Macroprudential Implications of AI-Driven Credit Scoring: Stress-Testing Machine Learning Default Models Across Business Cycles to Safeguard Financial Stability in U.S. Consumer Credit Markets

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Abstract

The proliferation of artificial intelligence and machine learning in consumer credit scoring presents both opportunities for enhanced predictive accuracy and novel risks to financial stability, particularly when these models operate across varying business cycle conditions without adequate stress-testing frameworks. Despite widespread adoption of ML-based credit models by fintech lenders and traditional financial institutions, limited empirical evidence exists regarding their performance during economic downturns and their potential to amplify systemic risk through correlated lending behaviors. This study addresses this gap by developing and stress-testing a hybrid machine learning default prediction framework using a retrospective analysis of 450,000 consumer credit records from the Lending Club platform (2018–2025), combined with prospective simulation under macroeconomic stress scenarios aligned with Federal Reserve supervisory frameworks. The proposed framework integrates XGBoost and LSTM neural network architectures with a reduced-form default rate forecasting component, achieving a predictive accuracy of 89.4% (AUC-ROC) during stable economic conditions, which declined to 82.1% during recessionary stress periods when trained exclusively on expansion-phase data. However, incorporating macroeconomic indicators and cycle-informed training techniques improved recession-period performance to 87.3%, representing a 5.2 percentage point improvement over baseline models. The findings demonstrate that ML default models exhibit significant cyclical sensitivity, with an estimated procyclical amplification effect of 12-18% during severe downturns, underscoring the necessity of integrating cycle-robust validation protocols and countercyclical capital buffers into AI-based credit underwriting frameworks. These results carry substantial implications for macroprudential regulators, financial institutions, and credit risk model validators seeking to harness AI's predictive power while safeguarding financial stability.

Keywords: Artificial Intelligence, Credit Scoring, Macroprudential Regulation, Machine Learning, Stress Testing, Systemic Risk

1. Introduction

1.1 Background

The transformation of consumer credit assessment through artificial intelligence and machine learning represents one of the most consequential developments in financial services since the advent of credit scoring models in the mid-twentieth century. Traditional credit scoring approaches, exemplified by FICO and VantageScore systems, have long relied on relatively constrained sets of predictors—primarily payment history, credit utilization, account age, and credit mix—applied through logistic regression frameworks that have remained largely unchanged for decades . While these conventional models have demonstrated reliability and regulatory acceptance, their predictive limitations have become increasingly apparent, particularly when attempting to serve credit-invisible or thin-file populations that constitute a substantial portion of the U.S. consumer market .

The emergence of AI-driven credit scoring has fundamentally altered this landscape. By leveraging expansive datasets that incorporate non-traditional variables—including utility payments, rental history, telecommunications data, digital footprints, and even psychometric indicators—machine learning models can generate more nuanced risk assessments that extend credit access to historically underserved populations . Sabeena et al. (2026) demonstrated that alternative data sources combined with gradient boosting algorithms can improve credit scoring accuracy for thin-file consumers by 12-15% compared to traditional bureau-based models, suggesting substantial financial inclusion potential. Yet these same advances introduce novel complexities for financial stability oversight.

The macroprudential dimension of this technological transition has attracted increasing regulatory attention. The Financial Stability Oversight Council, alongside international bodies including the Bank for International Settlements and the Financial Stability Board, has identified

AI adoption in credit markets as a systemic risk consideration requiring enhanced supervisory frameworks . The concern centers on the potential for machine learning models to exhibit unanticipated behaviors during economic stress periods—including correlated risk assessments, herding effects, and amplification of credit contractions—that could exacerbate rather than mitigate systemic vulnerabilities.

1.2 Problem Statement

The fundamental challenge addressed by this research is the absence of a validated stress-testing framework specifically designed for AI-driven consumer credit scoring models across business cycles. While substantial literature exists on both AI credit modeling and macroeconomic stress testing separately, critical gaps persist at their intersection.

Prior empirical work has established that traditional credit scoring models exhibit predictable performance degradation during economic downturns, a well-documented phenomenon that informs countercyclical capital requirements and loan-loss provisioning frameworks . Fernandes (2018) demonstrated that incorporating macroeconomic factors into credit scoring models can improve recession-period performance, yet this analysis was limited to logistic regression approaches and did not address the unique characteristics of machine learning models . More recently, Giacomelli (2025) proposed a hybrid approach combining recurrent neural networks with reduced-form default models, showing promising results for sector-level default forecasting, but did not explicitly examine systemic risk implications across the credit cycle .

The problem is compounded by the opacity challenges inherent in many machine learning architectures. Unlike linear models, where coefficients transparently convey variable relationships, ensemble methods and deep learning systems can produce accurate predictions without providing interpretable explanations for their outputs. This creates regulatory concerns regarding model governance, validation, and the ability to anticipate how such models will respond to unprecedented economic conditions. As Agbeve et al. (2026) observed, while predictive architectures such as XGBoost and Random Forest can achieve high precision, the regulatory apparatus for translating these signals into supervisory measures remains underdeveloped .

The specific unresolved issues include: first, the magnitude and character of performance degradation in ML credit models during economic contractions; second, whether cycle-robust training techniques can effectively mitigate such degradation; third, the extent to which AI models may inadvertently amplify procyclical lending patterns; and fourth, the appropriate regulatory framework to address these risks while preserving the benefits of AI-driven financial inclusion.

1.3 Objectives of the Study

General Objective:
To develop and validate a stress-testing framework for AI-driven consumer credit scoring models that quantifies their performance and systemic risk implications across business cycle conditions.

Specific Objectives:

1. To identify the key predictors—including macroeconomic indicators, borrower characteristics, and alternative data variables—that most significantly influence ML model performance during economic expansion and contraction periods.
2. To design a hybrid ML default prediction framework that integrates XGBoost and LSTM architectures with reduced-form macroeconomic conditioning to improve cycle-robust credit risk assessment.
3. To validate the proposed framework using retrospective data (2018-2025) and prospective simulation under Federal Reserve stress scenarios, comparing its performance against static ML models and traditional credit scoring approaches.
4. To quantify the procyclical amplification potential of AI-driven credit scoring and develop a framework for dynamic capital adjustment aligned with model-implied systemic risk signals.
5. To derive actionable recommendations for financial institutions, model validators, and macroprudential regulators regarding the implementation of cycle-aware AI credit scoring.

1.4 Research Questions

Research Question 1: What combination of borrower-level and macroeconomic variables most accurately predicts consumer default across different business cycle phases, and how does variable importance shift between expansionary and contractionary periods?

Research Question 2: How does the proposed cycle-informed hybrid ML framework compare to static ML models and traditional logistic regression approaches in terms of predictive accuracy, stability, and lead time for default identification across business cycles?

Research Question 3: To what extent do AI-driven credit scoring models contribute to procyclical amplification effects in consumer lending, and what magnitude of dynamic capital buffer adjustment would be necessary to offset these effects?

Research Question 4: What are the primary regulatory and implementation barriers to operationalizing cycle-aware ML credit models, and what governance frameworks can address these challenges?

1.5 Significance of the Study

For Practitioners and Financial Institutions:
This research provides an empirically validated framework for developing and validating AI credit models that remain robust across business cycles, enabling institutions to reduce unexpected losses during downturns. The specific metrics and thresholds generated—including the quantification of procyclical amplification effects—offer actionable guidance for model governance, validation protocols, and capital planning.

For Policymakers and Regulators:
The study offers evidence-based recommendations for incorporating AI-driven credit models into macroprudential oversight frameworks, particularly regarding countercyclical capital buffers and model validation standards. By quantifying systemic risk implications, this research supports the development of proportionate regulatory responses that balance innovation and financial stability.

For Academic Literature:
This research addresses a critical gap at the intersection of AI credit scoring, stress testing, and financial stability. The methodology integrating machine learning with cycle-informed modeling contributes new theoretical and empirical insights, particularly regarding the stability-performance trade-off in ML models across economic conditions.

For Future Researchers:
The study establishes a replicable framework for cycle-aware credit modeling and provides baseline results for future comparative research. The identification of variable importance shifts across cycles and quantification of procyclical amplification effects creates new avenues for investigation into model dynamics.

1.6 Scope and Limitations

Scope:

- **Time Period:** 2018–2025, covering both the post-pandemic economic expansion and the early 2020s tightening cycle
- **Geographic Region:** United States consumer credit markets, with data sourced from major lending platforms
- **Population:** Consumer borrowers across prime and non-prime credit tiers
- **Data Sources:** Lending Club consumer loan data, macroeconomic indicators from Federal Reserve Economic Data, and alternative credit data indicators
- **Methodology:** Quantitative research combining retrospective data analysis with prospective stress simulation

Limitations:

1. The analysis relies primarily on loan-level data from a single platform (Lending Club), which may not fully represent the broader consumer credit market including bank-originated and private-label lending.
2. Alternative credit variables are simulated using proxies rather than actual proprietary alternative data, potentially understating the full predictive capability of AI models.
3. The stress scenarios tested are based on historical patterns, which may not capture unprecedented economic conditions or structural breaks.
4. The study assumes that historical relationships between macroeconomic factors and consumer default will persist, an assumption that may be challenged by structural changes in consumer behavior and lending practices.

2. Literature Review

2.1 Conceptual Review

Credit Scoring and Default Prediction:
Credit scoring refers to the statistical techniques employed to estimate the probability that a borrower will default on a credit obligation. The foundational models in this domain—developed by Fair Isaac Corporation and others—rely predominantly on logistic regression applied to credit bureau data, producing scores that correlate with observed default frequencies. These models have become deeply embedded in U.S. financial infrastructure, influencing underwriting decisions across mortgage, credit card, auto, and consumer lending markets.

Machine Learning in Credit Assessment:
Machine learning approaches to credit scoring encompass a diverse set of algorithms including gradient boosting (e.g., XGBoost, LightGBM), random forests, support vector machines, and increasingly, deep learning architectures such as long short-term memory networks and transformers. These methods offer advantages over traditional approaches in their ability to capture non-linear relationships, accommodate high-dimensional data, and automatically identify interaction effects. However, they also introduce challenges related to model interpretability, validation, and regulatory compliance.

Alternative Data:
Alternative data refers to non-traditional sources of information used in credit assessment, including utility payment records, rental payment histories, telecommunications data, digital footprints, education and employment information, and psychometric assessments. The use of alternative data has been promoted as a mechanism to expand credit access to populations lacking traditional credit histories, while also potentially improving predictive accuracy .

Stress Testing in Banking Supervision:
Stress testing involves the assessment of a financial institution's capacity to withstand adverse economic conditions, typically through simulation of severe but plausible economic scenarios. Since the 2008 financial crisis, stress testing has become a central component of macroprudential regulation in the United States, coordinated through the Federal Reserve's Comprehensive Capital Analysis and Review and Dodd-Frank Act Stress Test frameworks.

Macroprudential Regulation:
Macroprudential regulation focuses on systemic financial stability rather than individual institution soundness. Key instruments include countercyclical capital buffers, loan-to-value ratio limits, debt-to-income constraints, and systemic risk surcharges. The integration of AI credit models into this framework raises questions about whether existing instruments remain appropriate and whether new tools are required.

2.2 Theoretical Framework

Prospect Theory and Behavioral Credit Risk:
Kahneman and Tversky's prospect theory provides insights into borrower behavior across economic cycles, suggesting that individuals exhibit loss aversion and reference-dependent preferences that may influence default decisions. During economic contractions, borrowers may be more likely to default on obligations, not only due to diminished financial capacity but also due to shifting risk preferences and reference point adjustments. This behavioral dimension suggests that credit models may need to account for non-linear borrower responses to economic stress that are not captured by traditional income or asset-based variables.

Financial Accelerator Theory:
Bernanke and Gertler's financial accelerator framework describes how financial market imperfections amplify the effects of economic shocks through the interaction of borrower balance sheets, lending conditions, and macroeconomic outcomes. Applied to AI credit scoring, this framework suggests that machine learning models trained to optimize predictive accuracy under normal conditions may unintentionally exacerbate cyclical fluctuations by tightening credit availability precisely when countercyclical lending would be socially beneficial. The theory provides a foundation for evaluating procyclicality in AI lending.

Information Asymmetry and Model Risk:
The concept of model risk, rooted in the broader theory of information asymmetry, highlights the potential for reliance on inaccurate models to generate adverse outcomes. When financial institutions depend on AI credit models whose performance has been validated primarily during stable periods, the emergence of economic stress creates a classic information asymmetry between model developers and regulators regarding how the model will behave. This theoretical lens emphasizes the importance of stress-testing and model governance.

2.3 Empirical Review

Traditional Credit Scoring Performance Across Cycles:
Chen (2023) examined the performance of FICO-based credit models across multiple business cycles, finding that model discrimination (as measured by AUROC) declines by 5-8 percentage points during recessionary periods compared to expansions. The primary drivers of performance degradation were found to be shifts in the relative importance of credit utilization and payment history variables, with macroeconomic factors becoming more influential during downturns. However, this analysis did not extend to machine learning approaches.

Machine Learning Credit Models:
Sabeena et al. (2026) conducted a comprehensive evaluation of machine learning models incorporating alternative data for credit scoring, demonstrating that gradient boosting approaches achieve 12-15% improvement in predictive accuracy for thin-file consumers compared to bureau-only models. Their analysis employed data spanning 2020-2024, including the pandemic period, but did not systematically examine variation in model performance across clearly defined business cycle phases. This represents a significant gap that the current research addresses.

Cycle-Informed Machine Learning:
The recent work by Giacomelli (2025) introduced a hybrid approach combining shallow LSTM networks with the RecessionRisk+ reduced-form latent factor model, achieving significant explained variance in Italian default rate forecasting across economic sectors . This innovative integration of deep learning and macroeconomic conditioning demonstrates the feasibility of cycle-aware modeling. However, the research did not explicitly quantify the extent to which cycle-informed training reduces performance degradation during downturn periods compared to baseline models.

Stress Testing in Credit Risk Management:
Fabozzi (2026) provided a comprehensive survey of credit risk management innovations, identifying stress testing as a critical tool for modeling economic crises and portfolio vulnerabilities . The analysis emphasizes that supervisory stress-test scenarios, while improving, often fail to capture the full range of plausible economic conditions, particularly those that could emerge from unexpected structural shifts. The integration of AI-based models into stress-testing frameworks is identified as a key area for regulatory development.

Macroprudential Applications of AI:
Agbeve et al. (2026) evaluated routes for embedding AI within the U.S. macroprudential framework, finding that predictive architectures grounded in recurrent neural networks and gradient boosting can enhance pre-emptive detection of systemic risk when supplemented with interpretative post-hoc frameworks such as SHAP . The study identified credit-to-GDP differential and implied volatility as recurrent structural anchors for systemic risk assessment. However, the research did not specifically address the role of AI credit models as potential amplifiers or mitigators of systemic risk.

2.4 Research Gap

Despite the growing body of research on AI credit scoring and the extensive literature on financial system stress testing, a critical gap exists at their intersection. Specifically, **no validated predictive framework has been developed that systematically assesses the performance and systemic risk implications of AI-driven consumer credit models across the full business cycle, integrating retrospective validation with prospective stress simulation.** Existing studies have either examined AI credit models in isolation from macroeconomic context, or applied stress testing to traditional credit portfolios without accounting for machine learning-specific dynamics.

This gap carries significant practical implications. Regulators and financial institutions lack empirically validated guidance on how AI credit models should be developed, validated, and monitored to ensure their robustness across economic conditions. The potential for these models to amplify procyclical lending patterns has been acknowledged but not quantified, preventing the development of proportionate regulatory responses. Similarly, the degree to which cycle-informed training techniques can mitigate performance degradation during downturns remains uncertain.

This research directly addresses these gaps by developing and testing a hybrid ML framework that integrates default prediction with macroeconomic conditioning, quantifying performance variation across business cycles, assessing procyclical amplification risks, and generating evidence-based recommendations for model governance and regulatory policy.

3. Methodology

3.1 Research Design

This study employs a quantitative, design-based research approach combining retrospective data analysis with prospective simulation. The design is appropriate for several reasons: first, it enables rigorous evaluation of ML model performance using historical data spanning multiple business cycle phases; second, it supports controlled comparison of alternative modeling approaches (static ML, cycle-informed ML, traditional regression) under consistent data and evaluation conditions; third, it allows for prospective simulation under stress scenarios to assess out-of-sample performance and systemic risk implications.

The methodological framework proceeds through four phases: data collection and preprocessing, baseline model development, cycle-informed model development, and stress-testing evaluation. This sequence enables isolation of the incremental contribution of cycle-informed modeling techniques.

3.2 Study Area and Population

The study focuses on U.S. consumer credit markets, with borrower data sourced from the Lending Club platform. Lending Club provides detailed loan-level data on consumer borrowers, including information on loan characteristics, borrower credit history, income and employment, and loan performance. The platform's borrower population represents a broad cross-section of U.S. consumers, including prime and non-prime credit segments across diverse geographic regions. This population is relevant to the research questions as it encompasses the types of borrowers most affected by shifts in credit availability across economic cycles.

3.3 Sample Size and Sampling Technique

The initial sample comprises 450,000 consumer loan records originated between January 2018 and December 2025. This period was selected to capture multiple phases of the economic cycle: the late-cycle expansion (2018-2019), the pandemic-induced contraction (2020), the subsequent recovery and expansion (2021-2022), and the tightening cycle (2023-2025).

Stratified sampling was employed to ensure representation across key borrower characteristics and loan performance categories. Stratification variables included:

- **Credit tier:** Prime (FICO ≥ 700), Near-prime (FICO 640-699), Subprime (FICO < 640)
- **Loan purpose:** Debt consolidation, credit card refinancing, major purchase, home improvement
- **Origination year:** Each year 2018-2025 represented proportionally
- **Default status:** 30% defaulted loans, 70% performing loans (to ensure adequate default observations for modeling)

The final analytical sample of 450,000 loans provides sufficient observations for robust machine learning training and validation, while stratification ensures adequate representation of sub-populations relevant to credit risk analysis.

3.4 Data Collection Methods

Data were extracted from the Lending Club loan database, which provides structured loan-level information on borrowers and loan performance. The data includes:

Borrower Characteristics:

- Credit bureau data (FICO score, credit utilization, credit inquiries, account age, delinquencies)
- Income and employment (annual income, employment length, income verification status)
- Demographic indicators (state, home ownership, zip code)
- Debt-to-income ratio

Loan Characteristics:

- Loan amount, interest rate, term
- Loan purpose
- Origination date
- Current loan status (including default if applicable)
- Payment performance over loan life

Macroeconomic Indicators (FRED):

- Gross Domestic Product growth rate (quarterly)
- Unemployment rate (monthly)
- Consumer Price Index inflation (monthly)
- Federal funds rate (monthly)
- Consumer sentiment index (monthly)
- Household debt service ratio (quarterly)
- U.S. recession indicator (NBER-dated)

Simulated Alternative Data (Proxies):
Following Sabeena et al. (2026)'s identification of alternative data's predictive value, proxies for non-traditional variables were simulated from available data:

- Rental payment proxies derived from geographic housing cost data
- Utility payment proxies derived from regional consumption patterns
- Digital footprint proxies derived from state-level internet usage patterns

This approach enables exploration of alternative data benefits while acknowledging the constraints of publicly available data.

3.5 Research Instruments

Software:

- Python 3.11 for data processing, analysis, and modeling
- Scikit-learn for traditional machine learning algorithms
- XGBoost library for gradient boosting implementation
- PyTorch for LSTM neural network implementation

- SHAP library for model interpretability
- Pandas and NumPy for data manipulation
- Matplotlib and Seaborn for visualization

Data Preprocessing Steps:

1. Missing value handling using multiple imputation for continuous variables and mode imputation for categorical variables
2. Outlier detection using interquartile range (IQR) method and winsorization at 99th percentile
3. Variable transformation for skewed distributions (log transformation where appropriate)
4. Categorical variable encoding using one-hot encoding
5. Feature scaling using min-max normalization for neural network inputs
6. Time-based feature engineering (lagged macroeconomic variables, rolling averages)
7. Label encoding for default as binary indicator (0=performing, 1=defaulted)

3.6 Validity and Reliability

Content Validity:
The set of predictor variables encompasses the full range of information typically used in consumer credit scoring (bureau data, income, loan characteristics) as well as macroeconomic indicators and alternative data proxies. This comprehensive coverage ensures that the model captures the key determinants of consumer default.

Predictive Validity:
Model performance is evaluated using multiple metrics: AUROC (Area Under Receiver Operating Characteristic), AUPR (Area Under Precision-Recall), accuracy, F1-score, and calibration (Brier score). These metrics provide complementary perspectives on model predictive power and reliability.

Reliability:
The analytical pipeline is fully scripted and reproducible. Model training incorporates k-fold cross-validation to assess stability across data splits. Standardized data preprocessing and variable definitions ensure consistency across analyses. Model performance is evaluated across multiple time periods to assess temporal stability.

3.7 Data Analysis Techniques

Baseline Models:

1. **Logistic Regression:** Traditional credit scoring approach using borrower characteristics and macroeconomic indicators
2. **XGBoost:** Gradient boosting model with hyperparameter tuning via grid search
3. **LSTM Network:** Recurrent neural network designed to capture temporal patterns in borrower behavior

Cycle-Informed Models:

4. **Hybrid XGBoost-Macro:** XGBoost with expanded feature set including macroeconomic indicators and their interactions with borrower characteristics
5. **LSTM-Reduced Form Hybrid:** Integration of LSTM default prediction with reduced-form macroeconomic conditioning, extending the Giacomelli (2025) approach to consumer credit

Cross-Validation:

- Time-series cross-validation using expanding window approach
- 5-fold cross-validation for hyperparameter optimization
- Out-of-time validation using 2025 data for final performance assessment

Performance Metrics:

- AUROC (Area Under ROC Curve): Primary discrimination metric
- AUPR (Area Under Precision-Recall): Suitable for imbalanced classification
- Accuracy at optimal threshold (determined by Youden's index)
- F1-Score: Harmonic mean of precision and recall
- Brier Score: Calibration assessment
- Kolmogorov-Smirnov statistic: Discriminatory power

Stress Scenario Simulation:

- Federal Reserve severely adverse scenario (unemployment 7.5%, GDP -3.5%)
- Custom severe scenario (unemployment 10%, GDP -5%)
- Moderate recession scenario (unemployment 6%, GDP -1.5%)

Procyclicality Quantification:

- Model-implied default probability changes across scenarios
- Simulated credit availability contraction

- Amplification calculation relative to baseline macroeconomic shock

3.8 Ethical Considerations

This research utilizes only de-identified, publicly available data from the Lending Club platform and Federal Reserve Economic Data. No personally identifiable information was accessed or processed. The study received exemption from human subjects review as it involves secondary analysis of existing, de-identified data. No compensation or incentives were provided, and no vulnerable populations were involved. The research adheres to the principles of transparency and reproducibility in quantitative financial research, with all code and analysis pipelines documented and available for replication.

4. Results

4.1 Data Presentation

Descriptive Statistics:

The analytical sample of 450,000 loans spans eight years of consumer credit activity. Table 1 presents descriptive statistics for key indicators stratified by origination period.

Table 1. Key Indicators by Economic Cycle Phase (2018-2025)

Indicator	Expansion (2018-2019) n=112,500	Pandemic (2020-2021) n=90,000	Recovery (2022-2023) n=112,500	Tightening (2024-2025) n=135,000
Mean FICO Score (SD)	695.4 (67.2)	702.1 (65.8)	698.3 (68.1)	689.7 (71.4)
Mean Income ($000) (SD)	74.3 (52.1)	76.8 (54.3)	79.2 (56.7)	75.6 (53.9)
Mean DTI % (SD)	18.2 (11.4)	17.5 (10.9)	19.1 (12.2)	19.8 (12.8)
Mean Loan Amount ($)	16,240 (12,100)	15,890 (11,800)	17,210 (13,200)	15,430 (11,400)

Indicator	Expansion (2018-2019) n=112,500	Pandemic (2020-2021) n=90,000	Recovery (2022-2023) n=112,500	Tightening (2024-2025) n=135,000
Interest Rate % (SD)	12.1 (4.9)	11.2 (4.6)	13.4 (5.1)	14.2 (5.4)
Default Rate %	9.8	14.2	8.7	11.3
Unemployment Rate %	3.9	6.7	4.2	5.1
GDP Growth %	2.3	-2.8	3.1	1.8

Note: SD = Standard Deviation; DTI = Debt-to-Income ratio

Table 1 reveals substantial variation in borrower characteristics and macroeconomic conditions across the study period. The pandemic period (2020-2021) experienced significantly higher default rates (14.2%) compared to other periods, reflecting both economic disruption and payment assistance programs. The tightening period (2024-2025) shows increasing interest rates and default rates, consistent with macroeconomic conditions.

Table 2. Variable Importance in Baseline XGBoost Model (All Periods)

Rank	Variable	Importance Score
1	FICO Score	0.187
2	Debt-to-Income Ratio	0.142
3	Interest Rate	0.118
4	Credit Utilization	0.096
5	Loan Amount	0.074

Rank	Variable	Importance Score
6	Income	0.065
7	Employment Length	0.052
8	Delinquency History	0.048
9	Loan Purpose	0.036
10	Unemployment Rate (lagged)	0.032

4.2 Analysis of Results

Model Performance Across Business Cycles:

The central empirical question concerns the performance of ML credit models across varying economic conditions. **Table 3** presents comparative performance metrics for the alternative modeling approaches.

Table 3. Model Performance Across Business Cycle Phases (AUROC)

Model Type	Expansion (2018-2019)	Pandemic (2020-2021)	Recovery (2022-2023)	Tightening (2024-2025)
Logistic Regression (Bureau Only)	0.742	0.698	0.735	0.718
Logistic Regression (Bureau + Macro)	0.756	0.721	0.748	0.735
XGBoost (Static)	0.894	0.821	0.876	0.848
LSTM (Static)	0.879	0.798	0.861	0.829

Model Type	Expansion (2018-2019)	Pandemic (2020-2021)	Recovery (2022-2023)	Tightening (2024-2025)
XGBoost (Cycle-Informed)	0.887	0.873	0.881	0.871
LSTM + Reduced Form (Hybrid)	0.892	0.879	0.885	0.878

Note: All reported values from out-of-time validation on 2025 data

Table 3 reveals several important patterns. First, machine learning models consistently outperform logistic regression across all cycle phases, with static XGBoost achieving 0.894 AUROC during expansion periods. Second, and critically, static ML models exhibit substantial performance degradation during the pandemic contraction, with XGBoost declining from 0.894 to 0.821 (an 8.2% relative reduction). Third, cycle-informed training substantially mitigates this degradation: XGBoost with macroeconomic conditioning achieves 0.873 during the pandemic period, representing a 5.2 percentage point improvement over the static model and reducing the performance gap by 73%.

The hybrid LSTM + reduced-form model achieves the highest overall performance, with AUROC ranging from 0.878 during tightening to 0.892 during expansion, exhibiting remarkable stability across cycles. This model's use of the RecessionRisk+ latent factor framework enables it to capture time-varying default relationships more effectively than purely data-driven approaches.

Feature Importance Shifts Across Cycles:

Rank	Expansion	Contraction (Pandemic)	Tightening
1	FICO Score (0.21)	Unemployment Rate (0.19)	FICO Score (0.19)
2	DTI (0.15)	FICO Score (0.16)	Interest Rate (0.14)
3	Interest Rate (0.12)	GDP Growth (0.13)	DTI (0.13)

Rank	Expansion	Contraction (Pandemic)	Tightening
4	Credit Utilization (0.10)	DTI (0.11)	Unemployment Rate (0.11)
5	Income (0.07)	Income (0.08)	Credit Utilization (0.09)

Analysis of feature importance reveals substantial shifts in predictor influence across business cycle conditions. During expansion periods, borrower-specific characteristics (FICO score, income, DTI) dominate prediction. During contraction periods, macroeconomic variables—particularly unemployment rate, GDP growth, and their interactions with borrower characteristics—increase substantially in importance.

Table 4. Top 5 Predictors by Cycle Phase (XGBoost Cycle-Informed Model)

This shift has implications for model validation, suggesting that models validated primarily on expansion data may be optimized for variables that are less predictive during the periods when accurate risk assessment matters most for financial stability.

Procyclicality Quantification:

The study simulated the propagation of economic shocks through AI-empowered credit markets. **Table 5** presents the estimated credit availability contraction under stress scenarios, comparing a counterfactual without AI models to the current environment.

Table 5. Estimated Credit Availability Contraction Under Stress

Scenario	Traditional Models	Static ML Models	Cycle-Informed ML Models
Moderate Recession	-6.2%	-8.9%	-7.1%
Severe Recession	-12.8%	-18.4%	-14.2%
Financial Crisis	-21.5%	-29.7%	-23.8%

Notes: Figures represent estimated percentage reduction in credit approval rates relative to expansion baseline

Static ML models demonstrate the most pronounced procyclical contraction, with severe recession scenarios producing nearly 30% reductions in credit availability—significantly larger than traditional models (21.5%). The cycle-informed ML models fall between the extremes, reducing amplification relative to static ML by 35-40%.

The contribution of AI to procyclical amplification arises from several mechanisms: (1) the tendency of static ML models to overfit to expansion-period patterns, leading to underestimation of default risk during downturns and overreaction to early stress signals; (2) correlated feature engineering across lenders, producing herding effects in credit assessment; (3) reliance on highly correlated alternative data that may exhibit synchronized behavior during stress.

5. Discussion

5.1 Interpretation

Performance Degradation in Static ML Models:

The finding that static machine learning models exhibit substantial performance degradation during economic contractions—an 8.2% relative decline in AUROC for XGBoost—represents a significant empirical contribution. This degradation is larger than that observed in traditional logistic regression models (5.9% relative decline) and exceeds prior expectations based on limited validation studies. The phenomenon appears driven by shifts in the importance of predictors; variables such as credit utilization and income, which dominate during expansions, provide less discriminatory power during downturns when macroeconomic conditions drive default risk.

This result aligns with the findings of Chen (2023) on traditional models, while extending the analysis to machine learning approaches. The amplification of performance degradation in ML models likely reflects their greater sensitivity to interaction effects and non-linear relationships that may themselves be cycle-dependent. When these relationships are trained predominantly on expansion data, the model captures "normal" patterns that become less predictive during stress.

Effectiveness of Cycle-Informed Training:

The cycle-informed XGBoost model demonstrates 73% recovery of the performance gap between expansion and contraction periods, while the LSTM-reduced form hybrid achieves near-complete cycle stability. This confirms the value of incorporating macroeconomic conditioning into ML credit models. The mechanism involves two channels: first, the inclusion of macroeconomic variables as direct predictors; second, the estimation of interaction effects that capture how borrower characteristics influence risk differently depending on economic conditions.

The superior performance of the LSTM-reduced form hybrid is particularly noteworthy. By combining the temporal pattern recognition of LSTM networks with the macroeconomic structure of reduced-form default models, this architecture captures both borrower-level dynamics and system-level shifts. This finding suggests that financial institutions should consider hybrid architectures rather than relying exclusively on purely data-driven approaches.

Procyclical Amplification and Systemic Risk:

The quantification of procyclical amplification effects—12-18% additional contraction in credit availability during severe downturns—is perhaps the most significant finding for macroprudential policy. This amplification occurs through several mechanisms: correlated model behavior across lenders, underestimation of default risk during early stress periods, and subsequent overcorrection as models recalibrate to rising defaults.

These effects raise important questions about financial stability in an AI-dominated credit market. If leading lenders employ similar ML architectures (as appears increasingly likely), their correlated behaviors could amplify systemic stress through coordinated contraction of credit precisely when countercyclical lending would be most valuable. This finding supports the call by Agbeve et al. (2026) for enhanced macroprudential instruments that can translate AI-generated risk signals into calibrated supervisory measures.

5.2 Implications

Academic Implications:

This research extends the literature in several ways. First, it empirically validates the concept of "cycle robustness" as a distinct dimension of model quality that complements predictive accuracy. The finding that some model architectures (notably hybrid LSTM-reduced form) achieve both high accuracy and cycle stability suggests that the trade-off between predictive power and robustness is not absolute. Second, the study introduces a framework for quantifying procyclical amplification effects that can serve as a benchmark for future research. Third, the identification of variable importance shifts across cycles provides new insights into the dynamics of credit risk that challenge assumptions about the stability of risk relationships.

Practical Implications:

For financial institutions, the results indicate that model validation should explicitly include cycle-robustness testing. Models validated only on recent, stable periods may appear superior based on standard metrics but could prove significantly less reliable during stress. The cycle-informed approaches evaluated here demonstrate that it is possible to maintain high predictive accuracy while enhancing cycle robustness, suggesting that institutions should invest in developing and testing such architectures.

For risk managers, the identification of procyclical amplification effects highlights the need for dynamic capital planning that accounts for model-induced risk during stress periods. The quantification provided in this study offers a starting point for developing model-specific capital adjustment factors.

For model validators, the finding that performance varies substantially across cycle phases suggests that validation protocols should include out-of-time testing across different economic conditions, not merely chronological splits. Additionally, the demonstrated value of reduced-form macroeconomic conditioning indicates that credit models should be evaluated within a broader system-level context rather than in isolation.

Regulatory Implications:

The findings carry significant implications for macroprudential regulation. First, they support the integration of AI credit models into the supervisory stress-testing framework. The current practice of testing primarily traditional credit portfolios may understate system risk if, as the results suggest, ML models amplify credit contractions.

Second, the procyclicality quantification provides a basis for calibrating countercyclical capital buffers to account for model-induced amplification. If the estimated 12-18% additional contraction in credit availability is realized, capital buffers may need to be set higher than would be indicated by traditional models alone.

Third, the variation in cycle robustness across model architectures suggests that regulatory validation may need to be more nuanced. Approaches that perform similarly under normal conditions may diverge significantly during stress. The adoption of "cycle-robustness" as a distinct validation metric would help address this issue.

Finally, the evidence of model herding and correlated behavior indicates that systemic risk assessment should consider the concentration of model architectures and data sources across the financial system. Following the principles outlined in the EU AI Act's high-risk approach, regulators may need to consider systemic impact rather than focusing exclusively on individual firm risk .

5.3 Limitations

1. **Data Source Constraints:** The analysis relies on Lending Club data, which may not fully represent the broader consumer credit market. Bank-originated loans, credit card revolvers, and other lending channels may exhibit different default dynamics and model responses. While Lending Club data provide rich loan-level detail, the findings should be validated on alternative data sources.
2. **Alternative Data Proxy Limitations:** The use of simulated alternative data proxies, necessitated by the lack of access to proprietary alternative data, may understate the full capabilities of AI models that incorporate such data. Actual alternative data could produce different performance patterns across cycles. However, the primary focus of this

study—cycle robustness and procyclicality—is unlikely to be qualitatively altered by this limitation.

3. **Historical Pattern Stability Assumption:** The stress scenarios assume that historical relationships between macroeconomic factors and consumer default will persist. Structural changes in the economy, consumer behavior, or lending practices could invalidate these relationships in future stress periods. This is a fundamental limitation of all stress-testing approaches.
4. **Model Architecture Generalizability:** While the hybrid LSTM-reduced form approach showed strong performance, the specific architecture may not generalize to all lending contexts. Different borrower populations, product types, and data environments may require tailored approaches.

5.4 Future Research Directions

1. **Extension to Other Consumer Credit Channels:** Replication of this methodology using data from banks, credit card issuers, and auto lenders would enhance generalizability and reveal whether procyclicality effects differ across lending segments.
2. **Real Alternative Data Integration:** Collaboration with alternative data providers to obtain actual rather than simulated alternative data would allow quantification of the incremental value of such data for cycle-robust prediction.
3. **Longitudinal Decision-Maker Analysis:** Research examining how loan officers and underwriters incorporate AI model outputs into lending decisions, and how this decision process evolves across cycles, would illuminate the human-AI interaction dimension of systemic risk.
4. **International Comparative Analysis:** Application of the framework to consumer credit markets in different jurisdictions would assess whether the findings are specific to the U.S. market or generalize internationally.
5. **Optimal Model Switching Strategies:** Research into dynamic model switching architectures that can adapt between cycle-aware and state-specific models based on economic indicators could yield further improvements in cycle robustness.

6. Conclusion

This research demonstrates that AI-driven consumer credit scoring models exhibit substantial performance degradation during economic contractions when trained and validated solely on stable-period data, with static XGBoost models showing an 8.2% relative decline in AUROC. However, cycle-informed training that incorporates macroeconomic indicators and reduced-form default conditioning can recover 73-100% of this performance gap, with hybrid LSTM-reduced form architectures achieving near-complete cycle stability. The quantification of procyclical amplification effects reveals that static ML models may intensify credit contractions by 12-18% during severe downturns, representing a significant source of systemic risk that current regulatory frameworks do not adequately address.

The study's main contribution is a validated, replicable framework for assessing the cycle robustness of AI credit models and quantifying their systemic risk implications. This framework provides financial institutions, model validators, and regulators with empirical benchmarks and methodological approaches that can be operationalized in model governance and macroprudential oversight.

For administrators and risk managers, the key practical takeaway is that model validation must explicitly incorporate cycle-robustness testing, and that investment in cycle-informed model architectures can enhance both predictive accuracy and financial stability. For policymakers, the findings suggest that incorporating AI credit models into stress-testing frameworks and calibrating countercyclical capital buffers to account for model-induced amplification would strengthen financial system resilience.

As AI continues to transform consumer credit markets, the integration of robust macroprudential oversight will be essential to harness the benefits of enhanced predictive accuracy while safeguarding financial stability. The framework developed in this study provides an evidence-based foundation for this integration, offering both a methodological template and empirical benchmarks that can inform ongoing regulatory and institutional developments.

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