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-RESEARCH ARTICLE-

EXPLAINING AND PREDICTING CREDIT RATINGS IN EMERGING MARKETS: THE ROLE OF FINANCIAL TRANSPARENCY AND EVIDENCE FROM NEURAL NETWORK MODELS

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—Abstract—

This study examines the extent to which financial reporting transparency, operationalized through earnings timeliness, influences corporate credit ratings in emerging market economies. Drawing on a balanced panel comprising 180 firms over the 2021–2023 period, yielding 540 firm-year observations, the analysis integrates proprietary financial information with disaggregated internal credit rating scores to facilitate a detailed evaluation of firm-specific credit risk. Random-effects panel regression models are employed to determine whether earnings timeliness provides additional explanatory power beyond established financial determinants, including firm size, leverage and profitability. The econometric investigation is further supplemented by a multilayer perceptron (MLP) neural network to assess predictive performance. The regression findings reveal statistically significant positive associations between credit ratings and both firm size and profitability, while leverage exhibits a pronounced adverse effect. Conversely, the relationship between earnings timeliness and credit ratings remains relatively weak, varies across analytical contexts and loses statistical significance at the individual firm level. Despite these limitations in explanatory significance, the MLP model demonstrates substantial predictive accuracy, highlighting the potential of artificial intelligence (AI) approaches for classifying corporate credit risk. By combining conventional econometric inference with machine learning-based prediction, this research advances understanding of the fac-tors shaping credit rating outcomes in emerging markets while distinguishing the explanatory contribution of financial reporting timeliness from the predictive capabilities of computational model-ling techniques.

Keywords: Credit Ratings, Emerging Markets, Financial Transparency, Earnings Timeliness, Panel Data Regression, Machine Learning, Neural Networks, Credit Risk, Firm-Specific Determinants

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

INTRODUCTION

Credit Rating Agencies (CRAs) occupy a fundamental position within international financial markets by evaluating corporate creditworthiness and assessing firms' capacity to fulfil their debt obligations. Their assessments convert extensive and often complex financial disclosures into standardised indicators of credit risk, thereby informing investment decisions and facilitating the efficient distribution of capital. Such functions assume particular significance in emerging economies, where inadequate information availability, limited regulatory transparency and pronounced information asymmetries frequently undermine market efficiency (Cheng & Zhang, 2024; Jaber et al., 2025).

Corporate credit ratings are principally determined by underlying financial characteristics that indicate an organisation's ability to service its liabilities. Existing empirical evidence consistently identifies firm size and profitability as favourable determinants of creditworthiness, whereas higher financial leverage generally corresponds to weaker credit assessments. Nevertheless, the determinants of credit ratings extend beyond conventional financial indicators. Increasing scholarly attention has been directed towards financial reporting transparency, particularly the timeliness of earnings dis-closures, as a mechanism through which informational disparities may be reduced and credit evaluations strengthened. Despite this theoretical rationale, empirical evidence concerning the influence of earnings timeliness remains inconclusive, particularly in institutional settings characterised by comparatively weak disclosure practices (Andrieș & Sprincean, 2023; Saleh & Abu Afifa, 2020).

The interaction between financial fundamentals and information quality becomes especially important in emerging markets, where institutional limitations and uneven disclosure standards create additional uncertainty in credit risk assessment. Although conventional financial indicators retain their explanatory relevance, their effectiveness may be conditioned by the reliability and accessibility of corporate reporting. This suggests that credit rating models should consider transparency-related characteristics alongside established financial determinants. Furthermore, despite considerable academic attention to internationally prominent rating agencies, the analytical practices and assessments of specialised providers, including World' Vest Base (WVB), have received comparatively limited investigation, particularly within Middle Eastern financial markets (Ellul et al., 2011). The relevance of this investigation is further demonstrated by weaknesses exposed during successive financial crises, when in-adequate credit evaluations, ineffective debt management and overly optimistic cash flow expectations contributed to financial instability and diminished investor confidence. These vulnerabilities have been particularly consequential for emerging economies, prompting greater policy emphasis on disclosure quality and effective corporate governance, including within Jordan. Such concerns are intensified by agency conflicts involving corporate managers, shareholders and creditors, whose competing

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

interests may encourage inefficient financial decisions or misleading reporting practices.

Within this environment, CRAs provide an external assessment mechanism capable of encouraging greater accountability and strengthening financial disclosure incentives. Methodological developments in credit rating research have also created opportunities for more comprehensive empirical investigation. Traditional studies have predominantly employed panel econometric techniques to identify the financial and organisational characteristics associated with creditworthiness. More recently, Machine Learning (ML) methods, particularly artificial neural networks, have attracted increasing interest because of their ability to represent nonlinear dependencies and improve classification performance. Nevertheless, research combining explicit measures of reporting transparency with both econometric inference and ML-based prediction remains relatively limited, especially in emerging market contexts (Ashbaugh-Skaife et al., 2006; Bi et al., 2024).

Against this background, the present study investigates whether earnings timeliness, employed as an indicator of financial reporting transparency, influences the credit ratings of non-bank companies listed on the Amman Stock Exchange (ASE) in Jordan during 2021–2023. Its principal analytical objective is to establish the incremental contribution of earnings timeliness to WVB Credit Rating Numerical Scores (CRNS), after accounting for firm size, financial leverage and profitability. In addition, the study examines whether a Multilayer Perceptron (MLP) neural network offers superior predictive performance in classifying credit ratings relative to conventional panel regression approaches. The Jordanian setting provides an opportunity to evaluate these relationships within a dis-tinct regulatory, institutional and financial disclosure environment. Accordingly, the findings constitute country-specific evidence that may also offer relevant insights for other emerging economies, subject to differences in their institutional characteristics.

The research advances the existing literature through three interrelated contributions. First, it evaluates the association between earnings timeliness and corporate creditworthiness within Jordan, thereby examining the potential relevance of reporting transparency in mitigating information asymmetry. Second, it draws upon a distinctive WVB dataset to investigate the relationship between CRNS and transparency indicators, addressing persistent limitations in the availability of detailed credit rating information across Jordan and the wider Middle East and North Africa (MENA) region. Third, the application of an MLP neural network extends the empirical analysis beyond conventional linear specifications by accommodating potentially complex nonlinear interactions among financial characteristics and transparency measures. Collectively, these contributions deepen understanding of the determinants and predictive dynamics of corporate credit ratings in Jordan while establishing an analytical framework suitable for subsequent examination in emerging economies with comparable institutional conditions.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

The paper proceeds as follows. Section 2 synthesises the relevant literature and formulates the re-search hypotheses. Section 3 describes the dataset and methodological framework, while Section 4 presents and evaluates the empirical findings. Section 5 concludes by discussing policy implications and identifying opportunities for further research.

OVERVIEW OF THE LITERATURE AND HYPOTHESIS DEVELOPMENT

This section critically synthesises research examining the relationships among Corporate Governance, Financial Transparency, and Credit Ratings, with particular attention to their implications for organisational performance and stakeholder confidence. Drawing upon the theoretical arguments and empirical evidence established in the literature, it subsequently formulates the hypotheses used to investigate the influence of governance and transparency mechanisms on corporate credit rating outcomes.

Literature Review

The development of corporate governance scholarship has progressively brought greater attention to financial transparency as a mechanism for protecting organisational resources and safeguarding the interests of shareholders, creditors and other stakeholders. Earlier contributions, including Kaplan and Urwitz (1979), did not fully incorporate the importance of transparency-related governance arrangements. Nevertheless, transparent financial reporting serves a broader function than simply communicating corporate performance: it supports accountability, limits informational advantages and reduces conflicts arising from differences in stakeholder objectives and risk preferences. These functions are particularly relevant to shareholder–creditor relationships, where divergent financial incentives may generate agency-related tensions. Evidence from 169 banks across twelve emerging economies during 2009–2014 indicates that institutions receiving higher credit ratings demonstrate stronger incentives to maintain extensive risk disclosure than their lower-rated counterparts (Grassa et al., 2020). This relationship is more pronounced among conventional banks than Islamic banks, whose comparatively limited disclosure of risk-related information reflects characteristics of their business activities and has implications for credit assessments.

The importance of institutional transparency extends beyond corporate reporting to the wider legal and regulatory environment governing debt financing. An investigation of Chinese A-share listed companies between 2003 and 2023 demonstrates that the establishment of bankruptcy courts significantly reduces corporate financing costs, partly through improvements in information transparency (Ding & Cheng, 2025). Financing constraints influence this relationship, with stronger cost reductions observed among smaller enterprises and firms located in eastern China than among larger businesses or those operating in central and western regions. Comparable relationships

emerge in research concerning corporate bonds and credit default swaps (CDSs), where greater transparency is associated with narrower spreads and lower perceived credit risk (Huang, 2025; Li et al., 2026). Further evidence from 21,066 firm-year observations involving publicly listed Chinese companies during 2013–2023 indicates that improved transparency concerning local government debt substantially reduces corporate financial risk, particularly among non-state-owned enterprises and high-technology firms (Li & Liu, 2025). Investor confidence constitutes an important mediating mechanism through which these benefits materialise.

The relationship between information environments and credit risk has also been examined through linguistic characteristics and the comparability of corporate disclosures. Using observations from 59 countries over 1995–2020, comprising 815 country-year and 2,466 bank-year observations, research identifies significantly greater credit risk in countries characterised by strong future-time-reference (FTR) languages (Huang, 2025). However, this association becomes weaker where formal institutions are stronger, disclosure standards are higher, information transparency is more extensive, and governance arrangements are relatively stable. Complementary evidence concerning Chinese corporate bonds and medium-term notes issued between 2009 and 2023, covering 1,817,500 bond pair-year observations, establishes a robust positive relationship between similarities in Management Discussion and Analysis (MD&A) disclosures and subsequent movements in bond credit spreads (Li et al., 2026).

Similarity in disclosure content also predicts convergence in firms' distance-to-default measures, suggesting that comparable information environments contribute to increasingly aligned perceptions of default risk. These associations are particularly pronounced for lower-rated bonds, securities arranged by less reputable underwriters and longer-maturity instruments. Stronger effects are additionally observed among firms experiencing greater analyst disagreement, adverse media coverage or negative investor sentiment, and during periods of heightened economic policy uncertainty. Taken together, these findings suggest that financial transparency influences credit assessments through three principal mechanisms: reducing adverse selection, constraining moral hazard and signalling organisational quality and governance effectiveness. By narrowing informational disparities between borrowers and lenders, more comprehensive disclosure can improve access to external finance, reduce perceived default exposure and lower borrowing costs (Grassa et al., 2020; Li et al., 2026). Greater information availability also enables creditors to evaluate repayment capacity with increased confidence, potentially reducing risk premiums associated with uncertainty (Ding & Cheng, 2025; Huang, 2025; Li & Liu, 2025).

A related body of scholarship emphasises the role of governance structures in establishing organisational credibility and limiting opportunistic managerial behaviour. Particular attention has been directed towards board independence (Sari, 2023), the transparency of corporate financial statements (Armstrong et al., 2016) and the effectiveness of audit committees (Pisano et al., 2016). These mechanisms collectively

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

strengthen oversight and support the integrity of corporate decision-making. Empirical research further demonstrates that governance arrangements can moderate agency conflicts involving executives, shareholders and bondholders, thereby influencing evaluations undertaken by CRAs (Ashbaugh-Skaife et al., 2006). Nevertheless, governance improvements do not necessarily distribute benefits equally among stakeholders. Enhanced financial transparency may facilitate wealth transfers towards shareholders, potentially intensifying conflicts with bondholders under particular financial conditions (Klock et al., 2005). This possibility highlights the importance of understanding whether fluctuations in credit ratings contribute to shareholder–creditor tensions. At the same time, effective transparency mechanisms can improve the alignment of stakeholder interests and strengthen capital allocation. Within this framework, CRNS provide an external monitoring signal through which corporate creditworthiness can be communicated, potentially reducing agency costs and supporting financial accountability (González et al., 2005; Hussein & Idris, 2023).

Agency theory provides a further explanation for the association between corporate reporting practices and credit rating outcomes. Managers possess informational advantages over shareholders and external creditors and may seek favourable credit assessments as evidence of satisfactory organisational performance. Shareholders, in turn, have incentives to support higher ratings because improved creditworthiness may reduce financing costs and enhance corporate value (Ashbaugh-Skaife et al., 2006). Consequently, credit ratings are expected to reflect both firm-specific financial characteristics and the transparency of information available to external stakeholders. Improvements in reporting quality can reduce monitoring expenditure, limit agency-related equity costs and diminish uncertainty surrounding corporate financial conditions. Existing evidence associates stronger disclosure practices with lower costs of equity (Leuz & Verrecchia, 2000, 2005) and debt financing (Sengupta, 1998). Effective governance additionally strengthens investor confidence in the reliability of financial intermediation, thereby contributing to lower equity risk premiums.

These relationships suggest that governance-related reductions in financing costs and improvements in CRNS may arise from common underlying mechanisms, particularly disclosure quality, accountability and the management of credit-related uncertainty (Durnev & Kim, 2005; Gompers et al., 2003). Timely financial disclosure has likewise been associated with more favourable credit rating outcomes. Evidence based on Association for Investment Management and Research (AIMR) disclosure ratings indicates that firms demonstrating stronger reporting transparency experience lower borrowing costs because bondholders perceive less information-related risk (Sengupta, 1998). Similarly, governance arrangements that restrict the expropriation of corporate resources by insiders can reduce financing costs and support stronger credit assessments (La Porta et al., 2000). Such arrangements also help limit non-diversifiable risks faced by shareholders, particularly when managers encounter restricted investment opportunities and consequently possess stronger incentives to pursue personal benefits (Johnson & Wichern, 2002; Kaddumi et al., 2023). By constraining opportunistic

conduct, effective governance contributes to more stable investor expectations and potentially more favourable credit rating outcomes.

The financial implications of transparency are also evident in its capacity to reduce shareholder monitoring requirements and discourage managerial opportunism, thereby lowering the cost of equity capital (Lombardo & Pagano, 2000). Corporate governance arrangements that improve reporting reliability can further mitigate agency costs associated with information asymmetry and facilitate more efficient capital mobilisation (Alawneh et al., 2023). Governance assessments undertaken by Standard and Poor's similarly recognise the relevance of disclosure practices to CRNS. Consistent with this perspective, companies exhibiting stronger governance arrangements generally obtain more favourable credit assessments and experience lower financing costs. Evidence from Spanish firms associates improved governance quality with reduced equity capital costs (Reverte, 2009), while related findings are reported in Chen et al. (2009). With respect to debt financing, weaker governance structures are associated with higher borrowing costs even after controlling for firm-specific risk characteristics (Ashbaugh-Skaife et al., 2006).

The empirical identification of credit rating determinants has traditionally relied upon econometric models incorporating corporate financial indicators and institutional characteristics. Common approaches include panel data estimation alongside regularised logistic and probit regression specifications (Lima et al., 2018; Teker et al., 2013). These techniques have helped establish the importance of conventional financial variables in explaining creditworthiness. In particular, liquidity, capital adequacy and asset quality have been identified as relevant determinants of credit rating outcomes (Oskonbaeva, 2020).

Beyond the overall quality of disclosed information, the timing of earnings announcements represents another potentially important dimension of corporate credit risk. Delayed or strategically scheduled disclosures may increase informational inequalities between corporate insiders and external capital providers, thereby intensifying adverse selection and restricting access to affordable financing (Kothari et al., 2009; Lee & Son, 2009). Evidence concerning managerial disclosure behaviour indicates that unfavourable information is frequently communicated later than favourable information. An analysis involving 7,044 dividend announcements during 1962–2004 and 4,016 management forecasts during 1995–2002 in the United States demonstrates that negative disclosures generate larger share-price reactions, while managers tend to postpone bad-news announcements and selectively release favourable information (Kothari et al., 2009). These findings illustrate how discretionary reporting decisions may influence market expectations and perceived information risk.

The relationship between reporting delays and earnings management has also been investigated using 10,191 United States firm-year observations covering 2001–2004 (Lee & Son, 2009). The results indicate a negative association between total reporting

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

lag and discretionary accruals, primarily attributable to audit report delays rather than discretionary postponements by management. However, managerial reporting lag is positively associated with earnings management when earnings announcements occur after the audit report date. This distinction suggests that the implications of delayed disclosure depend on the underlying source of the delay rather than its duration alone. Additional evidence concerning the interaction between earnings informativeness and managerial characteristics is provided through an investigation of 18,500 United States firm-year observations from 2013–2022, with a final analytical sample of 17,892 observations (Chen et al., 2009). The findings suggest that overconfident managers, including those with comparatively limited managerial ability, exhibit stronger preferences for debt financing when earnings are informative or communicate favourable developments. Conversely, their inclination towards debt financing declines when earnings convey limited information or unfavourable news. Strong internal control arrangements moderate these relationships.

A further strand of research considers the indirect implications of earnings disclosure practices for credit risk through their influence on uncertainty and information asymmetry. Evidence from 279 French non-financial companies, comprising 3,627 observations during 2002–2015 with 2005 excluded, examines whether earnings quality mediates the relationship between International Financial Reporting Standards (IFRS) adoption and informational disparities (Benkraiem et al., 2022). The findings indicate that information asymmetry declined following IFRS adoption, although faithful representation emerged as the only statistically significant earnings-quality channel explaining this improvement. This suggests that the credibility of reported financial information may be more consequential than other dimensions of earnings quality in reducing informational inequalities. The influence of uncertainty on financial reporting decisions is further demonstrated in the banking sector. An examination of 6,384 United States banks during 2009–2019 establishes that greater economic policy uncertainty is associated with increased loan loss provisioning, with news-based uncertainty and tax-expiration-related uncertainty accounting for important components of this relationship (Danisman et al., 2021).

Under heightened uncertainty, banks appear to employ provisions primarily for income smoothing rather than capital management, with this behaviour particularly evident among privately owned institutions. Earlier evidence from 78 major United States bank holding companies, comprising 1,120 observations between 1981 and 1996, similarly indicates that loan loss provisions can serve as signals of future financial prospects (Kanagaretnam et al., 2005). The propensity to engage in such signalling declines with bank size but increases with earnings variability, investment opportunities and income-smoothing activities. Moreover, signalling behaviour exhibits a positive association with information asymmetry, reinforcing the importance of reporting incentives in financial risk assessment.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

The broader institutional relevance of governance is also reflected in research examining stakeholder-oriented corporate practices. International evidence indicates that stakeholder governance exerts a stronger positive influence on Corporate Social Responsibility (CSR) than board governance, particularly where investor protection mechanisms and board oversight are comparatively weak (Jo et al., 2016). Although the available study description does not identify the sample size or observation period, its findings reinforce the importance of stakeholder-oriented governance arrangements in environments characterised by institutional limitations. Finally, the information-reducing function of earnings announcements is supported by evidence from 37 companies listed on the Oslo Stock Exchange, covering 203 announcement events between 1990 and 1995 (Eilifsen et al., 2001). Stock return volatility declines significantly following earnings disclosures among both smaller and larger firms, while the largest companies exhibit a statistically significant reduction in the noise component of returns. These results are consistent with the proposition that earnings announcements improve the information available to market participants and consequently reduce uncertainty arising from asymmetric information.

Hypotheses Formulation

This section establishes the theoretical arguments underpinning the study hypotheses and explains the expected relevance of four firm-level characteristics to CRNS. Specifically, firm size, leverage, profitability and earnings timeliness are examined as potential explanatory factors influencing corporate credit assessments.

Firm Size: Corporate size, commonly operationalised through total assets, represents an important determinant of creditworthiness because of its association with financial resilience, information availability and external market perceptions. Larger organisations generally possess more diversified resources, experience comparatively lower perceived default exposure and enjoy broader access to external financing. Furthermore, their greater visibility and exposure to public scrutiny may encourage more extensive financial disclosure, potentially strengthening their credit rating assessments (Chodnicka-Jaworska, 2020).

From the perspective of agency theory, organisational expansion may increase agency-related costs as managerial structures and operational activities become more complex. Nevertheless, larger enterprises typically have greater capacity to implement advanced governance arrangements, internal monitoring systems and comprehensive reporting procedures. These characteristics provide a theoretical basis for anticipating a positive association between firm size and CRNS.

H1: *There is no statistically significant relationship between firm size and CRNS.*

Leverage: Financial leverage, expressed as the proportion of total assets financed through debt, constitutes a fundamental measure of corporate financial exposure. Greater dependence on borrowed capital increases repayment commitments and may

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

heighten the probability of financial distress, thereby weakening perceived creditworthiness (Doumpos & Pasiouras, 2005). Nevertheless, the wealth redistribution hypothesis offers an alternative perspective, suggesting that highly indebted companies may seek more favourable CRNS to maintain creditor confidence. Such firms may strengthen disclosure practices and financial transparency to reassure bondholders and counteract concerns regarding elevated credit risk (Alhajjeah et al., 2025; Manelli et al., 2022; Șerbu et al., 2021).

H2: *There is no statistically significant relationship between leverage and CRNS.*

Profitability: A firm's profitability indicates its capacity to generate earnings from available assets and operating activities, making it a central consideration in evaluating financial strength and debt-servicing ability. Companies demonstrating sustained profitability are generally regarded as more financially secure because their earnings provide resources for meeting contractual obligations and absorbing adverse economic developments (Mishra & Bansal, 2019; Mustafa et al., 2024). Although the prevailing empirical literature identifies a favourable association between profitability and corporate credit ratings, the magnitude and statistical significance of this relationship may differ across economic, institutional and organisational settings (Hanandeh et al., 2024; Mahdi & Al-Naimi, 2021).

H3: *There is no statistically significant relationship between profitability and CRNS.*

Timeliness of Earnings: Earnings timeliness captures the extent to which information concerning corporate financial performance is disclosed promptly and therefore serves as an indicator of reporting transparency. More immediate communication of financial results can narrow informational disparities between managers and external stakeholders while strengthening confidence in the reliability and relevance of financial statements. However, managerial discretion over announcement timing may compromise these benefits, particularly when unfavourable earnings information is deliberately withheld or postponed. Consequently, the informational value of reporting timeliness may depend on the incentives governing disclosure decisions (Jung et al., 2012; Leventis et al., 2014).

H4: *There is no statistically significant relationship between earnings timeliness and CRNS.*

MODELLING APPROACHES AND METHODOLOGICAL EXTENSION

To accommodate relationships that may not be adequately represented through conventional linear specifications, the study incorporates an MLP, belonging to the broader family of Artificial Neural Networks (ANNs) (Rosenblatt, 1958). The development of neural network modelling has progressed considerably from its early conceptual foundations, particularly through the introduction of backpropagation

algorithms (Rumelhart et al., 1986), Rectified Linear Unit (ReLU) activation functions (Nair & Hinton, 2010), dropout-based regularisation (Srivastava et al., 2014) and batch normalisation procedures (Ioffe & Szegedy, 2015). Collectively, these advances have enhanced the ability of MLP architectures to process high-dimensional information, identify complex nonlinear associations and develop hierarchical representations of explanatory features. Such capabilities make neural networks particularly relevant to financial modelling, where interactions among risk determinants may be multidimensional and nonlinear.

Notwithstanding these methodological developments, empirical investigations that simultaneously incorporate financial reporting transparency into econometric estimation and ML-based prediction remain relatively uncommon, particularly within emerging economies. The present research addresses this methodological limitation by examining earnings timeliness as an explanatory determinant of credit ratings while independently evaluating the classification capabilities of neural network techniques. This combined perspective facilitates a distinction between understanding the statistical relationships underlying credit assessments and improving the prediction of credit risk categories.

Materials and Methods

The methodological framework combines econometric estimation with ML-based classification to investigate corporate credit ratings from complementary analytical perspectives. Initially, a Random Effects (RE) panel regression model is estimated to evaluate the contribution of conventional financial characteristics and reporting transparency, particularly earnings timeliness, to observed credit rating outcomes. Subsequently, an MLP model is implemented to identify potentially nonlinear dependencies among the explanatory variables and enhance the classification of corporate credit risk. Integrating these approaches allows the study to retain the interpretative advantages of econometric modelling while incorporating the predictive flexibility of neural networks, thereby supporting a broader assessment of creditworthiness within an emerging market environment.

The analytical procedure follows two sequential stages designed to strengthen the classification of CRNS. During the first stage, regression-based evaluation is undertaken to assess the explanatory and predictive relevance of the candidate variables. Indicators exhibiting redundancy or comparatively weak associations are considered for exclusion, whereas variables contributing meaningful variation in CRNS are retained for subsequent modelling. This preliminary screening is intended to establish a statistically informed predictor set and limit the inclusion of variables offering insufficient analytical value. In the second stage, the continuous CRNS measure is transformed into a binary classification outcome using a threshold of 3.75. Observations are assigned to the High category when CRNS $\geq$ 3.75 and to the Low category when CRNS $<$ 3.75. The MLP classifier is subsequently trained using the selected financial and transparency indicators, namely firm size, leverage, profitability

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

and earnings timeliness, to distinguish between these two credit rating categories. By combining regression-informed variable assessment with nonlinear classification, the proposed procedure seeks to improve predictive performance while preserving the relevance of established financial risk determinants.

Figure 1 presents the overall architecture of the integrated analytical framework. Firm-level observations, comprising financial ratios and earnings timeliness information, provide the common input variables for two complementary modelling components: the RE panel regression and the MLP neural network. The econometric component estimates the explanatory relationships between firm characteristics and numerical credit rating outcomes, whereas the neural network evaluates nonlinear patterns within the same information set to predict categorical credit risk classifications. Together, these components provide a methodological structure for examining both the determinants and the predictability of corporate credit ratings.

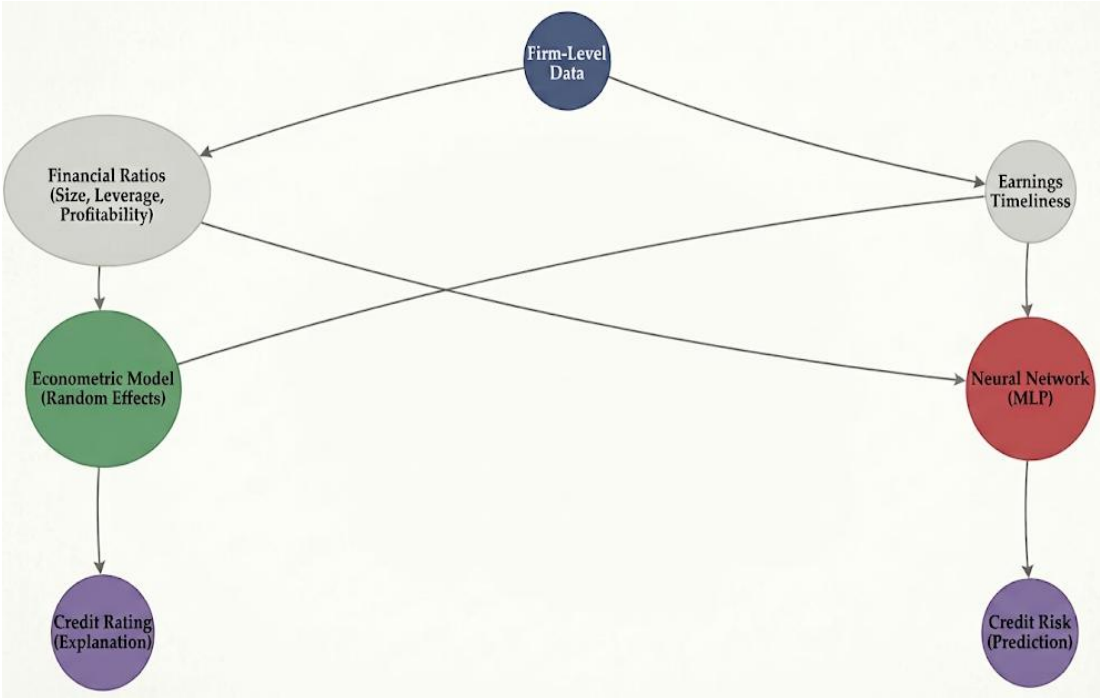

Figure 1: Econometric and Machine Learning Framework for Credit Rating Analysis

Regression Models

The study sample encompasses non-bank firms listed on the ASE at the end of 2021, 2022 and 2023, with companies lacking WVB credit rating information excluded from the analysis. The dependent variable is the long-term CRNS, constructed from the rating classifications assigned by WVB, which extend from BB1, representing the highest creditworthiness, to D, indicating default or bankruptcy. To facilitate quantitative estimation, these ordinal classifications are transformed into continuous numerical

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

values according to the conversion scheme presented in Table 1. The explanatory variables are identified through an extensive examination of the literature addressing firm-specific financial characteristics and reporting transparency. Both Ordinary Least Squares (OLS) regression and RE panel models are employed to investigate their associations with CRNS while accounting for the longitudinal structure of the dataset. The use of detailed numerical rating scores enables the analysis to distinguish more precisely between creditworthiness levels than approaches relying on broader or fewer rating categories.

Table 1: WVB Ratings and Numerical Scores

Category	Numerical Score Range
BB1	5.25 ≤Score ≤5.65
BB2	4.95 ≤Score< 5.25
BB3	4.75 ≤Score< 4.95
B1	4.50 ≤Score< 4.75
B2	4.15 ≤Score< 4.50
B3	3.75 ≤Score< 4.15
C1	3.20 ≤Score< 3.75
C2	2.50 ≤Score< 3.20
C3	1.75 ≤Score< 2.50
D	Score ≤1.75

Two alternatives RE specifications are estimated to examine the influence of unobserved heterogeneity at different organisational levels. Random Effects model 1 incorporates sector-specific random intercepts across the three sectors represented in the dataset: Financial, Services and Industry. This formulation accommodates unobserved differences between sectors that may influence credit rating outcomes and is particularly relevant when the underlying determinants of creditworthiness are expected to differ across economic activities. Random Effect model 2, by contrast, introduces firm-specific random intercepts for the 180 sampled companies, thereby accounting for persistent, unobserved characteristics associated with individual firms. Comparing these specifications provides an assessment of the robustness of the estimated relationships to alternative representations of unobserved heterogeneity. It also helps establish whether variation in credit rating outcomes is more closely associated with sector-level differences or firm-specific characteristics.

The estimated model is specified in Equation 1, as follows:

$$CRNS_{it} = \beta 0 + \beta 1\ Size_{it} + \beta 2\ Leverage_{it} + \beta 3\ Profitability_{it} + \beta 4\ EXP\text{-}TIMME_{i,t-1} + \varepsilon_{it} \quad (1)$$

Where:

- $CRNS_{it}$: is the credit rating numerical score for firm*i* at time *t*.
- $Size_{it}$: represents firm size, measured as the natural logarithm of total assets.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

- $Leverage_{it}$: is leverage, computed as the ratio of total debt to total assets.
- $Profitability_{it}$: denotes profitability, calculated as net income before extraordinaryitems divided by net sales.
- EXP-$TIMME_{i,t-1}$is the exponential lagged earnings timeliness measure
- (=exp($TIMME_{i,t-1}$), serving as a proxy for financial transparency.
- εit is the error term.

Financial reporting transparency constitutes an important dimension of creditworthiness assessment because it indicates the extent to which disclosed earnings accurately and promptly convey a firm's underlying economic performance. In the present study, transparency is operationalised by evaluating the association between accounting earnings and firm-specific equity returns, with stock returns adjusted according to the Capital Asset Pricing Model (CAPM) to account for systematic market influences (Donadelli et al., 2025; Sharpe, 1964). Firm-specific excess returns are obtained by deducting beta-adjusted market returns from observed stock returns, thereby distinguishing company-level performance from movements attributable to broader market conditions. A stronger positive correlation between reported earnings and these adjusted returns is regarded as an indication that financial disclosures communicate relevant performance information in a timely and credible manner. Conversely, a weaker association may reflect limitations in reporting transparency arising from delayed earnings announcements, discretionary earnings management or inadequate disclosure quality.

Multilayer Perceptron (MLP) Model

The MLP classifier is implemented to predict the binary categories derived from CRNS. Its architecture comprises four input neurons representing the explanatory variables SIZE, LEV, PM and TIMM, a single hidden layer containing four neurons, denoted h*1* to h*4*, and one output neuron responsible for generating the predicted credit rating category. A fully connected structure links each input neuron to every neuron in the hidden layer through individually weighted connections. Nonlinear activation functions, such as ReLU or sigmoid, are applied within the hidden layer to identify complex dependencies and interactions that may not be adequately captured through linear modelling. The resulting hidden-layer outputs are subsequently combined and processed through an additional activation function to generate the final classification outcome (Al Omari et al., 2023). Within this architecture, each perceptron processes the numerical input variables SIZE, LEV, PM and TIMM by assigning a separate connection weight to each predictor. These weights determine the relative contribution of the input features to the activation of individual hidden neurons. The perceptron then combines the weighted inputs to calculate an aggregate value, which forms the basis for subsequent nonlinear transformation. The weighted summation is expressed as follows:

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

Input to Hidden Layer (Equation 2)

For a hidden neuron j (where j = 1, 2, 3, 4), the pre-activation valuezj is calculated as shown in Equation 2 (Al Omari et al., 2023):

$$Z_j = \sum_{j=1}^{4} \omega_{ij} x_i + b_j \qquad (2)$$

Where:

- w_{ij} represents the weight from input feature$xi$to hidden neuron j,
- xi is the input feature value,
- bj is the bias term for hidden neuron j.

An activation function φ (such as sigmoid or ReLU) is applied tozj to produce the outputhj of the hidden neuron: $hj = \varphi(zj)$

Hidden Layer to Output (Equation 3)

The output neuron computes its pre-activation valueZ_{Out} as shown in Equation 3 (Al Omari et al., 2023):

$$Z_{Out} = \sum_{j=1}^{4} \omega_j a_j + b \qquad (3)$$

Here, ω_j represnts the weight from hidden neuron j to the output neuron, σ_j is the activated output of hidden neuron j , and b is the output bias, A final activation function ($CRNS = g(Z_{Out})$) (such as sigmoid for binary classification) is applied to Z_{Out} to generate the model's prediction.

Original Perceptron (Equation 4)

The original perceptron differs from the conventional MLP architecture in its reliance on a step activation function, which restricts its outputs to binary values of either 0 or 1. In contrast, MLPs employ differentiable activation functions that facilitate gradient-based optimisation and enable the modelling of more complex decision boundaries, thereby extending their predictive capabilities to multiclass classification problems (Al Omari et al., 2023).

$$Output = \begin{cases} 1 & , if\, Z_j > \theta \\ 0 & , otherwise \end{cases} \qquad (4)$$

where θ is a threshold parameter.

Learning Process and Rprop Algorithm

Through backpropagation, the network progressively refines the connection weights

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

between the input and hidden layers and between the hidden and output layers according to the prediction error E, defined as the discrepancy between estimated and observed values. This optimisation process is repeated across successive training epochs, during which the network seeks to minimise the error function specified in Equation 5, thereby improving agreement between predicted CRNS outputs and their corresponding actual values. The conventional backpropagation weight adjustment mechanism is mathematically represented in Equation 6 (Al Omari et al., 2023).

$$\omega_{ji}(t+1)=\omega_{ji}(t)-\eta\frac{\partial E}{\partial \omega_{ji}}(t) \tag{5}$$

$$\Delta\omega_{ji}(t)=\eta\frac{\partial E}{\partial \omega_{ji}}(t)+\mu\Delta\omega_{ji}(t-1) \tag{6}$$

$$\Delta_{ji}^{(t)}=\begin{cases}\alpha*\Delta_{ji}^{(t-1)}, if\ \frac{\partial E^{(t-1)}}{\partial \omega_{ji}}*\frac{\partial E^{(t)}}{\partial \omega_{ji}}>0\\ \beta*\Delta_{ji}^{(t-1)}, if\ \frac{\partial E^{(t-1)}}{\partial \omega_{ji}}*\frac{\partial E^{(t)}}{\partial \omega_{ji}}<0\\ \Delta_{ji}^{(t-1)}, otherwise\end{cases} \tag{7}$$

$$0<\beta<1<\alpha$$

where ω_{ji} is the weight between neurons i and j at iteration t, E is loss function (quantifying prediction error), $\frac{\partial E}{\partial \omega_{ji}}$ is the gradient (direction/magnitude of adjustment), and η (learning rate) governs the update step size.

To mitigate oscillations from high learning rates, the Resilient Propagation (Rprop) algorithm employs weight-specific updates governed by a local adaptation rule. Instead of relying solely on gradient magnitudes, Rprop adjusts each weight's step size Δ_{ji} by multiplying it with asymmetric factors (η^{+1} for increase, $\eta^{-}<1$ for decreases) based on gradient sign consistency. This method stabilizes training and enhances efficiency compared to traditional gradient-based approaches, as updates depend on direction rather than derivative magnitudes see Equation 7 (Al Omari et al., 2023).

Evaluation Metrics

The predictive performance of the model is assessed using a stratified partition of the dataset, with 80% of observations allocated to training and the remaining 20% reserved for testing. This stratification procedure maintains approximately equivalent proportions of the two CRNS categories across both subsets, supporting a more representative evaluation of the classifier's generalisation performance. Model effectiveness is examined through the following complementary evaluation measures:

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

- **True Positive Rate (Recall or Sensitivity):** Represents the proportion of observations belonging to the positive class that the classifier correctly identifies as positive (see Equation 8).
- **True Negative Rate (Specificity**): Quantifies the proportion of genuinely negative observations that are accurately assigned to the negative category (see Equation 9).
- **False Positive Rate (FPR):** Measures the fraction of actual negative observations incorrectly predicted to belong to the positive class (see Equation 10).
- **False Negative Rate (FNR):** Expresses the proportion of genuinely positive observations erroneously classified as negative (see Equation 11).
- **Accuracy:** Indicates the overall classification success rate, calculated as the proportion of correctly identified positive and negative observations relative to the total number of predictions (see Equation 12).
- **Precision:** Evaluates the reliability of positive classifications by determining the proportion of predicted positive observations that genuinely belong to the positive category (see Equation 13).
- **F1-Score:** Provides a combined assessment of precision and recall through their harmonic mean, offering a particularly informative performance measure when class frequencies are unequal (see Equation 14).
- **Receiver Operating Characteristic (ROC) Curve:** Illustrates the relationship between the true positive rate and the false positive rate across alternative classification thresholds, thereby depicting changes in sensitivity relative to false positive classifications.
- **Area Under the Curve (AUC):** Summarises the classifier's overall capacity to distinguish between positive and negative observations, with values approaching 1 indicating stronger discriminatory performance.

Among these measures, the F1-score is especially relevant when the dataset exhibits class imbalance because it jointly considers precision and recall rather than relying exclusively on the overall proportion of correct predictions. Consequently, it provides a more balanced assessment than accuracy alone under unequal class distributions. The ROC curve additionally demonstrates how classification sensitivity varies with the false positive rate as the decision threshold changes, while AUC condenses this relationship into a single measure of overall class discrimination. Together, these metrics enable a multidimensional evaluation of classification performance and predictive reliability (Al Omari et al., 2023).

$$Recall = TPrate = \frac{TP}{FN+TP} \tag{8}$$

$$TNrate = \frac{TN}{FP+TN} \tag{9}$$

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

$$FPrate = \frac{FP}{FP+TN} = 1 - TNrate \quad (10)$$

$$FNrate = \frac{FN}{FN+\mathrm{TP}} = 1 - TPrate \quad (11)$$

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

$$F1score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (13)$$

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

EMPIRICAL RESULTS

This section reports the empirical outcomes of the investigation, encompassing descriptive statistical analysis, multicollinearity assessments and estimates obtained from multiple regression specifications and the MLP model. Attention is devoted to identifying associations among the principal explanatory variables and examining the effectiveness of alternative modelling approaches in predicting the credit ratings of publicly listed Jordanian companies.

Descriptive Statistics

The empirical dataset comprises 180 companies listed in Jordan, for which credit rating assessments were obtained from WVB over the 2021–2023 period. The assigned ratings extend from category D, representing the weakest credit standing, to category BB, indicating the highest creditworthiness within the sample. This classification range captures considerable variation in the financial risk profiles of the participating firms. The balanced panel contains N = 540 firm-year observations covering five principal variables. Table 2 summarises their descriptive characteristics, including measures of central tendency, dispersion and distributional shape.

Table 2: Summary Statistics of Independent Continuous Variables

Variable	*N*	Min	Max	Mean	Std. Dev.	Skewness (SE)	Kurtosis (SE)
CRNS	540	-1.9630	5.65	1.4993	0.7682	-0.6460 (0.105)	2.7330 (0.210)
SIZE	540	5.6750	8.8230	7.2760	0.5342	0.3110 (0.105)	0.5710 (0.210)
LEV	540	0.0000	1.1690	0.3263	0.2230	0.8630 (0.105)	0.6100 (0.210)
PM	540	0.0000	4.3750	0.4257	0.6600	3.0120 (0.105)	10.2360 (0.210)
TIMME	540	-7.0100	0.0000	-0.4343	0.6738	-4.3350 (0.105)	27.7310 (0.210)

Note: CRNS = Credit Rating Score, SIZE = Logarithm of Total Assets, LEV = Leverage, PM = Profit Margin, TIMME = Timeliness of Earnings.

- **CRNS:** The numerical credit rating measure extends from a minimum of -1.9630 to a maximum of 5.6500, with a mean of 1.4993 and a standard deviation of 0.7682.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

Its distribution exhibits negative skewness (-0.6460; SE = 0.105), indicating a longer left tail, while the reported kurtosis of 2.7330 (SE = 0.210) characterises the distribution as platykurtic.

- **SIZE:** Measured as the logarithm of total assets, firm size ranges between 5.6750 and 8.8230, with an average of 7.2760 and a standard deviation of 0.5342. The distribution displays modest positive skewness (0.3110) and relatively low kurtosis (0.5710), suggesting comparatively limited departures from symmetry.
- **LEV:** Financial leverage varies from 0.0000 to 1.1690, producing a mean of 0.3263 and a standard deviation of 0.2230. Positive skewness of 0.8630 indicates a greater concentration of observations towards lower leverage values, whereas kurtosis of 0.6100 reflects a moderate degree of distributional concentration.
- **PM:** Profit margin exhibits substantial variability, with observations ranging from 0.0000 to 4.3750, a mean of 0.4257 and a standard deviation of 0.6600. Its pronounced positive skewness (3.0120) and elevated kurtosis (10.2360) indicate a highly asymmetric distribution characterised by substantial departures from normality.
- **TIMME:** The earnings timeliness measure ranges from -7.0100 to 0.0000, with an average value of -0.4343 and a standard deviation of 0.6738. The distribution is strongly negatively skewed (-4.3350) and exhibits exceptionally high kurtosis (27.7310), indicating substantial asymmetry and an unusually pronounced concentration of observations and extreme values.

The corresponding standard errors for skewness and kurtosis are 0.105 and 0.210, respectively, across the reported variables. These distributional diagnostics reveal considerable differences in the statistical characteristics of the dataset. In particular, PM and TIMME exhibit pronounced non-normality, as reflected in their extreme skewness and kurtosis estimates, whereas SIZE and LEV demonstrate comparatively moderate distributional irregularities. Figure 2 provides a graphical representation of these characteristics, illustrating the extent of asymmetry and distributional concentration across the study variables.

Multicollinearity Statistics

Prior to estimating the regression models, potential multicollinearity among the explanatory varia-bles was examined to assess whether substantial interrelationships could compromise coefficient stability and the reliability of statistical interpretation. Strong correlations between predictors may introduce estimation difficulties and reduce the precision with which their individual contributions can be distinguished.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

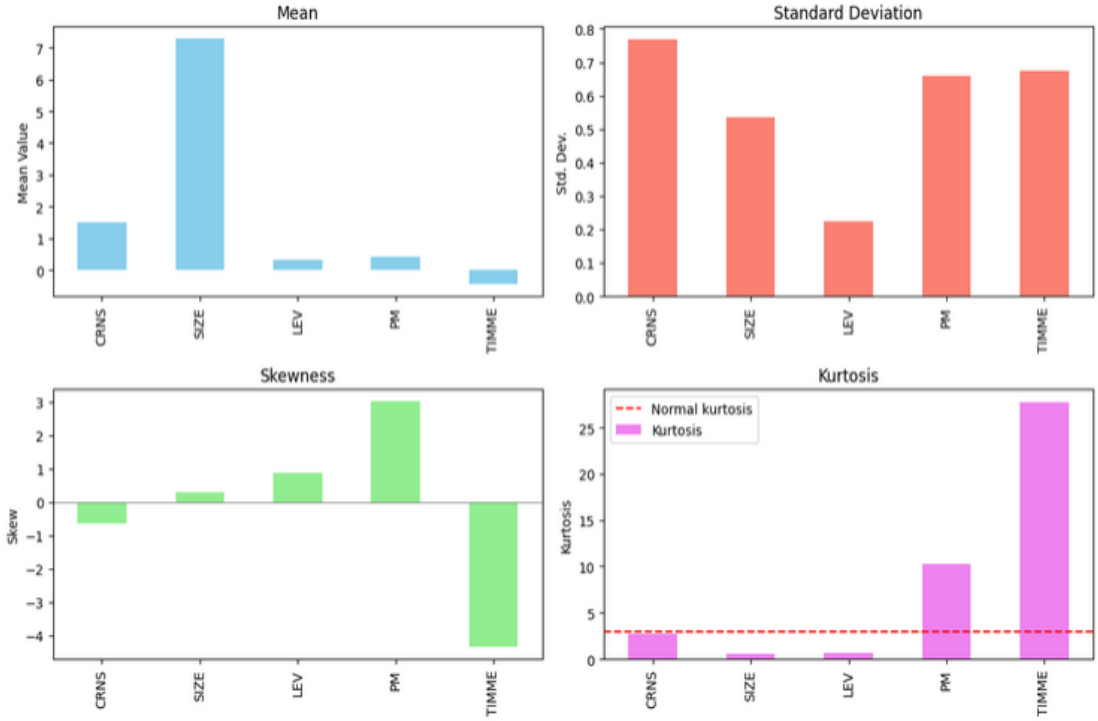

Figure 2: Summary Statistics of Independent Variables

Figure 3 illustrates the correlation matrix, with coefficients exceeding 0.5 classified as strong associations and those below 0.5 regarded as weak. The results reveal a substantial positive correlation between CRNS and firm size (SIZE), with a coefficient of 0.688, indicating that larger companies generally exhibit more favourable creditworthiness assessments. This relationship may reflect the advantages associated with organisational scale, including operational economies, greater financial resilience and an enhanced capacity to absorb potential default-related pressures. Larger enterprises are also commonly characterised by comparatively stable anticipated cash flows, lower perceived financial risk and reduced exposure to liquidation, factors that may contribute to stronger credit ratings. Additionally, the analysis recognises that industrial firms generally possess lower levels of fixed assets than their non-industrial counterparts.

The remaining explanatory variables exhibit comparatively weak correlations with CRNS. Specifically, leverage (LEV) is negatively associated with credit ratings (−0.043), whereas profit margin (PM) and earnings timeliness (TIMME) display marginal positive correlations of 0.069 and 0.006, respectively. Pairwise correlations among the independent variables (SIZE, LEV, PM and TIMME) are consistently below the specified threshold of 0.5. The largest correlation, observed between SIZE and LEV (0.267), suggests that substantial linear dependence among the predictors is unlikely to present a multicollinearity concern.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

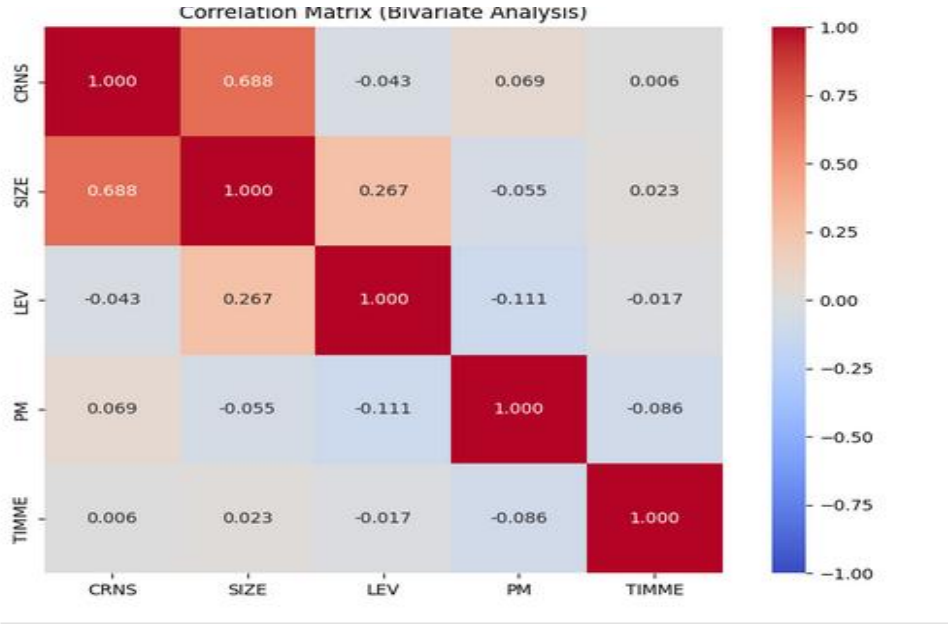

Figure 3: Structural Model

Further examination of the correlation structure indicates that larger firms tend to exhibit slightly higher leverage (0.267), although firm size has negligible associations with profitability (−0.055) and earnings timeliness (0.023). Similarly, LEV is weakly and negatively correlated with PM (−0.111), while the relationship between PM and TIMME is also negative but minimal (−0.086). None of the remaining pairwise coefficients exceeds 0.5, indicating limited linear associations among debt exposure, profitability and reporting timeliness. These findings identify firm size as the variable exhibiting the strongest bivariate relationship with CRNS, while providing no evidence of substantial redundancy among the explanatory variables within the observed dataset.

Multiple Regression Results

The empirical investigation initially employs multiple regression specifications to assess the extent to which selected firm-level characteristics explain variation in corporate credit ratings. Table 3 presents the estimates obtained from the Ordinary Least Squares (OLS) specification and the alternative random effects models, incorporating SIZE, LEV, PM and lagged exponential earnings timeliness (EXP-TIMME). Model evaluation considers the coefficient estimates, their statistical significance and overall explanatory performance, including R-squared and adjusted R-squared statistics. These conventional econometric specifications also establish a comparative benchmark against which the predictive capabilities of more advanced ML approaches can be evaluated.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

Table 3: OLS and Random Effect Models for CRNS

Model	Variables	Intercept	SIZE	LEV	PM	EXP-TIME(-1)
OLS	Estimate	-6.0008	1.0827	-0.8144	0.0954	-0.2088
	Std. Error	0.3238	0.0438	0.1055	0.0344	0.0935
	t-value	-18.5350	24.7100	-7.7180	2.7730	-2.2340
	p-value	$< 2 \times 10^{-16}$	$< 2 \times 10^{-16}$	0.0000	0.0058	0.0259
R-squared		0.5405				
Adjusted R-squared		0.5370				
F-statistic		157 on 4 and 534 DF, p-value:$< 2.2 \times 10^{-16}$				
Random Effect Model (1)	Estimate	-6.0007	1.0827	-0.8144	0.0954	-0.2088
	Std. Error	0.3238	0.0438	0.1055	0.0344	0.0935
	z-value	-18.5348	24.7101	-7.7183	2.7731	-2.2344
	p-value	$< 2.2 \times 10^{-16}$	$< 2.2 \times 10^{-16}$	0.0000	0.0056	0.0255
R-squared		0.5405				
Adjusted R-squared		0.5371				
Chi-square		628.102 on 4 DF, p-value:$< 2.22 \times 10^{-16}$				
Random Effect Model (2)	Estimate	-2.6393	0.5803	-0.2343	0.0379	-0.0390
	Std. Error	0.3353	0.0464	0.0802	0.0168	0.0356
	z-value	-7.8717	12.5143	-2.9229	2.2555	-1.0966
	p-value	3.50×10^{-15}	$< 2.2 \times 10^{-16}$	0.0035	0.0241	0.2728
R-squared		0.2173				
Adjusted R-squared		0.2114				
Chi-square		157.901 on 4 DF, p-value:$< 2.22 \times 10^{-16}$				

OLS Model

The OLS estimates provide statistically significant evidence against all four null hypotheses (H01–H04) at the 5% significance level. Firm size emerges as a substantial positive determinant of CRNS ($\beta = 1.0827$, $p < 0.05$), indicating that larger enterprises generally receive more favourable credit assessments. Conversely, financial leverage exhibits a pronounced negative coefficient ($\beta = -0.8144$, $p < 0.05$), consistent with the adverse implications of greater indebtedness for corporate creditworthiness. Profitability contributes positively, although its estimated effect is considerably smaller ($\beta = 0.0954$, $p < 0.05$). Lagged earnings timeliness is negatively associated with CRNS ($\beta = -0.2088$, $p < 0.05$), suggesting that delayed financial reporting may be linked to weaker credit ratings. Collectively, the explanatory variables account for 54.1% of the observed variation in CRNS ($R^2 = 0.541$), while the overall regression is statistically significant ($F = 157$, $p < 0.05$).

Random Effects Model 1

The first random effects specification applies the Wallace–Hussain estimation procedure to account for the panel structure across the Financial, Services and Industry sectors. The resulting estimates identify statistically significant relationships between CRNS and all four explanatory variables:

- Firm size (SIZE): A substantial positive coefficient ($\beta = 1.0827$, $p < 0.05$) indicates

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

that a one-unit increase in the logarithm of total assets corresponds to an approximately 1.08-unit improvement in CRNS, providing sufficient statistical evidence to reject H01.

- Leverage (LEV): The estimated negative association ($\beta = -0.8144$, $p < 0.05$) demonstrates that greater reliance on debt financing corresponds to lower credit rating scores, supporting rejection of H02.
- Profit margin (PM): Profitability exhibits a comparatively modest but statistically significant positive relationship with CRNS ($\beta = 0.0954$, $p < 0.05$), indicating that stronger earnings performance is associated with more favourable credit assessments and justifying rejection of H03.
- Lagged exponential timeliness (EXP-TIMME (-1)): The coefficient is negative and statistically significant ($\beta = -0.2088$, $p < 0.05$). Provided that higher values of this measure represent greater reporting delays, the result suggests a relatively weak adverse association between delayed earnings disclosure and creditworthiness, leading to rejection of H04.

The sector-level specification accounts for 54.05% of the variation in CRNS ($R^2 = 0.5405$) and demonstrates overall statistical significance ($\chi^2 = 628.1$, $p < 0.05$). The estimated sector-level random-intercept variance is approximately zero (0.000), indicating limited residual heterogeneity across the Financial, Services and Industry sectors. At the 5% significance threshold ($\alpha = 0.05$), all four null hypotheses (H01–H04) are rejected. Although SIZE and LEV exhibit the largest estimated associations with credit ratings, PM and EXP-TIMME (-1) retain statistically significant, albeit smaller, relationships with CRNS.

Random Effects Model 2

The second random effects specification also employs the Wallace–Hussain procedure but incorporates firm-specific random intercepts for the 180 companies included in the panel. Unlike the sector-level model, this specification identifies statistically significant relationships for three of the four explanatory variables.

- **Firm size (SIZE):** The estimated coefficient remains positive and statistically significant ($\beta = 0.580$, $p < 0.05$). A one-unit increase in logarithmic total assets is associated with an approximately 0.58-unit increase in CRNS, indicating a moderate positive relationship and supporting rejection of H01.
- **Leverage (LEV):** Financial leverage continues to exhibit a statistically significant negative association with creditworthiness ($\beta = -0.234$, $p < 0.05$), providing evidence for rejecting H02.
- **Profit margin (PM):** The profitability coefficient is positive but relatively small ($\beta = 0.038$, $p < 0.05$), indicating a modest favourable association with CRNS and supporting rejection of H03.
- **Lagged exponential timeliness (EXP-TIMME (-1)):** Although the estimated

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

coefficient remains negative ($\beta = -0.039$), its statistical significance disappears ($p \geq 0.05$). Consequently, the evidence is insufficient to reject H04, suggesting that earnings timeliness does not exhibit a statistically distinguishable relationship with CRNS after accounting for firm-level unobserved heterogeneity.

As reported in Table 3, Random Effects Model 2 explains 21.7% of the variation in credit rating scores ($R^2 = 0.217$) and remains statistically significant overall ($\chi^2 = 157.9$, $p < 0.05$). Nevertheless, its explanatory performance is weaker than that of the sector-based specification. The estimated firm-level random-intercept variance approaches zero, suggesting that persistent unobserved differences among companies contribute relatively little additional variation within this model. Although SIZE and LEV remain the principal statistically significant determinants, their estimated coefficients are smaller than those obtained from the sector-level analysis. Most notably, the loss of statistical significance for EXP-TIMME(-1) indicates that the relationship between earnings timeliness and credit ratings is sensitive to the treatment of unobserved heterogeneity. Figure 4 illustrates these differences in coefficient estimates and statistical significance across the alternative regression specifications.

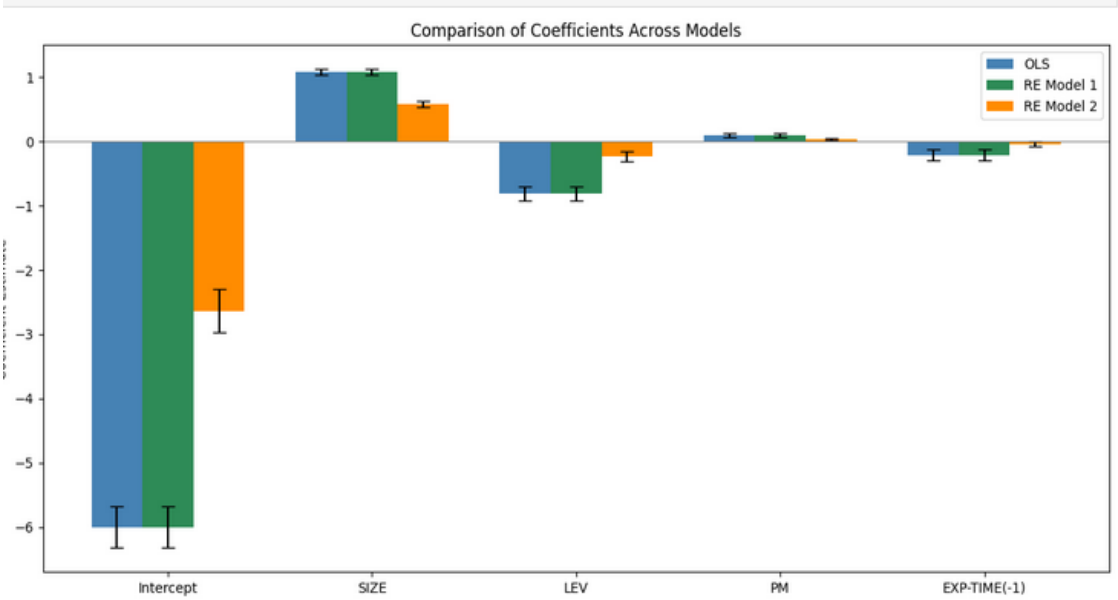

Figure 4: Comparison of Coefficients across Models

Multilayer Perceptron (MLP) Results

To complement the multiple regression analysis, an MLP classifier was implemented to identify potentially nonlinear associations among the explanatory variables and improve the prediction of credit rating categories. The dataset was partitioned into training and testing subsets comprising 80% and 20% of the observations, respectively. Using SIZE, LEV, PM and EXP-TIMME (-1) as input variables, the network was

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

trained to distinguish between two CRNS classifications based on a threshold of 3.75. The classification framework assigns observations to the "High" category when their scores meet the specified threshold and to the "Low" category otherwise. In terms of the stated risk interpretation, "High" corresponds to lower CRNS, whereas "Low" represents higher CRNS.

Table 4 summarises the classification outcomes obtained after 100 training iterations. The training dataset demonstrates moderate sensitivity, with a true positive (TP) rate of 0.5714, indicating that approximately 57% of actual positive observations were correctly identified. In contrast, the true negative (TN) rate reaches 0.9615, corresponding to the accurate classification of approximately 96% of negative observations. Nevertheless, the reported false positive (FP) rate of 0.4286 suggests a considerable frequency of incorrect positive classifications. Predictive performance deteriorates in the testing subset, where the TP rate declines to 0.4314 and the FP rate increases to 0.5686. These differences indicate weaker classification performance on previously unseen observations than on the training data.

Table 4: Statistical Criteria to Classify CRNS in MLP Model

Iterations	Size	Matrix			TP Rate	TN Rate	FP Rate	FN Rate
			Low	High				
n=100	Train (80%)	Low	200	8	0.5714	0.9615	0.4286	0.0385
		High	96	128				
	Test (20%)	Low	55	2	0.4314	0.9649	0.5686	0.0351
		High	29	22				
n=1000	Train (80%)	Low	195	13	0.6346	0.9375	0.3654	0.0625
		High	59	165				
	Test (20%)	Low	51	6	0.6667	0.8947	0.3333	0.1053
		High	17	34				
n=5000	Train (80%)	Low	191	17	0.7500	0.9183	0.2500	0.0817
		High	56	168				
	Test (20%)	Low	51	6	0.6863	0.8947	0.3137	0.1053
		High	16	35				

Extending the training process to 1,000 iterations produced appreciable improvements in classification performance. Within the training subset, the TP rate increased to 0.6346, while the FP rate decreased to 0.3654, indicating an enhanced ability to distinguish between credit rating categories. More substantial improvements were observed in the testing subset, where sensitivity increased to 0.6667, corresponding to the correct identification of approximately 67% of positive observations, and the FP rate declined to 0.3333. These changes suggest improved generalisation to previously unseen data. Nevertheless, the TN rate was slightly lower in the testing subset (0.8947) than in the training subset (0.9375), indicating differences in specificity between the two samples. Further increasing the number of iterations to 5,000 yielded the strongest training performance, with the TP rate reaching 0.7500 and the FP rate declining to 0.2500. However, improvements in testing performance were comparatively limited, as the TP rate increased only marginally to 0.6863, while the TN rate remained constant

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

at 0.8947. This pattern indicates diminishing improvements in out-of-sample classification performance despite continued gains during training.

Across the training subset (80%), classification sensitivity improved progressively as the number of iterations increased, with the TP rate rising from approximately 0.57 to 0.75. The larger training sample provided more observations from which the network could identify underlying relationships and progressively refine its classification boundaries. By contrast, improvements within the testing subset (20%) were less uniform. Although sensitivity increased from approximately 0.43 to 0.69 across the evaluated iteration counts, the smaller testing sample was more susceptible to variability in performance estimates, and additional training beyond 1,000 iterations produced relatively modest gains. Furthermore, the testing subset generally exhibited higher FP rates than the training subset, indicating persistent differences between in-sample learning and out-of-sample classification performance (see Table 4).

Performance Metrics at Different Iteration Counts

Table 5 presents a comparative summary of the classification performance measures obtained at the different iteration counts.

Table 5: Statistical Metrics for Classifying CRNS

Iterations	Size (Percentage)	Accuracy	Precision	Recall	F1-Score	Specificity	ROC
n=100	Train (80%)	0.7593	0.8899	0.9615	0.7937	0.5714	0.7665
	Test (20%)	0.7130	0.9184	0.9649	0.7801	0.4314	0.6981
n=1000	Train (80%)	0.7692	0.8741	0.9375	0.7831	0.6346	0.7861
	Test (20%)	0.7870	0.9529	0.8947	0.8160	0.6667	0.7807
n=5000	Train (80%)	0.8310	0.9305	0.9183	0.8396	0.7500	0.8341
	Test (20%)	0.7963	0.9559	0.8947	0.8226	0.6863	0.7905

At n = 100 iterations, the training subset (80%) demonstrates moderate classification accuracy (ACC = 0.7593), accompanied by relatively high recall (0.9615) and precision (0.8899) for the high CRNS category. Nevertheless, the comparatively low specificity (0.5714) indicates limited effectiveness in correctly identifying observations belonging to the low CRNS category. Performance deteriorates in the testing subset (20%), where accuracy declines to 0.7130 and specificity decreases substantially to 0.4314. These differences suggest potential overfitting and reduced stability when classifying lower-rated observations outside the training sample (see Figure 5). Increasing the number of itera-tions to n = 1,000 improves training specificity to 0.6346, while testing accuracy rises to 0.7870. Precision for the high CRNS category reaches its maximum of 0.9529, indicating stronger classifica-tion reliability and improved generalisation. At n = 5,000 iterations, the training model achieves its highest overall accuracy (ACC = 0.8310) and specificity (0.7500), alongside precision of 0.9305 and recall of 0.9183. These results indicate a more balanced classification performance across the two categories. However, the corresponding testing results exhibit signs of convergence, with accuracy

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

reaching 0.7963, specificity remaining at 0.6863 and recall stabilising at 0.8947. The relatively limited additional improvement suggests diminishing predictive benefits from extending the training process beyond 1,000 iterations.

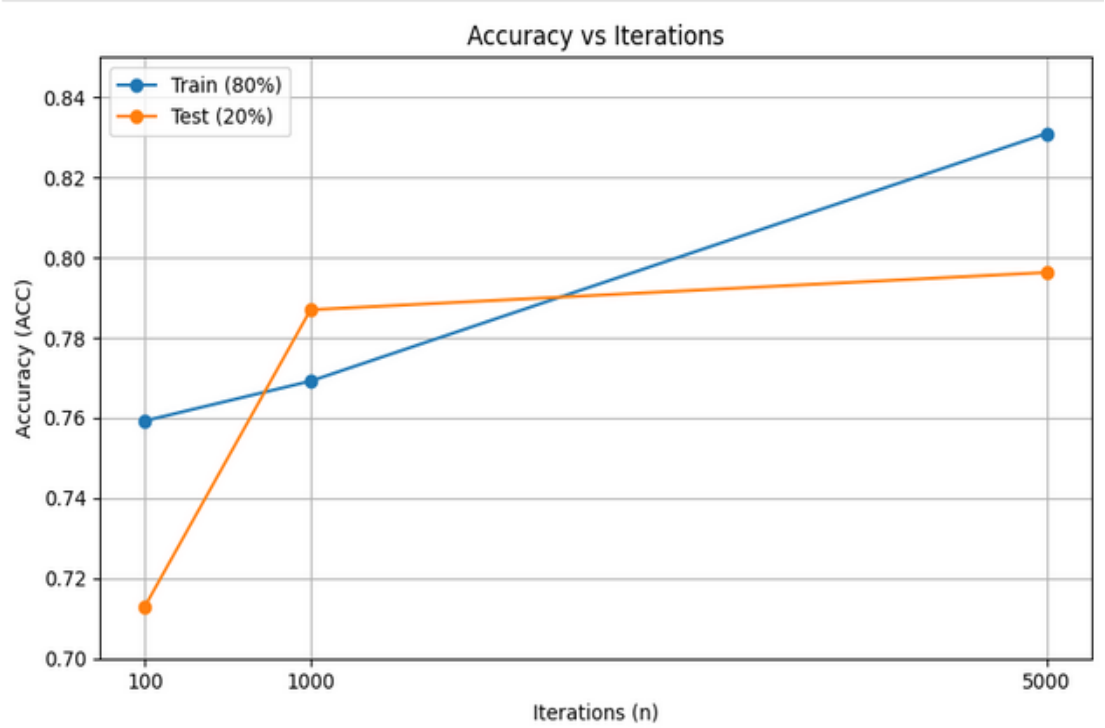

Figure 5: ACC Performance Metrics at Different Iteration Counts

Overall, increasing the number of iterations produces progressive improvements in training performance, including an increase in the F1-score from 0.79 to 0.84. The consistently favourable training ROC values, ranging from 0.76 to 0.83, indicate a relatively strong capacity to discriminate between credit rating categories. In comparison, the lower testing ROC values (0.69–0.79) suggest that out-of-sample discriminatory performance is more sensitive to the available sample size and the number of training iterations. These findings highlight the importance of balancing continued model optimisation against the diminishing improvements achievable in generalisation performance (see Figure 6).

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

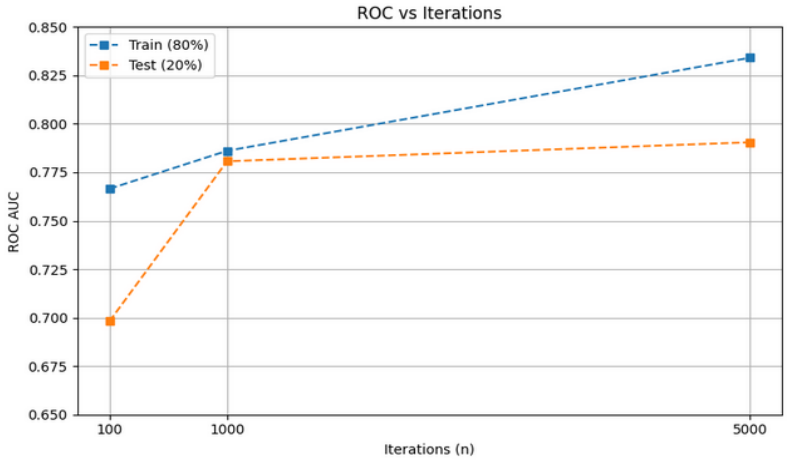

Figure 6: ROC Performance Metrics at Different Iteration Counts

The Weighted SSE vs. Iterations panel (upper-left, Figure 7) illustrates a rapid decline in prediction error during the initial stages of model training, followed by convergence of the testing subset's SSE towards zero after 5,000 iterations. This pattern suggests that the network progressively refined its parameter estimates and achieved increasingly stable learning outcomes.

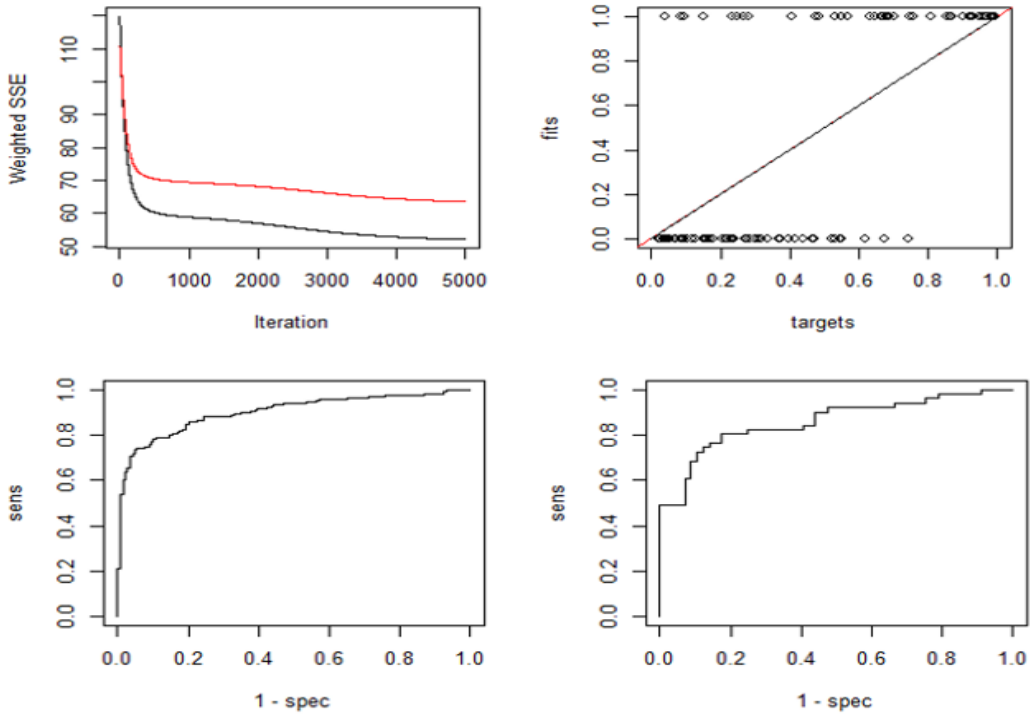

Figure 7: Performance of the MLP Model using an 80/20 Data Split with 5000 Iterations

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

The Fits vs. Targets panel (upper-right) further demonstrates a close correspondence between predicted and observed values, indicating satisfactory agreement between model outputs and their respective targets. Nevertheless, minor discrepancies remain, suggesting that the model retains some limitations in reproducing previously unseen observations with complete accuracy.

The ROC curve for the training subset (lower-left) exhibits a pronounced trajectory towards the up-per-left corner, reflecting strong discriminatory performance characterised by high sensitivity and specificity in distinguishing CRNS categories using approximately 80% of the available observations. By comparison, the ROC curve for the testing subset (lower-right) indicates a modest deterioration in classification performance, with slightly lower sensitivity and a greater incidence of false-positive predictions. Although these differences reveal some reduction in predictive effectiveness outside the training sample, the model maintains a comparatively robust capacity to distinguish be-tween credit rating categories across the remaining 20% of observations. Taken together, the four panels provide complementary evidence of effective model learning, favourable in-sample classification performance and reasonably consistent generalisation to unseen data under the adopted 80/20 partitioning strategy. The progressively smaller improvements observed beyond 5,000 iterations further indicate that extending the training process does not necessarily yield proportionate gains in predictive accuracy. These findings emphasise the importance of selecting an appropriate training duration while maintaining rigorous validation procedures to assess the reliability and generalisability of the resulting predictions.

DISCUSSION

Figure 8 provides a consolidated overview of the hypothesis-testing outcomes, highlighting the relationships between the selected firm-level characteristics and CRNS across the estimated models.

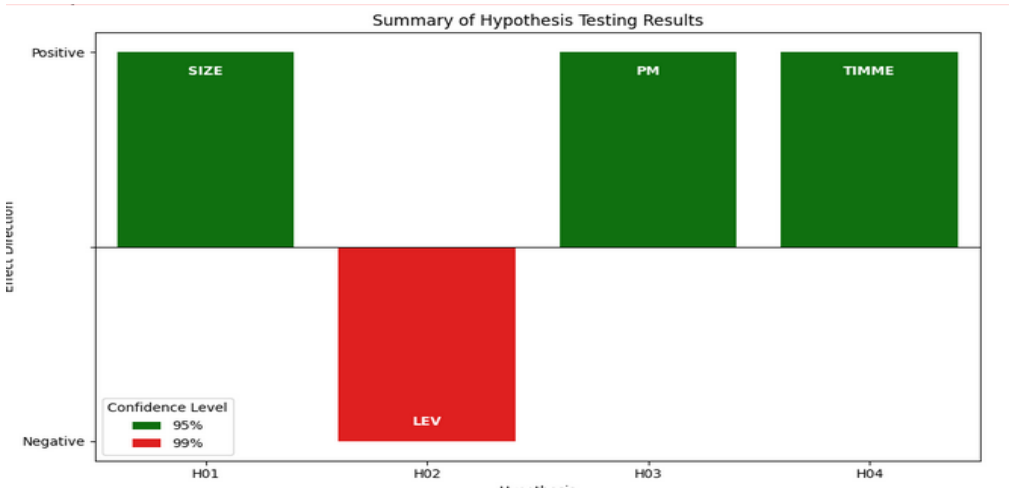

Figure 8: Summary of Hypothesis Testing Results

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

H01: The first hypothesis concerns the positive association between firm size, operationalised as the logarithm of total assets, and CRNS among Jordanian companies. The empirical findings establish a statistically significant positive relationship at the 95% confidence level, indicating that larger enterprises generally obtain more favourable credit ratings. This result is consistent with previous empirical evidence suggesting that organisational scale is positively associated with corporate creditworthiness.

H02: The second hypothesis addresses the anticipated negative relationship between financial leverage and CRNS. The findings provide strong statistical support for this association at the 99% confidence level, demonstrating that greater indebtedness corresponds to lower credit rating scores. Within the context of Jordanian listed companies, this inverse relationship suggests that higher debt exposure is associated with increased financial vulnerability and greater perceived credit risk. The result reinforces earlier empirical findings from emerging and developed economies, where elevated leverage has been identified as an important determinant of default exposure and deteriorating creditworthiness.

H03: The third hypothesis considers whether profitability contributes positively to corporate credit ratings. The regression estimates identify a statistically significant positive association between PM and CRNS at the 95% confidence level. Accordingly, firms generating stronger profit margins tend to receive higher credit rating scores, suggesting that favourable operating performance is associated with improved assessments of financial strength. This finding accords with previous research documenting the importance of profitability in evaluating corporate creditworthiness.

H04: The fourth hypothesis investigates the relationship between earnings reporting timeliness and CRNS, with the empirical evidence varying across model specifications. Under the OLS and sector-level random effects approaches, EXP-TIMME (-1) exhibits a statistically significant negative coefficient ($\beta = -0.2088$, $p < 0.05$), providing grounds for rejecting H04. This result indicates that delays in earnings disclosure are associated with less favourable credit ratings. Conversely, the firm-level random effects specification produces a considerably smaller negative coefficient that is not statistically significant ($\beta = -0.039$, $p = 0.2728$), meaning that H04 cannot be rejected under this model. The contrasting results suggest that the explanatory relevance of earnings timeliness is sensitive to model specification and becomes less pronounced when unobserved firm-specific heterogeneity is incorporated.

Notwithstanding this variation, the significant associations identified in the OLS and sector-level specifications are consistent with the proposition that prompt financial disclosure contributes to stronger perceptions of corporate creditworthiness. Timely earnings announcements may provide creditors and other stakeholders with more reliable information for assessing future cash flow prospects, thereby strengthening confidence in a firm's financial position. By improving information availability and potentially reducing information asymmetry, transparent and timely reporting may

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

facilitate more favourable credit assessments. These interpretations are consistent with the existing literature emphasising the relevance of earnings disclosure timeliness to creditors, although the absence of statistical significance in the firm-level specification indicates that its relationship with CRNS is not uniformly supported across all estimated models.

CONCLUSION

CRAs play a vital role in financial markets, yet the determinants of WVB credit ratings remain in-sufficiently explored, particularly in emerging economies. This study addresses this gap by examining the influence of firm characteristics and financial transparency on credit ratings among Jordani-an listed companies. Using WVB data from 180 firms comprising 540 firm-year observations, the study integrates conventional econometric methods with machine learning techniques. The OLS and sector-level random effects results indicate that firm size and profitability are positively associated with credit ratings, whereas leverage and delayed earnings reporting exhibit negative relationships. However, the firm-level random effects model reveals weaker associations, with earnings timeliness becoming statistically insignificant, suggesting that the relevance of financial transparency depends on model specification. The MLP model further demonstrates favourable predictive accuracy, highlighting the potential of machine learning for corporate credit risk assessment. Future research should extend the analysis to other MENA countries, incorporate corporate governance indicators, explore advanced machine learning models and examine sector-specific differences. These extensions could strengthen understanding of CRNS determinants and support more transparent, reliable and efficient financial systems in emerging markets.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

DATA AVAILABILITY

All data used in this study are fully available without restriction. The dataset consists of annual reports of publicly listed Jordanian firms on the Amman Stock Exchange (ASE https://www.ase.com.jo)). The firms included in the sample are rated by World'Vest Base (WVB http://www.wvb.com), which provides the credit rating data used in our analysis.

Vol: 18 **No:** 03 **Year:** 2026 **ISSN:** 1309-8055 (Online) (**pp.** 397-432) **Doi:** 10.34109/ijefs.2026180317

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