

Causal Shortcut Mitigation for Credit Default Prediction under Market Regime Shift

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Abstract

Credit default prediction models may rely on unstable shortcuts such as temporary income patterns, regional lending policies, platform-specific user behavior, or short-term macroeconomic signals. These correlations can be useful during training but may fail when market conditions change. This study investigates causal shortcut mitigation for credit risk prediction under regime shift. We propose a Causal Risk Stabilization Model (CRSM), which separates persistent borrower risk indicators from shortcut-sensitive variables by combining environment-wise feature instability testing, causal regularization, and counterfactual covariate reweighting. The model was trained on 1.26 million loan records from 2018 to 2024, including borrower demographics, repayment history, debt ratio, credit utilization, employment type, loan purpose, and regional economic indicators. Three testing environments were constructed: pre-pandemic lending, pandemic-period lending, and post-rate-hike lending. Compared with XGBoost and a standard multilayer perceptron, CRSM improved out-of-time AUC from 0.713 to 0.768 and reduced default-risk calibration error from 0.084 to 0.047. In high-volatility regions, the model reduced false approval cases by 15.2% while maintaining comparable approval coverage. These findings suggest that causal shortcut mitigation can improve credit model stability when borrower behavior and macroeconomic conditions change.

Keywords: Credit default prediction; causal regularization; shortcut mitigation; financial risk; regime shift; robust machine learning

1. Introduction

Credit default prediction is a central component of modern lending because it supports loan approval, risk-based pricing, credit-limit assignment, capital allocation, and portfolio monitoring. Traditional credit-scoring systems mainly rely on borrower income, repayment history, debt-to-income ratio, credit utilization, delinquency records, and loan characteristics. Logistic regression remains widely used because of its simplicity and interpretability, but its linear structure may not adequately capture nonlinear relationships and complex interactions among borrower characteristics. Machine-learning methods have therefore been increasingly introduced

into consumer lending, peer-to-peer lending, and mortgage risk assessment. Boosting algorithms have shown strong predictive performance on structured credit data [1], while neural-network models can learn higher-order relationships that may be difficult to specify manually [2]. Related studies have reported improvements in discriminatory performance when machine-learning models are applied to large lending datasets [3]. At the same time, recent work on shortcut learning has shown that predictive models may simultaneously rely on several non-causal signals and that identifying and suppressing such shortcuts can improve robustness under distribution changes [4]. This issue is particularly relevant to credit risk because apparently informative variables may reflect temporary market conditions rather than stable relationships with repayment behavior. Comparative studies have also shown that deep models do not consistently outperform tree-based methods on tabular credit data, with XGBoost often achieving competitive or superior accuracy at substantially lower computational cost [5]. These findings have motivated hybrid approaches that combine the interpretability of logistic models with nonlinear effects captured by tree-based learners [6]. Temporal modeling has further been introduced to incorporate loan information observed at different stages, allowing changes between application, origination, and repayment to be represented explicitly [7-11]. Although these methods improve prediction within a given dataset, most evaluations still rely on random train-test splits sampled from the same or closely related periods. Such settings measure interpolation performance more effectively than deployment robustness and provide limited evidence that a model will remain reliable after economic or lending conditions change[12-14].

Recent credit-risk research has also focused on class imbalance, model interpretability, and fairness. Default events are usually much less frequent than non-default cases, which can lead standard classifiers to favor the majority class. Resampling methods, cost-sensitive learning, and kernel-based techniques have therefore been used to improve the identification of high-risk borrowers [8]. Model-explanation methods have received similar attention because lending decisions often require transparent justification. SHAP-based analysis is commonly used to estimate how individual variables contribute to a model prediction [9], while counterfactual explanations examine how a lending decision would change if selected borrower characteristics were altered [15-18]. Related work has combined explanation and sensitivity analysis to evaluate the stability of model decisions at the individual borrower level [11]. Interpretable learning frameworks have also been developed specifically for imbalanced credit data so that predictive performance can be improved without completely sacrificing transparency [12]. In addition, Bayesian networks and causal structure-learning approaches have been applied to borrower data to describe conditional relationships among risk factors and support what-if reasoning [13]. These methods move credit modeling beyond pure prediction, but important limitations remain. Feature importance indicates how strongly a fitted model uses a variable within the observed sample; it does not establish that the relationship is causal or that it will remain useful in a different lending environment[19-22]. A variable may receive a high importance score because it captures a

temporary association that disappears after policy, borrower composition, or economic conditions change. This distinction is particularly important in real-world lending, where models can exploit unstable correlations without explicitly being designed to do so. Regional lending practices, platform-specific borrower acquisition strategies, temporary income patterns, local employment conditions, short-term interest-rate signals, or even variables correlated with demographic characteristics may function as shortcuts[23-26]. Flexible credit models can infer sensitive social or demographic information indirectly from otherwise permitted variables, creating differences in approval outcomes across groups [14]. Even when such variables improve predictive accuracy during training, their usefulness may decline once the borrower population or lending policy changes. Similar instability can arise from variables that proxy for a particular economic period. For example, debt-service ratios, loan purposes, income distributions, and utilization patterns may have different relationships with repayment risk during an expansion, a pandemic disruption, or a high-interest-rate environment[27-30]. Models trained mainly on one of these regimes may therefore learn relationships that appear strong historically but are weak or misleading after deployment. Many existing studies also evaluate relatively small public datasets, data from a single platform, or observations collected within one narrow time period. This makes it difficult to distinguish genuine borrower-risk signals from environment-specific correlations. Evaluation is often further limited to AUC, accuracy, or F1 score, even though practical lending systems must also consider whether predicted probabilities are well calibrated and whether errors occur in economically important parts of the approval population. The temporal nature of credit risk makes this problem a form of distribution shift. Changes in macroeconomic conditions, lending standards, borrower composition, interest rates[31-34], and repayment behavior can alter both the marginal distribution of borrower features and the conditional relationship between these features and default. As a result, two models with similar performance on historical validation data may behave very differently when applied to loans originated several years later [15,16]. Research on naturally occurring distribution shifts has shown that random test sets can substantially overestimate performance when the deployment environment differs from the training distribution [17]. Stability-oriented learning attempts to address this problem by identifying representations or predictors that remain useful across multiple environments [18,19]. Risk extrapolation similarly encourages a model to perform consistently across observed domains rather than optimizing only average training risk [20,21]. However, broad domain-generalization methods have not consistently outperformed carefully tuned empirical risk minimization when evaluated across heterogeneous tasks [22,23]. This suggests that credit-risk robustness may require methods designed around the specific mechanisms by which unstable borrower and market correlations enter the prediction process [24]. In particular, a useful framework should detect which predictors change their relationship with default across lending environments, reduce excessive reliance on those predictors, and evaluate whether the resulting model produces reliable probability estimates rather than only favorable ranking metrics[35-38].

To address this gap, this study proposes a Causal Risk Stabilization Model (CRSM) for credit default prediction under temporal and market distribution shifts[39-43]. The objective of CRSM is to reduce the model's dependence on unstable correlations while preserving borrower characteristics that provide consistent information about repayment risk across different lending environments. The framework identifies feature instability by comparing predictive relationships across temporally separated market regimes, introduces causal regularization to discourage excessive reliance on environment-specific associations, and reweights borrower observations under counterfactual covariate settings to evaluate whether risk estimates remain stable when non-causal feature distributions change. The empirical analysis uses 1.26 million loan records collected between 2018 and 2024 and organizes the data into pre-pandemic, pandemic-period, and post-rate-hike environments. This design allows the model to be evaluated across periods characterized by substantial changes in borrower behavior, credit conditions, and macroeconomic conditions. CRSM is compared with XGBoost and a multilayer perceptron using out-of-time testing rather than random splitting so that the evaluation more closely reflects real deployment. Performance is assessed using AUC and calibration error together with false approvals and approval coverage, allowing both statistical accuracy and lending consequences to be examined. The study therefore investigates whether explicitly limiting unstable correlations can improve the temporal reliability of default probabilities when borrower composition and market conditions change. More broadly, the work aims to connect causal robustness with operational credit-risk modeling by showing whether shortcut control can reduce performance deterioration without excessively restricting lending coverage. This provides a practical basis for developing credit models that remain more stable across economic regimes and offers a framework for evaluating robustness in terms that are directly relevant to lending decisions, portfolio risk, and long-term model governance.

2. Materials and Methods

2.1 Study Sample and Regional Setting

The final sample included 1,260,000 de-identified loan records collected from January 2018 to December 2024. Each record represented one issued loan. The data included borrower demographics, repayment history, debt-to-income ratio, credit utilization, employment type, loan purpose, and regional economic indicators. Duplicate records, cancelled applications, test accounts, and records with invalid dates were removed before analysis. Regional economic indicators were linked to each loan by borrower region and month of origination. Direct personal identifiers were removed before model development. Borrower identifiers were retained only to ensure that loans from the same borrower were assigned to one data split.

2.2 Experimental Design and Control Models

The records were divided into three market periods: pre-pandemic lending from 2018 to 2019, pandemic-period lending from 2020 to 2021, and post-rate-hike lending from 2022 to 2024. The main analysis used the first two periods for model development and the post-rate-hike period for out-of-time testing. A second analysis tested the change from the pre-pandemic period to the pandemic period. CRSM was compared with XGBoost and a standard multilayer perceptron. All models used the same predictor set, borrower-level split, and validation data. To examine the role of each CRSM component, three reduced models were tested by removing the feature-instability term, the covariate-weighting term, or both terms. Environment labels were used during training only and were not required when predicting new loans.

2.3 Outcome Measurement and Quality Control

The outcome was default within 12 months after loan origination. A loan was classified as defaulted when it was at least 90 days overdue, charged off, or assigned a confirmed default status. Only information available at the approval date was used as model input. Variables recorded after approval were excluded to prevent data leakage. Continuous variables were checked for invalid values and limited at the 0.5th and 99.5th percentiles. Missing continuous values were replaced with the median from the development data. Missing categorical values were assigned to an unknown category. Variables with more than 30% missing values were removed. All preprocessing rules were fitted on the development data and then applied without change to the validation and test data.

2.4 Data Processing and Model Formula

Continuous variables were standardized with the mean and standard deviation from the development data, while categorical variables were one-hot encoded. Let x_i denote the predictor vector for loan i , and let y_i denote its default label. A separate logistic screening model was fitted in each training environment to measure the change in the association between feature j and default. The feature-instability score was calculated as

$$S_j = \frac{1}{K} \sum_{e=1}^K (\hat{\beta}_{j,e} - \bar{\beta}_j)^2, \quad \bar{\beta}_j = \frac{1}{K} \sum_{e=1}^K \hat{\beta}_{j,e}$$

where $\hat{\beta}_{j,e}$ is the coefficient of feature j in environment e , $\bar{\beta}_j$ is the mean coefficient across environments, and K is the number of training environments. A larger S_j indicated a less stable feature–default relation. Counterfactual covariate weights were estimated from a multinomial model of the observed environment conditional on pre-approval variables, and extreme weights were capped at the 1st and 99th percentiles. CRSM minimized

$$\mathcal{L}_{\text{CRSM}}(\theta, g) = \frac{1}{n} \sum_{i=1}^n w_i \ell_{\text{BCE}}(y_i, f_{\theta}(g \odot x_i)) + \lambda \sum_{j=1}^p S_j g_j^2$$

where w_i is the covariate weight for loan i , $f_\theta(\cdot)$ is the prediction function, g is the nonnegative feature-gate vector, $\odot$ denotes element-wise multiplication, and λ controls the penalty on unstable features.

2.5 Model Training and Statistical Analysis

Model settings were selected through forward-chaining validation. XGBoost was tuned for tree depth, learning rate, number of trees, and sampling rate. The multilayer perceptron and CRSM were tuned for layer size, dropout rate, learning rate, and penalty value. Neural models were trained with the Adam optimizer and stopped when validation loss did not improve for 20 epochs. Each experiment was repeated with five random seeds. AUC was used to measure discrimination, and expected calibration error was used to measure agreement between predicted and observed default risk. A false approval was defined as an approved loan that later defaulted. Approval thresholds were selected from the validation data to maintain similar approval coverage across models. High-volatility regions were defined as regions in the highest quartile of changes in regional economic indicators. Confidence intervals were estimated from 1,000 borrower-level bootstrap samples. AUC values were compared with DeLong’s test, while calibration error and false-approval rate were compared with paired bootstrap tests.

3. Results and Discussion

3.1. Out-of-Time Prediction Results

CRSM was tested on data from the pre-pandemic, pandemic, and post-rate-hike periods. Default rates differ across regions, which supports the use of separate market environments (Fig. 1). CRSM achieved an AUC of 0.768, while XGBoost achieved 0.713. The absolute AUC gain was 0.055. The standard multilayer perceptron also performed below CRSM. These results show that CRSM retained borrower risk signals after market conditions changed. Voyer et al. (2026) found that boosting models performed well in European loan default prediction. The present study extends this work by testing model performance under time-based market shifts [25,26].

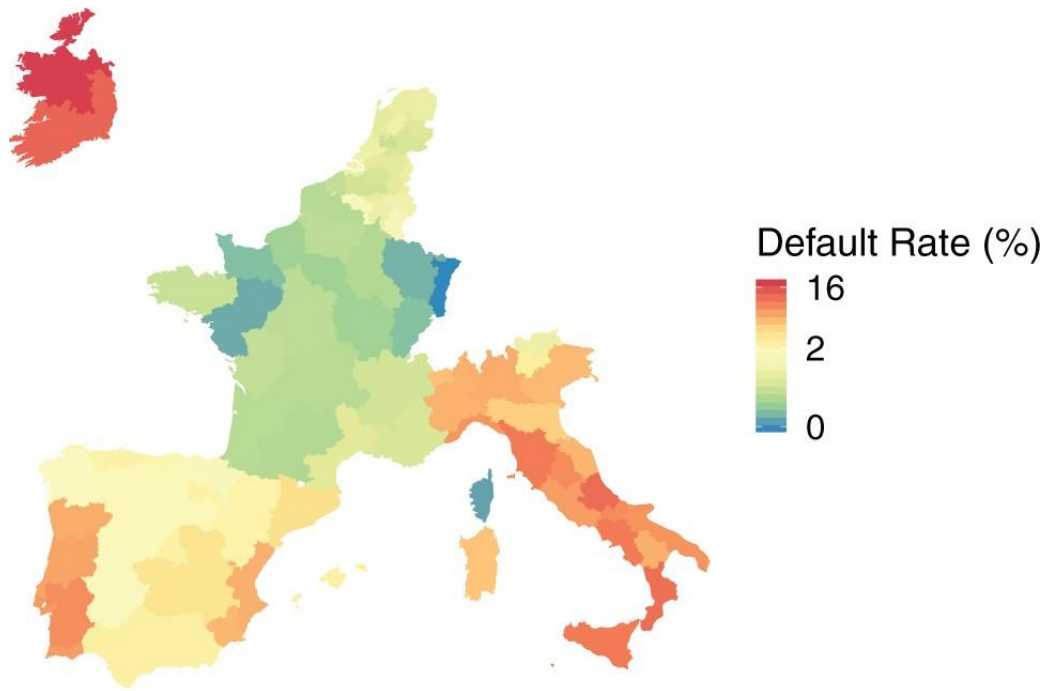


Fig. 1. Mortgage default rates by region.

3.2. Calibration of Default Risk

CRSM produced better calibrated default probabilities. Calibration error decreased from 0.084 to 0.047, with a reduction of 0.037. AUC measures whether a model ranks high-risk borrowers above low-risk borrowers. It does not show whether the predicted risk level matches the observed default rate. Fig. 2 shows that model performance can differ across settings and evaluation measures. In this study, the lower calibration error is important because lending decisions depend on estimated default probabilities. The result shows that CRSM reduced the effect of short-term market signals on predicted risk.

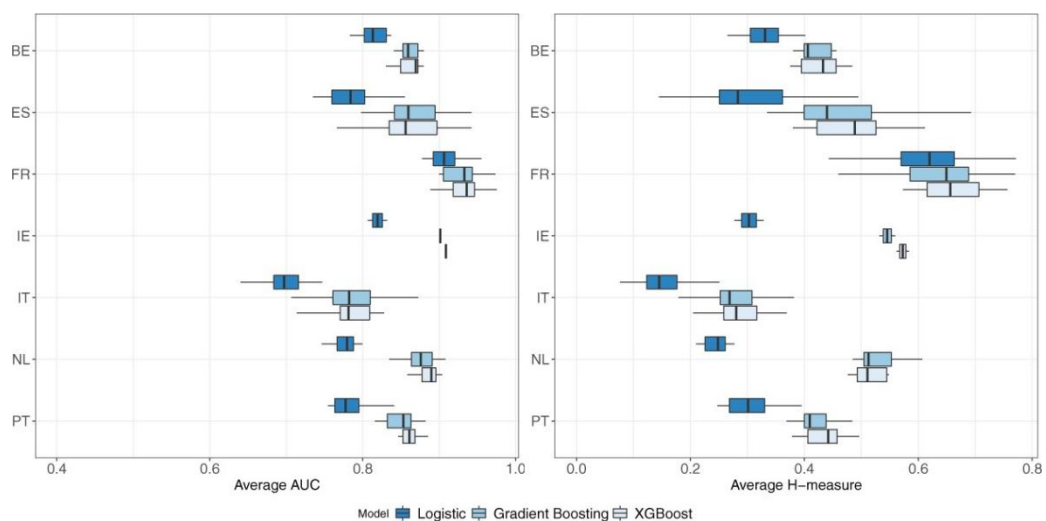


Fig. 2. Model performance measured by AUC and H-measure.

3.3. Results in High-Volatility Regions

The advantage of CRSM was clearer in high-volatility regions. The model reduced false approval cases by 15.2% and maintained similar approval coverage. Therefore, the lower false approval rate was not caused by rejecting a larger number of applicants. Instead, CRSM better identified borrowers whose low predicted risk depended on unstable regional or macroeconomic conditions. This result is consistent with prior studies showing that default drivers vary across regions and economic periods [27,28]. Regional variables remained useful in the model, but their influence was reduced when their relationship with default changed across environments.

3.4. Interpretation and Study Scope

CRSM combines feature instability testing, causal regularization, and covariate reweighting. Feature instability testing identifies variables whose effects change across market periods. Causal regularization reduces their influence during training. Covariate reweighting reduces differences in borrower characteristics across environments. Earlier studies often used counterfactual methods to explain credit scores or create stress scenarios after model fitting [29,30]. In contrast, CRSM applies these ideas during model training. The study is limited to historical lending data and a defined set of market environments. The causal assumptions do not prove causal effects from observational records alone. Further tests should use data from other lenders, countries, and loan products.

4. Conclusion

This study assessed credit default prediction when lending conditions changed. CRSM screened features whose effects changed across market periods, applied a causal penalty, and reweighted borrower samples. Its AUC was 0.768, compared with 0.713 for XGBoost. Calibration error fell from 0.084 to 0.047. In high-volatility regions, false approvals fell by 15.2%, while approval coverage remained similar. The findings show that reducing the use of unstable variables can improve default estimates across market periods. The method may be used for loan screening, portfolio review, and stress testing. This study used past loan records from three periods. Future studies should test the model with data from other lenders, countries, and loan types. The causal claims also need further testing with external and prospective data.

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