***Pakistan Economic Review***
*7:1 (Summer 2024), PP. 22-53*

# Bank-specific and Macroeconomic Determinants of Distance-to-Default: Evidence from listed Banks of Pakistan

Saifullah Khan[1], Ahmad Fraz[2], Waqar Khalid[3]*, Anum Zahra[4]

## Abstract

This study examines the efficacy of the distance-to-default (DTD) measure alongside its key bank-specific and macroeconomic predictors for 20 Pakistani commercial banks, analyzing panel data spanning 2009 to 2018. The results of the study identify significant factors affecting DTD which include bank size, market risk premium, non-performing assets, regulatory capital, management efficiency, and the indexes of liquidity, leverage, turnover, and profitability. Conversely, Tier-1 and Tier-2 capital, exchange rates, and the industrial production index do not show significant impact. These insights validate the effectiveness of market-based models in default risk prediction and underline the importance of incorporating both financial and macroeconomic variables in precise risk evaluations. The findings advocate for risk assessment teams to focus on these key determinants to mitigate default risks and recommend that the central bank might consider increasing policy rates to boost investment and further mitigate these risks.

**Keywords*:*** Distance-to-default; Default risk; Bank-specific determinants; Macroeconomic characteristics; Banks; Financial crisis.

**JEL Classification*:*** C23, C51, G21, G32

[1] Department of Business Studies, Pakistan Institute of Development Economics, Islamabad, Pakistan. Email: saifullah014@gmail.com
[2] Department of Business Studies, Pakistan Institute of Development Economics, Islamabad, Pakistan. Email: ahmad.fraz@pide.org.pk
[3] U.S.-Pakistan Center for Advanced Studies in Energy (USPCAS-E), National University of Sciences and Technology (NUST), Sector H-12, Islamabad 44000, Pakistan. Email: waqar.khalid@uspcase.nust.edu.pk
ORCID: https://orcid.org/0000-0002-5275-6665
*Corresponding author
[4] Faculty of Business & Law, Taylor's University, Malaysia. Email: anum.zahra@sd.taylors.edu.my

# 1. Introduction

Financial institutions, despite their critical role in the global economy, are frequently studied using standard default prediction models. These models, widely applied across various industries, provide a foundational framework for assessing default risk. However, they often fail to address the unique regulatory challenges and complex debt structures that characterize financial institutions (Schenck, 2014). While standard models are still widely utilized, their limitations underscore the need for more advanced approaches, such as the Distance-to-Default (DTD) model. The DTD model builds on foundational theories, including Black and Scholes' Option Pricing Model (1973) and Merton's Structural Model (1974), to offer a more nuanced and accurate assessment of default risk. These advanced models are essential for predicting the types of default risks that can lead to significant financial disruptions.

Financial institutions face a variety of risks, with default risk being particularly critical due to the far-reaching implications of bank failures. Several studies have identified early warning indicators of financial distress in banks, emphasizing the importance of effective risk detection mechanisms (Muvingi et al., 2015; Rashid & Abbas, 2011; Schenck, 2014). Coccorese and Santucci (2019) argue that maintaining asset values above liabilities is vital for a bank's solvency, noting that insufficient liquidity significantly increases the risk of default during economic crises. In today's highly interconnected and uncertain market environment, robust and effective risk management is increasingly challenging yet remains essential for maintaining financial stability.

Furthermore, financial institutions encounter a range of challenges, including globalization, heightened competition, economic liberalization, financial inclusion, and rapid innovation (Zahra, 2016). These factors have significantly increased the risk exposure for banks. Studying bank default risk is vital for credit risk managers, regulators, and investors to develop effective mitigation strategies. Default risk is commonly assessed using three main approaches: accounting-based, market-based, and external credit rating methods (Allen & Powell, 2011). Accounting-based techniques, such as the Altman Z-Score, Non-Performing Loans Ratio (NPL), and Ohlson O-Score, rely on financial statement data. In contrast, market-based methods, including Merton's Distance-to-Default (DTD) model, Value at Risk (VaR), and CreditMetrics™, utilize market data.

This study applies Merton's (1974) DTD model to measure the default risk of 20 Pakistani commercial banks using panel data spanning 2009 to 2018. The DTD model is a widely recognized method for assessing a bank's likelihood of default by calculating its proximity to financial insolvency (Duan & Wang, 2012). Market-based approaches offer distinct advantages, particularly when markets are efficient. Stock prices, which are updated at high frequency, reflect investors' expectations and provide real-time insights into default risk (Khan, 2021; Schenck, 2014). Moreover, these methods circumvent data confidentiality concerns (Zahra, 2016) and enhance the reliability of risk estimates by integrating both historical data and actual investor sentiments (Schenck, 2014; Khan, 2021) [5].

Schenck (2014) identified several bank-specific variables as significant determinants of Distance-to-Default (DTD), including total assets, net interest margin, operating efficiency, Tier-2 capital, and the non-performing assets ratio. Similarly, Rashid and Abbas (2011) highlighted the importance of metrics like earnings before interest and taxes (EBIT), the sales-to-total-assets ratio, and the cash flow ratio in predicting bankruptcy. Hu and Sathye (2015) emphasized gross profit ratio, current assets, and debt-to-total-assets ratio as critical factors influencing DTD, while Waqas and Md-Rus (2019) pointed to financial ratios such as income-to-total-assets, EBIT-to-total-assets, and working capital-to-total-assets as key indicators.

In addition to bank-specific factors, macroeconomic conditions play a crucial role in determining default risk. For instance, fluctuations in interest rates significantly affect bank lending and deposit activities, with a notable correlation to default risk (Gunji & Yuan, 2017; Andrei, 2017; Louzis et al., 2012). Exchange rate volatility also impacts the banking sector, particularly when deposits are held in foreign currencies, thereby increasing systemic vulnerabilities (Andrei, 2017). Furthermore, economic growth, often measured through the industrial production index, fosters borrowing and lending, which is vital for banking operations. Studies such as Adebola et al. (2011) emphasize the long-term influence of industrial production on default risk, highlighting the importance of maintaining macroeconomic stability to support financial health.

The likelihood of bank defaults differs significantly across countries due to varying economic conditions. For example, banks in the United States and Europe demonstrate a higher propensity for default compared to those in Australia (Zahra, 2016). In 2010, U.S. banks experienced a

[5] The accounting-based indicators rely on past information, which is inaccurate in some cases.

slight reduction in default risk, whereas European banks encountered heightened financial pressures. In contrast, Asian banks displayed strong performance, with low default tendencies indicative of greater stability within their banking sectors (Zahra, 2016).

In Pakistan, however, there is a notable gap in empirical research evaluating Distance-to-Default (DTD) using both bank-specific and macroeconomic determinants. This study seeks to address this gap by employing KMV's Merton model to measure DTD and analyze its influencing factors. The findings aim to provide meaningful insights for prospective investors, enabling them to make informed deposit decisions. Additionally, the study offers valuable guidance for bank regulators and policymakers in formulating strategies to mitigate default risks and enhance banking sector stability.

This study examines how macroeconomic and bank-specific variables interact to explain bank failure, contributing significantly to the growing literature on risk management. It offers comprehensive insights into measuring and predicting DTD. The analysis identifies key bank-specific indicators, such as bank size, non-performing loans, regulatory capital, management efficiency, liquidity, leverage, and turnover ratio, that are instrumental in guiding management and shareholders to mitigate potential risks. The study further examines the role of macroeconomic factors in shaping bank performance, providing valuable insights for policymakers to craft effective, bank-specific policies. Additionally, it assists investors in distinguishing between high- and low-risk banks for future investment opportunities, emphasizing the importance of DTD as a tool to avoid institutions prone to default.

Notably, this research applies KMV’s Merton model to calculate DTD for 20 commercial banks in Pakistan, offering a novel perspective on default risk assessment in the region. This unique contribution enhances the understanding of default risk, aiding stakeholders in decision-making and strengthening the region's banking stability.

The study is structured as follows: Section 2 reviews the literature, Section 3 discusses the variables, Section 4 outlines the methodology and estimation strategy, Section 5 presents the empirical results, and Section 6 concludes with policy recommendations.

## 2. Literature Review

Most market-based default risk models are based on the Black-Scholes theory (1973) and Merton’s structural model (1974), along with their variations. Duan and Wang (2012) compared the distance-to-default (DTD) model with alternative methods, such as Brockman and Turtle's (2003) market value proxy, Ronn and Verma's (1986) volatility constraint, Merton's (1974) KMV method, and Duan's (1994, 2000) maximum likelihood approach. They found that Merton's KMV method is less effective in measuring default risk, leading to potential bias in credit analysis. They concluded that the DTD method is superior for predicting default risk. Similarly, Bharath and Shumway (2008) found that Merton's KMV model performed poorly compared to other models in predicting default risk for U.S. non-financial firms. However, Bystrom's (2006) modified version of Merton's KMV model is considered a more suitable approach for assessing default risk in banks.

The empirical literature presents various approaches for modeling liquidity challenges in financial firms and the associated risks. One such approach is the compound option-based structural credit risk model, which has been utilized to evaluate the impact of financial crises on banks' operations (Eichler et al., 2011). This method employs the maximum likelihood function to optimize the probability of observed events, as detailed in the work of Duan (1994, 2000) and Duan and Wang (2012). Lehar (2005) extended Merton's (1974) standard call option model and integrated the maximum likelihood estimation (MLE) technique to estimate asset volatility while simultaneously monitoring credit risks within the banking sector. Similarly, Harada et al. (2010) analyzed Distance-to-Default (DTD) measures for eight failed Japanese banks during the period 1985 to 1992. Their findings affirmed the effectiveness of the DTD measure as an informative tool for predicting crises in the banking industry. Furthermore, the study highlighted DTD spreads as valuable indicators for identifying potential bank failures. However, Harada et al. (2010) also emphasized concerns regarding the reliability of estimation results, citing the lack of transparency in financial statements and disclosures as a significant limitation. Despite these challenges, numerous studies support the DTD measure as a robust tool for assessing default risk. Additionally, other empirical research has employed financial ratios as alternative methods to predict defaults in financial firms globally, further enriching the field of credit risk analysis.

Numerous studies have utilized financial ratios to predict corporate default (Beaver, 1966; Rashid & Abbas, 2011; Waqas & Md-Rus, 2019). For example, Altman (1968) evaluated financial ratios related to profitability, liquidity, and solvency, concluding that these ratios are significant and relevant predictors of default. Similarly, other research (Beaver, 1966; Ohlson, 1980; Rashid & Abbas, 2011; Shumway, 2001; Waqas & Md-Rus, 2019) identified a strong and negative correlation between profitability ratios and default risk. Conversely, some studies emphasized the predictive strength of financial leverage ratios in forecasting corporate failure, demonstrating their significant impact on bankruptcy (Altman, 1968; Bauer & Agarwal, 2014; Rashid & Abbas, 2011; Shumway, 2001). Elahi et al. (2014) tested the applicability of Moody's KMV model within Pakistan's volatile stock market. Their analysis of 307 non-financial firms during the period 2004–2011 revealed that Moody's KMV model outperformed conventional ratio-based approaches in predicting default risk. Meanwhile, Schenck (2014) compared data-transformed maximum likelihood methods with naïve approaches using data from 22 large U.S. banks from 2000–2012. The results highlighted nonperforming assets and operating efficiency as significant determinants of Distance-to-Default (DTD) for both methods, while Tier 1 capital was found to be statistically insignificant.These findings underscore the varying strengths of financial ratios and advanced modeling techniques in predicting default risk across different contexts.

Waqas and Md-Rus (2019) also examined the factors contributing to financial distress among 290 nonfinancial firms in Pakistan. Their findings identified significant predictors of financial distress, including income-to-total-assets, retained-earnings-to-total-assets, and EBIT-to-total-assets ratios. Additionally, liquidity indicators such as current-assets-to-total-liabilities, working-capital-to-total-assets, and current-assets-to-current-liabilities were confirmed to be critical determinants of financial distress. Similarly, Zhang et al. (2020) explored the determinants of default risk in 981 Chinese companies. Their study concluded that bank-specific variables, such as debt, liquidity, and firm size, along with external factors like interest rates and stock returns, significantly influence bank default risk. Furthermore, the study noted that smaller firms face greater difficulty managing financial distress due to liquidity constraints, whereas larger firms with greater liquidity are better positioned to mitigate default risk. These findings highlight the crucial role of both internal and external variables in predicting financial distress and default risk.

The number of empirical studies investigating default risk alongside bank-specific and macroeconomic variables remains limited for both financial and non-financial firms, particularly in the context of Pakistan. A review of the existing literature reveals that most research on distance-to-default has been conducted in developed economies, such as the United States, Japan, and China. However, studies specific to Pakistan predominantly focus on the relationship between profitability and default risk (Khan et al., 2021). Furthermore, the majority of these studies consider only the internal factors of firms when analyzing default risk, neglecting the broader macroeconomic influences. Additionally, prior research has mainly concentrated on non-financial firms in Pakistan, leaving a significant gap in understanding default risk within the banking sector. This paper addresses this gap in the risk management literature by examining the effects of bank-specific and macroeconomic factors on the probability of default in Pakistani banks, thus contributing valuable insights to the existing body of knowledge.

## 3. Data Description

### 3.1 Data Source

This study examines the determinants of DTD for predicting the bank default risk in Pakistan. It is noteworthy that Pakistan's banking sector consists of 46 scheduled banks[6], out of which 36 are commercial and Islamic banks, while the remaining 10 are microfinance banks. Pakistan's commercial banks consist of 25 local banks, three local Islamic banks, and eight foreign banks[7]. Also, the number of local commercial banks in Pakistan is 25, of which 18 are private banks, and 7 are public banks (State Bank of Pakistan, 2020). The sample consists of 20 scheduled banks, carefully selected to represent the diversity of Pakistan's banking sector, including private, public, and Islamic banks. This choice ensures that the analysis captures a balanced view of the sector, covering key players with sufficient data availability for the study period. The panel data has been considered for the time pertaining to 2009-2018. The reason for choosing this period is the general availability of the data. For this purpose, the daily stock price data has been collected from the Pakistan Stock Exchange, and KHI stocks to be specific. Moreover, data on bank-specific characteristics has been taken from the reports that have been published by the State Bank of Pakistan (SBP)[8]. In addition to this, the macroeconomic variables have been compiled from various data sources, including the World Development Indicators (WDI, 2021), Global Economy, and Business Recorder[9].

### 3.2 Definitions of Variables

[6] http://www.sbp.org.pk/ecib/members.htm
[7] https://www.export.gov/article?id=Pakistan-US-Banks
[8] Data on bank-specific factors have been taken from the 2009-2013 financial report until 2012, and the rest series has been updated from the 2014-2018 financial report published by the SBP.
[9] https://markets.brecorder.com/company-information/financial-highlights.html

Merton DTD is the most popular and effective technique among all the market-based methods that have thus far been used to measure the firm's default risk (Harada *et al.*, 2010). Merton's KMV model states that a bank is in default particularly if the market value of a bank asset is less than the book value of its debt (Coccorese & Santucci, 2019). Moreover, when the debt value is subtracted from the market value of equity, the result is the probability of default. When the resulting value is divided by the volatility of the bank, the calculated value is known as the distance-to-default. Merton's structural model and the option pricing theory have been referred to, so as to evaluate the firm's default risk. According to Merton's hypothesis, banks are liable for a single debt that must be paid on a given maturity date. If the value of the bank's assets exceeds the value of its debt, it is compelled to meet its payment obligations. A bank can survive only if its total assets exceed its total debts; otherwise, it becomes insolvent. When the value of a bank's assets falls below the value of its debt, the bank's equity becomes zero (Allen & Powell, 2011; Bharath & Shumway, 2008; Bohn & Crosbie, 2003; Coccorese & Santucci, 2019; Duan & Wang, 2012). Therefore, the probability of the default model is based on two crucial assumptions. First, the aggregate market value of bank assets follows a geometric Brownian motion, which is defined by the function:

$$dV_A = \mu V_A dt + \sigma_A V_A dW$$

(1)

In Equation 1, $V_A$ represents a firm's total assets, $\mu$ represents the expected total return on those assets $V$, $\sigma$ represents the volatility of the firm's assets, and $dW$ represents the standard Weiner process. According to the second assumption of Merton's model, a firm issues only one discount bond, with a maturity of T periods. Moreover, we also consider the bank's equity as a call option on the underlying value of the bank's assets. The strike price for the equity is denoted by $V_A$, which is equal to the face value of the banks' liability and maturity $T$. If $V_E$ represents the market value of equity, then the formula developed by Black and Scholes (1973) for option pricing is developed as follows:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2)$$

(2)

In Equation 2, $V_E$ represents the market value of the firm's equity, $X$ represents the face value of the firm's debt, $r$ represents the risk-free interest rate, and $N(d_1)$ and $N(d_2)$ represent the cumulative normal distribution function. The function, therefore, is represented as,

$$d_1 = \frac{ln\left(\frac{V_A}{X}\right)-\left(r+\frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}$$

(3)

Whereby, in Equation 3, $d_1$ and $\sigma_A^2$ stand for the cumulative normal probability, and the volatility of bank assets, respectively. According to Nielsen (1992), $d_1$ is the factor, by which the $PV$ of conditional receipts of shares exceeds the current share price. According to Nielsen (1992), the risk-adjusted probability *($d_2$)* can be calculated as follows:

$$d_2 = d_1 - \sigma_A\sqrt{T}$$

(4)

Where, DTD is calculated based on bank equity and equity volatility. Equation 2, therefore, expresses firms' equity as a function of firms' value, following the Black-Scholes-Merton model. The second part of the equation shows the volatility of the firm's equity, relative to its volatility. Another assumption pertaining to Merton's model is that the value of equity is related to the value of the firm and time.

$$\sigma_E = \left(\frac{V_E}{E}\right)\left(\frac{\partial E}{\partial V}\right)\sigma_A$$

(5)

Where,

$$\frac{\partial E}{\partial V} = N(d_1)$$

(6)

According to Merton's model, the equity volatility can be computed as presented in Equation 7.

$$\sigma_E = \left(\frac{V_E}{E}\right)N(d_1)\sigma_A$$

(7)

The distance-to-default (*DTD*), therefore, is derived as follows:

$$DTD_t = \frac{ln\left(\frac{V_{At}}{X_t}\right)+\left(\mu-\frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}$$

(8)

In Equation 8, $DTD_t$ represents the distance-to-default in period *t*, $V_A$ represents the value of assets, $\mu$ symbolizes the expected return on investments, and $\sigma_A^2$ represents the volatility of assets. Moreover, $T$ denotes the time dimension, and $X_t$ refers to the face value of debt. It is worth noting that the value of the liabilities in Merton's model is taken into consideration as the terminal value of assets. In this regard, Merton's (1974) model was slightly modified by Moody's KMV model, which postulates the default point as the sum of the short-term, and half of the long-term liabilities. It had been proposed that this model be modified after observing a large sample of banks with very high asset and liability values. This was particularly propagated when the banks' asset values fell to a critical level somewhere between total liabilities and short-term liabilities, and the bank defaulted at that point. Finally, the probability of default of a firm is calculated as follows:

$PD = N^{10}(-DD)$

(9)

In order make an informed estimation regarding Equation 9, we were required to calculate the volatility of the stocks. This value is usually computed using the daily stock price returns of the listed firms. The stock price returns are calculated according to the methodology proposed by (Hull, 1999), whereby:

$R_i = \ln(P_t - P_{t-1})$

(10)

The firm's volatility of equity for a particular period can thus be calculated using Equation 11, as seen below.

$\sigma_E = \frac{1}{\sqrt{\frac{1}{n}}} \sqrt{\frac{1}{(n-1)\sum_{i-1}^{n} r_i^2}} - \frac{1}{n(n-1)} (\sum_{i-1}^{n} r_i)^2$

(11)

In Equation 11, $n$ represents the number of trading days/year. Moreover, by substituting the market value of equity ($V_E$), total liabilities ($X$), and the risk-free interest rate ($r$)[11] into Equations 2 and 7, we can effectively calculate the value of market asset($V_A$), the volatility of assets($\sigma_A$), and the expected return on assets($\mu$). Moreover, we can then substitute these calculated values into Equation 8 to obtain the value of DTD. It is noteworthy that when the value of DTD is high, firms are far from the default point; therefore, the value of $PD$ would be lower. To examine the traditional determinants of default prediction, we have selected several accounting and regulatory measures:

[10] *N* stands for the cumulative probability distribution.

[11] Data on the risk-free rate (T-bills rates) has been taken from the "Open door for all (2020)" website. https://opendoors.pk/

A. **Bank size**: According to Poorman and Blake (2005), bank size is defined as a natural logarithm of a firm's total assets. We have measured this determinant using the procedure that has been developed by (Ahmad and Ahmad, 2004; Al- Khouri, 2012; Tseganesh, 2012; Vodová, 2013).

$$Bank\ size = ln\ (total\ assets) \tag{12}$$

B. **Net interest margin (NIM):** NIM is the ratio that calculates how efficiently a firm invests its liquid assets in better and more lucrative avenues. It particularly presents the efficiency of financial intermediation (Hamadi & Awdeh, 2012).

$$NIM = \frac{Total\ interest\ income - Total\ interest\ expenses}{Total\ assets} * 100 \tag{13}$$

C. **Management efficiency (MGT):** According to Rashid and Jabeen (2016), the management efficiency of a firm is determined by the ratio of total expenditures to total assets. That is to say, the ratio illustrates how effectively a firm can utilize its assets in a business.

$$\text{Bank efficiency} = \frac{\text{Earning Assets}^{12}}{\text{Total Assets}} \tag{14}$$

D. **Non-performing assets (NPA):** These loans are advances that are made to firms in default or arrears. Occasionally, debt tends to become non-performing, especially if a loan payment is not recovered within 90 days. Non-performing assets divided by total assets are usually used to compute this value (Ahmad and Ahmad, 2004; Schenck, 2014; Tajuddin et al., 2009).

$$\text{NPA} = \frac{\text{Non-performing assets}}{\text{Total Assets}} \tag{15}$$

E. **Tier-1 capital:** In accordance with the Basel II Accord, tier-1 capital consists of equity capital and published reserves (Schenck, 2014). Therefore:

Tier-1 capital = Equity capital + Statutory and general reserves as disclosed on the balance sheet + inappropriate profit + non-controlling interest – (book value of intangibles – shortfalls in provisions – reciprocal cross-holdings by banks – 50% investment in equity or other regulatory capital)

(16)

[12] Earning assets = Total assets – (cash + fixed asset + non-earning deposit)

F. **Tier-2 capital:** Tier-2 is a supplementary capital, and it is limited to 100% of tier-1 capital, as per the Basel II Accord. These include the loan loss reserves, hybrid debt capital instruments, and the subordinated debts (Schenck, 2014).

Tier-2 capital = Revaluation reserves + Hybrid debt capital instruments + Subordinated term debt + general loan loss reserves + undisclosed reserves. (17)

G. **Regulatory capital (REGCAP):** A regulatory capital, also known as capital adequacy, is the amount of capital required by a bank or other financial institution by its financial regulator. This is typically expressed as an equity capital adequacy ratio as a percentage of risk-weighted assets. In specific terms, it is the ratio of tier-1 capital to total loans (Ahmad and Ahmad, 2004; Ahmad & Ariff, 2007; Tajuddin et al., 2009).

$$\mathrm{REGCAP} = \frac{\mathrm{Tier{-}1\ capital}}{\mathrm{Total\ loans}} \quad (18)$$

H. **Market risk premium (MRP):** This refers to the difference between the returns on the KSE-100 index and the Treasury bills (Schenck, 2014).

$$\mathrm{MRP} = \mathrm{R_m} - \mathrm{R_f} \quad (19)$$[13]

I. **Liquidity index ratios:** The liquidity index measures the ability of a firm to pay off its short-term debt obligations. In this regard, Rashid and Abbas (2011) predicted the bankruptcy of non-financial firms based on these measures. Therefore, the study referred to the liquidity index in the financial sector, as the relevant data was readily available. Using PCA analysis, different proxies of the variables have been indexed into one principal component, in order to eliminate any factor of multicollinearity. The variables included in the liquidity ratio have been taken from the State Bank of Pakistan (2020), which can thus be calculated as follows:

(i) CACL = Current assets divided by current liabilities (20)

(ii) $\mathrm{LCCTA} = \frac{\textit{Cash and balance with banks}}{\textit{Total assets}} * 100$ (21)

(iii) $\mathrm{LITA} = \frac{\textit{Total investment}}{\textit{Total assets}} * 100$ (22)

[13] $\mathrm{R_m}$ = return on market portfolio, $\mathrm{R_f}$ = Risk-free rate

(iv) LDATA= $\frac{Total\ deposits\ and\ other\ accounts}{Total\ assets} * 100$ (23)

**J. Profitability index ratios:** The profitability index ratios are a class of financial metrics that measure a company's ability to generate revenue from its available assets, in an efficient manner. Thus, these ratios demonstrate the ability of a firm to generate revenue and value for its shareholders. In addition to this, various studies have considered the profitability ratios when predicting for the financial distress of financial and non-financial firms (Rashid & Abbas, 2011; Waqas & Md-Rus, 2019). To calculate the profitability index ratios, the following parameters have been taken from the State Bank of Pakistan (2020) website:

(i) Spread ratio (PSR) = $\frac{Net\ markup / interest\ income}{Markup / interest\ earned} * 100$ (24)

(ii) Return on assets (PROA) = $\frac{Net\ profit\ after\ tax}{Total\ Assets} * 100$ (25)

(iii) Net interest margin (PNIM) = $\frac{(Total\ Interest\ Income - Total\ interest\ Expences)}{Total\ Assets} * 100$ (26)

(iv) Return on equity (PROE) = $\frac{Net\ profit\ after\ tax}{Shareholder\ equity} * 100$ (27)

(v) Non-interest income to total assets ratio (PNITA) = $\frac{Total\ non{-}interest\ income{-}markup}{Total\ assets} * 100$ (28)

**K. Turnover index ratios:** Turnover index ratios tend to represent the number of assets/liabilities that the firm expresses in its sales, showing how efficiently a firm utilizes its available assets. It essentially means how quickly a firm receives its funds and how much inventory it can accumulate. In this regard, Rashid and Abbas (2011) used these ratios for predicting the default of firms:

(i) Sales to total assets (TSTTA) = Sales /total assets (29)

(ii) Working capital to sales (TWCTS) = Working Capital /sales (30)

**L. Leverage index ratios:** The leverage index ratio is a financial matrix that shows how much capital is financed by debt, and how capable a firm is of repaying its debt obligations. The ratio can also be used to measure how changes in output affect a firm's operating expenses. Rashid and Abbas (2011) have referred to these ratios to predict the default of firms:

(i) Current liabilities to total assets (LCLTA) = Current liabilities/total assets (31)

(ii) Capital ratio (LCR) = $\frac{Total\ shareholder\ equity}{Total\ assets} * 100$ (32)

(iii) Deposits to equity ratio (LDER) = $\frac{Total\ deposits}{Total\ shareholder's\ equity}$ (33)

(iv) Total debts to total assets (LTDTA) = Total debts / Total assets (34)

**M. Macroeconomic variables:** In the current study, three macroeconomic variables have also been considered to predict the default risk.

**(i) Interest rate:** Historically, the discount rate, or SBP's policy rate, has been referred to as a proxy for the interest rate. The interest rate has a significant effect on the credit cost of financial firms. For example, when the interest rate rises, it increases the cost of debt payments for the borrowers. Various studies have referred to the interest rate as a critical determinant of default risk (Khan, 2021).

$\text{Monetary policy} = \text{Interest rate}$

(35)

**(ii) Exchange rate:** The exchange rate measures the value of one currency against another currency (Khalid, 2017; Khalid & Khan, 2017). This study, therefore, examines the Pakistani Rupee against the USD, in order to capture the effect of the exchange rate dynamics on the financial distress that is faced. Many studies have used exchange rates as a critical determinant of default and credit risk (Andrei, 2017; Khan, 2021; Lu et al., 2005; Moinescu & Codirlasu, 2012; Zeitun, 2012).

**(iii) Industrial production index**[14]: The industrial production index measures the actual output of manufacturing, mining, and utilities. In this regard, studies such as those of (Adebola et al., 2011; Khan, 2021) have used the industrial production index to determine credit risk.

# 4. Model Specification and Methodology

## 4.1 Econometric Model

The risk management literature identifies various accounting and regulatory measures that can be used to determine bank default risk. This study therefore examines the firm-specific and macroeconomic aspects that estimate the DTD of Pakistani firms. Moreover, various studies have identified the critical determinants that affect the credit risk of commercial banks (Duan & Wang, 2012; Khan, 2021; Schenck, 2014; Zahra, 2016). Therefore, the general specification of

[14] This index is used as a proxy for economic growth.

the econometric model, for estimating the panel data in the context of Pakistani firms can be stated in Equation 36:

$$Y_{it} = \alpha_0 + \beta_1 X_{it} + \varepsilon_{it} \quad (36)$$

In Equation 36, $Y_{it}$ represents the dependent variable, where *i* and *t* represent the units of the cross-section and the time-series, respectively. Moreover, $\alpha_0$ denotes the intercept, and $\beta_1$ represents the slope of the regression model that is to be measured. Whereas, $X_{it}$ represents the set of independent variables (i.e., *i* =1, 2…, *N* and *t* = 1, 2,…, *T*). In addition to this, it is noteworthy that the independent variables are non-stochastic in nature, and the error terms follow the classical assumptions: $E(u_{it}) \sim N(0,\ \sigma^2)$. Researchers have proposed the linear multivariate regression model, which has been widely used in the existing literature in order to analyze the firm-specific and macroeconomic determinants of DTD. The specific econometric specification can therefore be written as follows:

$$DTD_{it} = \beta_0 + \beta_1 Size_{it} + \beta_2 Nim_{it} + \beta_3 MGT_{it} + \beta_4 Tier1_{it} + \ \beta_5 Tier2_{it} + \beta_6 REGCAP_{it} + \beta_7 NPA_{it} + \beta_8 MRP_{it} + \beta_9 LeqI_{it} + \ + \beta_{10} ProfI_{it} + \ \beta_{11} TurnI_{it} + \ \beta_{12} LevI_{it} + \ \beta_{13} IPI_{it} + \beta_{14} IR_{it} + \beta_{15} Ex_{it} + \ \varepsilon_{it} \quad (37)$$

In Equation 37, $DTD_{it}$ represents the measure of distance-to-default for different banks. Moreover, $\beta_0$ is the intercept term, and $\beta_1 - \beta_{15}$ are the slope coefficients of the explanatory variables. The explanatory variables include the bank size (*Size*), the net interest margin (*NIM*), the management efficiency (*MGT*), the nonperforming assets (*NPA*), the regulatory capital (*REGCAP*), the market risk premium (*MRP*), the liquidity index (*Leq*), the profitability index (*ProfI*), the turnover index (*Turnl*), the leverage index (*Levl*), the tier-1 capital (*Tier-1*), tier-2 capital (*Tier-2*), the interest rate (*IR*), the exchange rate (*Ex*), and finally, the economic growth (*IPI*) for all cross-sections (*i* = 20 commercial banks), and time (*t* = 2009-2018).

## 4.2 Methodology

The present study makes use of the panel data[15] in order to estimate the impact of firm-specific and macroeconomic characteristics on the DTD for Pakistani firms. In econometrics, there are two standard methods for analyzing panel data: the fixed-effects model (FEM), and the random-effects model (REM). The FEM assumes that the intercept changes, but the slope

[15] Panel data combines the time-series and cross-sectional data (Asteriou & Hall, 2011; Wooldridge, 2012).

coefficient is constant over time for all the firms (Gujarati, 2004). The fixed-effects model is represented as given in Equation 38.

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} \ldots + \beta_k X_{kit} + \varepsilon_{it} \quad (38)$$

When there is a variation in the observed characteristics, and the intercept differs for each firm, the appropriate procedure for estimating panel data is FEM (Asteriou & Hall, 2011). This model is also suitable for the autocorrelation between the error term and the explanatory variables that have been identified (Shah et al., 2018). In contrast, the REM assumes that the intercepts for all the firms are not fixed; rather, they are random parameters. Therefore, the variation in the constant terms of all the firms results ultimately from the following expression:

$$\alpha_i = \alpha + v_i \quad (39)$$

In Equation 39, $v_i$ denotes the standard random variable having a zero mean, and a standard deviation at a value of 1. Therefore, The REM can be written as follows:

$$Y_{it} = (\alpha + v_i) + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \cdots + \beta_k X_{kit} + \varepsilon_{it} \quad (40)$$

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \cdots + \beta_k X_{kit} + (v_i + \varepsilon_{it}) \quad (41)$$

The REM is more appropriate when there is no autocorrelation between the independent variables and the error terms. For the panel data, there is a possibility that the error terms and the independent variables are correlated, thus suggesting that FEM happens to be more appropriate as compared to REM. In any case, the choice between REM and FEM is made using Hausman's test (1978). The Hausman test tends to check the appropriate choice between FEM and REM, based on whether the coefficients are correlated with the individual unobserved effects. In addition to this, we know from the literature that FEM is more suitable for estimating balanced panel data. In contrast, REM is more convenient when the sample contains a limited number of cross-sectional observations (Asteriou & Hall, 2011). In Hausman's test, the null hypothesis states that the random-effect estimators are consistent and efficient, and the alternative hypothesis asserts that the random-effects estimators are inconsistent in nature (Ahn & Moon, 2001). Therefore, the test-statistics of the Hausman test can be written as follows:

$$H = \left(\beta^{\widehat{FE}} - \beta^{\widehat{RE}}\right)' \left[Var\left(\beta^{\widehat{FE}}\right) - Var\left(\beta^{\widehat{RE}}\right)\right]^{-1} \left(\beta^{\widehat{FE}} - \beta^{\widehat{RE}}\right) \sim \mathrm{X}^2(\mathrm{k}) \quad (42)$$

The difference between the two model estimates happens to be significant when Hausman's test statistic is large; therefore, keeping this outcome in consideration, we reject the null hypothesis that has been developed. In contrast, when Hausman's test statistic is small, we conclude that the random-effects estimators are better than the fixed-effects estimators. The Hausman test results in Table 5 indicate that the REM is a better fit than the FEM. Consequently, we have chosen the random-effects model for estimating the panel data.

For the purpose of this paper, four financial ratios have been constructed in this study. These included the liquidity index ratios, profitability index ratios, sales index ratios, and the leverage index ratios. Moreover, multiple proxies were used in their construction, there is a possibility of high correlation when referring to these proxy variables. Therefore, the principal component analysis (PCA) was proposed in order to reduce the number of proxy variables, and convert them into a set of uncorrelated variables.

## 5. Empirical Results

### 5.1 Descriptive Statistics

The purpose of the descriptive statistics is to understand the nature, as well as the overall behavior of the sample data. Therefore, these indicators provide a summary picture of the data that is used for estimation. The results of the descriptive statistics in Table 1 show an average value of 1.41 for the variable DTD, indicating that Pakistani commercial banks remained stable during the sample period. At the same time, the maximum and minimum values for the distance-to-default are 12.51 and -8.79, respectively, with a standard deviation of 2.80. During the sample period, the average value of the bank size has been 19.65. This clearly shows that the firms are large, and range from 21.83 to 16.98. The analysis shows that the management efficiency of Pakistani banks is about 31%, ranging from 0.807 to 0.145. Moreover, between the years pertaining to 2007 and 2016, Pakistani firms have attracted large deposits from customers. The financial entities can remain effective only if they maintain their level of profitability. In order to measure the profitability of the firms, profitability index ratios were used, so as to effectively represent their performance in the sample years. The average value of the profitability index is 1.60, varying between 2.19 to -6.05. In this regard, a significant positive value of the profitability index shows that Pakistani firms have been profitable during the sample time period.

In contrast, the mean value of the liquidity index is -1.00, ranging from 5.31 to -3.22. It is expected that the liquidity index has a significantly negative value, primarily because during the time period spanning between 2007-2012, many commercial banks suffered losses due to which there were mergers and acquisitions in the banking sector (e.g., HSBC Mergers and Acquisitions (M&A) with Meezan Bank, and recently M&A of Barclay Bank with Habib Bank).

Moreover, the average value of interest rate remains at 9.3%, while the average value of the exchange rate remains at 0.062%. The policy rate of Pakistan reached up to 14% during the sample time period, which shows an accurate picture of the trend of the interest rates. The maximum value of 0.268 for the exchange rate also shows an accurate picture, as the nominal exchange rate in Pakistan reached a value of 0.268 during the analysis period. However, the minimum values for the interest rate and the exchange rate remained at 5.75% and -0.041, respectively. The calculated probability value of all the variables is observed to be below 5%, indicating that the variables under study are normally distributed.

**Table 1: Descriptive Statistics**

| Variable | Obs. | Mean | Std. Dev. | Min. | Max. | Prob. |
|---|---|---|---|---|---|---|
| *DTD* | 200 | 1.41 | 2.80 | -8.79 | 12.51 | 0.000 |
| *Size* | 200 | 19.64 | 1.073 | 16.98 | 21.83 | 0.06 |
| *MGT* | 200 | 0.31 | 0.10 | 0.1447 | 0.8072 | 0.01 |
| *Tier-1* | 200 | 34262 | 34571.85 | -4248.68 | 135871.5 | 0.00 |
| *Tier-2* | 200 | 8022.81 | 10522.08 | -832.833 | 47110.56 | 0.00 |
| *REGCAP* | 200 | 0.08 | 0.044 | 0.016006 | 0.298122 | 0.00 |
| *NPA* | 200 | 25138052 | 27017970 | 741680 | 128277000 | 0.00 |
| *MRP* | 200 | 0.087 | 0.21 | -0.22657 | 0.345123 | 0.00 |
| *ProfI* | 200 | 1.60 | 1.0002 | -6.054 | 2.19 | 0.00 |
| *LeqI* | 200 | -1.0 | 1.003 | -3.22 | 5.31 | 0.00 |
| *LevI* | 200 | 1.2 | 1.001 | -1.21 | 2.21 | 0.00 |
| *TurnI* | 200 | 3.5 | 1.001 | -0.77 | 13.022 | 0.00 |
| *I* | 200 | 0.093 | 0.02 | 0.0575 | 0.14 | 0.00 |
| *EX* | 200 | 0.062 | 0.42 | 0.041 | 0.268 | 0.00 |
| *IPI* | 200 | 0.0293 | .031 | -0.033 | .0798 | 0.00 |

*Note: Descriptive statistics are calculated for each variable from 2009 to 2018.*

*Source: Data processed by the author*

### 5.2 Correlation Analysis

The relationship between the explanatory variables of the econometric model is usually considered in the correlation matrix. However, the strongest association between the explanatory variables is inappropriate in nature, primarily due to the strong multicollinearity[16], which violates the classical assumption of the Ordinary Least Squares. İn this regard, Kennedy (2008) reported that problematic multicollinearity comes into being when the relationship between the two explanatory variables is greater than 0.70. In addition to this, at another instance, Malhotra (2007) reported that the data suffers from severe multicollinearity when the correlation coefficient between the two independent variables exceeds the value of 0.75. In the presence of induced multicollinearity, we therefore obtain biased empirical results from the estimation. The results in Table 2 show that the variable DTD is positively correlated with the bank size, market risk premium, non-performing assets, regulatory capital, tier-1, tier-2, liquidity index, profitability index, and the leverage index. During the study period, it is observed that the DTD has negative correlations with management efficiency, turnover index, interest rate, and the exchange rate. The highest correlation between non-performing assets and the firm size is 0.65. The results confirm that there is no problematic multicollinearity in the studied variables, as all the pairwise correlations are below 0.7.

[16] It describes a situation where two or more explanatory variables are highly correlated to each other.

**Table 2: Pairwise Correlations**

| | *DTD* | *SIZE* | *MGT* | *MRP* | *NPA* | *REGCAP* | *Tier1* | *Tier2* | *LEQI* | *PROFI* | *LEVI* | *TURN* | *I* | *EX* | *IPI* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***DTD*** | 1 | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***SIZE*** | 0.36 | 1 | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***MGT*** | -0.21 | -0.37 | 1 | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***MRP*** | 0.31 | -0.20 | -0.02 | 1 | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***NPA*** | 0.01 | 0.65 | -0.19 | -0.05 | 1 | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***REGCAP*** | 0.13 | -0.33 | 0.22 | 0.13 | -0.09 | 1 | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***Tier1*** | 0.37 | 0.61 | -0.23 | -0.14 | 0.62 | 0.09 | 1 | --- | --- | --- | --- | --- | --- | --- | --- |
| ***Tier2*** | 0.22 | 0.56 | -0.14 | -0.12 | 0.55 | -0.04 | 0.55 | 1 | --- | --- | --- | --- | --- | --- | --- |
| ***LEQI*** | 0.05 | 0.20 | -0.20 | 0.15 | 0.19 | -0.47 | -0.01 | 0.06 | 1 | --- | --- | --- | --- | --- | --- |
| ***PROFI*** | 0.39 | 0.48 | -0.26 | -0.18 | 0.16 | 0.09 | 0.41 | 0.33 | 0.02 | 1 | --- | --- | --- | --- | --- |
| ***LEVI*** | 0.28 | 0.14 | -0.01 | -0.03 | 0.06 | -0.08 | 0.10 | 0.23 | 0.11 | 0.34 | 1 | --- | --- | --- | --- |
| ***TURNI*** | -0.05 | 0.19 | -0.06 | 0.00 | 0.18 | 0.01 | 0.25 | 0.31 | 0.09 | 0.03 | -0.07 | 1 | --- | --- | --- |
| ***I*** | -0.33 | -0.38 | -0.08 | 0.24 | -0.09 | 0.23 | -0.25 | -0.27 | 0.14 | -0.37 | -0.29 | 0.05 | 1 | --- | --- |
| ***EX*** | -0.15 | 0.13 | 0.04 | -0.33 | 0.01 | -0.14 | 0.10 | 0.08 | -0.07 | -0.07 | -0.39 | 0.18 | -0.17 | 1 | --- |
| ***IPI*** | 0.31 | -0.11 | -0.03 | 0.74 | -0.02 | 0.10 | -0.09 | -0.06 | 0.08 | 0.00 | 0.22 | -0.10 | 0.01 | -0.64 | 1 |

*Note: All variables are significant at the 0.05 level.*

*Source: Data processed by the author*

The study also applied the Variance Inflation Factor (VIF) to test whether there was significant multicollinearity. As shown in Table 3, the results of the VIF confirm that there is no induced multicollinearity in the data, as the VIF value for each explanatory variable is less than 10[17].

**Table 3: Variance Inflation Factor**

| Variable | VIF | 1/VIF |
|---|---|---|
| *Size* | 8.17 | 0.122 |
| *Tier_1* | 7.39 | 0.135 |
| *Tier_2* | 5.51 | 0.181 |
| *MRP* | 1.21 | 0.826 |
| *MGT* | 1.96 | 0.510 |
| *REGCAP* | 2.98 | 0.335 |
| *NPA* | 2.74 | 0.364 |
| *PROFI* | 2.03 | 0.492 |
| *LEVI* | 1.61 | 0.621 |
| *LEQI* | 1.67 | 0.598 |
| *TURNI* | 1.1 | 0.909 |
| *I* | 4.43 | 0.225 |
| *EX* | 4.01 | 0.249 |
| *IP1* | 4.76 | 0.210 |

*Source: Data processed by the author*

### 5.3 Likelihood Test

The likelihood test has been applied to deduce which panel estimation approach is more appropriate for the sample data between the common constant and fixed-effects model. The results that have been reported in Table 4 indicate that FEM is more appropriate, mainly because the calculated *p*-value is 0.00 < 0.05; therefore, we accept $H_0$ *and* reject $H_1$.

- $H_0$: The fixed-effects model is appropriate.
- $H_1$: The common constant model is appropriate.

[17] Based on the rule-of-thumb, multicollinearity will no longer be a severe issue in the data if the VIFs are lowers than 10 (Gujarati, 2004; Asteriou & Hall, 2011).

**Table 4: Likelihood Test**

| **Effects Test** | **Stat.** | ***d.f*** | **Prob.** |
|---|---|---|---|
| Cross-section F | 3.442282 | (19, 167) | 0.0000 |
| Cross-section Chi-square | 66.096131 | 19 | 0.0000 |

*Source: Data processed by the author*

### 5.4 The Hausman Test

The researchers have also applied Hausman's test to select a more appropriate approach between the FEM and REM for the sample data that has been considered. The results of Hausman's test in Table 5 show that the calculated chi-square value is lower than the critical value. Therefore, we accept $H_0$ and reject $H_1$. The results of Hausman's test also indicate that REM is more appropriate for estimating the parameters of the proposed model.

- $H_0$: The REM is suitable for the data.
- $H_1$: The FEM is suitable for the data.

**Table 5: The Hausman test**

| **Test Cross-Section Random Effects** | | | |
|---|---|---|---|
| Summary | Chi-sq. statistic | Chi-sq. d.f. | *p*-value |
| Cross-section random | 0.00000 | 13 | 1.0000 |

Source: Data processed by the author

### 5.5. Results of Regression Analysis

We have estimated the multivariate econometric model by using the random-effects model, after Hausman's test, for the sample period. The random-effects model is commonly used because it provides consistent and robust results. The estimation results of REM have been presented in Table 6. The results show that there is a significant positive relationship between DTD and the bank size, and the underlying relationship is significant at a 1% level of significance. İn their respective studies, (Ahmad & Arif, 2007; Schenck, 2014; Waqas & Md-Rus, 2019) also observed similar results. In contrast, Al-Wesabi and Ahmad (2013) reported that bank size is an insignificant determinant of credit risk. As the bank size grows, more opportunities for borrowers and lenders emerge, increasing the likelihood of default (default risk). İn this regard,  Shah et al. (2018) concluded that that the bank size affects liquidity in a different manner, particularly when the measurement of liquidity is changed.

The results show that the impact of management efficiency on DTD is significantly negative, which means that a 1% increase in the management efficiency of firms, leads to a 1.57% decrease in the DTD. Similarly, the studies of (Ahmad & Arif, 2007; Schenck, 2014) have shown that management efficiency is a significant determinant of DTD. Moreover, as expected, the market risk premium, regulatory capital and leverage index have been deduced to be positive and statistically significant for the measure DTD. This confirms the results of the other studies as well (Al-Wesabi & Ahmad, 2013; Schenck, 2014). Though, the study contradicts the findings of Ahmad and Ahmad (2004) who concluded that regulatory capital is negatively associated with any factor of risk that might exist. As expected, the estimated coefficient of the profitability index is negative, and statistically significant at a 1% level of significance, which supports the results of (Khan, 2021). The results also suggest that Pakistani banks need a rather solid capital base in order to be resilient to any losses. The SBP has also mandated that all DFIs and banks, on both a consolidated and stand-alone basis, must have a minimum capital ratio of 10 percent in order to withstand any potential losses[18]. Our analysis shows that the market risk premium is associated with a high level of risk. Non-performing assets, turnover index, and interest rate have a negative and significant impact on the measure of DTD. The results support the findings of (Ahmad & Ahmad, 2004; Schenck, 2014). In addition to this, the results also suggest that nonperforming loans are used as a control factor for expected losses, and that default events in these loans tend to trigger these provisions (Khan, 2021). The empirical results also show that the estimates of tier-1 and tier-2 capital ratios for the DTD measure of Pakistani firms are not statistically significant in nature. Thus, the study supports the findings of (Khan, 2021; Schenck, 2014). Other than that, macroeconomic variables such as exchange rate and industrial production index also do not contribute significantly to the DTD, thus supporting the findings of (Khan, 2021). The statistical diagnostic tests that have been carried out also indicate that the estimated model is fit, thus explaining about 56% of the total variation in DTD by the group of explanatory characteristics, as indicated by the value of $R^2$. Other critical diagnostics (e.g., adjusted $R^2$, *S.E.*, and *F*-statistics) also indicate that the proposed model is the best fit.

[18] https://dnb.sbp.org.pk/bprd/2013/Basel_III_instructions.pdf

**Table 6: Regression Results**

| Variables | Coefficient | S.E. | *t*-statistic | *p*-value | Significance |
|---|---|---|---|---|---|
| C | -28.57509 | 9.520066 | -3.001564 | 0.0031 | *** |
| SIZE | 1.635284 | 0.466376 | 3.506367 | 0.0006 | *** |
| MRP | 6.263208 | 0.936830 | 6.685530 | 0.0000 | *** |
| NPA | -3.88E-08 | 1.31E-08 | -2.964524 | 0.0034 | *** |
| REGCAP | 21.86250 | 6.422925 | 3.403823 | 0.0008 | *** |
| LEQI | 0.397055 | 0.172032 | 2.308028 | 0.0221 | ** |
| TIER-1 | 2.16E-05 | 1.36E-05 | 1.584449 | 0.1148 | |
| TIER-2 | -5.54E-05 | 3.55E-05 | -1.561632 | 0.1201 | |
| LEVI | 0.353979 | 0.182964 | 1.934690 | 0.0546 | ** |
| TURNI | -0.233031 | 0.132667 | -1.756515 | 0.0807 | * |
| MGT | -1.577189 | 1.844313 | -0.855163 | 0.0906 | * |
| PROFI | -0.028106 | 0.187284 | -0.121796 | 0.0010 | *** |
| I | -30.30977 | 7.006723 | -4.325812 | 0.0000 | *** |
| EX | -2.497064 | 2.368108 | -1.054455 | 0.2931 | |
| IPI | -8.328439 | 7.566458 | -1.100705 | 0.2725 | |
| $R^2$: 0.557205; Adjusted $R^2$: 0.521107; $F$-statistic: 15.43612; Probability ($F$-statistic): 0.000000 | | | | | |

*Note: *P<0.1, weak significant; **P<0.05, semi-strong significant; ***P<0.01, strong significant.*

*Source: Data processed by the author*

### 5.6 Distance-To-Default of Pakistani Firms

The *DTD* measures the likelihood that a firm will fail in a given time period that has been taken into account. In this regard, Merton's KMV model states that the firm is in a default position, and nearly bankrupt if the value of the market share falls to the point where it is less than the value of debt. Table 7 shows the mean *DTD* for the 20 Pakistani commercial firms that have been taken into consideration, for the time period pertaining to 2009-2018. It can be observed that the mean *DTD* value for some individual banks, including *BAFL, AKBL, BIPL, JSBL, SBL, SILK*, and *SNBL*, are 0.83, 0.12, 0.68, 0.26, 0.82, 0.21, and 0.53, respectively. The lowest *DTD* values indicate that these are small firms, and their default profitability is low. Moreover, there is a moderate performance of these firms in Pakistan's banking industry.

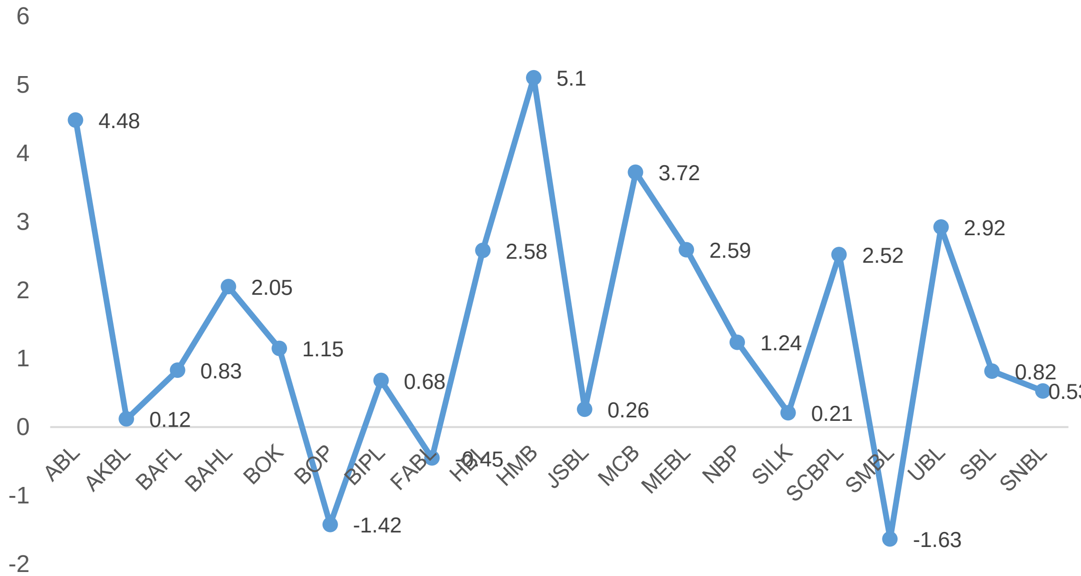
Furthermore, the mean *DTD* value for other major firms operating in Pakistan, including that for *ABL*, *BAHL*, *BOK*, *HBL*, *HMB*, *MCB*, *MEBL*, *NBP*, *SCBPL*, and *UBL*, are 4.48, 2.05, 1.15, 2.58, 5.10, 3.72, 2.59, 1.24, 2.52, and 2.92, respectively. In this context, the positive *DTD* values indicate that large firms have a low default risk since they have high market capitalization, profitability, maximum efficiency, and effective performance in the banking sector. Lastly, *BOP*, *FABL*, and *SMBL* have negative *DTD* values of -1.42, -0.45, and -1.63, respectively, indicating that these firms are close to default. More importantly, in the year 2019, the PSX declared Summit Bank a defaulter primarily because its share price value was lower than its face value. When we compare the estimated mean *DTD* with the banks' equity values, the analysis indicates that the *DTD* is a reliable measure of default risk, particularly in Pakistan's banking system. As per the study's findings, we can therefore conclude that Pakistan's banking sector is sound and stable, with a low default risk after the global financial crisis. It means that the banking sector of Pakistan has not been majorly affected due to the occurrence of the 2008 financial crisis. Figure 1, in this regard, displays the estimated mean DTD values for the sample period.

**Table 7: Estimates of Mean Distance-To-Default**

| Serial # | Bank Name | Mean DTD | Serial # | Bank Name | Mean DTD |
|---|---|---|---|---|---|
| 1 | ABL | 4.48 | 11 | JSBL | 0.26 |
| 2 | AKBL | 0.12 | 12 | MCB | 3.72 |
| 3 | BAFL | 0.83 | 13 | MEBL | 2.59 |
| 4 | BAHL | 2.05 | 14 | NBP | 1.24 |
| 5 | BOK | 1.15 | 15 | SILK | 0.21 |
| 6 | BOP | -1.42 | 16 | SCBPL | 2.52 |
| 7 | BIPL | 0.68 | 17 | SMBL | -1.63 |
| 8 | FABL | -0.45 | 18 | UBL | 2.92 |
| 9 | HBL | 2.58 | 19 | SBL | 0.82 |
| 10 | HMB | 5.10 | 20 | SNBL | 0.53 |

*Source: Data processed by the author*

Fig 1: Estimates of Mean Distance-To-Default




## 6. Conclusion and Policy Recommendations

This research evaluates the influence of bank-specific and macroeconomic variables on default risk, alongside assessing the predictive validity of the distance-to-default (DTD) measure using a random-effects model to analyze panel data from 2009 to 2018 across 20 commercial banks. The study examines a set of variables including bank size, management efficiency, regulatory capital, market risk premium, non-performing loans, and tier-1 and tier-2 capital ratios, alongside indices like profitability, liquidity, leverage, and turnover. Macroeconomic variables such as interest rates, exchange rates, and economic growth are also considered, with principal component analysis employed to refine the categorization of bank-specific variables.

The research findings indicate that variables such as bank size, market risk premium, management efficiency, regulatory capital, and indexes measuring liquidity, leverage, turnover, and profitability substantially influence corporate credit risk. With the expansion of a bank's size, its portfolio also grows, providing more opportunities for borrowers and lenders to manage their financial assets. This increase in portfolio size, in turn, elevates the probability of loan defaults, thereby escalating the overall risk of default. The study further reveals that the market risk premium is crucial in accurately forecasting default risk. An increase in the market risk premium demanded by investors typically correlates with heightened market risks. Additionally, the research underscores that banks in Pakistan possess a robust capital foundation, which offers substantial protection against potential financial setbacks. Should the likelihood of bank defaults rise, it would be prudent for the SBP to consider enhancing the regulatory capital requirements. Conversely, variables such as tier-1 capital, tier-2 capital, exchange rates, and economic growth appear to have minimal impact on corporate credit risk. Efficient management of banks has been shown to diminish default risk (Angbazo et al., 1998; Khan, 2021), corroborating the findings presented in this analysis. Consequently, the analysis highlights a negative correlation, indicating that decreased management efficiency is linked to an increased risk of default. The findings also validate the DTD as a robust predictor of default risk. The Pakistani banking system is found to be robust and stable, exhibiting a low propensity for default. To reduce the risk of bankruptcy, it is essential for the central bank to monitor bank-specific attributes that influence firm liquidity within Pakistan. Delays in addressing these critical issues could precipitate financial instability. Additionally, macroeconomic policies should aim to stabilize the broader economic climate. Specific recommendations include actions by monetary authorities to control inflation and maintain exchange rate stability, thereby fostering a supportive environment for banking operations and reducing default risks. Policymakers are also urged to reinforce fiscal discipline and execute structural reforms that strengthen the economic framework, thus decreasing the financial sector's exposure to external shocks. Furthermore, it is advisable for monetary authorities to increase the policy rate to spur investment, which is likely to diminish the risk of default. The effectiveness of a market-based default prediction model in forecasting corporate default risks in Pakistan is affirmed by the study. It also advises banks to integrate these specific determinants into their risk management strategies. Complementarily, the central bank of Pakistan should implement policies that promote macroeconomic stability and mandate commercial banks to report their DTD values in their annual disclosures.

This research has advanced the understanding of default risk, although it is constrained by certain limitations. The exclusion of several banks from the analysis was necessitated due to incomplete financial records and unavailable data from those institutions. Future studies could investigate the influence of bank-specific factors on default risk across banks of varying sizes in Pakistan. Additionally, the research scope could be expanded to include non-commercial banking entities such as microfinance institutions, investment banks, mutual funds, insurance companies, and leasing firms. This extension is crucial as these entities play diverse and pivotal roles in the financial system, often facing unique risk factors that could illuminate broader trends in default risk. Further inquiries should also explore firm-specific factors such as total liabilities, cost of capital, and credit growth, alongside macroeconomic indicators like real GDP, inflation, and trade balance. Integrating these elements would not only enrich the analysis but also provide a more holistic view of the economic and financial dynamics influencing default risk. By examining how these macroeconomic and firm-specific factors interact, researchers could develop more sophisticated models to predict default risk more accurately, offering valuable insights for policymakers and financial institutions alike.This comprehensive approach would enhance the robustness of the research and offer a more nuanced understanding of the complexities surrounding default risk in various sectors of the financial market.

## References


Adebola, S., Wan Yusoff, P., & Dahalan, D. (2011). An ARDL approach to the determinants of non-performing loans in Islamic banking system in Malaysia. *Kuwait Chapter of Arabian Journal of Business and Management Review, 1*(2), 1-12.

Ahmad, N. H., & Ahmad, S. N. (2004). Key factors influencing credit risk of Islamic bank: A Malaysian case. The Journal of Muamalat and Islamic Finance Research, *1*(1), 65-80.

Ahmad, N. H., & Arif, M. (2007). Multi-country study of bank credit risk determinants. *International Journal of Banking and Finance (IJBF), 5*(1), 35-52.

Ahn, S. C., & Moon, H. R. (2001). Large-N and Large-T Properties of Panel Data Estimators and the Hausman Test. USC CLEO Research Paper No. *C01-20*.

Al-Khouri, R. (2012). Bank characteristics and liquidity transformation: The Case of GCC Banks. *International Journal of Economics and Finance, 4*(12), 114-120.

Allen, D, E., & Powell, R, J. (2011). Credit risk Measurement Methodologies. *19th International Congress on Modelling and Simulation*, Perth, Australia, 1464-1470. Retrieved from http://mssanz.org.au/modsim2011.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589-609.

Al-Wesabi, H. A., & Ahmad, N. H. (2013). Credit risk of Islamic banks in GCC countries. *International Journal of banking and finance, 10*(2), 95-112.

Andrei, F. (2017). Macroeconomic variables impact on credit risk and influence in banking capital and job cuts in Romania. *Journal of Progressive Research in Social Sciences*, *5*(1), 319-328.

Angbazo, L., Mey, J., & Saunders, A. (1998). Credit spreads in the market for highly leveraged transaction loans. *Journal of Banking & Finance*, *22*(10-11), 1249-1282.

Asteriou, D., & Hall, S. (2011). *Applied Econometrics* (2nd Ed.). Palgrave Macmillan.

Bauer, J., & Agarwal, V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprerohensive test. *Journal of Banking and Finance, 40(C)*, 432-442.

Beaver, W. (1966). Financial Ratios As Predictors of Failure. *Journal of Accounting Research*, *4*, 71-111.

Bharath, S., & Shumway, T. (2008). Forcasting Default with the Merton Distance to Default Model. *The Review of Financial Studies, 21*(3), 1339-1369.

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, *81*(3), 637-653.

Brockman, P., & Turtle, H. (2003). A barrier option framework for corporate security valuation. *Journal of Financial Eonomics*, *67(3)*, 511-529.

Bystrom, H. N. E. (2006), Merton unraveled. *The Journal of Alternative Investments, 8*(4), 39-47.

Coccorese, P., & Santucci, L. (2019). The role of downward assets volatility in assessing the book value distance to default . *Journal of Financial Economic Policy*, *11*(4), 485-504.

Crosbie, P., & Bohn, J. (2003). *Modeling Default Risk-Modeling Methodology*. Moody's KMV Company LLC, 1-31.

Duan, J. C. (1994). Maximum Likelihood Estimation using Price Data of the Deravitive contract. *Mathematical Finance*, *4*(2), 155-167.

Duan, J. C. (2000). Correction: maximum likelihood estimation using price data of the derivative contract (mathematical finance 1994, 4/2, 155–167). *Mathematical Finance*, *10*(4), 461-462.

Duan, P. C., & Wang, T. (2012). Measuring Distance-to-Default for Financial and Non-Financial Firms. *Global Credit Review, 2*, 95-108.

Eichler, S., Karmann, A., & Maltritz, D. (2011). The term structure of banking crisis risk in the United States: A market data-based compound option approach. *Journal of Banking & Finance*, *35*(4), 876-885.

Elahi, R. A., Mehmood, B., & Awan, M. M. (2014). Macroeconomic Covariates of Default Risk: Case of Pakistani Non-financial Firms. *Zagred International review of Economics and Business, 17*(1), 15-26.

Gujarati, D. (2004). *Basic Econometrics* (4th Ed.) The McGraw− Hill Companies.

Gunji, H., & Yuan, Y. (2018). Bank diversification and monetary policy. *Applied Economics Letters*, *25*(15), 1087-1090.

Hamadi, H., & Awdeh, A. (2012). The determinants of bank net interest margin: Evidence from the Lebanese banking sector. *Journal of Money, Investment and Banking*, *23*(3), 85-98.

Harada, K., Ito, T., & Takahashi, S. (2010). Is distance-to-default a good measure in predicting Bank failures? Case Studies. *National Bureau of Economic Research*, Working Paper 16182.

Hausman, J. (1978). Specification Tests in Econometrics. *Econometrica, 46(6)*, 1251–71.

Hu, H., & Sathye, M. (2015). Predicting Financial Distress in the Hong Kong Growth Enterprises Market from the Perspective of Financial Sustainability. *Sustainability*, 7, 1186-1200.

Hull, D. (1999). Fractography: Observing, measuring and interpreting fracture surface topography. Cambridge University Press, New York. www.cambridge.org.

Kennedy, P. (2008). *A Guide to Econometrics* (4th Ed.). MIT Press.

Khalid, W. (2017). Effects of interest rate and exchange rate on the stock market performance of Pakistan: A cointegration approach. *Journal of Finance and Economics*, *5*(5), 219-232.

Khalid, W., & Khan, S. (2017). Effects of Macroeconomic Variables on the Stock Market Volatility: The Pakistan Experience. *International Journal of Econometrics and Financial Management, 5*(2), 42-59.

Khan, S. (2021). *Bank Specific and Macroeconomic Determinants of Distance-to-Default: Evidence from listed Banks of Pakistan* [Unpublished Master's Thesis]. Department of Business Studies, Pakistan Institute of Development Economics.

Khan, S., Zahra, A., Khalid, W., & Shah, N. H. (2021). Impact of Bank Profitability on Default Risk: Empirical Evidence from Pakistan. *Journal of Quantitative Methods*, *5*(2), 1-33.

Khemraj, T., & Pasha, S. (2009). The determinants of non-performing loans: An econometric case study of Guyana. MPRA Paper 53128,University Library of Munich, Germany.

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, *29*(10), 2577-2603.

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, *36*(4), 1012-1027.

Lu, D., Thangavelu, S. M., & Hu, Q. (2005). Biased Lending and Non-performing Loans in China's Banking Sector. *The Journal of Development Studies, 41*(6), 1071-1091.

Malhotra, N. K. (2007). *A Book of Marketing Research: An Applied Orientation* (5th Ed.). Pearson.

Merton, R. (1974). On the pricing of corporate debt: A risk structure of interest rates. *Journal of Finance*, *29*(2), 449-470.

Moinescu, B., & Codirlasu, A. (2012). Assessing the sectoral dynamics of non-performing loans: signs from financial and real economy. *Theoretical and Applied Economics, XIX*(2), 69-80.

Muvingi, J., Nkomo, D., Mazuruse, P., & Mapungwana, P. (2015). Default prediction models a comparison between market based models and accounting based: Case of the Zimbabwe stock exchange 2010-2013. *Journal of Finance and Investment Analysis, 4*(1), 39-65.

Nielsen, L. T. (1992). *Understanding N (d1) and N (d2): Risk Adjusted Probabilities in the Black-Scholes Model 1*. INSEAD Working Paper, 92/71/FIN.

Ohlson, J. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, *18*(1), 109-131.

Poorman, F. Jr., & Blake, J. (2005). Measuring and Modelling Liquidity Risk: New Ideas and Metrics. *Financial Managers Society Inc.* White Paper.

Rashid, A., & Abbas, Q. (2011). Predicting Bankruptcy in Pakistan. *Theoritical and applied Economics, 18*(9), 103-128.

Rashid, A., & Jabeen, S. (2016). Analyzing performance determinants: Conventional versus Islamic banks in Pakistan. *Borsa Istanbul Review*, *16*(2), 92-107.

Ronn, E. I., & Verma, A. K. (1986). Pricing Risk-Adjusted Deposit Insurance: An Option-Based Model. *The Journal of Finance*, *41*(4), 871–895.

Schenck, N. (2014). Distance-to-default measures and determinants for systemically important financial institutions. *Journal of Financial Regulation and Compliance*, *22(*2), 159-172.

Shah, S. Q. A., Khan, I., Shah, S. S. A., & Tahir, M. (2018). Factors affecting liquidity of banks: Empirical evidence from the banking sector of Pakistan. *Colombo Business Journal, 9*(1), 1-18.

Shumway, T. (2001). Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *The Journal of Business*, *74*(1), 101-124.

Tajuddin, S. S., Shahimi, S., & Hamid, M. A. (2009). Determinants of credit risk in Malaysian Islamic banks. *Capital Market Review*, *17*(1&2), 43-60.

Tseganesh, T. (2012). *Determinants of Banks Liquidity and their Impact on Financial Performance: Empirical Study on Commercial Banks in Ethiopia. Unpublished Master's Thesis. Addis Ababa University, Ethiopia.*

Vodová, P. (2013). Determinants of Commercial bank liquidity in Hungary. *Finansowy Kwartalnik Internetowy e-Finanse*, *9*(4), 64-71.

Waqas, H., & Md-Rus, R. (2019). Predicting financial distress: Importance of accounting and firm. *Cogent Economics and Finance*, *6*(1), 1-16.

World Bank. (2021). *World Development Indicators*. http://www.worldbank.org.

Zahra, A. (2016). *Default Risk and Efficiency Nexus: Evidence from Banking Sector of Pakistan* (Published MS Thesis). Capital University of Science & Technology.

Zeitun, R. (2012). Determinants of Islamic and Conventional Banks Performance in GCC Countries Using Panel Data Analysis. *Global Economy and Finance Journal*, *5*(1), 53-72.

Zhang, X., Ouyang, R., Liu, D., & Xu, L. (2020). Determinants of corporate default risk in China: The role of financial constraints. *Economic Modelling*, 92(C), 87-98.