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A Comparative Study on Credit Risk Measurement Models of Commercial Banks and Their Applicability

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Keywords: Commercial banks; credit risk measurement; abnormal loan growth; exposure-aligned loss rate; generalized additive model

Abstract: Abnormal loan growth can simultaneously alter commercial banks' risk exposure and future credit loss performance. This study uses publicly available quarterly regulatory data to construct an exposure-aligned net write-off ratio for the next four quarters, and examines the potential denominator impact of loan expansion using a growth-neutral net write-off ratio. Using the median loan growth rate of banks of similar size in the same quarter as a reference, the study identifies positive and negative abnormal loan growth, comparing dynamic regulatory risk models, nonlinear generalized additive models, and shallow XGBoost models under strict time sequence. Expanded window prediction and frozen threshold validation show that when the positive abnormal threshold is not triggered, the average error improvement of complex models is limited; after positive abnormal loan growth exceeds 10.8 percentage points, the nonlinear model performs better in terms of average error, tail loss prediction, and high-risk bank identification. The results indicate that commercial banks need to select credit risk measurement tools based on the state of loan expansion.

1 Introduction

Credit risk is a core risk in the operation and management of commercial banks. There is typically a time lag between loan disbursement and loss recognition. Changes in credit standards, industry allocation, and maturity arrangements often do not immediately manifest as non-performing loans or write-off losses. More commonly, risk accumulates gradually through increased delinquency, rising provisioning pressure, and changes in asset structure. If banks rely solely on current non-performing loan ratios, historical write-off rates, or single financial indicators to assess potential credit risk, they will struggle to identify pressures in their loan portfolios that have not yet been fully exposed.

Existing research suggests that commercial bank credit risk is influenced by a combination of factors, including asset quality, capital buffer, profitability, liquidity, loan structure, and sources of liabilities. Traditional statistical models have a clear structure and are commonly used for routine risk monitoring. Machine learning models can handle nonlinear relationships and variable interactions, giving them an advantage in identifying high-risk samples [1][2][9]. However, the advantages of complex models can change when the prediction object, data structure, and validation method change [3][4].

Existing comparative studies leave two unresolved issues. The risk metrics—bank failure, distance-to-default, borrower probability of default, and non-performing loan (NPL) ratios—each capture different aspects of risk. From the perspective of loan portfolio management, actual future credit losses more accurately reflect the risk a bank faces. Furthermore, loan growth alters future risk exposure and the denominator used to calculate loss rates. If future losses are consistently divided by the loan balance at the time of the forecast, rapid expansion inflates the denominator, potentially masking the accumulation of risk.

These issues point to a specific scenario: whether existing models can still provide reliable assessments when a bank's loan expansion deviates significantly from that of its peers. This study focuses on the net write-off losses of loan portfolios over the subsequent four quarters, constructing an "exposure-aligned credit loss rate" and using a "growth-neutral net write-off rate" to examine the impact of the denominator. It then identifies instances of positive and negative abnormal loan growth—using the median loan growth rate of peer banks of similar size during the same quarter as a benchmark—and compares the performance of three types of models under consistent information conditions.

The study examines two judgments. When the positive anomaly threshold is not triggered, the dynamic regulatory risk model incorporating asset quality, capital, liquidity, and structural variables should provide a stable benchmark, while the incremental changes in nonlinear models are limited. When abnormal expansion is coupled with a high non-performing loan ratio or CRE loan concentration, the nonlinear generalized additive model should have higher tail loss prediction value. Whether shallow XGBoost primarily improves the ranking of key risk banks is also examined within the same framework.

The study unifies the model results with future net write-off losses to avoid mixing different risk objects. After constructing ELR and GNLR in parallel, the impact of loan growth on the denominator can be examined. Combining threshold identification during the development period with frozen verification during the testing period, model comparison can generate applicable rules for daily monitoring and key audits.

2. Research Boundaries and Analytical Framework

2.1 Research Subjects and Comparison Boundaries

The study focuses on the future net credit losses of commercial bank loan portfolios, with the unit of observation being the bank-quarter. Net write-offs are calculated by subtracting recoveries from write-offs, reflecting the actual losses after loan disposal and recovery. Therefore, it can be directly linked to provision management, asset quality monitoring, and post-loan early warning. The study does not discuss the bank's own market default risk, nor does it discuss individual borrower credit scores.

The sample is drawn from publicly available quarterly regulatory reports of U.S. commercial banks. The original sample period is from the first quarter of 2001 to the fourth quarter of 2025, and the out-of-sample forecast period is from the first quarter of 2019 to the fourth quarter of 2024. For banks that have merged, exited, or changed their names, the study retains valid records prior to their exit. Because losses for the next four quarters require complete observation, observations that cannot be fully labeled are not included in the forecast sample.

KMV, CreditMetrics, and CreditRisk+ are not included in the main comparison model. KMV primarily reflects the default risk of listed banks themselves, while the latter two models require internal data such as borrower rating migration, loss-of-default ratios, and asset correlation. Publicly available regulatory reports do not provide complete information on this. Therefore, model comparisons are limited to loan portfolio loss predictions that can be completed under publicly available regulatory information to ensure consistency in risk targets, data foundations, and interpretation of conclusions.

2.2 Analytical Framework and Model Selection Principles

The analysis revolves around whether abnormal loan growth alters the applicability of current credit risk models. The study constructs a bank-quarter panel to generate the net write-off rate aligned with exposure for the next four quarters, and identifies positive and negative abnormal growth using the median loan growth of banks of similar size in the same quarter. After determining the model applicability threshold during the development phase, the threshold remains unchanged during the testing phase to compare the predictive performance of different models. Figure 1 illustrates the process.

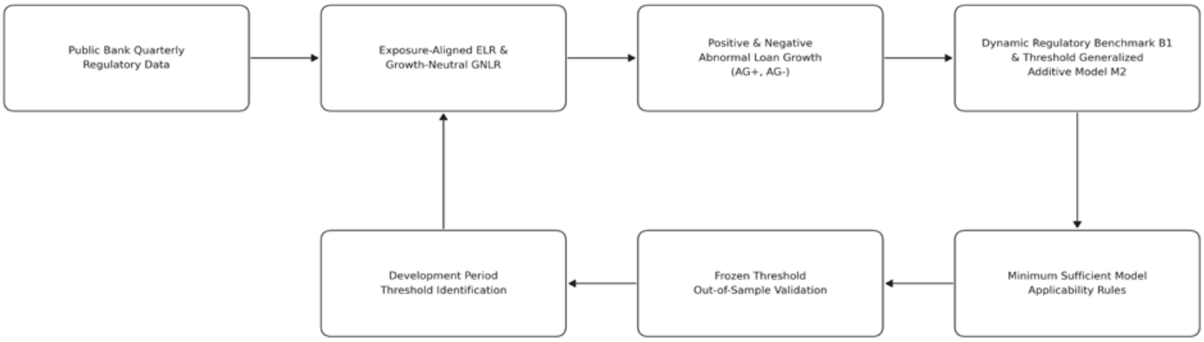

Figure 1. Comparison path of commercial bank credit risk models under abnormal loan growth.

Model selection follows the principle of minimum sufficient model. Increased complexity or expanded information dimensions do not necessarily reduce model risk. Banks also need to determine the model structure by combining data quality, prediction stability and purpose of use [5]. When the positive anomaly threshold is not triggered, if the complex model does not have stable error improvement, the dynamic regulatory risk model with strong interpretability and low maintenance cost is more suitable for daily use. After the anomaly expansion occurs, the nonlinear model is only necessary for key early warning if it demonstrates practical value in error and key risk identification.

3. Data, Variables, and Prediction Objectives

3.1 Data Processing and Sample Construction

The original regulatory data includes balance sheets, income statements, loan structures, deposit structures, asset quality, and bank identification information. Data processing includes bank identification verification, report matching, conversion of year-to-date cumulative items, outlier handling, and construction of future loss labels. Write-offs, recoveries, loan loss provisions, and net interest income are calculated on a year-to-date basis, therefore requiring differentiation between banks and calendar years, and recalculation starting in the first quarter of each year to avoid duplicate inclusion of previous information in the current period's flows.

Discontinuous quarterly records are not used to construct future loss labels across missing periods. Variable shrinking, missing value imputation, standardization, and parameter selection are all performed within the training sample before being applied to the test period. Table 1 shows the sample selection and variable construction. In actual use of regulatory reports, there are significant differences in bank size, report completeness, and loan structure. The study maintains a quarterly order and does not randomly split or mix samples from different time points, making the testing process closer to the scenario where banks assess risk based on currently disclosed information.

Table 1 Sample selection, variable construction, and prediction objectives

project	content
Original regulatory report observation	633,857 banks—Quarterly observation
After completing the verification of bank logo and quarterly date	621,438 observations
After retaining loan, capital, asset quality, and flow variables	578,946 observations
Labeled with consecutive losses for the next four quarters	542,671 observations
Out-of-sample testing and observation from Q1 2019 to Q4 2024	151,386 observations
Main forecast target	The net write-off rate will be exposed in the next four quarters.
Denominator diagnostic goals	Neutral net write-off rate for the next four quarters
Abnormal loan growth	Deviation from the median growth rate of bank loans of the same size group in the same quarter
Asset quality variables	Non-performing loan ratio, provision ratio, historical loss ratio
Structural variables	CRE loan ratio, industrial and commercial loan ratio, brokerage deposit ratio, loan concentration
control variables	Equity ratio, return on assets, net interest income ratio, ratio of liquid assets to deposits, and asset size

3.2 Exposure Alignment Loss Rate and Growth Neutral Loss Rate

To avoid the mechanical dilution of future cumulative losses by loan balances at a single point in time, the net write-off ratio for exposure alignment in the next four quarters is defined as follows:

$$ELR_{i,t}^{(4)} = 10\,000 \times \frac{\sum_{h=1}^{4} NCO_{i,t+h}}{\frac{1}{4}\sum_{h=1}^{4} GL_{i,t+h-1}}$$

Here, ELR represents the cumulative exposure aligned with net write-offs over the four quarters following the forecast date, in basis points; NCO represents the net write-off amount for a single quarter; and GL represents the loan balance at the start of the quarter. The study retains negative net write-offs to reflect situations where recoveries exceed write-offs. Average loan exposure over the same period, after absorbing cumulative net write-offs, ensures that future losses are not mechanically diluted by a single loan balance at the forecast date.

Using exposure alignment metrics alone is insufficient to completely eliminate the denominator effect of loan expansion; therefore, the growth-neutral net write-off ratio is further defined as:

$$GNLR_{i,t}^{(4)} = 10\,000 \times \frac{\sum_{h=1}^{4} NCO_{i,t+h}}{\frac{1}{4}\sum_{j=1}^{4} GL_{i,t-j}}$$

In this calculation, GNLR uses the average loan balance of the four quarters preceding the forecast as the denominator. This indicator only uses the loan volume already confirmed before the forecast point in time and is not directly affected by loan growth during the forecast period. ELR is used in the main analysis, while GNLR is used to examine whether the identification of abnormal expansion risk is affected by changes in the denominator.

3.3 Positive and Negative Abnormal Loan Growth

Loan growth itself does not necessarily imply an increase or decrease in risk. To identify growth patterns that significantly deviate from those of similar banks, the study constructs a model of abnormal loan growth relative to peers:

$$AG_{i,t} = \Delta_4 \ln\left(GL_{i,t}\right) - \mathrm{Median}_{j \in G_{q,t}}\left[\Delta_4 \ln\left(GL_{j,t}\right)\right]$$

The fourth-quarter loan logarithmic growth rate is used to characterize the speed of banks' short-term loan expansion; banks in the same quarter and the same asset size quartile form a comparison set. The higher the abnormal loan growth value, the more significantly the bank's loan expansion deviates from the level of similar banks.

Positive abnormal expansion and abnormal contraction may convey different risk signals; therefore, the study further defines:

$$P_{i,t} = \max\left(AG_{i,t}, 0\right), \qquad N_{i,t} = \max\left(-AG_{i,t}, 0\right)$$

Wherein, P represents positive abnormal loan growth and N represents the absolute degree of negative abnormal loan growth. Positive abnormal growth reflects the risk of relaxed credit standards and structural concentration that may occur when the expansion speed is significantly higher than that of similar banks; negative abnormal growth reflects the loan contraction that may be accompanied by the reduction of risk assets, deterioration of asset quality or financing constraints. The information set also includes historical loss rate, non-performing loan ratio (NPL), provision ratio, capital ratio, profitability, liquid asset ratio, loan-to-deposit ratio, asset size, CRE loan ratio, brokerage deposit ratio and loan concentration[6].

4. Model Setting and Experimental Design

4.1 Dynamic Regulatory Risk Benchmark Model

B1 is a dynamic regulatory risk benchmark model estimated using Elastic Net. This model preserves variable interpretability and reduces parameter instability caused by the correlation of regulatory indicators. The model form is as follows:

$$z_{i,t}^{(4)} = a_0 + r z_{i,t-1}^{(4)} + b' X_{i,t} + d' H_{i,t} + \sum_{q=2}^{4} c_q D_{q,t} + u_{i,t}$$

Where z represents the target variable after inverse hyperbolic sine transformation; X includes variables related to capital, profitability, liquidity, loan structure, and financing structure; and D is a calendar quarter dummy variable. The risk expansion term is defined as:

$$H_{i,t} = \left(P_{i,t}, N_{i,t}, P_{i,t} \times NPL_{i,t}, P_{i,t} \times CRE_{i,t}\right)'$$

Here, NPL represents the non-performing loan ratio, and CRE represents the proportion of commercial real estate loans. This setting includes both positive and negative abnormal loan growth in the risk information set, while also identifying situations where rapid expansion is coupled with asset quality pressure or concentrated loan structure risks.

4.2 Nonlinear Generalized Additive Model

M2 uses the same information variables as B1, but allows key risk variables to enter the model in a non-linear manner:

$$F_{i,t} = s_1\left(z_{i,t-1}^{(4)}\right) + s_2\left(NPL_{i,t}\right) + s_3\left(P_{i,t}\right) + s_4\left(N_{i,t}\right) + s_5\left(CRE_{i,t}\right)$$
$$+te_1\left(P_{i,t}, NPL_{i,t}\right) + te_2\left(P_{i,t}, CRE_{i,t}\right)$$

$$z_{i,t}^{(4)} = a_0 + F_{i,t} + w'W_{i,t} + \sum_{q=2}^{4} c_q\, D_{q,t} + u_{i,t}$$

Wherein, s(·) represents the penalized smoothing function, te(·,·) represents the low-dimensional tensor interaction term, and W represents the remaining linear control variables. M2 characterizes the nonlinear effects of positive and negative abnormal loan growth and examines whether there is a risk amplification effect between abnormal expansion and non-performing loan rate and CRE concentration. The smoothing term is only set on the core variables and the model degrees of freedom are controlled by penalty[7].

The 10.8 percentage point is not a pre-set structural breakpoint in the M2 function, but rather a model applicability threshold where the relative performance of B1 and M2 is determined during the development period. This threshold serves to determine when it is necessary to shift from a dynamic regulatory risk model to a non-linear model, rather than interpreting loan growth itself as a fixed risk breakpoint.

4.3 Shallow XGBoost Model

R1 is used to test whether the conclusion of M2 depends on a specific functional form. R1 uses the same original regulatory information variables as B1 and M2, the tree depth is limited to 2 to 4 layers, and the parameters are determined during the development period. The only difference between the three types of models is the way they express the same information. If R1 is only superior in ranking metrics, it is not suitable for routine loss quantification tasks [8].

4.4 Time Division, Threshold Identification, and Evaluation Metrics

The sample was divided into three phases: Q1 2001 – Q4 2014 was the initial training period; Q1 2015 – Q4 2017 was the development period (prediction starting point); and Q1 2019 – Q4 2024 was the formal testing period. The final prediction starting point of the development period was Q4 2017, and the losses for the next four quarters were fully realized by Q4 2018. Therefore, the threshold was fixed before testing began in Q1 2019. Only historical observations where the losses for the next four quarters had been fully realized were used for each prediction point.

Period-by-period time fixed effects can explain observed common shocks but cannot be used for forecasts of unseen quarters, and therefore are not included in the main model. Macroeconomic common fluctuations are mainly handled through three methods: relative abnormal growth, calendar quarter dummy variables, and extended window reestimation. B1 and M2 use the same information set and seasonal control in this part.

Threshold search was based on the relative performance of B1 and M2. During the development period, the 60%–90% quantile of positive abnormal loan growth constituted the candidate interval, with a threshold selected every 5 percentage points. The model compared Tail-MAE among samples where both models made effective predictions and positive abnormal loan growth exceeded the candidate thresholds. The final threshold required the following conditions to be met simultaneously: the difference between B1 Tail-MAE and M2 Tail-MAE was maximized, the abnormal expansion group accounted for no less than 15% of the samples, and at least 75% of the development period quarters showed a positive improvement. The threshold was fixed at 10.8

percentage points during the testing period.

The 90th percentile of the ELR during development was used to define the high-loss state and remained unchanged during the testing period. Tail-MAE was calculated only in the quarterly sample of actual high-loss banks. The top 10% capture rate was sorted by the testing quarter, and the coverage ratio of actual high-loss banks among the top 10% of banks with the highest predicted risk was statistically analyzed. The p-values in Tables 2 and 3 only tested the difference in MAE between B1 and M2, and were all derived from the quarterly block-paired bootstrap two-tailed test. The predicted values were evaluated at the original baseline scale after restoration.

5. Out-of-sample comparison results

5.1 Overall Forecast Performance

Table 2 shows that all three models can identify some future credit loss risks. The MAE of B1 is 45.8 basis points, indicating that after incorporating interaction terms of asset quality, capital, liquidity, structural risk, and abnormal growth, the dynamic regulatory risk model can capture major risk changes in normal operations. The MAE of M2 is 45.1 basis points, a decrease of 0.7 basis points compared to B1, with a 95% confidence interval of [-1.36, -0.08] and a p-value of 0.029. Although the improvement in error is limited, the nonlinear expression forms a stable increment in out-of-sample predictions.

R1 has the lowest MAE at 45.0 basis points, and its Top 10% capture rate is also higher than M2. However, the difference in MAE between R1 and M2 failed the error test, and its calibration slope is also lower than M2. Tree models provide higher predictions for banks with extreme risk and can improve tail ranking ability, but they tend to concentrate predictions for banks with medium and low risk. When used for routine loss quantification, M2 strikes a better balance between error, ranking, and calibration.

Table 2. Overall out-of-sample model comparison results

Panel A: Model Representation

Model	MAE (bp)	RMSE (bp)	Tail-MAE (bp)	Spearman ρ	Top 10% capture rate	Calibration Slope
B1 Dynamic Regulatory Risk Model	45.8	129.4	106.8	0.399	33.1%	0.75
M2 Nonlinear Generalized Additive Model	45.1	127.7	105.5	0.422	35.5%	0.83
R1 Shallow XGBoost Model	45.0	127.4	104.7	0.435	37.1%	0.67

Panel B: MAE Pair Comparison

Compare	MAE difference (bp)	95% confidence interval	p-value
M2-B1	-0.7	[-1.36, -0.08]	0.029
R1-M2	-0.1	[-0.63, 0.42]	0.648

Note: The p-values in panel B are derived from the quarterly paired Bootstrap two-tailed test of the absolute error difference of the corresponding models, and are used only to test the difference in MAE. Tail-MAE is calculated only in the actual high-loss banks—quarterly sample; the Top 10% capture rate is sorted separately by test quarter.

After replacing ELR with GNLR, the Tail-MAE of M2 within the abnormal expansion interval improved by 3.9 basis points compared to B1, which is lower than the 4.3 basis points in the ELR results, but the direction of improvement is consistent. The model applicability threshold of 10.8 percentage points still has discriminative power under the GNLR framework, indicating that the identification of abnormal expansion risk does not depend on the change in the denominator caused by loan growth.

5.2 Model Applicability Threshold under Abnormal Loan Growth

The applicability threshold for the positive abnormal loan growth model identified during the development phase was 10.8 percentage points, which remained unchanged during the testing phase, with abnormal expansion accounting for 19.8% of observations. Before the threshold was triggered, the MAEs of B1 and M2 were 42.9 and 42.7 basis points, respectively, with no statistically significant difference. After abnormal expansion occurred, the MAE of B1 was 61.2 basis points, and that of M2 was 56.9 basis points, with a difference of -4.3 basis points and a p-value of 0.003. M2 exhibits a lower Tail-MAE and a higher top-10% capture rate compared to B1, indicating that the incremental value of the non-linear model is primarily concentrated in scenarios involving high loss risks driven by extreme expansions. A comparison of the out-of-sample errors of B1 and M2 under the model applicability threshold is shown in Figure 2.

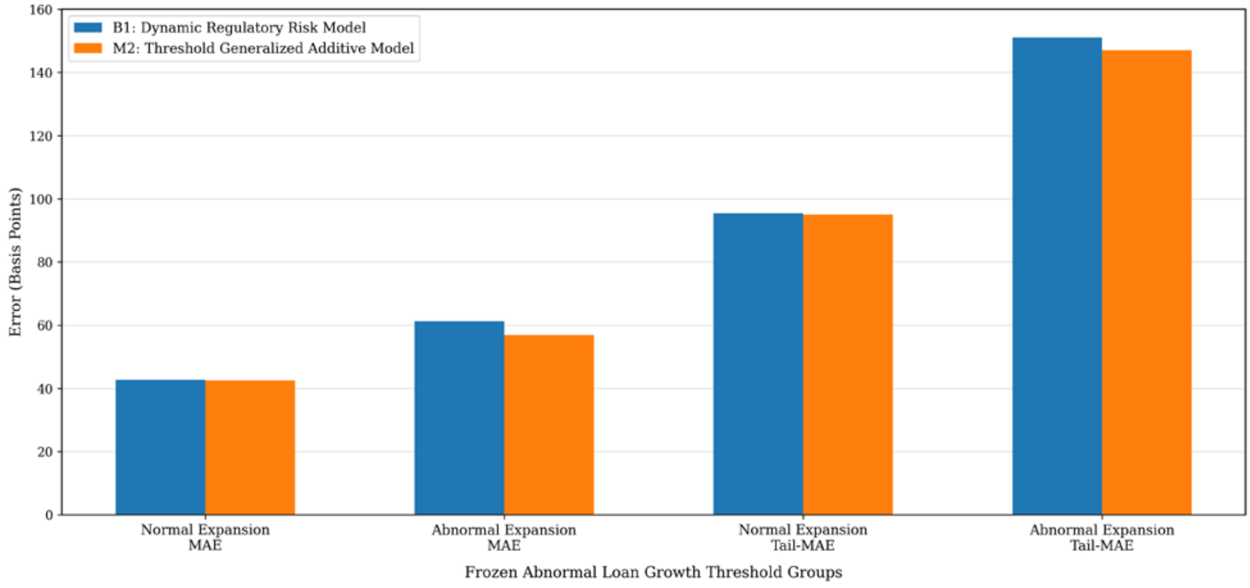

Figure 2. Comparison of out-of-sample errors of B1 and M2 at the model suitability threshold.

To observe model performance in high-stress samples, during the development period, higher-risk states were defined using the 75th percentile of the non-performing loan rate and the proportion of CRE loans, with two cutoff points of 3.1% and 30.2%, respectively. These two values were used only for descriptive grouping and were not included in the search for model applicability thresholds.

6. Discussion

6.1 Interpretation of Results and Applicability of the Model

Dynamic regulatory risk models and nonlinear models are not simply substitutes. When positive anomaly thresholds are not triggered, B1 already incorporates information such as historical losses, non-performing loan ratios, capital, profitability, liquidity, and loan structure, reflecting major risk changes in normal bank operations. When risk signals change relatively smoothly, the additional functional flexibility of M2 is unlikely to translate into a significant error advantage. B1 has fewer variables and a more direct interpretation, making it more suitable for daily monitoring and risk reporting.

The abnormal expansion range presents different risk states. When loan growth is significantly higher than that of similar banks, banks may simultaneously change credit recipients, industry investment directions or maturity arrangements. M2 identifies situations where growth rate, asset quality and structural risk change together through the interaction between positive abnormal growth and non-performing loan ratio and CRE loan ratio. GNLR does not use the loan balance in the forecast period as the denominator, but still retains the Tail-MAE improvement of M2. Therefore, the advantage of M2 does not come from the loan growth amplifying the denominator, but from the identification of abnormal expansion and existing risk pressure changes together. The advantage of complex models depends on the data status, result definition and usage objectives, rather than the model name itself [10].

R1 has a higher capture rate for high-risk banks, but a lower calibration slope. Tree models improve the discrimination of extreme samples through segmentation rules and are also more likely to compress predictions for medium- and low-risk banks. Based on this difference, banks can use B1 when the positive anomaly threshold is not triggered, use M2 when anomalies expand, and use R1 for ranking the list of key audit targets[11-15].

Table 3. Model Applicability Validation under Abnormal Loan Growth Threshold

Test period grouping	Sample proportion	MAE (B1/M2)	MAE differences (M2-B1, bp)	Tail-MAE (B1/M2)	Capture rate (B1/M2)	p-value	Recommended Model
P ≤ 10.8 percentage points	80.2%	42.9 / 42.7	-0.2	95.4 / 95.0	29.4% / 30.4%	0.450	B1
P > 10.8 percentage points	19.8%	61.2 / 56.9	-4.3	151.8 / 147.5	42.8% / 48.6%	0.003	M2
P > 10.8 percentage points, and NPL > 3.1% or CRE > 30.2%	8.7%	74.6 / 67.8	-6.8	182.5 / 174.6	47.9% / 54.1%	0.008	M2+R1 auxiliary sorting

Note: The p-values in Table 3 only test the MAE difference between B1 and M2, and are derived from the quarterly block pairing Bootstrap two-sided test.

6.2 Research Limitations and Future Research

The study still has several limitations. Publicly available regulatory reports cannot reveal information such as borrower internal ratings, loan terms, collateral conditions, industry segmentation, and loan batches. The model can only identify risk changes at the bank portfolio level and cannot determine the specific impact of individual loan types or credit decisions on losses. Future research could use loan-level data to decompose abnormal expansion into industry expansion, customer expansion, and term expansion, and combine model results with post-loan verification and manual judgment [16-20].

The complete fourth-quarter label may exclude some high-risk observations nearing exit. The study retained valid financial statements prior to exit, but the impact of this sample selection still needs further verification in conjunction with disposal events or M&A information. Net write-offs are also affected by write-off policies, recovery progress, and disposal pace, and cannot replace default probability, loss due to default, or expected credit losses. Future research could combine default rates, migration rates, provision changes, and net write-offs to observe the three stages of risk formation, recognition, and disposal[21-25].

Negative abnormal loan growth is included as an independent risk variable in B1 and M2, and its impact is characterized by linear and smoothing terms. This study did not search for a separate model applicability threshold for negative abnormal loan growth, as the focus was on positive abnormal expansion. Future research could examine whether an independent threshold exists for abnormal contraction, and its relationship with capital constraints and changes in asset quality.

The threshold, identified during the development phase and then fixed for the testing phase, can reduce information leakage during testing. However, changes in the financial cycle may still alter the normal range of abnormal growth. Macroeconomic shocks can only be partially addressed through relative growth, quarterly dummy variables, and rolling estimates. Future research could incorporate macroeconomic variables with clearly defined release dates to test the applicability of time-varying thresholds and validate the model rules across different banking systems[26-30].

7. Conclusion

This study compares the applicability of dynamic regulatory risk models, nonlinear generalized additive models, and shallow XGBoost models under conditions of abnormal loan growth. When the positive anomaly threshold is not triggered, the dynamic regulatory risk model, which incorporates information on non-performing loan ratio, capital, liquidity, loan structure, and financing structure, can provide stable predictions; the complex models do not exhibit a significant advantage in increasing MAE (Mean Absolute Error). After positive abnormal loan growth exceeds the median of similar-sized peers by 10.8 percentage points, a more pronounced nonlinear relationship emerges between loan expansion and future losses. The GNLR results also indicate that this finding is not due to a mechanical change in the denominator caused by loan growth.

Shallow XGBoost primarily enhances the ranking ability of banks with key risks, but its calibration performance is weaker than that of nonlinear generalized additive models. When positive anomaly thresholds are not triggered, banks can use dynamic regulatory risk models for routine monitoring; after abnormal expansion occurs, nonlinear generalized additive models are more suitable for strengthening future loss predictions; in key verification tasks, shallow XGBoost can serve as an auxiliary ranking tool. The core contribution of this research lies in linking loan expansion status with model selection, forming credit risk measurement rules that are closer to daily monitoring and key early warning scenarios.

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