Integrating Reversible Instance Normalization with a Multilayer Perceptron to Enhance Predictive Modeling for Panel Data

Sura Basim Fawzi and Sabah Manfi Ridha
Department of Statistics, College of Administration and Economics, University of Baghdad, 10011 Baghdad, Iraq
{sura.b.013, drsabah}@coadec.uobaghdad.edu.iq

Keywords: Reversible Instance Normalization (RevIN), Panel Data, Multilayer Perceptron (MLP), Distribution Shift, Financial Forecasting.

Abstract: This study addresses the problem of forecasting financial panel data in the presence of distributional shifts and cross-sectional heterogeneity, which often deteriorate the performance of traditional machine learning models. Conventional normalization methods are typically static and fail to adapt to non-stationary conditions, resulting in reduced predictive accuracy and model instability. To overcome these limitations, this paper proposes a hybrid framework that integrates Reversible Instance Normalization (RevIN) with a Multilayer Perceptron (MLP). The proposed approach applies instance-wise normalization during training and reverses the transformation at inference, thereby preserving the intrinsic statistical properties of each cross-sectional unit while improving model stability. The framework is evaluated using a balanced panel dataset of ten Iraqi banks over the period 2011-2024 to predict the Capital Adequacy Ratio (CAR). The results show that the proposed model outperforms the baseline MLP, achieving an R^2 of 0.824 and an RMSE of 0.555, indicating improved predictive accuracy and generalization. These findings demonstrate the effectiveness of adaptive normalization in enhancing model robustness under heterogeneous and non-stationary conditions. This study contributes by extending the application of RevIN to financial panel data and providing a practical, interpretable, and efficient tool for banking risk management and regulatory forecasting.

1 INTRODUCTION

Recent advances in artificial intelligence have significantly improved time-series forecasting and the analysis of panel data. Deep learning models, particularly Multilayer Perceptrons (MLPs), are effective in modeling non-linear relationships that are not well captured by traditional statistical methods. However, financial panel data exhibit significant cross-sectional heterogeneity, including differences in scale, mean, and variance across units, as well as non-stationary temporal dynamics, different scales, means, and variances among cross-sectional units, as well as non-stationary temporal dynamics. Such distributional shifts can significantly degrade the predictive accuracy and generalizability of standard neural networks, particularly when conventional global normalization methods are employed [1]. To address this limitation, RevIN has recently emerged as a robust and effective normalization approach. In contrast to other static normalization methods, RevIN estimates instance-specific statistics (mean and standard deviation) and inverts them during the inference phase. The process maintains the distinctive statistical identity of each cross-sectional unit and stabilizes gradient flow while reducing the impact of local variability on global temporal patterns [2]. Adaptive normalization has been proven effective in handling non-stationary data in recent studies. Deep Adaptive Input Normalization (DAIN) has demonstrated substantial performance improvements across various neural architectures as an example of adaptive normalization techniques [3]. In the same way, the introduction of RevIN into the simplified forecasting models has been highly effective in reducing the gap between training and testing performance [4], [5]. In spite of these developments, the use of RevIN-enhanced architectures on financial panel data, especially in emerging markets that are highly volatile and structurally heterogeneous, has not been well explored. This study addresses this gap by introducing a new hybrid model which combines RevIN with an MLP architecture in order to predict the Capital Adequacy Ratio (CAR) of a panel of ten Iraqi banks (2011-2024). This study contributes in three ways: (1) the design of a lightweight RevIN-

MLP framework to forecast financial panels; (2) empirical results demonstrate improved predictive performance (R2 = 0.824, RMSE = 0.55) and training stability compared to traditional baselines; and (3) practical implications of risk monitoring and regulatory forecasting in the developing economies. The remainder of the paper is organized as follows: Section 2 outlines the methodology and model architecture, Section 3 is devoted to the description of the experimental setup and results, Section 4 is devoted to the discussion of the findings, Section 5 concludes with limitations and future research directions.

2 RESEARCH METHODOLOGY

In this section the hybrid methodological framework merging the principles of statistics and deep learning designs will be established in order to increase predictive accuracy and robustness of the model proposed.

2.1 Panel Data

Panel data combine cross-sectional and time-series dimensions. It is a data structure in which the same units (e.g. individuals, firms, nations, or institutions) are observed across a time interval. They allow the analysis of both within-unit dynamics over time and between-unit heterogeneity. While controlling for unobserved unit-specific characteristics. The general linear model for panel data can be expressed as follows [6]:

$$Y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j X_{jit} + U_{it}. \quad (1)$$

Where:

- y_{it}: Represents the dependent variable for cross-sectional unit i at time t.
- i: Denotes the cross-sectional dimension (units), where =1,2,3, …, N.
- t: Denotes the temporal dimension (time periods/years), where t=1,2,3, …, T.
- β_0: Represents the model intercept (constant term).
- β_1: Represents the statistical parameters (coefficients) of the model.
- X_{jit}: Represents the vector of independent variables that vary across both units and time.
- U_{it}: The Panel error term.

2.2 Description of Data and Study Variables

The data include annual financial metrics of ten Iraqi commercial and state-owned banks between 2011 and 2024 based on the statistical bulletins of the Central Bank of Iraq. The resulting balanced panel comprises 140 observations (10 banks x 14 years). The variables will be classified into a dependent variable, three independent predictors and cross-sectional and time identifiers as represented in Table 1 in a summarized form.

Table 1: Study variables.

Variable Type	Variable Name	Symbol	Measurement Method / Definition	Modeling Rationale
Dependent Variable	Capital Adequacy Ratio	CAR	Ratio of regulatory capital to risk-weighted assets	The main regulatory variable of bank solvency; the predictor variable.
Independent Variable 1	Liquidity Ratio	L-Q	Liquid assets / Total assets	Imposes temporary capital resilience; influences capital resilience in times of stress.
Independent Variable 2	Non-Performing Loans Ratio	NPL-ratio	Doubtful loans / Total credit exposure	The warning sign of the decrease in asset quality and capital loss.
Independent Variable 3	Credit-to-Deposit Ratio	CDR	Cash credit facilities / Total deposits	Measures expand the intensity of credit expansion; nonlinear effect on capital adequacy
Control/Identifier Variables	Bank Identity and Year	Bank-ID / Year	Represent the cross-sectional and temporal dimensions of the panel data structure	-

2.3 The Statistical Diagnostic Tests

Prior to model estimation, diagnostic procedures are conducted to assess the suitability of the panel data and ensure the absence of statistical issues that may bias the results or compromise inference. The following tests are employed.

2.3.1 Multicollinearity Test

A Pearson correlation matrix is used to examine the degree of association among the explanatory variables (Table 2). The highest observed correlation coefficient is 0.35 (associated with the Cash Credit Ratio, CDR), which remains well below the commonly accepted threshold of 0.80, as suggested by Wooldridge [7]. This indicates that multicollinearity is not a concern in the dataset. The absence of significant multicollinearity enhances the stability and interpretability of the model and supports the reliability of subsequent analysis. These diagnostic results provide a sound basis for the empirical modeling framework and strengthen the robustness of the proposed hybrid approach.

2.3.2 Normality Test

To assess whether the dependent variable follows a normal distribution, the Jarque-Bera test was applied. Normality is commonly considered an assumption in parametric statistical tests, such as the t-test and F-test. The empirical results yielded a p-value of 0.0091, which is below the 5% significance level ($p < 0.05$), indicating statistical significance. Accordingly, the null hypothesis of normality is rejected, suggesting that the dependent variable, Capital Adequacy Ratio (CAR), is not normally distributed at the 5% level, as shown in Figure 1.

Table 2: Pearson correlation matrix.

	CDR	L_Q	NPL-ratio
CDR	1	-0.35	-0.13
L-Q	-0.35	1	0.35
NPL-ratio	-0.13	0.35	1

2.3.3 Heteroscedasticity Test

Heteroscedasticity is examined at two levels: (i) the cross-sectional dimension to assess variance differences across the sampled banks, and (ii) the time dimension to evaluate the stability of variance over the study period. The presence of heteroscedasticity in either dimension may bias model estimation and affect predictive performance. Therefore, applying Reversible Instance Normalization (RevIN) is justified, as it standardizes each cross-sectional unit over time and mitigates both cross-sectional and temporal heteroscedasticity prior to model training.

2.3.3.1 Cross-Sectional Heteroscedasticity Test

Residual-based tests are conducted to examine variance heterogeneity across the sampled banks. The results reported in Table 3 indicate significant variation in variance across cross-sectional units, suggesting that the sample does not exhibit homoscedasticity.

Table 3: Cross-Sectional Homoscedasticity test results.

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	98.601	45	0.0000
Pesaran scaled LM	5.650	-	0.0000
Pesaran CD	-0.798	-	0.4247

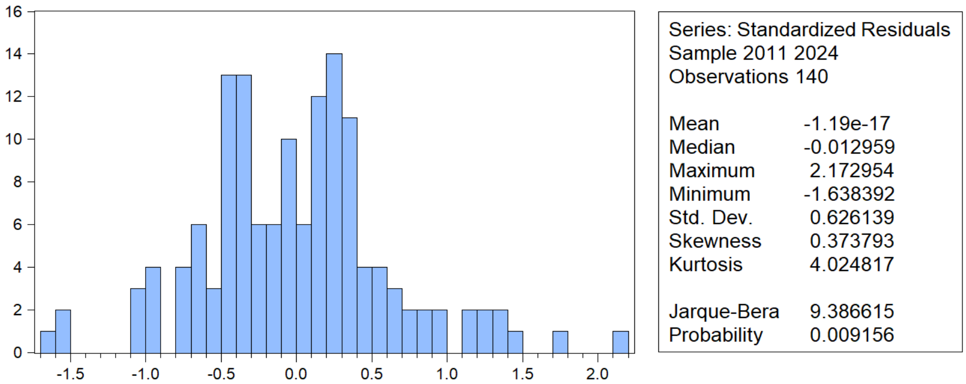

Figure 1: Frequency distribution and normality assessment of residuals.

2.3.3.2 Test of Time-Series Heteroscedasticity

The Likelihood Ratio (LR) test is employed to assess the constancy of error variance over time during the period 2011-2024. As shown in Table 4, both the F-statistic and Chi-square statistic are statistically significant ($p < 0.05$), leading to the rejection of the null hypothesis of homoscedasticity.

These findings indicate the presence of time-related heteroscedasticity. The results also suggest structural differences across banks over time, supporting the use of advanced preprocessing techniques to reduce the impact of heteroscedasticity on the prediction of capital adequacy ratios [8].

Table 4: Time-Series Heteroscedasticity test results.

Effects Test	Statistic	d.f.	Prob.
Cross-section F	26.762	9.127	0.0000
Cross-section Chi-square	148.892	9	0.0000

2.3.3.3 Stationarity Test (Unit Root Test)

Panel unit root tests are conducted to avoid spurious regression and ensure the validity of the data for predictive modeling. The Bai and Ng [9] methodology is applied. The results, presented in Table 5, indicate heterogeneous stationarity properties across the variables.

Non-Performing Loans Ratio (NPL): Stationary at level I(0), with a p-value of 0.00000, indicating rejection of the null hypothesis of a unit root.

Capital Adequacy Ratio (CAR) and Credit-to-Deposit Ratio (CDR): Non-stationary at level but become stationary after first differencing (I(1)), with statistically significant p-values of 0.00005 and 0.00000, respectively.

Liquidity Ratio (LQ): A logarithmic transformation is applied to stabilize variance and reduce skewness. After first differencing, the series becomes stationary (I(1)) with a p-value of 0.00000.

It is necessary to add that the null hypothesis (H_0) is a statement that there is a unit root (non-stationarity). When H_0 is rejected at 0.05 then this means that there is no unit-root behaviour.

2.4 The Proposed RevIN-MLP Hybrid Framework

To address the distributional shifts and heteroscedasticity identified in the diagnostic tests, we propose a hybrid framework that integrates instance-level Reversible Normalization with a Bayesian-regularized Multilayer Perceptron. This architecture combines dynamic, bank-specific scaling with robust neural regression to enhance predictive stability in heterogeneous financial panel data.

2.4.1 Instance-Wise RevIN Implementation

Unlike global normalization, RevIN is implemented as an explicit preprocessing and postprocessing pipeline applied independently to each cross-sectional unit. For each bank i, the temporal mean and standard deviation are computed across the sequence for both input features (X) and the target variable (Y). Normalization follows a standardized z-score transformation [5]:

$$\hat{x}_{it} = \frac{x_{it}-\mu_{ix}}{\sigma_{ix}} + \varepsilon,\ y_{it} = \frac{y_{it}-\mu_{iy}}{\sigma_{iy}} + \varepsilon. \quad (2)$$

Where = 10^{-8} is a numerical stability constant. Post-prediction, the inverse transformation restores outputs to the original financial scale using bank-specific target parameters:

$$\tilde{y}_{it} = \hat{y}_{it} * \sigma_{iy} + \mu_{iy}. \quad (3)$$

This design preserves unit-specific distributional identities while mitigating cross-sectional variance heterogeneity prior to neural processing.

Table 5: Panel unit root test results (Bai and Ng PANIC Test).

Variable	Symbol	p-value at Level $I(0)$	p-value at First Difference $I(1)$	Integration Order / Result
Capital Adequacy Ratio	CAR	0.78802	0.00005	Stationary at First Difference I(1)
Liquidity Ratio	L-Q	0.22816	0.00000	Stationary at First Difference $I(1)$ after Log Transformation
Non-Performing Loans Ratio	NPL-ratio	0.00000	-	Stationary at Level $I(0)$
Credit-to-Deposit Ratio	CDR	0.39482	0.00000	Stationary at First Difference $I(1)$

2.4.2 MLP Architecture and Training Configuration

The predictive model is based on a feedforward Multilayer Perceptron (MLP) implemented using MATLAB's Neural Network Toolbox. The network architecture consists of a single hidden layer with 10 neurons employing the hyperbolic tangent sigmoid (*tansig*) activation function, followed by a linear (*purelin*) output layer for continuous regression tasks. Model training is performed using the Bayesian Regularization (*trainbr*) algorithm, which optimizes a combined objective function incorporating both squared errors and network weights. This approach helps mitigate overfitting and improves generalization performance, particularly in small panel datasets [10], [11]. The training process uses the dividetrain function, allowing the model to be trained on the full dataset without internal validation splits, while standard convergence criteria are applied. To ensure reproducibility, all experiments are initialized with a fixed random seed (*rng*(7)) [12].

2.4.3 Data Partitioning Strategy

To preserve temporal causality and prevent look-ahead bias, the balanced panel (140 observations) is partitioned chronologically rather than randomly. The dataset is split into 80% training (112 samples, 2011-2019) and 20% out-of-sample testing (28 samples, 2020-2024). Feature scaling statistics are computed exclusively on the training partition, and the trained network is evaluated on the held-out test set to simulate real-world forecasting conditions [13].

2.4.4 The RevIN Mathematical Formulation and Integration Protocol

Reversible Instance Normalization (RevIN) operates via a two-step affine transformation of the time sequence of cross-sectional units. Wher the input sequence of bank *i* at time *t* [5].

Pass Forward (Normalization before MLP):

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} x_{it} \ , \sigma_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(x_{i,t}-\mu_i\right)^2 + \varepsilon} \quad (4)$$

$$\hat{x}_{it} = \gamma * \frac{x_{i,t}-\mu_i}{\sigma i} + \beta . \quad (5)$$

Where ϵ =10-5 is a numerical stability parameter, and γ, β are learnable affine parameters (initially 1 and 0)

Inverse Pass (Denormalization of MLP prediction):

$$\tilde{y}_{it} = \sigma_i * \frac{\hat{y}_{it}-\beta}{\gamma_i} + \mu_i . \quad (6)$$

Integration Point: RevIN is executed as a plug-and-play-unit:

- Input features.
- RevIN Normalization (5).
- MLP Backbone.
- RevIN Denormalization (6).
- Final Output.

As illustrated in Figure 2, this design has unit-specific statistical identity and stabilizes propagation of gradients during training.

2.5 Empirical Results and Discussion

This section presents the empirical results and discusses the performance of the proposed model.

2.5.1 Comparative Performance Analysis

In order to measure the performance of the suggested RevIN-MLP framework, we provided a thorough comparative analysis to a baseline MLP model that was trained on the globally normalized data. The models were evaluated based on various error and goodness-of-fit measures on the withheld test set (2023-2024). Table 6 is a summary of the key performance indicators.

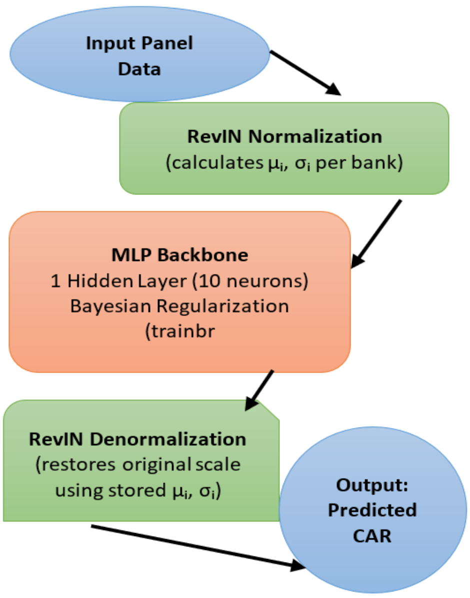

Figure 2: Architectural diagram of the Reversible Instance Normalization (RevIN) mechanism.

Table 6: Performance metrics comparison: MLP Model with vs. without RevIN.

Model Specification	MLP (Baseline)	MLP + RevIN (Proposed)
Mean Absolute Error (MAE)	0.446	0.402
Mean Squared Error (MSE)	0.395	0.309
Root Mean Squared Error (RMSE)	0.628	0.555
R-Squared (R^2)	0.775	0.824
Adjusted R-Squared (Adj-R^2)	0.732	0.791
Mean Absolute Percent Error (MAPE %)	114.95	179.35
Theils U-Coefficient	0.139	0.121

The findings prove that incorporating RevIN provides stable improvements in all major measures. The decrease in RMSE (0.628→0.555) and MAE (0.446→0.402) values demonstrates that on average the model point forecasts are closer to the observed values of Capital Adequacy Ratio (CAR). Moreover, the fact that R^2 (0.775→0.824) and the Adjusted R^2 (0.732 → 0.791) are higher confirms that the RevIN-enhanced architecture represents a higher proportion of variance in the target variable, even though the panel data inherently vary.

2.5.2 MAPE Behavior and Metric Selection Interpretation

The MAPE metric shows an increase in the proposed model (114.95% → 179.35%), which may appear counterintuitive given the improvements in other evaluation measures. However, this behavior is a well-documented limitation of MAPE in financial forecasting applications, particularly when actual values are close to zero or relatively small in magnitude [14]. In this study, the Capital Adequacy Ratio (CAR) for certain Iraqi banks occasionally approaches regulatory thresholds (approximately 9-12%), where even small absolute prediction errors can result in disproportionately large percentage errors due to the structure of the MAPE formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{y_t-\widehat{y_t}}{y_t}\right| \times 100. \quad (7)$$

Under such conditions, the denominator effect amplifies relative errors, making MAPE less reliable as a standalone performance measure. Therefore, consistent with best practices in financial forecasting, greater emphasis is placed on scale-independent metrics such as RMSE, MAE, and Theil's U, which demonstrate stable and consistent improvements. In particular, the reduction in Theil's U (0.139 → 0.121) further confirms the enhanced predictive reliability of the proposed RevIN-MLP model.

2.5.3 Forecasting Accuracy Visual Assessment

We also give graphical diagnostics to augment the quantitative metrics to bring out the predictive behavior of the model.

Figure 3 shows a scatter plot of the actual and predicted values of CAR. RevIN-enhanced model (blue dots) shows tendency to cluster much around the 45-degree line of perfect agreement (Y=X) than the baseline MLP (orange dots). Such a visual focus implies less dispersion and more fidelity in the process of capturing the true variation of the target variable.

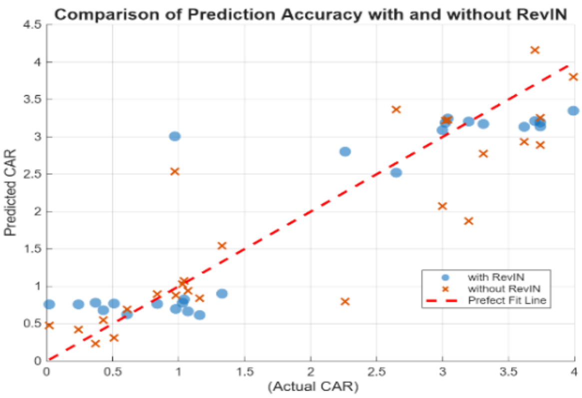

Figure 3: Scatter plot of actual vs. predicted capital adequacy ratio (caR).

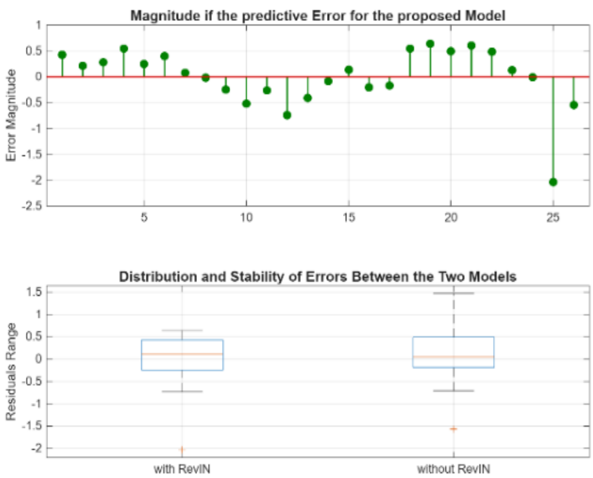

Figure 4: Error distribution and boxplot analysis - predictive performance assessment.

Figure 4 provides a two-tier error diagnosis. The upper panel (residual scatter) indicates that the forecast errors are distributed symmetrically around the zero with no apparent systematic pattern thus no model misspecification or omitted-variable bias. According to the lower panel (boxplot comparison), RevIN-MLP model has a smaller interquartile range (IQR) and reduced numbers of extreme outliers than the baseline. This minimization of error dispersion is a confirmation of increased robustness especially when there are circumstances of financial turbulence or anomalous observations.

2.5.4 Methodological Implications

There are empirical findings which substantiate a number of methodological observations:

1) Adaptive Normalization Reduces Distribution Shift: RevIN mitigates distribution shift by normalizing instance-specific statistics, enabling the MLP to concentrate on common predictive patterns.
2) Enhanced Signal-to-Noise Ratio: The decrease of out-of-sample error measures signifies that reduce unit-specific noise, which increases the prediction capability of the model to unseen data.
3) Maintenance of Interpretability: The reversibility of the transformation guarantees that the final predictions are in the original scale of the CAR, directly interpretable by regulators and use in practice.
4) Scalability to Heterogeneous Panels: The results of applying the framework to ten different Iraqi banks indicate that the framework can be used in other emerging-market financial panels with structural volatility and heterogeneous data.

To conclude, the combination of RevIN and the MLP backbone is a lightweight but powerful model to predict financial panel data, which has statistically significant results in accuracy, stability, and robustness without reducing interpretability.

3 CONCLUSIONS

This study addresses the challenge of forecasting financial panel data in emerging markets, where cross-sectional heterogeneity and distributional shifts significantly degrade the performance of traditional neural networks. A hybrid framework integrating Reversible Instance Normalization (RevIN) with a Multilayer Perceptron (MLP) is proposed to predict the Capital Adequacy Ratio (CAR) of ten Iraqi banks over the period 2011-2024.

The empirical results demonstrate that the proposed RevIN-MLP model consistently outperforms the baseline MLP model across all key performance metrics. It achieves an R^2 of 0.824, RMSE of 0.555, and MAE of 0.402, with improvements of 11.6% in RMSE and 8.1% in Adjusted R^2. These results confirm that instance-wise normalization significantly enhances predictive accuracy, generalization ability, and training stability under conditions of non-stationarity and heteroscedasticity in financial panel data.

The findings have important implications for banking risk management and regulatory forecasting. The proposed framework provides a lightweight and interpretable predictive tool that can support early warning systems and capital adequacy monitoring in emerging economies. Its simplicity and robustness make it suitable for real-world deployment in financial institutions where data heterogeneity and limited computational resources are common constraints.

The main contributions of this study are three-fold:

1) Extending Reversible Instance Normalization (RevIN), originally developed for univariate time-series forecasting, to heterogeneous financial panel data with strong predictive performance.
2) Demonstrating that lightweight architectures such as MLPs, when combined with adaptive normalization, can achieve competitive results compared to more complex deep learning models.
3) Developing a reproducible and interpretable forecasting framework suitable for financial risk modeling in emerging markets.

Despite these contributions, the study has certain limitations. The dataset is limited to Iraqi banks over a 14-year period, which may restrict the generalizability of the results to other countries or financial systems with different macroeconomic structures. In addition, the model relies on aggregated financial indicators and does not incorporate high-frequency transactional data or qualitative supervisory information. Moreover, although RevIN improves robustness, the sensitivity of MAPE to low-magnitude CAR values remain a limitation, highlighting the need for more reliable evaluation metrics in threshold-based forecasting.

Future research could extend this framework to multi-country panel datasets to evaluate cross-market generalization. The integration of attention mechanisms or temporal convolutional networks may further enhance the model's ability to capture complex temporal dependencies. Additionally, incorporating real-time macroeconomic variables and exploring online learning approaches could improve the applicability of the model in regulatory stress testing and dynamic early-warning systems.

In conclusion, the proposed RevIN-MLP architecture offers a lightweight, scalable, and interpretable solution for financial panel forecasting, effectively bridging the gap between model simplicity and predictive performance in volatile banking environments.

REFERENCES

[1] F. Jawadi, T. M. Pondie, and A. I. Cheffou, "New challenges for green finance and sustainable industrialization in developing countries: A panel data analysis," Energy Economics, vol. 142, p. 108120, 2025.

[2] D. Kotios, G. Makridis, G. Fatouros, and D. Kyriazis, "Deep learning enhancing banking services: a hybrid transaction classification and cash flow prediction approach," Journal of Big Data, vol. 9, no. 1, p. 100, 2022.

[3] N. Passalis, A. Tefas, J. Kanniainen, M. Gabbouj, and A. Iosifidis, "Deep Adaptive Input Normalization for Time Series Forecasting," Sep. 2019, , [Online]. Available: http://arxiv.org/abs/1902.07892.

[4] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "The M4 Competition: 100,000 time series and 61 forecasting methods," International Journal of Forecasting, vol. 36, no. 1, pp. 54-74, 2020, doi: 10.1016/j.ijforecast.2019.04.014.

[5] T. Kim, J. Kim, Y. Tae, C. Park, J.-H. Choi, and J. Choo, "Reversible instance normalization for accurate time-series forecasting against distribution shift," in International Conference on Learning Representations, 2021.

[6] C. Hsiao, Analysis of Panel Data, no. 64. Cambridge University Press, 2022.

[7] J. M. Wooldridge, Introductory Econometrics: A Modern Approach, Sixth Edition. Cengage, 2015, [Online]. Available: www.cengage.com/highered.

[8] W. H. Greene, Econometric Analysis, Eighth Edition. 2020.

[9] J. Bai and S. Ng, "A new look at panel testing of stationarity and the PPP hypothesis," Cambridge University Press, 2005.

[10] A. Saly-Kaufmann, K. Wood, J. Peter-Calliess, and S. Zohren, "Deep learning for financial time series: A large-scale benchmark of risk-adjusted performance," arXiv preprint arXiv:2603.01820, 2026.

[11] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.

[12] A. H. Abd-elaziem and T. H. M. Soliman, "A multi-layer perceptron (MLP) neural networks for stellar classification: A review of methods and results," International Journal of Advanced Applied Computer Intelligence, vol. 3, no. 10, p. 54216, 2023.

[13] R. J. Hyndman and G. Athanasopoulos, Forecasting: Principles and Practice. OTexts, 2018.

[14] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," International Journal of Forecasting, vol. 22, no. 4, pp. 679-688, 2006.