PREDICTING THE STABILITY OF KUWAITI BANKS: A COMPARISON OF ECONOMETRIC AND MACHINE LEARNING APPROACHES

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رؤية بنك الكويت المركزي والبنوك الكويتية لتطوير الشباب الكويتي

The 2024 First Place Research Paper Winner
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التنبـؤ باسـتقرار البنـوك الكويتيـة: دراسـة مقارنـة بين منهجيـات الاقتصـاد القيـاسي والتعلـم الآلي.

شـهدت العقـود الماضيـة العديـد مـن الاضطرابات في الأسـواق المالية العالميـة، مما عزز أهميـة البحـث عـن نمـاذج اقتصاديـة قياسـية تتنبأ وتـدرس الاسـتقرار المالي للمؤسسـات الماليـة والمصرفيـة، خاصـةً في الاقتصـادات الناشـئة مثـل الكويـت وبقيـة دول الخليـج. تناقـش هـذه الورقـة الاسـتقرار المالي للبنـوك مـن خلال توظيـف منهجيـتين مختلفـتين: نمـوذج اقتصـادي قيـاسي وآخـر معنـي بالتعلـم الآلي (Artificial Neural Network)، والتـي يعـد نموذجـاً حديثـاً نسـبةً إلى بقيـة الـنماذج الـدارج اسـتخدامها للتحليـل والتنبـؤ. نسـتخدم في هـذه الورقـة بيانـات اللوحـة (Panel data) للبنـوك الكويتيـة في الـفترة 2005-2024.

كذلـك نسـتخدم في هـذه الورقـة نسـبة كفايـة رأس المال (Capital Adequacy Ratio) ممثلـةً عـن السلامـة الماليـة للبنـوك (Financial soundness)، كما نبحـث أيضـاً عـن تـأثير محـددات الاقتصـاد الـكلي والمتـغيرات الخاصـة بالبنـوك على الاسـتقرار المالي لهـم، وذلـك باسـتخدام الآليـتين السـالف ذكـرهما. حسـب نتائـج النمـوذج الاقتصـادي القيـاسي، توجـد علاقـة طردية الاسـتقرار المالي وبين العوائد – إلى إجمالي الأصـول (ROA) وإجمالي القـروض إلى إجمالي الأصـول (Loan to Asset Ratio)، مـا يعنـي أن البنـوك الأكثر ربحيـةً وذات الفعاليـة العاليـة في توزيـع الأصـول هـي بنـوك أكثر اسـتقراراً. توصلـت أيضـاً هـذه الورقـة إلى وجـود علاقـة عكسـية بين نسـبتي إجمالي العوائـد إلى حقـوق المسـاهمين (Return on Equity) وحجـم البنـك (Bank size)، وبين نسـبة كفايـة رأس المال، بالإضافـة إلى وجـود علاقـة طرديـة بين نسـبة السـيولة والاسـتقرار المالي للبنـوك، وهـو مـا يـشير إلى أن السياسـات المندفعـة والاقتراض المفـرط والمخاطـر المتعلقـة بحجـم البنـك قـد تقـوض مـن قـدرة البنـك على امتصـاص الصدمـات وتفاديهـا. يتضـح في قسـم النتائـج مـن هـذا البحـث أن آليـات التعلـم الآلي تتفـوق على نمـاذج الاقتصـاد القيـاسي في قدرتهـا على التنبـؤ والتحليـل ورصـد التحذيـرات ومـؤشرات الخطـر مبكـراً. في المقارنـة بين الآليـتين/ النمـوذجين مـن خلال منحنيـات ROC، نجـد أن نمـوذج الانحـدار (Regression Model) حصـل على نسـبة AUC عاليـة (95.75 %)، لكـن نمـوذج التعليـم الآلي تفـوق عليـه، إذ حصـل على العلامـة الكاملـة (1.00) لـلAUC، مـا يعنـي أن نمـوذج التعلـم الآلي المسـتخدم يتفـوق على نمـوذج الاقتصـاد القيـاسي في قدرتـه على التنبـؤ وقـراءة الاسـتقرار المالي للبنوك. تـقترح الورقـة في نهايتهـا توظيـف المزيـد مـن أدوات التحليـل في دراسـة المؤسسـات الماليـة، والتـي مـن شـأنها أن ترفـع مسـتوى فعاليتهـا وجـودة إدارتهـا.

ABSTRACT

The growing frequency of global financial disruptions has underscored the importance of accurately forecasting the stability of financial institutions, particularly in emerging markets like the GCC and Kuwait. In this study, econometric and machine learning models for bank forecasting of its financial stability have been analyzed. The research utilized unbalanced panel data from 2005 to 2024 for the ten leading banks in Kuwait. The study uses the Capital Adequacy Ratio (CAR) to proxy for financial soundness and examines the impact of the macroeconomic and bank-specific variables on bank stability with Logistic Regression and Artificial Neural Network (ANN) models. Based on the econometric findings, financial stability is positively related to Return on Assets (ROA) and Loan to Asset Ratio, suggesting that banks with higher profitability and efficient asset allocation are more resilient. The ROE and Bank Size have a negative relationship with CAR, while there is a positive relation of Leverage Ratio to Financial-stability, indicating that aggressive profit strategies, excessive borrowing, and size-related risk exposure may undermine a bank's capital strength and risk-buffering capacity. In contrast, traditional econometric approaches that are used in testing a small group of data are outperformed by Machine Learning ANN models, especially by ensemble methods, in terms of classification accuracy and early warning. ROC curves comparison shows that logistic regression model had a very good AUC of 95.75% while the ANN model obtained a perfect AUC of 1.00, which means that the ANN model is able to do better discriminate financial stability.

Keywords: Financial Stability, Capital Adequacy Ratio (CAR), Machine Learning, Logistic Regression, Artificial Neural Network (ANN).

1. INTRODUCTION

Accurately predicting bank stability is crucial for safeguarding national economies, especially those that rely heavily on the banking industry. This study focuses on the unique context of Kuwait, an oil-dependent economy with a bank-centric financial system. To increase the predictive capabilities, it critically compares traditional econometric models with emerging machine learning (ML) models. The investigation assesses their relative performance and explores the potential of hybrid models in forecasting the stability of Kuwaiti banks.

1.1 Global Perspective on Financial Stability

Financial stability in the banking industry refers to financial institutions' capacity to endure systemic shocks without significantly disrupting their fundamental operations (Schinasi, 2005). The European Central Bank (ECB) identifies financial stability as a system where the financial setup can cope well, reducing the probability of financial intermediation disruption that could severely impede an efficient allotment of savings with investment opportunities (ECB, 2013). After the 2008 financial crisis, the global regulatory landscape evolved significantly, introducing reforms like Basel III, which emphasize capital adequacy, risk management, and liquidity coverage.

Maintaining stability is crucial not only for individual banks but also for the broader economy, as a breakdown in financial intermediation can have ripple effects leading to credit crunches, business failures, and prolonged economic recessions. Recent developments in technology have led to the remodeling of the banking sector has used data analytics more and more. There is nothing new about econometrics, a proven method of analysis developed in economic research for exploring relationships between variables and a theoretical basis for policy decisions and regulations in general. However, machine learning (ML) is comparatively much newer technology and has just become highly popular in recent years due to its ability to deal with large databases of information, to identify complex patterns, and to predict in real time. By embracing machine learning to process massive amounts of data, banking operations have become more efficient, with better customer satisfaction and lower operational costs in risk management, fraud detection, and portfolio optimization.

Globally, institutions are increasingly adopting data-driven tools such as econometrics and ML to enhance early warning systems and improve financial resilience. Econometric models are grounded in theory and focus on causal relationships (Greene, 2012). The econometric approach enables transparency and policy interpretability, while machine learning offers enhanced performance in large, noisy datasets where traditional assumptions often fail (Charpentier et al., 2018). ML excels in predictive performance, especially in complex, dynamic environments (Varian, 2014). For example, ML is being used to detect financial distress through algorithms like Random Forests and Neural Networks. These tools can process transaction data, macroeconomic indicators, market sentiment, and behavioral trends to forecast potential disruptions more efficiently (Lessmann et al., 2015; Frost et al., 2019).

With financial institutions increasingly pressured to develop automated decision processes that balance speed with regulatory framework transparency demands, this evaluation is timely, particularly as they pursue automated credit scoring, liquidity monitoring, and risk assessment on a systemic level. Structured hypothesis testing of known macro-financial risks is provided by econometric models, whereas ML permits tag-driven reclassification of the systemic risk on the fly as payment flows, digital banking activity, and market sentiment trends dynamically evolve in real time (Chapman & Desai, 2021). In addition, machine learning models can discover 'emerging risks' that are not easily recognized by traditional pointers, using massive and unstructured data sources such as financial news sentiment, high-frequency trading patterns, and social media chatter (Mullainathan & Spiess, 2017). Machine learning does, therefore, advance the capacity to detect vulnerabilities early and complements traditional econometric approaches towards stability assessment (Varian, 2014).

Machine learning also supports stress testing, regulatory compliance, and real-time risk monitoring. Techniques such as natural language processing (NLP) help automate regulatory filings and detect inconsistencies in corporate disclosures (Gomber et al., 2018), allowing policymakers to focus on strategic oversight. However, the challenge remains that ML models, while accurate, often lack interpretability, posing difficulties for regulators who require transparent decision-making frameworks (Athey & Imbens, 2019).

Hence, there is a growing call to merge econometric and machine learning models into hybrid frameworks. These models combine the transparency of econometrics with the predictive power of ML, offering both reliable forecasts and actionable insights. This approach is especially relevant in today's interconnected and rapidly evolving financial environments.

1.2 Financial Stability: The Case of Kuwait

Kuwait's financial system presents a unique case in the context of financial stability. As a bank-centric economy, its financial resilience is heavily influenced by the performance of its commercial banking sector. The country's dependence on oil exports, combined with external exposure to oil price volatility and geopolitical tensions, introduces systemic vulnerabilities that are distinct from those in more diversified economies.

Although Kuwaiti banks are generally well-capitalized and operate under Basel III regulations, there are challenges related to transparency, particularly in stress-testing disclosures. The CBK publishes pass/fail outcomes according to Basel III; however, it does not publicly disclose the underlying assumptions, scenarios, and metrics (CBK, 2020). It covers reporting of high-level indicators only, such as Capital Adequacy Ratio (CAR) and Liquidity Coverage Ratio (LCR), but not the other commonly used financial variables, which are of great interest in academic research. In response to this gap, this study completes an additional set of financial indicators and a careful selection of variables to curtail multicollinearity and survey sampling bias to bring a robust model in the context of GCC banking.

Recent empirical work indicates that in Kuwait, operational and liquidity risks play a larger role than credit risk in influencing bank profitability over the 2011–2021 period (AlAli & AlAskar, 2024). Effective corporate governance, such as that enforced by the Central Bank, has also been associated with improved profitability in the Kuwaiti banking sector (Al Hasawi, 2024). Moreover, the IMF's 2024 Article IV report confirms that Kuwaiti banks continue to maintain strong capital adequacy and liquidity buffers and sustain low NPL ratios under prudent supervision[1]. These findings underscore the unique risk and regulatory dynamics of Kuwait that inform the design of predictive stability models in this study.

Moreover, the Kuwaiti banking sector exhibits notable heterogeneity in terms of capital adequacy, leverage, and risk-taking strategies. This diversity suggests that a "one-size-fits-all" regulatory framework may be insufficient for capturing the nuances of financial stability in the region. Econometric models allow for interpretable links between macro-financial variables, such as how credit expansion affects default risk, by estimating precise coefficients and their significance (Wooldridge, 2015). Both methodologies have limitations: econometrics struggles

[1] https://www.imf.org/en/Publications/CR/Issues/2024/12/07/Kuwait-2024-Article-IV-Consultation-Press-Release-Staff-Report-and-Statement-by-the-559194

with capturing highly non-linear or rapidly evolving relationships, while machine learning may suffer from overfitting and lacks a solid causal inference structure. Consequently, ML improves the prediction, but the interpretability of ML remains a problem for regulators who demand transparency in risk assessment.

Recent research increasingly points to the advantages of merging econometrics with machine learning to create hybrid models that leverage the interpretability of traditional models and the predictive power of ML. Hybrid models can provide financial regulators, policymakers, and banking executives with both reliable forecasts and explainable results, essential for navigating today's complex financial landscapes. Therefore, this study aims to present a detailed comparison of econometric and machine learning models for predicting financial stability in Kuwait's banking sector. Additionally, the study examines the potential development of hybrid frameworks that combine the respective strengths of each approach.

This study contributes to the growing body of literature by comparing the performance, interpretability, and practical applications of econometric and machine learning models in predicting financial stability within the banking sector. Specifically, it focuses on Kuwait, analyzing unbalanced panel data from 2005 to 2024 for the country's leading banks. By applying both econometric and ML approaches, the research evaluates their predictive capabilities under Kuwait's unique macro-financial conditions and explores the potential of hybrid models that merge the transparency of econometrics with the predictive strength of ML. In doing so, the study addresses a critical gap in integrated financial stability forecasting frameworks, particularly for oil-dependent, emerging economies. It also highlights the growing relevance of data-driven tools in enhancing the effectiveness and agility of financial supervision in today's rapidly evolving regulatory landscape.

The remaining of the paper is structured as follows: Section 2 presents a review of the literature. Section 3 explains the dataset and methods. The empirical findings are presented in Section 4, and model diagnostics in Section 5. Finally, Section 6 concludes the study, and Section 7 discusses its implications.

2. LITERATURE REVIEW

Predicting financial stability is essential for understanding market trends, reducing systemic risks, and aiding evidence-based decisions by banks, regulators, and investors. Historically, econometric models like ARIMA, VAR, and Logistic Regression have been widely used in financial stability research because of their theoretical basis and clarity. These models help explain how macroeconomic and firm-level variables relate and measure the effect of external shocks with statistical significance. However, machine learning (ML) has brought a shift toward more data-driven and non-linear prediction methods that can analyze high-dimensional data and spot complex interactions that traditional econometrics might overlook.
There is no universal standard definition of the term ‘financial stability’ since it can be interpreted differently and is measured through various analytical methods. One quantitative measure of financial stability is how a company can sustainably weather events such as market crashes through data-based analyses of the events; one version being the market crash (Chatzis et al., 2018). But in price-based methods of financial stability analysis, only the stock price movement in the market behaves as the exclusive factor. As per Acharya et al. (2016), the suggested price-based measures of financial stability are VaR (Value at Risk) and ES (Expected Shortfall). The effectiveness of these methods stems from their ability to enable investors to look for the risk of stock price drops to occur at interest levels within the market crashes (5% or 1%).

Financial stability is estimated by using financial ratios and balance sheet accounts. Being among the most common ones, the CAMELS multifaceted approach is used to determine the financial well-being of a financial institution (Gambetta et al., 2019). Six CAMELS metrics, sophistication information (C), asset quality (A), management skills (M), earnings and profitability (E), liquidity risk (L), sensitivity to market risk (S), represent capital risk (C). Each of these variables is represented by certain proxies (financial ratios) that explain and represent the variable as closely as possible. A widely used tool for evaluating financial stability and the ability of banks to resist severe but realistic hypothetical situations is stress testing (Acharya et al., 2016). It is considered a forward-looking quantitative assessment in which institutions run adverse economic and financial conditions, simulated to assess the performance and bank risk aspect under stress after the Basel III framework (Violle, 2017). However, this shift was to a great extent a result of the global financial crisis of 2007–2008, and hence regulators had to be much more proactive in protecting financial systems against the very systemic shocks.

According to Damrah et al. (2023), financial inclusion has a complex impact on bank stability in Kuwait. Based on a Linear Mixed Model, the study found that access and depth measures of financial inclusion have a negative relationship with stability, with Islamic banks being more affected than conventional ones. These findings suggest that financial inclusion can positively influence stability in Kuwait's banking sector only when there are institutional improvements in quality. Additionally, Almutairi (2021) examined the effect of Financial Information Systems (FIS) on the financial stability of Kuwaiti commercial banks, using the Arab Financial Stability Index. The results showed that FIS has a significant positive effect on macroeconomic and financial market stability (r = 0.652 and 0.643), but only a moderate, insignificant positive effect on banks and overall financial stability. The research highlights the importance of digital infrastructure in enhancing decision-making and risk assessment in Qatar's financial institutions.

Additionally, Farag et al. (2025) emphasize the use of hybrid models, which combine econometric methods like GMM and fixed effects with machine learning algorithms such as Random Forest and SVM to assess how income diversification affects the financial stability of European banks. This approach is especially relevant in Kuwait, where oil dependence and sector concentration are key factors that support diversification and the use of predictive models. The hybrid method enhances both interpretability and predictive accuracy, which are key focuses of this study.
Several recent studies show that econometric models, like Logistic Regression, ARIMA, and VAR, are commonly used to forecast financial distress and predict macro-financial crises. For example, Lu (2024) used a Logistic Regression model combined with Principal Component Analysis (PCA) to reduce dimensionality and address multicollinearity, achieving a strong predictive performance (AUC = 0.86) in forecasting systemic risks across Asian banking sectors. Similarly, Nugroho et al. (2024) utilized an ARIMA-based time series model to predict banking sector volatility in Indonesia, demonstrating that econometric methods maintain high explanatory power when economic theory is well-founded. In the GCC context, Saab et al. (2024) employed a panel VAR model using regional macroeconomic indicators (such as oil prices, interest rates, and inflation) to analyze the dynamic effects of shocks on bank profitability and systemic vulnerability. These studies provide solid empirical support for using structured, interpretable models to explain causality and evaluate financial resilience.

On the machine learning front, Beutel et al. (2019) conducted a comparative study of multiple ML techniques, including Random Forest, Support Vector Machines, and Artificial Neural Networks (ANN), to predict early signs of banking crises across European and advanced non-European economies. The research shows that deploying many ML models proved to be ‘surprisingly hard to beat,’ efficiently predicting early warning signs of systemic risk better than most econometric approaches. All four of the tested ML techniques didn’t show much promise, except for neural networks, which appeared promising but not enough to significantly improve their prediction accuracy. However, recently developed machine learning methods have outperformed some traditional regression techniques in predicting financial distress. Dichtl et al. (2023) demonstrate that ML models outperform multivariate and univariate regression models when forecasting sudden market crashes with bank-level data from the five largest Eurozone economies. ML is shown to be capable of capturing non-linear relationships and interactive effects that conventional approaches tend to miss, especially in models that incorporate both price-based and fundamental predictors. Ranjan and Goldsztein (2022) also observed that neural networks can significantly enhance the assessment of financial stability in African financial institutions. Together, these studies highlight the growing connection between econometric and ML methodologies, where ML’s flexibility aids in forecasting the complex financial system, although its effectiveness remains somewhat inconsistent.

Machine learning techniques have been effectively applied to estimate banks’ culture and capital impact on liquidity creation (Thi Nguyen et al., 2024) and assess debt structure stability (Qi & Wang, 2021). As mentioned in Zheng et al. (2020), while ML models (e.g., neural networks) tend to outperform traditional econometrical models (e.g., Hidden Markov) in predicting stock direction, ML performs better when used properly, as in suggesting who is to default among those interesting qualities used to predict default (Sizan et al., 2025).

This further contributes to the growing body of literature in numerous important ways. It bridges this research gap to apply and compare econometric and machine learning models (specifically Artificial Neural Networks) in the context of Kuwait’s banking sector, an area largely underrepresented in financial stability research. Second, the analysis incorporates both macroeconomic and bank-specific variables, thus providing a more comprehensive picture of what forces stability in emerging markets’ banks. It also compares the performance assessment of traditional logistic regression and advanced ML models, and shows how modern predictive tools can complement or surpass econometric approaches to bank failure forecasting, in particular for bank systems with distinctive structures, as in the Kuwaiti and wider GCC settings.

3. DATA AND METHODOLOGY

This section discussed the dataset used for the analysis along with the key financial variables, and their sources. It also describes comparison methodology of econometric and machine learning models in terms of prediction of financial stability.

3.1. Dataset

This study utilizes the unbalanced data from 2005 to 2024 on ten leading commercial banks operating in Kuwait's financial sector. There are two main components of this dataset. First, bank-level financial ratios were extracted from Refinitiv, providing detailed information on the financial health and performance of individual institutions. Second, macroeconomic indicators are gathered through which external factors known to influence financial stability have been sourced from the International Monetary Fund (IMF) and the World Bank.

3.1.1 Dependent Variable

According to Al-Sabbagh (2004), banks use capital adequacy measurements to assess their risk potential and stability, with the Capital Adequacy Ratio (CAR) being a crucial indicator. Matters of financial sector position and risk coverage capacity among businesses receive the most frequent application of capital adequacy terminology (Abba, 2018). Moreover, Olawale (2024) investigates how Nigerian banks respond to monetary policy and capital regulation through their financial stability while addressing capital adequacy relationships. Banks that improve both the capital adequacy ratio and firm size demonstrate stronger resilience, yet financial instability can be lessened by enforcing strict nonperforming loan management and effective monetary policies. Furthermore, the research by Sang (2021) analyzes how the capital adequacy ratio and control variables influenced Vietnamese commercial banks' financial stability. The examination indicates that a favourable connection exists between the ratio value and bank stability level. CAR is a vital measure for bank health assessment. It can be calculated as:

$$CAR = \frac{\text{Tier 1 Capital} + \text{Tier 2 capital}}{\text{Risk Weighted Asstes}}$$

To evaluate financial stability, this study uses the Capital Adequacy Ratio (CAR) and, within that parameter, applies the average value of 23% as the cutoff point. Stable banks are banks with CAR ≥ 23%, and financially unstable banks are with CAR < 23%.

3.1.2 Independent Variables

The capital adequacy for banks is influenced by both internal and macroeconomic factors. Bank-specific variables such as size, profitability, leverage, and liquidity directly affect risk absorption, while the economic indicators like GDP growth, inflation, and interest rates are a reflection of the external environment. The tables below summarize their impact on CAR, backed by existing research.

Table 1: Bank-Specific Factors

VARIABLE		IMPACT ON CAR	SUPPORTING STUDIES
BANK SIZE	BANK SIZE = LN (TOTAL ASSETS)	LARGER BANKS CREATE ECONOMIES OF SCALE AND DEMONSTRATE BETTER RESISTANCE TO FINANCIAL DIFFICULTIES. THE EMPIRICAL FINDINGS REGARDING BANK SIZE MEASUREMENTS AND THEIR RELATIONSHIP WITH CAR HAVE CONFLICTING RESULTS, SOME STUDIES SHOW A POSITIVE, OTHERS A NEGATIVE CORRELATION WITH CAR.	BOGALE (2020); SHINGJERGJI & HYSENI (2015)
RETURN ON ASSETS (ROA)	RETURN ON ASSETS= $\frac{\text{Net income}}{\text{Total assets}} \times 100$	THE RETURN ON ASSETS (ROA) MEASURES THE EFFECTIVENESS OF HOW BANKING INSTITUTIONS USE THEIR ASSETS TO CREATE PROFITS. POSITIVE RELATIONSHIP; HIGHER ROA INDICATES BETTER RISK ABSORPTION AND FINANCIAL STRENGTH	BATENI ET AL. (2014); BOGALE (2020)
RETURN ON EQUITY (ROE)	RETURN ON EQUITY $= \frac{\text{Net Income}}{\text{Total Equity}} \times 100$	BANK'S PROFITABILITY ABOUT SHAREHOLDER EQUITY IS MEASURED BY RETURN ON EQUITY (ROE). STRONG BANK FINANCIAL HEALTH, INDICATED BY ELEVATED ROE, STANDS AS A TYPICAL INDICATOR. THE RELATIONSHIP IS POTENTIALLY NEGATIVE, HIGHER ROE MAY ENCOURAGE RISK-TAKING THAT REDUCES CAR	BÜYÜKŞALVARCI (2011); DAO & ANKENBRAND (2015)

LEVERAGE RATIO	LEVERAGE $\frac{\text{Total Assets}}{\text{Total Equity}}$	A LEVERAGE RATIO ESTIMATES THE FINANCIAL RISK OF A FIRM BY ANALYZING HOW MUCH DEBT IT LEVERAGES COMPARED TO EQUITY OR ASSETS. IT SHOWS A SIGNIFICANT RELATIONSHIP; HIGHER LEVERAGE CAN INCREASE RISK AND REDUCE CAR.	KALIFA & BEKTAŞ (2017)
LOAN-TO-ASSET RATIO	LOAN TO ASSET $= \frac{\text{Total Loans}}{\text{Total Assets}}$	THE CAPITAL ADEQUACY RATIO HAS A DIRECT ASSOCIATION WITH EXPOSURE TO CREDIT RISK THUS, IT LEADS TO A REDUCED CAPITAL ADEQUACY RATIO THROUGH INTEREST INCOME GENERATION OR RISK INCREASE.	BATENI ET AL. (2014); BOGALE (2020)
LIQUIDITY RATIO	LIQUIDITY= $\frac{\text{High Quality Liquid Assets}}{\text{Total Net cashflow amount}}$	A BANK'S ABILITY TO FULFILL SHORT-TERM OBLIGATIONS IS GAUGED BY THE LIQUIDITY RATIO. THEREFORE, IT IS BENEFICIAL; GREATER LIQUIDITY ENHANCES RESILIENCE TO SHOCKS.	AKTAS ET AL. (2015)

Table 2: Macroeconomic Indicators

MACROECONOMIC VARIABLE	IMPACT ON FINANCIAL STABILITY (CAR)	SUPPORTING STUDIES
GDP GROWTH	HIGHER GDP LEADS TO IMPROVED CAR DUE TO STRONGER ECONOMIC PERFORMANCE	OBEID (2023); DAO & NGUYEN (2020)
INFLATION	HIGH INFLATION IS ASSOCIATED WITH LOWER CAR; HOWEVER, POLITICAL STABILITY AND FOREIGN INVESTMENT CAN MITIGATE THE NEGATIVE EFFECTS.	HORTLUND (2005); OGEGE ET AL. (2012)
INTEREST RATES	RISING INTEREST RATES NEGATIVELY AFFECT LOAN REPAYMENT AND INCREASE NON-PERFORMING LOANS, REDUCING CAR.	MUSTAFA & MUMTAZ (2022); WILLIAMS (2011)
EXCHANGE RATE	EXCHANGE RATE VOLATILITY INCREASES MONETARY UNCERTAINTY; HOWEVER, SOME STUDIES SHOW A POSITIVE LINK WITH CAR.	KALIFA & BEKTAŞ (2017); WILLIAMS (2011)

3.2. Graphical Representation of Key Financial Variables

3.2.1. Average Profitability among Kuwaiti Banks

Figure 2 shows profitability trend of Kuwaiti banks, using the average values of ROA (Return on Assets) and ROE (Return on Equity) from 2005 to 2024, reflects a typical trend of higher ROE than ROA across all institutions indicating strong leverage effects within the sector. ROA values are very low and stable, indicating a modest level of asset efficiency, and ROE exhibits wide variance across banks, indicating the different equity management and profitability strategies adopted by banks. Kuwait Finance House and the National Bank of Kuwait achieve notably higher peaks in ROE, demonstrating better returns to shareholders when compared to other banks. Overall, while asset returns are generally subdued, equity returns reflect stronger profitability performance among leading Kuwaiti banks.

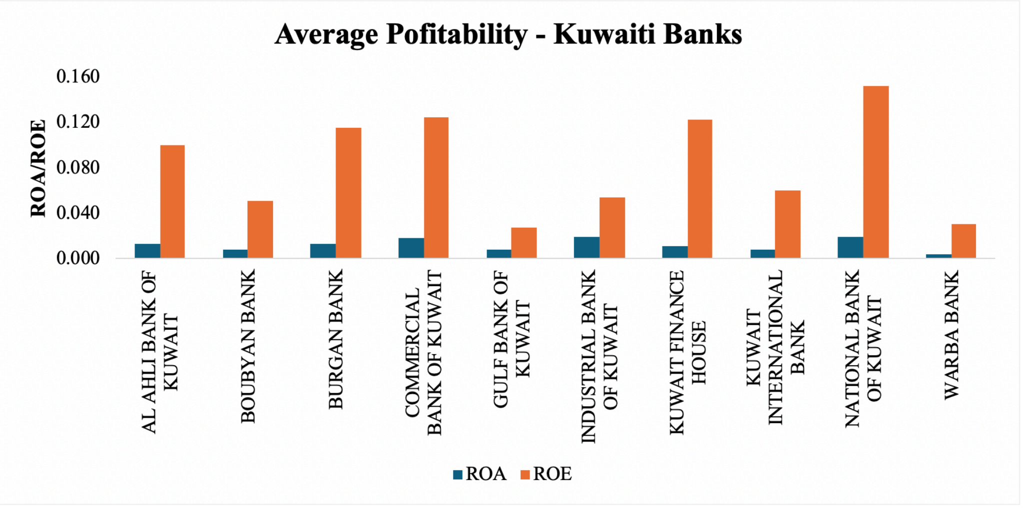

Figure 1: Profitability Trend of Kuwaiti Banks

3.2.2. Capital Adequacy Ratio on Average across Banks

Figure 2 illustrates the average Capital Adequacy Ratio (CAR) of major Kuwaiti banks over the period 2005 to 2024, highlighting variations in financial strength across institutions. The average CAR of 50% for the Industrial Bank of Kuwait and 40% for Warba Bank showed that both possess good capitalization and the capacity to buffer financial shocks. On the other hand, the CAR of several banks such as Kuwait Finance House, National Bank of Kuwait and Gulf Bank of Kuwait stood at lower rates ranging from 17% to 18%, still above the regulatory minimums. Overall, the data demonstrate a largely stable banking sector with some banks holding very high capital buffers relative to others. This disparity in CAR is due to asset composition and regulatory compliance strategies. Banks with higher CAR may be more conservative in lending and operate in less risky markets, and banks with lower CAR may prioritize profitability by being more aggressive in their asset deployment. It is important for regulators and investors assessing resilience, particularly given the economic stress and financial volatility.

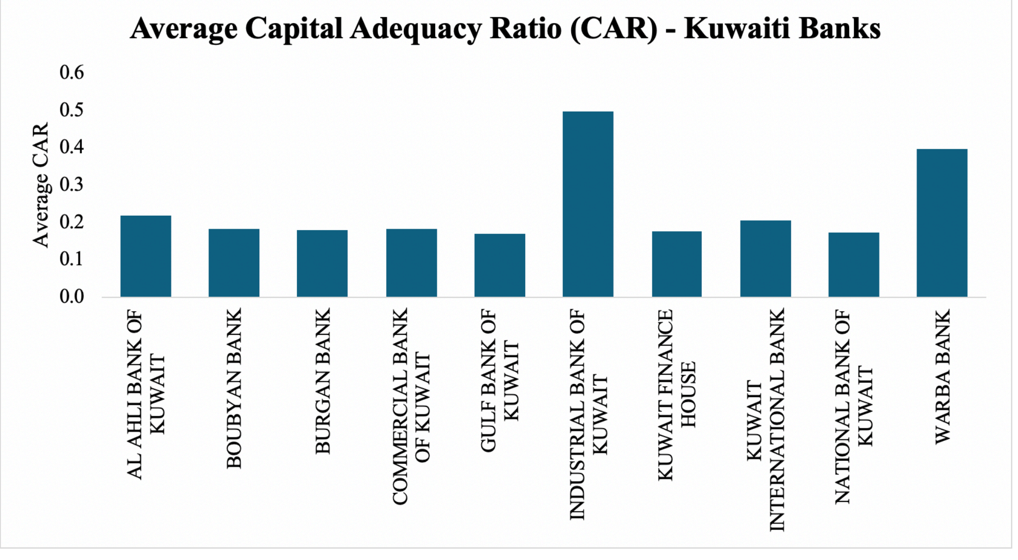

Figure 2: Capital Adequacy Ratio of Kuwaiti Banks

3.2.3. Leverage Ratio on Average among Banks

Figure 3 explains the leverage ratio of major Kuwaiti banks during 2005 - 2024. Leverage ratio is the ratio of bank's equity to the bank's total assets, a key measure of financial stability and risk management. The highest leverage ratio among the Industrial Bank of Kuwait is 15 times exceeding, which is indicative of conservative risk profile and strong capital support over assets. In contrast, other banks such as the Industrial Bank of Kuwait recorded lower leverage ratios around 3, indicating higher reliance on debt. Overall, the trend shows variability in solvency strength among Kuwaiti banks, reflecting different strategies in capital structure and risk tolerance.

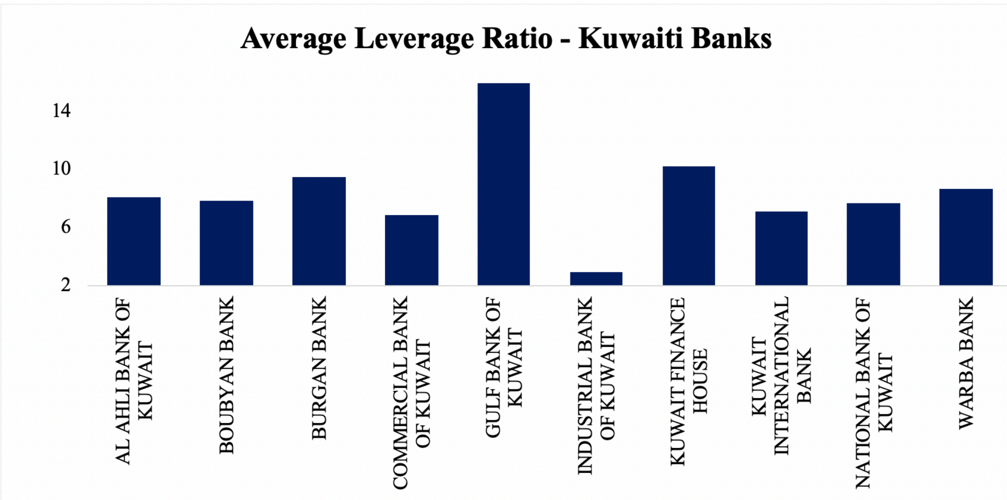

Figure 3: Trend of Leverage Ratio

3.2.4. Loan-to-Asset Ratio on Average among Banks

Figure 4 shows the average loan-to-asset ratio for major Kuwaiti banks from 2005 to 2024. A bank with a higher ratio will have a larger portion of its assets involved in loans, suggesting a more aggressive lending policy, whereas a bank with a lower ratio is more likely to be less aggressive and have higher liquidity. Among the highest loan-to-asset ratio are Boubyan Bank (0.771), Gulf Bank of Kuwait (0.764) and Warba Bank (0.734), that indicate high importance on credit operations. In contrast, National Bank of Kuwait (0.384) and Industrial Bank of Kuwait (0.493) report the lowest ratios, suggesting a more cautious stance or diversified asset structure. These variations reflect differing risk appetites, business models, and asset management strategies across Kuwaiti banks.

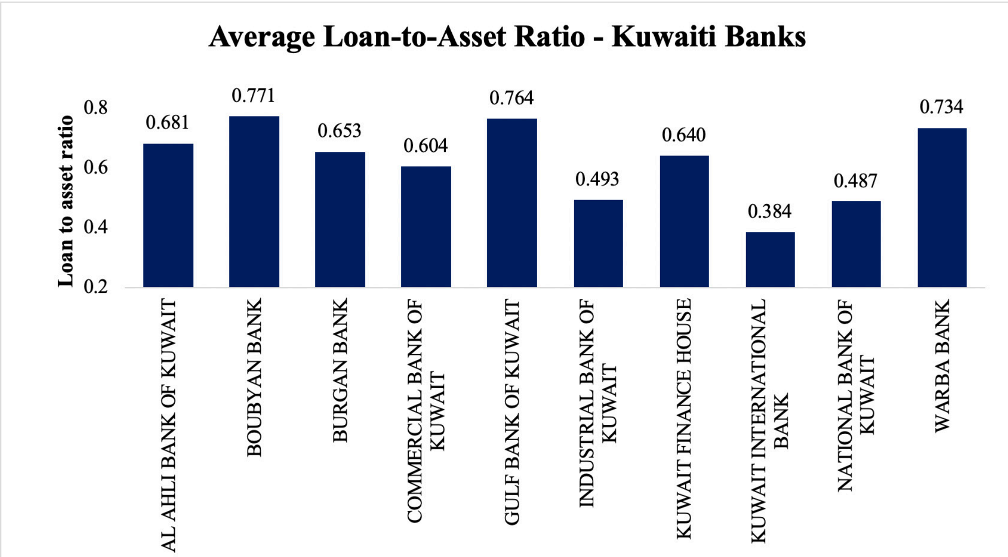

Figure 4: Average Loan-to-asset ratio among banks

3.2.5. Liquidity Ratio on Average among Banks

Figure 5 shows the average liquidity ratio for Kuwaiti banks which is indicative of their capacity to meet short term obligations from 2005 to 2024. Liquidity ratio is a measure of the availability of liquid assets to meet liabilities and a higher value expresses stronger short term financial resilience. A higher liquidity ratio generally points to a bank's ability to withstand sudden withdrawals, financial stress, or funding constraints, thereby reinforcing depositor confidence and institutional stability. In contrast, Kuwait International Bank (1.425) and Warba Bank (1.506) have low ratios indicating relatively less liquidity. Overall, while most banks maintain adequate liquidity buffers, the disparity underscores varied risk management strategies and asset-liability structures across the Kuwaiti banking sector.

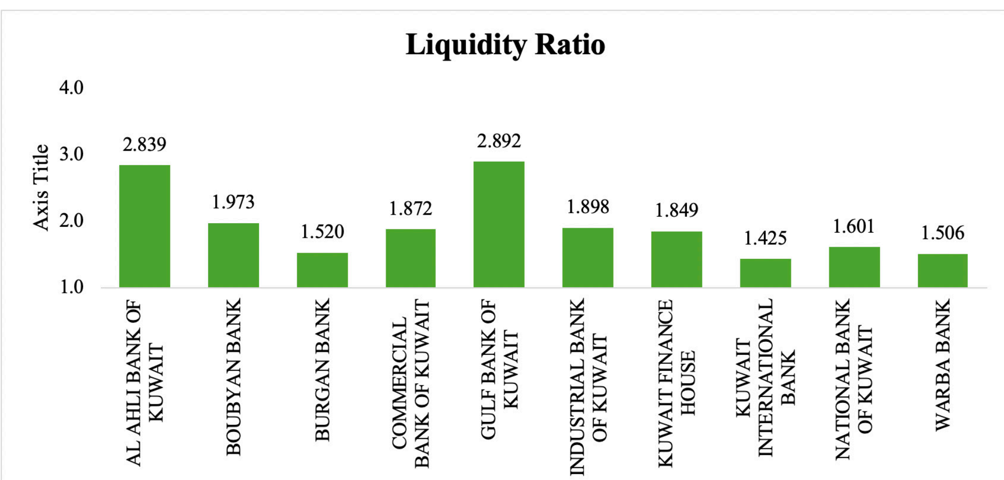

Figure 5: Liquidity Ratio on Average among Kuwaiti Banks

3.3. Descriptive Statistics

Table 3 demonstrates the descriptive statistics for each of the variables used in this research. Significant variation in banks' capital strength is demonstrated by the Capital Adequacy Ratio (CAR), which has a mean of 21.8% and values ranging from 0% to 100%. The Capital Adequacy Ratio (CAR) shows significant diversity in banks' capital strength. Return on equity (ROE) and return on assets (ROA), two measures of profitability, with respective averages of 8.3% and 1.2%; however, ROE exhibits more fluctuation, including negative values, which represent performance divergence. The logarithm of total assets (Bank Size) is used to calculate the banks' total assets, which has a moderate spread with a mean of 21.93. The Liquidity Ratio averages at 1.96, and therefore, most banks are over-covering with minimum thresholds. Capital structure difference implies different leverage — the mean is 8.48 and the maximum is 130.24. The Loan-to-Asset Ratio averages 61.9%, consistent with typical lending practices. The financial indicators shown here measure the differing risk appetites and operating strategies of banks within the sample. Such diversity to understand financial stability patterns is vital. Among macroeconomic variables, Kuwait's average GDP stands at KD 137.77 billion, while inflation and real interest rates average 3.54% and 3.11%, respectively. The exchange rate shows minimal fluctuation, reflecting the stability of the Kuwaiti dinar.

Table 1: Descriptive Statistics of Data

VARIABLE	N	MEAN	STANDARD DEVIATION	MIN	MAX
CAPITAL ADEQUACY RATIO	179	0.218	0.414	0.000	1.000
RETURN ON ASSETS	179	0.012	0.014	-0.072	0.091
RETURN ON EQUITY	179	0.083	0.140	-1.359	0.572
BANK SIZE	179	21.931	1.040	18.615	24.421
LIQUIDITY RATIO	179	1.958	0.559	1.016	3.248
LEVERAGE RATIO	179	8.478	9.493	1.250	130.240
LOAN TO ASSETS RATIO	179	0.619	0.153	0.000	0.791
GROSS DOMESTIC PRODUCT	179	137.769	27.599	80.799	183.940
INFLATION	179	3.536	1.917	0.543	10.583
EXCHANGE RATE	179	0.294	0.011	0.269	0.307
REAL INTEREST RATE	179	3.108	-15.389	19.469	40.860

3.4. Empirical Model

3.4.1. Logit Model

Logistic Regression is one of the approaches used to predict financial stability. It is a parametric method and a well-known statistical technique for modeling the probability of outcomes for a specific dependent variable. In this context, a logistic regression model estimates the likelihood of financial distress. This method was chosen for its interpretability and ability to model binary outcomes (stable/unstable). It enables us to evaluate the marginal impact of each financial indicator on bank stability, which is useful for regulatory analysis. Logistic regression is designed to predict and explain categorical variables with two groups. All variables are treated as dummy variables, and the target variable values are binary. The Capital Adequacy Ratio (CAR), an indicator of financial health, will be analyzed using the logistic regression model to assess the effects of macroeconomic variables and bank-specific factors. The significance level applied to all variables is 5%. Therefore, variables with p-values less than 5% are included in the model, while those with p-values greater than 5% are excluded. To illustrate this relationship, logistic regression employs the logistic curve to depict the connection between independent and dependent variables.

Mathematically,

The logistic curve ensures:

i) The forecasted values always lie between the range of 0 and 1.

ii) The dependent variable (Y) has the value 1 in case of default/bankrupt.

The dependent variable(Y) first has to be transformed, called the logit function, as shown below:

$$Logit\ (Y) = ln(odds) = a + k_1x_2 + k_2x_2 + ... + k_nx_n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where odds refer to the odds of Y being equal to 1.

$$Odds = \frac{Probability}{1 - Probability} \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

And odds can be defined mathematically as;

$$Probability = \frac{Odds}{1+Odds} \ldots\ldots\ldots eq\ (3)$$

Odds can be transformed into probabilities by the following expression: The right-hand side of Equation (3) does not ensure that the values lie between 0 and 1. Hence, taking exponential on both sides of equation

$$e^{ln(odds)} = odds = e^{(a + k1x1 + k2x2 + ...+ knxn)} \cdots\cdots\cdots\cdots (4)$$

Dividing both sides of Equation (2.4) by (1+odds):

$$\frac{Odds}{(1 + odds)} = \frac{e^{(a + k1x1 + k2x2 + ...+ knxn)}}{1 + e^{(a + k1x1 + k2x2 + ...+ knxn)}} \dots\dots\dots (5)$$

Now the equation looks like equation (3)

$$Probability = \frac{e^{(a + k1x1 + k2x2 + ...+ knxn)}}{1 + e^{(a + k1x1 + k2x2 + ...+ knxn)}} \dots\dots\dots (6)$$

The above equation (6) results in the probability of a group (Y=1, Stable) instead of the log of the odds of the same.
The model for this study is structured as follows:

$$\begin{aligned} CAR_{i,t} &= \alpha + \beta_1 \text{Bank Size}_{i,t} + \beta_2 \text{ROA}_{i,t} + \beta_3 \text{ROE}_{i,t} + \beta_4 \text{leverage Ratio}_{i,t} \\ &+ \beta_5 \text{Loan-to-Asset Ratio}_{i,t} + \beta_6 \text{Liquidity Ratio}_{i,t} + \beta_7 \text{GDP Growth}_t \\ &+ \beta_8 \text{Inflation}_t + \beta_9 \text{Interest Rate}_t + \beta_{10} \text{Exchange Rate}_t + \epsilon_{i,t} \end{aligned}$$

where,

- $CAR_{i,t}$ = Capital Adequacy Ratio (CAR) for bank i at time t, serving as the financial stability indicator (1 = Stable, 0 = Distressed).
- Bank $Size_{i,t}$ = Total assets of the bank, representing its scale and ability to absorb risks.
- $ROA_{i,t}$ = Return on Assets, measuring profitability per unit of assets.
- $ROE_{i,t}$ = Return on Equity, indicating how effectively a bank generates profits from shareholder equity.
- leverage $ratio_{i,t}$ = Measures the proportion of total assets relative to total equity, assessing funding stability of assets by equity.
- Loan-to-Asset $Ratio_{i,t}$ = Indicates the proportion of assets allocated to loans, showing lending risk exposure.
- Liquidity $Ratio_{i,t}$ = Estimate bank's ability to meet short-term obligations.
- GDP $Growth_t$ = Economic growth rate, influencing banking performance.
- $Inflation_t$ = Affects purchasing power and loan repayment abilities.
- Interest $Rate_t$ = Central bank policy rate affecting borrowing and lending costs.
- Exchange $Rate_t$ = Measures currency fluctuations, impacting foreign exchange exposure.
- α = Intercept term, capturing the base effect on CAR.
- $\beta_1,\beta_2,\dots,\beta_{10}$ = Regression coefficients, measuring the effect of each variable on CAR.
- $\epsilon_{i,t}$ = Error term, accounting for unobserved factors.

3.4.2. Artificial Neural Networks (ANN) Model

Artificial Neural Networks (ANNs) offer a strong alternative to mainstream econometric models through their ability to replicate complex, non-linear macroeconomic indicators and bank-specific financial variable relationships. Unlike conventional models, in ANNs multi multi-layered designs are used to independently learn patterns from data, and hence, they are suitable for financial risk measurement. This research employs a financial stability prediction for the banking sector using an Artificial Neural Network (ANN) model on two basic components, such as the Capital adequacy ratio (CAR) and macroeconomic indices. Alsaawy et al. (2020) use the feed-forward back propagation neural network approach to estimate the capital adequacy ratio. The results showed that the ANN model outperformed the regression model in MSE, RMSE, and MAPE, making it a better strategy for forecasting CRAR.
An artificial neural network (ANN) with three hidden layers was applied to capture complex, non-linear relationships among the input variables. The ReLU activation function was chosen for its computational efficiency and non-saturating property, and the model was optimized using the Adam optimizer with cross-entropy loss. This architecture was selected to enhance predictive accuracy in high-dimensional financial data.

Artificial Neural Network Architecture

The ANN model has a multi-layer feedforward architecture with the following elements:

• Input Layer: Considers macroeconomic factors (GDP growth, inflation, interest rates, exchange rates) as well as bank-specific financial variables (ROE, ROA, loan-to-asset ratio, liquidity ratio, and capital adequacy ratio).

• Hidden Layers: Two or more fully connected layers using ReLU (Rectified Linear Unit) activation to improve learning and introduce nonlinearity.

• Output Layer: One neuron with a sigmoid activity function, used for binary classification.
(Stable = 1, Distressed = 0).

Integration function: $$f_1 = f_1(x) = w_0 + \sum_{i=1}^{k} w_i\, x_i \quad (3)$$

Sigmoid function: $$f_2 = f_2\big(f_2(x)\big) = \frac{1}{1+e^{-f_1(x)}} \quad (4)$$

Output: $$\hat{Y} = f_2\big(f_1(x)\big) \quad (5)$$

Where,

$f_1(.)$ represents the integration function, which is simply the weighted sum of inputs.
$f_2(.)$ denotes the activation function, which is non-decreasing, nonlinear, and differentiable.
The cross-entropy (CE) error term is utilized instead of the sum of squared residuals (SSE) because CE is thought to be superior to SSE for binary classification issues.

$$\mathrm{E} = -\sum_{i=1}^{n}\left[Y_n \log\big(\widehat{Y_n}\big) + (1-Y_n)\log\big(1-\widehat{Y_n}\big)\right] \quad (6)$$

E= Error function (calculates the difference between predicted and actual output, where n=1, 2, ..., N are the observations corresponding to input-output pairs)
The weights used in equation (3) are taken from the ordinary normal distribution and then iteratively changed using the backpropagation process. Mathematically,

$$w_k^{(t+1)} = w_k^{(t)} - \eta_k^{(t)} \cdot \frac{\partial E^{(t)}}{\partial w_k^{(t)}} \tag{7}$$

where t denotes the index the iteration steps for the k-th weight
'η' is the learning rate.

The partial derivative (gradient), i.e. $\frac{\partial E^{(t)}}{\partial w_k^{(t,)}}$ is a sensitivity factor. It can be expressed as,

$$\frac{\partial E^{(t)}}{\partial w_k^{(t)}} = \frac{\partial E^{(t)}}{\partial f_2^{(t)}} \frac{\partial f_2^{(t)}}{\partial f_1^{(t)}} \frac{\partial f_1^{(t)}}{\partial w_k^{(t)}} \tag{8}$$

The last factor of the right-hand side of equation (8),

$$\frac{\partial f_1^{(t)}}{\partial w_k^{(t)}} = \frac{\partial}{\partial w_k^{(t)}} \left(w_0 + \sum_{i=1}^{k} w_i \, x_i \right) = x_i \tag{9}$$

The derivative of the output neuron in relation to its input is just the partial derivative of the sigmoid function, which entails

$$\frac{\partial f_2^{(t)}}{\partial f_1^{(t)}} = f_2(\cdot)\{1 - f_2(\cdot)\} \tag{10}$$

Finally, the first factor of the right-hand side of equation (8):

$$\frac{\partial E^{(t)}}{\partial f_2^{(t)}} = \frac{\partial E^{(t)}}{\partial \hat{Y}_2^{(t)}} = \hat{Y}\left(\widehat{Y_n} - 1\right) + \left(1 - \widehat{Y_n}\right) \left(\widehat{Y}\right) \tag{11}$$

3.4.3. Training Dataset

To avoid overfitting and evaluate model generalization, the dataset will be separated into three sets: training (70%), validation (15%), and test (15%). The Adam (adaptable Moment Estimation) optimizer is then used since it is effective at dealing with sparse gradients and adaptable learning rates. Furthermore, the model optimizes the binary cross-entropy loss function, which is ideal for classification problems involving financial stability. Finally, the accuracy of the model will be assessed using the AUC-ROC Curve.

3.4.4. AUC-ROC Curve and Evaluation Criteria

The ROC curve is a tool for evaluating binary classification issues. This is a typical probability curve (also known as ROC curve) that plots the TPR (True Positive rate) against the FPR (False Positive rate) at various threshold levels, effectively separating signal from noise. The ROC curve summarizes the AUC, which measures a classifier's ability to discern between classes.

ANN model is implemented for financial stability assessment having robust, data driven alternative to conventional econometrics. An ANN with multiple layers between each other does a good job of representing the complex and non-linear dependencies among macroeconomic indicators and bank-specific financial variables. Without the backpropagation step, the model treats its computational capability as a static target value, then iteratively optimizes its predictive capability through weight adjustment based on the error.

It is systematically partitioned dataset then the Adam optimizer is used for efficient training. Using the AUC-ROC curve, an appropriate way to estimate the performance of such model, it is rigorously evaluated. The higher the AUC value, the better it will work as a strong predictor of which banks are financially stable and which are distressed.

Overall, in comparison with the conventional models, the ANN model represents a powerful tool for the financial risk assessment, as clearly more accurate and thereby more flexible. Due to its ability to process large volumes of financial data and detect early warning signals, it is a useful tool for policymakers, financial institutions, and regulators to protect financial stability.

4. EMPIRICAL RESULTS

4.1. Results of Random Effect Logit Model

The Random Effects Logit model was applied to examine the key determinants of financial stability across Kuwaiti banks, with capital adequacy (CAR) serving as the dependent variable. Table 4 summarizes the variables influencing Kuwait banks' capital adequacy ratios (CARs). The results reveal that there is a positive link between ROA and CAR, indicating that profitable enterprises can build capital buffers and maintain stronger financial resilience during periods of stress. This relationship underscores the role of profitability as a fundamental driver of financial stability.

In contrast, a 'negative link' exists between CAR and Return on Equity, suggesting that CAR and Return on Equity are inversely related, implying that an aggressive pursuit of shareholder returns may often be accompanied by elevated risk levels, potentially undermining regulatory capital positions. The results are consistent with the findings by Büyükşalvarcı and Abdioğlu (2011), who identified a similar trade-off between profitability measures and capital adequacy among banks. It is also shown that bank size and leverage ratio have a negative relationship with CAR, lending support to prior evidence from Acosta-Smith et al. (2024) regarding the systemic risk implications of excessive borrowing. Larger banks tend to maintain lower leverage ratios to mitigate systemic vulnerabilities and avoid heightened regulatory scrutiny, as excessive leverage increases susceptibility to financial distress during economic downturns.

Secondly, the Loan to Asset Ratio has a positive and statistically significant effect on CAR ($p < 0.01$), indicating that productive credit allocation is crucial in supporting capital adequacy by ensuring that asset portfolios contribute effectively to banks' revenue streams. On the macroeconomic side, Gross Domestic Product growth exhibits a positive relationship with CAR ($p < 0.05$), aligning with the findings of Obeid (2023) and Dao and Nguyen (2020). Economic expansion typically improves corporate sector profitability and asset quality, thereby enabling banks to bolster their capital reserves more efficiently. Conversely, Hortlund (2005) observes that inflation exerts a negative influence on capital levels, as high inflationary pressures elevate credit risks, erode real asset values, and encourage banks to adopt a more conservative capital posture. Finally, the Wald chi-square statistic ($\chi^2 = 37.63$, $p < 0.001$) confirms the overall joint significance and robustness of the econometric model, validating the reliability of these findings.

These results confirm the logit model as a predictive tool in financial stability forecasting. More importantly, the findings validate that the conventional financial ratios and macroeconomic indicators are significant predictors, which is also considered the objective of the study to determine the relative merit of machine learning-based methods and econometric-based methods in the Kuwaiti banking sector.

Table 2: Results of Random Effect Logit Model

	COEFFICIENT	STANDARD ERROR	Z	P>|Z|
RETURN ON ASSETS(T-2)	4.766	1.690	2.820	0.005*
Δ RETURN ON EQUITY	-0.218	0.121	-1.800	0.072**
BANK SIZE	-0.147	0.029	-5.050	0.000*
LIQUIDITY RATIO	-0.019	0.036	-0.530	0.593
LEVERAGE RATIO	-0.017	0.008	-2.040	0.042*
LOAN TO ASSETS RATIO	0.305	0.090	3.380	0.001*
GROSS DOMESTIC PRODUCT	0.002	0.001	2.570	0.010*
INFLATION	-0.011	0.005	-2.310	0.021*
Δ EXCHANGE RATE	0.289	1.558	0.190	0.853
Δ REAL INTEREST RATE	0.000	0.000	0.280	0.776
CONSTANT	266.466	68.679	3.880	0.000*
LOG LIKELIHOOD	-18.054			
WALD CHI2(10)	37.630			
PROB > CHI2	0.000			

Note: * & ** indicate the level of significance at 5% & 10% confidence intervals, respectively.

4.1.1. Receiver Operating Curve (ROC)

The ROC curve for the logistic regression model is presented in Figure 6. The Area Under the Curve (AUC) value is 0.9575, reflecting excellent classification performance. This implies that the model effectively distinguishes between financially stable and distressed banks.

A high AUC indicates that the logit model strikes a strong balance between sensitivity (true positive rate) and specificity (true negative rate). The steep rise of the curve toward the top-left corner confirms that the model's predictive power is not random but rather robust across various classification thresholds. These results are comparable to Lu (2024), who reported an AUC of 0.86 when predicting financial crises using logistic regression. In this context, the logit model proves not only interpretable but also statistically sound and practically effective for regulatory risk assessment.

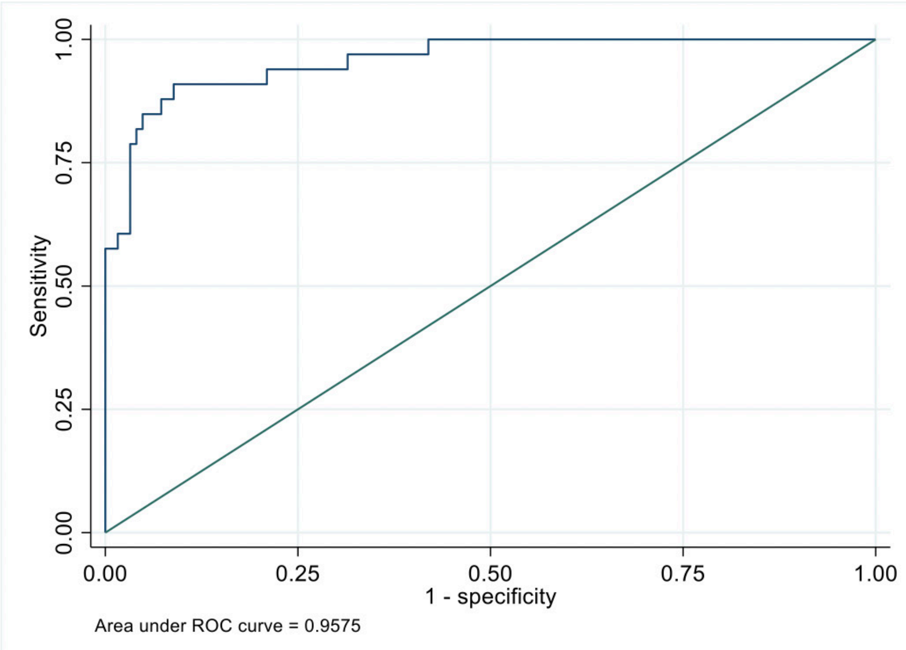

Figure 6: ROC Curve of Logit Model

4.2. Results of Artificial Neural Network (ANN) Model

The Artificial Neural Network (ANN) model was trained and evaluated using the same dataset to provide a comparative benchmark against the econometric approach. As shown in Table 3, the ANN model achieved 100% classification accuracy, correctly identifying all 40 stable and 11 distressed banks. This level of performance corresponds to perfect sensitivity (recall = 1) and specificity (no false positives or negatives), indicating the ANN's superior ability to learn and classify complex, non-linear patterns in the dataset. Given the model's architecture, which ANN's strength in capturing subtle interactions between financial and macroeconomic inputs that may be missed by traditional models.

Table 3: Classification Results

	FINANCIAL STABILITY	DISTRESS
FINANCIAL STABILITY	40	0
DISTRESS	0	11

An Artificial Neural Network (ANN) model illustrated in Figure 2 demonstrates perfect classification performance on its ROC (Receiver Operating Characteristics) curve with the AUC (Area Under the Curve) value of 1. 00. A perfect rating of 1 signifies that the model achieves a true positive rate of 1 (100%) and a false positive rate of 0 (0%), indicating it can make flawless predictions (i. e., differentiate between financially stable and troubled banks). The ROC curve sharply rises to the top-left corner of the graph, which is typical of an exceptionally effective classifier. These results indicate the ANN model's robust discriminative capability and appropriateness for predicting financial distress.

The ANN model shows the strength of machine learning to predict the financial stability with high precision, especially in an emerging market environment such as Kuwait. This aspect of prediction superiority over the logit model substantiates the fundamental premise of the article: that ML models, when calibrated well, can outperform the traditional methods in the areas of prediction and early-warning detection.

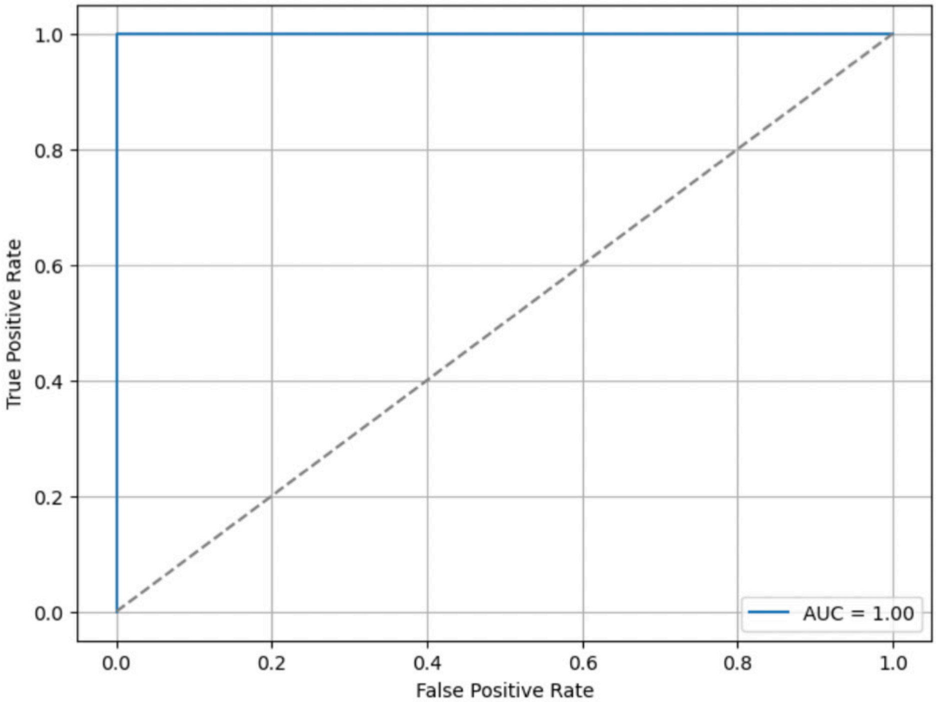

Figure 7: ROC Curve of ANN Model

5. MODEL DIAGNOSTICS

5.1. Cross-Validation Analysis

Cross-validation is a statistical approach for measuring the performance of a learning algorithm that involves dividing the given dataset into two parts (one for training the model and one for verifying the model's prediction). This approach is utilized in Zhang et al. (1999) on neural networks for bankruptcy forecasting; the technique is well-established as neural networks are used for financial prediction problems. This study also includes k-fold cross validation (with k-=5). The total number of observations given is divided into five equal portions, which demonstrates this. The first is that each class in both the training and validation stages must be represented at least once.

Predictive performance of these models is very strong, with the Artificial Neural Network (ANN) model outperforming the Panel Logit Model marginally in the forecast accuracy results, as shown in Table 4. In the in-sample evaluation, the ANN model had perfect accuracy at 100% accuracy reflecting how much the ANN model could learn from the training data. Its generalizability to unseen data is further confirmed by the out-of-sample accuracy of 97.58%. Additionally, the Panel Logit Model also performed very well, obtaining 95.75% in sample and 96.55% out of sample accuracy in prediction on financial stability. These results suggest that while both models are effective, the ANN model offers superior classification accuracy in this context.

Table 4: Model Comparison

MODELS	IN-SAMPLE FORECAST ACCURACY	OUT-OF-SAMPLE FORECAST ACCURACY
PANEL LOGIT MODEL	95.75%	96.55%
ANN-MODEL	100%	97.58%

6. CONCLUSION

Financial stability is a cornerstone of a healthy economy, ensuring that banks and financial institutions can operate consistently even during times of economic crisis. Using the Capital Adequacy Ratio (CAR) as the principal measure of financial stability, this research employs unbalanced panel data from 2005 to 2024, covering ten leading commercial banks in Kuwait. The factors influencing stability are categorized systematically into two groups of explanatory variables based on economic indicators as well as financial ratios. The study contributes to the existing literature in several meaningful ways. First, it provides a precise, operational definition of financial stability that integrates key financial and macroeconomic predictors. Second, it provides further empirical detail of the predictive capabilities of existing econometric models of financial stability. In the final, the research examines the predictive abilities of the machine learning techniques, namely Artificial Neural Network (ANN), and considers how its predictive performance compares to traditional econometric methods. Both modeling frameworks are evaluated on a comparative basis, with particular emphasis on the strengths, limitations, and policy implications.

The empirical analysis identifies how key financial factors influence stability in Kuwaiti banks. Panel logit model results imply that return on assets (ROA) and loan-to-asset ratio are positively correlated with CAR, which implies that more profitable institutions exhibit greater ability to build capital buffers, and efficient credit allocation is important in providing support for CAR. On the other hand, CAR is negatively associated with ROE, bank size, and leverage ratio, implying larger and more leveraged banks may suffer from higher capital burdens and exhibit increased risk-taking behavior. Additionally, the logit model's ROC Curve shows a good performance with an area under the curve (AUC) of around 95.75%, which is considered to be high discriminatory power. The findings of the Machine Learning Model (Artificial Neural Networks) are comparatively perfect, with 100% accuracy of classification. A true positive rate of 1 and a false positive rate of 0 means the ANN model's AUC-ROC score of 1.00, indicating that nothing can be better predicted. ANN outperforms the traditional techniques, such as logistic regression, in terms of predicting distressed banks, where it is better than the former in terms of accuracy, sensitivity, and specificity. In particular, these insights are particularly timely for the Kuwaiti context, where typical stress testing mechanisms may be less effective due to deficient risk disclosure practices and characteristics of the financial system. Accordingly, machine learning provides the opportunity to improve Kuwaiti banking sector early warning frameworks.

Finally, this study highlights the necessity of the combination of econometrics and machine learning in the financial stability forecasting.

This demonstrates clearly the potential of advanced analytics to transform early risk detection. A hybrid strategy of bridging the gap between traditional statistical rigor and the added dynamic data driven technique will provide better financial resilience of the GCC region in the future. A framework regulated both of these approaches will allow the institution to anticipate systemic risks better and promote economic stability. In addition, such integration also promotes the development of predictive models which do not only quantify historical trends, but the alternative estimation of parameters allows them to adjust to real time market fluctuations and macroeconomic shocks. Interpretability and predictive strength are leveraged together to improve the accuracy of stress testing, early warning systems and decision making under uncertainty. This also provides a dual approach to a culture of innovation in regulatory practice with oversight mechanisms that can parallel the evolution of financial technologies. Because such institutions depend on complex, interconnected financial activity for survival, soundness continues to be dependent on increasing accuracy of forecasting vulnerabilities, not only to preserve institutional soundness, but also with longer term economic confidence and growth.

6.1. Limitations and Future Research

This study has several limitations that indicate useful future research directions. Firstly, the use of annual data may obscure short-term volatility and the detection of substantial delays in financial shocks; future analysis should use quarterly data that could potentially reveal high-frequency fluctuations, seasonal patterns, and provide an early warning of changes. Secondly, the analysis mainly uses accounting-based ratios (e.g., CAR, leverage, ROA). Incorporating market-based indicators, such as credit spreads, bond yields, or default probabilities, can further increase the responsiveness of stability assessments to short-term market sentiment. Thirdly, while the focus on Kuwait provides valuable contextual depth, the generalizability of the outcomes to other economies remains limited. Future studies could extend to other GCC countries or engage in cross-national comparisons to provide a broader understanding that could relate to oil-dependent, bank-centric financial systems in general. Lastly, the high predictive performance of the ANN model is offset by its black box quality, unable to stand on its own in regulatory environments where transparency is paramount. The future research would recognize the explainable AI (XAI), such as SHAP or LIME, to make the model as transparent as possible and build trust.

IMPLICATIONS OF THE STUDY

In particular, this study provides unique insights for stakeholders, policymakers, and financial regulators about the emerging environment in financial stability assessment. As banks become heavily data-dependent and sensitive to various risks, advanced analytical inputs are no longer an option but an essential prerequisite for maintaining sustainable financial governance. While causal inference can be made using traditional econometric techniques, machine learning methods are increasingly used to complement these methods because they are more adaptable and stronger in terms of prediction. This research strongly underscores the potential to combine these approaches to improve financial stability forecasting framework accuracy, responsiveness, and robustness. Importantly, the findings emphasize the role of capital adequacy, liquidity, leverage, and loan-to-asset ratios as key indicators that should be integrated into data-driven risk models. Using historical patterns in these financial ratios for enhancing the early detection of bank distress, machine learning can be used to achieve this with higher precision. Through this, regulators can better tailor their responses and dedicate more of their supervisory resources. In addition, differences in banks' performance support the contention that the monitoring framework should be institution-specific rather than designed based on one-size-fits-all stress scenarios. Whichever hybrid modeling strategy is adopted, the development of early warning systems, enhancement of stress testing methodology, and improvement of regulators' decision-making can be significantly helped. Additionally, embedding machine learning tools into regulatory and supervisory processes can facilitate real-time monitoring of systemic risks, early detection of vulnerabilities, and more proactively intervention mechanisms. This study concludes by suggesting that strategic investment in predictive analytics capabilities in the realm of finance should be made to portray the institutions as the key element for the establishment of more dynamic, foresighted, and oriented toward the future financial governance models better adapted to the conditions of an increasingly complicated and interdependent environment.

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