Macroeconomic Determinants of the Credit Loss Forecasting

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Abstract

Macroeconomic variables are critical inputs in credit loss forecasting (LF) models and are mandated by regulators for stress testing to project potential credit losses under various economic scenarios. The COVID-19 pandemic introduces unprecedented volatility to macroeconomic indicators, disrupting their historically strong relationship with credit loss rates and challenging the robustness of LF and Current Expected Credit Loss (CECL) models.

This study examines the dynamic relationship between charge-off rates for U.S. commercial banks' loan portfolios—commercial and industrial (C&I) loans, consumer loans, and real estate loans—and macroeconomic factors from 1990 Q1 to 2024 Q3. By employing advanced machine learning and traditional regression-based approaches, we identify key macroeconomic variables, such as labor market indicators, housing market dynamics, and consumer financial conditions, that drive credit risk across these loan categories. The results highlight the need to reevaluate traditional relationships to ensure model robustness, particularly in the context of COVID-19-era data. This study provides practical insights for banks to enhance credit risk modeling frameworks, offers guidance for macroeconomic variable selection in LF and CECL applications, and supports policymakers in designing effective regulatory frameworks during periods of economic uncertainty.

Keywords: Macroeconomic factors; Loss forecasting; COVID-19 recession; Stress testing; CECL; Credit risk

JEL classification: C32, E17, G20

I. Introduction

In the past several decades, extensive research is conducted in the risk management area, especially in credit risk management. Credit risk is the most common risk for banks and is closely monitored by regulators. The recent global financial crisis (GFC) heightens the importance of credit risk management to financial institutions. After the GFC, bank regulators tighten the supervision in financial industry under the Dodd-Frank Act Stress Tests (DFAST). In particular, large banks are required to calculate their capital ratio under a hypothetical stressed economic scenario to determine their insolvency risk under a negative economic shock. In practice, banks have to incorporate scenario analysis and forward-looking macroeconomic indicators more rigorously, which leads to the evolution of credit-loss forecasting techniques. Therefore, the understanding of the relationship between macroeconomic factors and charge-off rates on loans becomes a worldwide issue for banks, policymakers, and regulators.

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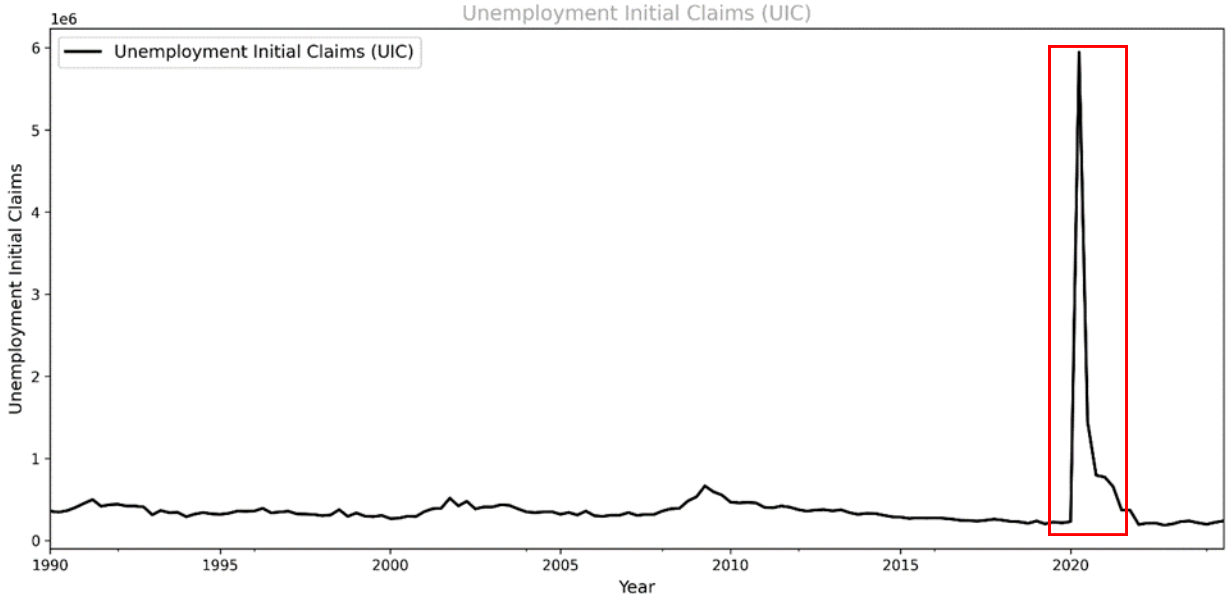
The stress testing requirement on banks initiates debates on a number of issues in the literature on credit risk management. The first issue is whether the macroeconomic environment and business cycles play a vital role in determining the delinquency risk of loans. There is a large body of literature study the link between charge-off risk and the overall economic climate (Virolainen 2004; Mählmann 2005; Hackbarth et al. 2006; Pesaran et al. 2006; Jakubik 2007; Bonfim 2009; Castro 2013; Djeundje and Crook 2018; Breeden and Crook 2020). They find that macroeconomic conditions have a direct impact on bad debts and charge-offs. In addition, it is also widely recognized that financial crises are more likely to occur in adverse economic conditions, where the unemployment rate increases and the gross domestic product (GDP) growth rate declines. For example, Bonfim (2009) finds that macroeconomic variables have a significant contribution to credit loss after controlling firm-level characteristics, suggesting that macroeconomic conditions are critical when assessing the firm's credit risk.

Starting in March 2020, the COVID-19 pandemic led to a "shelter in place" order across the country, which significantly disrupted economic activities. This disruption resulted in significant job losses and deterioration in the economic outlook. At the same time, both the U.S. government and financial institutions deployed several measures to help residents remain afloat during these uncertain times. The sudden change in the macroeconomic environment, as well as the government invention, led to extremely high volatility in the macro-variables. For example, the variables in the labor market category deteriorated significantly at the onset of the pandemic. As a result of the entire country's lockdown, the unemployment initial claims skyrocketed by more than 20 times from about 1 million in March 2020 to almost 20 million in April 2020 (Figure 1). However, the personal income variables experienced significant improvements (increases) because of the government stimulus bill (Figure 2). Unlike the extreme volatility observed in the macroeconomics variables, the charge-off rates on loans at U.S. commercial banks didn't increase. For example, the delinquency rate and charge-off rate for commercial and industrial (C&I) loans, consumer loans, and real estate loans dropped from Mar 2020 to Dec 2020 as shown in Figure 3. The unresponsive loss rates under pandemic were a result of various government relief supports and corporate forbearance programs. The volatile macroeconomic variable movement and delayed loss recognition process together contributed to the performance deterioration of loss forecasting/CECL models.

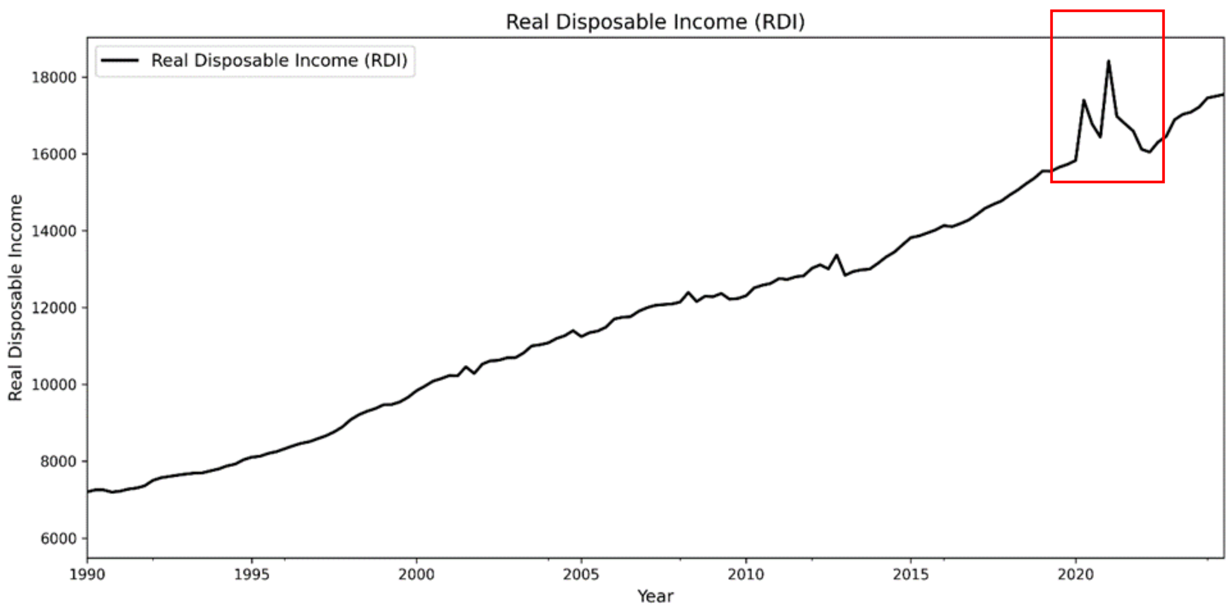
Although prior studies identify macroeconomic variables as key determinants of credit risk, the historically observed strong relationships between macroeconomic variables and charge-off rates disappeared during the COVID-19 pandemic. The volatile movement of macroeconomic variables, combined with the delayed loss recognition process, leads new challenges for banks when they use macroeconomic variables to model credit risk. There are two concerns for banks. First, whether the prior observed relationships between macroeconomic factors and loan charge off rates are still applicable to the current situation. Second, which macroeconomic variables have the strongest predictive power for future loan default rates given the COVID-19 impacts. Our study will shed light on these two questions.

Figure 1: Unemployment Initial Claims



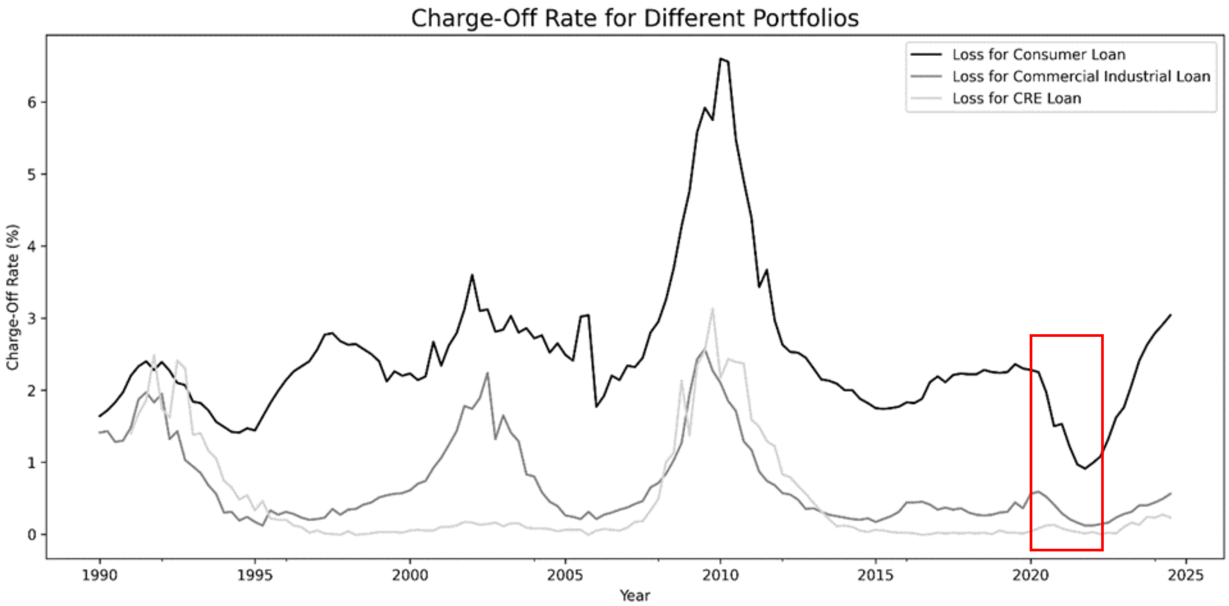
Source: U.S. Department of Labor

Figure 2: Real Disposable Personal Income



Source: U.S. Bureau of Economic Analysis

Figure 3: Charge-Off Rate for Loans of all U.S. Commercial Banks



Source: Federal Reserve Board

Most of the prior research is conducted based on data from the pre-pandemic period. Therefore, those studies have data limitations that are unable to capture the impact of the COVID-19 pandemic. Along with the fact that the recent data shows a missing link between the key macroeconomic variables and charge-off rates on loans, it is unclear whether the prior observed relationships between macroeconomic factors and default rates on loans still hold after including the pandemic data. The Federal Reserve heightens the standard on bank monitoring and highlights the importance of exploring a more robust relationship between macroeconomic variables and credit loss that can be used during the interim of the COVID-19 pandemic. Given the uncertainty about the economic outlook is quite large under COVID-19, ensuring the stability and accuracy of the loss forecasting framework are imperative for banks, regulators, and policymakers. This study helps address these concerns and our research will fill this gap by incorporating the data of the COVID-19 pandemic period. To the best of our knowledge, this is the first paper to study the relationship between macroeconomic factors and loan delinquency including the COVID-19 impacts. The results present in our research have practical implications for the financial industry and can be directly used by banks to build or enhance their credit loss/reserve forecast models. Finally, the findings in our research can help regulators and policymakers to design appropriate guidelines for the use of advanced machine learning models in the banking industry.

This paper is structured as follows. In the following section, we review the related literature. In Sections III and IV, we describe the data sources and present the descriptive statistics of all variables used in this study. In Sections V and VI, we move to present our analysis and empirical evidence. We present model selection and prediction in section VII. Finally, we discuss the results and summarize the conclusion in Section VIII.

II. Literature Review

The impact of macroeconomic variables (i.e., GDP growth, unemployment rates, and inflation) and banking sector variables (i.e., loan-to-deposit ratios and capital adequacy) on credit risk and non-performing loans are discussed extensively in the prior literature as they influence both borrower behavior and bank resilience. Agarwal and Liu (2003) find that country-level unemployment rates significantly impact credit card delinquency rates, highlighting the connection between regional macroeconomic fluctuations and delinquency rates. To capture non-linear relationships between macroeconomic conditions and defaults, Pesaran et al. (2006) introduce an innovative approach to modeling conditional credit loss distributions by isolating the systematic risk from firms' idiosyncratic risk. Their findings reveal that the default probabilities are linked to business cycles. Giesecke et al. (2011) further investigate the predictive power of macroeconomic variables for U.S. corporate bond defaults using a regime-switching model. Their results indicate that stock returns, stock return volatility, and GDP changes are robust predictors of default rates. These predictors reflect that both market dynamics and economic health are critical in assessing creditworthiness. Furthermore, macroeconomic factors not only affect the default rates but also influence the credit loss resulting from non-performing loans. Betz et al. (2020) find that loan resolution time doubled during a recessionary period compared to benign periods due to higher borrower defaults and strained banking resources. This finding indicates that the prolonged resolution process results in highly skewed loss distributions and elevates levels of systematic risk within bank portfolios.

The relationship between macroeconomic factors and credit risk are widely documented beyond the United States. Fung and Wong (2002) examine interaction of macroeconomic variables, bankruptcies, and credit card charge-off ratios in Hong Kong. Their findings reveal that the CPI, unemployment rate, bankruptcy cases, and credit card charge-off percentages are cointegrated, suggesting a long-term equilibrium relationship among these variables. Declines in the CPI are associated with falling asset values and reduced economic activity, which contribute to rising unemployment, bankruptcies, and personal credit defaults. These findings explain how commercial banks predict the risk of retail credit operations and estimate credit loss provisioning. Similarly, Castro (2013) analyzes data from five European countries, Greece, Ireland, Portugal, Spain, and Italy (GIPSI) from 1997 to 2011 and concludes that the macroeconomic conditions significantly influence banking credit risk. Specifically, credit risk tends to increase during periods of declining GDP growth, rising unemployment, and falling house prices. Additionally, real exchange rate appreciation is found to have a positive correlation with credit risk. Koju et al. (2019) extend the scope of analysis by examining the effects of macroeconomic variables on credit risk across 49 developed countries between 2000 to 2015. Their findings indicate that loan performance and default risk are closely related to the growth of industrial sectors and export activities. The study also highlights that expansionary fiscal policies can play a crucial role in strengthening the stability of the banking system.

Although prior research suggests that macroeconomic conditions are linked to credit risk, the current literature could not find consistent evidence for the effects of macroeconomic factors on charge-offs over different business cycles. Ausubel (1997) finds that loan default rates rise during a benign economic environment in which GDP is growing moderately and unemployment is low. This finding seems against the foundational belief that the charge-off rate will decrease in robust economic periods and increase in a downtown period. More recent research shows that other economic factors may contribute to charge-offs. Stavins (2000) identifies that personal debt variables, such as debt-to-disposable income ratio, have a strong correlation with credit card charge-offs and bankruptcy rates. Gross and Souleles (2002) examine the relationship between personal bankruptcy and credit card defaults, concluding that the impact of macroeconomic factors, such as unemployment rate, on charge-off rate changes significantly over time and that there is no conclusive evidence to prove a relationship between charge-off rate and macroeconomic factors.

The existing literature also points out that macroeconomic factors alone cannot perfectly predict the future default rate, they have to be used in conjunction with other factors, such as firm-specific factors or unobservable factors, to predict the default rates. Pu and Zhao (2012) examine a comprehensive set of credit risk drivers, including industry and macroeconomic factors. They find that there is an economically significant credit risk that remains to be unexplained even after controlling observable factors. They also suggest that unobservable risk factors should be incorporated into credit risk models in addition to macroeconomic factors. Figlewski et al. (2012) study how different factors, including overall economic conditions and specific company characteristics, affect loan losses (charge-offs) and big changes in credit ratings. They find that both factor categories are significant, but macroeconomic variables are highly dependent on the inclusion of other factors. In an extension of their work by Bellotti and Crook (2013), a discrete-time survival model is proposed to predict the probability of charge-off. They claim that using macroeconomic variables along with behavioral factors produces the best predictive fit.

Our research is also related to another strand of literature on using macroeconomic factors to forecast future credit losses. Liu and Xu (2003) adopts a step-wise regression and vector autoregression to select macroeconomic variables that are useful for predicting credit card charge-offs in the U.S. By using the data from the period of 1986-1998. They find the unemployment rate, consumer confidence index, household debt service burden, inflation rate, personal bankruptcy filings, and stock market returns are powerful variables in predicting the future charge-off rate. However, their research has limitations. The data period is relatively short and excludes the GFC period. In addition, their sample period also does not reflect the most recent changes in the credit card industry. Taghiyeh et al. (2021) adopts more advanced model selection techniques and machine learning algorithms to build models that can be used to forecast credit card charge-off rates. They use 19 key macroeconomic indicators as the potential drivers and find that unemployment initial claims have the highest relative importance in determining the credit loss forecast.

Prior studies, such as those by Liu and Xu (2003) and Taghiyeh et al. (2021), extensively analyzes the macroeconomic determinants of credit risk; however, they can't capture the unprecedented economic disruptions caused by the pandemic. Our study uniquely extends this line of inquiry by analyzing how these extraordinary circumstances alters previously observed economic relationships, providing new insights into credit risk modeling during periods of severe economic stress.

III. Data

This study uses quarterly observations of charge-off rates on commercial and industrial loans, consumer loans, and real estate loans of all commercial banks from 1990 Q1 to 2024 Q3. The loan charge-off rate data are downloaded from the Board of Governors of the Federal Reserve System (U.S.). Although the credit charge-off loss data begins in 1985, some key macroeconomic indicators (i.e., market volatility index) only begin to available in 1990 Q1. We believe the data period of 1990 Q1 to 2024 Q3 is sufficient long because it covers multiple business cycles including 1990 oil price shock, 2000 internet bubble, 2007-2008 global financial crisis as well as the COVID-19 pandemic period. The historical macroeconomics variables are downloaded from the Board of Governors of the Federal Reserve System. The Federal Reserve consolidates the historical data as well as forecasting series of 28 core macroeconomic indicators (14 domestic and 14 international) for bank stress testing purposes. The 28 variables cover the key indicators from different categories of macroeconomic variables (i.e., unemployment rate represent the condition in the labor market). Because we are interested in the charge-off rates in the U.S., only the 14 domestic macroeconomic variables are used in this study. In addition, we also obtain some key macroeconomic indicators not provided by the Federal Reserve, such as non-farm employment, retail sales, and personal bankruptcy, from the Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis. It is worth noting that Household Financial Obligations (HFO) data is only available until 2023 Q4, resulting in a total of 135 observations for this variable. The total number of macroeconomic variables used in the study is 26, in addition to the 3 charge-off rates. Detailed descriptions of the data and their sources are provided in Appendix A.

For selected macroeconomics variables, we also consider the following transformations: i) logarithm transformation; ii) year-over-year (yoy) change, iii) quarter-over-quarter (qoq) change, and iv) 1 to 4 quarters lagged of both raw and transformed variables. The yoy and qoq changes are calculated by using the logarithm growth rate instead percentage growth rate because the logarithm growth is more symmetric and less skewed than the percentage growth rate.

IV. Descriptive Statistics

Table 1 reports descriptive statistics for all variables used in this study. The average charge-off rates of real estate loans, consumer loans, and C&I loans over the sample period are 2.48%, 0.70%, and 0.47%. On average, unemployment rate is 5.76%. In addition, the average mortgage rate, prime rate, 3-month treasury rate, and 5-year treasury rate are 6.01%, 5.86%, 2.66%, and 3.76%, respectively.

Table 2 reports the pair-wise correlation coefficients of the variables. To save space, we only report the correlation coefficients of macro factors and charge-offs rate. The correlation coefficients among the charge-off rates of three different loans are in the range of 0.62 to 0.71, indicating there is some heterogeneity across products. For C&I loans, unemployment rate (UR) and BBB corporate yield have the highest correlation coefficients; for consumer loans, UR and debt service burden are highly correlated with the charge-off rate; for real estate loans, UR, new housing unit, and non-farm employment exhibit the highest correlation. These results suggest that UR is a shared potential risk factor for all three loans. In addition, the correlation coefficients for the same macro variables show significant differences across loans, suggesting the risk drivers for different loans are different. For example, the correlation coefficient of BBB corporate yield with consumer loans charge-off rate is only 0.18 while with C&I loans charge-off rate is 0.46. Therefore, it is reasonable to separate the analysis for different loans in our study.

Table 1 Descriptive Statistics

This table presents the descriptive statistics for the charge-off rates and macroeconomic variables used in the study. The data spans from 1990 Q1 to 2024 Q3, covering multiple business cycles. We include variable distributions and their respective sources for GDP growth, unemployment rate, interest rates, and other financial metrics.

Variable Name	N	Mean	Std. Dev.	Min	Median	Max	Source
Real Estate Loans Charge-off Rate	139	2.48	0.998	0.91	2.28	6.60	Federal Reserve Board
Consumer Loans Charge-off Rate	139	0.70	0.588	0.12	0.44	2.57	Federal Reserve Board
C&I Loans Charge-off Rate	135	0.47	0.739	-0.01	0.10	3.13	Federal Reserve Board
Real GDP	139	16101.93	3751.73	9951.92	16420.74	23400.29	U.S. Bureau of Economic Analysis
Nominal GDP	139	14463.34	6190.37	5872.70	14381.24	29374.91	U.S. Bureau of Economic Analysis
Real Disposable Income	139	11882.53	3050.02	7195.15	12055.32	18411.66	U.S. Bureau of Economic Analysis
Nominal disposable Income	139	10743.84	4745.07	4232.90	10406.08	21710.15	U.S. Bureau of Economic Analysis
UR	139	5.76	1.82	3.40	5.40	14.80	U.S. Bureau of Labor Statistics
CPI Inflation	139	205.83	48.10	127.50	205.90	313.53	U.S. Bureau of Labor Statistics
3M Treasury Rate	139	2.66	2.24	0.02	2.33	7.77	Federal Reserve Board
5Y Treasury Rate	139	3.76	2.16	0.28	3.69	8.77	Federal Reserve Board
10Y Treasury Rate	139	4.27	1.99	0.62	4.15	8.79	Federal Reserve Board
BBB Corporate Yield	139	5.93	2.05	2.06	5.83	10.90	WARGA and Merrill Lynch Database
Mortgage Rate	139	6.01	1.87	2.67	6.16	10.22	Federal Home Loan
Prime Rate	139	5.86	2.28	3.25	5.50	10.50	Federal Reserve Board
Dow Jones Index	139	13914.27	9437.37	2452.48	10850.66	39807.37	Dow Jones
House Price Index	139	327.66	129.71	165.25	323.26	688.42	CoreLogic
CRE Price Index	139	191152.80	78162.63	86351.00	179529.00	351613.00	Federal Reserve Board
Market Volatility Index	138	19.59	7.69	9.51	17.67	53.54	Chicago Board Options Exchange
Non-Farm Employment	139	132816.50	13115.42	108290.00	132455.00	158692.00	U.S. Bureau of Labor Statistics
Retail Sales- Motor	139	431.32	132.10	120.15	449.00	658.90	U.S. Bureau of Economic Analysis
New Housing Unit	139	1351.99	406.20	521.00	1378.00	2212.00	U.S. Dept. of Housing and Urban Dev.
Personal Consumption Expenditures (PCE)	139	9669.40	4249.90	3730.70	9643.60	19866.30	U.S. Bureau of Economic Analysis
Personal Saving	139	6.15	3.31	1.40	5.80	32.00	U.S. Bureau of Economic Analysis
WTI Oil Price	139	51.10	29.70	12.47	47.22	133.44	Federal Reserve Bank of St. Louis
Initial Claims	139	396230.20	493968.70	187000.00	340000.00	5946000.00	U.S. Employment and Training Admin.
PPI	139	168.34	42.69	114.10	169.10	272.27	U.S. Bureau of Labor Statistics
Debt Service Burden	139	12.09	1.56	9.08	11.65	15.85	Federal Reserve Board
Household Financial Obligations	135	16.07	1.20	12.43	16.32	18.16	Federal Reserve Board

Table 2 Correlation Matrix

Table 2 presents the correlation matrix for the charge-off rates and macro variables. Column (1) presents the correlations between real estate loans and macro variables. Column (2) presents the correlations between consumer loans and macro variables. Column (3) presents the correlations between C&I loans and macro variables.

Variables	(1)	(2)	(3)
(1) Real Estate Loans Charge-off Rate	1.00		
(2) Consumer Loans Charge-off Rate	0.62	1.00	
(3) C&I Loans Charge-off Rate	0.70	0.71	1.00
(4) Real GDP Growth	-0.32	-0.07	-0.32
(5) Nominal GDP Growth	-0.28	-0.13	-0.33
(6) Real Disposable Income	-0.28	-0.07	-0.29
(7) Nominal Disposable Income	-0.26	-0.12	-0.31
(8) UR	0.66	0.49	0.46
(9) CPI Inflation	-0.25	-0.06	-0.30
(10) 3M Treasury Rate	-0.14	-0.24	-0.10
(11) 5Y Treasury Rate	0.07	-0.13	0.10
(12) 10Y Treasury Rate	0.20	-0.04	0.21
(13) BBB Corporate Yield	0.35	0.18	0.46
(14) Mortgage Rate	0.19	-0.03	0.24
(15) Prime Rate	-0.14	-0.21	-0.08
(16) Dow Jones Index	-0.40	-0.29	-0.40
(17) House Price Index	-0.28	-0.12	-0.29
(18) CRE Price Index	-0.35	-0.19	-0.35
(19) Market Volatility Index	0.18	0.36	0.40
(20) Non-Farm Employment	-0.47	-0.09	-0.35
(21) Retail Sales- Motor	-0.07	-0.15	0.00
(22) New Housing Unit	-0.69	-0.45	-0.37
(23) PCE	-0.27	-0.11	-0.32
(24) Personal Saving	0.13	-0.12	0.05
(25) WTI Oil Price	0.09	0.18	-0.14
(26) Initial Claims	0.05	0.06	0.10
(27) PPI	-0.14	-0.06	-0.31
(28) Debt Service Burden	0.24	0.61	0.31
(29) Household Financial Obligations	0.17	0.43	0.42

V. Correlation Analyses

Correlation without Optimal Transformation

This section contains the results for correlation analysis. All macro variables have several transformations to capture the lag-lead relationships between the charge off rates and macro variables. The initial macro variables list only contains 26 unique variables (listed in Table 2), while after transformation there are 266 variables in total.

We conduct two types of correlation analysis — correlation without optimal transformation and with optimal transformation. In the without optimal transformation analysis, we first compute the correlation coefficients between the charge off rates and each transformed variable, then we rank transformed variables by the correlation coefficients in descending order and count how many times a macro variable is selected among the top 50 list. The more frequently a variable is selected in the top 50 list, the more likely this variable is highly correlated with credit loss. For a more comprehensive review, we report the ranking results using three different correlation measures-Pearson, Spearman, and Kendall Tau correlation coefficients. Pearson correlation coefficient is widely used in the research as it measures the linear relationship among variables. In contrast, the Spearman correlation coefficient can capture the nonlinearity relationship among variables. Finally, Kendall's Tau rank correlation is a nonparametric measure and not affected by nonlinearities because Kendall's Tau relies only on the concordance of the two variables. This correlation measure is used in prior research of credit risk. The results for the correlation without optimal transformation are displayed in Table 3.

Table 3 Correlation without optimal transformation

This table presents the frequency of macroeconomic variables being selected in the top 50 correlations with charge-off rates across three measures—Pearson, Spearman, and Kendall's Tau—for C&I loans, consumer loans, and real estate loans in Panel A, Panel B, and Panel C, respectively.

Panel A: C&I Loans - Number of times selected in the Top 50 list based on

Variable Name	Pearson	Spearman	Kendall's Tau	Row Total
Unemployment Rate	3	10	10	23
Non-Farm Employment	3	8	9	20
3M Treasury Rate	6	4	4	14
BBB Corporate Yield	5	4	4	13
House Fin. Obligations	4	4	4	12
CRE Index	4	3	3	10
Market Volatility Index	3	3	2	8
New House Unit	3	2	2	7
Initial Claims	0	3	3	6
5 Year Treasury Rate	0	3	3	6
Real GDP Growth	4	0	0	4
Mortgage Rate	1	2	1	4
Nominal GDP Growth	3	0	0	3
House Price Index	3	0	0	3
DJ Index	1	0	0	1
Grand Total	**50**	**50**	**50**	**150**

Panel B: Consumer Loans - Number of times selected in the Top 50 list based on

Variable Name	Pearson	Spearman	Kendall's Tau	Row Total
Non-Farm Employment	3	10	10	23
Unemployment Rate	2	10	10	22
House Fin. Obligations	6	7	7	20
Debt Service Burden	6	6	7	19
New House Unit	6	3	3	12
House Price Index	10	0	0	10

Market Volatility Index	0	5	4	9
Nominal GDP Growth	5	1	1	7
Initial Claims	0	3	3	6
Personal Saving	0	3	3	6
CRE Index	5	0	0	5
Real GDP Growth	4	0	0	4
DJ Index	2	0	0	2
Consumption Exp.	1	0	0	1
3M Treasury Rate	0	1	0	1
5 Year Treasury Rate	0	1	0	1
BBB Corporate Yield	0	0	1	1
Prime Rate	0	0	1	1
Grand Total	**50**	**50**	**50**	**150**

Panel C: Real Estate Loans - Number of times selected in the Top 50 list based on

Variable Name	**Pearson**	**Spearman**	**Kendall's Tau**	**Row Total**
House Price Index	10	10	10	30
Non-Farm Employment	3	11	11	25
CRE Index	9	5	5	19
New House Unit	8	5	5	18
Unemployment Rate	4	6	7	17
Initial Claims	0	5	5	10
BBB Corporate Yield	3	3	3	9
Real GDP Growth	3	3	2	8
DJ Index	1	2	2	5
Prime Rate	4	0	0	4
3M Treasury Rate	3	0	0	3
House Fin. Obligations	1	0	0	1
Debt Service Burden	1	0	0	1
Grand Total	**50**	**50**	**50**	**150**

The results in Table 3 show that, UR, non-farm employment, 3-month treasury rate, and BBB corporate yield have a higher frequency of being selected among all the variables across the three correlation measures for C&I loans. For consumer loans, non-farm employment, UR, and house financial obligations have a higher frequency of being selected across all three correlation measures. Finally, house price index, non-farm employment, and CRE index are more likely to be selected in the real estate loans. It is worth noting that non-farm employment is highly rated by Spearman and Kendall's Tau correlation coefficients while ranked relatively low in the Pearson measure in both consumer loans and real estate loans. These results imply that non-farm employment is more concordant with the consumer and real estate charge-off rates and also have a strong nonlinear relationship.

Correlation with Optimal Transformation

Correlation with optimal transformation analysis only allows each macro variable to show up once in the top list by using its optimal transformation. The advantage of this analysis is that we can observe the optimal transformation as well as the magnitude of the correlation for each variable. In this section, we only select one transformed value that has the highest correlation coefficient with credit loss within each macro variable and its transformations, and then the transformed macroeconomic variables are ranked by correlation coefficients in descending order.

Table 4 displays the variables with their optimal transformation being selected based on three different correlation measures. We rank the variables from highest to lowest based on its correlation coefficients. The optimal transformation used and correlation coefficients are reported in Table 4. The p-value for all the transformed variables are 0.00. Therefore, they are omitted in the Table 4.

The results In Table 4 show that there are some common risk factors, such as labor market variables and housing market variables, across the three loan categories. However, the importance of these factors varies by loan type. For C&I loans, labor market variables, such as the unemployment rate and non-farm employment, are highly correlated with charge-offs, along with interest rate variables like the 3-month Treasury rate and the prime rate. For consumer loans, household financial conditions, including the debt service ratio and household financial obligations, show the strongest correlations, followed by variables related to housing, such as the house price index and new home units. Additionally, personal financial variables, such as personal savings and nominal GDP, are also significant. For real estate loans, housing market variables, including new home sales and the house price index, are dominant, with unemployment rate variables playing a secondary role. Across all categories, the transformations (e.g., year-over-year, lagged, or logarithmic) highlight the different dynamics and time sensitivities of these macroeconomic factors in explaining credit losses.

VI. Feature Selection

The correlation analysis examines which variables are most strongly associated with credit loss by evaluating the strength and direction of individual relationships. The correlation analysis is univariate, focusing on one variable at a time to determine its standalone correlation with credit loss. In contrast, feature selection is multivariate, considering the combined effects and relative importance of variables when used together in a predictive model. While correlation analysis helps identify promising candidates for inclusion, feature selection determines which variables contribute most significantly to the model when considered in conjunction with others. By combining insights from both approaches, we can better understand the unique and collective importance of variables in predicting credit loss.

To examine the variable importance across different macroeconomic variables, we use four feature selection algorithms – stepwise selection, gradient boot machine (GBM), random forecast (RF), and Lasso regression. The rationale behind using four different feature selection algorithms is to include both black-box (with less interpretability) and regression-based models with a high level of interpretability. GBM and RF are black-box models which can capture complex nonlinear trend, consequently improving forecasting accuracy. The traditional stepwise regression has high interpretability. However, it only focuses on selecting between the correlated covariates without considering the improvement in prediction accuracy. Finally, the lasso penalty regression not only improves the forecasting accuracy but also mitigates the overfitting issue.

In order to avoid the abuse and misuse of machine learning algorithms as well as the circles of “Garbage in, garbage out”, we further narrow down the number of variables used in the feature selection algorithms based on the results from the correlation analysis. For the feature selection stage, we include only the top 10 transformed variables that have the highest Pearson correlation coefficients.. The final result is reported in Tables 5, 6, and 7 for C&I loans, consumers loans, and real estate loans, respectively. We retain the top 5 most important variables for each algorithm based on their relative importance.

In Panels A of Tables 5 to 7, we report the variables selected by stepwise and lasso regressions. Both models are generalized linear models. The variables selected by them show similarities, with lasso regression typically including more variables due to its penalty mechanism. In Panels B, the variables selected by the two tree-based models, GBM and RF, are presented. These black-box models capture nonlinear relationships. While the variables they select are largely consistent, RF tends to include a broader set of variables.

For the C&I loans charge-off rate, non-farm employment is the most important variable in tree-based models. Variables such as the CRE price index and new home units also demonstrate strong predictive power, emphasizing the importance of labor market and commercial real estate dynamics for C&I loan performance.

For the consumer loans charge-off rate, Panel B of Table 6 highlights that the house price index is the most important variable across tree-based models. In addition, variables reflecting household financial conditions, such as the debt service burden, and labor market indicators like the unemployment rate, play significant roles. Macroeconomic indicators, including GDP growth and consumer expenditure, also contribute meaningfully to the prediction of consumer loan charge-offs.

Finally, for the real estate loans charge-off rate, house price index has the highest predictive power across all models, followed closely by new home units and other housing market variables such as the CRE price index. These findings proof the dominant role of housing market variables in determining the performance of real estate loans.

Overall, the results suggest that while certain variables, such as labor market indicators, play a crucial role across multiple loan types, the relative importance of housing market and consumer financial variables varies depending on the loan category. The combination of feature selection algorithms highlights the diverse set of factors influencing credit losses across different loan products.

Table 4 Correlation with Optimal Transformation (Ranked from High to Low)

This table ranks macroeconomic variables by their highest correlation coefficients with charge-off rates across three measures—Pearson, Spearman, and Kendall's Tau—using their optimal transformations for each loan category.

Panel A: C&I Loans

Variables	Transformation	Pearson	Variables	Transformation	Spearman	Variables	Transformation	Kendall
Unemployment Rate	yoy_lag1	61.63%	Non-Farm Employment	yoy	-71.54%	Unemployment Rate	yoy_lag1	55.59%
Non-Farm Employment	yoy	-54.14%	Unemployment Rate	yoy	71.49%	Non-Farm Employment	yoy	-55.08%
3-Month Treasury Rate	yoy	-58.83%	3-Month Treasury Rate	yoy	-60.97%	Prime Rate	yoy	-43.67%
Prime Rate	yoy	-61.13%	Prime Rate	yoy	-59.79%	BBB Corporate Bond Yield	lag4	43.48%
BBB Corporate Bond Yield	lag4	50.35%	BBB Corporate Bond Yield	lag4	58.13%	3-Month Treasury Rate	yoy	-42.77%

Panel B: Consumer Loans

Variables	Transformation	Pearson	Variables	Transformation	Spearman	Variables	Transformation	Kendall
Debt Service Ratio	lag4	70.94%	Debt Service Ratio	lag1	64.60%	Debt Service Ratio	lag2	47.71%
House Price Index	yoy	-62.76%	Non-Farm Employment	qoq	-57.94%	Non-Farm Employment	yoy	-43.67%
New Home Units	yoy_lag4	-62.30%	Household Fin. Obligations	lag4	57.78%	Household Fin. Obligations	lag3	41.52%
Household Fin. Obligations	lag4	55.26%	Personal Savings	lag4	-50.50%	Personal Savings	lag4	-36.02%
Nominal GDP	yoy_lag1	-50.89%	New Home Sales	yoy_lag4	-49.41%	Unemployment Rate	yoy_lag1	35.49%

Panel C: Real Estate Loans

Variables	Transformation	Pearson	Variables	Transformation	Spearman	Variables	Transformation	Kendall
New Home Sales	ln	-75%	Unemployment Rate	raw	70.43%	Unemployment Rate	raw	52.52%
Commercial Real Estate Price	yoy_lag2	-69%	House Price Index	yoy	-63.46%	Unemployment Insurance Claims	raw	46.12%
House Price Index	yoy_lag2	-68%	UIC	raw	61.95%	House Price Index	yoy	-45.09%
Unemployment Rate	raw	66%	CRE Price Index	yoy_lag1	-58.33%	CRE Price Index	yoy_lag1	-41.85%
BBB Corporate Bond Yield	lag4	50%	New Home Units	raw	-53.75%	New Home Units	raw	-38.60%

Table 5 Feature Selection C&I Loans

Table 5 reports the variables selected for C&I loans by stepwise regression, lasso regression (Panel A), and tree-based models GBM and RF (Panel B), with their standardized coefficients and variable importance.

Panel A: Stepwise and Lasso

Stepwise			Lasso		
Variables	Transformation	Std. Coef.	Variables	Transformation	Std. Coef.
Real GDP Growth	yoy_lag1	8.827	CRE Price Index	yoy	1.362
Nominal GDP Growth	yoy_lag1	5.281	New Home Unit	yoy_lag4	0.520
Non-Farm Employment	yoy	1.678	House Fin. Obligations	lag4	0.108
CRE Price Index	yoy	1.200	Prime Rate	yoy	0.097
New Home Unit	yoy_lag4	0.483	BBB Corporate Yield	lag4	0.057

Panel B: GBM and RF

GBM			Random Forest		
Variables	Transformation	Importance	Variables	Transformation	Importance
Non-Farm Employment	yoy	0.719	Non-Farm Employment	yoy	0.712
BBB Corporate Yield	lag4	0.138	BBB Corporate Yield	lag4	0.131
New Home Unit	yoy_lag4	0.049	New Home Unit	yoy_lag4	0.033
Market Volatility Index	lag2	0.023	House Fin. Obligations	lag4	0.024
CRE Price Index	yoy	0.022	Real GDP Growth	yoy_lag1	0.022

Table 6 Feature Selection Consumer Loans

Table 6 reports the variables selected for consumer loans by stepwise regression, lasso regression (Panel A), and tree-based models GBM and RF (Panel B), with their standardized coefficients and variable importance.

Panel A: Stepwise and Lasso

Stepwise			Lasso		
Variables	Transformation	Std. Coef.	Variables	Transformation	Std. Coef.
Real GDP Growth	yoy_lag3	5.195	Debt Service Burden	lag4	0.334
CRE Price Index	yoy_lag2	2.588	UR	raw	0.100
Nominal GDP Growth	yoy_lag1	2.137	House Fin. Obligations	lag4	0.028
New Home Unit	yoy_lag4	1.231	House Price Index	yoy	0
DJ Index	yoy_lag3	0.611	New Home Unit	yoy_lag4	0

Panel B: GBM and RF

GBM			Random Forest		
Variables	Transformation	Importance	Variables	Transformation	Importance
House Price Index	yoy	0.601	House Price Index	yoy	0.520
Debt Service Burden	lag4	0.122	Debt Service Burden	lag4	0.140

DJ Index	yoy_lag3	0.096	UR	raw	0.093
Real GDP Growth	yoy_lag3	0.042	New Home Unit	yoy_lag4	0.054
UR	raw	0.036	CRE Price Index	yoy_lag2	0.049

Table 7 Feature Selection Real Estate Loans

Table 7 reports the variables selected for real estate loans by stepwise regression, lasso regression (Panel A), and tree-based models GBM and RF (Panel B), with their standardized coefficients and variable importance.

Panel A: Stepwise and Lasso

Stepwise			**Lasso**		
Variables	Transformation	Std. Coef.	Variables	Transformation	Std. Coef.
House Price Index	yoy_lag2	4.167	House Price Index	yoy_lag2	1.902
Real GDP Growth	yoy_lag4	2.499	CRE Price Index	yoy_lag2	1.643
Non-Farm Employment	log	2.077	New Home Unit	log	1.275
CRE Price Index	yoy_lag2	1.701	BBB Corporate Yield	lag4	0.121
New Home Unit	log	1.423	UR	raw	0.049

Panel B: GBM and RF

GBM			**Random Forest**		
Variables	Transformation	Importance	Variables	Transformation	Importance
UR	raw	0.374	CRE Price Index	yoy_lag2	0.233
New Home Unit	log	0.180	UR	raw	0.183
BBB Corporate Yield	lag4	0.145	New Home Unit	log	0.166
DJ Index	log	0.081	House Price Index	yoy_lag2	0.165
House Price Index	yoy_lag2	0.065	Real GDP Growth	yoy_lag4	0.083

VII. Model Selection and Prediction

Table 8 compares the predictive performance of four models—Stepwise Regression, Lasso Regression, Gradient Boosted Machine (GBM), and Random Forest (RF)—across three loan portfolios. Using quarterly data for training (1990 Q1–2021 Q3) and testing (2021 Q4–2024 Q3), tree-based models (GBM and RF) consistently outperform regression-based models (Table 8).

For real estate loans, GBM achieves the best results, with the lowest in-sample MSE (0.0003) and out-of-sample MSE (0.0068), demonstrating its strong generalization and ability to capture nonlinear relationships. RF follows closely (out-of-sample MSE: 0.0191), while regression models have higher errors due to limited capacity to model data complexity.

In consumer loans, RF slightly outperforms GBM (out-of-sample MSE: 0.3416 vs. 0.3449), confirming tree-based models' effectiveness in modeling charge-off rates. Lasso performs better than Stepwise regression but worse than tree-based models.

For C&I loans, GBM again leads with the lowest in-sample (0.0009) and out-of-sample (0.0091) MSE, followed by RF (out-of-sample MSE: 0.0265). Tree-based models significantly outperforms regression methods, highlighting their ability to capture complex interactions.

Overall, GBM and RF demonstrate superior predictive accuracy and robustness across all loan portfolios, proving their effectiveness in modeling credit losses during volatile economic periods.

Table 8 Model Performance Comparison for Different Loan Portfolio

Table 8 compares the performance of predictive models (Stepwise, Lasso, GBM, and RF) for three loan portfolios using quarterly data from 1990 Q1 to 2024 Q3. The in-sample period is from 1990 Q1 to 2021 Q3, while the out-of-sample period is from 2021 Q4 to 2024 Q3 (12 quarters). The table reports the in-sample and out-of-sample Mean Squared Errors (MSE) for each model.

Portfolio	Model	In-Sample MSE	Out-of-Sample MSE
Commercial Real Estate	Stepwise	0.0929	0.2843
Commercial Real Estate	Lasso	0.0999	0.2471
Commercial Real Estate	GBM	0.0003	0.0068
Commercial Real Estate	RF	0.009	0.0191
Consumer Loans	Stepwise	0.3009	0.7738
Consumer Loans	Lasso	0.7848	0.6341
Consumer Loans	GBM	0.0022	0.3449
Consumer Loans	RF	0.0173	0.3416
Commercial & Industrial Loans	Stepwise	0.0739	0.0342
Commercial & Industrial Loans	Lasso	0.0812	0.0718
Commercial & Industrial Loans	GBM	0.0009	0.0091
Commercial & Industrial Loans	RF	0.0063	0.0265

Using the best models identified in Table 8, we conduct in-sample testing (1990 Q1 to 2021 Q3) and out-of-sample testing (2021 Q4 to 2024 Q3) for each portfolio. The actual charge-off rates alongside the model predicted charge-off rates are presented in Figures 4, 5, and 6.

Figure 4 shows the GBM model's performance in predicting charge-off rates for the C&I loans. The GBM model demonstrates strong predictive accuracy and effectiveness in capturing trends and fluctuations. The close alignment between the model's predictions and actual data during both in-sample period and out-of-sample period highlights its robustness and reliability for forecasting.

Figure 5 illustrates the RF model's predicted charge off rate for the consumer loans, comparing them to actual charge-off rates. The model accurately reflects charge-off rate trends, effectively capturing the cyclical and volatile nature of consumer loan performance. Its strong generalization during the out-of-sample period demonstrates the RF model's ability to incorporate macroeconomic factors, such as unemployment rates and household financial obligations, to produce reliable forecasts even under varying economic conditions.

Figure 6 highlights the GBM model's performance in predicting charge-off rates for the real estate loans. The model exhibits high accuracy, closely mirroring actual charge-off rates and successfully capturing cyclical trends and volatility. Its effectiveness in incorporating complex macroeconomic indicators, such as house price indices and unemployment rates, further emphasizes its reliability for forecasting the performance of real estate loans under diverse economic scenarios.

Figure 4

Predictions for the C&I loans using the GBM model. The figure compares actual values, in-sample predictions, and out-of-sample predictions. The training period is from 1990 Q1 to 2021 Q3, and the testing period is from 2021 Q4 to 2024 Q3.

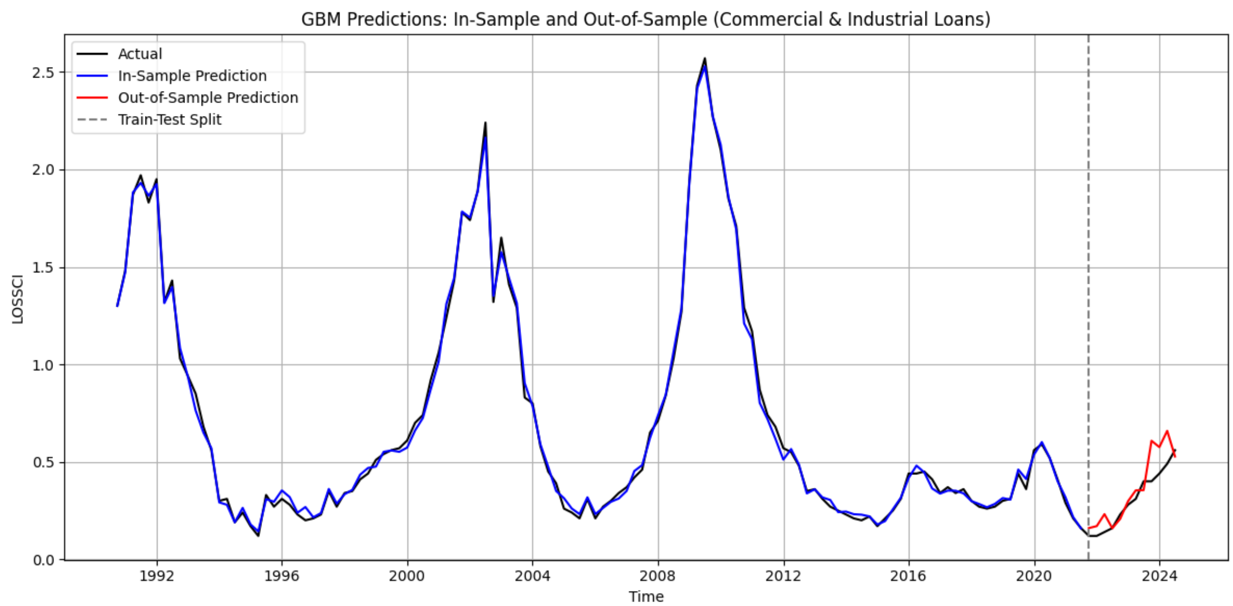


Figure 5

Predictions for the consumer loans using the RF model. The figure compares actual values, in-sample predictions, and out-of-sample predictions. The training period is from 1990 Q1 to 2021 Q3, and the testing period is from 2021 Q4 to 2024 Q3.

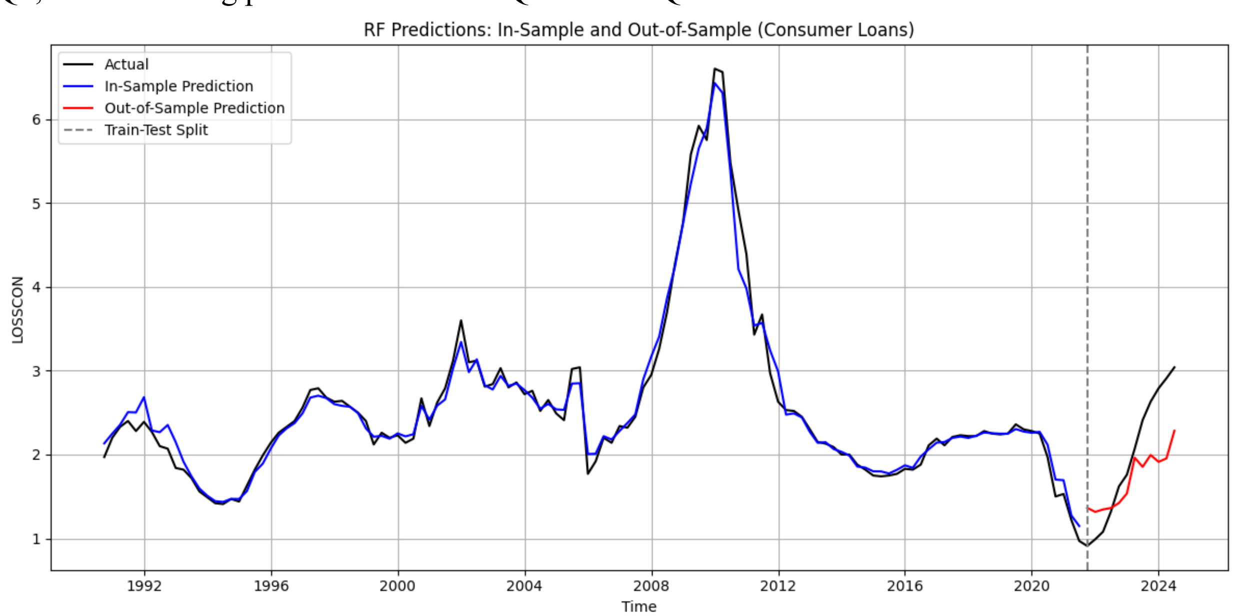
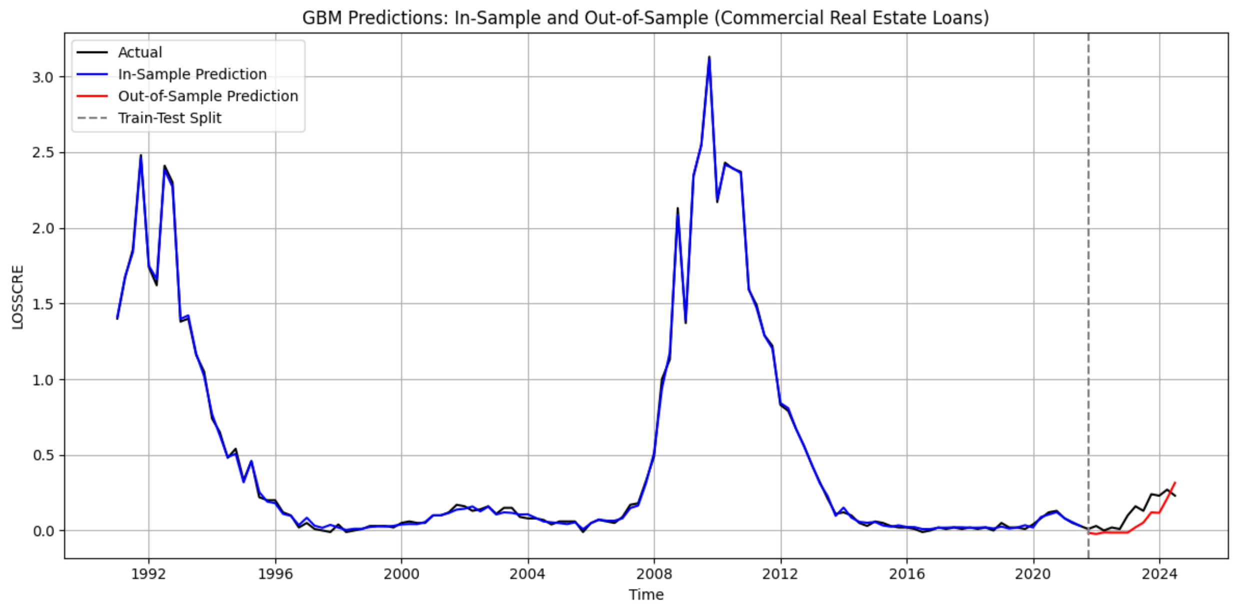


Figure 6

Predictions for the real estate loans using the GBM model. The figure compares actual values, in-sample predictions, and out-of-sample predictions. The training period is from 1990 Q1 to 2021 Q3, and the testing period is from 2021 Q4 to 2024 Q3.



VIII. Results Discussion and Implications to Credit Risk Modelling

Credit risk management becomes a critical focus for financial institutions, particularly following the 2008–2009 global financial crisis (GFC) and the unprecedented volatility introduced by the COVID-19 pandemic. This study examines the relationship between macroeconomic factors and charge-off rates for C&I loans, consumer loans, and real estate loans issued by U.S. commercial banks from 1990 to 2024. Our findings provide a comprehensive analysis of macroeconomic risk factors that can be effectively used in credit loss forecasting (LF) and CECL models.

The results highlight key macroeconomic variables that have the strongest predictive power for credit loss forecasting across different loan portfolios. For C&I loans, non-farm employment, CRE price index, and new housing units emerged as the most significant predictors, emphasizing the importance of labor market and commercial real estate dynamics. For consumer loans, house price index, debt service burden, and household financial obligations are the most critical variables, reflecting the influence of household financial conditions and housing market trends. Finally, for real estate loans, house price index, new housing units, and CRE price index demonstrate the strongest predictive power, underscoring the dominance of housing market variables in determining real estate loan performance.

By incorporating these macroeconomic factors, banks can improve the robustness of their credit risk models, particularly under stress-testing scenarios. This study also demonstrates the advantages of combining feature selection techniques with traditional correlation analyses to identify the most relevant macroeconomic variables. Importantly, the inclusion of COVID-19-era data provides a unique opportunity to assess the stability and relevance of these relationships during periods of extreme economic stress.

Given that most banks primarily rely on limited datasets covering a single business cycle (e.g., GFC), our long-term analysis spanning multiple business cycles—including the COVID-19 pandemic—offers a more robust understanding of the dynamic relationship between macroeconomic factors and credit loss. While our findings are robust, they should be interpreted with caution due to potential differences between the COVID-19 pandemic and prior recessions. Nonetheless, this research provides practical insights for banks, regulators, and policymakers to enhance credit risk modeling frameworks and to design more effective stress-testing and loss forecasting methodologies.

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Appendix A: Variable Explanations and FRED Data Series Codes

Variable Name	Description	Source	FRED Data Series Code
Commercial Real Estate Charge-Off Rate	Quarterly percentage of commercial real estate loans charged off. Reflects credit risk in CRE markets.	Federal Reserve Board	CORCREXFACBS
Consumer Loans Charge-Off Rate	Quarterly percentage of consumer loans (e.g., credit cards, personal loans) charged off.	Federal Reserve Board	CORCACBS
Commercial and Industrial Loans Charge-Off Rate	Quarterly percentage of commercial and industrial loans charged off. Reflects credit risk in business lending.	Federal Reserve Board	CORBLACBS
Real GDP Growth	Quarterly percentage change in real GDP, representing overall economic activity.	U.S. Bureau of Economic Analysis	GDPC1
Nominal GDP Growth	Quarterly percentage change in nominal GDP, measuring the overall value of goods and services.	U.S. Bureau of Economic Analysis	GDP
Real Disposable Income	Quarterly real disposable personal income, adjusted for inflation.	U.S. Bureau of Economic Analysis	DPIC96
Nominal Disposable Income	Quarterly nominal disposable personal income, not adjusted for inflation.	U.S. Bureau of Economic Analysis	DPI
Unemployment Rate (UR)	Percentage of unemployed individuals in the labor force.	U.S. Bureau of Labor Statistics	UNRATE
CPI Inflation	Consumer Price Index for all urban consumers, reflecting overall inflation trends.	U.S. Bureau of Labor Statistics	CPIAUCSL
3-Month Treasury Rate	Yield on 3-month U.S. Treasury bills, reflecting short-term interest rates.	Federal Reserve Board	TB3MS
5-Year Treasury Rate	Yield on 5-year U.S. Treasury notes, representing medium-term interest rates.	Federal Reserve Board	GS5
10-Year Treasury Rate	Yield on 10-year U.S. Treasury notes, representing long-term interest rates.	Federal Reserve Board	GS10
BBB Corporate Yield	Yield on BBB-rated corporate bonds, indicating credit market conditions.	ICE BofA	BAMLC0A4CBBBEY
Mortgage Rate	Average interest rate on 30-year fixed-rate mortgages in the U.S.	Federal Reserve Board	MORTGAGE30US
Prime Rate	Interest rate charged by banks to their most creditworthy customers.	Federal Reserve Board	WPRIME
Dow Jones Index	Dow Jones Industrial Average, reflecting overall stock market performance.	Dow Jones & Company	DJIA
House Price Index	All-transactions house price index for the U.S., reflecting real estate market conditions.	Federal Housing Finance Agency	USSTHPI
CRE Price Index	Commercial real estate price index, capturing trends in CRE markets.	Federal Reserve Board	BOGZ1FL075035503Q
Market Volatility Index (VIX)	A measure of expected market volatility derived from S&P 500 index options.	Chicago Board Options Exchange	VIXCLS
Non-Farm Employment	Number of employed individuals outside the agricultural sector, reflecting labor market strength.	U.S. Bureau of Labor Statistics	PAYEMS

Retail Sales - Motor	Retail sales in the automotive sector, an indicator of consumer demand.	U.S. Census Bureau/Federal Reserve Board	DAUTOSA
New Housing Units	Number of new privately-owned housing units authorized in permit-issuing places.	U.S. Census Bureau	PERMIT
Personal Consumption Expenditures (PCE)	Total expenditures by households on goods and services.	U.S. Bureau of Economic Analysis	PCE
Personal Saving Rate	Percentage of disposable personal income saved by households.	U.S. Bureau of Economic Analysis	PSAVERT
Spot Crude Oil Price (WTI)	Price of West Texas Intermediate crude oil per barrel.	U.S. Energy Information Administration	WTISPLC
Initial Claims	Weekly initial claims for unemployment benefits, capturing labor market stress.	U.S. Employment and Training Administration	ICSA
Producer Price Index (PPI)	Index measuring average change over time in the selling prices received by domestic producers for their output.	U.S. Bureau of Labor Statistics	PPIACO
Debt Service Burden	Ratio of debt payments to disposable income, indicating consumer financial health.	Federal Reserve Board	TDSP
Household Financial Obligations	Financial obligations as a percentage of disposable income, covering mortgages, rent, and debt payments.	Federal Reserve Board	FODSP