Available online www.jsaer.com

***Journal of Scientific and Engineering Research*, 2023, 10(7):110-116**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

A Machine Learning Approach for Estimating Probability of Default in Lending Portfolios

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Abstract This study introduces an innovative framework based on machine learning techniques to assess the influence of climate change on credit risk within lending portfolios. The proposed framework utilizes a hybrid methodology that integrates bottom-up and top-down approaches to determine borrowers' likelihood of default (PD) across different climate change scenarios. The bottom-up method employs financial and emissions data specific to individual companies. In contrast, the top-down methodology utilizes industry-level data for companies with limited information. The framework utilizes climate scenarios, specifically those formulated by the Network for Greening the Financial System (NGFS), to generate pathways for risk factors and make necessary adjustments to financial data at the company level. Subsequently, the modified data calculates PD utilizing sophisticated credit scoring models. The evaluation of the framework's performance is conducted through the utilization of scenario analysis, benchmarking, and sensitivity analysis. The findings illustrate the capacity of the framework to assist financial institutions in evaluating and controlling credit risks associated with climate change, thereby facilitating the creation of lending portfolios that are more resilient in the context of climate change.

Keywords Climate Risk Modeling, Probability of Default, Financial Stability, Scenario Analysis, Machine Learning, Sector-Specific Impacts, Transition Risks, Physical Risks

1. Introduction

Climate change poses a substantial and escalating threat to the financial industry, specifically concerning credit risk management. With the increasing visibility of climate change's physical and transitional consequences, financial institutions are confronted with quantifying and effectively managing the potential impacts on their lending portfolios. This is particularly crucial considering the growing regulatory and stakeholder demands to reveal and address financial risks associated with climate change. The probability of default (PD) is a significant metric susceptible to climate change's impacts. It quantifies the likelihood of a borrower's failure to meet their contractual obligations. Estimating the correlation between climate change and the Probability of Default (PD) is a multifaceted undertaking that necessitates the amalgamation of climate science, financial modeling, and machine learning methodologies. Conventional credit risk models frequently depend on past data and presuppose a steady economic climate, which may not be applicable considering climate change. This paper introduces an advanced framework based on machine learning that tackles the challenge by integrating bottom-up and top-down methodologies to assess the influence of climate change on physical disabilities (PD) in diverse sectors and geographical locations. The utilization of this framework can provide financial institutions with valuable insights that can enhance their decision-making processes, optimize their risk management strategies, and contribute to the overarching objective of constructing a financial system that is more resilient and sustainable [1, 2, 8].

2. Climate Change Risks for Financial Institutions

Climate change presents a substantial and complex hazard to financial institutions, carrying extensive consequences for their activities, investments, and overall financial soundness. Climate change risks can be categorized into two main groups: physical risks and transition risks.

The direct consequences of climate change on physical assets and infrastructure give rise to physical risks. The main factors contributing to these risks are the growing occurrence and intensity of severe weather phenomena, such as hurricanes, floods, and wildfires, along with the gradual impacts of rising sea levels and shifting temperature patterns. Financial institutions are susceptible to various physical risks, which can manifest differently, including harm to collateral assets, interruption of business operations, and heightened insurance obligations. An instance can be illustrated wherein a financial institution that has extended loans to coastal properties may encounter elevated rates of loan defaults and devaluation of collateral if said properties sustain damage or become uninhabitable due to escalating sea levels or more frequent storm surges. Moreover, insurance companies may encounter elevated claims and payouts due to the increased occurrence and intensity of natural disasters.

In contrast, transition risks emerge due to transitioning towards a low-carbon economy. With the growing emphasis on sustainability and climate change mitigation by governments, businesses, and consumers, financial institutions face risks stemming from policy, technology, and market sentiment shifts. For example, implementing carbon pricing mechanisms, such as carbon taxes or emissions trading schemes, can augment operational expenses and diminish the profitability of carbon-intensive sectors, such as fossil fuel corporations. Consequently, the creditworthiness of these companies and the valuation of their assets may be impacted, thereby posing risks for banks and investors with vested interests in these industries. Likewise, the expeditious advancement and integration of environmentally friendly technologies, such as sustainable energy sources and electric transportation, can disrupt conventional business frameworks and generate stranded assets, resulting in financial setbacks for institutions with significant investments in these industries.

Financial institutions must establish comprehensive risk assessment and management frameworks encompassing physical and transition risks to efficiently handle climate change risks. The process entails performing scenario analysis to evaluate the potential consequences of various climate change scenarios on investments while incorporating climate risk factors into credit risk models, stress testing frameworks, and investment decision-making procedures. Financial institutions must actively engage with their clients and investee companies to promote sustainable practices and facilitate the transition to a low-carbon economy.

In addition, financial regulators and supervisors are increasingly acknowledging the systemic nature of climate change risks. Consequently, they formulate guidelines and establish expectations for financial institutions to mitigate these risks effectively. As an illustration, the Task Force on Climate-related Financial Disclosures (TCFD) has formulated a comprehensive structure for corporations to divulge their climate-related hazards and prospects. Concurrently, central banks and supervisors are actively investigating the application of climate stress tests to evaluate the capacity of financial institutions to withstand climate-induced disturbances [3].

3. Climate Credit Risk Assessment Framework

The CCRA framework is a comprehensive tool created to measure the influence of climate change scenarios on the likelihood of borrowers defaulting on their credit obligations. The primary objective of the framework is to furnish financial institutions with a detailed and prospective evaluation of credit risks associated with climate change. This assessment empowers them to make well-informed decisions and formulate efficient risk management strategies. The models above encompass a diverse array of industries. The framework can enhance its ability to evaluate the influence of climate change on the financial performance and creditworthiness of companies in different sectors by creating tailored models for each industry [9].

The CCRA framework utilizes a two-pronged methodology to evaluate credit risks associated with climate change, contingent upon the accessibility and reliability of data about specific corporations. The framework employs a bottom-up approach for companies with ample financial and industry-specific data. This methodology entails conducting a comprehensive examination of data at the company level, including financial statements, emissions profiles, and geographic exposure, to assess the potential effects of climate change scenarios on their performance indicators. Utilizing the bottom-up approach facilitates a more accurate and organization-specific evaluation of credit risks associated with climate change. This approach considers various factors, including the company's carbon intensity, energy composition, and susceptibility to physical climate-related risks.

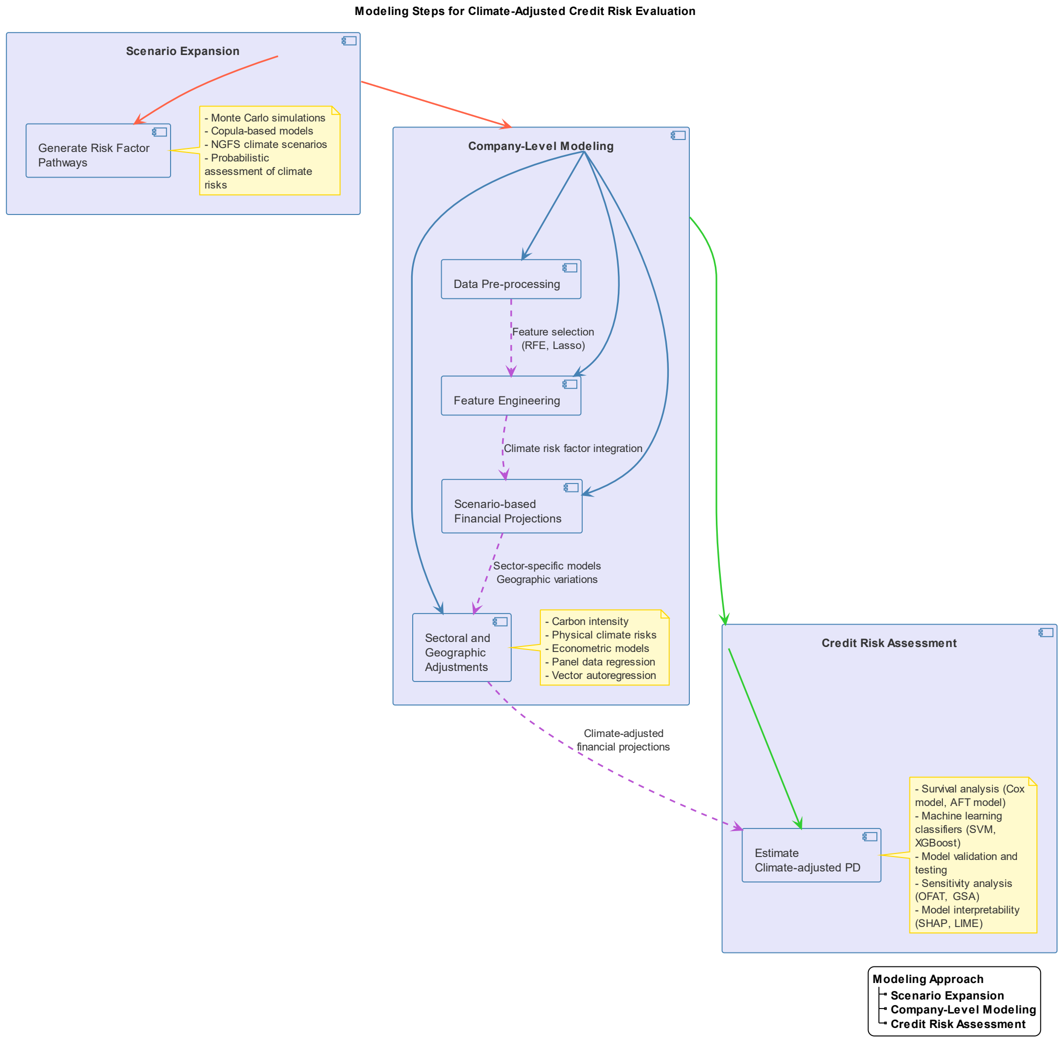
The CCRA framework utilizes a top-down approach for companies with limited or incomplete data. This methodology entails utilizing industry-level data and benchmarks to assess climate change scenarios' influence on these companies' profitability. The top-down method is especially advantageous in evaluating the credit risks associated with climate change for small and medium-sized enterprises (SMEs) or companies operating in emerging markets, where there may be limited or unreliable company-specific data available.

The CCRA framework integrates various climate change scenarios formulated by the Network for Greening the Financial System (NGFS) to evaluate the potential financial risk associated with different transition pathways. These scenarios encompass various future states, from well-organized and chaotic transitions to scenarios resembling a hothouse world. They offer a systematic approach to examining the consequences of multiple assumptions regarding climate policy and technology.

The CCRA framework incorporates climate risk factors into conventional credit risk models to produce PD estimates across various climate change scenarios. This entails modifying financial forecasts and credit risk factors according to the results of sector-specific models and the selected climate scenario. The proposed framework employs sophisticated machine learning methodologies, including neural networks and decision trees, to effectively capture the intricate and non-linear associations between climate risk factors and credit risk.

Incorporating various risk management tools and analytics within the CCRA framework enables financial institutions to effectively monitor and manage their exposure to credit risks associated with climate change. Institutions can evaluate the resilience of their lending portfolios under various climate change scenarios through portfolio-level risk dashboards, scenario analysis tools, and stress testing frameworks.

4. Modeling Approach



The Climate Credit Risk Assessment (CCRA) framework utilizes an advanced modeling methodology to convert climate scenario variables into financial consequences at the organizational level. This allows for estimating credit risk metrics adjusted for climate conditions, such as the probability of default (PD). The modeling process involves three essential steps: scenario expansion, company-level modeling, and credit risk assessment.

During the scenario expansion phase, the CCRA framework employs climate scenarios created by the Network for Greening the Financial System (NGFS) to produce a comprehensive collection of risk factor pathways. The pathways encompass the progression of significant climate-related factors, including carbon prices, energy composition, and technology expenses, across diverse temporal periods and assuming different transition scenarios. The framework utilizes sophisticated statistical methodologies, including Monte Carlo simulations and copula-based models, to produce a substantial quantity of credible risk factor pathways encompassing a broad spectrum of potential climate outcomes. This methodology enables a more detailed and probabilistic evaluation of risks related to climate change, considering the inherent uncertainties and non-linearities associated with this phenomenon.

The step of company-level modeling entails the incorporation of climate risk factor pathways with company-specific financial and non-financial data to evaluate the potential consequences of climate change on individual companies. The CCRA framework employs machine learning methodologies, including gradient boosting and neural networks, to capture the intricate connections between climate risk factors and company-level variables. The framework utilizes geospatial analysis and asset-level data to simulate the vulnerability of companies to physical climate risks, including floods, droughts, and sea-level rise. This enables a more accurate assessment of the potential financial consequences of climate change, considering each company's distinct attributes and susceptibilities.

The company-level modeling process involves several sub-steps, including [4]:

1. Data pre-processing and feature engineering: The framework cleanses and normalizes company-level data and creates a set of relevant features that capture the company's financial health, carbon intensity, and exposure to climate risks.
2. Scenario-based financial projections: The framework uses the climate risk factor pathways to adjust the company's financial projections, such as revenue growth, operating costs, and capital expenditure, under different climate scenarios.
3. Sectoral and geographic adjustments: The framework considers the specific characteristics of each sector and geography, such as the carbon intensity of different industries and the vulnerability of various regions to physical climate risks, to refine the company-level projections.

The CCRA framework utilizes the adjusted financial projections during the credit risk assessment phase to estimate climate-adjusted credit risk metrics for each company. The framework also utilizes sophisticated credit scoring models, including survival analysis and machine learning-based classifiers, to forecast the probability of default across various periods. These models are calibrated using historical data pertaining to credit defaults and transitions.

5. Validation and Testing

To guarantee the strength and dependability of the Climate Credit Risk Assessment (CCRA) framework, it is imperative to implement a thorough validation and testing protocol. The process entails employing advanced statistical techniques and performance metrics to conduct back-testing, sensitivity analysis, and scenario testing [5].

The back-testing process compares the model's predicted probability density (PD) estimates with the observed default rates over historical periods. The procedure above entails the utilization of walk-forward optimization and nested cross-validation techniques to evaluate the performance of the model on data that is not part of the original dataset. The model's discriminatory power and calibration accuracy are quantified using key performance metrics, including the area under the receiver operating characteristic curve (AUC-ROC), the Brier score, and the Kolmogorov-Smirnov (KS) statistic. Using survival analysis methodologies, such as the Cox proportional hazards model and the Kaplan-Meier estimator, enables the evaluation of the model's efficacy across various temporal intervals.

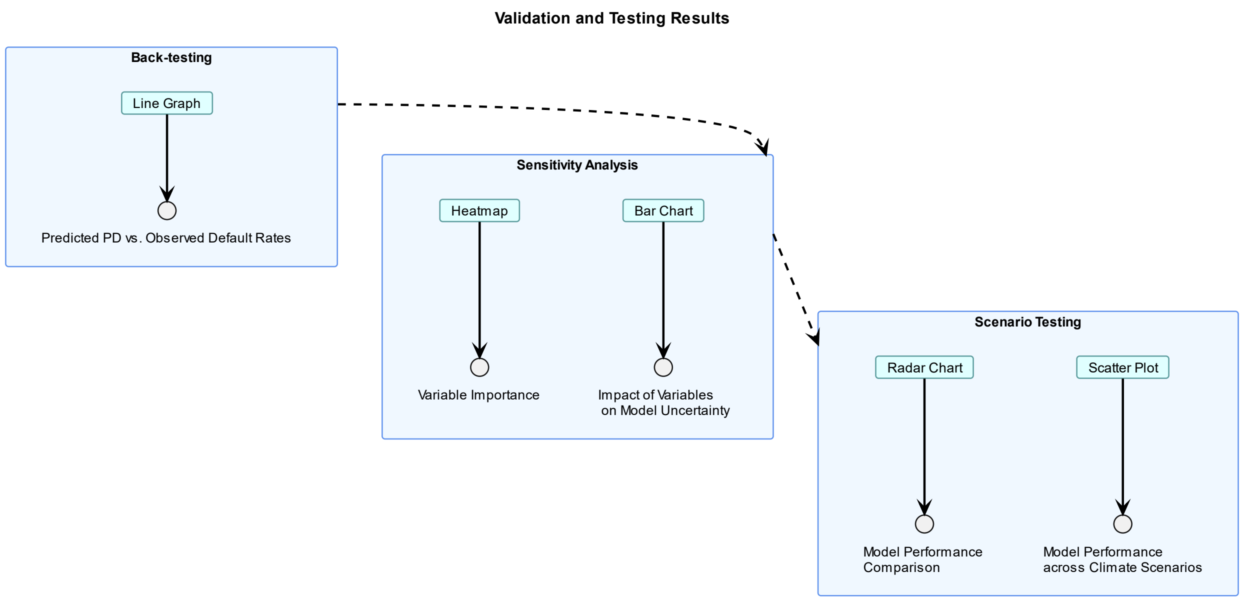


Figure 2

A sensitivity analysis evaluates the influence of crucial model assumptions and parameters on the projected PD estimates. The application of global sensitivity analysis techniques, such as Sobol indices and Morris screening, is employed to ascertain the variables that exert the most significant influence and quantify their impact on the uncertainty of the model. The model's response to small perturbations in input variables is assessed through local sensitivity analysis, which involves one-at-a-time (OAT) and derivative-based methods. The outcomes of the sensitivity analysis are employed to enhance the conjectures of the model and enhance its resilience.

Scenario testing aims to evaluate the model's effectiveness across various realistic climate scenarios, including those created by the NGFS. In this context, stress testing frameworks and reverse stress testing techniques are employed to ascertain the scenarios presenting the highest risk level to the portfolio. The model's predicted probability of default (PD) estimates and observed default rates are compared across various scenarios. This comparison is based on metrics such as the weighted average probability of default (WAPD) and the expected shortfall (ES). Scenario testing results are utilized to guide risk mitigation strategies and evaluate the sufficiency of capital buffers.

The process of validation and testing also encompasses the utilization of explainable AI (XAI) methodologies, including Shapley additive explanations (SHAP) and local interpretable model-agnostic explanations (LIME), to enhance the transparency and interpretability of the model's predictions. This enables stakeholders to comprehend the primary factors influencing credit risk and evaluate the validity of the model's results.

6. Applications and Limitations

The Climate Credit Risk Assessment (CCRA) framework has many applications within the financial sector. However, it is imperative to acknowledge and address the inherent limitations associated with its implementation in practical contexts.

Applications:

1. **Climate Stress Testing:** The CCRA framework can be incorporated into current stress testing systems, such as those employed for the Internal Capital Adequacy Assessment Process (ICAAP) and the Comprehensive Capital Analysis and Review (CCAR). The framework possesses scenario expansion and company-level modeling capabilities, enabling credit risk evaluation across various climate stress scenarios. These scenarios encompass both transition risks and physical risks.
2. **Risk management:** Involves using the CCRA framework to obtain detailed, company-level assessments of climate-adjusted portfolio damage (PD). These estimates can be combined to evaluate the potential influence of climate change on credit risk metrics at the portfolio level, including expected loss (EL) and risk-weighted assets (RWA). This data can be utilized to enhance risk appetite statements, provide guidance for capital allocation decisions, and develop risk-based pricing strategies.

3. **Strategic Planning:** Using the CCRA framework outcomes in strategic planning enables the identification of potential vulnerabilities within the portfolio, facilitating the development of contingency plans and risk mitigation strategies. Financial institutions can utilize this approach to synchronize their business strategies with the shift towards a low-carbon economy and effectively handle climate change's associated risks and opportunities.

Limitations:

1. **Data Availability and Quality:** The CCRA framework's predictive accuracy is contingent upon the accessibility of detailed financial and emissions data at the company level. Often, this data may be deficient, contradictory, or susceptible to reporting prejudices. Utilizing proxy data and estimation techniques can effectively address these concerns; however, it is essential to acknowledge that they may introduce supplementary uncertainties into the modeling procedure.
2. **Climate Scenario Uncertainty:** The development of the CCRA framework is contingent upon assumptions regarding forthcoming policy, technology, and socioeconomic advancements, all of which are susceptible to substantial uncertainty. Employing various scenarios and conducting sensitivity analysis can aid in quantifying this uncertainty, although it cannot completely eradicate it. Effectively conveying these uncertainties to relevant stakeholders and incorporating the findings of the framework within a comprehensive and multifaceted strategy for climate risk management are crucial aspects to consider.
3. **Model Complexity and Maintenance:** Significant data, expertise, and computational resources are necessary to create sector-specific models within the CCRA framework. The cost reduction potential of the framework can be attributed to its modular design and utilization of open-source libraries. However, it is essential to note that substantial investments in personnel and infrastructure may still be necessary. Ongoing challenges may arise in the maintenance and updating of the framework to align with the latest advancements in climate science and risk management practices [6, 7].

7. Conclusion

The Climate Credit Risk Assessment (CCRA) framework offers a robust instrument for financial institutions to assess and effectively handle credit risks linked to climate change. The framework allows institutions to make informed decisions and develop effective risk management strategies by providing detailed and future-oriented estimates of the climate-adjusted probability of default (PD). The comprehensive solution for evaluating climate-related credit risks is facilitated by the framework's utilization of advanced machine learning techniques and its capacity to incorporate physical and transition risk factors. Notwithstanding the constraints presented by data availability, uncertainty surrounding scenarios, and the complexity of models, the CCRA framework signifies a notable advancement in quantifying and managing the financial consequences associated with climate change. Given the ongoing evolution and escalation of climate risks, it is imperative to implement these frameworks to establish a financial system that is both resilient and sustainable.

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