

# Developing a Credit Risk Stress-Testing Model under Alternative Scenarios

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**Abstract:** Banks, as a major component of the financial system, play a critical role in financing the production, commercial, consumer, and even governmental sectors. The banking industry is of considerable importance in the Iranian economy because, due to the insufficient development of the capital market, the money market—operating primarily through the banking system—has effectively assumed responsibility for providing both long-term and short-term financing to firms. Credit risk arises when borrowers, either intentionally or unintentionally, are unable to repay their loan installments and other financial obligations to banks. The level of credit risk in Iran is considered critical when compared with the global average. The objective of the present study was to develop a credit risk stress-testing model under alternative scenarios for banks. EViews Version 10 was employed to conduct the econometric analyses. One of the most important findings of the study was that the coefficient of determination ( $R^2$ ) for the GARCH model examining fluctuations between the study's target variable and the economic growth rate, interest rate, unemployment rate, inflation rate, and per capita income growth rate was calculated as 0.978. Furthermore, the  $R^2$  for the GARCH model incorporating the liquidity growth rate, oil revenue growth rate, bank deposit rate, and exchange rate was calculated as 0.891. These results indicate the very high predictive power of the econometric models developed in this study.

**Keywords:** financial crisis; macroeconomics; credit risk.

## 1. Introduction

Banks constitute one of the central pillars of modern financial systems because they mobilize savings, allocate credit, facilitate investment, support consumption, and provide the liquidity required for productive and commercial activity. Their ability to perform these functions efficiently depends heavily on the quality of their credit portfolios and on the effectiveness with which they identify, measure, price, monitor, and control credit risk. Credit risk, broadly defined as the possibility that a borrower or counterparty will fail to meet contractual financial obligations in full and on time, is therefore among the most consequential risks facing banking institutions. Its importance extends beyond the balance sheet of an individual bank because widespread deterioration in asset quality can constrain lending, weaken profitability, erode capital adequacy, reduce confidence in financial intermediaries, and amplify macroeconomic instability. Evidence from international banking markets confirms that credit risk is closely linked to bank profitability, and that deterioration in credit quality may materially affect earnings performance and the resilience of banking institutions across different institutional and regulatory settings [1]. In the Iranian banking

context, this issue is particularly important because banks retain a dominant role in financial intermediation, and changes in financing structures and credit-risk exposure can significantly influence their operating and financial performance [2]. Credit-risk management should consequently be understood not simply as a loan-level screening activity but as a strategic function integrating portfolio composition, capital allocation, macroeconomic conditions, borrower characteristics, governance mechanisms, and forward-looking risk assessment. Research focusing on Iranian private banks has likewise highlighted the interdependence between corporate governance, capital adequacy, and credit-risk exposure, reinforcing the view that credit risk is embedded in broader institutional and managerial structures rather than being an isolated operational variable [3]. Moreover, the relationship between corporate governance and financial performance may itself be conditioned by credit risk, indicating that effective governance structures can influence organizational outcomes partly through their capacity to constrain or mitigate risk-taking behavior [4].

The management of credit risk has become more challenging as banking portfolios have become increasingly exposed to macroeconomic volatility, structural changes in financial markets, environmental shocks, interconnected balance sheets, and rapidly changing borrower behavior. Traditional credit assessment approaches commonly rely on historical financial ratios, repayment records, collateral values, and borrower-level indicators; however, these variables may provide an incomplete basis for assessing portfolio vulnerability when economic conditions change abruptly. Credit quality is inherently state-dependent: economic contractions, inflationary pressures, interest-rate shocks, exchange-rate depreciation, unemployment, income losses, and liquidity constraints can simultaneously weaken borrowers' debt-servicing capacity and alter the value of collateral and other credit-risk mitigants. Studies examining the relationship between financial development, economic growth, and credit-risk indicators have demonstrated that credit conditions may change across different economic regimes, implying that linear and static models may fail to capture important shifts in the underlying risk process [5]. Similar concerns arise at the sovereign level, where synchronization between credit and financial cycles can materially influence sovereign credit risk and can strengthen the transmission of shocks across markets and sectors [6]. Credit risk can also be transmitted through shocks that are not traditionally classified as financial. For example, empirical evidence on natural disasters indicates that severe physical shocks may affect sovereign creditworthiness and generate contagion effects, illustrating how exogenous disturbances can propagate into financial-risk measures through fiscal, macroeconomic, and market channels [7]. At the same time, emerging transition risks associated with environmental and energy restructuring are altering the composition of bank portfolios. Concentration in carbon-intensive assets can interact with both capitalization and credit risk, while portfolio efficiency may depend increasingly on how banks manage exposures arising from the transition toward lower-carbon economic structures [8]. Conversely, the expansion of renewable energy may affect bank credit risk indirectly through economic-growth channels, indicating that macroeconomic development and sectoral transformation can mediate the relationship between environmental investment patterns and financial stability [9].

These developments have increased the importance of stress testing as a forward-looking component of credit-risk management. Unlike conventional risk measures that predominantly summarize historical or current portfolio conditions, stress testing evaluates the consequences of adverse but plausible scenarios by estimating how changes in economic and financial variables may influence credit losses, default probabilities, nonperforming exposures, capital positions, or other measures of financial soundness. A credit-risk stress-testing framework can therefore help banks move beyond point-in-time assessments by examining the sensitivity of their credit portfolios to combinations of macroeconomic shocks. Such an approach is particularly valuable when relationships among risk

factors are nonlinear, dynamic, or regime-dependent. Macroeconomic stress testing typically requires explicit specification of the channels through which variables such as gross domestic product growth, unemployment, inflation, interest rates, liquidity conditions, exchange rates, deposit rates, and sectoral income influence borrower repayment capacity and portfolio performance. The selection and calibration of these variables should be grounded in both economic theory and empirical evidence. Research on credit-risk measurement in Iran has emphasized the relevance of firm characteristics, ownership structures, capital adequacy, and dynamic estimation methods such as the generalized method of moments, illustrating the importance of models capable of accounting for persistence, heterogeneity, and endogeneity in financial-risk relationships [10]. Likewise, research on the management of guarantees and collateral in bank lending has shown that deficiencies in collateral valuation, legal enforceability, documentation, and monitoring can undermine credit-risk control, which means that portfolio vulnerability cannot be adequately understood solely through default frequencies without considering institutional mechanisms that influence loss severity and recovery prospects [11]. Accordingly, stress-testing models should be sufficiently flexible to incorporate both macroeconomic conditions and structural features of banking systems, particularly in economies where financial intermediation remains concentrated in banks and where credit-market frictions may amplify macroeconomic shocks.

Recent advances in data science have substantially expanded the methodological landscape of credit-risk assessment. Machine-learning models are increasingly used to identify nonlinear associations, complex interactions, latent risk structures, and high-dimensional patterns that conventional statistical models may overlook. Comparative research applying logistic regression, artificial neural networks, and support vector machines has demonstrated the usefulness of machine-learning techniques in distinguishing credit-risk categories and improving predictive performance under certain data structures [12]. Evidence from Turkish participation and conventional banks similarly suggests that machine-learning approaches can provide effective tools for credit-risk modeling, although their relative performance may depend on institutional characteristics, data availability, and the composition of banking systems [13]. A broader systematic review of machine learning and metaheuristic methods for individual credit-risk assessment has shown substantial growth in the application of computational intelligence to borrower classification and risk prediction, while also highlighting continuing issues related to feature selection, model validation, class imbalance, interpretability, and external generalizability [14]. Analytical comparisons of machine-learning models further demonstrate that model choice, data preprocessing, hyperparameter configuration, and validation procedures materially affect prediction quality, meaning that methodological sophistication must be accompanied by careful attention to robustness and practical usability [15]. For credit environments with limited labeled observations, semi-supervised approaches combining label propagation and complex-network methods can also expand the information available for credit classification and improve risk inference when conventional supervised learning is constrained by insufficient default labels [16]. These developments indicate that contemporary credit-risk analysis is increasingly moving toward hybrid and data-intensive frameworks, yet they also underscore the need to maintain clear links between predictive accuracy, economic interpretation, and managerial decision-making.

The latest generation of credit-risk research has extended these developments through deep learning, ensemble learning, network-based analysis, and artificial intelligence. Models combining ensemble learning and deep-learning architectures with three-way decision mechanisms seek to improve classification by distinguishing cases that can be confidently accepted or rejected from those requiring further evaluation, thereby addressing uncertainty more explicitly in credit decisions [17]. Graph convolutional networks have also been employed to model relational

structures among borrowers and financial entities, offering an alternative to conventional independent-observation assumptions by recognizing that credit risk may be transmitted or clustered through economic and financial connections [18]. Bayesian networks and machine-learning approaches similarly allow credit-risk assessment to incorporate probabilistic dependency structures, providing a framework through which interrelationships among financial indicators can be represented more explicitly and used for prediction under uncertainty [19]. Other dynamic approaches draw on self-exciting point processes, such as Hawkes processes, to identify temporal clustering and endogenous propagation in credit events, emphasizing that defaults and deterioration in credit quality may emerge through dynamic patterns rather than independent occurrences [20]. The expansion of artificial intelligence in this domain is reflected in scientometric evidence showing that AI-supported credit-risk assessment has become a major interdisciplinary research frontier, connecting banking, finance, decision science, explainable artificial intelligence, and advanced predictive analytics [21]. However, increasingly complex models create a significant interpretability problem. Systematic research on interpretable large language models and related explainability approaches in credit risk stresses that financial institutions require not only accurate predictions but also transparent reasoning, traceable decision criteria, and outputs that can withstand regulatory and managerial scrutiny [22]. Thus, the frontier of credit-risk analytics is characterized by a dual imperative: models must become more capable of detecting complex patterns while remaining sufficiently interpretable to support risk governance, regulatory compliance, and accountable banking decisions.

Despite the rapid expansion of artificial-intelligence-based credit scoring, traditional econometric models continue to play an essential role in stress testing because they provide interpretable relationships between macroeconomic variables and financial outcomes, particularly when the objective is scenario analysis rather than individual borrower classification. Stress testing is fundamentally concerned with conditional behavior: how the credit portfolio is expected to respond when one or more macroeconomic variables move beyond their normal historical ranges. For this purpose, models that capture volatility, persistence, and time-varying variance are especially relevant. Generalized Autoregressive Conditional Heteroskedasticity models offer an established framework for modeling volatility clustering and changing conditional variance, characteristics that frequently appear in macrofinancial time series. Although GARCH methods were initially developed primarily for financial-market volatility, the logic underlying conditional heteroskedasticity is applicable to broader risk processes in which periods of relative stability are followed by periods of substantially elevated volatility. Their use in a credit-risk stress-testing framework can therefore help distinguish average relationships from instability in the variance process and can provide additional information concerning how risk intensifies under changing macroeconomic conditions. This is especially pertinent where the banking sector is exposed to simultaneous movements in real activity, inflation, interest rates, exchange rates, liquidity growth, oil-related revenues, and deposit-market conditions. In economies characterized by significant dependence on commodity revenues and banking-based financing, interactions among these variables may generate nonlinear or clustered changes in credit conditions. Moreover, the increasing attention given to environmental, social, and governance dimensions of creditworthiness suggests that the universe of relevant risk drivers is expanding. Research on local ESG ratings and default distance, for example, indicates that context-specific ESG assessments can contribute meaningful information to credit-risk evaluation and may outperform less locally grounded measures in particular institutional environments [23]. This broader evidence supports the principle that effective risk models should be adapted to the structural and institutional characteristics of the financial system under investigation rather than transferred mechanically across countries.

For Iran, the development of a context-sensitive credit-risk stress-testing framework is particularly important because macroeconomic volatility, banking-sector concentration, financing constraints, inflationary episodes, exchange-rate movements, and dependence on oil revenues can jointly affect both borrower solvency and bank balance-sheet resilience. Iranian banks operate within an environment in which credit allocation, interest and deposit conditions, macroeconomic policy, and the structure of financial intermediation are closely interconnected. Therefore, analyzing credit risk exclusively through borrower-specific indicators may underestimate the role of systematic factors that simultaneously influence large segments of the loan portfolio. Domestic studies have already documented the importance of financing structure for bank performance [2], the significance of governance and capital adequacy for bank risk [3], the mediating role of credit risk in organizational financial outcomes [4], the value of dynamic estimation in credit-risk and capital-adequacy analysis [10], and the need to improve institutional mechanisms associated with guarantees and collateral [11]. Nevertheless, these streams of research do not eliminate the need for a unified macroeconomic stress-testing model capable of evaluating the sensitivity of a bank credit portfolio under multiple adverse scenarios. Such a model should connect the probability of default and credit-portfolio vulnerability to movements in variables representing economic growth, interest rates, unemployment, inflation, per capita income growth, liquidity growth, oil revenue growth, deposit rates, and exchange rates. This approach is consistent with contemporary international research emphasizing the interaction between credit risk and macroeconomic cycles [6], structural and environmental shocks [7, 9], evolving portfolio composition [8], and increasingly sophisticated predictive architectures [17-19]. At the same time, an econometric stress-testing framework offers a degree of interpretability that is particularly valuable for policy analysis and bank management, enabling decision-makers to identify which macroeconomic variables are most strongly associated with changes in credit-portfolio risk and to evaluate the potential magnitude of stress under alternative scenarios.

The methodological gap is therefore not simply a lack of credit-risk prediction models, because the literature now contains an extensive range of statistical, econometric, machine-learning, network-based, and artificial-intelligence approaches [14, 15, 21]. Rather, the key challenge is to develop a framework that is simultaneously macroeconomically grounded, empirically estimable, scenario-sensitive, interpretable, and adapted to the characteristics of the Iranian banking system. Individual credit-scoring algorithms are typically designed to distinguish high-risk from low-risk borrowers, whereas macroprudential and portfolio-level stress testing requires a different analytical orientation: the objective is to determine how aggregate or portfolio credit risk changes when the economic environment deteriorates. Similarly, highly complex predictive models may achieve superior classification performance but may be less transparent for scenario construction and policy interpretation, an issue that has become increasingly salient as explainability and model governance receive greater attention in advanced credit-risk analytics [22]. The need to accommodate limited or imperfect data also remains important, as highlighted by methods specifically designed for credit-risk assessment under limited labeled information [16]. Furthermore, dynamic temporal dependence must be considered because credit deterioration may cluster in periods of economic stress rather than occur as independent events, an insight consistent with event-intensity approaches to credit-risk identification [20]. Regime changes in the relationship between financial development, growth, and credit risk also suggest that the effects of explanatory variables may differ across macroeconomic states [5]. Taken together, these considerations provide a strong rationale for using scenario-based econometric stress testing to complement borrower-level risk assessment and advanced predictive analytics, particularly where the primary managerial question concerns the resilience of an entire bank credit portfolio under adverse macroeconomic conditions.

Accordingly, the aim of this study is to develop and empirically evaluate a credit risk stress-testing model for the banking industry under alternative macroeconomic scenarios by examining the effects of GDP growth, interest rates, unemployment, inflation, per capita income growth, liquidity growth, oil revenue growth, bank deposit rates, and exchange rates on the bank credit portfolio and the probability of default.

## 2. Methods and Materials

The procedure adopted to design and explain the credit risk stress-testing model for the banking industry under alternative macroeconomic scenarios involved the use of scientific documents and reports, together with the analysis of panel data derived from financial reports and banking-industry datasets based on statistics concerning nonperforming loans in the banking network, expressed as normalized rates of change. Econometric analyses were performed using EViews. In terms of its purpose, the present study is applied research, whereas in terms of data collection it can be classified as survey-based and exploratory research. Because all of the research objectives were directed toward obtaining the knowledge required to address a specific and identified practical need, the study is categorized as applied research in terms of its intended use. From a temporal perspective, the research is cross-sectional because the data required to test the research questions were collected within a specified period. This section examines all stages of the research methodology because selecting an appropriate research method guides the researcher toward procedures that facilitate more accurate and efficient answers to the research questions. For the modeling component of the present study, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) econometric model was estimated using panel data obtained from economic reports on the banking industry in the EViews econometric environment. Accordingly, in terms of purpose, the research may more specifically be characterized as applied-modeling research because, on the one hand, it provides a detailed description of the concepts and principles associated with designing and explaining a credit risk stress-testing model for the banking industry under alternative macroeconomic scenarios and, on the other hand, the relationships among these concepts and principles are evaluated and determined by experts.

To collect information concerning the research background, library documents and records, information obtained from online databases, reputable domestic and international journals, and other sources related to the research subject were used. The principal data-collection instruments employed in this study were questionnaires and datasets. In addition to the documents and reports used for research modeling, annual panel and time-series data derived from economic reports and banking-industry datasets covering the period from 1991 to 2016—a 26-year annual time series—were analyzed using EViews. The statistical population of the study consisted of banking-industry experts and documents, as well as professors and students in economics, banking, financial management, accounting, and financial and industrial engineering. In designing and explaining the credit risk stress-testing model for the banking industry under macroeconomic scenarios, econometric modeling was applied. Where instrumental-variable estimation was required, the generalized method of moments (GMM) framework was used, whereas volatility dynamics were modeled through GARCH specifications. Econometrics is concerned with the systematic study of economic phenomena using observed data. In other words, econometrics integrates statistics, economic theory, and mathematics. Within dynamic panel estimation, lagged variables may be employed as instruments to address the correlation between lagged dependent variables and the error term. Because the consistency of GMM estimators depends on the validity of the instruments employed, the statistics proposed in the Arellano–Bond, Blundell–Bond, and Arellano–Bover frameworks can be used to assess model validity. The Sargan test, in particular, evaluates the overall validity of the instrumental variables included in the model.

The stages of the research were as follows:

1. **Review of the theoretical foundations:** Identification of the input and output components of the research model.
2. **Data collection:** Collection of data from the Securities and Exchange Organization, the Ministry of Economic Affairs and Finance, and the Central Bank according to the variables specified in the econometric model.
3. **Econometric estimation:** Estimation of the GARCH econometric model in the EViews environment.
4. **Conclusion and model development:** Modeling the bank credit portfolio to reduce the probability of default.

The principal capabilities of the EViews econometric environment include:

- Calculation and construction of time-series variables.
- Linear and nonlinear estimation of single-equation systems and simultaneous-equation systems.
- Use of matrices and built-in software functions.
- Estimation of econometric models using techniques such as vector autoregression (VAR), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and ordinary least squares (OLS).
- Application of various diagnostic tests to evaluate estimation accuracy and examine errors, correlation, structural breaks, and related econometric problems.
- Programming capabilities within the software environment for the analysis of macroeconomic systems.

### 3. Findings and Results

At this stage, the data relating to the study entitled “Developing and Explaining a Credit Risk Stress-Testing Model for the Banking Industry under Macroeconomic Scenarios Using EViews Econometric Software” were presented and analyzed through graphs, tables, figures, and similar analytical tools so that each finding, together with the overall trend of changes, could be summarized and explained. Using panel data derived from financial reports and datasets of the banking industry based on statistics on nonperforming loans in the banking network, measured in terms of normalized rates of change, annual data covering 1991–2016, representing a 26-year time series, were analyzed. The analysis examined the relationship between the “bank credit portfolio for reducing the probability of default” and the GDP growth rate factor (A1), interest rate factor (A2), unemployment rate factor (A3), inflation rate factor (A4), and per capita income growth rate factor (A5). In addition, the relationships between the liquidity growth rate factor (B3), oil revenue growth rate factor (B1), bank deposit rate factor (B4), and exchange rate factor (B2), on the one hand, and the bank credit portfolio aimed at reducing the probability of default, on the other hand, were investigated in the EViews environment. The preliminary descriptive statistics and econometric characteristics of the research dataset are presented in Table 1 and Figure 1.

**Table 1. Descriptive Statistics and Preliminary Econometric Analysis of the Dataset**

| Preliminary Dataset Analysis | GDP Growth Rate (A1) | Interest Rate (A2) | Unemployment Rate (A3) | Inflation Rate (A4) | Per Capita Income Growth Rate (A5) |
|------------------------------|----------------------|--------------------|------------------------|---------------------|------------------------------------|
| Mean                         | 0.51                 | 0.34               | 3.28                   | 2.74                | 0.34                               |
| Maximum                      | 1.05                 | 0.58               | 5.66                   | 8.67                | 0.58                               |
| Minimum                      | 0.24                 | 0.14               | 1.38                   | 0.55                | 0.14                               |
| Standard deviation           | 0.23                 | 0.10               | 1.45                   | 2.79                | 0.10                               |
| Probability                  | 0.13                 | 0.79               | 0.34                   | 0.03                | 0.79                               |
| Observations                 | 26                   | 26                 | 26                     | 26                  | 2.74                               |

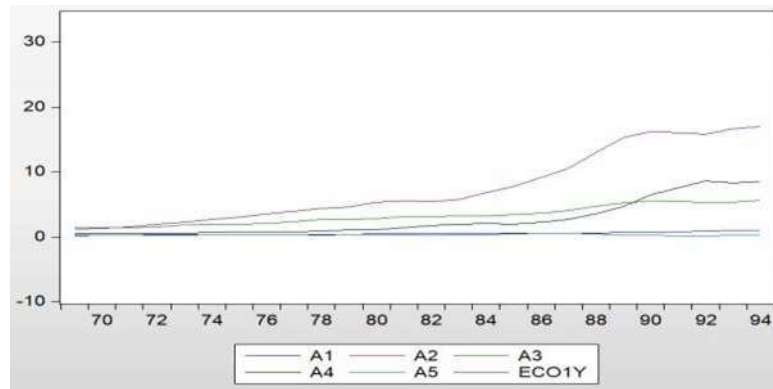


**Figure 1. Fluctuations between the target variable and the independent variables of the study.**

Analysis of the preceding graphs indicates that, based on panel data derived from the financial reports and datasets of the banking industry, the inflation rate factor (A4) experienced the greatest increase between 2010 and 2015. By contrast, the GDP growth rate factor (A1) and the per capita income growth rate factor (A5) remained relatively stable during the same period. Additional econometric analyses concerning fluctuations between the target variable and the independent variables of the study, together with the preliminary econometric analysis of the research dataset, can be evaluated on the basis of the preceding figure and table. Further descriptive statistical and preliminary econometric analyses of the research dataset are presented in Table 2 and Figure 2.

**Table 2. Descriptive Statistics and Preliminary Econometric Analysis of the Dataset**

| Preliminary Dataset Analysis | Oil Revenue Growth Rate (B1) | Exchange Rate (B2) | Liquidity Growth Rate (B3) | Bank Deposit Rate (B4) |
|------------------------------|------------------------------|--------------------|----------------------------|------------------------|
| Mean                         | 2.74                         | 3.28               | 0.34                       | 0.51                   |
| Maximum                      | 8.67                         | 5.66               | 0.58                       | 1.05                   |
| Minimum                      | 0.55                         | 1.38               | 0.14                       | 0.23                   |
| Standard deviation           | 2.79                         | 1.46               | 0.10                       | 0.23                   |
| Probability                  | 0.03                         | 0.35               | 0.80                       | 0.13                   |
| Observations                 | 26                           | 26                 | 26                         | 26                     |

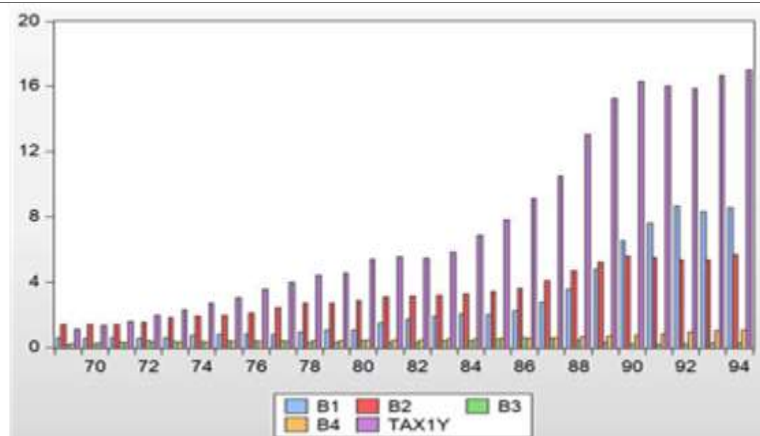


**Figure 2. Fluctuations between the target variable and the independent variables of the study.**

According to the calculations, the oil revenue growth rate factor (B1) and the exchange rate factor (B2) exhibited the greatest increases in the research model between 2011 and 2015, whereas the liquidity growth rate factor (B3) experienced the greatest decrease during the same period. Additional econometric analyses of the fluctuations between the target variable and the independent variables, as well as the preliminary econometric characteristics of the research dataset, can be evaluated from the preceding figure and table. Subsequently, the econometric analysis of the research dataset was conducted using covariance and correlation tests. Based on the covariance and

correlation analysis, the components exerting the strongest effects on the research model were, in descending order, the unemployment rate factor (A3), with an econometric coefficient of 0.990343; the GDP growth rate factor (A1), with an econometric coefficient of 0.959256; and the inflation rate factor (A4), with an econometric weight of 0.943734. Based on the covariance and correlation analysis of the second group of variables, the exchange rate factor (B2) exhibited the strongest association, with an econometric coefficient of 0.990413. The bank deposit rate factor (B4) had an econometric weight of 0.959346. Multicollinearity is present to some extent in virtually all regression models; therefore, the principal concern is the severity of multicollinearity among the independent components. Table 3 presents information concerning the first econometric model estimated using EViews.

**Table 3. First EViews Econometric Model of the Study**

| Indicator                                 | Value                         |
|-------------------------------------------|-------------------------------|
| Coefficient                               | 0.69                          |
| Standard error                            | 0.54                          |
| <i>t</i> statistic                        | 1.51                          |
| Probability ( <i>p</i> )                  | 0.15                          |
| R <sup>2</sup>                            | 0.978                         |
| Adjusted R <sup>2</sup>                   | 0.978                         |
| Mean of dependent component               | 6.49                          |
| Standard deviation of dependent component | 4.93                          |
| Standard error of regression              | 1.66                          |
| J-statistic                               | 8.20                          |
| Durbin–Watson statistic (D–W)             | 0.16                          |
| Model specification                       | Ya = B1 + B2 + B3 + B4 + C(1) |

The coefficient of determination (R<sup>2</sup>) associated with the first EViews econometric model—that is, the GARCH model examining fluctuations among the oil revenue growth rate factor, liquidity growth rate factor (B3), bank deposit rate factor (B4), and exchange rate factor (B2)—was reported as 0.924, indicating a very high predictive capacity for the econometric model estimated using EViews. Furthermore, the statistics related to the Durbin–Watson (D–W) test presented in the preceding table were used to evaluate serial correlation. Given the use of lag structures in dynamic econometric estimation, the Durbin–Watson statistic reported for the liquidity growth rate factor (B3), oil revenue growth rate factor (B1), bank deposit rate factor (B4), and exchange rate factor (B2) was 1.66, which was interpreted as supporting the null hypothesis of no autocorrelation among the residuals. According to the preceding table, the standard error of the econometric regression was calculated as 1.66, which was interpreted as indicating an acceptable degree of dispersion in the data. Table 4 presents information on the econometric model concerning the bank credit portfolio developed to reduce the probability of default, estimated using EViews.

Based on the GARCH method, the coefficient of determination (R<sup>2</sup>) associated with the second EViews econometric model—that is, the GARCH model assessing fluctuations between the target variable and the independent variables of the study—was calculated as 0.891. This value indicates the high explanatory and predictive power of the research econometric model. Furthermore, the Durbin–Watson (D–W) statistic was used to assess residual autocorrelation. Given the use of lagged components in dynamic econometric estimation, the Durbin–Watson statistic for GDP growth (A1), interest rate (A2), unemployment rate (A3), inflation rate (A4), and per capita income growth rate (A5) was reported as 1.65. This result was interpreted as supporting the null hypothesis of no autocorrelation among the error terms. According to the preceding results, the standard error of

the econometric regression was calculated as 1.60, which was interpreted as indicating an acceptable degree of dispersion in the data.

**Table 4. Second EViews Econometric Model of the Study**

| Indicator                                 | Value                                 |
|-------------------------------------------|---------------------------------------|
| Coefficient                               | 0.41                                  |
| Standard error                            | 0.54                                  |
| <i>t</i> statistic                        | 0.81                                  |
| Probability ( <i>p</i> )                  | 0.51                                  |
| R <sup>2</sup>                            | 0.891                                 |
| Adjusted R <sup>2</sup>                   | 0.891                                 |
| Mean of dependent component               | 6.49                                  |
| Standard deviation of dependent component | 4.93                                  |
| Standard error of regression              | 1.60                                  |
| J-statistic                               | 0.00                                  |
| Durbin–Watson statistic (D–W)             | 0.16                                  |
| Model specification                       | ECO1Y = A1 + A2 + A3 + A4 + A5 + C(1) |

*Note.* The model is a GARCH specification examining fluctuations between the target variable and the independent variables of the first research model.

#### 4. Discussion and Conclusion

The present study developed and evaluated a credit risk stress-testing model for the banking industry under alternative macroeconomic scenarios using econometric modeling in the EViews environment. The findings demonstrated that macroeconomic variables have substantial explanatory power in accounting for variations in the credit-risk-related target variable and the bank credit portfolio. In the first group of variables, which included GDP growth, interest rate, unemployment rate, inflation rate, and per capita income growth, the estimated model produced a very high coefficient of determination, indicating that a large proportion of the variation in the target variable could be explained by the selected macroeconomic indicators. Among these variables, unemployment exhibited the strongest association with the research model, followed by GDP growth and inflation. In the second group of variables, exchange rate, bank deposit rate, liquidity growth, and oil revenue growth also displayed strong associations with the credit-risk framework, with the exchange rate emerging as the most influential component. These findings indicate that credit risk within the banking system should not be viewed solely as an outcome of borrower-specific characteristics; rather, it is strongly embedded in the broader macroeconomic environment. This interpretation is consistent with international evidence showing that credit risk and financial conditions respond systematically to macroeconomic and cyclical developments [1, 6]. It also supports domestic evidence indicating that financing structures and credit-risk exposures can materially affect the financial performance and resilience of Iranian banks [2].

The strong relationship identified between unemployment and the credit-risk model is economically plausible because unemployment directly influences household income, consumption capacity, debt-servicing ability, and the financial position of firms whose revenues depend on aggregate demand. A rise in unemployment can increase the probability of delinquency and default among retail borrowers, while simultaneously weakening business revenues and increasing the likelihood of corporate repayment difficulties. The relatively high econometric weight of the unemployment variable therefore suggests that adverse labor-market conditions may act as an important transmission mechanism through which macroeconomic stress becomes banking-sector credit stress. The result also aligns with the broader argument that credit-risk assessment should incorporate dynamic economic conditions

rather than relying exclusively on static borrower characteristics. Research using Markov-switching approaches has similarly shown that the relationship between financial development, economic growth, and credit-risk indicators can change across economic regimes, suggesting that credit-risk exposure tends to intensify when an economy moves from favorable to adverse conditions [5]. Moreover, studies on international banks have shown that credit risk and profitability are strongly interconnected, implying that an increase in borrower distress can reduce interest income, raise impairment expenses, and weaken the overall financial position of banks [1]. The present findings extend this reasoning by indicating that labor-market deterioration should be explicitly incorporated into macroeconomic credit stress scenarios.

GDP growth was also identified as one of the most influential variables in the estimated model. This finding reinforces the countercyclical nature of credit risk: when economic activity weakens, corporate cash flows decline, household incomes become less secure, loan repayment capacity deteriorates, and banks face increasing nonperforming exposures. Conversely, stronger economic growth tends to improve the financial position of borrowers and reduce the probability of default. The relationship between credit risk and economic growth is widely supported in the recent literature. Research examining renewable-energy development and bank credit risk has shown that economic growth can play a mediating role in shaping bank risk outcomes, demonstrating the importance of macroeconomic activity as a channel through which sectoral developments influence credit conditions [9]. Similarly, synchronization between credit cycles and financial cycles can influence sovereign credit risk, suggesting that financial vulnerabilities intensify when economic and credit contractions occur simultaneously [6]. The current findings are therefore consistent with the view that GDP growth should constitute a core variable in stress-testing exercises because it summarizes broad changes in economic activity that affect multiple borrower categories simultaneously.

Inflation was another influential factor in the model, and the descriptive analysis indicated that the inflation variable experienced particularly pronounced increases during the later years of the observation period. Inflation can influence credit risk through several competing channels. Moderate inflation may temporarily reduce the real value of nominal debt; however, persistent or high inflation can increase production costs, weaken household purchasing power, create uncertainty, distort relative prices, and lead to tighter monetary and credit conditions. In economies characterized by high macroeconomic volatility, inflation may also interact with interest rates and exchange rates, thereby magnifying the financial burden on borrowers. Consequently, the significant role of inflation in the present model suggests that stress-testing frameworks should consider not only isolated shocks but also joint macroeconomic scenarios in which inflation interacts with other variables. This conclusion is compatible with studies emphasizing the importance of broader systemic factors in credit-risk assessment. Research on credit-risk forecasting using graph convolutional networks has shown that relational and systemic dependencies among financial entities provide information that cannot be captured through isolated indicators alone [18]. Bayesian-network and machine-learning approaches likewise demonstrate that credit risk is generated through interconnected dependencies among multiple variables rather than through a single explanatory factor [19]. The present econometric findings support the same conceptual principle from a macroeconomic perspective.

The second model demonstrated that exchange-rate movements were among the most influential determinants of credit-risk behavior. This finding is especially important in economies where exchange-rate volatility affects the cost of imported inputs, foreign-currency obligations, asset valuations, inflation expectations, and the operating performance of firms. Currency depreciation can increase the domestic-currency burden of foreign liabilities and raise input costs for firms dependent on imported materials, thereby reducing repayment capacity. Exchange-rate

instability may also contribute indirectly to credit deterioration by increasing inflation and uncertainty. The strong association between the exchange rate and the research model therefore indicates that exchange-rate shocks should occupy a central position in banking stress tests. This result is also consistent with the broader literature demonstrating that external shocks can rapidly transmit into sovereign and financial credit conditions. For example, natural disasters have been shown to generate both direct credit-risk effects and broader contagion across financial systems [7]. Although the nature of the shock differs, the underlying mechanism is comparable: a major external disturbance can propagate through macroeconomic and financial channels and ultimately alter creditworthiness. Accordingly, exchange-rate instability in the Iranian context may represent a particularly important source of systemic credit vulnerability.

The significant role of the bank deposit rate also deserves attention because deposit rates affect banks' funding costs and can influence credit pricing, liquidity management, profitability, and borrower behavior. Higher deposit rates may increase the cost of attracting funds and place upward pressure on lending rates, thereby increasing the debt-service burden faced by borrowers. At the same time, deposit-rate policies can influence the allocation of financial resources across banking and nonbank investment alternatives. The relationship between credit risk, bank funding structures, and capital positions has received growing attention in recent research. Studies of carbon concentration in bank portfolios, for example, have shown that the relationship between portfolio characteristics and bank efficiency is mediated by credit risk and capitalization, emphasizing that credit exposure cannot be separated from funding and balance-sheet structures [8]. Domestic evidence also indicates that governance, capital adequacy, and credit risk are interconnected in Iranian private banks [3]. Similarly, credit risk has been found to play an important role in the relationship between corporate governance and financial performance [4]. Taken together, these findings suggest that credit stress testing should consider how macroeconomic shocks influence both borrowers and the financial structure of banks themselves.

The behavior of liquidity growth and oil revenue growth further reinforces the need for a macro-financial approach to credit-risk management. In the Iranian economy, oil revenues can influence government expenditure, foreign-exchange availability, aggregate liquidity, investment, and overall economic activity. Variations in oil revenues can therefore generate indirect effects on bank customers and banking balance sheets. Liquidity growth, in turn, can affect inflation, credit expansion, asset prices, and risk-taking behavior. Rapid liquidity expansion may initially support credit availability but can also generate inflationary pressure and contribute to asset-price distortions or excessive lending if credit standards deteriorate. The present results suggest that these variables should be analyzed jointly rather than independently because their effects may interact over time. This interpretation is compatible with dynamic credit-risk research emphasizing temporal clustering and endogenous propagation. The application of Hawkes processes to credit-risk identification, for example, indicates that credit events may cluster and reinforce one another over time rather than occurring independently [20]. Similarly, recent models using complex networks and limited labeled data demonstrate that connections among borrowers and financial entities can provide important information about systemic credit vulnerability [16]. Although the present study employs an econometric rather than a network-based approach, its findings similarly imply that credit risk is generated by interacting financial and macroeconomic mechanisms.

The high explanatory power of the estimated models also demonstrates the usefulness of quantitative modeling for banking credit-risk management. Recent studies increasingly rely on machine learning and artificial intelligence to improve risk classification and prediction. Comparative assessments involving logistic regression, artificial neural networks, and support vector machines have demonstrated that advanced algorithms can improve credit-

risk discrimination under certain conditions [12]. Evidence from Turkish participation and conventional banks also shows that machine-learning models can perform effectively in assessing credit risk across different banking structures [13]. Systematic reviews further confirm that machine learning and metaheuristic approaches have become central components of contemporary credit-risk analysis [14]. Analytical comparisons of machine-learning models likewise demonstrate substantial potential for improving prediction accuracy through appropriate model selection and validation [15]. However, the present findings emphasize that econometric stress testing continues to offer an important complementary advantage because it provides interpretable estimates of the relationships between macroeconomic drivers and credit outcomes. For bank managers and regulators, such interpretability is essential when the purpose is not merely to predict default but to understand how a particular macroeconomic scenario could affect portfolio risk.

This issue becomes even more important as credit-risk modeling adopts increasingly sophisticated artificial-intelligence techniques. Recent models combining ensemble learning, deep learning, and three-way decision frameworks have demonstrated high predictive potential while explicitly addressing uncertainty in classification decisions [17]. Graph convolutional networks have also been proposed to capture the relational structure of credit risk and improve financial-risk forecasting [18]. The growing convergence between artificial intelligence and credit-risk assessment has become sufficiently substantial to constitute a major research frontier [21]. Nevertheless, one of the principal challenges associated with these methods is explainability. Systematic research on interpretable large language models in credit risk emphasizes that models used in financial decision-making must produce outputs that are transparent, auditable, and understandable to managers, regulators, and other stakeholders [22]. The econometric framework used in the present study contributes to this requirement because the estimated coefficients and model diagnostics provide direct information regarding the relative importance of macroeconomic variables. Thus, the findings support a complementary rather than competitive relationship between econometric stress testing and advanced machine-learning methods.

The results also have implications for the design of bank-level credit-risk governance. The importance of macroeconomic variables indicates that individual borrower screening, collateral assessment, and conventional credit scoring are insufficient when used in isolation. Credit decisions should be embedded within a wider portfolio-level monitoring system that evaluates exposure concentration and tests resilience under adverse scenarios. This is particularly important because weaknesses in collateral and guarantee structures may increase loss severity once default occurs. Research on the pathological dimensions of guarantees and collateral in banking facilities has shown that deficiencies in these mechanisms can undermine credit-risk management effectiveness [11]. Likewise, studies applying generalized method of moments models to credit risk and capital adequacy emphasize the value of dynamic approaches capable of accounting for persistence and institutional characteristics [10]. The present results therefore suggest that stress testing should be integrated with capital planning, collateral management, portfolio diversification, and early-warning systems. Such integration may improve the capacity of banks to anticipate deterioration rather than merely respond after nonperforming loans have already increased.

The study's findings can also be interpreted in the broader context of changing definitions of creditworthiness. Traditional models have focused primarily on financial ratios and repayment history, whereas contemporary research increasingly considers environmental, social, governance, technological, and network dimensions of risk. Evidence that locally developed ESG ratings can improve default-distance assessment suggests that context-sensitive nonfinancial information may add explanatory value to credit-risk models [23]. Similarly, the relationship between carbon-intensive lending and bank efficiency demonstrates that sectoral composition and transition risks

are becoming increasingly relevant to portfolio-level credit risk [8]. These findings do not reduce the relevance of the macroeconomic variables examined in the present study; instead, they imply that future stress-testing frameworks may benefit from integrating traditional macroeconomic variables with emerging sources of financial risk. The strong explanatory performance of the present models provides a foundation for such extensions.

Overall, the findings demonstrate that the credit risk of banks is highly sensitive to movements in macroeconomic and financial variables and that a scenario-based econometric framework can provide meaningful information for bank risk management. GDP growth, unemployment, inflation, exchange rates, liquidity conditions, oil revenue growth, deposit rates, and per capita income jointly constitute an interconnected risk environment capable of influencing borrower solvency and bank portfolio quality. The high explanatory power of the estimated models supports the use of stress-testing approaches for identifying portfolio vulnerability under adverse conditions. These results are broadly consistent with contemporary evidence emphasizing the dynamic, systemic, and multidimensional nature of credit risk [5, 6, 19]. They also reinforce the relevance of combining interpretable econometric analysis with emerging computational tools in order to achieve both explanatory transparency and predictive effectiveness [21, 22]. From a banking-management perspective, the principal implication is that effective credit-risk control requires continual evaluation of portfolio sensitivity to macroeconomic shocks rather than reliance exclusively on historical borrower performance.

The present study is subject to several limitations that should be considered when interpreting its findings. First, the empirical analysis was based on a relatively limited annual time series, which restricts the number of observations available for estimating dynamic relationships and may reduce the statistical power of the models. Second, the study concentrated primarily on selected macroeconomic and banking variables and did not incorporate detailed borrower-level characteristics, sector-specific default rates, collateral recovery values, credit ratings, loan maturity structures, or differences among individual banks. Third, the use of annual data may conceal short-term fluctuations and rapid transmission mechanisms that could be detected using quarterly, monthly, or higher-frequency observations. Fourth, the study relies on historical relationships, whereas structural changes in monetary policy, banking regulation, exchange-rate regimes, credit-allocation rules, and financial technologies may alter the stability of estimated coefficients over time. Fifth, the econometric approach captures important macroeconomic relationships but may not fully represent nonlinear interactions, threshold effects, regime changes, and network contagion. Finally, some available data were constrained by consistency and reporting limitations, which may affect the precision of the estimated relationships and the comparability of the variables over the full observation period.

Future research should extend the present framework by using longer and higher-frequency datasets and by distinguishing among different categories of banks, borrowers, industries, and credit products. Researchers could estimate separate stress-testing models for corporate loans, household loans, mortgages, small and medium-sized enterprise financing, and sector-specific credit portfolios in order to identify heterogeneous responses to macroeconomic shocks. Future studies should also incorporate nonlinear and regime-switching models to determine whether the effects of unemployment, inflation, interest rates, liquidity, and exchange-rate movements differ during expansionary and recessionary periods. Hybrid modeling approaches that combine econometric stress testing with machine learning, deep learning, network analysis, and explainable artificial intelligence could also be developed to improve predictive performance while preserving interpretability. Additional research may incorporate climate risk, environmental transition risk, geopolitical shocks, sanctions, fiscal variables, asset prices, borrower-specific financial indicators, and governance variables. Scenario design could further be improved by

examining simultaneous shocks rather than isolated changes in individual variables and by developing baseline, adverse, and severely adverse scenarios with explicit probability-of-default and loss-given-default projections. Comparative studies across countries with similar bank-centered financial systems could also help determine the extent to which the relationships identified in this study are institution-specific or generalizable.

Bank managers and regulators should incorporate systematic macroeconomic stress testing into routine credit-risk governance and capital-planning processes. Credit portfolios should be evaluated periodically under adverse scenarios involving economic contraction, rising unemployment, inflation acceleration, exchange-rate depreciation, changes in deposit rates, reduced oil revenues, and abnormal liquidity growth. Banks should establish quantitative early-warning thresholds for macroeconomic variables that exhibited strong relationships with credit risk and use those thresholds to trigger enhanced monitoring, tighter underwriting standards, additional provisioning, or portfolio rebalancing. Credit-risk management systems should also integrate borrower-level information with portfolio-level macroeconomic indicators so that emerging vulnerabilities can be identified before they materialize as nonperforming loans. Institutions with significant exposures to sectors that are highly sensitive to exchange rates, inflation, or economic growth should apply more conservative concentration limits and capital buffers. Management should also strengthen scenario governance by assigning responsibility for stress-test design, model validation, documentation, and periodic recalibration. Finally, stress-testing results should be incorporated directly into strategic decisions concerning credit allocation, pricing, collateral requirements, provisioning, liquidity management, and capital adequacy so that credit-risk management functions as a forward-looking component of bank strategy rather than solely as a mechanism for responding to realized defaults.

#### **Authors' Contributions**

Authors equally contributed to this article.

#### **Ethical Considerations**

All procedures performed in this study were under the ethical standards.

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#### **Conflict of Interest**

The authors report no conflict of interest.

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