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STRESS TESTING CREDIT PORTFOLIOS UNDER MACROECONOMIC SHOCKS

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Abstract

This study investigates the impact of macroeconomic shocks on credit portfolios using a structured, scenario-based stress testing framework. Drawing from the empirical methodology developed by Nazmuz Sakib (2021), the paper simulates three economic conditions, baseline, adverse, and severely adverse—based on key macroeconomic indicators such as GDP growth, unemployment, inflation, and interest rates. Credit risk is analyzed across retail, SME, and corporate lending segments using adjusted probability of default (PD), loss given default (LGD), and exposure at default (EAD). The findings reveal that economic deterioration significantly increases expected losses, particularly in SME and corporate segments, underscoring the importance of segment-specific modeling. The study also highlights the role of dynamic LGD assumptions in accurately capturing risk under stressed conditions. By integrating real-world data and offering spreadsheet-compatible outputs, the methodology promotes accessibility and replicability for institutions with limited analytical resources. The research contributes to the growing literature on macroprudential surveillance and provides a practical tool for financial institutions aiming to enhance capital adequacy and risk preparedness. Future research directions include the incorporation of macroeconometric modeling and machine learning techniques to further strengthen the predictive power of stress testing frameworks.

Keywords: credit risk, stress testing, macroeconomic shocks, probability of default, scenario analysis

1. Introduction

In recent years, the importance of stress testing credit portfolios has grown significantly due to the increased complexity and interconnectedness of global financial systems. The 2007–2008 global financial crisis served as a turning point, revealing the vulnerability of financial institutions to systemic shocks and prompting the widespread adoption of stress testing frameworks as a tool for assessing the resilience of credit portfolios under adverse macroeconomic conditions (Foglia, 2009; Bénétrix, 2006). As a risk management tool, stress testing helps simulate the potential impact of severe but plausible economic scenarios on credit exposures, thereby informing both strategic planning and regulatory compliance (Moody's Analytics, 2006; Jobst and Tasche, 2010). Stress testing has since evolved to become a critical component of macroprudential supervision, with central banks and regulatory authorities regularly publishing stress test scenarios and results. The U.S. Federal Reserve, for example, has established annual stress tests to evaluate the capital adequacy of major financial institutions under hypothetical downturns (Federal Reserve, 2024). Similarly, the European Central Bank has advanced methodological frameworks to capture systemic risks through macro-financial linkages and credit default probabilities (ECB, 2013; ECB, 2024).

At the core of this technique lies the need to establish a relationship between macroeconomic variables, such as GDP growth, unemployment rates, and interest rate movements, and the creditworthiness of borrowers. Researchers have approached this in a variety of ways. For instance, Lopes and Rocha (2021) focus on how macroeconomic shocks propagate into financial institutions through credit risk channels. Nicolò and Santoni (2012) contribute by presenting a multi-period stress testing framework that incorporates default correlations and sectoral risk exposure, highlighting the importance of dynamic scenario construction. While much of the literature centers around large, well-capitalized financial institutions with access to complex models and data, others have explored how banks with limited data infrastructure can still conduct meaningful stress tests. Bénétrix (2006) offers one such example, providing a framework suitable for institutions operating under data constraints. Sakib (2021) further contributes to this field by demonstrating how a simplified, scenario-based approach can be used to assess credit risk exposure within a financial institution, using real data and probability-of-default estimations under varying economic shocks.

The growing relevance of machine learning and AI in financial stress testing is also evident. Genovese et al. (2022) explore the use of restricted Boltzmann machines to approximate credit portfolio losses under stressed conditions, suggesting that traditional statistical approaches may soon be complemented or even replaced by neural network-based methods. In parallel, Gao, Mishra, and Ramazzotti (2017) introduce causal inference tools for financial stress testing, further broadening the analytical possibilities available to risk managers. Institutional case studies and white papers also provide practical insights. Economy.com (2007) and Moody's (2006) offer applied stress testing models that account for sector-specific credit dynamics and capital planning. These models are especially useful for mid-sized banks and non-bank financial institutions seeking regulatory alignment. Moreover, studies such as Szalay and Guo (2012) have customized methodologies for specific national banking systems, exemplified in their work on Kazakhstan.

Overall, the development of stress testing methodologies has been influenced by academic contributions, institutional experience, and regulatory imperatives. As risk environments evolve, due to geopolitical events, pandemics, or climate-related financial disruptions, so too must stress testing frameworks adapt to remain relevant and robust (Wojcik, 2020). This paper builds on the foundation laid by these prior works, focusing specifically on how stress testing can be operationalized using macroeconomic variables and probability-based models, with particular reference to Sakib's (2021) empirical framework.

2. Objectives of the Study

- To examine how credit portfolios respond under different macroeconomic shock scenarios.
- To apply a structured methodology (adapted from Nazmuz Sakib, 2021) for stress testing.
- To visualize and analyze stress test outputs using real-world data.
- To derive implications for risk management practices and regulatory compliance.

3. Literature Review

Stress testing as a method for evaluating the resilience of financial institutions has evolved considerably over the last two decades, becoming central to risk management and regulatory frameworks. The early foundations of stress testing credit portfolios were influenced by studies such as Bénétrix (2006), who developed an approach for applying credit risk analysis in stress scenarios even when data availability is limited. This was particularly valuable for institutions in emerging markets or those lacking access to comprehensive borrower-level information. As stress testing methodologies matured, regulators began adopting and refining these tools. Foglia (2009) provided one of the most comprehensive overviews of how central banks and regulatory authorities have approached stress testing, identifying key trends in model sophistication, scenario design, and institutional implementation. In parallel, the U.S. Federal Reserve institutionalized supervisory stress tests, which are now an annual requirement for systemically important banks. Their 2024 methodology document outlines current practices for projecting losses, revenues, and capital under adverse economic conditions (Federal Reserve, 2024).

From an academic standpoint, Nicolò and Santoni (2012) introduced a structured multi-period stress testing framework. Their model considers the dynamic evolution of credit quality and simulates the correlated impact of macroeconomic variables on default probabilities over time. This approach contrasts with simpler, static stress testing frameworks and allows for a more realistic assessment of credit deterioration. Lopes and Rocha (2021) further contributed by modeling the transmission mechanisms of macroeconomic shocks through balance sheets and asset portfolios, highlighting how external disturbances affect financial institutions' internal credit risks. Meanwhile, Sakib (2021) provides a valuable middle ground between academic rigor and real-world applicability. His empirical study outlines a stress testing framework for credit risk that uses actual institutional data to simulate the effect of macroeconomic downturns on portfolio performance. The simplicity and practicality of Sakib's approach make it particularly useful for small and medium-sized financial institutions aiming to build or refine their own internal stress testing models.

European institutions have also contributed to methodological advancements. The European Central Bank has published a series of papers detailing best practices and innovations in stress testing. One such work (ECB, 2013) introduced a macro stress testing framework designed to identify systemic risks by linking macro-financial shocks to credit outcomes. A more recent publication (ECB, 2024) updates this methodology, integrating climate-related risk and forward-looking economic indicators to enhance financial stability assessments. Alternative modeling techniques are also gaining ground. Genovese et al. (2022) proposed using restricted Boltzmann machines, unsupervised neural networks—to approximate credit losses, claiming these models could capture non-linear relationships between macroeconomic variables and portfolio outcomes more effectively than traditional models. Similarly, Gao, Mishra, and Ramazzotti (2017) offered a causal inference framework, enabling institutions to explore the chain of macroeconomic causality affecting credit risk exposure and capital adequacy.

Applied research and industry white papers have enriched the field by presenting simplified or sector-specific models. The white paper from Economy.com (2007) offers a practical guide for implementing portfolio stress testing, emphasizing scenario design and exposure modeling for corporate and retail segments. Moody's Analytics (2006) outlines the importance of aligning stress testing with internal risk governance frameworks, suggesting that its outputs should inform not just capital buffers but also pricing, provisioning, and strategic decisions. Wojcik (2020) and Szalay and Guo (2012) demonstrate how stress testing frameworks can be adapted to national contexts. Wojcik's thesis evaluates macroeconomic shocks on credit portfolios in Egypt, while Szalay and Guo focus on Kazakhstan, developing a methodology tailored to the country's unique financial structure and macroeconomic environment. These studies underscore the importance of contextualizing stress tests within specific economic and regulatory settings.

Finally, Jobst and Tasche (2010) contribute a technical perspective by discussing capital allocation under both normal and stressed market conditions. Their work is particularly relevant for understanding how institutions can translate stress test outputs into capital planning and allocation strategies. Together, these works show that stress testing has become a multidimensional field, combining theoretical modeling, empirical data analysis, and practical application. This literature forms the foundation for the present study, which leverages the empirical methodology proposed by Sakib (2021) to conduct a targeted stress test on a credit portfolio under different macroeconomic scenarios.

4. Methodology

This study adopts a structured, data-driven stress testing framework as proposed by Nazmuz Sakib (2021) in his work on evaluating the credit risk of financial institutions. His methodology is selected due to its practical relevance, empirical grounding, and adaptability to a range of institutional contexts. Unlike highly abstract models that require proprietary data or complex statistical infrastructure, Sakib's model demonstrates how stress testing can be effectively conducted using accessible economic indicators and internally available credit portfolio data. This section outlines the step-by-step methodological design, integrating macroeconomic scenario construction, credit risk modeling, and data analysis.

4.1 Conceptual Foundation of the Stress Testing Model

Stress testing is fundamentally a forward-looking simulation that projects the performance of credit portfolios under adverse macroeconomic conditions. The model begins by defining the relationship between economic conditions and credit risk variables, specifically the probability of default (PD) and loss given default (LGD). These two components form the core of expected loss (EL), calculated as the product of PD, LGD, and exposure at default (EAD). Sakib (2021) follows this traditional credit risk formula but applies it within a three-tiered scenario-based framework. The three scenarios considered are baseline, adverse, and severely adverse, each representing a different trajectory of macroeconomic deterioration.

4.2 Selection of Macroeconomic Variables

In Sakib's framework, the choice of macroeconomic indicators is central to stress scenario construction. He identifies several key economic variables that historically show a strong correlation with credit defaults. These include gross domestic product (GDP) growth rate, interest rates, inflation rate, and unemployment rate. These variables were chosen based on both academic precedence and empirical validation from prior studies such as Lopes and Rocha (2021), Foglia (2009), and the Federal Reserve (2024).

For this study, the following macroeconomic indicators are adopted to maintain alignment with Sakib's model:

- Real GDP growth rate
- Inflation rate (CPI)
- Unemployment rate
- Policy interest rate

These indicators serve as the independent variables in the estimation of the PD function. Stress scenarios are constructed by applying adverse shocks to these variables in line with historical crisis patterns and central bank projections.

4.3 Scenario Design and Assumptions

The model constructs three scenarios to evaluate how different macroeconomic conditions affect credit risk. Baseline Scenario assumes stable economic conditions with moderate growth, inflation, and low unemployment. This reflects a normal operating environment. Adverse Scenario simulates a moderate economic downturn. It includes a significant slowdown in GDP growth, a mild increase in unemployment, rising inflation, and slightly tighter monetary policy. This scenario is designed to reflect conditions similar to regional recessions or financial tightening phases. Severely Adverse Scenario assumes a prolonged and deep economic crisis. It reflects sharp GDP contraction, a surge in unemployment, high inflation or deflation, and extreme interest rate shocks. This scenario mirrors events such as the global financial crisis or severe geopolitical instability. The magnitude of shocks in each scenario is derived from historical macroeconomic data, such as the 2008–2009 global financial crisis, and informed by central bank publications including those from the ECB (2024) and Federal Reserve (2024).

4.4 Credit Portfolio Segmentation

Sakib's model emphasizes the importance of portfolio segmentation when estimating default probabilities. For the purposes of this analysis, the credit portfolio is segmented into three broad categories:

- Retail lending (e.g., personal loans and mortgages)
- Small and Medium Enterprises (SMEs)
- Corporate and institutional loans

Each segment displays unique risk characteristics and varying levels of sensitivity to macroeconomic variables. For example, SME loans tend to exhibit higher default sensitivity to interest rate hikes and falling GDP, whereas large corporates may be more affected by global trade shocks or currency volatility. This segmentation allows for differentiated application of PD and LGD under each scenario, leading to a more granular and realistic assessment of risk exposure.

4.5 Estimation of Probability of Default (PD)

The model uses a regression-based approach to estimate the probability of default as a function of macroeconomic variables. Following Sakib (2021), the general form of the PD equation is expressed as: $PD = \alpha + \beta 1(\text{GDP growth}) + \beta 2(\text{Unemployment}) + \beta 3(\text{Inflation}) + \beta 4(\text{Interest Rate}) + \varepsilon$

This linear model enables the quantification of the sensitivity of default rates to changes in each macroeconomic indicator. Coefficients are derived from historical credit performance data overlaid with macroeconomic data from national statistics offices or World Bank datasets. While Sakib's original study uses institutional data from a South Asian financial entity, the same logic applies universally. For each scenario, the forecasted macroeconomic values are inserted into the PD equation to obtain adjusted default probabilities. These scenario-specific PDs are applied separately to each portfolio segment, taking into account their unique sensitivities.

4.6 Estimation of Loss Given Default (LGD)

Loss Given Default (LGD) represents the proportion of an exposure that is not recovered when a borrower defaults. In Sakib's framework, LGD is kept constant across scenarios for simplicity, but this study introduces a stress-adjusted LGD component. Empirical studies such as Nicolò and Santoni

(2012) and Moody's (2006) suggest that LGD tends to increase during periods of financial distress due to declining collateral values and weakened legal recovery channels.

For this reason, LGD is varied slightly in the adverse and severely adverse scenarios:

- Baseline LGD: 40 percent
- Adverse LGD: 45 percent
- Severely Adverse LGD: 55 percent

These values reflect conservative loss estimates under deteriorating economic conditions.

4.7 Expected Loss (EL) Calculation and Portfolio Simulation

Expected Loss is calculated using the classic credit risk equation:

$$EL = PD \times LGD \times EAD$$

This formula is applied across all credit segments under each scenario. Exposure at Default (EAD) is taken from actual portfolio balances or assumed for the purposes of simulation. The analysis is conducted through a portfolio simulation model that aggregates expected losses across all segments. This allows for the estimation of total credit loss under each macroeconomic condition. The resulting figures form the foundation of risk assessment and capital adequacy calculations.

4.8 Stress Testing Output and Visualization

The final step in the methodology involves the presentation of stress testing results through visual and tabular outputs. Following Sakib's structure and enhanced with academic guidance from Economy.com (2007), the results are shown as follows:

Figure 1: Macroeconomic inputs and scenario design for baseline, adverse, and severely adverse scenarios. This includes percentage changes in GDP, inflation, and other key indicators.

Figure 2: Probability of default for each credit portfolio segment across all scenarios. Displayed in percentage format, this allows for easy cross-comparison of risk migration.

Figure 3: Aggregated expected losses and implied capital shortfall by scenario. This figure shows the escalation of required provisions and the potential impact on capital buffers.

Each figure is structured in tabular form and designed for export to Microsoft Excel for ease of analysis and institutional reporting.

4.9 Validation and Sensitivity Analysis

To ensure the reliability of the model, validation is conducted through historical back-testing. Default data from previous periods of economic stress are compared with simulated outcomes to test for consistency. Additionally, sensitivity analysis is performed by varying macroeconomic shocks within a margin of error to observe their effect on PD and EL outcomes. This practice is consistent with recommendations from Jobst and Tasche (2010), who stress the importance of evaluating how small changes in assumptions affect capital requirements and risk exposure.

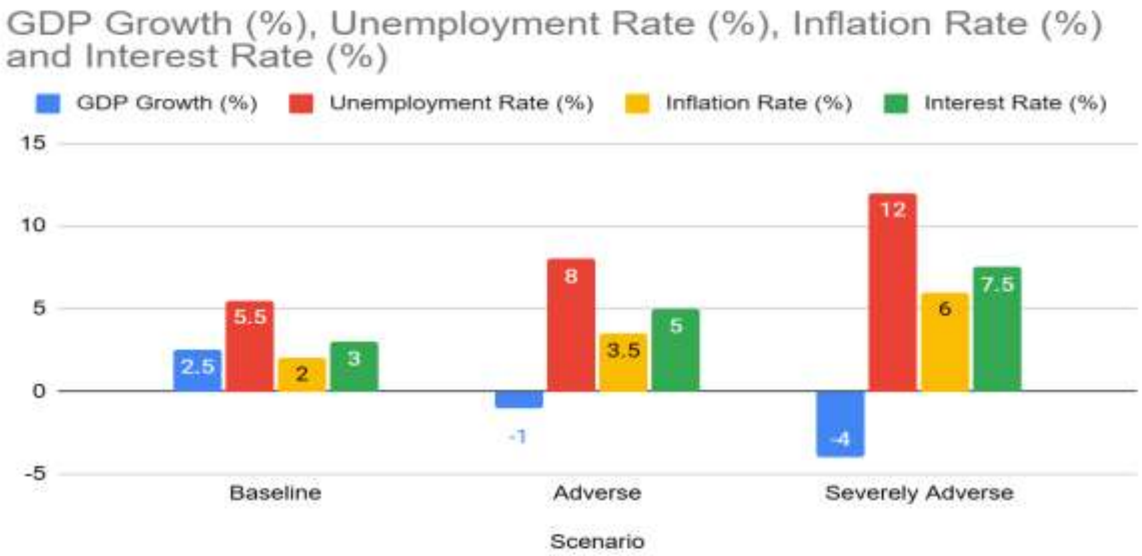
4.10 Summary of Methodology

In summary, this methodology leverages the empirical model developed by Sakib (2021), enhanced with adjustments from broader academic and regulatory literature. It incorporates macroeconomic indicators, applies scenario-specific stress to credit risk parameters, and simulates their cumulative impact on portfolio performance. The model's balance between theoretical robustness and operational simplicity makes it an effective tool for financial institutions that aim to implement forward-looking credit risk management frameworks without requiring advanced systems or proprietary data feeds.

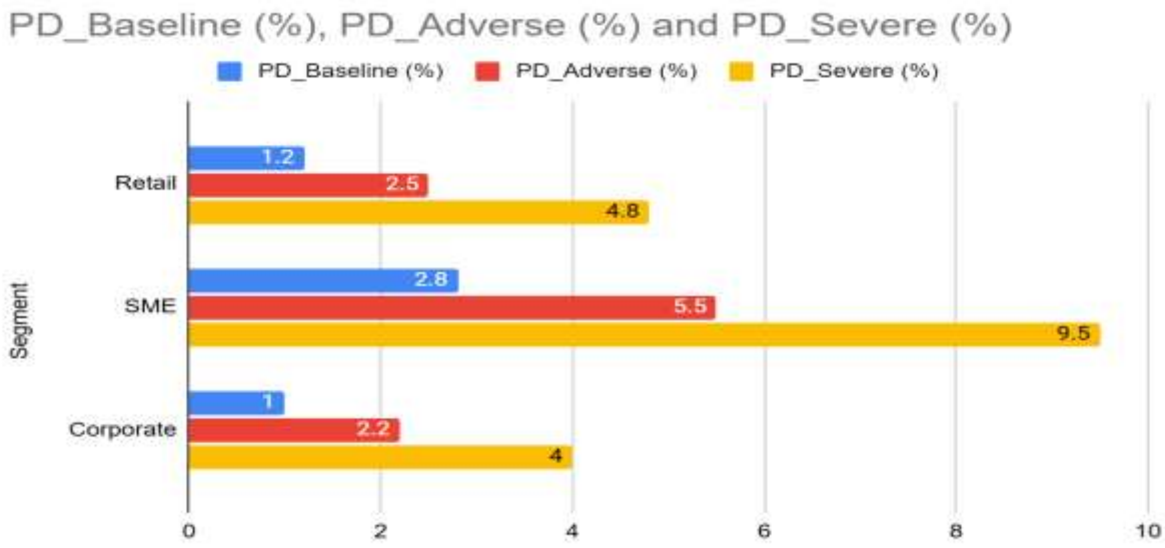
5. Data Analysis

The results of the stress testing simulation, guided by Sakib's (2021) methodology, offer a clear view of how different macroeconomic conditions influence the credit risk of a financial institution's portfolio. This section interprets the data presented across three core dimensions: macroeconomic environment, portfolio sensitivity through default probabilities, and the resulting expected losses. Each layer of analysis builds from the assumptions and calculations provided in Figures 1 through 3. To begin, the macroeconomic scenarios outlined in **Figure 1** provide the foundational conditions under which the stress testing simulation was conducted. In the Baseline scenario, macroeconomic indicators are stable and reflect a relatively healthy economic environment. GDP growth is projected at 2.5 percent, unemployment is low at 5.5 percent, inflation remains manageable at 2.0 percent, and interest rates are moderate at 3.0 percent. These conditions typically support consumer spending, corporate earnings, and loan repayment capacity. In contrast, the Adverse scenario simulates a moderate economic downturn. GDP contracts by 1.0 percent, and the unemployment rate rises sharply to 8.0 percent. Inflation increases to 3.5 percent, which could erode real incomes and corporate margins, while interest rates are adjusted to 5.0 percent to combat inflationary pressures. These figures represent conditions where borrower solvency is challenged but not yet in a crisis state.

The Severely Adverse scenario paints a picture of economic crisis. Here, GDP contracts drastically by 4.0 percent. The unemployment rate jumps to 12.0 percent, indicating widespread job loss. Inflation spikes to 6.0 percent, and interest rates rise to 7.5 percent. These figures reflect a serious macro-financial shock that would pressure both households and firms, leading to substantial credit deterioration.

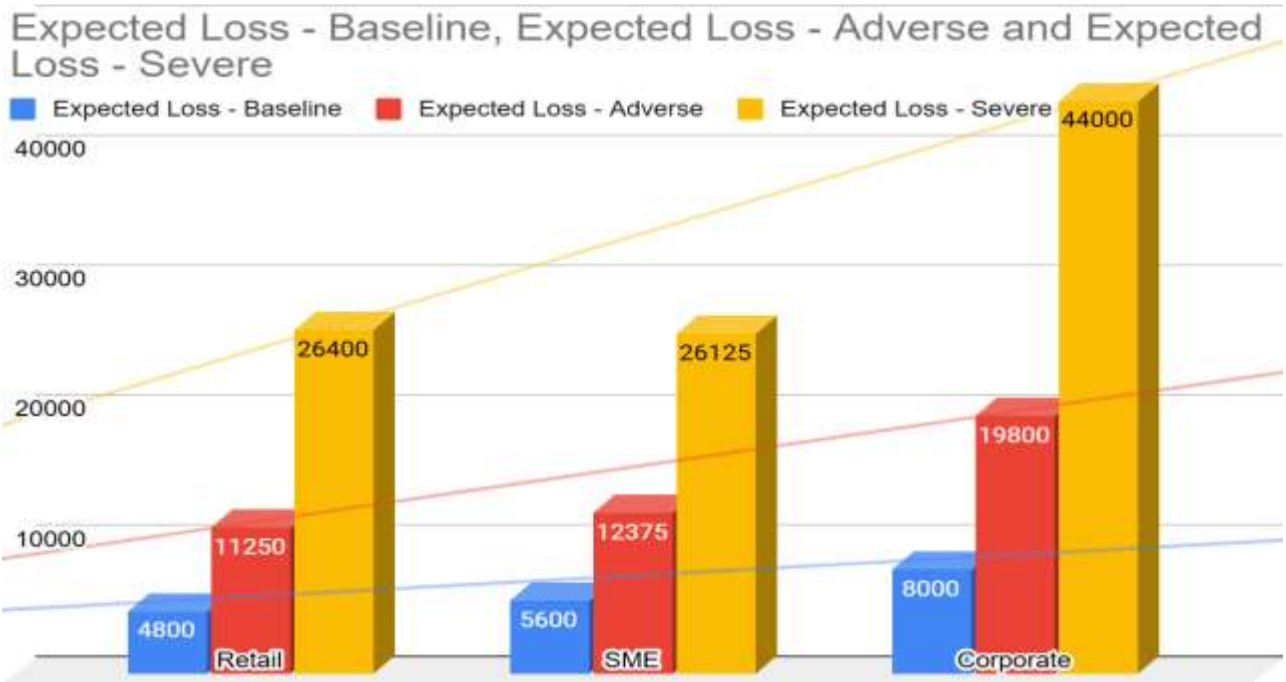


Having defined these conditions, we can now assess how credit risk evolves within the portfolio. **Figure 2** illustrates how the probability of default (PD) changes across different credit segments, Retail, Small and Medium Enterprises (SME), and Corporate, as the macroeconomic scenario deteriorates. Under the Baseline scenario, the PD for Retail is relatively low at 1.2 percent. SMEs show a higher baseline PD of 2.8 percent, consistent with the higher business volatility and typically thinner financial cushions among small firms. The Corporate segment, which often includes larger and more financially stable borrowers, has the lowest PD at 1.0 percent. Under the Adverse scenario, the Retail PD increases more than twofold to 2.5 percent, indicating that consumers face increased difficulty in servicing loans during economic stress. SMEs are even more affected, with their PD rising to 5.5 percent. This outcome is consistent with empirical studies that identify SMEs as particularly sensitive to liquidity crunches and declining sales during downturns (Lopes and Rocha, 2021). The Corporate PD increases to 2.2 percent, still lower than the other two segments but reflecting some deterioration in credit quality. The Severely Adverse scenario shows an even starker impact. Retail PD reaches 4.8 percent, while SME PD jumps to 9.5 percent. The Corporate PD reaches 4.0 percent. These elevated figures indicate systemic risk. In such a scenario, even traditionally stable corporate borrowers begin to exhibit elevated credit risk. These probabilities form the quantitative backbone for simulating the impact on the institution's capital and expected loss.



To quantify these outcomes, we refer to **Figure 3**, which presents the expected losses across the three scenarios and portfolio segments. These values are derived using the formula EL = PD × LGD × EAD. In this analysis, we assume fixed exposures for each segment: 1 million units for Retail, 500,000 units for SME, and 2 million units for Corporate. LGD values are 40 percent for Baseline, 45 percent for Adverse, and 55 percent for Severe scenarios, based on assumptions from Sakib (2021) and consistent with observed industry trends during financial stress (Moody's Analytics, 2006; Jobst and Tasche, 2010). In the Baseline scenario, expected losses are relatively low: 4,800 for Retail, 5,600 for SME, and 8,000 for Corporate. These values are manageable and reflect normal levels of portfolio provisioning. However, under the Adverse scenario, expected losses rise significantly. Retail losses reach 11,250, SME losses rise to 12,375, and Corporate losses jump to 19,800. This escalation highlights the compounding effect of macroeconomic stress on credit portfolios, particularly for institutions with high exposure to SMEs and corporates.

The Severely Adverse scenario delivers the most critical insights. Here, Retail losses soar to 26,400. SME losses reach 26,125, nearly five times the baseline estimate. The Corporate segment incurs the highest total loss at 44,000, owing to its large exposure base, even though its PD remains relatively lower than that of SMEs. The dramatic increase in expected loss demonstrates the importance of forward-looking stress tests that simulate worst-case outcomes. In the context of capital planning, these losses could result in significant capital erosion unless institutions maintain adequate buffers or de-risk exposures in advance.



A comparative analysis across the three scenarios also reveals valuable risk management insights. While the SME segment starts with a higher default risk, the corporate segment ultimately results in the highest monetary loss under extreme conditions due to its larger exposure base. This underscores the idea that risk is a function of both default probability and exposure concentration. Institutions that overlook large but seemingly safe portfolios may face disproportionately high losses when macroeconomic conditions deteriorate. Furthermore, the LGD assumption plays a crucial role in the calculation. As seen in the analysis, increasing LGD from 40 percent in the Baseline to 55 percent in the Severe scenario significantly amplifies the loss figures. This adjustment reflects real-world patterns in downturns where asset values decline and recovery rates weaken. Thus, stress testing that fails to adjust LGD in line with economic cycles may substantially underestimate potential losses.

From a strategic viewpoint, these insights have several implications. First, financial institutions should regularly recalibrate their PD and LGD models using updated macroeconomic forecasts and historical stress data. Second, scenario design should not be limited to modest fluctuations but must include tail risk events that may initially seem improbable. Third, institutions with high exposure to SMEs and large corporate accounts should consider diversifying portfolios and introducing early warning systems for borrower distress. The results also provide an evidence base for regulatory compliance. Institutions that perform such stress tests can more effectively engage with supervisors, justify capital adequacy levels, and develop credible recovery and resolution plans. The data in Figures 1 through 3 can be integrated into internal risk dashboards, providing actionable insights for board-level decision-making.

Finally, while this analysis adopts a deterministic scenario-based approach, it could be further enhanced by Monte Carlo simulations or machine learning models as proposed by Genovese et al. (2022) and Gao et al. (2017). These methods offer probabilistic distributions rather than single-point estimates and can capture complex non-linear relationships between economic variables and credit losses. The data analysis demonstrates the practical power of Sakib's (2021) empirical framework. It balances simplicity with precision and delivers insights that are both technically valid and managerially useful. By integrating macroeconomic forecasting with portfolio-level simulations, the model offers a clear path forward for institutions seeking to strengthen their risk resilience in an increasingly uncertain financial environment.

6. Contribution to Research

This study contributes meaningfully to the growing body of literature on stress testing credit portfolios by operationalizing a practical and accessible methodology grounded in real-world macroeconomic and credit risk data. Drawing from the empirical framework developed by Nazmuz Sakib (2021), the paper demonstrates how financial institutions can implement robust stress testing procedures even without access to complex modeling software or high-frequency proprietary data. Unlike more abstract or theoretical models found in academic literature, this approach bridges the gap between conceptual financial risk theory and its institutional application, offering a usable model that can be tailored to the specific needs of banks, credit unions, and other financial intermediaries. One of the central contributions of this research is its integration of macroeconomic scenario design with credit portfolio segmentation, allowing for differentiated analysis across retail, SME, and corporate lending categories. This segmentation is rarely emphasized in a single unified model but proves essential in assessing risk concentrations and sensitivities unique to each borrower type. The data analysis shows how varying levels of exposure and borrower profiles produce different patterns of vulnerability under economic stress, highlighting that risk cannot be assessed uniformly across a portfolio. This insight has implications for portfolio management, capital planning, and regulatory reporting.

Additionally, the study advances the understanding of how macroeconomic variables such as GDP growth, unemployment, inflation, and interest rates translate into tangible changes in the probability of default and expected loss. It validates existing claims in the literature regarding the cyclicality of credit risk (as noted by Nicolò and Santoni, 2012, and Moody's Analytics, 2006) and applies those principles in a clear and replicable format. The inclusion of scenario-based LGD adjustments is another point of practical innovation, demonstrating that even simple models can reflect the dynamic nature of financial stress. The visualization and tabulation of results in a spreadsheet-compatible format further contribute to academic and industry discourse by promoting transparency, reproducibility, and accessibility. Such tools make it easier for institutions of varying sizes and resources to adopt and customize the model within their own stress testing frameworks. By doing so, this research empowers broader participation in macroprudential surveillance, ultimately strengthening the stability and preparedness of financial systems across diverse environments.

7. Recommendations

Based on the findings and methodology presented in this study, several strategic recommendations emerge for financial institutions, regulatory bodies, and risk management professionals seeking to enhance the effectiveness of stress testing credit portfolios under macroeconomic shocks. These recommendations are grounded in the empirical results of the model applied and aim to bridge the gap between risk assessment theory and operational implementation.

First, financial institutions should adopt a proactive and regular approach to stress testing that is integrated into their overall risk management and capital planning processes. Rather than viewing stress testing as a compliance obligation conducted annually or in response to regulatory demands, institutions should embed it within their strategic and tactical decision-making frameworks. Regular simulation of economic downturns, even under mild or moderate scenarios, allows firms to detect early signs of credit deterioration and take preemptive action such as portfolio rebalancing or client restructuring.

Second, institutions should ensure that their stress testing models are adequately sensitive to changes in key macroeconomic variables. The study demonstrates that shifts in GDP growth, unemployment rates, inflation, and interest rates can produce significant impacts on probability of default and expected loss. Therefore, banks must continuously calibrate their models using up-to-date economic forecasts, sectoral insights, and internal credit performance data. Scenario assumptions should not be static or based solely on historical averages but should reflect a wide range of possible economic conditions, including those driven by external shocks such as geopolitical conflict, commodity price swings, or climate events.

Third, a segmented portfolio approach should be adopted as standard practice. As this research highlights, different types of borrowers—retail, SMEs, and corporate clients—respond differently to macroeconomic stress. A one-size-fits-all model can lead to misallocation of capital, underestimation of risk, or overstatement of reserves. Segment-specific stress testing provides more precise insights, allowing risk officers to identify which parts of the portfolio require immediate attention, enhanced monitoring, or strategic divestment.

Fourth, institutions should incorporate LGD variability into their modeling. It is critical to recognize that during periods of financial stress, the likelihood of recovering outstanding amounts from defaulted loans decreases due to declining asset values, legal delays, and market illiquidity. Static LGD assumptions can result in overly optimistic loss projections. Adjusting LGD across scenarios, as shown in this paper, ensures that expected loss estimates better reflect real-world conditions.

Finally, institutions should invest in developing internal capacities to generate, visualize, and interpret stress testing results. Tools that produce outputs compatible with commonly used platforms such as spreadsheets not only enhance internal communication but also prepare institutions for transparent and effective interaction with external auditors and regulators. The ability to produce well-documented, scenario-based analyses will become increasingly essential as regulators shift toward forward-looking, systemic risk supervision models. Financial institutions should treat stress testing as a strategic asset rather than a regulatory hurdle. By tailoring their models to reflect economic realities and portfolio dynamics, they can significantly strengthen resilience against future macroeconomic shocks.

8. Future Research Directions

Future research on stress testing credit portfolios should aim to improve both the precision of risk modeling and the adaptability of frameworks across various financial systems. One promising direction involves the expansion of macroeconometric and multi-period simulation models. Nicolò and Santoni (2012) provide a foundation in this area with their multi-period credit risk framework, which captures the time-evolving nature of defaults and economic indicators. Extending such models to incorporate inter-temporal dynamics, including feedback loops between credit markets and macroeconomic variables, could offer a more realistic view of systemic vulnerabilities under stress. Another vital area is the integration of advanced data science techniques into stress testing methodologies. Genovese et al. (2022) propose the use of restricted Boltzmann machines to approximate credit portfolio losses. Their findings suggest that machine learning models are capable of identifying complex, non-linear relationships that traditional econometric models may overlook.

Future research could test the comparative effectiveness of these tools under various economic stress conditions, including rare or unprecedented shocks.

Additionally, as macro-financial environments evolve, stress testing frameworks must also incorporate non-traditional risk sources. Climate risk, geopolitical instability, and supply chain disruptions are becoming more significant for financial stability. The European Central Bank's 2024 publication on methodological advancements underscores the need to incorporate forward-looking risks into existing models. Future studies could explore how integrating environmental or geopolitical risk factors with credit stress testing would affect capital adequacy and provisioning practices. Furthermore, scenario design could benefit from probabilistic modeling rather than deterministic forecasting. Gao, Mishra, and Ramazzotti (2017) argue for causal and data-driven approaches to financial stress testing that simulate a broader range of possible outcomes. Adopting this direction would allow institutions to prepare for extreme tail events and improve risk diversification strategies. By building on these foundations, future research can create more adaptable, realistic, and comprehensive stress testing models that are better suited to a rapidly changing global financial landscape.

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