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Factors Influencing Non-Performing Loans between Islamic and Conventional Banks in Malaysia

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Abstract

This study reveals the long-term effects of several variables on Non-Performing Loans (NPLs) in Islamic banks (IBs) and conventional banks (CBs) in Malaysia. Using the Autoregressive Distributed Lag (ARDL) technique, the study supports a proactive approach and finds a persistent association between NPLs and asset quality, loan quality, unemployment rate, and inflation rate. Using the ARDL approach, the analysis covers the monthly period from 2018 to early 2021. This study aims to investigate NPLs at two different times: before and after the COVID-19 epidemic. The findings indicate that The ARDL model identifies Loan Quality 1 and 2 as significant influencers of NPLs in Malaysia's CBs. At the same time, asset quality and the unemployment rate show no significant impact. In contrast, IBs show a strong positive correlation between Asset Quality and NPL, with economic factors like the Unemployment Rate and Inflation Rate significantly affecting NPL, reflecting the unique risk-sharing nature of Islamic finance. These findings necessitate improved risk management strategies in both banking sectors.

Keywords: Non-Performing Loans, Asset Quality, Conventional, Islamic Banks, Loan Quality

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1.0 Introduction

A key component of financial management is credit risk, which is the possibility that a contractual party does not keep their end of the bargain (Brown & Moles, 2014). This risk highlights how credit affects a company's transactions. Thus, financial institutions must pay attention to Non-Performing Loans (NPLs) since they will affect the credit risk of the financial institutions (İncekaraa & Çetinkayaa, 2019). This management method entails identifying, assessing, and mitigating any losses associated with credit. Because a sizable amount of assets is linked to financing portfolios, credit risk becomes the primary source of risk for Malaysian banks, necessitating credit risk analysis (Central Bank of Malaysia, 2001). High or rising percentages of NPLs in the banking industry jeopardize the economy's stability, making it more difficult for money to move from savers to borrowers, and may discourage investment and long-term growth (Staehr & Uusküla, 2021).

The complexities of credit risk in IBs significantly affect loans that are not performing. In Islamic banking, special financing arrangements like Salam, a form of a forward contract being paid upfront for later delivery, or exemption agreements raise credit issues when assets are transferred without timely payment. Due to the possibility of loan quality degradation brought on by late or non-payment under these arrangements, this dynamic exposes IBs to possible NPLs (İncekaraa & Çetinkayaa, 2019). Financing techniques like Murabaha, a cost-plus financing that requires the provision of assets without prompt payment, increase the risk of NPLs. Payment failures or delays might cause the loans associated with these arrangements not to perform. In Islamic banking, credit risk analysis is much more critical when considering situations such as the non-binding Murabaha. In these situations, IBs are exposed to price and market risks when product delivery is refused, which has a direct effect on asset quality and, as a result, raises the possibility of NPLs. The complexity of Islamic financing arrangements highlights the necessity of a comprehensive credit risk analysis that considers their characteristics, with an emphasis on reducing the risk of NPLs brought on by missed payments, defaults, or difficulties in the market (Rahman & Shahimi, 2010).

The COVID-19 epidemic has created previously unheard-of difficulties for the banking sector. Credit risk has been heightened in Malaysia due to forecasts of limited credit expansion and estimates that NPLs will make up a sizable amount of existing loans (Ahmad et al., 2022). The study attempts to identify the factors influencing NPLs to improve risk assessment methods and models for Islamic banks (IBs) and conventional banks (CBs) to assess credit risk analysis. The research objectives are listed as follows:

1) To describe the trend of NPLs of IBs and CBs in Malaysia before and during COVID-19.

2) To determine the significant factors that affect NPLs in IBs and CBs in Malaysia.

3) To determine the long-term relationship between NPLs of IBs and CBs in Malaysia regarding loan quality, asset quality, unemployment rate, and inflation rate.

This study's importance stems from its ability to provide light on the relationship between independent factors and the dependent variable of NPLs. The study questions focus on examining the trends in NPLs and determining what essential variables impact NPLs. Another goal of the study is to determine which independent variables will have long-term correlations with NPLs. These independent variables include loan quality, asset quality, unemployment rate and inflation rate.

The research's scope spans the years 2018 to 2021 using monthly data. It examines the NPLs of Malaysian IB and CBs, focusing on asset quality, loan quality, unemployment rate, and inflation rate. The study is organized as follows: an introduction section that gives background information and context, a literature review, a methodology, and a presentation of the findings. A closing section summarizing the study's goals, conclusions, and implications is also given. This research aims to provide risk managers with knowledge about NPLs so that more accurate risk assessment models and successful risk management plans can address adverse outcomes such as the pandemic.

2.0 Literature Review

This section reviews the studies on NPLs, sometimes termed credit risk, in more detail based on a few earlier studies on the subject. All the data from earlier studies also revealed the basic structure of the research since their research focused on the relationship between non-performing loan variables. To ascertain the link between the factors that impact NPLs for IBs and CBs, several variables that can be relevant to this subject have been explored in previous research, which will be discussed in the following paragraphs.

Numerous factors have been explored from the previous research that may be connected to this study to determine the linkage of loan quality, asset quality, unemployment rate, and inflation rate aspects that may impact the NPLs. All variables can be divided into two groups: economic and macroeconomic factors. For example, Ekinci and Poyraz (2019) studied the impact of credit risk on the performance of banks in Turkey from 2005 to 2017. A proxy for the credit risk in this study is data on NPLs, while return on asset (ROA) and return on equity (ROE) were used as performance indicators. This study found a negative relationship between NPL and the two performance proxies.

A different study by Siddique et al. (2021) looked into the effect of credit risk management and bank-specific factors on the performance of South Asian commercial banks. Similar to other studies, NPL was used as a proxy for the credit risk factor, while the bank-specific factors include capital adequacy ratio, average lending rate, and liquidity ratio. The findings of this study show that the liquidity ratio is significantly related to performance; however, the link is negative. On the other hand, it was found that the average lending rate is positively significant in terms of performance.

While most studies focus on the link between NPL and performance, it is also essential to look at those that specifically aim to find the factors influencing credit risk. One such study is by Khan et al. (2020), which focused on bank profitability, operating efficiency, capital adequacy, and income diversification to see these factors' impact on NPLs in Pakistan's banks. It is found that the significant factors are operating efficiency and profitability. In a more recent study, Masud and Hossain (2021) found that underlying determinants of NPL include both bank-specific (ROA) and macroeconomic factors (Gross Domestic Product (GDP) growth rate, interest rate, unemployment, and inflation) using the generalized method of moments.

2.1 Dependent Variable

The existence of notable or increasing amounts of NPLs in the banking industry severely threatens the financial system's stability (Staehr & Uusküla, 2021). The results show that a wide range of macroeconomic and macro-financial characteristics may be used as advanced indicators to forecast NPLs in countries that are members of the European Union (EU) for several years ahead of time. Higher GDP growth, lower inflation, and lower debt levels are all regularly found to be good indicators of a lower percentage of NPLs in the future. Furthermore, although their importance is not reflected in the Central and Eastern European subgroups, the current account balance and real estate prices are important indicators for the Western European subset.

Staehr (2021) findings imply that certain financial and economic variables may be used to predict, even years in advance, the probability of NPLs in EU member states. Future loan non-performing ratios are typically associated with factors like robust economic development, lower inflation, and lower debt levels. It is interesting to note that although real estate prices and the current account balance are essential indicators for countries in Western Europe, they are not as predictive for countries in Central and Eastern Europe.

Research conducted by Tham et al. (2021) is an experimental research technique employing time series analysis to build a dynamic model that accurately represents the influence of macroeconomic factors on property NPLs in Malaysia. This approach is selected because it is well known and often used in research utilising time series macroeconomic data, which makes it ideal for testing. The autoregressive distributed lagged-error correction model (ARDL-ECM) is a data analysis approach used in the research to achieve the study's aims. This method works well when measuring and evaluating time series data and offers insights into the short-, medium-, and long-term effects. The study uses a specialised model called ARDL-ECM to investigate the long-term effects of macroeconomic variables on NPLs associated with properties in Malaysia.

Darmawan (2018) wrote that a higher ratio of these loans is a proxy for NPLs, representing a higher risk for the bank. A higher ratio of NPLs indicates a larger non-performing loan load on the bank. Because of the high percentage of NPLs, the bank's capital will eventually decline because of the need for more reserves. Conversely, the amount of bank capital has a major influence on the extent of lending growth.

2.1.1 Asset Quality

Following previous research by Mostak (2017), the study focused on a homogenous sample of banks that operated in India between 1998 and 2014. The study used the diversity measure of the Herfindahl-Hirschman-index income diversification indicator known as FOCUS. According to the study's conclusions, banks with lower-than-average asset quality may benefit more from having a more diverse revenue stream regarding how loan loss provisions are distributed and non-performing loan management. This suggests that banks with asset quality issues might benefit from diverse income strategies more significantly than banks with better asset quality.

Alber (2014) carried out a thorough investigation of the effects of banking laws and regulations on asset quality. From 2006 to 2012, a sample of fourteen countries was included in the study. The ratio of impaired loans to equity and the proportion of NPLs held byIBs relative to total loans were the best metrics for assessing asset quality, which was the dependent variable. The Basel implementation reaction was used to measure the independent variable in this investigation, which was banking regulation.

2.1.2 Loan Quality

According to Onuko et al. (2015), when a loan portfolio has no or a small amount of non-performing assets, it is said to be of excellent quality. Loans with poor possibilities of being repaid in full or part are classified as non-performing assets. This study used a sample of five commercial banks and their financial statement reports from 2009 to 2013. Each bank underwent evaluation, measurement, and analysis. The findings demonstrated that loan quality significantly positively impacted the level of Non-Performing Assets.

Based on the study from Stefanelli and Cotugno (2012), the research aims to examine how well banks' boards oversee the quality of the banks' loan portfolios. The sample used in the research includes all Italian banks listed on Borsa Italiana SpA between 2006 and 2008, and this research used a Multivariate Regression Model (OLS). This research used three models, and NPLs are significant in loan quality. The study found that lowering the percentage of NPLs implementing the "Standardised Approach" and "Pillar 2" in banking rules showed a possible improvement in asset quality. On the other hand, it seems that the "Capital Conservation Buffer" and the 2 Basic Indicator Approach "increased the percentage of NPLs. This highlights the necessity for customised strategies based on discrete regulatory measures and the complex link between certain regulatory implementations and their varying effects on asset quality.

2.1.3 Unemployment Rate

Research conducted by Khumalo et al. (2021) analysed how the long-term effects of the cointegration of credit risk and macroeconomic dynamics on South African banks. A literature review and an empirical investigation employing secondary data were both used in this study. A statistical analysis was completed for the empirical analysis. The research uses the most recent aggregate data on SARB and StatsSA from 2009 to 2018/1. This study's findings aimed to identify long-term relationships between credit risk and macroeconomic variables. The unemployment rate, market/leading rate, and money supply all showed positive relationships, indicating a significant long-term relationship between credit risk and these three macroeconomic variables.

Furthermore, in research by Louzis et al. (2012), NPLs in the Greek banking industry are examined individually for each loan type (consumer loans, corporate loans, and mortgages) using dynamic panel data techniques. This study panel data set comprised nine Greek commercial banks spanning the first quarter of 2003 to the third quarter of 2009. The study discovers that the number of NPLs is strongly influenced by macroeconomic factors, particularly the real GDP growth rate, the unemployment rate, the lending rates, and the public debt.

2.1.4 Inflation Rate

A study from Indonesia written by Darmawan (2018) states that loan interest rates, NPLs, and third-party funds are internal banking industry factors that affect how credit is distributed. In addition to these internal components, the inflation rate is an external factor that influences how credit is distributed. The distribution of credit in the banking industry can be greatly impacted by the inflation rate, which is an external issue. Inflation is the overall upward trend in prices over time that reduces money's buying power. A high inflation rate reduces the value of money, and lenders could be less willing to give credit. Increased uncertainty brought on by higher inflation rates may affect interest rates and increase the cost of borrowing. Because of this, banks may modify their credit lending policies in reaction to current inflation conditions, considering the wider economic effects on borrowers' capacity to repay loans and credit risk in general. In their study, Tham et al. (2021) found that inflation significantly impacts the non-performing aspect of property. Similarly, in another study by Koju et al. (2019), inflation has also been found as an indicator that increases NPLs due to its effect on decreasing consumers' purchasing power, leaving them with less money to pay on the principal and interest on loans.

3.0 Methodology

3.1 Overview

This section will cover the data and methodology used to conduct this study. The study includes obtaining data, analysis, and formula drafting. In this study, secondary data is used to investigate whether conventional and Islamic banking factors have a positive or negative effect on NPLs. The study's data collection involving both dependent and independent variables is a monthly time series of data obtained from the Department of Statistics Malaysia and Bank Negara Malaysia website from 2018 until December 2021. This study aims to investigate NPLs at two different times: before and after the COVID-19 epidemic. The pre-COVID phase is defined in this study from January 2018 to December 2019, while the during-COVID phase is from January 2020 to December 2021.

3.2 Data Description

The dependent variable that is used in this study is NPLs between IBs and CBs in Malaysia. This study has five independent variables, and two of the independent variables are macroeconomic factors: the unemployment rate and the inflation rate. The number of unemployed individuals calculates the unemployment rate as a percentage of the total labour force. The measure of inflation represents the degree to which overall costs of goods and services in the economy have changed over a certain time frame. It shows how quickly the total level of prices fluctuates, giving information about the general pattern of growing or declining prices in the economy. In simpler terms, inflation measures variations in a currency's buying power that affect decisions made by firms, consumers, and the economy. Specific ratios based on available data are used to calculate loan quality and asset quality. The measures for loan quality are the ratio of total assets growth (LQ1) and the ratio of gross loan growth (LQ2). On the other hand, the ratio of impaired loans to gross loans (AQ) is used to assess the assets' quality. The specific data related to banks are gathered from the Bank Negara Malaysia website, which represents aggregate data of the whole banking industry, in this case, the CBs and IBs. These independent variables and the dependent variable are outlined below in Table 1.

Table 1: Dependent and Independent Variables Formula

Variables	Abbreviation	Formula	Source
NPLs	NPL	$\frac{Impaired\ Loans}{Gross\ Loans}$	Bank Negara Malaysia
Asset Quality	AQ	$\frac{Impaired\ Loan}{Equity}$	Bank Negara Malaysia
Loan Quality 1	LQ1	$\frac{Total\ Assets_t - Total\ Assets_{t-1}}{Total\ Assets_t}$	Bank Negara Malaysia
Loan Quality 2	LQ2	$\frac{Loans_t - Loans_{t-1}}{Loans_t}$	Bank Negara Malaysia
Unemployment Rate	UN	The number of unemployed individuals expressed as a percentage of the total labour force	Department of Statistics Malaysia
Inflation Rate	IR	The overall level of prices of goods and services in the economy has changed over a period.	Department of Statistics Malaysia

3.3 Descriptive Analysis

The primary characteristics of the data and scale variables for NPLs are summarised using descriptive statistics. The minimum and maximum values, standard deviation, and variance are used to assess variability, whereas the mean, median, and mode measure central tendency. If the mean and median values are extremely high, converting the data values to percentages or logarithms might be necessary to get useful results. A monthly dataset from 2018 to 2021 in Malaysia is used for the descriptive statistics that comprise macroeconomic and quantitative variables (unemployment rate, inflation rate, asset quality, loan quality, and NPLs).

3.4 Unit Root Test

Based on Herranz (2017) study, the Augmented Dickey-Fuller (ADF) test is commonly used to determine the presence of a unit root in each time series dataset. ADF test can accommodate higher orders of autoregressive processes by incorporating AQ1, LQ1, LQ2, UN, and IR in the model.

To identify the presence of unit roots, it is essential to assess both the stationarity and significance requirements. For a data series to be considered stationary, the ADF test should reject the null hypothesis of a unit root with coefficients and p-values below the threshold of 0.05.

The hypothesis for this is below:

H_0 = The series has the unit root and is not stationary.

H_1 = The series has no unit root and is stationary.

In statistical analysis, the unit root test is important because it determines if data is stationary, which affects the data's behaviour and characteristics. This test can be neglected, which can lead to a phenomenon called spurious regression. In this situation, one important metric to consider is the Durbin-Watson value, which indicates a high probability of meeting false regression when it exceeds the R-squared value. Practically speaking, this can impair the validity of statistical measures, resulting in t-statistics that are ineffective and p-values for the computed variable that are not legitimate. In the end, this might lead to incorrect inferences being made from the analysis. Consequently, by addressing the problem of non-stationarity in the data, the unit root test is essential in guaranteeing the robustness and validity of statistical conclusions.

3.5 Autoregressive Distributed Lag (ARDL) Model

Based on the ADF test results, the ARDL model is applied to a particular set of variables that include both level and first difference stationary components (Nkoro & Uko, 2016). This modelling technique is quite helpful when working with a small sample size and in situations where the variables in the model show different optimal numbers of delays. These features are considered in the building of the ARDL model for IBs and the conventional:

The linear model of the IBs ARDL model is shown as follows:

$$NPLI_t = \beta_0 + \beta_1 AQI + \beta_2 LQ1I + \beta_3 LQ2I + \beta_4 UN + \beta_5 IR + \varepsilon_T \quad (1)$$

where:

$NPLI$ are the NPLs for Islamic banks.

AQI is the ratio of impaired loans over equity for Islamic banks.

$LQ1I$ is the ratio of growth of total assets for Islamic banks.

$LQ2I$ is the ratio of growth of total loans for Islamic banks.

UN is the unemployment rate in Malaysia.

IR is the inflation rate in Malaysia.

ε_T is the error term.

The linear model of the CBs ARDL model is shown as follows:

$$NPLC_t = \beta_0 + \beta_1 AQC + \beta_2 LQ1C + \beta_3 LQ2C + \beta_4 UN + \beta_5 IR + \varepsilon_T \quad (2)$$

where:

$NPLC$ are the NPLs for CBs.

AQC is the ratio of impaired loans over equity for CBs.

$LQ1C$ is the ratio of growth of total assets for CBs.

$LQ2C$ is the ratio of growth of total loans for CBs.

UN is the unemployment rate in Malaysia.

IR is the inflation rate in Malaysia.

ε_T is error term.

The ARDL representation of the equation for IBs is as follows:

$$\Delta NPL_t = \alpha_0 + \sum_{i=1}^{n} \alpha_1 \Delta NPLI_{t-1} + \sum_{i=1}^{n} \alpha_2 \Delta AQI_{t-1} + \sum_{i=1}^{n} \alpha_3 \Delta LQ1I_{t-1} + \sum_{i=1}^{n} \alpha_4 \Delta LQ2I_{t-1} + \sum_{i=1}^{n} \alpha_5 \Delta UN_{t-1} + \sum_{i=1}^{n} \alpha_6 \Delta IR_{t-1} + \beta_1 NPLI_{t-1} + \beta_2 AQI_{t-1} + \beta_3 LQ1I_{t-1} + \beta_4 LQ2I_{t-1} + \beta_5 UN_{t-1} + \beta_6 IR_{t-1} + \varepsilon_T \tag{3}$$

where:

Δ refers to the first difference operator.

a_i is a short-run coefficient.

β_i is a long-run coefficient.

ε_T is the error term.

The ARDL representation of the equation for CBs is as follows:

$$\Delta NPL_t = \alpha_0 + \sum_{i=1}^{n} \alpha_1 \Delta NPLC_{t-1} + \sum_{i=1}^{n} \alpha_2 \Delta AQC_{t-1} + \sum_{i=1}^{n} \alpha_3 \Delta LQ1C_{t-1} + \sum_{i=1}^{n} \alpha_4 \Delta LQ2C_{t-1} + \sum_{i=1}^{n} \alpha_5 \Delta UN_{t-1} + \sum_{i=1}^{n} \alpha_6 \Delta IR_{t-1} + \beta_1 NPLC_{t-1} + \beta_2 AQC_{t-1} + \beta_3 LQ1C_{t-1} \tag{4}$$

where:

Δ refers to the first difference operator.

a_i is a short-run coefficient.

β_i is a long-run coefficient.

ε_T is the error term.

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3.5.1 ARDL Bounds Testing Approach for Cointegration

The ARDL bound testing technique is applied to determine if a long-term relationship exists between the dependent variable (NPL) and independent variables such as asset quality, loan quality, inflation rate, and unemployment rate. It uses an F-test, which is predicated on the following hypothesis:

$$H_0: B_1 = B_2 = B_3 = B_4 = B_5 = B_6 = 0$$

There are no cointegration effects in the model.

$$H_0: B_1 \neq B_2 \neq B_3 \neq B_4 \neq B_5 \neq B_6 \neq 0$$

There is a cointegration effect among the variables.

In other words, the purpose of this test is to determine if the variables have a permanent relationship. The F-test evaluates if a significant correlation exists between NPL and several parameters, such as asset and loan quality, unemployment, and inflation rates. It does this by concentrating on certain hypotheses. We compute the F-statistic value to determine whether a long-term association exists. We reject the null hypothesis if this number is more than the upper bound critical value of 5%, which shows that all variables are cointegrated. On the other hand, the null hypothesis, which suggests that there is no cointegration among the variables, is supported if the F-statistic is less than the lower bound critical value of 5%. The results are considered inconclusive when the F-statistic is between the lower and higher boundaries.

3.5.2 ARDL Error Correction Model (ECM)

ECM is correlated with the long-run equation (2) to create a short-run model as follows:

Islamic banks:

$$\begin{aligned}\Delta NPL_t = \alpha_0 &+ \sum_{i=1}^{n} \alpha_1 \Delta NPLI_{t-1} \\ &+ \sum_{i=1}^{n} \alpha_2 \Delta AQI_{t-1} + \sum_{i=1}^{n} \alpha_3 \Delta LQ1I_{t-1} + \sum_{i=1}^{n} \alpha_4 \Delta LQ2I_{t-1} \\ &+ \sum_{i=1}^{n} \alpha_5 \Delta UN_{t-1} + \sum_{i=1}^{n} \alpha_6 \Delta IR_{t-1} + \beta_1 NPLI_{t-1} + \beta_2 AQI_{t-1} \\ &+ \beta_3 LQ1I_{t-1} + \beta_4 LQ2I_{t-1} + \beta_5 UN_{t-1} + \beta_6 IR_{t-1} + \lambda EC_{t-1} \\ &+ \varepsilon_T\end{aligned} \tag{5}$$

Conventional banks:

$$\begin{aligned}\Delta NPL_t = \alpha_0 &+ \sum_{i=1}^{n} \alpha_1 \Delta NPLC_{t-1} \\ &+ \sum_{i=1}^{n} \alpha_2 \Delta AQC_{t-1} + \sum_{i=1}^{n} \alpha_3 \Delta LQ1C_{t-1} + \sum_{i=1}^{n} \alpha_4 \Delta LQ2C_{t-1} \\ &+ \sum_{i=1}^{n} \alpha_5 \Delta UN_{t-1} + \sum_{i=1}^{n} \alpha_6 \Delta IR_{t-1} + \beta_1 NPLC_{t-1} + \beta_2 AQC_{t-1} \\ &+ \beta_3 LQ1C_{t-1} + \beta_4 LQ2C_{t-1} + \beta_5 UN_{t-1} + \beta_6 IR_{t-1} + \lambda EC_{t-1} \\ &+ \varepsilon_T\end{aligned} \tag{6}$$

where:

λ is the speed adjustment to long equilibrium in the short run.

EC are the residuals.

4.0 Results and Discussion

The empirical comparative findings between IBs and CBs will be examined in this section. This section provides descriptive statistics, trend analysis, the Augmented Dickey-Fuller (ADF) unit root test, the correlation test, and the results of the ARDL test.

4.1 Descriptive Analysis

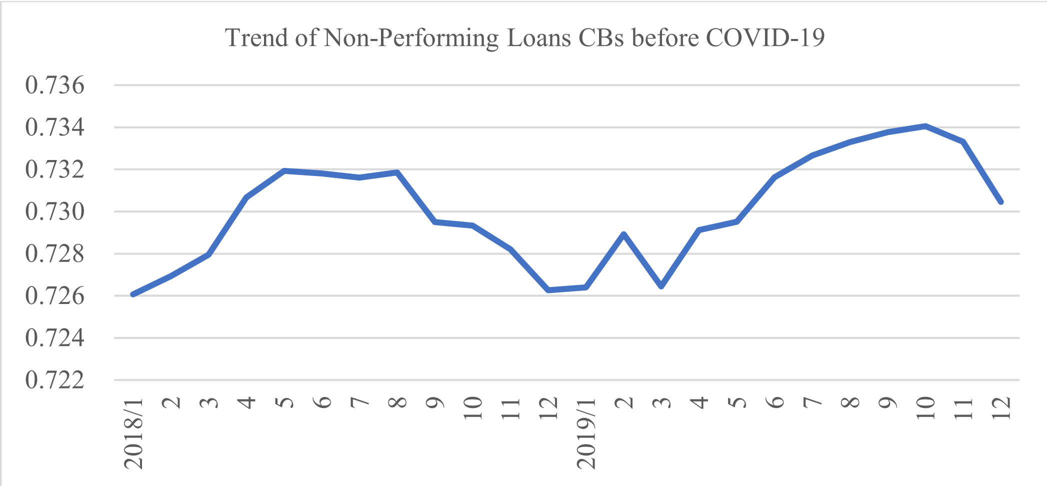

Figure 1 (i): Trend of NPLs Before COVID-19 for CBs

Figure 1 (i) shows the trend of NPLs for CBs before COVID-19, starting in January 2018 and continuing until December 2019. From 0.7261 in January 2018 to 0.7305 in December 2019, the NPL ratio showed a continuously rising trend, suggesting a slow increase in credit risk in the banking industry. The NPL ratio increased overall, although it did so gradually, with a reasonably stable fluctuation between 0.726 and 0.734 throughout the observation period. Significantly higher increases were seen in the middle of 2018 and the end of 2019, indicating possible pressures from the economy or a particular industry during those periods. Even if there were sporadic, minor drops in NPLs, the general direction of the data remained upward, underscoring the ongoing issues the banking industry has with credit risk.

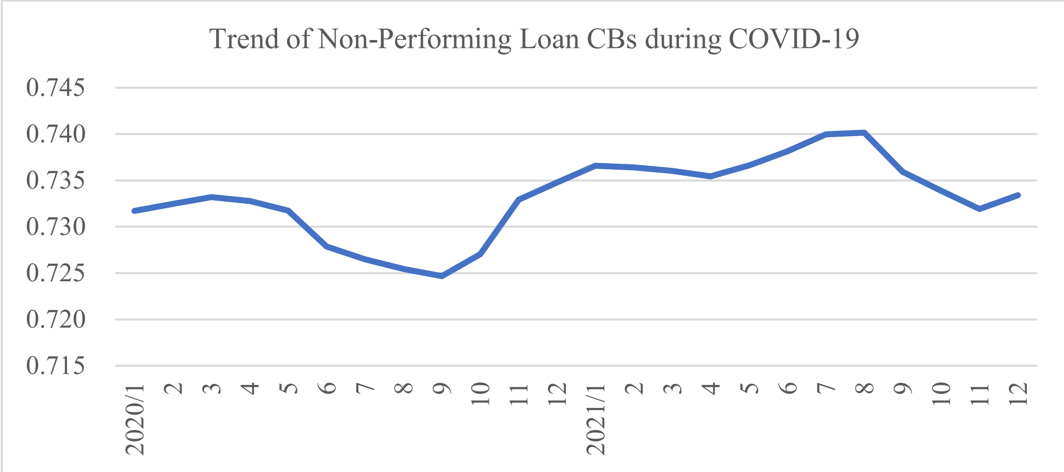

Figure 1 (ii): Trend of NPLs During COVID-19 for CBs

Figure 1 (ii) shows the trend for NPLs for CBs during the period of COVID-19 from January 2020 to December 2021. Overall, the NPL ratio showed a pattern that was initially stable in the first half of 2020, hovering around 0.732. There was a noticeable rising trajectory from mid-2020 to the end of 2021. December 2021 was the NPL ratio's greatest point, recorded at 0.7401. This noticeable rise in NPLs is consistent with the economic upheavals brought on by the COVID-19 outbreak in Malaysia. The negative consequences of the pandemic, including job losses and lower income because of company closures and lockdowns, might account for this increase and probably make it more difficult for borrowers to repay their debts.

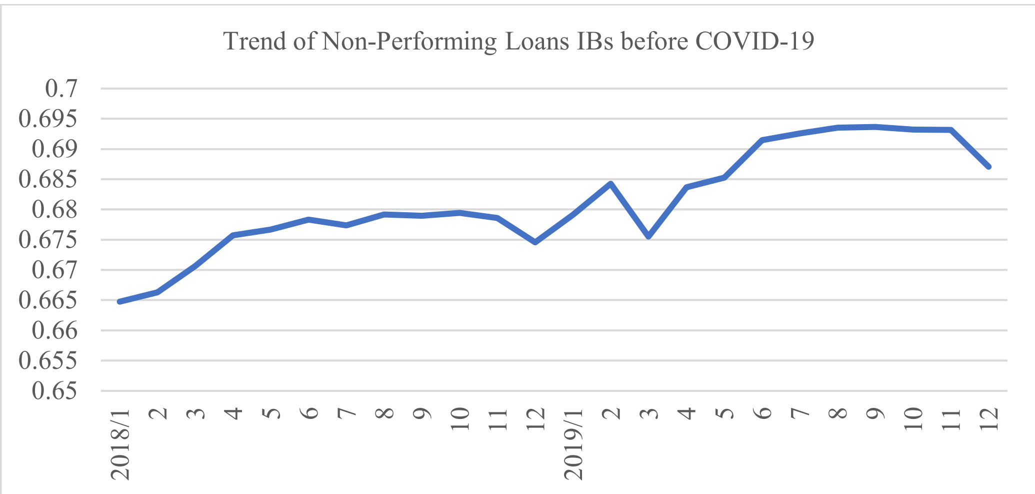

Figure 2 (i): Trend of NPLs Before COVID-19 for IBs

Figure 2 (i) shows the trend of NPLs (or non-performing financing) for IBs from January 2018 until December 2019. From 0.6647 in January 2018 to 0.6870 in December 2019, the Non-Performing Loan (NPL) ratio showed a modest increasing trend, suggesting a minor rise in credit risk within the banking industry. The trajectory was not continuously linear, with brief dips and plateaus interspersed with the general climb. Steeper rises were observed in late 2019 and mid-2018, indicating possible sector-specific or economic pressures at those times. On the other hand, brief decreases happened in late 2018 and early 2019, which can point to advantageous changes in the economy or pre-emptive risk control. Generally, throughout the last months of 2019, the NPL ratio steadied at about 0.69, indicating a very stable level of credit risk during that time.

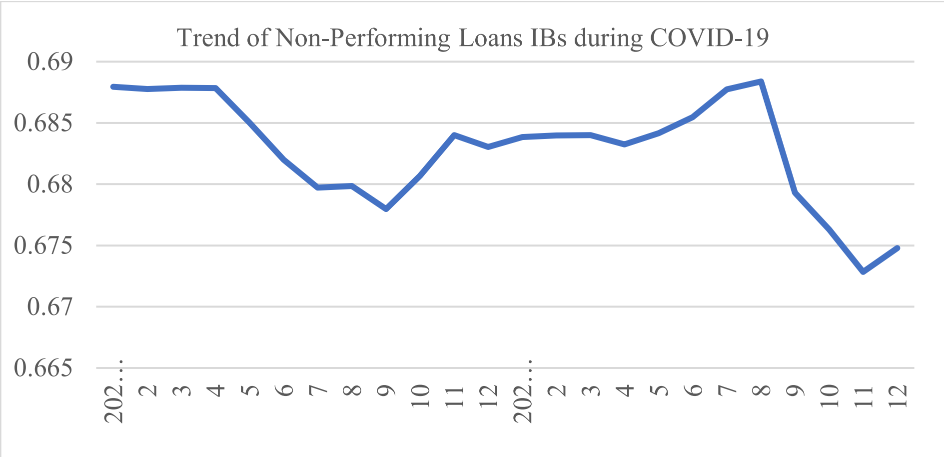

Figure 2 (ii): Trend of NPLs During Covid-19 for IBs.

Figure 2 (ii) shows the trend for non-performing financing among IBs from the period January 2020 to December 2020. Malaysian IBs' NPL ratio showed a mixed picture, declining generally from 0.6879 in January 2020 to 0.6748 in December 2021. After being constant for the first half of 2020 at 0.685–0.688, a more noticeable fall started in the middle of the year and persisted into 2020. Interestingly, the NPL ratio showed a paradoxical reduction during the COVID-19 pandemic-related economic disruptions, which runs opposite to the expected tendency of higher loan defaults during similar periods. Initiatives by the government and banks, such as loan moratoriums and repayment aid, may be to blame for this unanticipated development. By providing borrowers with financial relief, these programs probably helped to avert a surge in NPLs temporarily.

4.2 Unit Root Test

An ADF is used in time series samples to avoid unclear results that lead to incorrect conclusions. Table 2 displays the result of the ADF unit root test at level I(0) and the difference form I(1) for CBs. In contrast, Table 3 displays the ADF unit root test results at level form I(0) and the difference between form I(1) for IBs. For CBs, the variables of LQ1 and LQ2 are stationary at level form, while NPL, AQ, UN, and IR are stationary at first difference level form. For IBs, the variables of LQ1 and LQ2 are stationary at level form, while NPL, AQ, UN, and IR are stationary at the first difference level form.

Table 2 (i): Result for Unit Root Test at 5% Significant Level at the Level Form for CBs

Variable	Coefficient	T-stat	P-value	Result	Implication
NPLC	-0.24536	-0.609702	0.8603	H0 is not rejected	Not stationary
AQC	-0.054954	-1.150773	0.6900	H0 is not rejected	Not stationary
LQ1C	-1.217393	-9.235006	0.0000	H0 is rejected	Stationary
LQ2C	-1.165387	-9.062122	0.0000	H0 is rejected	Stationary
UN	-0.050538	-1.410739	0.5711	H0 is not rejected	Not stationary
IR	-0.105462	-2.129370	0.2342	H0 is not rejected.	Not stationary

Table 2 (i) displays the ADF results for commercial banks. As the p-values for NPLC, AQC, UN, and IR all surpass the 5% significance level, the observed series does not show a stable level. As a result, these findings do not support the rejection of the null hypothesis, suggesting that the variables in question do not exhibit stationarity within the designated significance level.

Table 2 (ii): Result for Unit Root Test at 5% Significant Level at First Difference Form for CBs

Variable	Coefficient	T-stat	P-value	Result	Implication
NPLC	0.773297	-6.037524	0.0000	H0 is rejected	Stationary
AQC	-0.813144	-6.304489	0.0000	H0 is rejected	Stationary
UN	-0.755131	-5.790265	0.0000	H0 is rejected	Stationary
IR	-0.802105	-5.474797	0.0000	H0 is rejected.	Stationary

Table 2 (ii) displays the results of the CBs ADF. The p-values for NPLC, AQC, UN, and IR are all less than 5%, which indicates that the series display stationarity at the first difference form, according to the results. As a result, the null hypothesis is rejected, showing that the variables are integrated in the first order (I (1)) and stationary.

Table 3 (i): Result for Unit Root Test at 5% Significant Level at the Level Form for IBs

Variable	Coefficient	T-stat	P-value	Result	Implication
NPLI	-0.121027	-2.316901	0.1701	H0 is not rejected	Not stationary
AQI	-0.129393	-2.085157	0.2513	H0 is not rejected	Not stationary
LQ1I	-1.098234	-8.474738	0.0000	H0 is rejected	Stationary
LQ2I	-0.942573	-7.250498	0.0000	H0 is rejected	Stationary
UN	-0.050538	-1.410739	0.5711	H0 is not rejected	Not stationary
IR	-0.105462	-2.129370	0.2342	H0 is not rejected.	Not stationary

Table 3 (i) displays the results of the ADF that was administered to IBs. The p-values of NPLI, AQI, UN, and IR are more than the 5% significance level, indicating that the series is not in stationary-level form. The ADF test findings show that none of those variables display stationarity at the specified significance level, so the null hypothesis cannot be rejected.

Table 3 (ii) Result for Unit Root Test at 5% significant level at First Difference form for IBs

Variable	Coefficient	T-stat	P-value	Result	Implication
NPLI	0.972006	-7.407721	0.0000	H0 is rejected	Stationary
AQI	-1.018886	-7.741229	0.0000	H0 is rejected	Stationary
UN	-0.755131	-5.790265	0.0000	H0 is rejected	Stationary
IR	-0.802105	-5.474797	0.0000	H0 is rejected.	Stationary

Table 3 (ii) displays the results of the IBs ADF. The p-values for NPLI, AQI, UN, and IR are all less than 5%, which indicates that the series display stationarity at the first difference form, according to the results. As a result, the null hypothesis is rejected, showing that the variables are integrated at the first order I(1) and stationary.

The variables for both CBs and IBs clearly show integration orders at I(0) or I(1) based on the findings that were obtained. The requirement for a modeling strategy that can account for these variances is shown by the divergence in integration orders across variables. In this case, the ARDL model makes the greatest sense because of its adaptability to variables with varying integration orders. Because of this, ARDL is a useful and adaptable method for capturing the dynamics of the variables that have been found in both CBs and IBs, enabling a thorough examination of their interactions.

4.3 The ARDL Approach for Cointegration

The Akaike Information Criterion (AIC) is used in the first stage of using the ARDL model to determine the lag length of each variable, where two distinct AIC models are used. The ideal model for CBs is shown in Figure 3, while the ideal model for IBs is shown in Figure 4.

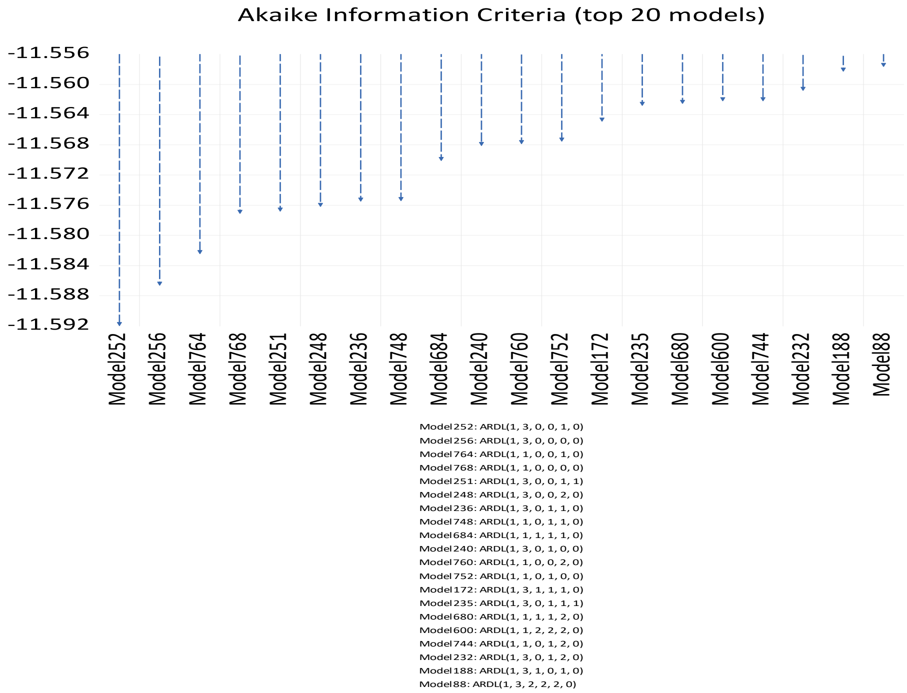

Figure 3: Akaike's Information Criterion for CBs

The lag for CBs is (1,3,0,0,3,0) based on the AIC for CBs, as seen in the above figure.

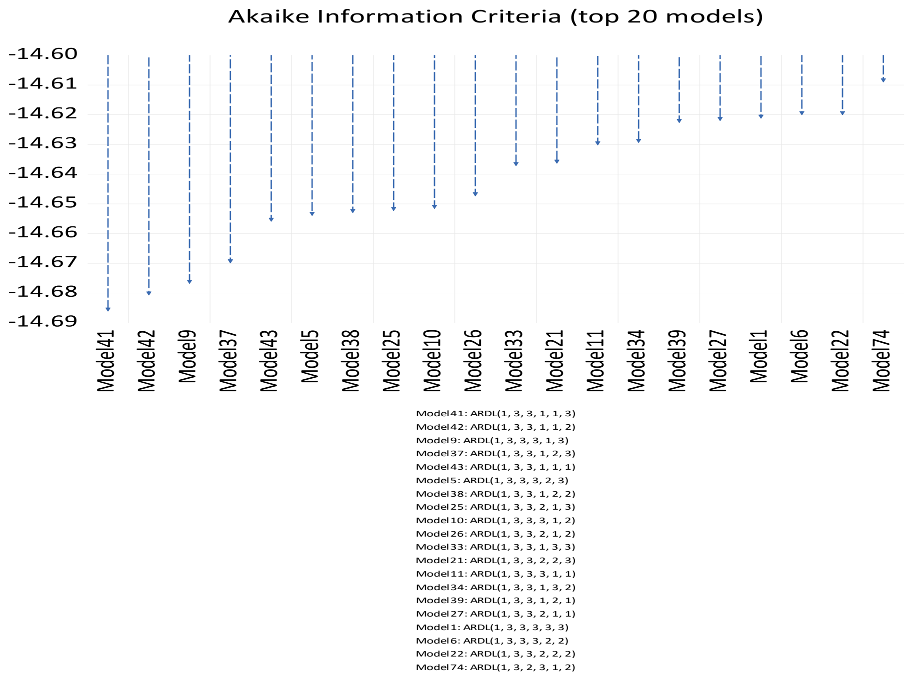

Figure 4: Akaike's Information Criterion for IBs

The lag for IBs is (1,3,3,1,1,3) based on the AIC for IBs, as seen in the above figure.

Once the lag lengths for every variable in both models have been determined, residual diagnostic tests and residual homoscedasticity tests are performed. These tests are necessary to make sure that the residuals in the models show signs of homoscedasticity and serial uncorrelation. By discussing potential problems with autocorrelation and variance stability in the residuals and evaluating the suitability of the selected lag lengths, this comprehensive analysis adds to the models' resilience and dependability.

Both banks have the same hypothesis. Hypothesis for residuals diagnostic as follows:

$$H_0 = Residuals\ are\ not\ serially\ correlated$$
$$H_1 = Residuals\ are\ serially\ correlated$$

Table 4: Results for Residuals Serial Correlation LM Test at 5% Significant Level for CBs

Variable	Coefficient	Standard Error	T-stat	P-value
AQC	0.000136	0.014330	0.009501	0.9925
LQ1C	-0.005350	0.042478	-0.125937	0.9004
LQ2C	-0.026961	0.106838	-0.252351	0.8021
UN	2.26E-05	0.000142	0.159225	0.8743
IR	2.79E-06	3.44E-05	0.081067	0.9358
F-stat	1.356761			
Prob. F (2,39)	0.2694			

The probability value of the Prob. F, precisely 0.2694, is larger than 0.05, as shown in Table 4. Because of this, it is not possible to reject the null hypothesis. It follows that no independent variable must be excluded because all the model's variables show serial uncorrelation. As a result, the model's comprehensiveness and dependability are enhanced by the capacity to keep each of the detected independent variables safe.

Table 5: Results for Residuals Serial Correlation LM Test at 5% Significant Level for IBs

Variable	Coefficient	Standard Error	T-stat	P-value
AQI	0.002784	0.024911	0.111742	0.9115
LQ1I	-0.020519	0.158783	-0.129225	0.8977
LQ2I	0.023770	0.374678	0.063441	0.9497
UN	-9.03E-06	0.000561	-0.016094	0.9872
IR	-1.51E-05	6.09E-05	-0.247303	0.8058
F-stat	1.014522			
Prob. F (2,46)	0.3705			

The probability value of the Prob. F, precisely 0.3705, is larger than 0.05, as shown in Table 5. Because of this, it is not possible to reject the null hypothesis. It follows that no independent variable must be excluded because all the model's variables show serial uncorrelation. As a result, the model's comprehensiveness and dependability are enhanced by the capacity to keep each of the detected independent variables safe.

As for the residual's homoscedasticity test, both banks have the same hypothesis. Hypothesis for residuals diagnostic as follows:

$$H_0 = Residuals\ are\ homoskedastic.$$
$$H_1 = Residuals\ are\ not\ homoskedastic$$

Table 6: Results for Residuals Homoscedastic at 5% Significant Level for CBs

Variable	Coefficient	Standard Error	T-stat	P-value
AQC	-3.36E-06	1.38E-06	-2.429485	0.0196
LQ1C	7.17E-06	4.05E-06	1.769254	0.0843
LQ2C	1.76E-07	1.01E-05	0.017441	0.9862
UN	9.43E-10	1.37E-08	0.068675	0.9456
IR	4.95E-09	3.33E-09	1.483524	0.1456
F-stat	1.367320			
Prob. F (17,41)	0.2028			

The probability value of the Prob. F (17,41), precisely 0.2028, is larger than 0.05, as shown in Table 6. Because of this, the null hypothesis failed to be rejected, and the residuals are homoscedastic. This proves that there is heteroscedasticity instead of homoscedasticity.

Table 7: Results for Residuals Homoscedastic at 5% Significant Level for IBs

Variable	Coefficient	Standard Error	T-stat	P-value
AQI	1.16E-05	1.69E-05	0.685482	0.4963
LQ1I	6.60E-05	0.000106	0.622163	0.5368
LQ2I	-4.47E-05	0.000252	-0.177726	0.8597
UN	9.69E-07	3.75E-07	2.584568	0.0128
IR	1.98E-08	4.01E-08	0.493196	0.6241
F-stat	1.064623			
Prob. F (10,48)	0.4071			

The probability value of the Prob. F (10,48), precisely 0.4071, is larger than 0.05, as shown in Table 7. Because of this, the null hypothesis failed to be rejected, and the residuals are homoscedastic. Similar to CBs, this proves that there is heteroscedasticity for IBs instead of homoscedasticity.

Table 8: Bound Test ARDL for CBs

Variable	F-Statistic	Significance	I (0)	I (1)	Decision
F (NPLC|AQC|	12.57241	10%	2.08	3	Cointegrated
LQ1C|LQ2C|		5%	2.39	3.38	Cointegrated
UN|IR)		2.5%	2.7	3.73	Cointegrated
		1%	3.06	4.15	Cointegrated

Strong evidence of cointegration across all variables was found in the bound test for the ARDL model for CBs from Table 8. All variables showed a common long-term relationship. The data highlights the intricate relationships and reciprocal impacts of these pivotal elements in the framework of traditional banking in Malaysia. Based on the known cointegration, which suggests that these variables move together over time, a thorough and reliable analysis of their combined effects on the banking industry may be conducted.

Table 9: Bound Test ARDL for IBs

Variable	F-Statistic	Significance	I (0)	I (1)	Decision
F (NPLC|AQI|	5.4890855	10%	2.08	3	Cointegrated
LQ1I|LQ2I|		5%	2.39	3.38	Cointegrated
UN|IR)		2.5%	2.7	3.73	Cointegrated
		1%	3.06	4.15	Cointegrated

In the bound test for the ARDL model for IBs from Table 9, there was strong evidence of cointegration across the board. Every variable displayed the same long-term association. The information demonstrates the complex interactions and mutual effects of these essential components inside Malaysia's IBs system. A comprehensive and trustworthy examination of these factors' combined impacts on the banking sector may be carried out based on the established cointegration, which implies that these variables move together throughout time.

Table 10: Estimates of the Long Run Coefficients based on the ARDL Model for CBs

Long run coefficient				
Variable	**Coefficient**	**Standard Error**	**T-stat**	**P-value**
AQC	0.029174	0.041106	0.709739	0.4818
LQ1C	1.090856	0.150526	7.246953	0.0000
LQ2C	-0.818179	0.173270	-4.721982	0.0000
UN	1.79E-05	3.72E-05	0.482160	0.6322
IR	-2.00E-05	2.15E-05	-0.926893	0.3593
R-squared	0.999695			

The ARDL model for CBs has a very high degree of explanatory power, as indicated by the R-squared value of 99.97% in Table 10. Asset Quality (AQC) has a p-value of 0.4818, indicating that it is not statistically significant in explaining the variance in the dependent variable, according to an examination of the individual p-values for each variable's long-run coefficients. Conversely, Loan Quality 1 (LQ1C) and Loan Quality 2 (LQ2C) have statistically significant p-values of 0.000, signifying their substantial contribution to the long-term association. With p-values of 0.6322 and 0.3593, respectively, the unemployment rate and inflation rate are not statistically significant contributions to the long-run coefficients based on the ARDL model for traditional banks.

A rise in AQC relates to an increase in NPLC for CBs in Malaysia, according to the coefficients associated with the variable Asset Quality (AQC), which in the model represents impaired loans over equity. On the other hand, a drop in NPLC is linked to a drop in AQC. NPLC declines, and equity also declines as problematic loans increase. Since the p-value is greater than 0.05, the null hypothesis cannot be ruled out, indicating that Asset Quality (AQC) at CBs does not appear to have a statistically significant effect on NPLs.

Turning now to Loan Quality 1 (LQ1C), Table 10 results show that LQ1C is a considerably positive indication of Malaysia's CBs' NPLs (NPLC). This suggests that a rise in LQ1C is correlated with a rise in NPLC. The statistical significance of the p-value for Loan Quality 1 (LQ1C) indicates that it has a substantial effect on NPLs in traditional banks, hence supporting the rejection of the null hypothesis.

In Malaysia, CBs are negatively and statistically significantly impacted by Loan Quality 2 (LQ2C). According to the results, NPLs for NPLC decline in proportion to an increase in loan growth within these institutions. The null hypothesis is rejected, and the alternative hypothesis is accepted due to the significance of the p-value associated with LQ2C, confirming the considerable effect of Loan Quality 2 (LQ2C) on NPLs in CBs.

In Malaysia, there is a statistically significant positive correlation between the unemployment rate and NPLs for conventional banks (NPLC). The null hypothesis cannot be rejected since the p-value is greater than 0.05, even in cases when statistical significance is present. This implies that, even while the association is statistically significant, it might not be big or practically significant enough to draw firm conclusions about the significance of the relationship between the unemployment rate and NPLs in CBs.

NPLs for CBs (NPLC) in Malaysia and the variable Inflation Rate (IR) show a strong negative correlation. The findings show that traditional banks' net present value (NPLC) significantly declines when inflation rises. It's important to remember that the p-value is greater than 0.05, which means that the null hypothesis cannot be rejected. This suggests that, even with the noted relevance, care should be used when extrapolating the effect of the inflation rate on the net present value of capital.

Table 11: Estimates of the Long Run Coefficients based on the ARDL Model for IBs.

Long run coefficient				
Variable	**Coefficient**	**Standard Error**	**T-stat**	**P-value**
AQI	0.331822	0.070865	4.682456	0.0000
LQ1I	0.236375	0.155584	1.519279	0.1353
LQ2I	-0.637639	0.368941	-1.728295	0.0904
UN	0.000695	0.000260	2.670245	0.0103
IR	0.000192	5.88E-05	3.270459	0.0020
R-squared	0.991618			

Based on the outcome displayed in Table 11, the model's R-squared is 99.16%. This suggests that 99.16% of the variance in NPLs made by IBs that can be accounted for by the model's independent variables is presented by the model.

A significantly substantial positive relationship can be seen in the model's coefficient linked to the Asset Quality (AQI). This clearly shows that when AQI rises, IBs' NPLs (NPLI) also rise at the same time. This statement is consistent with the hunch that an increase in NPLs in the equity of banks is correlated with an increase in NPLs for IBs. The null hypothesis is categorically rejected by the remarkably low p-value of 0.000, which indicates that AQI does have a statistically significant and large influence on IBs' NPLs. As a result, the alternative theory is accepted, supporting the idea that variations in AQI have a major impact on the dynamics of NPLs in IBs.

Focusing our attention on Loan Quality 1 (LQ1I), the results shown in Table 11 highlight a strong positive correlation between LQ1I and NPLs for Malaysian

IBs (NPLI). This suggests that for IBs, an increase in LQ1C is linked to an increase in NPLs at the same time. A significant influence on NPLs in IBs is shown by the significantly higher p-value for Loan Quality 1 (LQ1C), which offers strong evidence for the failure to reject the null hypothesis.

Loan Quality 2 (LQ2I) has a statistically significant negative impact on IBs in Malaysia. The findings show that NPLs for IBs (NPLI) decrease in direct proportion to the rise in loans made by these organizations. Due to the significance of the p-value linked to LQ2I, the alternative hypothesis is accepted, and the null hypothesis is rejected, indicating the significant impact of Loan Quality 2 (LQ2I) on NPLs in IBs.

There is a strong and statistically significant positive correlation between NPLI and the unemployment rate in the Malaysian setting. The p-value is below the traditional cutoff of 0.05, which indicates that the association between the unemployment rate and NPLI is still very significant, even in cases of statistical significance, supporting the rejection of the null hypothesis.

In a similar vein, IBs' NPLs show a noticeably strong positive association with the inflation rate (IR). In this case, the null hypothesis was rejected, indicating a highly serious impact of the inflation rate on the NPLs. This suggests that Malaysian IBs' NPLs are significantly impacted when the country's inflation rate rises. The significant statistical impact attests to the reliability of the observed relationship between NPLI and inflation rate.

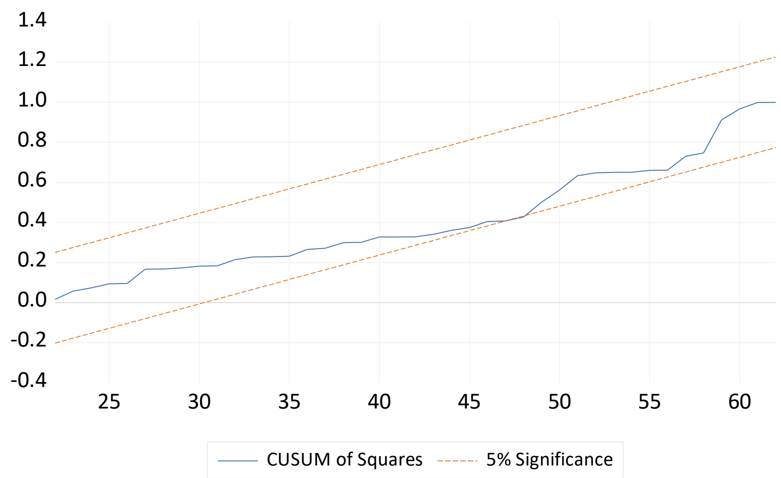

Figure 5: CUSUM of Squares Test for CBs

Borders or reference lines are shown by the red dotted lines. The stability of the coefficients in the equation model is indicated by the blue line remaining inside these lines as shown in Figure 5. Borders or reference lines are shown by the red dotted lines. The blue line suggests that the model's coefficients are very stable if it remains inside these lines.

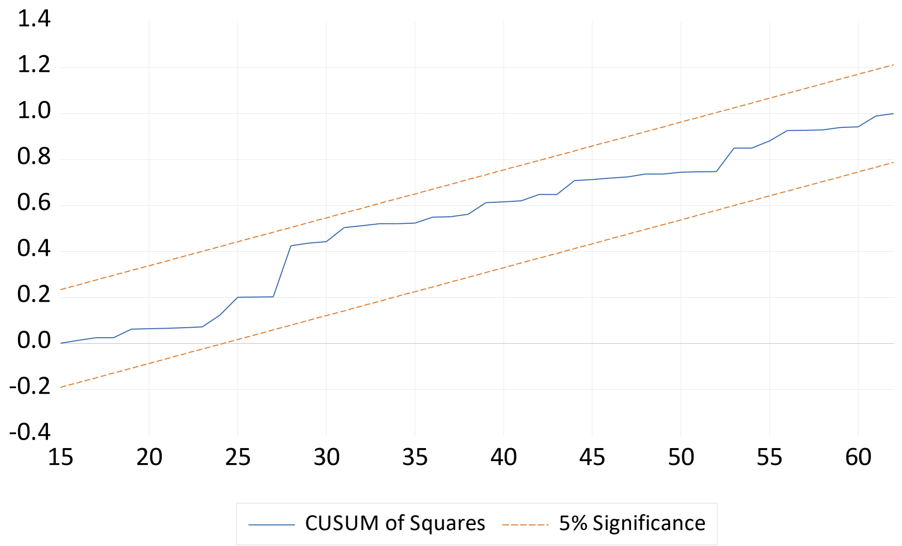

Figure 6: CUSUM of Squares Test for IBs

In this study, the Cumulative Sum of Squares (CUSUM) of squares test is a diagnostic tool that is used to evaluate the stability of the coefficients over time, especially in equation models. Regarding IBs, Figure 6 shows this test assists in determining whether there have been any structural discontinuities or changes to the model's parameters within the observed duration. The estimation is stable based on the blue line placed inside the two red dotted lines.

5.0 Conclusion

Key contributors to Malaysia's NPLs in CBs are identified using the ARDL model analysis. Because Asset Quality does not show statistical significance, it is possible that it is not a significant factor influencing NPLC. On the other hand, Loan Quality 1 and

Loan Quality 2 are important variables that have a favorable effect on long-term correlation. The findings demonstrate that whereas LQ2C has a negative connection, indicating that as loan growth grows, NPLC in CBs decreases, an increase in LQ1C relates to an increase in NPLs. The null hypothesis is not rejected, suggesting that the unemployment rate has no discernible impact on NPLC. Furthermore, there is a significant inverse relationship between NPLC and Inflation Rate (IR). However, caution is advised in interpreting the practical significance of this correlation, given the non-rejection of the null hypothesis.

Among the significant factors influencing net present condition in traditional banks are Loan Quality 1 (LQ1C), Loan Quality 2 (LQ2C), and the inverse relationship with inflation rate (IR). The limited impact of Asset Quality (AQC) and the non-significant impact of the unemployment rate UN highlight the complexity of the relationship between economic variables and NPLs in the conventional banking sector, even though these factors help to explain the dynamics of NPLs for the CBs.

Significant determinants are shown by the examination of the variables influencing NPLs in Malaysian IBs (NPLI). The connection between Asset Quality (AQI) and (NPLI) is significantly positive, suggesting that an increase in AQI is associated with a rise in NPLs in IBs. The alternative hypothesis is supported by the rejection of the null hypothesis with a low p-value (0.000), which highlights the statistically significant and large effect of AQI on NPLI. Furthermore, Loan Quality 1 (LQ1I) shows a substantial positive connection with NPLI, supporting the idea that, while the null hypothesis is not rejected, an increase in LQ1I is linked to an increase in NPLs for IBs.

On the other hand, Loan Quality 2 (LQ2I) shows a statistically significant negative influence at the 10% significance level, meaning that as the amount of loans provided by IBs rises, NPLI decreases. Strong positive correlations between the unemployment rate, inflation rate, and non-performing loan index (NPLI) indicate that shifts in these economic indicators have a major effect on NPLs in Malaysian IBs. The strength of these correlations is shown by the rejection of the null hypothesis for both UN and IR. The unique features of Islamic finance principles may explain why unemployment and inflation rates matter to IBs but not to CBs. IBs may be more sensitive to economic factors that have an immediate impact on inflation and employment as they frequently use distinct risk-sharing procedures. CBs, for instance, may depend on interest-based lending during a recession. In contrast, IBs—which follow Sharia—would have more difficulty maintaining ethical standards and handling risk-sharing agreements when the economy is shaky. The socioeconomic variables influencing inflation and unemployment may also have distinct effects on Islamic financial instruments, which adds to their importance in anticipating NPLs in IBs.

Given the significant results showing the long-term impacts of several factors on NPLs (NPL), Malaysian IBs and CBs had to take note of the implications for their risk management procedures. It's critical to improve non-performing loan management techniques, especially for IBs where special funding structures and models bring credit risks. Proactive actions are desperately needed, considering the long-term effects of factors like Asset Quality (AQI), Loan Quality (LQ1I and LQ2I), unemployment rate, and inflation rate.

To overcome obstacles related to credit risk, IBs should improve their risk assessment models and create more potent risk management plans. Reinforcing governance structures with the knowledge gained from the study's identification of key variables influencing NPLs is essential. Re-examining and refining financing agreements such as Murabaha, Salam, and exception agreements may be necessary to reduce credit risks related to possible losses and delayed payments. Additionally, this study can serve as a guide for comparable future research that considers other variables, including GDP, interest rates, and the numerous risks involved.

The study is not exempt from limitations. One limitation is the limited data period due to the consistency of available data, which was not in the same format for years before 2010. This issue could have resulted in the data not being stationary. It is suggested that future researchers could look into different data periods to compare the findings and add more macroeconomic variables other than the unemployment rate and inflation rate.

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