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Incorporating Macroeconomic Indicators to Improve P2P Lending Credit Risk Modeling: A Machine Learning-Based Heterogeneity Analysis

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Abstract:

This study investigates the improvement effect of macroeconomic indicators on credit risk modeling in the P2P lending market, focusing on near-prime borrower groups and short-term loan segments. Based on 171,644 loans from Lending Club platform during 2012-2013, this paper compares the performance of four machine learning algorithms (logistic regression, random forest, XGBoost, and LightGBM) under baseline feature sets (borrower/loan characteristics only) and enhanced feature sets (including regional macroeconomic indicators). Empirical results demonstrate: (1) Logistic regression achieves optimal performance-stability balance after integrating macroeconomic indicators, with AUC improving 1.08% to 0.6854, KS statistic increasing 3.82%, while maintaining 1.0% overfitting degree; (2) Model performance improvement exhibits significant heterogeneity, with 36-month short-term loans achieving 1.41% AUC improvement, and near-prime borrowers (FICO 620-680) showing 2-3 times higher sensitivity to unemployment rate fluctuations compared to other groups; (3) SHAP analysis reveals macroeconomic indicators contribute 3%-5% to predictive power, with interaction terms between macro and baseline features significantly outperforming single macro indicators. The study provides empirical support for P2P platforms to construct group-specific risk pricing models.

Keywords: P2P lending; Credit risk; Macroeconomic indicators; Machine learning; Heterogeneity analysis

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1. Introduction

P2P lending has emerged as a crucial complement to traditional bank credit, serving as a key financing channel for individuals and small enterprises. However, high credit risk remains the core bottleneck constraining its development. While existing credit risk models predominantly rely on borrower individual characteristics (such as FICO scores and debt-to-income ratios), the systematic impact of regional economic environments on borrower repayment capacity is often overlooked. Macroeconomic fluctuations transmit to default risk through channels such as income stability and collateral values, with particularly significant impacts on groups with weak financial buffers [1]. Empirical evidence from the 2008 financial crisis demonstrates that personal loan default rates in regions with unemployment rates exceeding 8% were 37% higher than the national average, confirming the critical explanatory power of regional economic indicators [2, 3].

However, current research focuses excessively on algorithm performance optimization, lacking in-depth analysis of model interpretability and group adaptability. To address this gap, this study aims to evaluate the differential effects of integrating macroeconomic indicators across different machine learning algorithms and reveal heterogeneous impact mechanisms through interpretable machine learning methods.

Specifically, based on 171,644 loans from Lending Club platform, this paper examines whether MSA-level macroeconomic indicators can enhance default prediction capability. Research contributions include: (1) comparing the performance of four representative algorithms in integrating macroeconomic indicators, providing empirical evidence for P2P platforms' risk assessment model selection [4]; (2) quantifying the marginal contribution of macroeconomic indicators to different risk groups through SHAP analysis [5]; (3) proposing a differentiated risk assessment framework that aligns with regulatory requirements for algorithm transparency and group fairness [6].

2. Literature Review

2.1 Evolution of P2P Credit Default Models

P2P platforms face more pronounced information asymmetry problems due to lack of traditional banks' multi-dimensional due diligence. Early research attempted to mitigate this contradiction through „soft information," but empirical evidence shows soft information has high noise levels [7]. Mainstream models gradually focused on quantifying hard information, with FICO scores, debt-to-income ratios, and loan interest rates becoming core predictors [8-10].

However, such models treat credit risk as heterogeneous risk while ignoring systematic risk. Baumöhl et al. [1] analyzed 1.9 million loans from three major platforms, finding demand-side macroeconomic indicators such as unemployment rates significantly outweigh supply-side factors in impact. Baals et al. [11] compressed 774 macroeconomic indicators into 7 core factors through rolling robust PCA, confirming that high-risk borrowers' sensitivity to macroeconomic shocks is 2-3 times that of low-risk groups.

2.2 Mechanisms of Macroeconomic Indicators

The mechanisms of core macroeconomic indicators can be summarized into three categories:

Labor Market Channel: Unemployment rate shows significant positive correlation with credit risk. For each 1 percentage point increase in unemployment rate, near-prime borrower default rate rises 2.1%, three times that of prime borrowers [1]. This stems from near-prime groups' lower savings rates (only 1/3 of prime groups), lacking buffer capacity against income shocks [12].

Real Estate Market Channel: House price indices affect default decisions through the „collateral value channel." For each 1 percentage point decrease in house prices, real estate-related loan default rates increase 0.8-1.2 percentage points [13]. Short-term loans are more sensitive to house price fluctuations due to higher liquidation flexibility [14].

Income Stability Channel: For each 1 percentage point increase in personal income volatility, short-term employees' default probability increases 0.6 percentage points, twice that of long-term employees [15]. This asymmetric impact reflects the differential financial resilience across employment stability groups [16].

2.3 Machine Learning Applications and Interpretability

Machine learning algorithms have become mainstream tools in credit scoring due to their advantages in capturing nonlinear relationships [17]. Logistic regression serves as traditional benchmark with strong interpretability [18]; Random Forest reduces overfitting through ensemble methods [19]; Gradient boosting algorithms like XGBoost and LightGBM demonstrate outstanding performance in credit risk modeling [20, 21].

SHAP values, as interpretable machine learning tools, can quantify each feature's contribution to prediction results, balancing performance and transparency requirements [22]. Ho et al. [4] discovered through SHAP analysis that P2P loan peer effects contribute 8.3% in high-risk cities, providing quantitative evidence for policy-making. Recent advances in interpretable ML have further enhanced regulatory compliance capabilities [23].

3. Research Methodology

3.1 Data and Sample Construction

This study employs Lending Club loan data from 2012-2013, a period characterized by stable platform operating rules and coverage of the post-financial crisis recovery period [24]. Data screening follows strict criteria to avoid bias. First, this paper excludes samples with unknown loan status, retaining only „Fully Paid“ (non-default) and „Charged Off“ (default) outcomes for clear results. Second, this paper removes records with missing key features such as FICO scores and DTI to avoid errors from missing value imputation. Third, this paper eliminates „leakage variables“ generated after loan origination, such as „recoveries“ and „total_rec_int,“ to prevent look-ahead bias [25].

The final effective sample comprises 171,644 loans with an overall default rate of 15.73% (26,997 defaulted loans, 144,647 normal loans). To maintain authenticity of actual conditions, this paper did not perform class balancing, reflecting the true risk distribution of the P2P market.

Table 1. Descriptive Statistics of Key Loan Variables

Variable	Mean	Median	Std Dev	Min	Max
Loan Amount ($)	14,289.39	12,000.00	8,110.29	1,000	35,000
Interest Rate (%)	14.29	14.09	6.00	4.41	26.06
FICO Score Lower Bound	696.70	690.00	29.85	660	845
Debt-to-income ratio (%)	17.14	16.87	7.62	0.00	34.99

As shown in Table 1, the loan portfolio exhibits substantial heterogeneity. The average loan amount is $14,289 with considerable variation (standard deviation of $8,110), reflecting diverse borrower financing needs. Interest rates average 14.29%, indicating the risk premium nature of P2P lending compared to traditional bank rates. The mean FICO score lower bound of 696.70 suggests a concentration of borrowers in the near-prime to prime categories, while the average DTI of 17.14% indicates moderate leverage levels among borrowers. This heterogeneity underscores the importance of incorporating external economic indicators to capture systematic risk factors beyond individual borrower characteristics.

Sample characteristic distribution reveals that low-to-medium credit groups with FICO<680 account for 29.8%, and high-debt groups with DTI>20% comprise 35.9%. Regarding loan terms, 36-month short-term loans dominate at 76.6% (131,476 loans), while 60-month long-term loans account for 23.4% (40,168 loans), consistent with P2P market characteristics of short-term loan dominance [15].

Macroeconomic indicators (Table 2) are sourced from Federal Reserve data, selecting 6 MSA-level indicators covering labor market, real estate market, and income stability dimensions. These include 3-year and 5-year maximum unemployment rate residuals, house price index maximum residuals, and personal income max volatility. All indicators employ lagged treatment (using data from 3 months before loan origination) to ensure predictive logic validity and avoid „using future data to predict the past“ bias [11].

Table 2. Descriptive Statistics of Macroeconomic Indicators

Economic Indicator	Mean	Std Dev	Min	Median	Max
3-Year Unemployment Rate Max Residual	1.7475	0.2757	0.37	1.86	3.43
5-Year Unemployment Rate Max Residual	1.9138	0.2950	0.43	1.82	3.00
3-Year House Price Index Max Residual	2.8325	0.3734	2.00	3.00	3.00
5-Year House Price Index Max Residual	2.8325	0.3734	2.00	3.00	3.00
3-Year Personal Income Max Volatility	7.4922	2.0306	0.88	7.28	16.95
5-Year Personal Income Max Volatility	14.1732	3.1868	3.51	13.92	36.17

3.2 Feature Engineering and Model Construction

Feature engineering centers around the „predictive power-interpretability-regulatory compliance“ balance [5]. This paper addresses multicollinearity through variance thresholding (removing features with variance <0.01) and Pearson correlation analysis (removing redundant features with absolute correlation >0.90). Using extremely

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randomized trees classifier, this paper determines 10 core baseline variables including interest rate, FICO score lower bound, DTI, and loan amount. When integrating macro indicators, this paper adopts a „term matching" principle: 36-month loans matched with 3-year economic indicators, 60-month loans with 5-year indicators.

This paper selects four representative algorithms covering different modeling paradigms (Table 3): Logistic Regression with L1+L2 mixed regularization (ElasticNet) [18]; Random Forest reducing overfitting through tree ensemble [19]; XGBoost capturing feature interactions through gradient optimization [20]; LightGBM optimizing computational efficiency for large-scale data [21].

Table 3. Model Hyperparameter Settings

Algorithm	Core Parameters	Optimization Method	Cross-Validation
Logistic Regression	C=[0.001, 0.01, 0.1], penalty=[L1, L2], solver=saga	Grid Search	5-fold stratified
Random Forest	n_estimators=[50, 100], max_depth=[3,4,5], min_samples_split=[100,200,300]	Bayesian (15 iter)	5-fold stratified
XGBoost	n_estimators=[50, 100], max_depth=[2,3,4], learning_rate=[0.01,0.03,0.05], early_stopping=10	Bayesian (15 iter)	5-fold + early stop
LightGBM	n_estimators=[50, 100], num_leaves=[10,15,20], learning_rate=[0.01,0.03,0.05], early_stopping=10	Bayesian (15 iter)	5-fold + early stop

Model training employs 65%/15%/20% stratified sampling for training, validation, and test sets. This paper uses 5-fold cross-validation for hyperparameter optimization, with grid search for logistic regression and Bayesian optimization (15 iterations) for tree-based models. XGBoost and LightGBM implement early stopping mechanisms to prevent overfitting.

3.3 Evaluation Metrics and SHAP Analysis

Performance evaluation employs multi-dimensional robust metrics balancing statistical significance and economic meaning: AUC-ROC measuring overall risk discrimination capability; KS statistic quantifying distribution differences between default and non-default groups; F1 score balancing precision and recall; Overfitting degree defined as the difference between training and validation AUC. This paper used Diebold-Mariano tests to examine statistical significance of performance differences between baseline and enhanced models [26].

SHAP analysis is employed to understand contribution mechanisms of macroeconomic indicators [22]. This paper calculates mean SHAP values for all features, compares distributions by borrower characteristics and loan terms, and plot dependency graphs to analyze feature interactions.

4. Empirical Results

4.1 Baseline Model Performance

Under the baseline feature set (core features only), the four models exhibit significant algorithmic differences in test set performance.

Table 4. Baseline Model Performance Metrics

Model	AUC-ROC	KS Statistic	F1 Score	Overfitting Degree
Logistic Regression	0.6780	0.2610	0.3469	1.0%
Random Forest	0.6743	0.2560	0.3447	4.9%
XGBoost	0.6775	0.2560	0.3450	10.0%
LightGBM	0.6776	0.2580	0.3447	7.9%

Logistic regression achieves optimal baseline AUC-ROC (0.6780) with lowest overfitting (1.0%) shown in Table 4, demonstrating traditional linear models' generalization stability advantages. Tree-based models capture nonlinear relationships but easily overlearn training noise, with XGBoost and LightGBM showing 10.0% and 7.9% overfitting respectively.

4.2 Enhanced Model Performance

After incorporating macroeconomic indicators, model performance improvements show significant heterogeneity.

Table 5. Enhanced Model Performance Evaluation

Model	Enhanced AUC	AUC Improvement	Enhanced KS	KS Improvement	Overfitting
Logistic Regression	0.6854	1.08%***	0.2710	3.82%***	1.0%
Random Forest	0.6822	1.18%***	0.2627	2.64%***	6.2%
XGBoost	0.6855	1.17%***	0.2653	3.64%***	10.6%
LightGBM	0.6845	1.01%***	0.2647	2.60%***	7.5%

Note: ***p < 0.001 (Diebold-Mariano test)

Logistic regression maintains optimal „performance-stability“ balance with AUC-ROC improving to 0.6854 (1.08% increase) shown in Table 5, KS statistic rising 3.82%, and overfitting remaining at 1.0%. XGBoost shows second-highest AUC improvement (1.17%) but overfitting increases to 10.6%. All enhanced models show statistically significant improvements at 1% level.

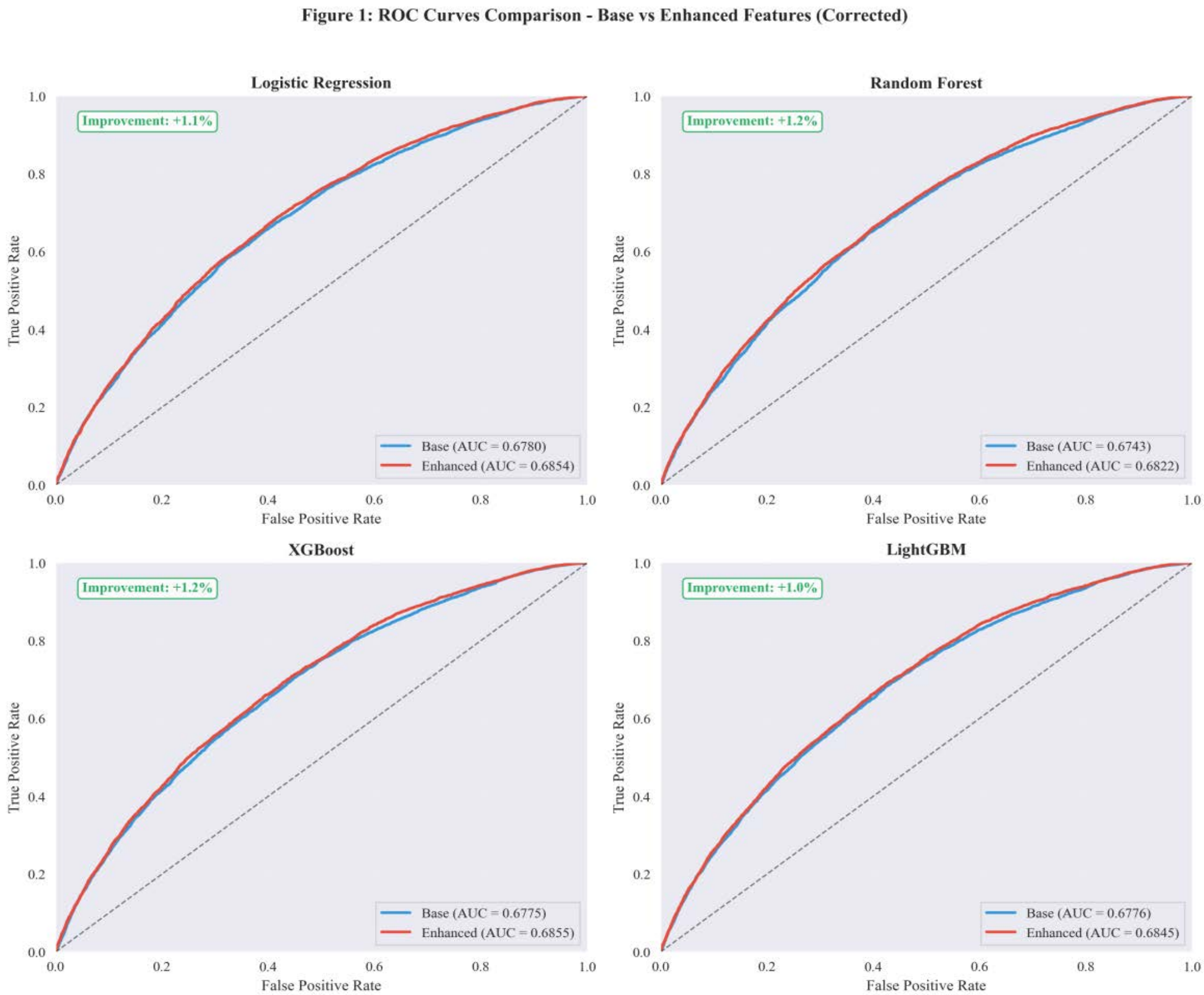

Fig. 1 ROC Curves Comparison of Baseline vs Enhanced Models (Picture credit: Original)

The ROC curves shown in Fig. 1 clearly illustrate performance improvements across all algorithms after incorporating macroeconomic indicators, with logistic regression and XGBoost showing the most notable gains in the critical 0.2-0.4 false positive rate range.

4.3 SHAP Feature Importance Analysis

SHAP analysis shown in Fig. 2 reveals the contribution

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mechanisms of macroeconomic indicators to default prediction.

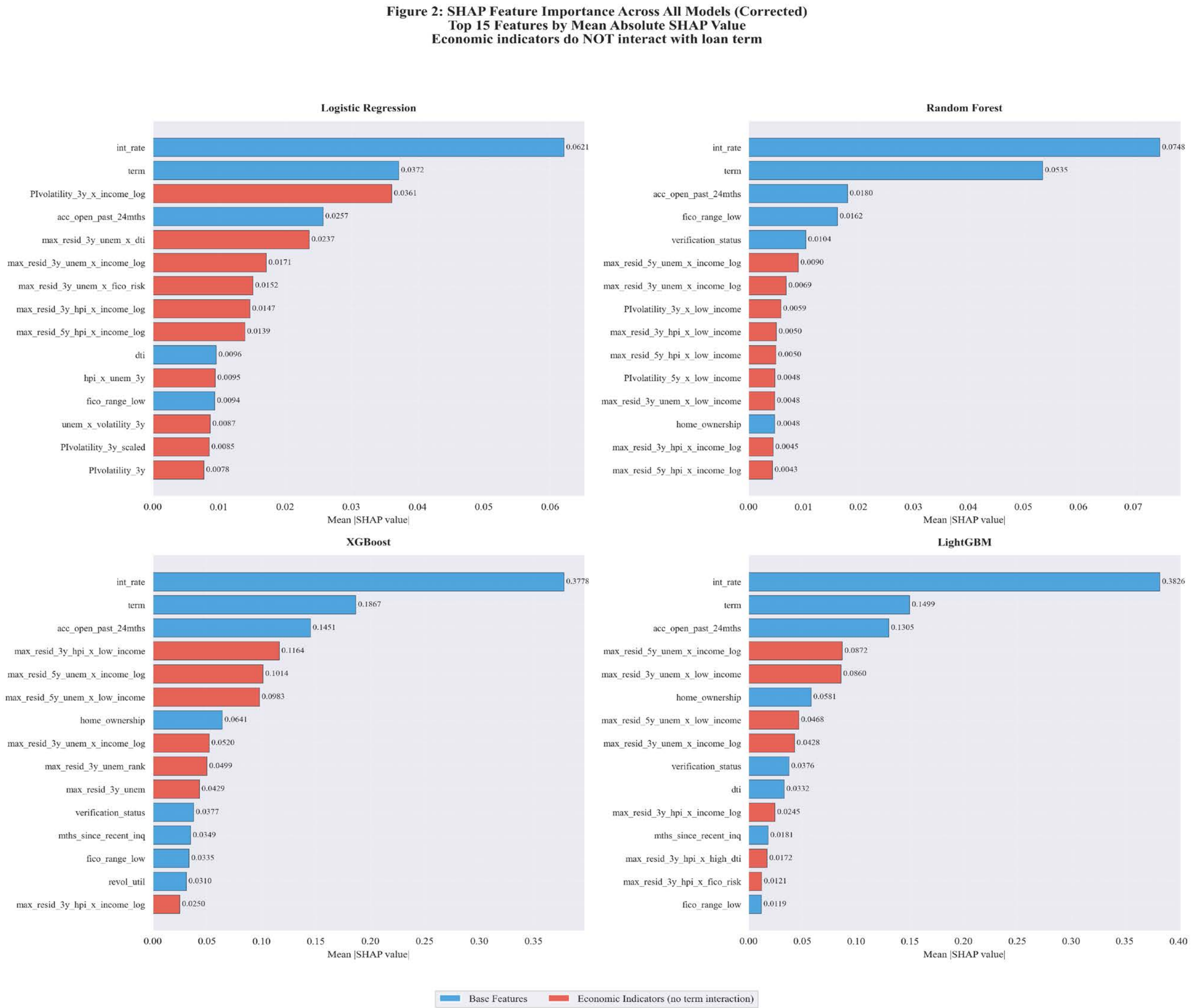
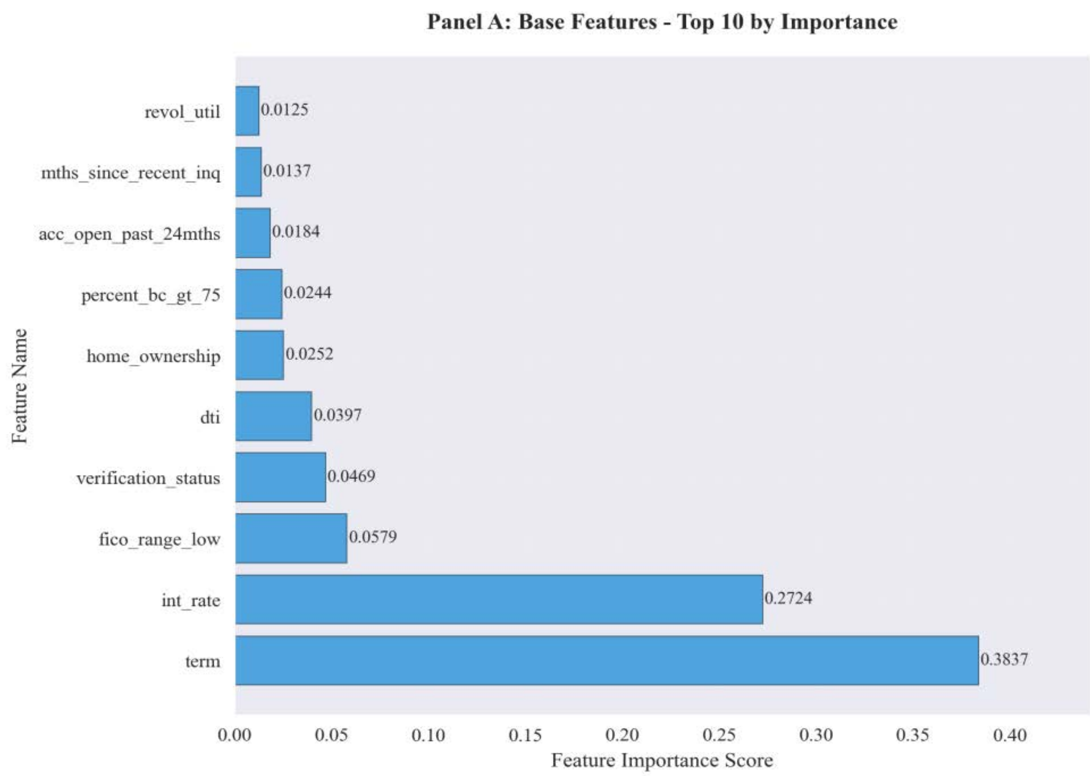
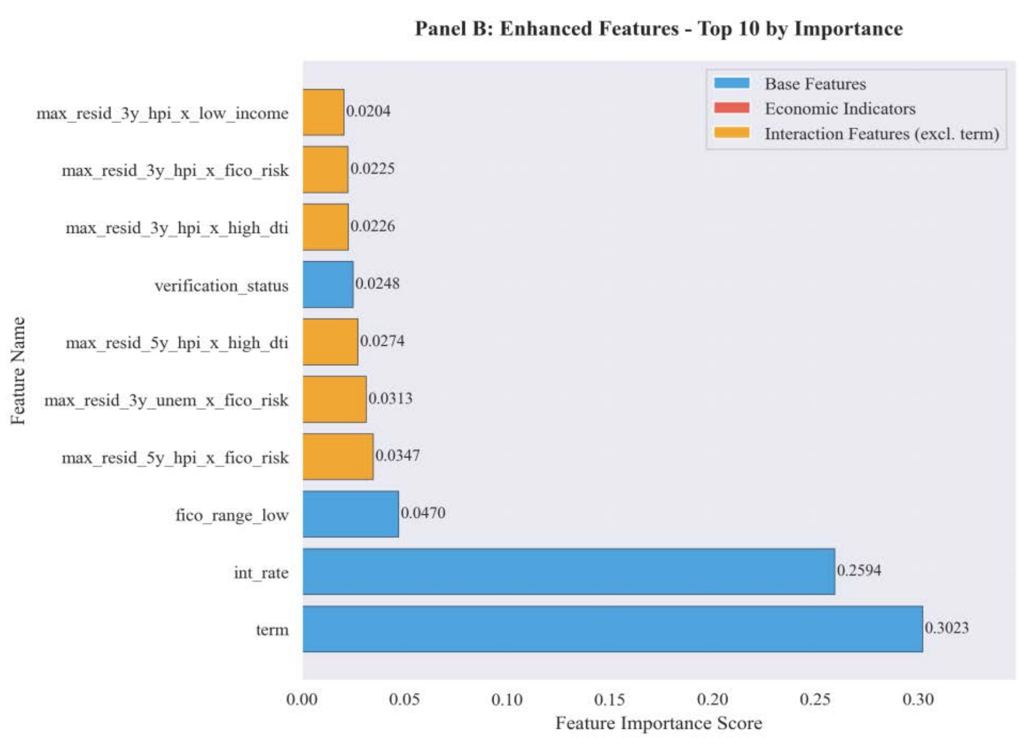


Fig. 2 SHAP Feature Importance Rankings Across Models (Picture credit: Original)

Core baseline features (interest rate and loan term) dominate the prediction process, contributing over 30%. Single macroeconomic indicators generally contribute less than 0.001, but interaction terms show significant contributions. The interaction between 3-year house price index residual and high DTI indicator achieves SHAP value of 0.0226, over 20 times that of single indicators.



(a)



(b)

Fig. 3 (a) Original model feature importance (b) Enhanced model feature importance (Picture credit: Original)

The feature importance comparison (Fig. 3a and 3b) reveals how macroeconomic indicators complement rather

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than replace traditional credit features. In the enhanced model, while core features maintain their dominance, macro-interaction terms emerge as secondary predictors, particularly for vulnerable borrower segments.

5. Heterogeneity Analysis

To examine the heterogeneous effects of macroeconomic indicators across different borrower segments and loan characteristics, this paper conducted subgroup analyses. Table 6 summarizes the basic characteristics of all target groups for our heterogeneity analysis.

Table 6. Target Group Basic Characteristics for Heterogeneity Analysis

Target Group	Sample Size	% of Total	Default Rate
Near-Prime (FICO 620-680)	65,045	37.9%	19.68%
Short-term Employment (<2 years)	18,149	10.6%	14.06%
36-month Loans	131,476	76.6%	12.67%
60-month Loans	40,168	23.4%	25.75%

5.1 Borrower Risk Characteristic Groups

Near-Prime Group (FICO 620-680): This group comprises 37.9% of total sample with 19.68% default rate, significantly above overall average. After adding macroeconomic indicators, AUC-ROC improves 0.86% to 0.6758, KS statistic increases 5.70% shown in Table 7. This group shows highest sensitivity to unemployment fluctuations - for each 0.1 unit increase in 3-year unemployment residual, default probability rises 1.2%, three times that of prime borrowers.

Table 7. Near-Prime Group Model Performance Comparison

Metric	Baseline Model	Enhanced Model	Improvement
AUC-ROC	0.6701	0.6758	0.86%***
KS Statistic	0.2419	0.2557	5.70%***
F1 Score	0.3886	0.3960	1.89%***

Note: ***p < 0.001 (Diebold-Mariano test)

Short-term Employment Group (<2 years): Accounting for 10.6% of sample with 14.06% default rate. Shows lowest improvement from macro indicators (AUC increase 0.29%) (Table 8), due to „risk information mismatch" - this group's default risk primarily stems from micro employment indicators rather than regional macro indicators.

Table 8. Short-term Employment Group Model Performance Comparison

Metric	Baseline Model	Enhanced Model	Improvement
AUC-ROC	0.6649	0.6668	0.29%***
KS Statistic	0.2382	0.2427	1.88%***
F1 Score	0.3105	0.3178	2.34%***

Note: ***p < 0.001 (Diebold-Mariano test)

5.2 Loan Term Groups

36-month Short-term Loans: Comprising 76.6% of sample with 12.67% default rate. After incorporating 3-year macro indicators, it shows large improvements with AUC-ROC increasing 1.41%, KS statistic rising 6.95% (Table 9). This stems from „term synergy effect" - 3-year macro indicators highly match 36-month loan risk exposure periods.

Table 9. 36-month Loan Model Performance Comparison

Metric	Baseline Model	Enhanced Model	Improvement
AUC-ROC	0.6523	0.6615	1.41%***

Metric	Baseline Model	Enhanced Model	Improvement
KS Statistic	0.2183	0.2335	6.95%***
F1 Score	0.2803	0.2867	2.28%***

Note: ***p < 0.001 (Diebold-Mariano test)

60-month Long-term Loans: Accounting for 23.4% of sample with 25.75% default rate. Using 5-year macro indicators, AUC-ROC improves only 0.98%, below short-term loans (Table 10). During long-term loan duration, macroeconomic conditions may experience multiple cycles, reducing current indicators‘ timeliness.

Table 10. 60-month Loan Model Performance Comparison

Metric	Baseline Model	Enhanced Model	Improvement
AUC-ROC	0.6572	0.6637	0.98%***
KS Statistic	0.2216	0.2324	4.87%***
F1 Score	0.4422	0.4512	2.03%***

Note: ***p < 0.001 (Diebold-Mariano test)

6. Conclusions

6.1 Core Findings

Based on 171,644 Lending Club loans, this study yields three statistically significant core conclusions. First, logistic regression achieves optimal „performance-stability“ balance after integrating macroeconomic indicators, with enhanced AUC-ROC reaching 0.6854 (1.08% improvement), KS statistic increasing 3.82%, while maintaining 1.0% overfitting degree, significantly outperforming XGBoost (10.6% overfitting) and LightGBM (1.01% AUC improvement only). This demonstrates that while linear models are weaker at capturing nonlinear relationships than tree-based models, they more efficiently integrate incremental information from macro indicators through regularization control, better meeting P2P platforms‘ practical requirements for regulatory compliance and low overfitting.

Second, short-term loans and credit-vulnerable groups show highest sensitivity to macroeconomic indicators. The 36-month loans achieve 1.41% AUC improvement, driven by synergy effects between 3-year macro indicators and loan risk exposure periods. Near-prime borrowers‘ SHAP values for unemployment-credit risk interactions are 2.34 times those of prime groups, though overall AUC improvement remains modest at 0.86% due to internal risk structure heterogeneity.

Third, macro-interaction features prove critically valuable. Interaction terms between macro and baseline features (such as 3-year HPI residual × high DTI indicator) contribute 0.0226 in SHAP values, over 20 times single indicators, confirming „macro shock × individual vulnerability“ interactions as key to default prediction rather than macro indicators alone.

6.2 Practical Implications

The research findings provide actionable guidance for P2P market participants. For P2P platforms, implementing group-customized risk models with macro-borrower characteristic interactions can enhance risk management precision while maintaining regulatory compliance. Platforms should prioritize integrating 3-year economic indicators for 36-month loans, supplement financial buffer variables for near-prime groups, and leverage SHAP analysis to generate transparent decision explanations satisfying GDPR and Federal Reserve SR 11-7 guidelines. For investors, the heterogeneous sensitivities enable sophisticated portfolio strategies - prioritizing 36-month loans in low-unemployment MSAs while reducing near-prime exposure in high-volatility regions. The consistent low overfitting of logistic regression enhanced models ensures robust risk assessment across different market conditions. Regulatory authorities should mandate disclosure of macro indicator adaptation logic, monitor near-prime loan concentrations in high-unemployment areas, and require combined assessment models for vulnerable groups to balance risk control with credit accessibility.

6.3 Research Limitations and Future Directions

This study‘s limitations provide clear pathways for future research extensions. The sample period (2012-2013) does not cover extreme macroeconomic shock events such as the 2020 pandemic. Future research could employ updated 2019-2023 data to test macro indicators‘ predictive validity during „black swan“ events. Regarding indicator granularity, this study uses only MSA-level macro indicators; future work could explore county-level or zip code-level geographic indicators, or incorporate non-traditional data sources such as social media employment sentiment

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and satellite nighttime light data. While heterogeneous impacts across different groups have been identified, the marginal contributions of „repayment willingness“ versus „repayment ability“ in default decisions remain unquantified. Future research could combine behavioral economics experimental designs to reveal internal mechanisms of how macro shocks affect default behavior through dual channels. Additionally, extensions to other P2P lending scenarios including financing success rates and interest rate pricing could comprehensively clarify macroeconomic transmission paths and effects in P2P markets.

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