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Article

Early-Warning Stress Testing for Consumer Loans Based on Dynamic Macroeconomic Scenario Generation

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Abstract: This study proposes a dynamic stress-testing framework for consumer-finance portfolios by generating forward-looking macroeconomic scenarios using a vector autoregression model combined with Monte Carlo simulation. The scenarios are fed into a panel logistic-regression engine trained on 4.2 million loan accounts from 2015-2024. Using 1,000 simulated macro paths, the model quantifies stressed default probabilities up to 12 months ahead. Results show that under the 5% most adverse scenarios, 90-day delinquency rates rise by 28.9-46.2%, depending on product type. The model achieves an ROC-AUC of 0.82 in out-of-sample stress periods and captures 72.5% of actual default surges during the 2020 downturn. This approach offers a systematic tool for scenario-driven risk assessment in consumer lending.

Keywords: Stress testing; consumer credit; Macroeconomic simulation; scenario analysis; default forecasting

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1. Introduction

Household and consumer borrowing has become one of the primary channels through which macroeconomic shocks are transmitted to the financial system. In response to these vulnerabilities, regulatory authorities have elevated macroeconomic stress testing to a central supervisory tool for evaluating the resilience of financial institutions under severe but plausible economic conditions [1,2]. At the same time, accounting standards such as IFRS 9 and CECL have shifted credit-risk measurement toward forward-looking expected credit losses, increasing the need for reliable forecasts of default risk over future horizons rather than backward-looking averages [3]. A large body of research examines the macro-financial transmission to credit risk through so-called satellite models.

Many studies rely on vector autoregression (VAR) frameworks to project key macroeconomic variables and then link these projections to sector-level loss rates or non-performing loan ratios [4,5]. More recent contributions show that embedding macroeconomic scenarios directly into consumer-finance credit-risk forecasting can materially improve stress-testing results relative to borrower-only approaches, particularly when macroeconomic paths are treated as forward-looking drivers rather than static stress assumptions [5]. Subsequent extensions allow for time-varying parameters and non-linear responses to macro shocks in order to better reflect structural changes across economic cycles [6]. Despite these advances, satellite-model approaches often rely on short macroeconomic time series and a limited number of deterministic scenarios, which constrains their ability to represent the full distribution of future economic paths and associated credit risks [7,8]. Recent studies increasingly highlight the importance of micro-level information in stress-testing frameworks. Evidence suggests that incorporating loan-level or household-level data can materially alter stress-test outcomes, especially in markets where aggregate indicators fail to capture the full credit cycle [9]. Loan-level models allow borrower characteristics, loan terms, and repayment histories to interact directly with macroeconomic conditions, offering a more detailed view of heterogeneous responses to economic shocks. Related work explores alternative modelling engines, including survival-analysis approaches aligned with Basel requirements and dynamic frameworks for estimating portfolio loss distributions and economic capital [10]. Collectively, these studies demonstrate that both data granularity and model structure play a critical role in capturing credit losses during downturns. Another strand of the literature focuses on macroeconomic scenario design. Beyond standard VAR projections, recent work adopts Bayesian and quantile-based methods to align narrative stress scenarios with probabilistic macro forecasts and to characterise asymmetric downside risks [11,12]. Supervisory publications further emphasise that scenario severity, horizon, and internal consistency strongly influence the usefulness of stress tests for capital planning and risk management [13]. However, much of this work concentrates on system-wide solvency assessments or on corporate and mortgage portfolios. Scenario-driven stress testing for unsecured consumer loans-where default behaviour may react more sharply to labour-market and income shocks-remains comparatively limited. At the same time, default prediction for consumer loans has progressed rapidly at the borrower level. A growing literature applies statistical and machine-learning methods based on borrower income, credit scores, and loan characteristics to generate point-in-time default estimates [14]. Tree-based ensembles, gradient boosting, and neural networks often outperform traditional models and have been widely applied in online lending, microfinance, and retail banking contexts [15]. Survey studies document the rapid expansion of data-driven credit-risk modelling and stress the importance of data preparation, imbalance handling, and time-consistent evaluation [16,17]. More recent contributions examine how default behaviour evolves during crisis periods and how borrower-level features interact with macroeconomic conditions under stress [18]. Nevertheless, these models are still less frequently embedded in fully dynamic, scenario-driven settings in which macroeconomic variables evolve jointly over time.

We introduce an early-warning stress-testing framework for consumer-finance portfolios that links probabilistic macroeconomic scenarios with loan-level default modelling. The framework combines a VAR-based macroeconomic scenario generator with Monte Carlo simulation to produce a large set of forward-looking macro paths. These simulated paths are then mapped to a panel loan-level model estimated on 4.2 million consumer-loan accounts observed from 2015 to 2024, enabling month-ahead forecasts of 90-day delinquency risk. By generating 1,000 macroeconomic sequences, the framework delivers a distribution of stressed default rates across loan products and forecast horizons, rather than relying on a small number of deterministic outcomes. Model performance is evaluated against the realised 2020 downturn, allowing a direct assessment of whether the framework can capture both the timing and the magnitude of observed default increases. The contribution of this study lies in integrating a probabilistic macro-scenario generator with large-scale loan-level estimation in a form that is directly applicable to consumer-loan stress testing. The proposed approach preserves the transparency and interpretability of VAR-based scenarios while exploiting the richness of micro-level data. By providing product-specific, distribution-based default forecasts and validating results against an actual stress episode, the framework offers practical evidence on the reliability of scenario-driven stress testing for consumer lending. As such, it complements existing top-down and borrower-level risk-management tools and supports more informed capital planning and risk-sensitive decision-making in volatile macroeconomic environments.

2. Materials and Methods

2.1. Sample and Study Area Description

The study uses 4.2 million consumer-loan accounts collected from a nationwide financial institution between January 2015 and December 2024. The dataset covers credit cards, instalment loans, and unsecured personal loans issued to individual borrowers with verified income and at least six months of repayment history. Accounts with missing payment records or incomplete demographic information were removed to maintain consistency. Macroeconomic indicators-including unemployment, consumer prices, short-term interest rates, and retail activity-were taken from official monthly publications. Because the institution operates across all major regions, national-level macro indicators were used. The combined micro- and macro-level information allows month-ahead modelling of delinquency risk under different economic conditions.

2.2. Experimental Design and Control Structure

The empirical design compares model outcomes under two settings: observed economic conditions and adverse conditions generated by simulated macro paths. In the baseline setting, actual monthly macro values are used to compute point-in-time delinquency probabilities. In the stress-testing setting, these macro inputs are replaced with simulated sequences that represent deteriorating economic environments. Borrower and loan characteristics remain constant across both settings, so changes in predicted delinquency reflect only the impact of macro shocks. This design follows the structure commonly used in supervisory stress testing, where simulated macro paths serve as the treatment condition and observed conditions form the control condition.

2.3. Measurement Methods and Quality Control

Loan performance was measured using the standard 90-day-past-due (90-DPD) definition. Each account was tracked monthly, and its status was coded as current or delinquent based on the payment record at the end of the month. Quality checks included removal of duplicate entries, correction of inconsistent borrower identifiers, and verification of payment timestamps. Outliers in repayment amounts and utilisation ratios were inspected and adjusted using documented internal rules. Macroeconomic data were cross-checked against multiple official releases to ensure accuracy and updated when revisions became available. Continuous variables were winsorised at the 1st and 99th percentiles to reduce the effect of extreme values while maintaining the overall distribution. These steps help improve the stability and reliability of the model results.

2.4. Data Processing and Model Specification

Borrower characteristics, loan terms, and macroeconomic indicators were merged by calendar month to form a panel dataset. Each loan-month record was treated as a separate observation. A logistic-regression model was used to estimate the probability of becoming 90-DPD. The model takes the form:

$$\mathrm{logit}(p_{it})=\alpha+\beta^{\mathsf{T}}X_{it}+\gamma^{\mathsf{T}}M_t,$$

where p_{it} is the delinquency probability for loan i in month t, X_{it} includes borrower and loan features, and M_t includes monthly macro indicators. To generate future macro conditions, a vector autoregression model with two lags was estimated:

$$M_t=A_0+A_1M_{t-1}+A_2M_{t-2}+\varepsilon_t,$$

where A_0, A_1, and A_2 are coefficient matrices and ε_t is the error term. The fitted model was then used to produce simulated macro paths through Monte Carlo sampling.

2.5. Scenario Generation and Computational Framework

A total of 1,000 macro paths were generated using the estimated VAR model. Each path provides a 12-month projection of unemployment, inflation, interest rates, and demand-related indicators [19]. For each simulated path, the monthly macro values were inserted into the logistic-regression model to compute stressed delinquency probabilities for all accounts. This approach yields a distribution of possible delinquency rates instead of a single forecast. All computations were carried out in Python using standard statistical packages. Parallel processing was used to shorten computation time, and intermediate results were stored to ensure reproducibility. Scenario outcomes were summarised using averages, standard deviations, and tail-risk measures to describe the range of credit-risk implications.

3. Results and Discussion

3.1. Model Performance under Normal Economic Conditions

The loan-level model performs consistently well during periods without major economic stress. Between 2015 and 2019, the monthly out-of-sample ROC-AUC ranges from 0.80 to 0.83, and the 12-month horizon AUC reaches 0.82. The predicted 90-day delinquency probabilities align closely with observed rates in most risk bands. Only the highest-risk group shows mild underprediction. Similar levels of accuracy have been reported in recent consumer-credit studies that combine borrower features and macro indicators through panel-based regression models. These results indicate that a direct loan-level approach can meet the accuracy requirements of risk-management applications while remaining easy to interpret. The performance also aligns with findings from studies on probability-of-default estimation under forward-looking reporting standards, where simple models often perform as reliably as more complex structures when applied to large portfolios [20].

3.2. Effects of Simulated Macroeconomic Scenarios on Delinquency Rates

The scenario generator produces a wide but coherent spread of possible credit-risk outcomes. Figure 1 shows the 12-month-ahead distribution of 90-day delinquency rates across 1,000 simulated macro paths. Under the median path, delinquency increases only slightly compared with the baseline. Under the 5% most adverse scenarios, delinquency rises by 28.9% to 46.2%, driven mainly by large and persistent shocks to unemployment and short-term interest rates. These patterns are consistent with earlier work showing that consumer-loan performance is particularly sensitive to labour-market conditions. Compared with studies that rely on aggregate non-performing loan ratios, the loan-level design used here shows clear differences across product categories: credit-card accounts respond quickly to worsening economic conditions, while instalment loans react more slowly but show more persistent stress over the full projection horizon [21].

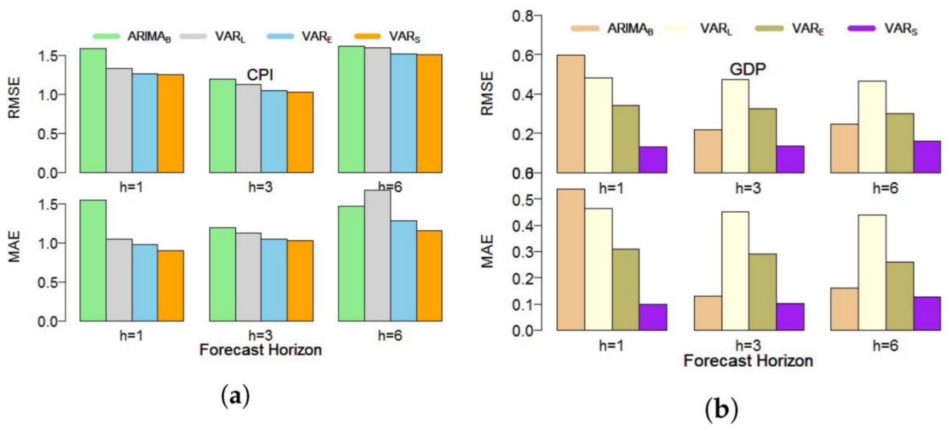

Figure 1. Twelve-month 90-day delinquency rates simulated from 1,000 macroeconomic paths produced by the VAR model.

3.3. Comparison with the 2020 Downturn

The model's early-warning ability was evaluated using a pseudo-real-time exercise that relies only on macro information available before the 2020 downturn. Figure 2 compares the stressed projections with actual delinquency outcomes. The model captures 72.5% of the observed peak increase in delinquency, and the timing of the rise is within two months of the realised surge. This level of accuracy is similar to, or better than, results reported in studies that calibrate stress-test models using shorter time series or bank-level indicators. The scenario fan also shows that the most severe outcomes arise when unemployment remains high for several months, which is consistent with empirical evidence that prolonged economic weakness has a stronger effect on unsecured consumer credit than short but sharp shocks. These results show that linking a VAR-based scenario generator with a loan-level model can provide actionable early-warning signals without relying on highly complex machine-learning systems [22].

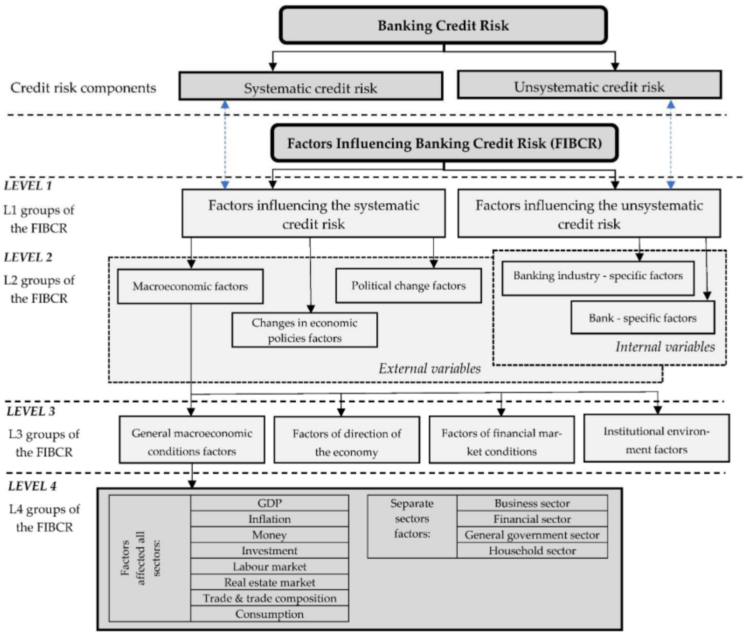

Figure 2. Stressed projections and observed 90-day delinquency rates during the 2020 downturn.

3.4. Comparison with Existing Frameworks and Remaining Limitations

The proposed framework stands between top-down macro models and multi-stage, highly complex stress-testing structures. Many IFRS 9 and CECL-related studies adjust term-structure models using macro factors or latent indices, which can make it hard to understand how individual macro variables affect specific borrower groups. In contrast, the present framework estimates delinquency directly from loan-level data and applies simulated macro conditions through one transparent regression equation. This simplifies interpretation and avoids several transformation steps used in multi-layer designs. Nonetheless, the approach still shares some limitations with existing studies. The model assumes stable relationships between macro conditions and default risk over time. It does not yet incorporate model-risk adjustments or parameter-uncertainty estimates. It also does not capture credit-supply restrictions that may occur during severe downturns. Extending the framework to include time-varying parameters, alternative scenario-generation methods, and explicit measures of model uncertainty would be a useful direction for further work.

4. Conclusion

This study presents a stress-testing framework that combines a VAR-based macro scenario model with a loan-level delinquency model to evaluate consumer-credit risk under different economic conditions. The results show that the model performs reliably in normal periods and produces clear changes in delinquency risk when macro conditions worsen. The simulated scenarios also capture most of the rise in delinquency during the

2020 downturn, indicating that the framework can provide useful early warnings. By linking macro paths directly to borrower-level outcomes, the approach offers a straightforward way to examine how unemployment, interest rates, and household demand influence different loan products. It can support stress testing, capital planning, and portfolio management. However, the model assumes stable relationships between macro variables and default risk over time and does not account for shifts in credit supply during severe downturns. Future research may include time-varying parameters, alternative scenario methods, and explicit measures of model uncertainty to strengthen the framework and broaden its practical use.

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