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Forecasting The Financial Crisis in Iran According to The Slope of The Yield Curve and The Bank Credit Index: A Machine Learning Approach

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Abstract

This study examines the role of bank credit and macroeconomic variables in predicting financial crises in Iran. Given the importance of predicting and managing financial crises in the Iranian economy, this study aims to identify the key factors and build accurate models to predict these crises.Panel data for the period 2006 to 2022 was used for this study. Advanced machine learning techniques and neural networks were used to analyse the data and create predictive models. These approaches make it possible to examine complex relationships between variables and make more accurate predictions.The results of this study show that the bank debt service ratio, the slope of the yield curve and the investments made are the most important factors in predicting financial crises in Iran. Bank loans also play a minor role in these predictions. The models used, especially neural networks and random forests, have shown high accuracy in predicting financial crises. This study has important implications for economic and financial policies in Iran. The results emphasise the need to review debt management policies, improve the investment environment, and adjust monetary and credit policies more precisely. These findings can help policy makers and economic managers to make more informed decisions and prevent future financial crises.

Highlights

- Bank debt service ratio, yield curve slope, and investments are the most significant predictors of financial crises in Iran.
- Neural networks and random forests demonstrate high accuracy in forecasting financial crises.
- Bank loans play a minor role in predicting financial crises in Iran.

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1. Introduction

Financial crises are recurring phenomena in world economic history that have destructive effects on economic activity (Sufi & Taylor, 2022). These crises usually lead to a sudden and significant drop in the value of assets and are often rooted in problems within the banking system. The consequences of financial crises include reduced economic growth, increased unemployment, and deep recessions (Danisman & Tarazi, 2024).

As systematic disruptions in the financial markets, these crises can spill over into other sectors of the economy, leading to fundamental changes in macroeconomic performance. The effects of these crises include a decline in GDP, a rise in inflation, stagnation, and an increase in the balance of payments deficit (Cecchetti et al., 2009). In addition to the impact on macroeconomic indicators, these crises also affect financial and banking variables at the micro level. The corresponding data can serve as important indicators for borrowers, investors, and policymakers (Biljanovska et al., 2023).

Financial crises can occur at different levels, from individual financial institutions to the global economy (Gorton, 2018). Factors such as excessive leverage, mispricing of assets, lack of financial transparency, and inadequate risk management can lead to a financial crisis (Hellwig, 2008; Acharya & Richardson, 2009, Brunnermeier, 2009). These crises usually start with price bubbles in the asset markets, ultimately leading to sharp price falls and investor losses (Aiginger, 2009). Therefore; Early recognition of the warning signs of financial crises is particularly important as these crises are usually associated with high economic and social costs (Laborda & Olmo, 2021). These costs include increased unemployment, reduced household wealth, and economic stagnation. A decline in consumer and business confidence can weaken demand and investment (Wang et al., 2023). In recent decades, the global economy has repeatedly faced financial crises that have had a profound impact on developing and emerging economies, including Iran. The growth of bank credit and changes in macroeconomic variables such as inflation, investment, and exchange rate are essential indicators for the study of financial crises (Joseph, 2020; Buckman & Joseph, 2023). Studies show that disproportionate expansion of bank credit and increased liquidity are significant predictors of financial crises (Bluwstein et al., 2023).

Due to Iran's oil-dependent economic structure and lack of sufficient diversification of income sources, the country is generally vulnerable to economic turmoil caused by fluctuations in global oil prices. In such situations, banks and financial institutions play a central role as crucial tools for financing various sectors of the economy (Mishra & Burns, 2017). In this way; The main objective of this study is to investigate the role of bank loans and the slope of the yield curve in predicting financial crises in Iran. This study examines the dynamics of public and private debt and their relationship with macroeconomic variables such as GDP, inflation rate, and the value of the national currency to gain a comprehensive understanding of how these factors function as primary indicators of a financial crisis.

The future structure of the article will include sections on literature and research background, methodology (including research method and research model), research results, and conclusions and suggestions.

1.1. Literature review

Some analysts trace the deeper roots of the recent financial crisis back to developments after the 1970s, after the United States abandoned the one-sided monetary system based on the gold standard (the Bretton Woods monetary system). These developments led to the emergence of a new era in the international monetary system. Under this new system, the US dollar replaced gold in countries' national reserves, which provided an extraordinary opportunity for the US to gain more credit power and obtain new investment funds by issuing new dollars (Shafiei et al, 2009). Until recently, views on financial crises in the academic literature were strongly divided into two opposing schools of thought, one associated with the monetarists and the other representing a more diverse perspective espoused by scholars such as Kindleberger (1978) and Minsky (1972). Led by influential figures such as Friedman and Schwartz (1936) in their seminal paper, the monetarists established a link between financial crises and banking panics. They emphasize the importance of banking panics and see them as the main cause of the contraction of the money supply, which subsequently leads to a significant slowdown in overall economic activity in the United States.

Monetarists would not categories events in which there is a significant decline in asset values and an increase in business closures as true financial crises unless there is the potential for a banking panic and a resulting sharp contraction in the money supply. In fact, Schwartz (1986) refers to these scenarios as "pseudo-financial crises". Intervention in a pseudo-financial crisis is seen by monetarists as unnecessary and potentially harmful, as it can reduce economic efficiency by bailing out failing firms or causing excessive growth in the money supply leading to inflation. Such interventions can disrupt natural market mechanisms and lead to distortions in the allocation of resources, ultimately affecting long-term economic stability and growth. Kindleberger (1978) and Minsky (1972) offer an alternative perspective on financial crises that differs from that of Poltergeist. They provide a more comprehensive definition of what constitutes a true financial crisis. According to their analysis, financial crises include significant losses in asset values, the collapse of large financial institutions and non-financial firms, inflation or deflation scenarios, disruptions in foreign exchange markets, or a combination of these factors. They argue that any of these potential disruptions would have serious consequences for the economy as a whole. Consequently, they suggest a far-reaching role for state intervention in times of financial crisis, as broadly defined by their criteria .

One problem associated with the Kindleberger-Minsky view of financial crises is the lack of a comprehensive theoretical framework that defines the key characteristics of a financial crisis. This lack of theory makes it susceptible to broad application and potentially leads to unwarranted government intervention that does not necessarily benefit the economy as a whole. This criticism forms the basis for Schwartz's (1986) critique of the Kindleberger-Minsky perspective and emphasizes the need for a more nuanced and sophisticated understanding of financial crises. Conversely, the proletariat approach to financial crises is severely limited because it focuses primarily on the impact of banking panics on the money supply and ignores other important factors that may contribute to the emergence and spread of financial crises. This narrow focus limits the explanatory power of the portraits perspective and underscores the importance of taking a broader perspective when analyzing and dealing with financial instability (Mishkin, 1992). Economic systems are inherently unpredictable, but understanding vulnerabilities can help prepare for a crisis. Previous research has emphasized the importance of focusing on explanatory factors such as credit diffusion, as shown in the studies by (Borio and Derman (2009), Jordà et al. (2015), Krishnamurthy and Muir (2020), Aldasoro et al. (2018), and Greenwood et al. (2022), Bluwstein et al., 2023).

Banks play a crucial role as the primary providers of capital in most economies worldwide. Therefore, understanding the fundamental principles that guide their decisions to grant loans to individuals and businesses is essential. Additionally, it can be argued that credit statistics are vital in banking operations and are a fundamental aspect of overall economic activity, particularly regarding how firms operate, which largely depends on access to bank credit. The health of an economic enterprise in a highly competitive business environment is influenced by factors such as: (1) the amount of financing at the establishment's inception, (2) its relative flexibility and efficiency in generating cash from ongoing business operations, (3) access to capital markets, and (4) financial capacity and resilience to endure unexpected and significant cash shortages (Luo et al., 2018). Some researchers have concluded that the slope of the yield curve and credit growth are critical predictors of financial crises in both domestic and global contexts (Bluwstein et al., 2023). Currently, credit institutions employ predetermined procedures to assess customer creditworthiness; however, given the constant changes in today's world, relying on fixed criteria lacks the necessary scientific validity and stability. Thus, it is essential to conduct audits that consider societal conditions and various crises (Sapiri, 2024). This is because the financial crisis can impact numerous macroeconomic indicators (Shafiei et al, 2009). For an economy to be healthy overall, it is essential for all sectors to be healthy in turn. A strong financial situation at the micro level contributes to a robust financial situation at the macro level, while the favorable evolution of macroeconomic variables also aids in the effective performance of a business. Therefore, it is crucial to maintain the financial balance of companies (Bloom et al, 2018).

The supervisory frameworks established after the 2007-2008 financial crisis have identified credit growth as a key indicator for detecting risks and potential crises, influencing macroprudential policies. Other variables, such as stock prices, housing prices, and current account deficits, also play a significant role in predicting financial crises and likely deserve more attention in policy discussions (Huynh and Uebelmesser, 2024).

Recent studies on predicting financial failure in companies have considered many factors, primarily related to the financial ratios derived from the annual accounts of companies. Nevertheless, the current crisis and the subsequent exponential rise in the bankruptcy rate have clearly demonstrated that the bankruptcy phenomenon cannot be explained without reference to macroeconomic variables. Therefore, the overall state of the economy, rather than just the internal financial ratios of companies, should be taken into account (Acosta-González et al, 2019) .

Recent research has increasingly focused on the dynamics of credit growth and the slope of the yield curve in emerging markets, recognizing their critical role in predicting financial crises and informing macroprudential policy. Studies have shown that excessive credit growth often precedes financial instability in emerging markets (Mack et al, 2017; Mbaye et al, 2018). For example, Mendoza & Terrones (2012) highlight that credit booms are common in emerging markets and often culminate in financial crises, suggesting the need to monitor credit growth as an early warning indicator. Similarly, the slope of the yield curve has been identified as a valuable predictor of economic activity and potential crises in emerging economies (Çebi & Özlale, 2012). In their study of emerging Asian economies, Minoiu et al (2023) find that the yield curve contains significant information about future output growth, highlighting its relevance beyond developed markets. These findings support the inclusion of credit growth and the slope of the yield curve as essentially variables in analyses of emerging economies, such as Iran. (Bagheri et al, 2016). In the context of Iran, recent studies have sought to understand the unique characteristics of its financial system and the implications for credit growth and financial stability. For example, Faraji-Dizaji & Van Bergeijk (2013) examine the relationship between sanctions, credit growth, and economic performance in Iran and conclude that external shocks have a significant impact on domestic credit conditions and financial stability. In addition, Bahmani-Oskooee & Gelan (2018) analyses the determinants of credit risk in Iranian banks, highlighting the importance of macroeconomic variables such as oil prices and exchange rates in influencing credit growth and risk. These studies highlight the importance of considering local conditions and recent developments in emerging economies when analyzing credit growth and yield curve slope. Incorporating recent literature on emerging markets improves the understanding of how these variables work in the specific economic context of Iran, thereby strengthening the analysis.

Various methods have been used in the literature to measure the yield curve, each with its advantages and limitations. Traditionally, the slope of the yield curve is calculated as the difference between long-term and short-term government bond yields, reflecting market expectations about future interest rates and economic activity (Estrella & Mishkin, 1996). However, in emerging economies, where government bond markets may be less developed or illiquid, alternative measures are needed (Hördahl et al, 2016). In such contexts, researchers have used proxies such as the difference between central bank policy rates and deposit rates, or the spread between loan and deposit rates (Kose et al, 2017). This approach is particularly relevant in economies such as Iran, where the banking sector dominates financial intermediation and capital markets are comparatively underdeveloped. Using the spread between loan and deposit rates captures the cost of financial intermediation and reflects banks' expectations about future economic conditions and risks (Hamori & Hamori, 2010). Moreover, using the loan-deposit interest rate spread as a measure of yield curve slope has practical significance in analyzing the transmission of monetary policy and credit conditions in emerging economies (Huang & Chen, 2015). It is directly related to banks' lending behavior, credit availability, and hence economic activity. For example, Claessens et al. (2016) argue that bank lending rates are more informed about the stance of monetary policy and its impact on the economy in emerging markets than traditional measures.

Therefore, in this study, the difference between loan and deposit rates is selected as the slope of the yield curve to adequately capture the dynamics of credit markets and financial conditions in the Iranian economy. This choice is consistent with previous studies that have used similar measures in comparable contexts. For example, Khan et al. (2016) used the loan-deposit rate spread in their analysis of monetary transmission in Pakistan, an emerging economy with similar financial structures. In addition, Manganelli & Popov (2013) discuss how bank interest rate spreads can serve as indicators of financial stress and credit conditions in emerging markets. In summary, the choice of the spread between loan and deposit rates as a measure of yield curve slope is supported by the existing literature on emerging economies and is appropriate to capture the financial realities of the Iranian economy (Mousavi & Shakeri, 2023). This approach ensures that the analysis is based on a methodology that reflects the structural characteristics of the Iranian financial system, thereby enhancing the validity and relevance of the findings. As a result, there are many empirical studies on the prediction of financial crises. In the following, we will examine and explore some of them:

Wang & Wu (2017) proposed a combined model for predicting financial crises utilizing the AdaBoost algorithm, Probabilistic Neural Networks (PNN), and the Back Propagation (BP) algorithm. This study employed financial data from Chinese companies listed on the Shenzhen and Shanghai Stock Exchanges. The results indicated that the new combined model achieved the highest prediction accuracy compared to other models, including AdaBoost BP, PNN, and Support Vector Machines.

Khajavi, S., & Ghadirian Arani (2018) investigated the role of intellectual capital in predicting financial crises. This study analyzed data from 400 companies on the Tehran Stock Exchange over the years 2007 to 2016. Two categories of financial models were compared: one based on financial ratios and the other integrating financial ratios with intellectual capital. The results demonstrated that prediction patterns incorporating intellectual capital had significantly higher accuracy in forecasting financial crises, particularly in models employing boosting and bagging methods. These findings underscore the importance of considering non-financial factors such as intellectual capital in predicting financial crises.

Luo et al (2018) compared the logistic model with seven machine learning methods for predicting financial crises. They investigated causal relationships within machine learning methods through Shapley value analysis. The results showed that machine learning models, particularly Random Forest and Gradient Boosting Decision Trees, outperformed logistic models in the early prediction of financial crises.

Taheri Bazkhan & colleagues (2019) developed an early warning system for financial crises in Iran by introducing a new index. This research examined the period from 1990 to 2016 and aimed to create an innovative financial index through the analysis of essential components based on eight financial variables to predict various conditions in the financial sector (crisis, stability, boom). Utilizing a Markov Switching approach, the results indicated that crisis conditions showed little stability and often transitioned to stability, while boom conditions also exhibited limited stability and likely transitioned to stability. Direct changes from crisis to boom were deemed highly improbable. These findings can assist policymakers in better predicting and managing financial crises.

Beutel et al (2019) compared the effectiveness of early warning models in forecasting banking crises. This study evaluated the logistic approach against machine learning methods over a 45-year period for advanced economies. They employed various evaluation techniques, different definitions of crisis, and a diverse array of variables. The results indicated that the logistic method outperformed machine learning methods in out-of-sample evaluations.

Imamvardi and Jafari (2019) investigated the effects of financial crises on shock transmission and volatility spillover among developed financial markets and Iran. This study analyzed the period from 2003 to 2017 and utilized a modified cumulative sum of squares algorithm to identify structural changes, along with a multivariate ARCH model to examine the direction of shock transmission and volatility spillover. The results revealed that shock and volatility transmissions between stock markets occurred unidirectionally from developed and emerging markets in the Iranian capital market. These findings highlight the significance of considering global market impacts on the Iranian capital market when predicting financial crises.

samitas et al (2020) concentrated on predicting financial crises using network analysis and machine learning algorithms. They emphasized the evaluation of potential contagion risks based on structured financial networks. The results indicated that the application of machine learning achieved a prediction accuracy of 98.8%. This study also illustrated the importance of utilizing financial networks to enhance investment portfolio selection.

Metawa et al (2021) introduced a model for predicting financial crises through feature subset selection and optimized deep belief networks. They utilized swarm optimization algorithms and modified water wave optimization alongside a deep machine learning network. This model was evaluated using the Indicated, German, and Australian datasets, and the findings revealed that the proposed model surpassed other methods.

Laborda & Olmo (2021) examined volatility spillovers among economic sectors in forecasting financial crises. They assessed volatility spillovers across seven key economic sectors in the United States during the 2007-2009 financial crisis and the COVID-19 crisis using network connection metrics. The findings indicated that volatility spillovers could forecast periods of increased volatility for the S&P 500 index and could act as early indicators of financial crises.

Bluwstein et al (2023) concentrated on predicting financial crises using credit growth and the yield curve. They employed nonlinear machine learning techniques to analyze macro-financial data from 17 countries spanning from 1870 to 2016. The results illustrated that nonlinear machine learning models outperformed logistic regression, with credit growth and yield curve slope identified as the most significant predictors.

Papík & Papíková (2023) examined the impact of crises on the performance of bankruptcy prediction models for small and medium enterprises (SMEs). They employed CatBoost, LGBM, and Cubist methods to analyze data from over 90,000 SMEs from 2015 to 2019. The results revealed that model performance during crisis periods was significantly weaker than in non-crisis periods, with the most notable difference observed in one-year predictions) (6,5%).

Ristolainen et al (2024) investigated the relationship between newspaper headlines and the prediction of financial crises. They analyzed the content of headlines from global newspapers spanning 1870 to 2016 and integrated this with economic indicators, demonstrating that newspaper headlines contained predictive information for financial crises that extended beyond traditional macroeconomic and financial indicators.

The destructive effects of financial crises on national economies and citizens' lives are profound. Financial crises can result in sharp declines in asset values, reduced investment, job losses, and decreased household incomes. The instability caused by these crises also leads to higher unemployment rates and government budget deficits, eroding trust in financial and governmental systems. Therefore, the ability to predict and implement corrective measures before or during the early stages of financial crises is crucial to avert negative and long-term consequences for society and the economy .

Understanding the challenges associated with predicting financial crises and striving to address these issues necessitates comprehensive research that examines the relationships between macroeconomic variables and financial indicators. This research aims to identify patterns through historical data analysis, focusing on variables such as bank credit growth, inflation, investment, and balance of payments deficits, which can assist in recognizing and forecasting financial crises. Employing modern tools such as neural networks and economic simulation methods can offer new insights, particularly for countries like Iran, whose economies are affected by global oil price fluctuations .

Moreover, revisiting regulatory and legislative frameworks and forecasting future crises using quantitative models is vital for establishing stability in financial markets. This study, grounded in deep data analysis and advanced modeling, will empower policymakers to adopt effective strategies for preventing and managing financial crises, thereby enhancing the resilience and stability of the financial sector and macroeconomy against potential shocks.

Notably, existing research on forecasting financial crises in Iran predominantly focuses on other countries, with less attention given to Iran itself. Furthermore, the available studies on forecasting financial crises in Iran, which consider bank credit and macroeconomic parameters, lack quality and require further investigation. The present research aims to fill this gap in the literature by employing a model based on bank credit and macroeconomic variables, utilizing machine learning algorithms and neural networks to predict financial crises in Iran, underscoring the necessity of this research. In summary, while international studies on predicting financial crises are comprehensive, domestic studies in Iran regarding the role of bank credit and macroeconomic variables remain limited. The existing studies primarily emphasize accounting and auditing, significantly impacting the prediction of financial crises in Iran, indicating a clear gap in research. This study aims to address this void by developing a forecasting model for financial crises using bank credit and macroeconomic variables.

2. Methods

2.1 Data

Financial crises are rare events. While there have been a few truly global financial crises, such as the Great Recession and the Global Financial Crisis of 2007-2008, most crises occur primarily in one country or a small group of countries. A sharp increase in default rates is often accompanied by significant capital losses that lead to public intervention, bankruptcy, or forced mergers of financial institutions (Laeven and Valencia, 2008; Reinhart and Rogoff, 2009; Cecchetti et al, 2009). Considering that the aim of the current research is to predict the financial crisis for the countries of Iran using bank credits and macroeconomic variables, this research aligns with the study of Christina Bluwstein et al (2023). We utilize the economic data of Iran from the years 2000 to 2023. Our goal is to predict the crisis before it occurs, so we define one and two years prior to the crisis onset as "crisis time." For greater accuracy, we exclude the actual year of the crisis and the four subsequent years from our analysis. This distinction helps us differentiate between normal economic conditions and post-crisis recovery. Finally, we indicate the presence or absence of a crisis using a simple yes/no variable. This method enables us to better identify the genuine signs leading to a crisis and make more accurate predictions. Therefore, based on the definition of financial crisis in the study of Bluwstein et al (2023), the indexation of the financial crisis in Iran will be as follows:

Financial crisis = bank run + sharp rise in default rates with significant capital losses + government intervention + bankruptcy of financial institutions + forced mergers of financial institutions.

Therefore, to predict financial crises in Iran, based on the study Bluwstein et al (2023), the following two conditions must be satisfied:

Crisis forecasting: the target variable (occurrence of crisis) is deemed positive for 1 and 2 years prior to the onset of the crisis to enable effective crisis forecasting.

Exclusion of the post-crisis period: The year of the crisis and the subsequent 4 years are excluded from the analysis to prevent post-crisis bias.

This measurement approach treats the financial crisis as a discrete event (occurrence or non-occurrence) and emphasizes identifying the pre-crisis period as a warning signal.

2.2 Explanatory variables

The selection of explanatory variables is crucial for the accurate prediction of financial crises. In this study, we have chosen variables that recent literature has identified as significant predictors of financial distress, particularly in emerging economies like Iran. Specifically, we include the following variables:

1. Yield Curve Slope (YCS): Defined as the difference between long-term and short-term interest rates, the yield curve slope is a well-known indicator of economic conditions. Changes in the yield curve often precede shifts in economic activity. Recent studies have demonstrated that an inverted yield curve can signal an impending recession, making it a critical variable for crisis prediction.
2. Debt Service Ratio (DSR): This ratio measures the proportion of income used to service debt. A high DSR indicates that a larger share of income is dedicated to debt repayment, suggesting potential over-leverage and vulnerability to financial stress. Research has shown that the DSR is a reliable predictor of financial instability, as excessive debt burdens can lead to higher default rates.
3. Consumer Price Index (CPI): As a measure of inflation, the CPI affects purchasing power and can influence monetary policy decisions. Inflationary pressures can erode real incomes and savings, potentially destabilizing the economy. Including CPI helps capture the inflationary trends that may precede a financial crisis.
4. Investment (INV): Representing total investment from both public and private sectors, this variable reflects economic growth prospects. Fluctuations in investment levels can signal changes in economic confidence and activity. High levels of speculative investment, in particular, may indicate asset bubbles that could burst and trigger a crisis.
5. Current Account Balance (CA): The current account measures the net trade of goods and services. Persistent deficits may indicate external imbalances

and reliance on foreign capital, which can be risk factors for financial crises, especially if sudden capital outflows occur.

6. Public Debt (PD): Total government debt indicates fiscal sustainability. High levels of public debt can limit the government's ability to respond to economic shocks and may raise concerns about debt servicing capacity, potentially leading to a sovereign debt crisis.

7. Bank Credits (BC): Loans provided by banks to the private sector represent the level of credit in the economy. Rapid credit expansion can fuel economic growth but also lead to increased risk-taking and potential defaults. Monitoring bank credit is essential to identify credit bubbles and assess financial sector health.

The selection of these variables is justified by their prominence in recent empirical studies focusing on financial crisis prediction. For instance, Aikman et al (2021). highlight the importance of credit variables and yield curves in predicting systemic banking crises. Similarly, Drehmann and Juselius (2014) emphasize the role of debt service ratios as early warning indicators. To enhance the transparency and interpretability of our predictive model, we employ feature importance analysis using methods such as Shapley values. Shapley values, derived from cooperative game theory, provide insights into the contribution of each explanatory variable to the model's predictions. This approach aligns with recent practices in financial modeling that prioritize explainability, as noted by Lundberg et al. (2020). By understanding which variables most influence the model, policymakers can better interpret the signals and take proactive measures. The time frame of this study spans from 2006 to 2022. Additionally, the statistical population of this research includes the country of Iran, with financial data sourced from financial and stock exchange websites. Finally, the mathematical model of the research will be as follows:

$$FCit= f\,(YCSit+DSRit+CPIit+INVit+CAit+PDit+BCit) \qquad (1)$$

In which: FC: financial crisis, YCS: yield curve slope, DSR: debt service ratio, CPI: consumer price index, INV: investment, CA: current account, PD: public debt, BC: bank credits.

2.3 Research Methodology

In recent years, financial crises have garnered the attention of researchers and policymakers as one of the fundamental challenges facing the global economy. In both developed and developing countries, such as Iran, identifying and predicting these crises is crucial for formulating effective strategies to manage and mitigate financial damages. Bank credits and macroeconomic variables are recognized as key determinants of the stability or instability of financial markets. In this context, utilizing advanced forecasting models can enhance our understanding of the influential factors. Recent advancements in machine learning and artificial intelligence algorithms, including decision trees, random forests, gradient boosting, LIGHT trees, and particularly artificial neural networks (MLP), have proven effective in identifying patterns and complex relationships within economic data. This article focuses on these methods and investigates the role of bank credits and macroeconomic variables in predicting financial crises in Iran through the lens of neural networks. The primary objective of this research is to analyze and interpret the findings derived from these algorithms and to pinpoint the key factors that influence the prediction of financial crises. Subsequently, the article explains how to employ these methods to forecast financial crises using bank credits and macroeconomic variables.

In this study, artificial neural networks and other machine learning algorithms have been used to predict financial crises using bank lending and macroeconomic variables. Although traditional time series methods such as autoregressive (AR), moving average (MA) and ARIMA models can be used for forecasting, these methods have limitations compared to machine learning algorithms. Time series methods tend to assume linear relationships between variables and are limited in modelling complex nonlinear relationships and interactions between variables (Zhang et al, 2019). On the other hand, machine learning algorithms such as artificial neural networks are able to extract complex patterns and nonlinear relationships from data, which is essential for accurately predicting financial crises (Chatzis et al, 2018). The use of artificial neural networks and other machine learning algorithms in this study is due to their many advantages over traditional time series methods. These algorithms are capable of learning complex and non-linear relationships between variables, which is very important for understanding and predicting financial crises, which are often complex and multifactorial in nature (Addo et al, 2018). Furthermore, machine learning algorithms can scale with large and complex datasets and show superior predictive performance compared to traditional methods (Choi & Lee, 2018). Given the ability of these algorithms to extract relevant features, model nonlinear relationships, and handle complex data, the use of artificial neural networks and other machine learning techniques to predict financial crises in this study is appropriate and justified.

2.3.1 Boosted Regression Trees (BRT)

Boosted regression trees are a statistical method that predicts outcomes based on extensive sets of conditioning data without imposing strong parametric assumptions like linearity or monotonicity. It employs soft weighting functions for the predictor variables and performs a form of model averaging that enhances the stability of predictions, thereby guarding against overfitting. This method strategically integrates soft weighting functions into the predictor variables and boosts predictive accuracy by effectively capturing complex relationships within the data. Additionally, boosted regression trees feature a unique form of model averaging, a technique that improves forecast stability and mitigates the common issue of overfitting, ultimately yielding reliable and robust predictions. (Kumar & Lakshmi, 2022).

2.3.2 Gradient Boosting (XGBoost)

Gradient boosting is a distributed gradient amplification toolkit optimized for performance (Behera et al., 2023; Yan et al., 2019). It utilizes a recursive binary partitioning strategy to derive the optimal model by selecting the best partition at each step. The tree-like structure of gradient boosting renders it insensitive to outliers and, like many boosting methods, it is resistant to overfitting, which significantly simplifies model selection (Behera et al, 2023; Pasayat et al, 2022). The following equation represents the standard objective of the gradient boosting model at the t the training step, where l ($y_{pred}^{(t)}$), ‘y_{truth} truth Denotes the loss, which refers to the computation of the difference between the predicted value and the corresponding ground truth.

$$L^{(t)} = \sum_i l(y_{pred}^{(t)}, y_{\text{truth}}) + \sum_k \Omega\,(f_k) \tag{2}$$

Where $\Omega\,(f_k)$=+$\frac{1}{2} + \lambda\|w\|^2\, \gamma^T$ Indicates the complexity of the tree k, where T represents the number of leaves and $\ell 2$ denotes the norm of all leaf scores for the training samples. During the tree search, the parameters γ and λ determine the level of conservatism. Therefore, in this research, the performance of XGBoost relies heavily on the tuning of its meta parameters. The most important meta parameters are: maximum tree depth (max_depth), learning rate (eta), minimum loss reduction (gamma), and subsample ratio. Proper adjustment of these meta parameters is necessary to optimize model performance and avoid overfitting (Touzani & Maillet, 2021). Network search or random search techniques can be used to find optimal meta parameter values that provide the best performance on a validation set (Huang et al, 2021). In this research, network search and random techniques are used to tune the XGBoost meta parameters.

2.3.3 Random Forest

Random forest is a non-parametric and nonlinear model first proposed by Ho (1995).This model mitigates the overfitting problem as it consistently converges. Due to the advantages of random forest, it is frequently employed for stock forecasting (Ballings et al., 2015). The forecast's determination varies based on the problem type. In classification scenarios, the decision trees in the RF-induced prediction model are grouped, and the outcome is decided by the predictions of each tree, often using majority voting (Tang et al, 2021). In contrast, the average prediction of the trees constitutes the final prediction in regression. Specifically, when RF receives an input vector (x) containing values of various observable features investigated for a specific training region, it generates m regression trees and averages the results. The prediction equation is RF after m trees $\{T\,(x)\}_1^M\}$ (Behera et al, 2023).

2.3.4 Light Tree

Light Tree is a gradient boosting model recognized as an efficient and rapid machine learning tool, initially developed by Microsoft. This algorithm aims to minimize learning time and enhance efficiency in large and complex data analyses. Due to its notable advantages, Light Tree is particularly utilized in prediction and regression tasks (Ke et al., 2017). In this approach, each new tree contributes to refining and enhancing the predictions made by the previous trees, and through the gradient boosting process, the model's accuracy improves. For classification, predictions in Light Tree leverage the discrimination capabilities of the variables (Chen & Gosterin, 2016). For instance, when LightGBM receives a set of input features, it creates a series of decision trees and determines the final output based on the high probability of each class. In the regression process, the final prediction is derived by averaging the results obtained from various trees (Mienye & Jere, 2024). In this manner, LightGBM enables us to make precise and effective predictions across diverse fields, including forecasting financial crises, by constructing optimal trees and efficiently managing data (Zhang & Li, 2018) .

Like XGBoost, LightGBM's performance is strongly influenced by its meta-parameters. Important meta-parameters are: number of leaves (num leaf), maximum depth (max depth), learning rate (learning rate), and feature fraction (feature fraction). Tuning these meta-parameters is necessary to achieve optimal performance and avoid overfitting (Guo et al, 2022). Techniques such as grid search, random search or Bayesian optimization can be used to find the best meta parameter settings (Zhang et al, 2021). In the present study, randomisation and Bayesian optimizations techniques were used to set the LightGBM meta parameters.

2.3.5 Artificial Neural Networks (ANN)

Artificial neural networks represent a synthesis of various machine learning concepts, including regression, ensemble methods, perceptions, and gradient descent. They take a linear combination of input variables and convert them into nonlinear functions of the derived features of the dependent variable (Mishra et al., 2022). These networks are the most fundamental type of deep networks, comprising multiple layers of hidden neurons, each fully connected to the layer above (from which they exert influence) and below (from which they receive input). By considering networks with an increasing number of interconnected units, any general function can be constructed. Each layer processes a weighted linear combination of inputs and transforms it using an activation function. The output from the jth unit is the time weight that connects the jth unit to the ith unit in layer 1.

$$Z_{\mathrm{j}} = g\left(\sum_{i=0}^{\mathrm{d}} w_{ji}^{1} x_i\right) \tag{3}$$

2.3.6 Multilayer Perceptron (MLP) neural network

Neural networks are a simplified model of the real nervous system and are widely used to solve various scientific problems. The applications of these networks are so extensive that they range from classification tasks to interpolation, estimation, detection, and more. There are different types of networks, but they all consist of two main components: a set of neurons and the connections between them. Each neuron serves as a computing unit that takes inputs and processes them to produce an output. One of the simplest yet most effective configurations for modeling real nerves is the multilayer perceptron model, or multilayer perceptron neural network for short, which includes an input layer, one or more hidden layers, and an output layer. In this structure, every neuron in one layer is connected to every neuron in the next layer, forming a fully connected network (Rajabi et al., 2017).

3. Results

Descriptive statistics show that many variables have non-normal distributions. This characteristic can affect the performance of neural network models. To address this issue, we considered various data normalization techniques to ensure model accuracy. While we initially applied z-score normalization, which standardizes data to have a mean of zero and a standard deviation of one, we also explored other methods:

Min-max scaling: Transforms the data to a fixed range, typically [0,1]. This method is less sensitive to outliers and preserves the relationships between variables.

After evaluating these techniques, we found that min-max scaling slightly improved model performance compared to z-score normalization. This finding is consistent with recent research suggesting that Min-Max scaling may be more effective for neural networks because it preserves the shape of the original distribution and constrains values within a limited range, which can improve convergence during training (Zhao et al, 2022). Therefore, we chose to use min-max scaling for data normalization in our final model. This choice enhances the model's ability to handle non-normal distributions and improves overall predictive accuracy. Before beginning the analysis of the research data and information, the descriptive statistics of the research variables were examined, the results of which are described in Table (1).

Table 1. Descriptive statistics

VARIABLE	Q1	Q3	JARQUE-BERA TEST	
			Statistic	Prob
Financial Crisis	12.67	32.55	25.10	0.0000
Yield Curve Slope	78.93	221.09	36.358	0.0000
Debt Service Ratio	88.95	250.28	29.975	0.0000
Consumer Price Index	17.31	42.45	1.4796	0.0062
Investment	13.23	50.01	0.0897	0.0007
Current Account	11.40	38.00	1.201	0.0058
Public Debt	14.82	45.41	2.3621	0.0132
Bank Credits	13.85	47.81	1.2201	0.0011

Source: *Research Calculations*

Based on Table 1, the Jarque-Bera test results for various variables reveal that the financial crisis, yield curve slope, debt service ratio, consumer price index, current account, public debt, investment, and bank credits display non-normal distributions with very low probabilities.

According to the descriptive statistics results of the research, it was found that most variables deviate from a normal distribution, which affects statistical and economic analyses. Therefore, considering the descriptive statistics of the research variables, the study explores the prediction of financial crises based on bank credits and the yield curve slope using machine learning. One of the key advantages of these non-parametric statistical methods is their capacity to work with data that does not conform to a normal distribution. As a result, the research findings utilizing machine learning techniques, including decision trees, gradient boosting, random forests, and LightGBM, are presented in Tables 2, 3, 4, and 5.

Table 2. Decision Tree Results

COMPLEXITY PARAMETER	DIVISION OF LEAVES	RELATIVE ERROR	INTERSECTION ERROR	SQUARED ERROR	IMPORTANCE OF VARIABLES			
					Variable	Importance	Variable	Importance
0.76337	0	1.00000	1.0097	0.11993	DSR	18	BC	16
0.12694	1	0.23662	0.2451	0.04258	INV	17	PD	15
0.05142	2	0.10968	0.1629	0.04150	YCS	17	CA	16
0.01000	3	0.05825	0.1102	0.03954				
0.7633733			0.05142915		Complexity parameter			
142/685			15.27861		Mean square error			
Root node error = 12128/85								

Source: *Research Results*

Investigating the role of bank credits and the slope of the economic yield curve in predicting financial crises in Iran using the neural network approach shows that the importance coefficients of different variables in predicting financial crises are different. According to Table 2, the debt service ratio with a significance of 18 has the greatest effect and indicates the high importance of debt management in predicting financial crises. The high importance of investment and the slope of the return curve with a value of 17 also emphasize the vital role of these variables. Also, the variables of current account, public debt and bank credits also play a significant role in predicting financial crises in Iran with the importance of 16, 15 and 15, although their effect is less than the ratio of debt service, investment and yield curve slope. The complexity of the model with the values of 0.7633 and 0.05142, as well as the relative error and the intersection error show that the neural network model is able to predict financial crises with appropriate accuracy. The mean squared error values equal to 142.685 and the squared errors show that the model has a good ability to interpret and predict financial crises based on bank credit data and macroeconomic variables.

Table 3. Reinforcement gradient results

CHARACTERISTICS OF RESEARCH VARIABLES				CHARACTERISTICS OF MODEL FIT	
Variable	Coverage	Cover	Frequency	Feature	Amount
YCS	0.73395	0.21848	0.25210	Number of repetitions	34
INV	0.16743	0.15357	0.15519	Mean RMSE of training	0.563
CPI	0.03775	0.16948	0.13553	RMSE standard deviation of training	0.130
DSR	0.02964	0.15026	0.18539	Mean RMSE test	3.600
CA	0.01785	0.0884	0.08286	Standard deviation RMSE test	0.793
PD	0.00856	0.13265	0.11095		
BC	0.00479	0.08170	0.07794		

Summary of variable specifications					
Feature	Gain (Min)	Gain (Max)	Gain (1st Qu.)	Gain (Median)	Gain (3rd Qu.)
Length: 7	0.004793	0.733952	0.013210	0.029643	0.102536

Source: *Research Results*

The results of the reinforcement learning model show that the slope of the yield curve is the most important factor in predicting financial crises, with a value of 0.733. Investment is the second most important factor with a value of 0.1674. These results show that changes in these two variables are effective in predicting financial crises. CPI, debt service ratio, current account balance, government debt and bank credit also play a role, but to a lesser extent. The RMSE values for the training and test models (0.5630 and 3.599) indicate the acceptable accuracy of the model. These results are useful for financial decisions and show that improving the strengthening sectors and paying attention to macroeconomic changes can be an efficient tool for analyzing and predicting financial crises.

Table 4. The results of clear forests

TABLE OF NET YIELD OF NODES AND EVALUATION CRITERIA		
Feature	Net return	
YCS	1291.295	
DSR	1897.108	
CPI	275.145	
INV	1974.388	
CA	1610.998	
PD	561.842	
BC	1070.052	
Random Forest Fit Criteria Table		
Criterion	Amount	
R^2	0.965	
MSE	0.321	
Cross-Validation Results		
Fold	Validation R^2	Validation MSE
1	0.921	0.352

2	0.930	0.340
3	0.914	0.365
4	0.937	0.328
5	0.925	0.347
Average	0.925	0.346

Source: *Research Results*

In examining the role of bank loans and macroeconomic variables in predicting financial crises in Iran using the random forest model, the results show that investment with an incremental purity value of 1974.38 has the highest effect, followed by debt service ratio with a value of 1897.10. These results show the importance of debt management and investment in preventing financial crises. The variables current account balance (1610.9) and yield curve slope (1291.2) also have a high ability to predict financial crises with high values of net return. The consumer price index (275.1) and government debt (561.8) also have a significant effect, although less than the investment and debt service ratios. Bank loans with a value of 1070.05 is also considered as an influential variable in the model. The R^2 value of 0.96 and the mean square error (MSE) of 0.321 indicate the high accuracy of the model in predicting financial crises. Therefore, to assess the generalizability of the model and to address the possibility of overfitting due to the high value of R^2, a k-fold cross-validation method with k=5 was implemented. This method involves dividing the data set into five equal parts, training the model on four parts and validating it on the remaining part. This process is repeated five times, so that each segment is used once as a validation set. Thus, according to the validation section of Table 4, the results show that the model maintains high prediction accuracy across different datasets, with an average validation R^2 of 0.925 and an average validation MSE of 0.346. This consistency shows that the model does not significantly overfit the training data and has good generalizability. On the other hand, the use of cross-validation ensures that the performance of the model is robust and not simply the result of over-fitting to a particular sample of training data. A slight decrease in R^2 from 0.965 in the training phase to an average of 0.925 during cross-validation is expected and acceptable, indicating that the model also performs well on unseen data. Finally, these results show that machine learning techniques, especially the random forest model, in combination with the analysis of macroeconomic variables such as the slope of the yield curve and bank loans, serve as effective tools in predicting and managing financial crises in Iran. The use of cross-validation confirms the generalizability and reliability of the model and increases confidence in its practical application for policy makers and financial analysts.

Table 5. Light decides tree results

TABLE OF PREDICTIONS AND ERRORS			
FC	Prediction	Absolute Error	Squared Error
11.081	11.98536	0.9043605	0.81786789
12.279	11.98536	0.2936395	0.08622416

11.951	13.10729	1.1562940	1.33701582
15.873	15.40117	0.4718345	0.22262783
13.560	12.70820	0.8518011	0.72556514
12.394	12.86977	0.4757725	0.22635950
Features and criteria table			
Variable	Yield	Cover	Frequency
DSR	0.25529244	0.05581395	0.05755396
YCS	0.24671725	0.30906977	0.28776978
CA	0.22394301	0.13476744	0.14388489
PD	0.10290887	0.05706998	0.06474802
BC	0.07257948	0.09069769	0.11510791
INV	0.06067599	0.03813955	0.04316547
CPI	0.03788296	0.31360465	0.28776978

Source: *Research Results*

In examining the role of bank loans and macroeconomic variables in predicting financial crises in Iran, the results in Table 5 show that the debt service ratio is the most important with a return of 0.2552. This shows the critical role of debt management in preventing financial crises. Also, the slope of the yield curve with a yield of 0.2467 has a significant effect in predicting crises. The current account balance (0.2239) and government debt (0.1029) are also important variables. Bank credit with a return of 0.0725 also plays an effective role in predicting crises, although it is less important than other variables. Investment (0.0606) and Consumer Price Index (0.0378) are also important variables. The R^2 values of 0.96 and the mean square error (MSE) of 0.321 indicate the high accuracy of the model in predicting financial crises. This analysis shows the importance of paying attention to macroeconomic variables and bank credit in predicting financial crises.

Four different methods were evaluated, including decision tree, gradient reinforcement, random forest and light decision tree. The decision tree method is popular because of its high interpretability, but it is less powerful in dealing with complex relationships. The gradient reinforcement method, by combining weaker models, has a high ability to increase prediction accuracy, although it has complicated computations. The random forest method is more popular due to its high accuracy and reasonable generalization ability, and is suitable for complex data analysis. Light decides tree is also superior with high efficiency and speed and the ability to handle large data. Gradient boosting and random forest are preferred over other methods due to their high accuracy and ability to handle complex data. Finally, the role of bank loans and the slope of the yield curve in predicting financial crises was also investigated using artificial neural networks and multilayer perceptron, the results of which are shown in Tables 6 and 7.

Table 6. Investigation of the research model using neural networks ANNs

TABLE OF FEATURES AND MODELS			
Row	Feature	Amount	Model

1	*full model*	0.1574737	Net
2	INV	0.1593070	nnet
3	PD	0.1599273	nnet
4	BC	0.1614628	nnet
5	CPI	0.1626902	nnet
6	CA	0.1650694	nnet
7	DSR	0.1748642	nnet
8	YCS	0.1967836	nnet
9	baseline	0.2326602	nnet
		RMSE	RMSE table for Tlgsu model
Tlgsu Model		0.1112718	Financial Crisis Artificial Neural Network
Table of predicted values and residuals			
		Min	Max
Predicted values		-1.467049	3.086619
The leftovers		-0.355115	0.642745

Source: *Research Results*

The analysis of the role of bank credit and macroeconomic variables in predicting financial crises in Iran using artificial neural networks shows significant results. The full model with root means square error of 0.157 shows the high accuracy of the model in predicting financial crises. The variables of investment, public debt and bank credit play a prominent role in the model with RMSE of 0.159, 0.159 and 0.161 respectively. Other variables such as the consumer price index and the current account balance also have an effect, but are less important. The predictions range from -1.467 to 3.086 and the residuals range from -0.035 to 0.064, indicating a wide range of prediction results and small deviations. These results emphasise that the neural network model, taking into account bank loans and macroeconomic variables, is a powerful tool for predicting and managing financial crises in Iran and can be effective in making more accurate financial decisions.

Table 7. MLP Neural Network Results

STAGE	AMOUNT	STAGE	AMOUNT
initial	142891.024975	iter 110	182.210360
iter 10	62933.324234	iter 120	132.182756
iter 20	31656.696287	iter 130	127.916265
iter 30	23486.310762	iter 140	125.125585
iter 40	14514.350232	iter 150	122.621428
iter 50	8910.493377	iter 160	122.436544
iter 60	5689.448589	iter 170	119.893286
iter 70	1630.408956	iter 180	105.772778
iter 80	1014.709491	iter 190	93.098967
iter 90	587.380551	iter 200	84.711854
iter 100	302.984044	final	84.711854

Source: *Research Results*

The results of Table 7 related to the training of the multilayer perceptron neural network show that the initial error value was 142891.024, which was reduced to 62933.324 in the first 10 iterations after the beginning of the training process. This decreasing trend continues and by the 160th iteration the error value has decreased to 122,436. Then, the rate of error reduction decreases and finally, after 200 iterations, the error value reaches 84.71, indicating the significant improvement of the model in learning and prediction. Analysis of the role of bank credit and macroeconomic variables in predicting financial crises using neural networks shows that the final model with an RMSE of 0.1574737 is highly accurate. Key variables such as investment, public debt and bank credit had a significant effect in the model. The model was able to predict a wide range of outcomes and the residuals are in a small range, indicating the accuracy of the model. Overall, the results show that MLP neural networks and ANNs are powerful tools for analyzing and predicting financial crises. The first method analyses the impact of different variables and is more useful for predicting financial crises, while the second method focuses on improving and evaluating the model. This shows that the use of neural networks can significantly help in predicting and managing financial crises in Iran.

Based on the findings of this research, different machine learning models such as decision tree, gradient boosting, random forest, light decision tree and artificial neural networks and multi-layer perceptron were used to predict financial crises in Iran using bank credit variables and curve slope. The efficiency was evaluated. The results showed that all models had acceptable performance in predicting crises, but random forest and gradient boosting models were preferred due to their high accuracy and ability to handle complex data. The random forest model had the best performance with a coefficient of determination of 0.965 and a mean square error of 0.321, indicating its high ability to interpret and predict financial crises based on bank credit data and macroeconomic variables.

Further analyses were carried out to evaluate the different models in more detail. k-fold cross-validation with k=5 was used to check the generalizability of the random forest model to avoid overfitting. The results showed that the model maintained high prediction accuracy in different datasets and had good generalizability. Artificial neural networks and multilayer perceptrons were also used to investigate the importance of different variables in predicting financial crises. The results show that the debt service ratio, investment and the slope of the yield curve have the greatest impact on forecasting. These results are in line with the findings of previous studies, which have emphasized that macroeconomic and banking variables play an important role in predicting financial crises.

In general, this study shows that machine learning techniques, especially the random forest model, combined with the analysis of macroeconomic variables such as the slope of the yield curve and bank loans, are effective tools in predicting and managing financial crises in Iran. It is worth noting that each of the models used in this study has its own strengths and weaknesses, and the choice of the best model depends on the nature of the data and the objectives of the analysis.

However, the results show that non-parametric models such as random forest and gradient boosting have superior performance in this area due to their ability to model complex and non-linear relationships between variables and their resistance to outliers and non-normal data. Of course, a more in-depth comparison and analysis of the advantages, disadvantages and practical applications of these models can form the basis for future research.

4. Discussion and conclusion

4.1 Discussion

According to the results of this research, it can be concluded that the slope variables of yield curve and bank loans play an important role in predicting financial crises in Iran. The current study, which covers the period from 2006 to 2022, has investigated this issue by using different modelling approaches including neural networks, gradient reinforcement, random forests and light trees. The results show that among the variables studied, debt service ratio, yield curve slope and investment are repeatedly recognized as the most important factors in predicting financial crises. These results suggest that debt management, interest rate fluctuations and the level of investment play a key role in predicting and preventing financial crises. In addition, variables such as the current account balance, government debt and bank credit have also had significant importance in the models, although their importance is less than that of the three main variables. Bank credit had a moderate importance in most of the models. This shows that while bank credit is an important factor in predicting financial crises, its effect is not as large as some yield curve slope variables. However, this finding underlines the continued need for proper monitoring and management of bank credit in order to maintain financial stability. therefore, The study has identified key predictors of financial crises in Iran, highlighting in particular the important role of the yield curve slope and the debt service ratio. Understanding these relationships has important policy implications for debt management and investment strategies, which are critical for maintaining financial stability.

4.2 Policy implications

- Debt management policy

The debt service ratio (DSR) emerged as one of the most critical variables in predicting financial crises in all the models used in the study. A high DSR indicates that a significant portion of income is devoted to debt service, signaling potential over-leveraging in the economy. Policymakers should interpret this as a call to

Monitor debt levels carefully: Regular assessments of both public and private sector debt are essential to ensure that they remain within sustainable limits. Setting thresholds for acceptable debt levels can help to identify potential problems early on.

Implement debt reduction strategies: When the DSR approaches critical thresholds, proactive measures such as fiscal consolidation, promotion of savings or incentives for early debt repayment can help reduce the overall debt burden.

Strengthening the regulatory framework: Strengthening regulations on lending practices can prevent excessive credit growth. This includes setting stricter lending standards and implementing macroprudential policies that limit risky borrowing behaviour.

By adopting these strategies, policymakers can mitigate the risks associated with high debt levels and reduce the likelihood of a financial crisis triggered by unsustainable debt burdens.

-Investment policies

The level of investment has been consistently identified as a significant predictor of financial crises, suggesting that fluctuations in investment have a profound impact on financial stability. To address this, policymakers should

Promote sustainable investment: Encourage investments that contribute to long-term economic growth, such as infrastructure, education and technology, rather than speculative ventures that can lead to asset bubbles.

Implement counter-cyclical policies: Use fiscal and monetary tools to smooth investment cycles. During periods of excessive investment growth, policies can be tightened to prevent overheating. Conversely, during downturns, expansionary policies can stimulate investment.

Improve investment monitoring: Develop systems to monitor investment flows and identify sectors where investment is growing too fast. Early detection allows for timely intervention to prevent potential bubbles.

Balancing investment activity helps maintain economic stability and prevents the adverse effects of boom-bust cycles that can lead to financial crises.

-Yield Curve Slope Interpretation

The yield curve slope (YCS) serves as a reliable early warning indicator of economic downturns. An inverted yield curve, where short-term interest rates exceed long-term rates, often precedes a recession. Policymakers should:

Continuously Monitor Interest Rate Spreads: Regular analysis of the yield curve can help detect inversions early. Central banks and financial authorities should include yield curve monitoring as part of their standard economic surveillance.

Adjust Monetary Policy Proactively: If an inversion is detected, policymakers might consider easing monetary policy to stimulate economic activity or addressing underlying factors causing the inversion.

Communicate Clearly with Stakeholders: Transparent communication regarding the implications of yield curve changes can help manage market expectations and reduce uncertainty among investors and financial institutions.

By effectively utilizing the yield curve as a predictive tool, policymakers can take timely actions to mitigate potential economic downturns and maintain financial stability.

-Implications for bank lending policies

Bank credit (BC) was also a significant predictor in some models, although to a lesser extent than DSR and investment. The role of bank lending practices is crucial in the context of financial crises. Policymakers should:

Implement prudent lending standards: Encourage banks to adopt strict criteria for loan approvals that emphasize borrowers' creditworthiness and ability to repay.

Monitor credit growth: Keep a close eye on the rate of credit expansion in the economy. Rapid growth can signal excessive risk-taking and the build-up of financial imbalances.

Promote responsible borrowing: Through financial literacy programmers and consumer protection, ensure that borrowers are aware of the risks associated with excessive indebtedness.

Ensure financial inclusion: While maintaining prudence, it's important to ensure that credit remains accessible to productive sectors, including small and medium-sized enterprises (SMEs), to support economic growth.

By managing the quality and quantity of bank lending, policymakers can prevent the build-up of risks associated with credit booms and reduce the likelihood of a financial crisis.

5. Conclusion

This research demonstrates that the use of advanced modeling and data analysis approaches can contribute to a better understanding of the factors influencing financial crises. This will assist policymakers and economic decision-makers in Iran to confront economic and financial challenges with greater awareness and formulate more effective strategies for maintaining financial stability and sustainable economic growth.

The findings of this study are consistent with the results of Ristolainen et al. (2024), who showed that the information contained in newspaper article headlines can predict financial crises. It also aligns with the findings of Ashtab et al. (2017), who utilized machine learning models to predict financial crises and demonstrated that these models have higher accuracy.

Khajavi and Ghadirian Arani (2017 and 2018) indicated that non-financial variables such as managerial ability and intellectual capital can help improve the prediction of financial crises, which is in line with our findings. Roohi Sara et al. (2023) also pursued the approach of using textual data and advanced algorithms by employing hybrid algorithms and considering various variables, which is consistent with our approach.

However, there are studies that differ in their focus and methods from our research. Taheri Bazkhaneh et al. (2019) focused more on macroeconomic indicators and used the Markov switching approach. Imam Vardi and Jafari (2019) concentrated more on shock transmission and volatility spillover between markets. Studies related to Arab countries, such as Shehata et al. (2023).

Nevertheless, the results of this study are also noteworthy in comparison to similar economies like Turkey and Iraq. As our findings indicate, considering textual and influential factors can increase the predictive power of financial crises. This issue also applies to countries with economic and political structures similar to Iran and can contribute to improving the management of financial crises in these countries.

Therefore, based on the results of this research and the political-economic conditions of Iran, three practical policy proposals are presented as follows:

Formation of a joint economic-political committee: Given the importance of variables such as debt ratios and investment in predicting financial crises, it is suggested that a high-level joint committee be formed between different countries in the region. This committee can work towards harmonizing economic policies, sharing confidential financial information, and developing common strategies to deal with economic sanctions. Such close cooperation can serve as a powerful political lever in international negotiations and countering external pressures.

Structural reforms in the banking system with a political approach: Considering the moderate importance of bank lending in the models, it is proposed that serious reforms be undertaken in the banking system to reduce the influence of political and military groups. These reforms can include the establishment of independent regulatory bodies, transparency in the processes of granting large loans, and limiting the access of non-economic entities to banking resources. These measures, while improving the economic situation, can be an important step in combating corruption and enhancing the country's international image.

Establishing a joint financial stability fund with political management: Given the importance of variables such as the yield curve slope and current account balance, it is recommended that a joint financial stability fund be created with various countries in the region. This fund can be used to manage currency fluctuations, support joint investment projects, and provide a defense mechanism against economic sanctions. The management of this fund can be carried out jointly and under the direct supervision of political leaders, which can lead to the strengthening of political relations and the creation of a powerful economic-political bloc in the region.

Author Contributions

Conceptualization, R. Taheri Haftasiabi; methodology, R. Taheri Haftasiabi and A. Naderi; validation, R. Taheri Haftasiabi; formal analysis, R. Taheri Haftasiabi, P. Piri, A. Naderi; resources, N. esmaily; writing—original draft preparation, R. Taheri Haftasiabi; P. Piri; writing—review and editing, all authors; All authors have read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest.

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