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Article: **Impact of Bank Profitability on Default Risk: Empirical Evidence from Pakistan**

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Impact of Bank Profitability on Default Risk: Empirical Evidence from Pakistan

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Abstract

This empirical study investigates the effects of bank-specific determinants of profitability on the default risk of 20 banks listed on the Pakistan Stock Exchange (PSX). For this purpose, this study employed balanced panel data covering 20 selected commercial banks of Pakistan for the period 2009-2018. Probability of default (PD) was used to measure the default risk of these banks. Bank profitability was measured using bank-specific determinants such as the net interest margin (NIM), non-interest income to total assets (NITA), return on assets (ROA), return on equity (ROE), and spread ratios (SR). The empirical findings of the fixed effects model (FEM) revealed that NIM, NITA, and SR are significant determinants of default risk. The findings also highlighted that these determinants can act as early warning signs of a bank's deteriorating stability. This study recommends that the State Bank of Pakistan (SBP) should compel the commercial banks to disclose their probability of default in their financial reports. This study also recommends that the risk management department of these banks should assess the bank-specific determinants of profitability to manage default risk.

Keywords: bank profitability, commercial banks, bank-specific determinants, default risk, Pakistan
JEL Classification: C23, G21, G32

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Introduction

After the financial crisis of 2008-09, financial economists and policymakers became increasingly concerned about the stability of the banking sector. To recover from the aftermath of this crisis, many structural changes took place in the banking sector. A review of the structural reforms revealed that they advocate a robust and stable banking system since such a system can easily absorb global financial shocks (Athanasoglou et al., 2008). Despite making substantial financial recoveries, many banks are still struggling with the challenges of bank profitability (Xu et al., 2019). Regarding the challenge of bank profitability, Keeley (1990) stated that profitable banks are comparatively more stable because they have more capacity to endure financial shocks. Several key figures in the global banking community strongly support this view. For instance, Ravi Menon, the head of Singapore's Monetary Authority, said on April 20, 2017, that "banks must be profitable to be strong". High bank profitability translates into the long-term expectation that the banks will remain profitable and there will be less temptation for them to indulge in riskier activities.

According to Martynova et al. (2015), high bank profitability urges banks to take more risks. However, high bank profitability also expands their capacities and operational activities, enabling them to withstand a financial crisis. The instability in the banking sector has knock-on effects on the global economy, that is why many researchers across the globe have tried to find early warning signs of financial distress in banks (Rashid & Abbas, 2011; Schenck, 2014; Muvingi et al., 2015). Bank profitability is a well-researched area in the field of risk management (Short, 1979; Berger, 1995; Adusei, 2015). Few studies in the existing literature explored the connection between bank profitability and stability of banks (Martynova et al., 2015). The findings of these studies showed mixed evidence on the nature of the linkage between profitability and stability of banks. Furthermore, most of the studies that address the connection between profitability and stability of European banks were conducted in a cross-country context (Pasiouras & Kosmidou, 2007; Arena, 2008; Flamini et al., 2009), which restricts the policy implications since the obtained results are difficult to generalize for a particular country given the countrywide differences (Ali, 2015). Therefore, the current study intended to cover the research gap mentioned above by investigating the connection between bank profitability and default risk of 20 Pakistani banks listed on the *PSX* website.

The World Bank improved the ranking of Pakistan as a business destination due to a few significant transformations in its financial sector. The geographical location of Pakistan is considered strategically important on the map due to its vicinity to China and Russia. Pakistan can also provide a link to Gulf countries such as Africa, Europe, and Central Asia. The geostrategic location of Pakistan, increasing trends of regional connectivity (CPEC Agreement), and the trend of globalization highlights the importance of the Pakistani banking sector to foreign investors. This study examined the determinants of profitability influencing the default risk of Pakistani banks to expand the literature on profitability-default risk nexus. The objective of this study was to check whether or not the probability of default (*PD*) is a reliable measure for inspecting the default risk in a banking sector. The probability of default (PD) was used in this study to measure the default risk of Pakistani banks. Similarly, bank profitability was measured using bankspecific determinants such as net interest margin (NIM), non-interest income to total assets (NITA), return on assets (ROA), return on equity (ROE), and spread ratio (SR). The findings demonstrated that the net interest margin (NIM), non-interest income to total assets (NITA), and spread ratio (SR) were significant determinants of default risk. The findings also revealed that profitability indicators can act as early warning signs of a bank's deteriorating stability. The current study contributes to the existing literature in two ways. First, this study addressed the connection between profitability and default risk in the context of Pakistani banks. Second, it provided an insight into country specific guidelines. This insight would help economists and policymakers design a suitable policy to strengthen the banking sector of Pakistan against the next financial crisis.

Section 2 of this study reviewed existing literature. Section 3 explained data sources and the description of the variables. Section 4 presented model specifications and the applied econometric methodology.

The findings are presented in Section 5, while Section 6 reports the discussion and policy recommendations.

Literature Review

In this literature review, the existing literature on profitability-default risk nexus is categorized into two major groups based on the selection of variables. Some studies investigated the effects of bankspecific factors on profitability and default risk (Podpiera & Weill, 2008; Calmes & Theoret, 2010; Engle et al., 2014; Ali & Puah, 2019); whereas, other studies examined the effects of macroeconomic variables on profitability-default risk nexus (Freixas & Rochet, 2008; Albertazzi & Gambacorta, 2009; Festic et al., 2011; Castro, 2013; Drechsler et al., 2017). The remaining studies considered both bankspecific and macroeconomic variables to gauge their effects on profitability and default risk of banks in various countries (Louzis et al., 2012; Dietrich & Wanzenried, 2014; Schenck, 2014; Chaibi & Ftiti, 2015).

Flamini et al. (2009) carried out a study to investigate the profitability-default risk nexus. It explored the impact of bankspecific and macroeconomic factors of profitability on credit risk by selecting 41 central Sub-Saharan African banks. The results were determined using a two-step GMM model, which reported that credit risk is a positive and significant determinant of profitability. However, Curak et al. (2012) concluded that credit risk was a negative and insignificant determinant of profitability for sixteen Macedonian banks. This study used the dynamic panel data of banks from the period 2005-2010. Its empirical findings suggested that profitability was negatively connected with credit risk. In contrast, Jadah et al. (2020) conducted a study on eighteen Iraqi banks and concluded a significant negative impact of credit risk on bank profitability.

Similarly, the findings of Abdelaziz et al. (2020) showed a negative and significant relationship between profitability and credit risk of banks in the Middle East and North African countries. The authors also concluded that profitability significantly decreases credit risk in MENA banks. Moving one step forward, Leon (2020) analyzed the impact of macroeconomic variables and credit risk on the profitability of 20 ASEAN banks over the period 2012-2017. Its findings reported that credit risk and

GDP growth negatively influence ROE and ROA. Funso et al. (2012) explored the impact of credit risk on bank profitability for five Nigerian commercial banks. This study took panel data from the period 2000-2010. Its findings revealed that the increase in non-performing loans and loan loss provisions decrease bank profitability. Conversely, the increase in total loans and bank advances increases profitability since interest bearing loans constitute a significant portion of a banks' revenue. The analysis advocated that Nigerian banks should strengthen their capacity in credit analysis, and the regulatory authorities should accord priority to compliance and prudential guidelines of banks.

In the existing literature, some researchers used profitability ratios to determine the default risk of banks located in various countries. For instance, Schenck (2014) investigated the accounting determinants of default risk by employing panel data covering 22 large U.S. banks from 2000-2010. The cluster analysis' findings indicated that the net interest margin (NIM) was a crucial factor of default risk. The findings also showed that non-performing assets, operating efficiency, Tier 2 capital ratio, and asset size were the deciding factors of default risk for the studied banks. Another study conducted by Munangi and Sibindi (2020) examined the impact of credit risk on the financial performance of 18 banks operating in South Africa. This study used various panel estimation techniques to demonstrate that credit risk was negatively related to financial performance. Furthermore, the results reported that capital adequacy was positively related to financial performance; however, there was no significant relationship between bank size and financial performance. Finally, it was determined that there was a negative relationship between bank leverage and the financial performance of the studied banks. A study conducted by Salih and Afifa (2020) found that the profitability of Jordanian banks is mainly affected by bankspecific variables (bank capital, credit risk, and liquidity risk). This study employed the GMM method to determine its results, revealing that bank capital, credit risk, and liquidity risk significantly impact bank profitability. The study recommended a change in the credit policies of commercial banks to reduce bad credit and improve bank profitability in the future.

It was concluded from existing literature that the relationship between credit risk and bank profitability differs for different types of banks. For instance, the most recent study carried out by Yin et al. (2021) investigated the determinants of green credits on the credit risk and profitability of Chinese banks. This study used the GMM approach to determine its findings, which revealed that profitable and large banks tend to lend more green credits. Furthermore, it was also identified that green lending practices significantly affect the risk and profitability of the studied banks. The findings also demonstrated that green lending practices increase the profitability level of non-state-owned banks and reduce their risks, while state-owned banks provide green credits at the expense of their profitability. Another relevant study conducted by Mudugi et al. (2020) identified a positive relationship between profitability and credit risk for 11 local and foreign banks in Ghana. The findings of the fixedeffects model (FEM) further reported that the effect of credit risk on bank profitability was huge for local banks compared to foreign banks in the banking industry.

To understand the rationale behind the failure of banks, an influential study conducted by Wheelock and Wilson (2000) examined the determinants of the United States' bank failures and acquisitions by considering panel data from the period 1984-1993. This study considered bankspecific factors to estimate the computing-risk hazard model. The estimation results revealed that management inefficiency increases the risk of bank failure and reduces the probability of U.S. banks. The analysis also concluded that the return on assets (ROA) has a significant negative effect on bank failures in this economy. In the same context, another relevant study attempted by Cleary and Hebb (2016) explored the causes of 132 U.S. bank failures during the period 2002-2009 by employing the discriminant analysis model. The authors emphasized loan quality and bank capital to determine the financial health of the studied banks. The study also highlighted the importance of profitability in predicting the financial distress of banks. Conversely, Cloe and White (2012) analyzed the negative association between return on assets (ROA) and default probability (PD) of U.S. banks. More importantly, the studies conducted by (Lin & Yang, 2016; Arena, 2008) on the banking sector of Asia and East Asia, respectively, found that the return on asset (ROA) is a key predictor for measuring bank distress. Conversely, other studies such as (Männasoo & Mayes, 2009; Betz et al., 2014) found no connection between profitability and default probability (PD) of the European banks. These studies concluded that bank profitability does not reduce the default likelihood of banks.

The overall review of the existing empirical literature on the profitability-default risk nexus highlights bank profitability as a determinant of default risk and shows mixed evidence about the role of bank profitability in reducing the default likelihood (PD) in the banking sector. For instance, some studies concluded that bank profitability is a significant determinant of default risk (Schenck, 2014); whereas, other studies concluded that there is no association between the above-mentioned phenomena (Betz et al., 2014). It means that the nature and the direction of the association between bank profitability and default risk are ambiguous. For example, Flamini et al. (2009) found a positive association between profitability and default risk; whereas, Cloe and White (2012) concluded a negative association between profitability and default risk. More importantly, available literature also highlights that countrywide differences exist in the case of profitability-default risk nexus. In particular, one study concluded that bank profitability is a significant determinant of default risk for U.S. banks compared to other banks (Männasoo & Mayes, 2009; Cleary & Hebb, 2016).

The literature review on the profitability-default risk nexus highlighted that most of the empirical studies were made by researchers from the USA, China, UK, and Europe. In Pakistan's banking sector, this research area is still in the early stages. Therefore, this empirical study attempted to fill the existing research gap in the field of risk management by investigating the impact of profitability on default risk in the banking sector of Pakistan.

Data and Variables Description

Data Sources

The current study empirically investigated the impact of bank profitability on the default risk of scheduled commercial, public sector, and Islamic banks of Pakistan listed on the *PSX* website. The banking sector of Pakistan consists of 46 financial firms, out of which 36 are commercial and Islamic banks while the remaining 10 are microfinance banks. The commercial banks of Pakistan are further divided into 25 local banks, 3 local Islamic banks, and 8 foreign banks. The local commercial banks of Pakistan are 25, out of which 18 are private, and 7 are public sector banks (State Bank of Pakistan, 2020). In this study, a sample of 20 banks listed on the *PSX* website for a period of 10 years (2009-2018) was used for further investigation (see Appendix). This data was selected due to its ease of availability in the SBP financial reports. Data of daily stock prices was taken from PSX (2020) website; whereas, data on bankspecific determinants was taken from the State Bank of Pakistan (*SBP*) published reports[1].

Definitions of Variables

The Merton distance-to-default (DtD) is one of the most popular and efficient techniques among all the marketbased techniques used to measure default risk (Harada et al., 2013). In 1993, Moody's KMV modified the Merton structural model (1974) by calculating the profitability and default risk at a specified point of time. These estimation techniques are applied to both financial and non-financial institutions. According to the Merton KMV approach, if the market value of a bank asset declines in such a way that it becomes less than the book value of debt, the bank will be termed as default (Coccorese & Santucci, 2019). If the debt value is subtracted from the market equity value, the resulting outcome is the default probability. Consequently, if the resulted value is divided by a bank's esteemed volatility, the end value is called distance to default (*DtD*), it shows how far a bank is away from a default.

The Merton (1974) structural model is the foundation of Moody's KMV model. For the current study, the option pricing theory and the structural model of Merton were considered in the context of banking firms. We also deemed that the equity of a bank is the same as the call options on bank's asset. It provides shareholders the right to have the

[1]Data on bankspecific factors were taken from the 2009-2013 financial report upto 2012. The remaining series was updated from the 2014-2018 financial report published by the SBP.

residual claims on a bank's assets after the settlement of all liabilities. As per Merton's hypothesis, a bank's liability is a single debt which demands payment at a certain maturity time. The bank will meet its obligation only if the bank asset value exceeds the debt value. The bank will survive only if the value of the total assets is higher than the debt value; otherwise, the bank will default. Similarly, if the bank's asset value falls below the bank's debts, then the bank equity will be zero (Crosbie & Bohn, 2003; Bharath & Shumway, 2008; Allen & Powell, 2011; Duan & Wang, 2012; Coccorese & Santucci, 2019).

The probability of default model makes two important assumptions. First, the total market value of bank assets follows a geometric Brownian motion:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{1}$$

In equation 1, V_A denotes the value of a bank's total assets, μ denotes the expected compounded return on bank assets V, σ denotes a bank's asset volatility, and dW represents the standard Weiner process. The Merton model's second assumption states that a bank will issue only one discount bond for the maturity of T time periods. Similarly, if we consider bank equity as a call option for the value of bank assets, the equity strike price would be V_A, which is equal to the face value of a bank's liability and maturity time T. If V_E represents the market value of equity, then according to (Black & Scholes, 1973) the option pricing formula is:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) \tag{2}$$

In Equation 2, V_E indicates the market value of a firm's equity, X represents the face value of a firm's debt, r stands for the risk-free rate, $N(d_1)$ and $N(d_2)$ denote the cumulative normal distribution function.

$$d_1 = \frac{ln\left(\frac{V_A}{X}\right) - \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}} \tag{3}$$

In Equation 3, d_1 and σ_A^2 represent 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 contingent receipts of the stocks exceeds the current stock price. According to Nielsen (1992), the risk-adjusted probability *(d_2)* can be calculated as follows:

$$d_2 = d_1 - \sigma_A \sqrt{T} \tag{4}$$

The bank equity value (V_E) and volatility of equity are needed to compute the DtD value. Black-Scholes-Merton's Equation 2 expresses that a firm's equity value is the same as the function of the firm's value. The second part of the equation shows a firm's volatility to the volatility of a firm's equity. The second assumption of Merton's model states that equity is determined by the value of a firm over time.

$$\sigma_E = \left(\frac{V_E}{E}\right)\left(\frac{\partial E}{\partial V}\right)\sigma_A \tag{5}$$

Where:

$$\frac{\partial E}{\partial V} = N(d_1) \tag{6}$$

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

$$\sigma_E = \left(\frac{V_E}{E}\right) N(d_1)\sigma_A \tag{7}$$

The distance to default (*DtD*) is derived as follows:

$$DTD_t = \frac{ln\left(\frac{V_{At}}{X_t}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}} \tag{8}$$

In Equation 8, DTD_t stands for the distance to default in the period t, V_A denotes the value of the assets, μ symbolizes the expected return on assets (ROA), σ_A^2 represents the assets' volatility, T indicates the time dimension, and X_t refers to the debt face value. It should be noted that the value of liabilities is considered as the terminal value of assets in Merton's model. However, Moody's KMV model has modified Merton's model (1974) slightly by assuming the default point as the sum of the short-term and half of the long-term liabilities. This modification was suggested after observing a large sample of banks when their assets and liability values were very high. If the asset value declines to a critical point, which lies somewhere between the total liabilities value and short-term liabilities, then the bank is termed as default. Finally, the default probability of a bank is calculated as follows:

$$PD = N^2(-DD) \tag{9}$$

To estimate Equation 9, we need to calculate the volatility of equity value. This value can be computed by using the daily stock price return of the public companies listed on the PSX. The stock price return is calculated by using a method proposed by (Hull, 1999):

$$R_i = \ln(P_t - P_{t-1}) \tag{10}$$

The volatility of equity of a bank for a particular year can be calculated by using Equation 11.

$$\sigma_E = \frac{1}{\sqrt{\frac{1}{n}}}\sqrt{\frac{1}{(n-1)\sum_{i-1}^{n} r_i^2} - \frac{1}{n(n-1)}\left(\sum_{i-1}^{n} r_i\right)^2} \tag{11}$$

In Equation 11, n represents the number of trading days in a year. The market assets value (V_A), assets volatility (σ_A), and the expected assets return (μ) can be computed by substituting the market value of equity (V_E), which is the product of stock price and the number of outstanding shares, the value of total liabilities (X), which consists of short-term debts and half of the long-term debts, and the risk-free rate (r)[3] with the return of treasury bills per year in Equations 2 and 7. Therefore, we substituted these computed values in Equation 8 to get the value of the distance-to-default (DtD). When the distance-to-default (DtD) score is high, it indicates that a particular bank is far away from the default point; therefore, the *PD* value would be lower.

Probability ratios consist of those financial metrics that evaluate a financial firm's ability to generate revenue by efficiently and effectively utilizing its available assets. Profitability ratios show a firm's ability to generate revenue and shareholders' value. Various studies in the literature used profitability ratios to predict bankruptcy/financial distress of non-financial firms (Siriopoulas & Tziogkidis, 2010; Rashid & Abbas, 2011; Dar & Qadir, 2019; Waqas & Md-Rus, 2018). According to the SBP Financial Report of 2014-2018, SBP uses profitability ratios as proxy

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

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

variables to find out the profitability of commercial banks. The probability ratios used in the study are calculated as follows:

A – The spread ratio (*SR*):

$$SR = \frac{Net\ markup/_{interest\ income}}{Markup/_{interest\ earned}} * 100 \tag{12}$$

B – Return on assets (*ROA*):

$$ROA = \frac{Net\ profit\ after\ tax}{Total\ Assets} * 100 \tag{13}$$

C – Net interest margin (*NIM*):

$$NIM = \frac{Total\ interest\ income - Total\ interest\ expenses}{Total\ assets} * 100 \tag{14}$$

D – Return on equity (*ROE*):

$$ROE = \frac{Net\ profit\ after\ tax}{Shareholder\ equity} * 100 \tag{15}$$

E – Non-interest income to total assets (*NITA*):

$$NITA = \frac{Total\ non-interest\ income-markup}{Total\ assets} * 100 \tag{16}$$

Model Specification and Econometric Methodology

To estimate the panel data within the framework, a general specification of the econometric model can be written as shown in Equation 17.

$$Y_{it} = \alpha_0 + \beta_1 X_{it} + \varepsilon_{it} \tag{17}$$

In Equation 17, Y_{it} denotes the dependent variable where *i* and *t* denote the crosssection and time-series units, respectively. Similarly, α_0 denotes the intercept term and β_1 denotes the slope of the regression model which needs to be empirically estimated. X_{it} denotes the set of explanatory variables, where *i* =1, 2, …, *N* and *t* = 1, 2, …, *T*. The set of explanatory variables $(X's)$ are nonstochastic in nature and the error term follows the classical assumptions, that is, $E(u_{it}) \sim N(0,\ \sigma^2)$.

To determine the effect of profitability determinants on the default risk of banks, we can develop the single-equation econometric model as shown in Equation 18.

$$PD_{it} = \beta_0 + \beta_1 NIM_{it} + \beta_2 NITA_{it} + \beta_3 ROA_{it} + \beta_4 ROE_{it} + \beta_5 SR_{it} + \varepsilon_{it} \quad (18)$$

In equation 18, the variable *PD* stands for the default probability of banks. It measures the probability of whether a particular commercial bank will be able to fulfill its debt obligations within due time or not. β_0 is the intercept term, while $\beta_i' s$ are the slope coefficients of explanatory variables that need to be empirically estimated. The set of independent variables include the net interest margin (*NIM*), non-interest income to total assets (*NITA*), return on assets (*ROA*), return on equity (*ROE*), and the spread ratio (*SR*) for all cross-sections (*i* = 20 banks) and time (*t* = 2009-2018).

In our study, the panel data approach was used to investigate the effect of profitability on the credit risk of the 20 selected banks of Pakistan. Basically, longitudinal data is the amalgamation of time-series plus crosssection data (Gujarati, 2004; Asteriou & Hall, 2011; Wooldridge, 2012; Studenmund & Johnson, 2016). The study used different methods for the empirical investigation of the selected panel data since it is imperative for researchers to decide the most suitable model for panel data estimation. In Econometrics, the linear panel data models can be estimated considering 3 standard methods such as the common constant model, the fixedeffects model (FEM), and the random-effects model (REM).

The common constant model (or the pooled OLS model) provides results based on the principal postulation that there are no differences between the estimated intercept (α) for all crosssectional units. Therefore, this panel estimation model was applied in this study under the strict assumption that the data under consideration is priori homogeneous, while intercept α is constant for all entities (Asteriou & Hall, 2011; Studenmund & Johnson, 2016). However, this panel estimation method is quite restrictive as compared with fixed and random effects models (REM) (Asteriou & Hall, 2011). In general form, the model can be written as in Equation 19.

$$Y_{it} = \alpha + \beta' X_{it} + \varepsilon_{it} \quad (19)$$

The fixedeffects panel estimation method is purely based on the postulation that α is changing for all entities, yet it assumes that the slope coefficient (β) is constant for all crosssections over time (Gujarati, 2004).

In a notational form, the fixed effects model (FEM) can be formulated as in Equation 20.

$$Y_{it} = a_i + \beta' X_{it} + \varepsilon_{it} \tag{20}$$

It is worth mentioning that the subscript i with α denotes changing intercept for all crosssections, while β is constant across different crosssections over time. It should be noted that the constant α in this panel estimation approach was treated as group-specific. For this reason, it can be deduced that the fixed-effects panel estimation method allows for different $\alpha's$ for each entity. It is also assumed that $\beta's$ for all crosssections do not change over time. To allow for different constants for each section, this estimation technique uses a dummy variable (*D*) for each specific group, which is commonly known as the least squares dummy variable estimator (Gujarati, 2004; Asteriou & Hall, 2011; Wooldridge, 2012; Studenmund & Johnson, 2016). The fixed-effects model (FEM) can be written as in Equation 21.

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} \ldots + \beta_k X_{kit} + \varepsilon_{it} \tag{21}$$

In a matrix notation, the model can be structured as in Equation 22.

$$Y = D\alpha + X\beta' + \varepsilon \tag{22}$$

In this case, the inclusion of a dummy variable in the model allows the researchers to consider various groupspecific coefficients for all constants for each different group. For the selection of FEM, we applied a statistical test to check whether this panel estimation method should be utilized for estimation purposes or not. For this purpose, the F-test can be applied to check *FE* against the ordinary OLS technique. The formulated null hypothesis (H_0) of this method revealed that all the constants are homogenous; whereas, the alternative hypothesis (H_1) revealed that all the constants are heterogeneous.

$$H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \cdots = \alpha_N \tag{23}$$

The F-statistic can be calculated as:

$$F = \frac{(R^2_{FE} - R^2_{CC})\,(N-1)}{(1 - R^2_{FE})/(NT - N - k)} \sim F(N-1, NT-N-k) \tag{24}$$

In Equation 24, R_{FE}^2 denotes the R^2 of the fixedeffects model (FEM) and R_{CC}^2 denotes the R^2 of the common constant model. The decision rule states that if the statistical value of the F-test is higher than the critical value of the F-test. Furthermore, H_0 acceptance confirms the suitability of the common constant model, while H_1 acceptance confirms the appropriateness of the fixed effects model (FEM) for panel estimation purposes. Consequently, we rejected H_0 and accepted H_1. If there is variation in the data and the intercept α is different for each cross section, then the appropriate method for panel data estimation is FEM (Asteriou & Hall, 2011). This model is superior to the common constant model since it primarily captures all key effects that are certain to a specific crosssection and does not change over a period of time. It also calculates a huge number of dummy constants when the panel data comprises thousands of individual members (Asteriou & Hall, 2011).

The randomeffects panel data model is based on the postulation that α for each entity is selected from a distribution that is centered on a mean intercept. Therefore, each α is mainly chosen from "intercept distribution," and the error term is independent for any observation. The randomeffects model (REM) has more degree of freedom as compared to the fixedeffects model (FEM). This method estimates the parameter of the distribution of intercepts. This method also assumes that the coefficient of the explanatory variables is not meaningful since it follows a random path. The random effects model (REM) does not take into account the constants for each group as determined; however, this approach considers that the constants are random parameters. Therefore, the variation of the constants in each group is derived from the following expression:

$$\alpha_i = \alpha + v_i \tag{25}$$

In Equation 25, v_i represents the standard random variable having zero mean and standard deviation 1. Therefore, the randomeffects models (REM) can be specified as follows:

$$Y_{it} = (\alpha + v_i) + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \cdots + \beta_k X_{kit} + \varepsilon_{it} \tag{26}$$

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \cdots + \beta_k X_{kit} + (v_i + \varepsilon_{it}) \tag{27}$$

One drawback of this method is that the researchers are required to set prior assumptions regarding the distribution of the random variable. It also assumes that the unobserved groupspecific effects are correlated with the independent variables of the models (Studenmund & Johnson, 2016). Hence, the estimated coefficients of the fixedeffects model (FEM) will be inconsistent and biased (Asteriou & Hall, 2011). This model is superior to the fixedeffects model (FEM) due to two main reasons. First, it estimates fewer parameters. Second, it allows the researchers to use dummy variables. Thus, it is concluded from the panel data econometrics that FEM is more suitable for a balanced panel data estimation. Conversely, REM is more suitable when the selected sample includes a limited number of crosssection observations (Asteriou and Hall, 2011).

Empirical Results

Descriptive Statistics

Descriptive statistics are the summary of statistics. They describe the nature and the overall behaviour of data under consideration. For example, these statistics include the mean value of a variable that provides information about the average value of a variable. The statistics of standard deviation show the degree of dispersion of the data from its mean value. The skewness measures the degree of distortion in the data, and kurtosis measures whether the data is heavy-tailed or light-tailed. The results in Table 1 report that the average value of the probability of default is 0.288, which is a positive value, showing that, on average, Pakistani banks remain stable for ten years. The maximum and minimum values for *PD* are 3.22 and 1, respectively, with a *S.D* of 0.35. The mean value of the net interest margin (NIM) is 0.032 with a *S.D* of 0.019. The mean value of the *NITA* is 0.085 with a *S.D* of 0.10. Similarly, the average value for *ROA*, *ROE*, and *SR* is 0.49, 0.07, and 0.42, respectively. The calculated probability value of the *J-B* statistic showed that the examined variables are normally distributed at the 1% level of significance.

Table 1

Descriptive Statistics

Variable	N	Mean	S.D	Min. value	Max. value	Probability
PD	200	0.28836	0.3512	3.22E-36	1	0.00
NIM	200	0.03286	0.019799	-0.015603	0.19086	0.00
NITA	200	0.08508	0.104869	-0.0024	0.6078	0.00
ROA	200	0.49659	0.975602	-5.41	2.64	0.00
ROE	200	0.07109	1.100963	-14.7427	2.3471	0.00
SR	200	0.42361	0.136117	-0.0321	0.927	0.00

Source: Data processed by the author

Correlation Analysis

This analysis is mainly used to check for the presence of severe multicollinearity among the explanatory variables of the model. Multicollinearity describes a situation where two or more than two explanatory variables are highly correlated to each other. Kennedy (2008) reported that high multicollinearity is found when the relationship between the two independent variables exceeds 0.7. In addition, Malhotra (2004) reported that when the correlation coefficient between the two explanatory variables is greater than 0.75, then the data is a victim of significant multicollinearity. In the presence of induced multicollinearity[4], the precise model estimation is challenging, which leads to biased empirical results. Table 2 reports intercorrelations signifying that all the explanatory variables were negatively correlated with the dependent variable (*PD*); whereas, all the explanatory variables were positively correlated to each other. The results reported in the correlation matrix confirmed that our data was not a victim of perfect/imperfect multicollinearity because all the pair-wise correlations of the explanatory variables were less than 0.7.

[4]The practical consequences of imperfect multicollinearity also include the obtaining of imprecise OLS estimates, the opposite signs of estimated coefficients, much wider confidence intervals, the higher R-squared value, insignificant t-values, etc.

Table 2

Correlation Matrix

Variable	PD	NIM	NITA	ROA	ROE	SR
PD	1					
NIM	-0.190	1				
NITA	-0.156	0.001	1			
ROA	-0.393	0.205	0.134	1		
ROE	-0.110	0.178	0.057	0.427	1	
SR	-0.425	0.418	0.178	0.507	0.282	1

Source: Data processed by the author

Default Probability (*PD*) of Pakistani Banks

The probability of default (PD) is a parameter that measures the likelihood of a default of a firm over a particular time span. According to the Merton KMV model, if the market shares of a bank declines in such a way that it becomes less than the debt value, then that particular bank is in the position of a default or close to default. Table 3 reports the mean *PD* value of the 20 selected banks of Pakistan over the course of 10 years (2009-2018). The findings reported that the mean *PD* value for some individual banks of Pakistan such as ABL, BAHL, BOK, HBL, HMB, MCB, MEBL, and UBL were 0.02, 0.16, 0.22, 0.11, 0.12, 0.04, 0.09, and 0.10, respectively. It also indicated the lowest *PD* value. These results revealed that these banks have low default risk because they are large banks having high market capitalization and profitability, maximum efficiency, and optimal performance in the banking industry of Pakistan. Similarly, the mean *PD* value for some banks such as BAFL, AKBL, BIPL, JSBL, SBL, SILK, and SNBL was 0.41, 0.40, 0.32, 0.42, 0.28, 0.41, and 0.37, respectively. It indicated a relatively high *PD* value. This shows that these individual banks have a lower default risk since they are small banks performing moderately in the banking industry of Pakistan. However, the mean *PD* value of banks such as BOP, FABL, and SMBL was 0.63, 0.50, and 0.78, respectively, which indicated that these banks are close to default since the calculated mean *PD* value for these banks was higher than 0.5. More importantly, the PSX website declared Summit Bank as a defaulter in 2019 since its share price value was lower than the face value. When the computed mean *PD* value is compared with the market's equity value of banks, it indicated that *PD* is a reliable measure to predict the default risk in the banking sector of Pakistan. The analysis also demonstrated that the banking system of Pakistan is quite strong and stable and has a low default risk. Figure 1 plots the default probability (PD) values for the 20 selected individual banks of Pakistan over the sampling years.

Table 3

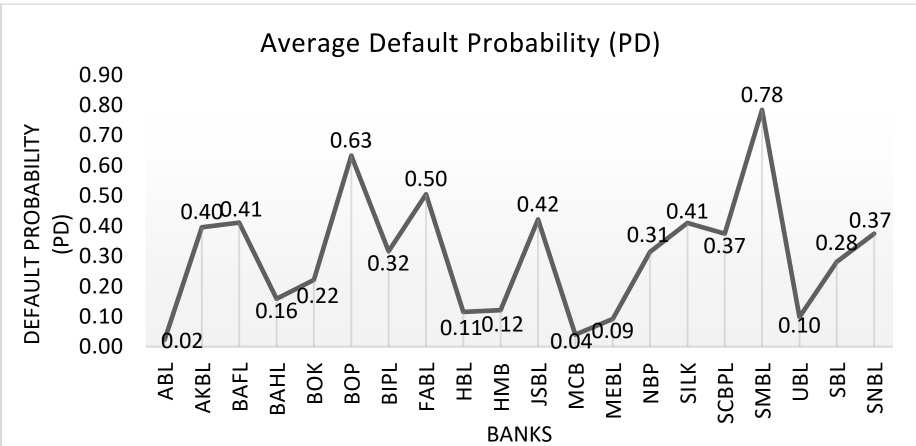
The Results of Default Probability

Serial #	Bank Name	PD	Serial #	Bank Name	PD
1	ABL	0.02	11	JSBL	0.42
2	AKBL	0.40	12	MCB	0.04
3	BAFL	0.41	13	MEBL	0.09
4	BAHL	0.16	14	NBP	0.31
5	BOK	0.22	15	SILK	0.41
6	BOP	0.63	16	SCBPL	0.37
7	BIPL	0.32	17	SMBL	0.78
8	FABL	0.50	18	UBL	0.10
9	HBL	0.11	19	SBL	0.28
10	HMB	0.12	20	SNBL	0.37

Source: Data processed by the author

Figure 1

Probability of Default (PD) of Pakistani Banks for the Period 2009-2018



Model Specification

The study examined the impact of profitability on the default risk of 20 individual banks in Pakistan by taking panel data ranging from 2009-2018. Different models of panel data estimation such as the common constant model, FEM, and REM were suggested to estimate the parameter coefficients. Different tests were applied to select the most suitable method of estimating precise results.

Likelihood Test

The likelihood test can predict which panel estimation model is more suitable for the examined data. In this study, this test was applied on the common constant model and the fixed-effects model (FEM) to asses their goodness of fit. H_0 stated that FEM is appropriate, while H_1 stated that the common constant effects model is more suitable for the panel data under examination. The likelihood test's findings given in Table 4 conclude that FEM is more suitable for the selected panel data since the calculated p-value is $0.00 < 0.05$. Therefore, we accepted H_0 and rejected H_1.

H_0: The fixedeffects model is suitable.
H_1: The common constant effects model is appropriate.

Table 4

Redundant FE Tests

Test cross-section fixed effects			
Effects Test	Statistic	*d.f.*	Prob.
Cross-section F	3.083662	(19, 175)	0.0000
Cross-section Chi-square	57.755938	19	0.0000

Source: Data processed by the author

The Hausman Specification Test

The Hausman test (1978) was applied to decide which model between FEM and REM is more appropriate for panel data estimation. This test is formulated based on H_0 of no correlation, where the GLS and OLS estimators are consistent, but the OLS estimator is insufficient. Conversely, H_1 stated that the OLS method is consistent, while GLS method is not consistent. In the case of selected panel data, the Hausman test investigated whether the coefficients of FEM and REM were correlated with the individual unobserved effect. According to the analysis of Ahn and Moon (2001), H_0 of the Hausman test stated that the random-effect estimator was consistent and efficient, while H_1 stated that the random-effect estimator was not consistent. The statistics of the Hausman test can be formulated as follows:

$$H = \left(\beta^{\widehat{FE}} - \beta^{\widehat{RE}}\right)' \left[Var\left(\beta^{\widehat{FE}}\right) - Var\left(\beta^{\widehat{RE}}\right)\right]^{-1} \left(\beta^{\widehat{FE}} - \beta^{\widehat{RE}}\right) \sim \mathrm{X}^2(\mathrm{k}) \tag{28}$$

If Hausman's test statistic value is big, the difference between the two model estimates would be significant. In such a case, we reject H_0 and accept H_1. Conversely, if Hausman's test statistic value is small, we conclude that the random-effect estimator is more appropriate than the fixed-effect estimator. The Hausman test results given in Table 5 reported that the chi-square statistic value was 21.144, which is higher than the chi-square critical value. For this reason, we rejected H_0 and accepted H_1. The Hausman test concluded that the fixedeffects estimators are more suitable, which is why we select the fixedeffects model for estimation purposes[5].

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

Table 5

Correlated Random Effects

Test cross-section random effects			
Test Summary	*Chi-sq. statistic*	*Chi-sq. d.f.*	*P-value*
Cross-section random	21.143800	5	0.0008

Source: Data processed by the author

The Results of Fixed Effects Model

The estimated findings for the FEM are given in Table 6. The analysis of the findings revealed that the association between the *NIM* and *PD* is

[5]The results can also be confirmed from the highly statistically significant p-value of less than 1%, therefore, we select the fixed effects model.

positive, showing that a 1% fall in *NIM* would lead to a 4.1% rise in *PD.* This association has a significance level of 1%. The findings also revealed that *NIM* is a significant predictor of *PD* for Pakistani banks. This outcome is in line with Schenck's (2014) results. Similarly, the association between *NITA* and *PD* is negative, showing that a 1% increase in *NITA* would lead to a 1.03% decrease in *PD.* This association has a significance level of 1%. We can say that *NITA* is a significant determinant of *PD* in the case of Pakistani banks. This outcome is supported by the findings of (Beaver, 1966; Altman, 1968; Ohlsan, 1980; Shumway, 2001; Rashid & Abbas, 2011; Waqas & Ms-Rus, 2018). The findings also demonstrated that the relationship between *SR* and *PD* is negative, revealing that a 1% increase in the *SR* would lead to a 0.58% decrease in *PD*. The results reported that the *SR* is a significant determinant of *PD.* This relationship has a significance level of 5%. This outcome supports the findings of other studies (Shumway, 2001; Rashid & Abbas, 2011; Waqas & Ms-Rus, 2018). In contrast, the relationship between *ROA* and *PD* and *ROE* and *PD* is positive and negative, respectively. However, outcome of both cases is statistically insignificant for both relationships. Finally, the summary statistics (i.e. R^2, adjusted R^2, *S.E*, and *F-statistic*[6]) support the fitness of the model. Similarly, the *D-W* statistic indicated that our proposed model specification is not a victim of serial correlation[7] and its results are not spurious[8]. Hence, after assessing the different statistical testing indicators, it was concluded that the proposed model specification is best fitted.

Table 6

The Results of FEM

Explained Variable: *PD*
Method: Panel Least Squares
Sample: 2009-2018
Periods: 10
Cross-sections: 20
Total panel observations: 200

[6] The result of the F-statistic reveals that the coefficients of the FEM are not equal to zero.

[7] *D-W* ≈ 2

[8] *D-W* > R^2

Variable	*Coefficient*	*S.E*	*t-Stat.*	*Prob.*	*Significance*
Ni					
C	0.503731	0.114042	4.417067	0.0000	***
NIM	4.118041	1.592331	2.586172	0.0105	***
NITA	-1.038356	0.282678	-3.673278	0.0003	***
ROA	-0.033995	0.031499	-1.079248	0.2820	
ROE	0.011065	0.022448	0.492908	0.6227	
SR	-0.581314	0.251672	-2.309803	0.0221	**

Effects Specification
Cross-section fixed (dummy variables)

R^2	0.428413	*Mean dependent var*	0.288363
Adjusted R^2	0.350024	*S.D. dependent var*	0.351200
S.E. of regression	0.283141	*AIC*	0.430727
SSR	14.02957	*SC*	0.843017
Log likelihood	-18.07271	*HQ criterion*	0.597574
F-statistic	5.465216	*D-W statistic*	2.044049
Prob. (F-statistic)	0.00 0000		

*Note. '*P' < 0.1 Weak Significance, '**P' < 0.05 Semi-strong Significance, '***P' < 0.01 Strong Significance*

Source: Data processed by the author

Conclusion and Policy Recommendations

This study investigated bank-specific determinants of profitability in order to measure their influence on the default risk of Pakistani banks. It also investigated whether or not the probability of default (PD) is a reliable measure to predict default risk. For this purpose, 10 years of balanced panel data for the period 2009-2018 was collected and analyzed from 20 Pakistani commercial banks. The bankspecific determinants affecting the default risk include the net interest margin (NIM), non-interest income to total assets (NITA), return on assets (ROA), return on equity (ROE), and spread ratio (SR). The empirical findings of the fixed effects model (FEM) reported that the relationship between *NIM* and *PD* was positive and significant. It shows how efficiently these banks earn from their investment expenditures, advancing loans, and mortgages. The increase in *NIM* ultimately increases PD. When interest earnings (bank's profit) from loans increase, banks invest their idle funds keeping in view the higher returns, whilst simultaneously taking higher risks. Consequently, it increases the probability of default. The empirical findings also revealed that *NITA* has a significant negative effect on the probability of default. *NITA* is the fee received from a bank's deposits and transactions, annual fees, monthly account service charges, and credit card fee. It comprises extra return received by banks that increases bank profitability. It was concluded that when *NITA* increases, *PD* decreases as a result. The empirical findings of the study also reported that SR is negatively linked to PD. Whenever SR increases, the probability of default decreases for the given banks. The findings also revealed that *ROA* and *ROE* are insignificant and do not adequately explain the default risk. The empirical findings reported that the mean *PD* value reliably predicts the default risk of Pakistani banks.

The relationship between bank profitability and default risk brings to light several policy implications. The findings demonstrated that default risk is an indicator of financial instability in the banking sector of a country. However, The PD statistic revealed that the Pakistani banking industry is perfectly stable. Our study also highlighted that the marketbased default prediction model provides reliable estimates when predicting the default risk of Pakistani banks. Based on the empirical findings, it recommended that the State Bank of Pakistan (SBP) should compel the commercial banks to disclose their *PD* value in their annual reports. It also recommended that the risk management department of commercial banks should keep in view the bankspecific determinants of profitability to manage their default risks. The current study showcased the importance of default risk and informed the current and potential depositors and savers about its dangers so they could make rational investment decisions.

Future researchers can consider other bankspecific variables for measuring the default risk (bank size, management efficiency, regulatory capital, market risk premium, total liability, operating cost, and interest earned). They may also incorporate macroeconomic variables (the interest rate, exchange rate, the industrial production index, and trade balance) into their study for the same purpose. Future studies can also extend the current analysis to the non-financial sector. Future researchers can also conduct a similar study by taking panel data from investment banks, microfinance banks, mutual fund companies, insurance companies, and leasing organizations.

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Appendix

PD	Probability of Default	FABL	Faysal Bank Limited
SBP	State Bank Of Pakistan	HBL	Habib Bank Limited
PSX	Pakistan Stock Exchange	HMB	Habib Metropolitan Bank Ltd.
UBL	United Bank Limited	JSBL	JS Bank Limited
ABL	Allied Bank Limited	MCB	MCB Bank Limited
AKBL	Askari Bank Limited	MEBL	Meezan Bank Limited
BAFL	Bank Al-Falah Limited	NBP	National Bank Of Pakistan
BAHL	Bank Al-Habib Limited	SBL	Samba Bank Limited
BOK	Bank Of Khyber Limited	SILK	Silk Bank Limited
BOP	Bank Of Punjab Limited	SNBL	Soneri Bank Limited
BIPL	Bank Islami Pakistan Limited	SCBPL	Standard Chartered Bank Ltd.