	0.429	0.431	0.401
R2 overall	0.864	0.871	0.872	0.873	0.866
Wald chi2	2286	2426	2456	2465	2323
Prob > chi2	0.00	0.00	0.00	0.00	0.00
z-statistics in parentheses & *** p<0.01, ** p<0.05, * p<0.1					

Source: Author's analysis using STATA

From Table-13, it can be seen that key variables, namely CRAR, NPLE, ROE, and LCR, exhibit significant changes in their significance and directional impact when alternative variable definitions are incorporated into the baseline model. With coefficients of 59.57 in the NPLL model, 67.55 in the INOE model, and 69.14 in the LTD model, the CRAR variable continually shows a substantial positive association with DFD and is still highly significant and positive across all models in which it is included. This implies that Capital Adequacy (CA) has a positive impact on default risk regardless of model specifications.

For Asset Quality (AQ), NPLE in the baseline model has a significant negative effect, which diminishes as it becomes statistically insignificant across the alternate models: the ETA model and the combined model. However, the directional impact holds across all the significant models, implying that Asset Quality (AQ) has a negative impact on default risk regardless of model specifications.

Regarding Profitability (P), ROE loses its significance when replaced by INOE, though not consistently significant. Interestingly, INOE itself approaches significance in the combined model, suggesting a potential negative relationship. This makes the predictor less robust in terms of model selection.

In terms of Liquidity (L), though insignificant, LCR remains negatively related to default risk across all models, showing minimal sensitivity to alternate liquidity definitions. However, when LTD is taken, it becomes significantly negative in the LTD model and in the combined model, highlighting a stronger inverse relationship with default risk than observed with LCR. This indicates that LTD may better capture liquidity-related risks compared to LCR.

Overall, these results suggest that Capital Adequacy (CA), Asset Quality (AQ) and Liquidity (L) measures are well defined and their directional impact hold along with different alternative models. However, profitability measures are not significant across different models.

5.5 Robustness Check

The robustness test checks whether the baseline regression model remains stable and reliable under different model specifications and data conditions. Leamer (1983) expressed that for a model to be robust its coefficient values must remain consistent when alternate definitions of dependent variables are taken. It will test the reliability of the model, thereby minimizing the risk of specification bias. Huber (1981) addresses outliers can influence the coefficient estimates and introduces a process called winsorizing to limit the extreme values in the dataset. According to Huber (1981), if regression results remain stable after winsorizing the data, it will indicate a robust generalizable underlying pattern in the baseline regression. For this study, we have conducted the baseline regression analysis by introducing an alternate definition of default risk called Merton's (1974) Distance to Default (DTD) and after performing winsorizing at 1 percent level on the dataset.

5.5.1 Distance to Default (DTD) and Model Specification

DTD was calculated using the methodology of Merton (1974). The DTD is a similar index like DFD that captures default risk. DFD measures how far a bank is from reaching the point of default. The study conducted the same panel methodology and used random effect model to interpret the impact of financial stability proxies on the DTD. The findings are shown in Table-14.

Table 14: Result of DTD and Baseline (DFD) Models

VARIABLES	(1) DTD	(2) Baseline (DFD)
CRAR	3.942*	55.14***
	(1.777)	(12.71)
NPLE	-0.176*	-2.52***
	(-1.960)	(0.54)
ROE	5.694***	5.06**
	(10.48)	(2.51)
LCR	0.128***	-0.12
	(2.984)	(0.25)
COVID	-1.693	15.86
	(-1.172)	(10.18)
AGE	-0.0314	-0.09
	(-0.663)	(0.33)
GDPGR	171.8	-1744.65*
	(1.234)	(980.76)
CONSTANT	14.95**	137.4***
	(2.292)	(2.886)
Observations	406	406
Number of Code	29	29
Firm RE Effect	Yes	Yes
Year effect	Yes	Yes
R^2 within	0.500	0.426
R^2 overall	0.746	0.872
Wald chi^2	1054	2439
Prob > chi^2	0	0
z-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1		

Source: Author's Analysis using STATA

From Table-14, it can be interpreted that when comparing the DTD model with the Baseline model using DFD, CRAR shows a strong positive and highly significant relationship with default risk (55.14, $p<0.01$), indicating that higher capital adequacy reduces default risk for both DFD and baseline model though the magnitude of coefficient has gone down. For NPLE, both DFD and DTD models indicate a negative relationship with default risk, reflecting that a low asset quality increases default risk. For ROA, a highly significant and positive association with default risk can be found in the DTD model, showing a stronger effect than in the baseline model. For LCR, the DTD model shows a significant positive relationship, while it is insignificant and negative in the baseline model.

5.5.2 Winsorizing and Model Specification

Winsorizing is the process of eliminating the extreme values in the coefficients of the baseline regression model. For the study, winsorizing has been done on the four financial stability indicators on 1 percent level on both end of the dataset. The result of the winsorized model is given in Table-15.

Table 15: Result of Winsorized and Baseline Models

VARIABLES	**(1) Winsorized (DFD)**	**(2) Baseline (DFD)**
CRAR1	43.09***	55.14***
	(2.79)	(12.71)
NPLE1	-1.878***	-2.52***
	(-2.86)	(0.54)
ROE1	4.29	5.06**
	(1.180)	(2.51)
LCR1	-0.0332	-0.12
	(-0.109)	(0.25)
COVID	-6.154	15.86
	(-1.338)	(10.18)
AGE	-0.144	-0.09
	(-0.417)	(0.33)
GDPGR	-82.46	-1744.65*
	(-0.945)	(980.76)
CONSTANT	27.66**	137.4***
	(2.274)	(2.886)
Observations	406	406
Number of groups	29	29
Firm Effect	Yes	Yes
Year Effect	Yes	Yes
R^2 within	0.438	0.426
R^2 overall	0.874	0.872

VARIABLES	(1) Winsorized (DFD)	(2) Baseline (DFD)
Wald chi^2	2505	2439
Prob > chi^2	0.00	0.00
z-statistics in parentheses & *** p<0.01, ** p<0.05, * p<0.1		

Source: Author's Analysis Using STATA

From Table-15, CRAR remains positively significant in both models, but its magnitude decreases slightly in the winsorized model. For NPLE, both models show a significant negative relationship with default risk reflecting that lower asset quality in terms of higher non-performing loans increase default risk. For ROE, though the positive sign persists, it is significant in the baseline model, it becomes insignificant in the winsorized model. Lastly, LCR remains insignificant in both models.

6. Findings and Discussion

The study presents the model's findings in this section and discusses each of the variables in great detail. According to Table-16, the result of each of the variables is discussed below:

Table 16: Variable-wise summary findings of the study

Stability Indicators of Banks	Variables	Expected Sign with Default Risk	Merton's DTD Model	Altman's DFD Model
			Actual Sign	Actual Sign
Capital Adequacy (CA)	CAR	+	(+)*	(+)***
Asset Quality (AQ)	NPLE	-	(-)*	(-)***
Profitability (P)	ROE	+	(+)***	(+)**
Liquidity (L)	LCR	+	(+)***	(-)

Source: Author's Analysis
Note: Comprises the sign of the variables with the dependent variables; *** means significant at 1% level; ** means significant at 5% level; *Means significant at 10% level; Underline represents a match with expected sign

Capital Adequacy (CA)

CAR was taken as the proxy for capital adequacy. It was found that a positive and significant relationship across all the models tested indicating that a higher capital adequacy ratios are associated with a higher Z-scores (DFD) and DTD and a greater stability. It implies that well capitalized banks tend to be more resilient to financial distress.

Asset Quality (AQ)

Non-performing Loan to Equity (NPLE) was taken as a proxy for measuring asset quality where negative association between NPLE and default risk is expected. The negative and significant relationship for both Z score (DFD) and DTD found in our study that aligns with the expectation. It indicates that poor asset quality is associated lower Z score and thereby a higher default risk.

Profitability (P)

In the study, profitability, as measured by ROE, is found to have a significant positive relationship with default risk for both DTD and DFD model as expected. However, for winsorizing model and after endogeneity test, the profitability significance does not hold much though the positive relationship holds across the models. Conventional and shariah-based banks also show a positive and significant relationship as expected.

Liquidity (L)

Table-16 indicates that LCR, a proxy for bank liquidity, has a positive correlation with some models and a negative correlation with others. However, this association was negligible across all models, indicating that the influence of liquidity as a measure of financial stability on default risk is not that substantial. However, when LTD is taken, it becomes significantly negative in the LTD model and in the combined model highlighting a stronger inverse relationship with default risk than observed with LCR. This indicates that LTD may better capture liquidity-related risks compared to LCR.

7. Conclusion and Limitation

Default risk in the banking industry has been an unprecedented event in the last decades. To determine which factors influence the default probability most, financial stability indicators can be tested to understand the dynamics. To exercise that theory, this study incorporates a sample of 29 banks from 2010 to 2023 with 406 observations to analyze the predictive power of capital adequacy, asset quality, liquidity and profitability on the default probability listed banks. The study exhumes that Capital Adequacy (CA), Asset Quality (AQ) and Profitability (P) are consistently significant across all models, highlighting their crucial role in determining default risk. CAR's positive association, ROE's positive association, and NPLE's negative association with Altman's Z-score and Merton's DTD having an exact sign match with expected theory assigns that regulatory body should peruse over these ratios to understand the overall financial stability of the banks. The study also unwraps that shariah-based banks are more sensitive to asset quality and profitability where changes in these factors have a heightened effect on default risk, but conventional banks tend to be more sensitive to capital adequacy, suggesting that capital adequacy management is critical for these banks' default risk.

Finally, the study has several limitations that future research should address. The dataset covers only 2010-2023, potentially missing long-term trends. Future studies should extend the dataset, include the Sensitivity component, or conduct a comparative analysis with other countries can reveal potential variations and inform policy adjustments where necessary.

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Appendix

Appendix 1: List of Conventional Banks and Shariah based Banks

No.	Name of the Conventional Banks	No.	Name of the Shariah-based Banks
1	AB Bank PLC.	1	Al-Arafah Islami Bank PLC.
2	Bank Asia PLC.	2	Exim Bank PLC.
3	BRAC Bank PLC.	3	First Security Islami Bank PLC.
4	Dhaka Bank PLC.	4	Islami Bank Bangladesh PLC.
5	Dutch-Bangla Bank PLC.	5	Shahjalal Islami Bank PLC.
6	Eastern Bank PLC.	6	Social Islami Bank PLC.
7	IFIC Bank PLC.	7	Standard Bank PLC.
8	Jamuna Bank PLC.		
9	Mercantile Bank PLC.		
10	Mutual Trust Bank PLC.		
11	NCC Bank PLC.		
12	National Bank PLC.		
13	ONE Bank PLC.		
14	The City Bank PLC.		
15	The Premier Bank PLC.		
16	Prime Bank PLC.		
17	Pubali Bank PLC.		
18	Rupali Bank PLC.		
19	Southeast Bank PLC.		
20	Trust Bank PLC.		
21	United Commercial Bank PLC.		
22	Uttara Bank PLC.		