Journal of Technological Innovations

Est. 2020

Harnessing Machine Learning for Comparative Analysis of Bottom-Up and Top-Down Approaches in Climate Credit Risk Modeling

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Abstract:

This research paper examines the utilization of machine learning methodologies to conduct a comparative analysis between bottom-up and top-down approaches regarding climate credit risk modeling. The significance of evaluating climate-related credit risks is increasingly acknowledged by financial institutions, leading to a crucial decision between granular, asset-level models and aggregate, portfolio-level models. Our proposed framework utilizes a combination of supervised and unsupervised learning algorithms to methodically examine and assign attributes to distinctions between these two modeling paradigms. By using predictive models and implementing clustering and dimensionality reduction techniques, this study showcases the potential of machine learning in augmenting comprehension of model disparities and bolstering the resilience of climate credit risk evaluations. The potential of this approach for model validation and benchmarking is exemplified by a case study conducted on the oil and gas industry. In conclusion, we will address optimal strategies, potential avenues for future research, and the significance of integrating bottom-up and top-down approaches to achieve comprehensive risk management.

Keywords: climate credit risk, bottom-up modeling, top-down modeling, machine learning, model comparison, risk assessment, oil and gas industry, model validation, scenario analysis

Introduction:

Financial institutions face substantial challenges due to climate change, as the inherent risks and uncertainties associated with a shifting climate can significantly affect borrowers' creditworthiness and financial markets' stability. Developing robust methodologies for assessing and quantifying potential credit losses arising from climate-related factors is imperative for banks and other financial institutions to manage these risks effectively. Two main methods are used to model climate credit risk: bottom-up models that focus on individual borrowers and capture the specific effects of climate scenarios and top-down models that estimate the overall risk exposure based on the composition and characteristics of the loan portfolio. Although both approaches have advantages, they can occasionally yield contrasting outcomes, posing challenges for risk managers in reconciling and interpreting the results. Machine learning techniques present a promising opportunity to compare and analyze the disparities between bottom-up and top-down models in this context. This allows financial institutions to understand better the factors that influence risk and make more knowledgeable decisions. Institutions can explore the relationships between model inputs, assumptions, and outputs, identify key sources of uncertainty, and develop more robust and reliable climate credit risk assessments by utilizing supervised and unsupervised learning algorithms. This white paper presents a structure for machine learning to compare bottom-up and top-down climate credit risk models. This will be done by examining a case study in the oil and gas industry to demonstrate the advantages and difficulties associated with this method.

Top-Down Portfolio Modeling Approach:

Assessing aggregate climate risk exposure based on portfolio composition: The objective of top-down portfolio modeling approaches is to evaluate the comprehensive climate risk exposure of a financial institution's loan book or investment portfolio by examining its composition and overall characteristics. Typically, this process entails dividing the portfolio into different groups based on industry, sector, or geographic region. The average risk profile of each group is then estimated using historical data, expert opinion, or market benchmarks. For instance, a financial institution may compute the ratio of its loan allocation to industries with high carbon emissions, such as oil and gas, utilities, or transportation. Subsequently, it may employ sector-specific risk factors or sensitivity analysis to assess the potential consequences of climate-related disturbances or policy alterations in these sectors. One notable benefit of employing top-down methodologies is their ability to offer a straightforward and effective means of evaluating a vast and varied portfolio for climate-related risks without necessitating comprehensive information regarding individual assets or borrowers. Top-down models can efficiently identify areas of concentrated risk or vulnerability to specific climate scenarios by examining the distribution of exposures across different segments at a macro-level. This can be especially advantageous for institutions with intricate or diverse portfolios, where conducting a comprehensive bottom-up analysis may be unfeasible or financially burdensome.

Estimating shifts in average industry/sector risk under climate scenarios: Top-down models commonly utilize scenario analysis to assess the potential effects of climate change on a portfolio. This involves estimating the possible changes in the average risk profile of various industries or sectors over time. The process entails establishing a collection of credible climate scenarios, exemplified by the Network for Greening the Financial System (NGFS), delineating various trajectories for crucial factors, including greenhouse gas emissions, temperature escalation, policy measures, and technological advancements. The model estimates the probable alterations in credit risk drivers, such as revenue, costs, asset values, or market demand, for various sectors in each scenario. These estimations are based on the sensitivity of these drivers to climate-related factors. Risk estimates at the sector level can be obtained from various sources, such as econometric models, expert interviews, or market data about similar companies or assets. Subsequently, the model consolidates these risk estimates throughout the portfolio to compute each scenario's comprehensive anticipated loss or capital prerequisites [2, 3].

Limitations compared to bottom-up modeling: Although top-down approaches provide a practical and scalable method for evaluating climate risk exposure, they differ significantly from bottom-up modeling regarding essential limitations. A significant concern revolves around the possibility of averaging or diversification effects concealing a portfolio's actual degree of risk. Using sector-level risk estimates in top-down models may result in an inadequate representation of the extensive vulnerability and resilience exhibited by individual firms or assets within a specific sector. This can result in an underestimation of the risk associated with specific exposures, especially those with a high degree of unique risk or are highly sensitive to climate factors. Using top-down risk management and decision-making approaches may yield fewer practical insights due to their lack of direct association between climate risks and individual borrowers or transactions. Financial institutions may struggle to effectively target their risk mitigation efforts or engage with clients to support their transition plans without a detailed understanding of the specific assets or counterparties that are most vulnerable. On the other hand, bottom-up models that encompass the unique risk profiles of individual exposures have the potential to offer more accurate and pertinent insights for guiding portfolio composition and effectively managing climate-related risks in the long run.

Machine Learning for Comparative Model Analysis:

A. Supervised learning to predict bottom-up results from top-down inputs

Supervised learning techniques can be utilized to reconcile the disparity between top-down and bottom-up climate credit risk models to forecast asset-level outcomes based on portfolio-level inputs. The objective is to develop a machine learning model capable of effectively predicting the consequences of a comprehensive bottom-up model by utilizing solely the aggregate risk factors and scenario assumptions accessible to a top-down model. To accomplish this, creating a training dataset that encompasses both the inputs from higher levels and the corresponding outputs from lower levels for a wide range of exposures is necessary. One possible approach is to apply the bottom-up model to a portion of the portfolio or utilize historical data from past risk evaluations. To ensure the model can effectively generalize to new inputs, it is crucial to ensure that the training data encompasses a diverse range of scenarios and risk profiles.

Feature engineering: An analysis of portfolio metrics about underlying factors. Transforming the raw top-down inputs into features that can accurately predict the bottom-up risk measures is crucial in constructing the supervised learning model. The process referred to as feature engineering necessitates a comprehensive comprehension of the fundamental risk factors and their interconnections with the existing portfolio metrics. An illustrative scenario involves utilizing top-down data about the sector composition of a loan portfolio in conjunction with aggregate scenario variables encompassing carbon prices, energy demand, and policy stringency. To establish a connection between these inputs and the underlying factors influencing credit risk, it is possible to compute sector-level averages or distributions of significant financial ratios, such as debt-to-equity, profitability, or asset turnover. Additionally, we can incorporate interaction terms that measure the degree to which each sector is influenced by particular scenario variables, such as the carbon intensity of its activities or the responsiveness of its revenues to changes in energy prices. Feature engineering aims to extract the most pertinent and enlightening signals from the primary data while simultaneously converting them into a format that aligns with the input prerequisites of the secondary model. The process may encompass various methodologies, including normalization, discretization, or dimensionality reduction, contingent upon the characteristics of the data and the particular learning algorithm employed.

Model training and evaluation: After creating the feature matrix, we can utilize a supervised learning model to forecast the initial risk measures based on the inputs from the top down. The selection of an algorithm is contingent upon various factors, including the intricacy of the association between features and targets, the magnitude and caliber of the training data, the comprehensibility of the results, computational effectiveness, and resilience. For instance, linear models such as ordinary least squares or ridge regression are appropriate for analyzing straightforward, linear associations. In contrast, decision trees, random forests, and neural networks can capture non-linear patterns and feature interactions. Cross-validation techniques can be employed to estimate the predictive accuracy outside the sample and quantify the degree of agreement between predicted and actual bottom-up measures to assess the model's performance. This can be achieved using mean squared error, R-squared, or agreement index metrics. It is possible to identify the optimal combination that achieves a harmonious equilibrium between bias and variance by exploring various feature sets, model architectures, and hyperparameter configurations. This combination is crucial for generating stable and reliable predictions across diverse scenarios. The ultimate objective is to construct a model that can faithfully replicate the insights derived from the bottom-up approach while exhibiting enhanced speed and ease of execution on extensive and intricate portfolios.

Unsupervised learning to identify critical drivers of model divergence

Unsupervised learning methodologies have the potential to facilitate the identification of primary factors contributing to the divergence observed between bottom-up and top-down climate credit risk models. This is achieved by exploring patterns and structures within the data without needing predetermined labels or targets. By utilizing clustering algorithms or dimensionality reduction techniques on the inputs and outputs of the model, it becomes possible to reveal latent clusters or dimensions that elucidate the disparities in risk assessments among various methodologies. This analysis has the potential to yield significant insights regarding the origins of model uncertainty and contribute to endeavors aimed at aligning or reconciling the outcomes.

Clustering analysis of bottom-up vs. top-down PD projections: A comparative analysis of clustering techniques for bottom-up and top-down PD projections. Grouping exposures based on their similarity in bottom-up and top-down probability of default (PD) projections can be achieved using clustering algorithms, such as k-means, hierarchical clustering, or DBSCAN. The identification of critical factors that differentiate exposures with high divergence from those with low divergence between the two models can be achieved by comparing the composition and characteristics of the resulting clusters. For instance, it is possible to observe that specific sectors, regions, or risk factors consistently exhibit more significant disparities in PD estimates, indicating that these dimensions are the primary drivers of the overall variations in the model.

Dimensionality reduction techniques (e.g., PCA) Dimensionality reduction: Diffusion techniques, such as Principal Component Analysis (PCA), Dimensionality reduction methods, such as Principal Component Analysis (PCA), t-SNE, or autoencoders, can effectively represent and condense the complex and multi-dimensional domain of model inputs and outputs into a more concise and understandable format. These methods can uncover the underlying factors or gradients that account for the disparities between bottom-up and top-down risk measures by projecting the data onto a lower-dimensional subspace that captures the most significant patterns of variation. As an illustration, using Principal Component Analysis (PCA) on a dataset comprising scenario variables and PD projections may reveal that the initial principal component aligns with a comprehensive transition risk factor. In contrast, the subsequent component encompasses regional disparities in policy stringency or technology adoption.

Case study:

A Top–Down Bottom–Up Modeling Approach to Climate Change Policy Analysis:

The research conducted by Tuladhar et al. (2009) titled "A Top-Down Bottom-Up Modeling Approach to Climate Change Policy Analysis" presents an innovative investigation into the macroeconomic consequences of climate change policies in the United States. This study achieves this by incorporating both top-down and bottom-up modeling methodologies. This hybrid model integrates a comprehensive examination of the electricity sector in the United States, with a particular focus on energy technologies and their potential for reducing emissions. Additionally, it incorporates a more comprehensive economic analysis that considers the effects of climate policies on the country's GDP, employment, and investment throughout the economy. This comprehensive approach enables a detailed evaluation of the interaction between technological capabilities and policy measures in addressing climate change, emphasizing the sector's crucial role in efforts to mitigate the effects.

The research offers valuable perspectives on the cost-effectiveness of different climate policies, such as carbon pricing and renewable energy mandates. This statement highlights the benefits of implementing market-based abatement incentives that integrate adaptation mechanisms, such as emissions trading. The results emphasize the significance of formulating policies that utilize market mechanisms to reduce emissions while effectively minimizing economic disturbances.

The study demonstrates the importance of technological innovation and various measures to address climate targets by analyzing the relationship between technological limitations and policy choices. The comprehensive perspective offered by the integrated model provides valuable insights into the intricate interplay between economic policies and technological advancements. This framework assists policymakers in formulating strategies that promote sustainable economic growth and facilitate effective climate action [1].

Best Practices and Future Research Directions:

Hybrid bottom-up/top-down approaches: There is a growing trend in climate credit risk modeling to adopt hybrid approaches that integrate the detailed and accurate characteristics of bottom-up models with the effectiveness and scalability of top-down methods. Financial institutions can balance accuracy and practicality by employing bottom-up analysis to the most significant or uncertain exposures while utilizing top-down techniques to cover the remaining portfolio. Hybrid methodologies can additionally enable the comparison and evaluation of diverse models, thereby aiding in detecting and resolving any disparities or incongruities.

Incorporating asset-level data in top-down models: An additional avenue for enhancing the precision and pertinence of top-down climate credit risk models involves integrating more detailed, asset-level information about the attributes and susceptibilities of individual exposures. This may entail integrating geospatial data about the geographical location and physical risk characteristics of assets or utilizing machine learning methodologies to group exposures according to their resemblance to financial risk factors. By surpassing the limitations of sector-level aggregation, top-down models can more effectively capture the diversity and unique risks present in portfolios while preserving their computational efficiency.

Leveraging ML for dynamic model updating and monitoring: The continuous evolution of climate risks and the availability of new data necessitate the dynamic updating and monitoring of credit risk models to maintain their accuracy and relevance. Machine learning methodologies can significantly contribute to this procedure by autonomously identifying patterns and anomalies within the data, adjusting model parameters in response to dynamic circumstances, and identifying potential concerns or incongruities for subsequent examination. By continuously using machine learning techniques to validate and enhance their models, financial institutions can guarantee the durability and dependability of their climate risk assessments, even when confronted with unparalleled challenges and uncertainties.

Conclusion:

The incorporation of machine learning techniques in climate credit risk modeling, specifically by employing hybrid bottom-up/top-down methodologies, integrating asset-level data, and dynamically updating models, signifies a notable progression in the domain. These methodologies provide a thorough and subtle comprehension of climate risks, facilitating more precise evaluations and well-informed decision-making. Further investigation is warranted to delve into and enhance these methodologies, guaranteeing that the models possess resilience, scalability, and the ability to adjust to the dynamic characteristics of climate change and its financial ramifications. Implementing these optimal methods is essential to establish robust financial systems that can withstand environmental uncertainties.

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