Financial Reporting Quality and Earnings Management in Bahraini Islamic Banks: Evidence from the Modified Jones Model (2017–2024)

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Abstract:
The study aimed to measure the financial reporting quality of Bahraini Islamic banks over the period 2017–2024, using the modified Jones model to determine the extent to which the banks in the sample engaged in earnings management. Data were collected from the reports and financial statements of the banks under study, and statistical software such as Excel and DATAtab was used to conduct the empirical analysis. The study reached several findings, the most important of which is the stability of the Bahraini Islamic banks under investigation and the absence of earnings management practices, despite the crises that occurred during the study period.
Keywords: Financial Reporting Quality, Modified Jones Model, Bahraini Islamic Banks

INTRODUCTION

The banking environment is witnessing increasing complexity and continuous changes, which makes the availability of accurate tools for assessing bank health and predicting financial crises essential for decision-makers, investors, and regulatory bodies. In this regard, financial deficit forecasting models, which rely heavily on accounting information extracted from financial statements, are among the most important of these tools.

However, the effectiveness of these models is not solely linked to their mathematical formulas or statistical properties; rather, it is significantly affected by the quality of their inputs, which are primarily derived from the quality of financial reports. Numerous studies indicate that financial reporting quality is a pivotal element in ensuring the effectiveness of forecasting models, as this quality reflects the degree of transparency, accuracy, and faithful representation of the published accounting information (Dechow, Ge, & Schrand, 2010). High-quality financial reports enable the early prediction of financial distress, whereas distorted reports may lead to misleading results, thereby failing to accurately assess the actual risks (Bushman & Landsman, 2010).

Specifically in the banking context, this challenge becomes more acute, as banks rely on a sensitive financial system based on trust and credibility. Literature suggests that weak financial reporting quality was a contributing factor to the failure of many banking institutions during financial crises (Barth, Landsman, & Lang, 2008). Therefore, studying the relationship between financial reporting quality and the effectiveness of financial deficit forecasting models constitutes an important contribution to developing monitoring and early warning tools in the banking sector.

Recent years have seen the emergence of numerous modern studies focusing on developing financial deficit forecasting models in the banking sector, utilizing advanced techniques.

For instance, the European Banking Authority (EBA) developed an early warning system for large EU banks using machine learning techniques and a novel definition of distress (Malikkidou & Strohbach, 2025). Quentin Bro (2025) also examined the ability of financial analysts and rating agencies to predict bank defaults in Europe, demonstrating that the use of financial analysts can provide greater accuracy compared to traditional credit agencies in certain cases.
Despite these modern efforts, the integration of financial reporting quality as an explanatory variable in financial deficit forecasting models remains limited. Furthermore, studies that combine financial reporting quality and early warning of financial deficit in the banking sector are few, which justifies the need for a dedicated study linking disclosure quality and the performance of forecasting models, with a focus on banks as a key application area.
Metwally et al. (2025) addressed the financial and economic factors associated with financial distress in banks in the Middle East and North Africa region, emphasizing the necessity of integrating non-financial variables into forecasting models to increase their accuracy in complex banking environments. Recent studies, such as Hoang Nguyen et al. (2024), which used multi-factor copula models to analyze systemic risk in banks, also demonstrated the importance of dealing with banks' systemic risk in a way that integrates both financial and non-financial data, which is a notable development in current literature.

The financial sustainability of banking institutions is a fundamental pillar for the stability of the global financial system, given their pivotal role in mobilizing financial resources and directing them towards optimal uses, as well as their role in achieving a dynamic balance between savings and investment. Consecutive financial crises, particularly the 2008 crisis and its extended repercussions, revealed the fragility of the banking sector in the face of credit and structural risks , prompting researchers and regulatory bodies to intensify efforts towards developing more efficient tools for the early prediction of financial distress, and strengthening early warning systems and timely preventative response.
In this framework, financial default forecasting models emerged as essential analytical tools aimed at distinguishing between sound financial institutions and those exposed to the risk of collapse. Accounting and financial literature have contributed to developing multiple predictive models based on a set of accounting indicators; however, the effectiveness and reliability of these models largely depend on the quality of the data used, as financial ratios do not reflect the financial position accurately and transparently unless they are based on accurate and reliable information. Hence, financial reporting quality emerges as a main determinant contributing to enhancing the efficiency and raising the credibility of predictive models.
Financial reporting quality in accounting literature refers to the institution's commitment to the principles of transparency, faithful representation, relevance, and verifiability, which are characteristics that ensure that the published financial information truly reflects the institution's actual economic situation (Dechow et al., 2010). Nevertheless, despite the growing recognition of the role of this report quality in explaining market behavior, research that directly tested the relationship between financial reporting quality and the effectiveness of financial deficit forecasting models – especially in the banking sector – remains limited. Most studies focus either on developing the model itself without considering the quality of its inputs , or on financial reporting quality in non-banking contexts (Costa et al., 2022; Gandhi et al., 2019). Moreover, some studies that addressed banks were limited to traditional quantitative indicators and overlooked the qualitative dimension of the reports, such as disclosure content, conservatism, or the linguistic formulation of the reports (Citterio, 2024).
Here emerges the research gap represented by the **absence of applied studies that combine financial reporting quality and financial deficit forecasting models for**

banks in real banking environments, despite its utmost importance in supporting banking oversight policies and systemic risk management.
From this standpoint, this research aims to investigate the role of financial reporting quality in the effectiveness of financial deficit forecasting models in banks, by testing the relationship between financial reporting quality indicators (such as accruals quality, timeliness, and faithful representation) and the performance of predictive models. This work is expected to contribute to expanding the literature related to early warning in the banking sector, by integrating information quality elements into the model design, which would improve its ability to monitor real risks in a timely manner. The research also provides practical recommendations for decision-makers and regulatory bodies to enhance the effectiveness of proactive oversight, by emphasizing disclosure quality as a necessary condition for sound financial evaluation.

I- LITERATURE REVIEW

In light of the repeated financial crises that have affected the global banking system, the importance of developing accurate models for predicting financial deficit in banks has increased, given their central role in economic stability. Traditionally, the literature relied on analytical models based on quantitative accounting indicators, such as Altman's Z-Score model, the Zmijewski model, and the Ohlson model, which were based on measures like liquidity, leverage, and profitability (Paule-Vianez et al., 2020). However, these models, despite their historical value, showed limitations in keeping pace with the complexities of contemporary banking data , especially in terms of their ability to capture early signals of financial distress. A recent applied study in the Indonesian banking sector covering the period 2014–2023 showed that traditional models suffered from a high rate of Type II errors, while the XGBoost model outperformed in terms of overall accuracy and avoiding the misclassification of defaulted banks (Saputra, B, 2025).
In this context, some researchers began to point to the importance of non-traditional factors in supporting the effectiveness of predictive models, foremost among which is financial reporting quality. This concept embodies a set of characteristics such as relevance, reliability, comparability, transparency, timeliness, continuity, and understandability, which accurately reflect the true financial position of the institution under study. Dechow, Ge, & Schrand (2010) confirmed that earnings quality, as a central indicator within financial reporting quality, cannot be separated from the institution's actual economic performance, making it a pivotal element in interpreting the credibility of financial data. In the same context, Bushman & Landsman (2010) suggest that weak financial disclosure quality may mislead users and negatively affect market efficiency, especially in the absence of strict regulation of report content.
In the context of emerging markets, a recent study on a sample of companies listed on the Egyptian Stock Exchange (Zedan, Azzam, & ElBasuony, 2023) provided empirical evidence that earnings quality, as one of the main dimensions of financial reporting quality, is inversely related to the probability of financial deficit measured by the Altman Z-Score model. The results showed that weak earnings quality substantially raises the level of financial risks, especially with high financial leverage. The importance of this study lies in highlighting the ability of financial reporting quality indicators to improve the effectiveness of predictive models, which reinforces the need to test this relationship in the banking context, which is characterized by greater sensitivity to systemic risks.
At the applied level, a study by Costa et al. (2022) showed that integrating financial reporting quality indicators such as Accruals Quality and Timeliness into default prediction models for small and medium enterprises significantly improved the model's predictive

performance, compared to models relying on traditional financial indicators only. The study, using the Logit model and the Random Forest algorithm, clarified that financial reporting quality directly affects the quality of the accounting ratios used, and increases the reliability of estimates related to financial default. Although this study does not directly relate to the banking sector, it presents strong justifications for the possibility of generalizing the results to banking institutions, especially given the convergence in the logic of accounting reports between sectors.

In parallel with quantitative indicators, research trends have emerged in recent years aimed at expanding the concept of financial reporting quality to include the **qualitative dimension of disclosure**, by analyzing the content of financial reports using text analysis tools. In this regard, Gandhi, Loughran, & McDonald (2019) proposed adopting sentiment analysis in banks' annual reports as an alternative indicator of financial stress , and found that the intensive use of negative expressions in the texts is associated with a decrease in return on assets , a decline in the ability to pay dividends, and an increase in loan loss provisions , which, according to them, reflects a direct benefit of language analysis in predicting financial risk in banks , especially when traditional indicators are insufficient. This qualitative trend confirms that financial report quality is not just a matter of numbers, but is also related to the clarity of the financial discourse and user confidence in it.

However, a review of the literature reveals that most studies dealing with financial reporting quality were outside the banking sector. Citterio (2024), in his analytical review of bank failure models during the period 2000–2022, confirmed that the majority of these models rely almost exclusively on quantitative indicators such as financial variables and accounting ratios , without sufficient attention to non-financial components such as disclosure, governance, or environmental and social performance. The researcher recommended at the end of his review the need to develop models that systematically integrate these variables to improve the effectiveness of early warning systems in banks.

Some studies have provided partially relevant contributions, such as Muñoz-Izquierdo et al. (2019) , who tested the impact of integrating disclosures contained in statutory audit reports on the accuracy of the traditional Altman model in default prediction. They found that including elements from the external auditor's report (such as disclosure of doubt about going concern) improved the model's accuracy from 77% to 87%. Although the study was conducted on non-banking Spanish private companies, it highlights the important role of information complementing financial reports in improving predictive models.

In the Islamic banking context, a study by Asutay & Othman (2020) showed that components of the financing structure, such as the financing-to-deposit ratio and the composition of deposits, represent factors with important explanatory power in predicting performance during crisis periods, especially in the absence of effective market indicators. Although the study did not integrate financial reporting quality as an independent concept, it re-emphasizes the importance of the banking financial report components in explaining risks. Similarly, the study by Paule-Vianez et al. (2020), which is one of the first studies to apply Artificial Neural Networks to the Spanish banking sector for financial deficit prediction, stands out , but it did not include financial reporting quality as a variable input, which reinforces the need to expand the framework of future models.

Specifically in the banking context, some important studies have emerged in recent years. Citterio (2024) provided a comprehensive review of bank failure models during the period 2000–2022, confirming their near-exclusive reliance on traditional quantitative indicators. The European Banking Authority (EBA, 2025) also developed early warning models for European banks based on supervisory indicators such as the Core Equity Tier 1 ratio and regulatory liquidity. Quentin Bro (2025) studied the ability of financial analysts and rating agencies to predict bank default in Europe, while Metwally et al. (2025) analyzed the

determinants of financial distress in banks in the Middle East and North Africa region using the GMM methodology, confirming the role of classical financial performance indicators such as ROA and ROE. Hoang Nguyen et al. (2024) used multi-factor copula models to measure banks' systemic risk via CDS contracts.
Despite the scientific value of this research, it focused on quantitative and regulatory indicators, and did not give sufficient attention to **financial reporting quality as an independent component** in explaining the effectiveness of predictive models. This is where the gap that this research seeks to address emerges.
Based on the foregoing, it is clear that the relationship between financial reporting quality and the effectiveness of financial deficit forecasting models in banks is still insufficiently explored in academic literature, despite banks being more exposed to systemic risks, especially in applied studies. This creates a genuine research gap, especially since banks, due to their systemic sensitivity, are more in need of accurate early warning tools. Hence stems the importance of this study in testing the role of financial reporting quality in improving the effectiveness of financial deficit forecasting models in the banking context.

II- METHODOLOGY;

A. **Data collection**: this study will utility data collected from the annual reports of commercial banks in kingdom of Bahrain for the period 2017-2024.
B. **Population and simple**: the population in this study includes all banks in the kingdom of Bahrain. The sample was drawn from the different off banks in Bahrain. It was selected about condition is:
- ✓ The financial report is published in period of study 2017-2024
- ✓ We don’t have a fission with bank

Table 01: simple banks

N	name	type
01	Salam bank	Islamic bank
02	Baraka bank	Islamic bank

a- **Model:** The Jones model is one of the most popular and widely used models in accounting literature for measuring earnings quality, particularly with regard to detecting accounting practices related to earnings management. This model relies on separating accrual items into discretionary and non-discretionary accruals to identify the extent of earnings manipulation. The basic equation for the modified Jones model is as follows:
NDACijt/Aijt-1 =a1 (1) Aijt-1) +a2 (AREVijt/Aijt-1) + a3 (PPEijt / Aijt-1)
In order for this model to be used effectively in measuring the quality of earnings, it is first necessary to identify the basic variables that go into its composition, which are an essential component of the equation.

- ✓ **NDACijt**: Non-optional receivables of the institution belonging to sector (j) during period (t). AREVI
- ✓ **AREVijt:** Change in turnover of the enterprise belonging to sector (j) between periods t and (t-1).
- ✓ **Aijt-1:** Total assets of the institution belonging to sector (j) at the end of the period (t-1)
- ✓ **PPEijt:** Total real estate, property, and machinery for the institution belonging to sector (j) during period (t).
- ✓ a1،a2،a3: The model parameters of the institution are estimated for the group of sample institutions that belong to each year of study

The model variables are classified into a dependent variable, which is non-discretionary benefits, while the independent variables include the change in turnover, total assets, and total property, plant and equipment. These variables are used to estimate the non-discretionary portion of benefits.

Discretionary accruals, which may be the result of accounting manipulation, are calculated as the difference between the total accruals and the expected value of non-discretionary accruals, i.e., those resulting from the actual operating activity of the organization. These discretionary accruals are an important indicator of poor earnings quality, as the higher their value, the greater the likelihood of manipulation of the financial results.

The importance of this model lies in its provision of a reliable quantitative tool for analyzing financial performance beyond mere figures, enhancing the transparency and reliability of financial reporting. Therefore, using the Jones model to measure earnings quality helps make decisions based on more accurate and realistic information

III- Applying the model to the study sample banks:

In order to apply the Jones model to measure earnings quality in the banks under study, we will;

1- **Calculation of total accruals**; total accruals have been calculated for each bank in the sample based on the available financial data for the period 2017–2024, i.e., over a span of eight years according to the following equation:

Total Accruals = Net Income − Cash Flows from Operating Activities.

The following table shows the total accruals of the banks under study;

Table 02: the total accrual

years	Salam bank	Baraka bank
2017	-44 135	-31 111
2018	-66 418	-8 482
2019	-70 613	-6 250
2020	-87 461	-9 597
2021	-86 027	-17 390
2022	-63 326	-81 725
2023	42 819	-99 411
2024	-142 505	-36 767

Source: Prepared by the researcher using EXCEL

We observe fluctuations in the total accruals of both banks over the study period, as a result of several factors, including the COVID-19 crisis, which affected the performance of banks in general and those listed on the financial market in particular.

2- Calculation of non-discretionary accruals;

After calculating the total accruals, we computed the non-discretionary accruals by applying the Johnson model through the estimation of the coefficients a1, a2 and a3. This was done by entering the data related to the model, as previously explained, into the SPSS 23 statistical package. The following table presents the results obtained ;

years	Salam bank	Baraka bank
2017	0.000821025-	0.000479380728
2018	0.000797548-	0.0005344221
2019	0.000467851-	0.0005905817
2020	0.000119199-	0.0006097137

2021	0.001377741	0.0004509942
2022	0.00059953-	0.000144317
2023	0.00130543-	0.00007938244318
2024	0.000962976	0.0004481396

Table 03: the non-discretionary accruals
Source: Prepared by the researcher using spss23

From the table, we conclude that:

✓ The negative sign of non-discretionary accruals is possible and normal, as it reflects the way revenues and expenses are recorded and the timing of cash flows, and it is not, by itself, interpreted as evidence of manipulation. Since these accruals are considered "non-discretionary", they represent the normal component related to operating activities and business conditions (such as a decline in activity or an increase in cash collections); therefore, being negative does not indicate deliberate earnings management.

✓ Regarding the small magnitude, the fact that the value is around 10−410−4 indicates that the size of non-discretionary accruals relative to the measurement base (often total assets) is small, which means that the "normal" component of accruals is limited during this period for the two banks.

3- Calculation discretionary accruals;

In order to calculate discretionary accruals, and based on the relationship for total accruals, we proceed as follows:

Total accruals = discretionary accruals + non-discretionary accruals
Discretionary accruals = total accruals − non-discretionary accruals.

The following table shows the discretionary accruals for the study sample

Table 04: discretionary accruals

years	**Salam bank**	**Baraka bank**
2017	-44 135	-31 111
2018	-66 418	-8 482
2019	-70 613	-6 250
2020	-87 461	-9 597
2021	-86 027	-17 390
2022	-63 326	-81 725
2023	42 819	-99 411
2024	-142 505	-36 767

Source: Prepared by the researcher using EXCEL

The results in Table (4) show that both Salam Bank and Baraka Bank exhibit predominantly negative discretionary accruals over the period 2017–2024, indicating income-decreasing earnings management in most years. Salam Bank records negative discretionary accruals from 2017 to 2022 and again in 2024, while in 2023 it reports a positive value (42,819), suggesting income-increasing adjustments in that year. In contrast, Baraka Bank shows consistently negative discretionary accruals throughout the entire period, with the largest magnitudes in 2022 (−81,725) and 2023 (−99,411), reflecting stronger downward adjustments to reported earnings in those years. Overall, the magnitude and sign of discretionary accruals indicate that the normal pattern for both banks is to reduce reported earnings, with only a single year of upward earnings management for Salam Bank.

4- The relationship between earnings quality and accruals:

In order to measure the relationship between earnings management and accruals, we calculate the variables of the following model:

Y= B0 +B1X1+B2X2+B3X3+B4X4+e

Y = Total Accruals / Aijt-1

X1= 1/ Aijt-1

X2= PPEijt / Aijt-1

X3= AREVijt / Aijt-1

X4= ROA it's calculated as Net Income divided by Total Assets.

B0, B1, B2, B3, B4 firm-specific parameters

After calculating the values of the variables for the two banks under study over the period 2017–2024, we enter these values into the DATAtab software.

DATAtab: A powerful tool for analyzing and exploring data, it is considered one of the data-mining programs that help users better understand their data and make strategic decisions based on the analyses. DATAtab provides a user-friendly interface and robust features that enable users to explore and analyze data quickly and efficiently.

1- **Data description:** The following table presents the descriptive statistics of the model variables

Table 05: Data description

	Y	X1	X2	x3	X4
Mean	7.2	0	0.02	0.41	0.91
Std. Deviation	4.39	0	0.02	0.9	0.76
Minimum	0.01	0	0	0	0.23
Maximum	14.01	0	0.05	3.07	3.13
Number of values	16	16	16	16	16
95% Confidence interval for mean	4.86 - 9.53	0 - 0	0.01 - 0.03	-0.07 - 0.89	0.51 - 1.32

Source: Prepared by the researcher using DATAtab

The table shows descriptive statistics for 5 related groups (*Y*, *X1*, *X2*, *x3* and *X4*). Here's the interpretation of each column in the table,

✓ Number of values: This column indicates the number of data points or observations you have for each group.

- Y: 16 observations
- X1: 16 observations
- X2: 16 observations
- x3: 16 observations
- X4: 16 observations

✓ **Mean (Average) :** The mean value represents the average of all observations in each group. For instance, the average for the Y group is 7.20.

✓ **Std. Deviation (Standard Deviation):** Standard deviation measures the amount of variation or dispersion in a set of values. A low standard deviation indicates that the values tend to be close to the mean of the set, while a high standard deviation indicates that the values are spread out over a wider range.

When discussing the descriptive analysis of the data, it is necessary to address their normal distribution. The following tables analyze the normal distribution of the study variables for the Bahraini banks under investigation Normal test:

Table 06: Tests for normal distribution of baraka bank-Y

	Statistics	p
Kolmogorov-Smirnov	0.10	1
Kolmogorov-Smirnov (Lilliefors Corr.)	0.10	1
Shapiro-Wilk	0.97	.933
Anderson-Darling	0.13	.961

Source: Prepared by the researcher using DATAtab

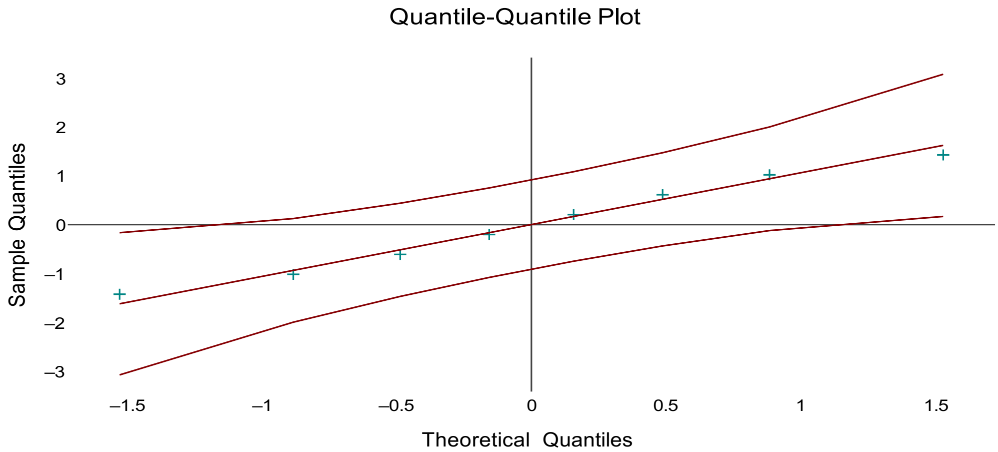

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Table 07: Tests for normal distribution of salam bank-Y

	Statistics	p
Kolmogorov-Smirnov	0.29	.411
Kolmogorov-Smirnov (Lilliefors Corr.)	0.29	.039
Shapiro-Wilk	0.79	.02
Anderson-Darling	0.76	.028

Source: Prepared by the researcher using DATAtab

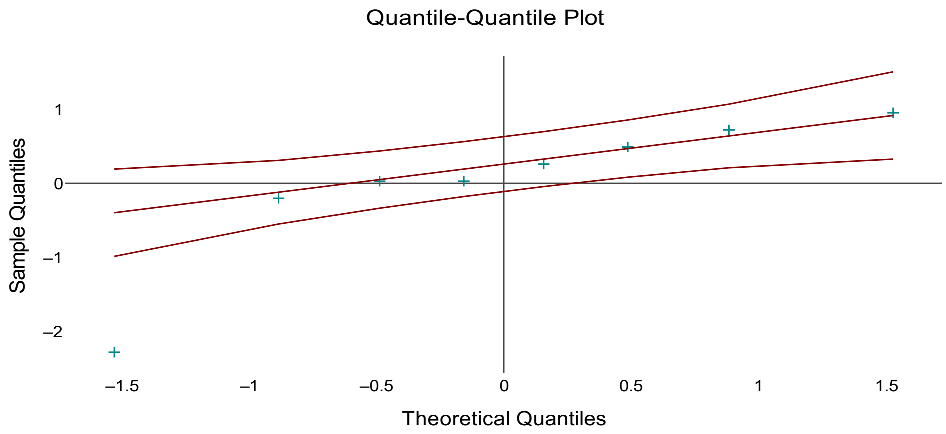

Table 08: Tests for normal distribution of baraka bank-X1

	Statistics	p
Kolmogorov-Smirnov	0.28	.461
Kolmogorov-Smirnov (Lilliefors Corr.)	0.28	.058
Shapiro-Wilk	0.85	.09
Anderson-Darling	0.58	.085

Source: Prepared by the researcher using DATAtab

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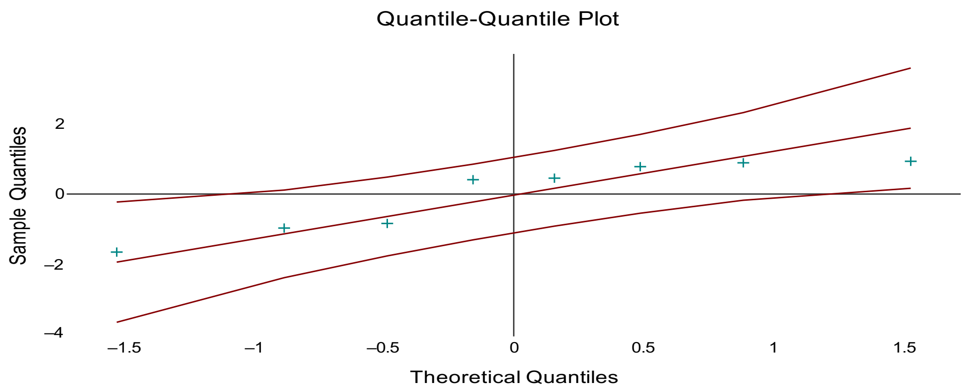


Table 09: tests for normal distribution of salam bank-X1

	Statistics	p
Kolmogorov-Smirnov	0.20	.844
Kolmogorov-Smirnov (Lilliefors Corr.)	0.20	.525
Shapiro-Wilk	0.93	.518
Anderson-Darling	0.29	.525

Source: Prepared by the researcher using DATAtab

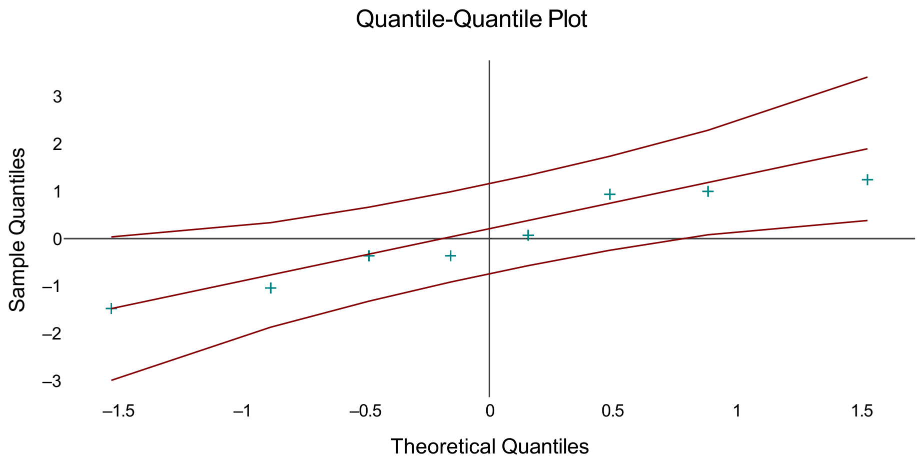


Table 10: Tests for normal distribution of baraka bank-X2

	Statistics	p
Kolmogorov-Smirnov	0.16	.971
Kolmogorov-Smirnov (Lilliefors Corr.)	0.16	1
Shapiro-Wilk	0.97	.921
Anderson-Darling	0.20	.833

Source: Prepared by the researcher using DATAtab

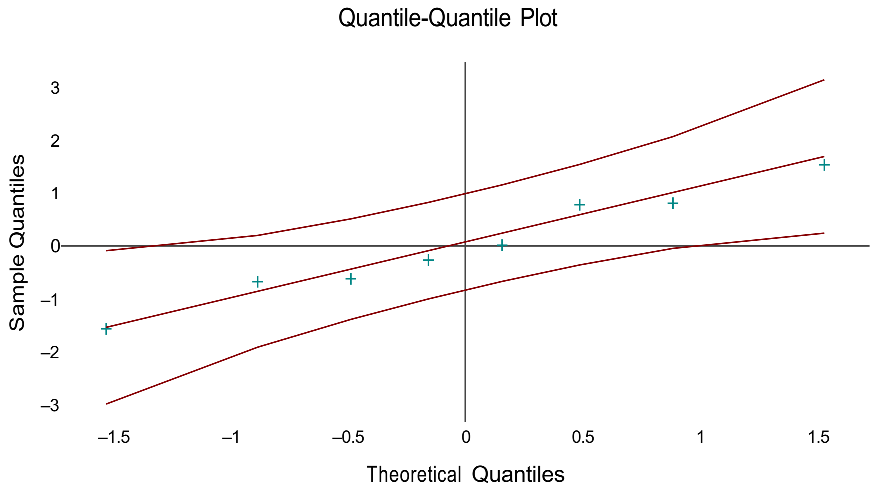


Table 11: Tests for normal distribution of salam bank-X2

	Statistics	p
Kolmogorov-Smirnov	0.19	.888
Kolmogorov-Smirnov (Lilliefors Corr.)	0.19	.656
Shapiro-Wilk	0.94	.58
Anderson-Darling	0.27	.561

Source: Prepared by the researcher using DATAtab

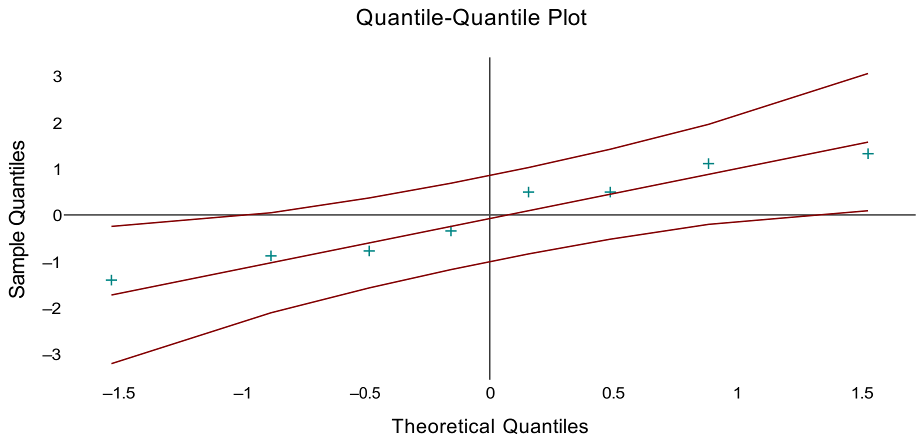


Table 12: Tests for normal distribution of baraka bank-x3

	Statistics	p
Kolmogorov-Smirnov	0.47	.037
Kolmogorov-Smirnov (Lilliefors Corr.)	0.47	<.001
Shapiro-Wilk	0.48	<.001
Anderson-Darling	2.05	<.001

Source: Prepared by the researcher using DATAtab

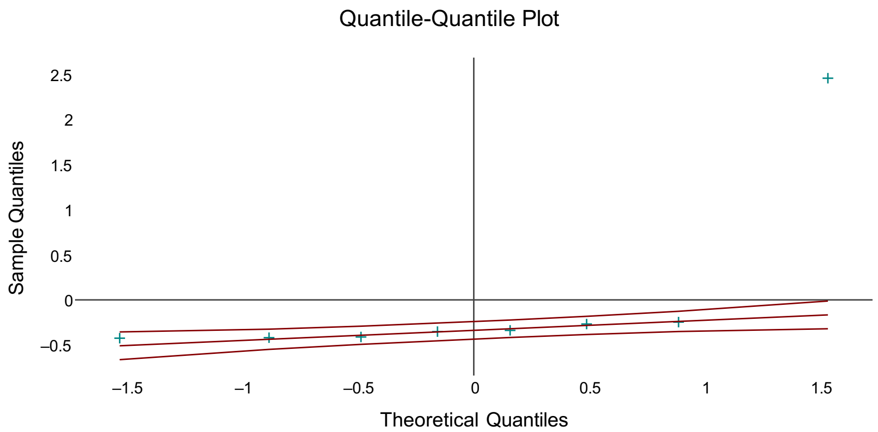


Table 13: Tests for normal distribution of salam bank-x3

	Statistics	p
Kolmogorov-Smirnov	0.44	.061
Kolmogorov-Smirnov (Lilliefors Corr.)	0.44	<.001
Shapiro-Wilk	0.63	<.001
Anderson-Darling	1.52	<.001

Source: Prepared by the researcher using DATAtab

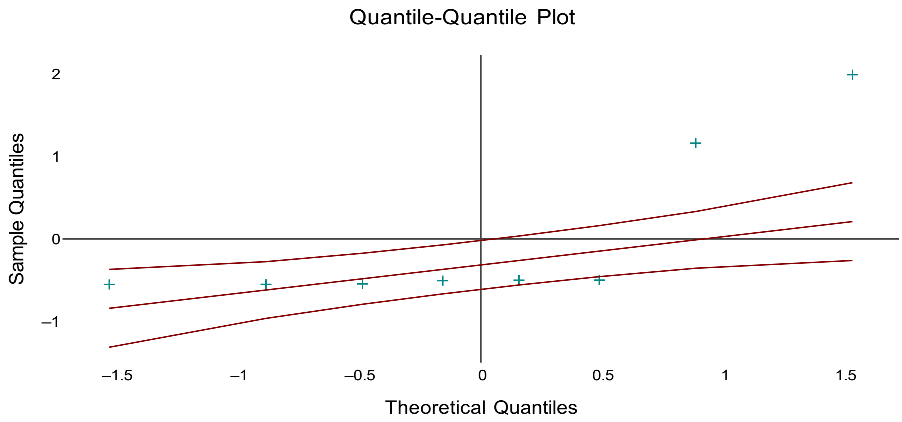


Table 14: Tests for normal distribution of baraka bank-X4

	Statistics	p
Kolmogorov-Smirnov	0.37	.169
Kolmogorov-Smirnov (Lilliefors Corr.)	0.37	.002
Shapiro-Wilk	0.72	.003
Anderson-Darling	1.08	.003

Source: Prepared by the researcher using DATAtab

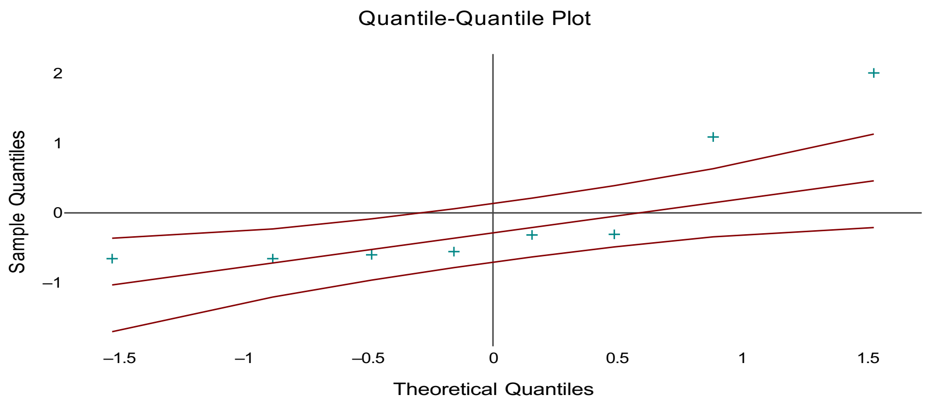
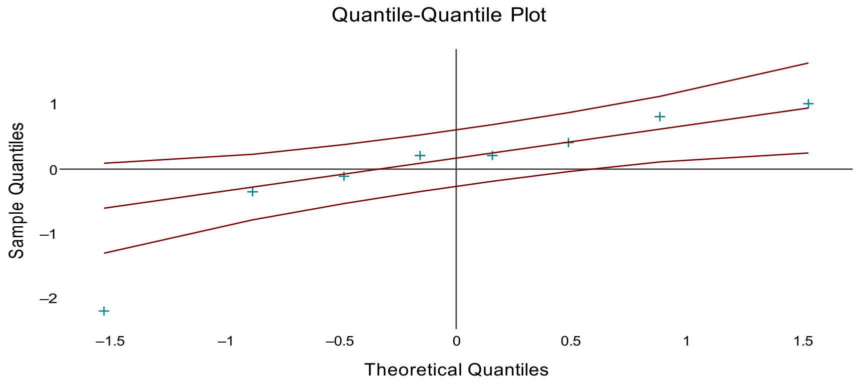


Table 14: Tests for normal distribution of salam bank-X4

	Statistics	p
Kolmogorov-Smirnov	0.24	.677
Kolmogorov-Smirnov (Lilliefors Corr.)	0.24	.228
Shapiro-Wilk	0.84	.067
Anderson-Darling	0.59	.081

Source: Prepared by the researcher using DATAtab



2- **Linear Regression** : A multiple linear regression analysis was performed to examine the influence of the variables *X1, X2, x3 and X4* on the variable *Y*.

- Model Summary :

R	R^2	Adjusted R^2	Standard error of the estimate
0.65	0.43	0.22	3.88

The model shows a high positive relationship between the observed values and the prediction, explains 42.60% of the variance in the dependent variable, but the predictions are on average 3.88 units away from the actual values, which may or may not be significant depending on the context of the data.

- **ANOVA:** the ANOVA (Analysis of Variance) table in regression analysis helps you understand how well your model fits the data. Here's how to interpret the components of the ANOVA table:

Table 15: anova

Model	df	F	p
Regression	4	2.04	.137

Source: Prepared by the researcher using DATAtab

- Degrees of Freedom (df): there are 4 independent variables.
- F-Statistic (F): The F statistic of 2.04 is then used together with the degrees of freedom to calculate the p-value.
- p-value: With a p-value of .137, which is greater than 0.05, the results are not statistically significant.

- Coefficients: the table shows the results for each independent variable in the model, including the constant (intercept). The unstandardized coefficient B indicates the expected change in the dependent variable *Y* for each one-unit increase in the respective independent variable

Table 16 Coefficients

Model	Unstandard. Coef. B	Standard. Coef. Beta	Std. Error	t	p	95% CI for B lower bound	95% CI for B upper bound
Constant	4.57		3.08	1.48	.166	-2.21	11.35
X1	-1953580.75	-0.17	2846742.85	-0.69	.507	-8219219.46	4312057.97
X2	120.67	0.47	66.87	1.80	.099	-26.52	267.86

Model	Unstandard. Coef. B	Standard. Coef. Beta	Std. Error	t	p	95% CI for B lower bound	95% CI for B upper bound
x3	0.52	0.11	1.22	0.42	.68	-2.18	3.21
X4	1.29	0.22	1.34	0.96	.356	-1.66	4.25

Source: Prepared by the researcher using DATAtab

- Constant: This is the y-intercept of the regression line. It represents the expected value of the dependent variable when all independent variables are zero. In this context, it means that when *X1, X2, x3 and X4* are zero, the dependent variable *Y* is expected to be around 4.57. The p-value is .166, indicating that the intercept is not statistically significantly different from zero. More precisely the null hypothesis that the coefficient of *Constant* is zero in the population is not rejected.
- X1: If the value of the variable *X1* changes by one unit, the value of the variable *Y* changes by -1953580.75 units. The p-value is .507, indicating that this coefficient is not statistically significantly different from zero, which means we cannot confidently say that X1 impacts the dependent variable. More precisely the null hypothesis that the coefficient of *X1* is zero in the population is not rejected.
- X2: If the value of the variable *X2* changes by one unit, the value of the variable *Y* changes by 120.67 units. The p-value is .099, indicating that this coefficient is not statistically significantly different from zero, which means we cannot confidently say that X2 impacts the dependent variable. More precisely the null hypothesis that the coefficient of *X2* is zero in the population is not rejected.
- x3: If the value of the variable *x3* changes by one unit, the value of the variable *Y* changes by 0.52 units. The p-value is .68, indicating that this coefficient is not statistically significantly different from zero, which means we cannot confidently say that x3 impacts the dependent variable. More precisely the null hypothesis that the coefficient of *x3* is zero in the population is not rejected.
- X4: If the value of the variable *X4* changes by one unit, the value of the variable *Y* changes by 1.29 units. The p-value is .356, indicating that this coefficient is not statistically significantly different from zero, which means we cannot confidently say that X4 impacts the dependent variable. More precisely the null hypothesis that the coefficient of *X4* is zero in the population is not rejected.

The following regression model is obtained:

Y = 4.57 - 1953580.75 · X1 + 120.67 · X2 + 0.52 · x3 + 1.29 · X4

RESULTS

Through the financial and statistical analysis of banking in Bahrein, the study shows the important role played by the financial statements in providing accurate and reliable information. in predicting financial failure.

The study relied on the Modified Jones model to separate accruals into discretionary and non-discretionary components, as a statistical tool that enables the detection of the presence or absence of accounting manipulation. The financial data required to build the model were collected using statistical tools and software such as Excel and DATAtab.

The results for the banks under study showed, in most years, stable earnings and a close alignment between total and non-discretionary accruals, which indicates a clear absence of earnings management practices and reinforces the transparency of these banks' financial statements,

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