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Relationship between credit risk and return on assets in Yemeni banks using panel data models for the period (2004 - 2020)

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Abstract: This study examines the optimal econometric model that best captures the relationship between credit risk (CR) and bank performance, measured by Return on Assets (ROA), within Yemeni banks during 2004–2020. Credit risk is proxied by the ratio of loan loss provisions to total loans (PDL/TL), and the ratio of total loans to total deposits (TL/TD). To analyze this relationship, panel autoregressive distributed lag (Panel ARDL) models were employed, namely, the Dynamic Fixed Effects (DFE), Pooled Mean Group (PMG), and Mean Group (MG) estimators. After comparing the model estimates using the Hausman test, the PMG model was found to be the most appropriate for capturing both the short- and long-run dynamics of CR's impact on ROA. The findings indicate that CR has no statistically significant short-run effect on ROA. However, in the long run, CR has a weak positive impact on ROA. Specifically, a 1% increase in PDL/TL leads to a 3.3% increase in ROA, whereas a 1% increase in TL/TD results in a 1.3% ROA increase. The study concludes that banks should emphasize long-term strategies, including credit portfolio diversification and sound financial policies, to mitigate credit risk and improve their financial performance.
Keywords: *Credit Risk (CR), Return on Assets (ROA), Yemeni banks, Panel data model.*

1. Introduction

Banks are the economic backbone of any country. The extent of their success, development, and growth directly influences the stability and sustainable development of the economy. Conversely, the risks they face due to broad and uncertain environmental fluctuations may expose them to severe financial risks, potentially leading to bankruptcy and collapse, which would consequently harm depositors, shareholders, employees, and the economy as a whole.

As financial intermediaries, banks seek to maximize their financial returns by attracting savings from various sources at lower costs and then investing these funds in financing investment projects or providing their clients with various credit facilities. These facilities are granted through their credit portfolios to finance projects at a return rate higher than the interest and commissions paid to banks at their due dates [1, 2]. However, banks are highly sensitive institutions because they rely heavily on their clients' deposits, which constitute more than 85% of their liabilities [3]. Although credit is one of the primary income-generating mechanisms in banks, its effect on bank profitability and financial returns remains unclear. The effect can be positive, increasing with CR, or negative when banks fail to manage their loan collections [4], which can lead to the erosion of bank capital and, subsequently, a decline in public confidence in banks' ability to meet their obligations and invest funds in various profit-generating activities [5].

In this connection, Boahene et al. [6] highlighted that high-quality credit is a key factor in the financial strength and **stability** of banks, whereas poor-quality credit significantly contributes to bank

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bankruptcies. Chen and Pan [7] pointed out that this type of risk is one of the greatest financial risks faced by banks and is a major factor leading to their insolvency and collapse. The Basel Committee on Banking Supervision [8] emphasized that one of the main sources of risk faced by banks is the poor management of loan portfolio risks and credit standards, according to which loans are granted to counterparties.

Among the most prominent examples of CR that led to bank bankruptcies and failures are the collapse of the Bank of Credit and Commerce International (BCCI) in the United Kingdom in 1991, the financial crises in East Asia and Russia in 1997, and the U.S. credit crisis that triggered global economic crises in 2008. One of the major causes of these crises was the excessive expansion in granting credit and reliance on short-term financing from financial markets, instead of depending on customer deposit savings, leading to inadequate bank capital [9].

At the local level, Yemeni banks play a vital role in driving the country's economic and social development. Their role in financing economic activities and state loans increased by approximately 13.2 times during the period 2000–2014, reaching 1,844.8 billion Yemeni Riyals. During the same period, the ratio of banking finance to the gross domestic product (GDP) rose from 8% in 2000 to 22.4% in 2013 [10]. However, in 2014, the role of banks in financing economic activities and state loans decreased by 22% compared to previous years, dropping to 7.1%, due to economic and political challenges that plunged Yemeni banks into a prolonged state of dormancy. Under these circumstances, banks are unable to meet their obligations or perform core functions.

One of the most significant issues was Yemeni banks' heavy reliance on investing their financial assets in purchasing treasury bills and government bonds to finance the state's budget deficit. These instruments were favored because they were quickly convertible to cash, highly secure, and provided substantial returns.

For a period, financing the state's budget provided banks with a safe environment to earn financial returns from the public debt interest. However, owing to the country's ongoing crisis, these funds and their associated returns became inaccessible. By 2017, bank loans to the public budget accounted for about 59.7% of the total bank deposits, resulting in a severe liquidity crisis. Approximately 65% of the total bank assets remained beyond the banks' control, depriving depositors of access to their funds deposited before 2016. Consequently, deposit rates declined because of diminished customer trust, leading to reduced credit offerings and, ultimately, lower financial returns for banks [11].

To achieve a precise scientific analysis of the CR and ROA relationships in Yemeni banks, panel data models are employed to develop an optimal model representing the relationship between the variables. Accordingly, the research problem can be framed by addressing the following main question: What is the optimal model for representing the relationship between CR and ROA in Yemeni banks using panel data models for the period (2004–2020)?

2. Objectives of the Study

The primary objective of this study is to identify the optimal model for describing the relationship between CR, measured by PDL/TL, TL/TD, and ROA, represented by the ratio of net profit to total assets in Yemeni banks. This analysis used panel data models covering the period from 2004 to 2020.

3. Hypotheses Development and Literature Review

3.1. The Relationship between Credit Risk (CR) and Return on Assets (ROA)

Many previous studies on the relationship and impact between CR and ROA have been reviewed. For example, Kolapo et al. [12] emphasized the consistent effect of CR on ROA in Nigerian banks. Similarly, studies by Tirwa et al. [13] and Hawaldar et al. [14] conclude that CR has a minimal effect on ROA. Conversely, Isanzu [15] and Afriyie and Akotey [16] demonstrated that non-performing loans, as a measure of credit risk, positively influence financial performance when measured by ROA.

By contrast, Jreisat [17] claimed that CR negatively affects financial performance by increasing non-performing loans and reducing the overall quality of loans study Munangi and Sibindi [18] also indicated a negative impact of CR on financial performance as measured by ROA. Similar negative relationships were reported in other studies, Singh [19], Poudel et al. [20], Haris et al. [21], Abdelaziz et al. [22], Khanal [23], Mendoza and Rivera [24], Ruziqa [25], Opoku et al. [26], De Leon [27], and Staikouras and Wood [28], confirming that CR adversely affects ROA.

Furthermore, Noman et al. [29] identified a significantly strong negative statistical relationship between CR-defaulted loans to total loans and loan loss reserves to total loans, and profitability benchmarks (ROA). In addition, Kargi [1], Islam and Rana [30], Silaban [31], and Al-Eitan and Bani-Khalid [32] conclude that defaulted loans negatively affect the ROA.

After reviewing the related studies, the current study formulates the following hypothesis: There is a statistically significant relationship between CR measured by (PDL/TL and TL/TD) and ROA, represented by the (net income-to-total assets ratio) in Yemeni banks for the period (2004–2020).

3.2. Measurement of Study Variables

3.2.1. Credit Risks (CR)

Credit refers to the borrowing and lending of funds**,** in which banks borrow funds to ensure adequate liquidity to meet their obligations, such as increased demand for loans from customers and investors. In contrast, banks lend money to individuals and organizations at interest rates higher than those paid to depositors. Interest and loans granted to customers constitute a significant portion of the bank's assets. However, defaults on these loans and advances pose severe setbacks, not only for borrowers and lenders but also for the economies of entire countries [6]. The risk associated with a loan granted by a bank that is not repaid partially or fully on time is known as a CR [33]. The risk of credit is considered one of the most significant financial risks facing banks and is a primary factor contributing to bankruptcy and collapse [7].

CR is defined as the loss incurred by a bank when the counterparty (borrower) fails to fulfill loan obligations upon maturity, potentially leading to the bank's bankruptcy if not managed properly [34]. CR is also defined by the Basel Committee on Banking Supervision [8] as the probability of failure of a borrower or counterparty to meet their obligations according to the agreed terms. For Bouteille and Coogan-Pushner [35], the probability of money loss is due to a counterparty's inability or unwillingness to fulfill their financial obligations to the bank.

Many studies on measuring CR have employed indicators such as the by (PDL/TL and TL/TD), such as Singh [19], Poudel et al. [20], Haris et al. [21], Abdelaziz et al. [22], Opoku et al. [26], Al-Eitan and Bani-Khalid [32], Olalere et al. [36], Al-Qurashi and Al-Maqdashi [37], Al-Ghussain and Al-Ali [38], Ogboi and Unuafe [39], Abubakar et al. [9], Hawaldar et al. [14], Kolapo et al. [12] and Noman et al. [29].

3.2.2. Return on Assets ROA

Financial assets are a basic element of the investment and operational strategies for funds available in banks. Banks use financial assets acquired through borrowing, deposits, or shareholder contributions to generate financial returns that balance profitability, liquidity, and security. Each type of financial asset corresponds to a specific investment, and the degree to which banks exploit these assets and their efficacy in generating profits from such investments are assessed using the ROA metric [40].

ROA contains all assets under the bank’s control, including those resulting from obligations to creditors and investors [41]. ROA is used as a measure of bank efficiency and performance quality when exploiting all financial resources and assets to generate profit [42]. It is also defined as a measure of management’s efficiency in making profits from each monetary unit of the bank's total assets and reflects the degree to which management leverages available assets to generate income, regardless of the way these assets are financed Arsew et al. [43]. Ruslan et al. [44] state that ROA is an earnings measure that centers on a bank’s capacity to produce earnings from diverse activities and operations.

Several studies have used the net income-to-total assets ratio as a key indicator to assess banks’ efficiency in generating profits from each monetary unit of their total assets. Studies by Ali et al. [45], Puspitasari et al. [42], Akhtar et al. [46], Iloska [47], Saleh and Abu Afifa [3], Kolapo et al. [12], Arias [48], Roman and Danuletiu [49] and Ruslan et al. [44].

4. Study Methodology and Procedures

4.1. Study Population and Sample

According to reports issued by the Yemen Banks Association [50], 18 banks are operating in Yemen. However, the majority of these banks lack transparency and fail to disclose their financial performance adequately. Therefore, the current study population was limited to Yemeni banks that issue annual financial reports on their official websites. These banks are the Yemen Bank for Reconstruction and Development, the National Bank of Yemen, Yemen Commercial Bank, Yemen Kuwait Bank, International Bank of Yemen, and Cooperative and Agricultural Credit Bank (CAC Bank).

The data obtained by the researcher cover the period from 2004 to 2020, representing the longest available time span with consistent time-series data across those banks. Other banks were excluded because of the unavailability of sufficient financial data or because their data spanned only very short periods, which did not align with the rest of the financial records.

Based on the above, the study sample included financial data related to CR indicators:

- PDL/TL
- TL/TD

Additionally, the ROA indicator was assessed as follows:

- The portion of net profit to total assets

These indicators were analyzed over the period 2004–2020 for the six selected Yemeni banks (study scope). This resulted in 102 observations for each indicator.

4.2. Econometric Models

To achieve the study's objectives and answer its questions, in harmony with previous studies, Poudel et al. [20], Al-Qurashi and Al-Maqdashi [37], Kolapo et al. [12], Al-Eitan and Bani-Khalid [32], Saleh and Abu Afifa [3], De Leon [27], Puspitasari et al. [42], and Sang Tang My [51], the current study employed panel data models that are characterized by their ability to combine the properties of both cross-sectional data and time series data. Cross-sectional data describe the behavior of multiple entities or cross-sectional units (such as countries, banks, and regions) at a single point in time. However, time-series data describe the behavior of a single entity over a specific period (years, months, etc.). The significance of using panel data models lies in their capacity to account for the effects of both temporal and cross-sectional changes [51].

When both cross-sectional and temporal dimensions are present in the panel data, Green identified two primary models for analyzing panel data, as outlined in [52]:

The Fixed Effects Model represents the general linear model for panel data under the assumption of parameter homogeneity (α, β) across all cross-sectional units (i), and takes the following mathematical equation:

$$y_{it} = \alpha + \sum_{j=1}^{k} \beta x_{j(it)} + u_{it} \qquad (1)$$

Where:

1. (i) represents the cross-sectional unit (i = 1, …, N)
2. (t) represents the time period (t = 1, …, T)
3. (k) represents the number of independent variables (k = 1, …, N)
4. (αit) is the intercept term (individual effect), representing the intercept for cross-sectional unit i at time period t
5. (xj(it)) is the observed value of the independent variable j for cross-sectional unit i during time period t.

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6. (βj) is the slope coefficient of the regression line
7. (uit) is the random error term for cross-sectional unit i during time period t
8. ($y$it) is the observed value of the dependent variable for cross-sectional unit i during time period t

The random-effects model represents the general linear model for panel data under the assumption of parameter heterogeneity (α, β) across all cross-sectional units (i), with variations from one unit to another. This model uses the following mathematical equation:

$$y_{it} = a_{it} + \sum_{j=1}^{k} B_j x_{j(it)} + u_{it} \qquad (2)$$

Where:

1. $a_{it} = 1, \dots, n$
2. $B_j = 1, \dots, n$

In light of equations (1) and (2), if the behavior of the data in the current period is not influenced by its behavior in the previous period, and the individual effect of the cross-sectional units is the main determinant in selecting the appropriate model for data analysis, in addition to the overall homogeneity and stationarity of the data at the level and the absence of cross-sectional correlation between the units, the most suitable models for estimating the relationship between variables are the Fixed Effects Models..

In contrast, the most appropriate models for estimating the relationship between variables are random-effects panel data models. If the behavior of the data in the current period is influenced by its behavior in the previous period, the random effects of the cross-sectional units are the main determinants in selecting the appropriate model for data analysis, along with the absence of overall homogeneity, nonstationarity at the level, and the presence of cross-sectional correlation between the units. These models allow for the simultaneous estimation of both short- and long-term effects and are primarily based on autoregressive models, taking into account the lag of the dependent variable by including it in the model as an independent variable [53].

In the current study, the application of the Hsiao [54] test, along with unit root tests represented by Pesaran [55] and Pesaran [56] tests (CIPS - CADF), Breitung test, and Hadri test, as well as cointegration tests such as the Kao and Pedroni tests, revealed that the data exhibit both total and partial variance among parameters and constants.

The data related to the ROA ratio (Net Profit to Total Assets) and the CR Ratio PDL/TL were found to be non-stationary at the level, indicating that these variables are unstable at the level but become stationary after taking the first differences, with an integration order of I(1).

In contrast, the data for the CR Ratio TL/TD indicated the absence of a unit root at this level. Additionally, the results indicate that all study variables exhibit cointegration.

Based on these findings, the current study employed the Random Effects Model using the Panel Autoregressive Distributed Lag Model (PANEL ARDL) to assess the relationship between CR and ROA in Yemeni banks within the study scope.

5. Results and Discussion

To assess the relationship between CR and ROA in Yemeni banks within the scope of this study (2004–2020), several panel data model tests were conducted as presented below:

5.1. Multicollinearity Test

To confirm that the independent variables are free from multicollinearity, which can result in biased and misleading estimates, the study applied correlation coefficient tests conducted using the Stata software. Table 1 explains the multicollinearity test.

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Table 1.
Exhibits the results of the multicollinearity test.

Variable	PDL/TL	TL/TD
PDL/TL	1.0000	
TL/TD	-0.3708	1.0000

The correlation matrix in Table 1 indicates that there is no strong correlation among the study's independent variables, with a correlation coefficient of -0.3708, which suggests the absence of multicollinearity among the independent variables and that they do not lead to biased estimates.

5.2. Homogeneity Test

To determine whether the study's data aligned with fixed effects or random effects models, Hsiao [54] was used to assess the overall homogeneity of the data and the partial homogeneity of coefficients and constants. This approach aids in selecting appropriate panel data models (fixed or random effects) that best fit the study data, thereby enhancing its quality and reliability [57]. Table 2 presents the results of the homogeneity test for the panel data using Hsiao's [54] test.

Table 2.
Results of the Homogeneity Test for Panel Data Using the Hsiao Test.

Test	F – Test	P-value	Decision
F1 (Total homogeneity)	4.380501	0.000	H_o^1 : Reject
F2 (partial homogeneity)	2.170986	0.027	H_o^2 : Reject
F3 (Total heterogeneity)	7.824775	0.000	H_o^3 : Reject

As shown in Table 2, the Fisher test value for overall homogeneity is 4.380501 at a significance level below 0.05, indicating the rejection of the null hypothesis of overall homogeneity, which posits that there is overall homogeneity among the banks under study, and the acceptance of the alternative hypothesis, which states that there is no overall homogeneity. Consequently, we proceed to the second step of the Hsiao test to determine whether the source of overall heterogeneity in the data stems from intercepts (αi), coefficients (βi), or both. Based on the p-value for the homogeneity test of coefficients and intercepts, the null hypothesis, which posits the homogeneity of coefficients or intercepts, is rejected at a significance level below 0.05. Therefore, there are individual differences among the banks under study in terms of both the coefficients and intercepts, confirming the results of the overall heterogeneity test. Based on these findings, fixed-effects panel data models are unsuitable because of their inconsistency with data exhibiting individual differences; thus, we employ dynamic panel data models (random effects models).

5.3. Unit Root Tests

The phenomenon of data non-stationarity refers to changes in the mean and variance over time, and regression obtained in the absence of stationarity is considered spurious [58]. To assess the stability of the study sample data at the level and at the first difference, the study employed first-generation unit root tests, represented by the Breitung test, which is based on the null hypothesis of the presence of an individual unit root in the panel data, and the Hadri test, which is based on the null hypothesis opposite to that of the unit root tests, stating that the panel data do not contain a unit root. The study also utilized second-generation unit root tests, represented by Pesaran [55] and Pesaran [56] tests of the CIPS-CADF type, which are based on testing the null hypothesis that there is a common unit root in the panel data against the alternative hypothesis (H1) that at least one variable in the panel data does not contain a unit root [59]. are discussed. Table 3 illustrates the results of the unit root tests.

Table 3.
Results of Unit Root Tests.

Second-Generation Unit Root Tests					
Test			ROA	PDL/TL	TL/TD
CIPS	Levels	Constant & Trend	-2.969	-2.882	-4.028***
	1ST Difference	Constant & Trend	-4.395***	-4.228***	-5.587***
CADF	Levels	Constant & Trend	-2.969*	-2.882	-4.028***
	1ST Difference	Constant & Trend	-4.395***	-4.228***	-5.587***
First-Generation Unit Root Tests					
Breitung	Levels	Constant & Trend	-1.5302	2.0306	-0.3652**
	1ST Difference	Constant & Trend	-3.8801***	-4.7060***	-3.9430***
Hadri	Levels	Constant & Trend	2.3883***	12.1659***	10.4735***
	1ST Difference	Constant & Trend	-0.4089	-0.7906	-1.4886

Note: The signs (***) (**) (*) refer to the significance levels of 1%, 5%, and 10%, respectively.

According to Table 3, the p-values for the data on ROA and PDL/TL indicate the presence of a unit root at the level and the absence of a unit root at the first difference, with p-values of 0.01 and 0.05 based on the CADF, CIPS, Breitung, and Hadri tests. This suggests that the data for these indicators are nonstationary at the level and become stationary after taking the first differences, with integration orders equal to 1. Additionally, the table shows that the p-values for the data on the ratio of TL/TD indicate the absence of a unit root at the level, with p-values of 0.01 and 0.05 based on the CADF, CIPS, and Breitung tests. This implies that the data for this indicator are stationary at this level.

5.4. Panel Data Cointegration Tests

To ensure the existence of cointegration relationships between the panel data of the study in both the long and short terms, the study employed the Kao test, which accounts for individual fixed effects specific to each cross-sectional unit, and the Pedroni test, which considers both homogeneity and heterogeneity among the panel data. Table 4 presents the results of the panel data cointegration tests.

Table 4.
Results of Panel Data Cointegration Tests.

Cointegration Test		Statistic	p-value
kao	Modified Dickey–Fuller t	-4.9255	0.0000
	Dickey–Fuller t	-3.4778	0.0003
	Augmented Dickey–Fuller t	-2.0199	0.0217
	Unadjusted modified Dickey–Fuller t	-5.3188	0.0000
	Unadjusted Dickey–Fuller t	-3.5646	0.0002
Pedroni	Within the dimension		
	Modified variance ratio	-1.3678	0.0857
	Modified Phillips–Perron t	-0.0390	0.4845
	Phillips–Perron t	-2.6761	0.0037
	Augmented Dickey–Fuller t	-2.4577	0.0070
	Between the dimensions		
	Modified Phillips–Perron t	0.9635	0.1676
	Phillips–Perron t	-2.3116	0.0104
	Augmented Dickey–Fuller t	-2.0265	0.0214

According to Table 4, the p-values for the majority of the cointegration tests, represented by the Kao and Pedroni tests, indicate the rejection of the null hypothesis, which states that there is no cointegration relationship among the panel data at a significance level of 0.05. This implies acceptance of the alternative hypothesis, which posits the existence of a cointegration relationship between ROA and CR indicators, specifically PDL/TL and TL/TD.

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Based on these test results, it can be concluded that there is a cointegration relationship between ROA as the dependent variable and CR indicators (PDL/TL and TL/TD) as independent variables in the Yemeni banks under study for the period (2004–2020).

5.5. Estimation of Model Parameters Using the Panel Autoregressive Distributed Lag (PANEL ARDL) Model

PANEL ARDL models are beneficial because they help estimate panel data parameters and determine the dynamic cointegration relationship between variables in both the long and short term. They are also used to assess the impact of each variable on the other while accounting for time lags and heterogeneity in the data. This permits more variability and cross-sectional differences in model parameters to attain the best estimation of panel data, indicating the diverse behaviors of the study's panel data [60]. PANEL ARDL models depend on the Error Correction Mechanism (VECM) for longitudinal data based on the MG, PMG, and DFE models. To determine the regression parameters between ROA as the dependent variable and CR as the independent variable, PANEL ARDL models were first estimated. Then, using the Hausman test, the models were compared, and the most appropriate model was selected as representative of the varying behaviors of the sample under study. Table 5 presents the results of estimating the panel data parameters according to the MG, PMG, and DFE models, which are presented in Table 5.

Table 5.
Results of Estimating Panel Data Parameters According to MG, PMG, and DFE Models.

PANEL ARDL						
Var	**Panel PMG**		**Panel MG**		**Panel DFE**	
	Coefficient	**P>z**	**Coefficient**	**P>z**	**Coefficient**	**P>z**
Short–term (ST)						
ECT	-0.4752459	0.000	-0.7316673	0.000	-0.5939998	0.000
PDL/TLD1.	-0.0488012	0.125	-0.0481301	0.125	-0.0261781	0.032
TL/TDD1.	0.0202694	0.695	0.0051408	0.695	-0.0189612	0.072
_cons	-0.0050274	0.000	-0.0057981	0.000	0.0015274	0.624
Long–term (LT)						
PDL/TL	0.0701631	0.000	0.0472705	0.000	0.0249399	0.038
TL/TD	0.0267934	0.034	0.0628635	0.034	0.0157613	0.215

According to Table 5, the Error Correction Term (ECT) values, adjusting for short-term shock effects to return to equilibrium, are negative and significant at the 0.001 significance level for all PANEL ARDL models. This implies the presence of cointegration and a short-term equilibrium relationship, which leads to a long-term equilibrium between ROA as the dependent variable and CR as the independent variable. To compare the estimation results of the MG, DFE, and PMG models for long- and short-term parameters and to select the optimal model for parameter estimation, the Hausman test was employed. This test aids in choosing the most appropriate model to represent the diverse behaviors of the studied sample. Table 6 presents the results of the Hausman test comparing the PANEL ARDL models represented by the MG, PMG, and DFE.

Table 6.
Hausman Test Results of Comparing PANEL ARDL Models (MG, PMG, DFE).

Test		chi^2	**(Prob)**	**Decision**	
				Acceptance	**To Reject**
Hausman	PMG/MG	1.64	0.4410	PMG	MG
	PMG/DFE	0.9999	0.000	PMG	DFE

As shown in Table 6, the p-value (Prob) for the chi-squared (chi^2) statistic used to compare the PMG and MG models is greater than 0.05. This suggests that, when comparing the PMG and MG models, the null hypothesis of the Hausman test is accepted, indicating that the PMG model is optimal.

The alternative hypothesis, which posits that the MG model is optimal, is rejected. When comparing the PMG and DFE models, the p-value (Prob) for the chi-squared (chi^2) statistic is less than 0.05. This means the null hypothesis of the Hausman test is rejected when comparing the PMG and DFE models, which asserts that the DFE is optimal. Instead, the alternative hypothesis is accepted, indicating that the PMG model is the preferred choice.

Based on the results of the model comparisons among the PANEL ARDL models (MG, PMG, DFE) using the Hausman test, it was concluded that the PMG model is the most suitable and efficient for representing the diverse behaviors of the panel data in this study. The PMG model is based on the homogeneity of long-term parameters, variability in short-term parameters, error-correction adjustments, and differences in error terms. The PMG model can be expressed in terms of the original values of the panel data of the study, as outlined in Table 6, according to the following mathematical equation:

$$\Delta \mathrm{ROA}_{1it} = -0.0050274 + (-0.4752459)(\mathrm{ROA}_{1i,t-1} - 0.0701631\mathrm{PDL/TL}_{i,t-1} - 0.0267934\mathrm{TL/TD}_{i,t-1}) \quad (3)$$

By multiplying the Error Correction Term (ECT) by the long-term parameters, we obtain Equation (4).

$$\Delta y\mathrm{ROA}_{1it} = -0.0050274 - (0.4752459\mathrm{ROA}_{i,t-1}) + (0.033344726\,\mathrm{PDL/TL}_{i,t-1}) + (0.012733453\mathrm{TL/TD}_{i,t-1}) \quad (4)$$

Given that: $\Delta \mathrm{ROA}_{i,t} = \mathrm{ROA}_{i,t} - \mathrm{ROA}_{i,t-1}$ substituting this into equation (4) yields equation (5):

$$ROA_{i,t} - ROA_{i,t-1} = -0.0050274 - \left(0.4752459 ROA_{i,t-1}\right) + (0.033344726\frac{\mathrm{PDL}}{\mathrm{TL}}_{i,t-1}) + (0.012733453\frac{\mathrm{TL}}{\mathrm{TD}_{i,t-1}}) \quad (5)$$

By combining the terms in equation (5), we obtain equation (6):

$$ROA_{i,t} = -0.0050274 + (0.5247541 ROA_{1i,t-1}) + (0.033344726\frac{\mathrm{PDL}}{\mathrm{TL}}_{i,t-1}) + (0.012733453\frac{\mathrm{TL}}{\mathrm{TD}_{i,t-1}}) \quad (6)$$

5.6. Cross-Sectional Dependence (CSD tests) Test for the Estimated PMG Model Residuals

Cross-sectional dependence tests (CSD tests) are used to assess the quality of the estimated model by ensuring that the residuals are independent of the errors associated with other cross-sectional units. These tests help determine whether the residuals are free from CSD resulting from common external factors or correlated effects. If such dependence is present, it becomes necessary to adopt models that account for common factors among the estimated residuals. Key tests used to evaluate CSD in estimated model residuals include the Pesaran and Xie [61] Test, CDw Test with Power Enhancement from Fan et al. [62], Juodis and Reese [63] Test, Pesaran [64], and Pesaran [65] test. Table 7 explains the results of the (CSD tests) for the estimated PMG model residuals.

Table 7.
(CSD tests) Results for the Estimated PMG Model Residuals.

	CSD Tests - Cross-Sectional Dependence			
	CD*	**CDw+**	**CDw**	**CD**
Resid_pmg	0.82 (0.411)	30.08 (0.000)	1.07 (0.286)	3.95 (0.095)

Table 7 indicates that the results of most (CSD tests) for the estimated model residuals accept the null hypothesis, which states that there are weak (CSD tests) among the residuals, and reject the alternative hypothesis, which suggests that the residuals exhibit strong (CSD tests). This implies that there are no common factors influencing the residuals and that each bank in the study is affected by factors distinct from those affecting other banks, with no shared factors among them. Therefore, the PMG is suitable for estimating the CR and ROA relationships in the Yemeni banks under study.

6. Conclusions

The study utilized the PMG model for Panel ARDL data to discuss the results, answer its questions, achieve its objectives, and test its hypotheses. The findings indicate that CR, measured by PDL/TL and TL/TD, does not affect ROA, measured by the portion of net profit to total assets, in Yemeni banks during the short term. However, this relationship becomes positive over the long term. More specifically, a 1% increase in PDL/TL results in a 3.3% increase in the growth of ROA in the long term. Likewise, a 1% increase in the TL/TD ratio leads to a 1.3% increase in the growth of ROA in the long term. The error correction term, which corrects short-term imbalances to return to long-term equilibrium, is negative (-0.4752459), with a significance level below 0.01. This indicates the presence of a long-term balance relationship between the dependent variable ROA and the independent variable CR in the banks investigated in this study. The model includes a correction mechanism for short-term imbalances in the independent variable, with a correction speed of 47.52%, indicating that any short-term deviations can be corrected within approximately two years and a quarter.

The lack of a relationship between CR and ROA in the short term may be because banks set aside precautionary provisions to protect against potential loan defaults, which can obscure the direct relationship between CR and ROA. Alternatively, banks may maintain reserve liquidity, allowing flexibility in handling emergencies without significantly impacting profits. Another explanation could be that banks reschedule loans and adjust terms to facilitate repayment, postponing the classification of loans as doubtful, and thus not reflecting defaulted loans as losses in ROA. Conversely, the positive relationship between CR and ROA in the long term may be attributed to banks expanding their loan portfolios while increasing their financial provisions to address defaulted loans. This approach enhances investor confidence, demonstrating that banks proactively manage CR and improve their asset quality.

Therefore, this study recommends that Yemeni banks focus on developing effective strategies and policies to manage credit risk (CR) and reduce non-performing loans (NPLs). They should analyze clients' repayment capabilities to direct lending to those most likely to repay, exercise caution against excessive loan expansion to maintain portfolio quality, and develop effective monitoring tools for the early identification of NPLs. Additionally, banks should oversee the mechanisms and conditions under which loans are granted, focus on structural indicators and financial policies, such as diversifying the credit portfolio by directing loans to various economic sectors to reduce risks associated with concentrating loans in a single sector, which affects return on assets (ROA) in the long term, and conduct regular loan evaluations to assess creditworthiness and mitigate potential risks. Finally, Yemeni banks should enhance customer trust and encourage deposits, thereby reducing reliance on high-cost short-term financing. The results of this study align with those of Kolapo et al. [12], Tirwa et al. [13], Hawaldar et al. [14], Isanzu [15], and Afriyie and Akotey [16].

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

References

[1] H. S. Kargi, *Credit risk and the performance of Nigerian banks*. Zaria, Nigeria: Ahmadu Bello University, 2011.

[2] V. Rivai, A. P. Veithzal, and N. I. Ferry, *Bank and financial institution management: Conventional and sharia systems*. Jakarta, Indonesia: PT RajaGrafindo Persada, 2007.

[3] I. Saleh and M. Abu Afifa, "The effect of credit risk, liquidity risk and bank capital on bank profitability: Evidence from an emerging market," *Cogent Economics & Finance*, vol. 8, no. 1, p. 1814509, 2020. https://doi.org/10.1080/23322039.2020.1814509

[4] F. Abbas, S. Iqbal, and B. Aziz, "The impact of bank capital, bank liquidity and credit risk on profitability in postcrisis period: A comparative study of US and Asia," *Cogent Economics & Finance*, vol. 7, no. 1, p. 1605683, 2019. https://doi.org/10.1080/23322039.2019.1605683

[5] H. Pasaribu and R. L. Sari, "Analysis of capital adequacy level and loan to deposit ratio on profitability," *Jurnal Telaah dan Riset Akuntansi*, vol. 8, no. 1, pp. 9-18, 2011.

[6] S. H. Boahene, J. Dasah, and S. K. Agyei, "Credit risk and profitability of selected banks in Ghana," *Research Journal of Finance and Accounting*, vol. 3, no. 7, pp. 6-14, 2012.

[7] K. Chen and C. Pan, "An empirical study of credit risk efficiency of banking industry in Taiwan," *Web Journal of Chinese Management Review*, vol. 15, no. 1, pp. 1-16, 2012.

[8] The Basel Committee on Banking Supervision, *Principles for the management of credit risk*. Basel, Switzerland: Bank for International Settlements, 2000.

[9] M. Y. Abubakar, Y. Shaba, M. O. Ezeji, and S. S. a. Ahmad, "Effect of credit risk management on return on assets and return on equity: Empirical evidence from Nigerian Banks," *IOSR Journal of Business and Management*, vol. 18, no. 12, pp. 96-104, 2016.

[10] A. R. Central Bank of Yemen, "Sana'a, Yemen," Central Bank of Yemen, Annual Report, 2018.

[11] A. M. Sharhan, "Development of banking activity in Yemeni banks during the period (2000–2017)," *University of Al-Bayda Journal*, vol. 2, no. 2, pp. 147–169, 2020.

[12] T. F. Kolapo, R. K. Ayeni, and M. O. Oke, "Credit risk and commercial banks'performance in nigeria: A panel model approach," *Australian Journal of Business and Management Research*, vol. 2, no. 2, p. 31, 2012.

[13] I. P. Tirwa, U. Bhuyan, H. Magd, and S. A. Khan, "Implications of liquidity risk and credit risk on the bank of bhutan's financial performance (BOB)," *Global Business & Management Research*, vol. 14, 2022.

[14] I. T. Hawaldar, B. K. Meher, P. Kumari, and S. Kumar, "Modelling the effects of capital adequacy, credit losses, and efficiency ratio on return on assets and return on equity of banks during COVID-19 pandemic," *Banks and Bank Systems*, vol. 17, no. 1, pp. 115-124, 2022.

[15] J. S. Isanzu, "The impact of credit risk on financial performance of Chinese banks," *Journal of International Business Research and Marketing*, vol. 2, no. 3, pp. 14-17, 2017. http://dx.doi.org/10.18775/jibrm.1849-8558.2015.23.3002

[16] H. O. Afriyie and J. O. Akotey, "Credit risk management and profitability of rural banks in the Brong Ahafo region of Ghana," *Management*, vol. 5, p. 24, 2013.

[17] A. Jreisat, "Credit risk, economic growth and profitability of banks," *International Journal of Economics and Business Research*, vol. 20, no. 2, pp. 152-167, 2020.

[18] E. Munangi and A. B. Sibindi, "An empirical analysis of the impact of credit risk on the financial performance of South African banks," *Academy of Accounting and Financial Studies Journal*, vol. 24, no. 3, pp. 1-15, 2020.

[19] K. Singh, "Credit risks, national governance and profitability in microfinancing sector: Evidence from some emerging economies of world importance," *International Journal of Emerging Markets*, vol. 20, no. 5, pp. 2110-2131, 2025. https://doi.org/10.1108/IJOEM-04-2023-0665

[20] S. R. Poudel, B. Kunwar, T. R. Kharel, S. Dahal, and R. Panthi, "Impact of credit risk, liquidity risk, and operational risk on commercial bank's profitability," *Journal of Nepalese Business Studies*, vol. 17, no. 1, pp. 117-128, 2024. https://doi.org/10.3126/jnbs.v17i1.75271

[21] M. Haris, H. Yao, and H. Fatima, "The impact of liquidity risk and credit risk on bank profitability during COVID-19," *Plos One*, vol. 19, no. 9, p. e0308356, 2024. https://doi.org/10.1371/journal.pone.0334269

[22] H. Abdelaziz, B. Rim, and H. Helmi, "The interactional relationships between credit risk, liquidity risk and bank profitability in MENA region," *Global Business Review*, vol. 23, no. 3, pp. 561-583, 2022. https://doi.org/10.1177/0972150919879304

[23] K. Khanal, "Evaluation of effects of credit-risk on return on assets of commercial banks in Nepal," *Journal of Balkumari College*, vol. 10, no. 1, pp. 7-12, 2021. https://doi.org/10.3126/jbkc.v10i1.42082

[24] R. R. Mendoza and J. P. R. Rivera, "The effect of credit risk and capital adequacy on the profitability of rural banks in the Philippines," *Scientific Annals of Economics and Business*, vol. 64, no. 1, pp. 83-96, 2017.

[25] A. Ruziqa, "The impact of credit and liquidity risk on bank financial performance: The case of Indonesian Conventional Bank with total asset above 10 trillion Rupiah," *International Journal of Economic Policy in Emerging Economies*, vol. 6, no. 2, pp. 93-106, 2013. https://doi.org/10.1504/IJEPEE.2013.055791

[26] R. T. Opoku, P. L. Angmor, and L. A. Boadi, "Credit risk and bank profitability: Evidence from Ghana stock exchange," *Journal for Studies in Management and Planning*, vol. 2, no. 3, pp. 89-96, 2016.

[27] M. De Leon, "The impact of credit risk and macroeconomic factors on profitability: the case of the ASEAN banks," *Banks and Bank Systems*, vol. 15, no. 1, pp. 21-29, 2020. https://doi.org/10.21511/bbs.15(1).2020.03

[28] C. K. Staikouras and G. E. Wood, "The determinants of European bank profitability," *International Business & Economics Research Journal*, vol. 3, no. 6, pp. 57–68, 2004.

[29] A. H. M. Noman, S. Pervin, M. M. Chowdhury, and H. Banna, "The effect of credit risk on the banking profitability: A case on Bangladesh," *Global Journal of Management and Business Research*, vol. 15, no. 3, pp. 41-48, 2015.

[30] M. A. Islam and R. H. Rana, "Determinants of bank profitability for the selected private commercial banks in Bangladesh: A panel data analysis," *Banks & Bank Systems*, no. 12,№ 3 (cont.), pp. 179-192, 2017. http://dx.doi.org/10.21511/bbs.12(3-1).2017.03

[31] P. Silaban, "The effect of capital adequacy ratio, net interest margin and non-performing loans on bank profitability: The case of Indonesia," 2017. https://www.um.edu.mt/library/oar//handle/123456789/43353

[32] G. N. Al-Eitan and T. O. Bani-Khalid, "Credit risk and financial performance of the Jordanian commercial banks: A panel data analysis," *Academy of Accounting and Financial Studies Journal*, vol. 23, no. 5, pp. 1-13, 2019.

[33] A. Campbell, "Bank insolvency and the problem of nonperforming loans," *Journal of Banking Regulation*, vol. 9, pp. 25-45, 2007. https://doi.org/10.1057/palgrave.jbr.2350057

[34] A. Graham and B. Coyle, *Framework for credit risk management*. London, UK: Global Professional Publishing, 2000.

[35] S. Bouteille and D. Coogan-Pushner, *The handbook of credit risk management: Originating, assessing, and managing credit exposures*. Hoboken, NJ, USA: John Wiley & Sons, 2021.

[36] O. Olalere, M. A. Islam, M. Z. M. Junoh, W. S. Yusoff, and M. M. Iqbal, "Revisiting the impact of intrinsic financial risks on the firm value of banks in ASEAN-5 countries: a panel data approach," *Banks and Bank Systems*, vol. 15, no. 2, pp. 200-213, 2020. https://doi.org/10.21511/bbs.15(2).2020.18

[37] A. Al-Qurashi and A. Al-Maqdashi, "Using artificial neural networks to analyze the impact of banking risk management," *Journal of Financial, Accounting, and Administrative Studies*, vol. 6, no. 4, pp. 10–46, 2019.

[38] R. Al-Ghussain and A. Al-Ali, "The impact of financial risks on the evaluation of banks' performance: An applied study on Syrian commercial banks," *Algerian Journal of Economics and Management*, vol. 4, pp. 30–40, 2013.

[39] C. Ogboi and O. K. Unuafe, "Impact of credit risk management and capital adequacy on the financial performance of commercial banks in Nigeria," *Journal of Emerging Issues in Economics, Finance and Banking*, vol. 2, no. 3, pp. 703-717, 2013.

[40] S. N. M. A. Qurban, "The effect of liquidity and rate of return risks on the profitability of Islamic and conventional banks in GCC countries," Doctoral Dissertation, Effat University, 2018.

[41] N. Nataraja, N. R. Chilale, and L. Ganesh, "Financial performance of private commercial banks in India: Multiple regression analysis," *Academy of Accounting and Financial Studies Journal*, vol. 22, no. 2, pp. 1-12, 2018.

[42] E. Puspitasari, B. Sudiyatno, N. Aini, and G. Anindiansyah, "The relationship between net interest margin and return on asset: Empirical study of conventional banking in Indonesia," *Academic Journal of Interdisciplinary Studies*, vol. 10, no. 3, pp. 362-374, 2021. https://doi.org/10.36941/ajis-2021-0090

[43] V. T. Arsew, Z. Kisman, and N. N. Sawitri, "Analysis of the effect of loan to deposit ratio, non-performing loans and capital adequacy ratio on return on assets with good corporate governance as intervening variable in banking companies listed in the corporate governance perception index (cgpi) for the period 2014–2018," *Journal of Economics and Business*, vol. 3, no. 1, p. 17, 2020.

[44] A. Ruslan, C. Pahlevi, S. Alam, and M. Nohong, "The role of efficiency mediation in the effect of banks size on bank profitability in Indonesia," *Hasanuddin Economics and Business Review*, vol. 3, no. 1, pp. 49-58, 2019. https://doi.org/10.26487/hebr.v3i1.1846

[45] K. Ali, M. F. Akhtar, and H. Z. Ahmed, "Bank-specific and macroeconomic indicators of profitability-empirical evidence from the commercial banks of Pakistan," *International Journal of Business and Social Science*, vol. 2, no. 6, pp. 235-242, 2011.

[46] M. F. Akhtar, K. Ali, and S. Sadaqat, "Factors influencing the profitability of Islamic banks of Pakistan," *International Research Journal of Finance and Economics*, vol. 66, no. 66, pp. 1-8, 2011.

[47] N. Iloska, "An analysis of bank profitability in Macedonia," *Journal of Applied Economics and Business*, vol. 2, no. 1, pp. 31-50, 2014.

[48] J. C. Arias, "Banking profitability determinants," *Business Intelligence Journal*, vol. 4, no. 2, pp. 209-230, 2011.

[49] A. Roman and A. E. Danuletiu, "An empirical analysis of the determinants of bank profitability in Romania," *Annales Universitatis Apulensis: Series Oeconomica*, vol. 15, no. 2, p. 580, 2013.

[50] Yemen Banks Association, "Homepage," 2025. https://yba.org.ye/index.php/ar/. [Accessed Jan. 12, 2025]

[51] A. N. Q. Sang Tang My, "The relationship between credit risk and bank financial stability: The mediating role of bank profitability," *Journal of Hunan University Natural Sciences*, vol. 49, no. 1, 2022. https://doi.org/10.55463/issn.1674-2974.49.1.32

[52] A. C. Cameron, *Microeconometrics: Methods and applications*. Cambridge, UK: Cambridge University Press, 2005.

[53] W. H. Greene, *Econometric analysis*, 8th ed. Harlow, England: Pearson, 2021.

[54] C. Hsiao, *Analysis of panel data*. Cambridge: Cambridge University Press, 1986.

[55] M. H. Pesaran, "A simple panel unit root test in the presence of cross-section dependence," Cambridge Working Papers in Economics, No. 0346, 2003.
[56] M. H. Pesaran, "A simple panel unit root test in the presence of cross-sectional dependence," *Journal of Applied Econometrics*, vol. 22, no. 2, pp. 265–312, 2007. https://doi.org/10.1002/jae.951
[57] R. Bourbonnais, *Econometrics – 9th edition: Course and solved exercises*. Paris: Dunod, 2015.
[58] M. Verbeek, *Panel methods for finance: A guide to panel data econometrics for financial applications*. Berlin, Germany: De Gruyter, 2021.
[59] C. Hurlin and V. Mignon, "Second generation panel unit root tests," 2007. https://shs.hal.science/halshs-00159842/
[60] A. A. Rafindadi and Z. Yosuf, "An application of panel ARDL in analysing the dynamics of financial development and economic growth in 38 sub-Saharan African continents," in *Proceeding-Kuala Lumpur International Business, Economics and Law Conference*, 2013.
[61] M. H. Pesaran and Y. Xie, "A bias-corrected scaled LM test of error cross-section independence in panel data models," *Journal of Econometrics*, vol. 220, no. 2, pp. 448–465, 2021.
[62] J. Fan, Y. Liao, and J. Yao, "Power enhancement in high-dimensional cross-sectional independence testing," *Test*, vol. 24, no. 1, pp. 86–111, 2015.
[63] A. Juodis and S. Reese, "Robust testing for cross-sectional dependence in large heterogeneous panels," *Journal of Business & Economic Statistics*, vol. 39, no. 2, pp. 280–294, 2021.
[64] M. H. Pesaran, "Testing weak cross-sectional dependence in large panels," *Econometric Reviews*, vol. 34, no. 6–10, pp. 1089–1117, 2015.
[65] M. H. Pesaran, "General diagnostic tests for cross-sectional dependence in panels," *Empirical Economics*, vol. 60, no. 1, pp. 13–50, 2021.

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