



Dipartimento di Economia Marco Biagi

DEMB Working Paper Series

N. 244

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September 2024

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ISSN: 2281-440X online











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Abstract

We investigate how the application of advanced predictive models could help investors to assess and manage climate risk in their portfolios, contributing to the development of more sustainable and resilient investment practices. We highlight the possible applications of predictive analytics as a key tool in climate finance. It emerges how emerging technologies (blockchain and Artificial Intelligence) can improve transparency, efficiency, and climate risk analysis in sustainable investments. Further lines of research are highlighted, focusing on how investors and portfolio managers can develop strategies to manage the risks associated with climate events and the integration of climate risks into the management of Supply Chain Finance to ensure greater resilience and sustainability.

Keywords: Climate Risk, Machine Learning, Supply Chain Finance, Blockchain, Predictive Models

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1. Introduction

Climate change significantly impacts the global economy and financial markets, making climate risk and uncertainty central themes in asset pricing. Climate risks include potential economic losses from extreme weather events and gradual changes such as sea level rise. These risks can affect the profitability of companies, the stability of infrastructure and supply chains. The uncertainty associated with climate change arises from the complexity of natural systems and the unpredictability of human responses. Despite advancements in scientific research, unknown variables, such as the speed or intensity of climate change, remain. Overall, climate risk and uncertainty are crucial elements in asset pricing and investment decisions. Environmental sustainability and strategies to mitigate climate risks are essential for ensuring the long-term stability of financial markets and global economies. Predictive analytics is a key tool in climate finance, providing investors with critical information about climaterelated risks and opportunities. Despite challenges related to data quality, model uncertainty, regulatory complexities and the integration of climate-related factors, predictive analytics has the potential to transform and enhance the resilience and sustainability of investment portfolios.

The paper proceeds as follows. Section 2 reviews recent studies based on machine learning techniques that measure financial exposure to climate risks, which are understood as physical risks (extreme weather events such as floods and hurricanes) and transition risks (legislative changes and shifts in investment preferences). Section 3 suggests new directions for future research, based on machine learning methods. Section 4 is devoted to supply chain finance. The last section concludes.

2. Machine learning approaches to climate risk, uncertainty and financial dynamics of related assets.

Climate finance is a growing field in the literature, using machine learning (ML) to analyze climate-related information and model complex relationships.

Athey and Imbens (2019) evidence that the traditional approach in econometrics involves specifying a target, or estimand, which is a functional of a joint distribution of the data. This target is often a parameter of a statistical model that describes the distribution of a set of variables, typically conditional on some other variables, using a finite or infinite set of parameters. Given a random sample from the population of interest, the parameter of interest and the nuisance parameters are estimated by identifying the parameter values that best fit the full sample, utilizing an objective function such as the sum of squared errors or the likelihood function. The emphasis is on the quality of the estimators of the target, traditionally assessed through large sample efficiency, and there is often interest in constructing confidence intervals. Researchers generally report point estimates and standard errors. On the other hand, machine learning (ML) literature primarily focuses on developing algorithms. The primary goal of these algorithms is typically to make predictions about certain variables given others or to classify units based on limited information, such as classifying handwritten digits based on pixel values.

Alonso et al. (2023) review the academic literature to assess how machine learning is enabling the growth of climate finance. They identify seven granular areas where machine learning plays a significant role in the climate finance literature: natural hazards, biodiversity, agricultural risk, carbon markets, energy economics, ESG factors, and climate investing and data. The paper also analyzes publishing trends and applied ML methods by research area.

Predictive analytics is a crucial tool in climate finance, as it provides investors with valuable insights into climate-related risks and opportunities. It helps anticipate and mitigate risks, such as extreme weather events and sea level rise, and identifies emerging opportunities in sustainable sectors such as renewable energy and clean technologies. However, challenges such as data quality, model uncertainty, regulatory complexities, and the integration of climate-related factors require interdisciplinary collaboration, robust risk assessment frameworks, and continuous innovation. Despite these challenges, predictive analytics has transformative potential in improving the resilience and sustainability of the investment portfolio, contributing to a low-carbon economy. Assessing financial exposure to climate change is complex due to the various impacts on businesses, including damage to physical resources and operational shifts towards low-carbon economies. Changing social attitudes and technological developments complicate these influences, making business disclosure texts valuable resources (Ofodile et al., 2024).

Hu et al. (2022) use context-sensitive machine learning techniques (LDA, word2vec, and FinBERT) to classify climate-related sentences, improving the objectivity and interpretability of enterprise-wide climate change exposure measures. It differentiates risks, mitigation strategies, and physical exposures, revealing unique economic implications and reducing human bias.

Jabeur et al. (2021) use advanced ML techniques to predict oil prices during the Covid-19 pandemic, focusing on green energy resources, global environmental indices, and stock markets. The research uses a large data set and SHapely Additive exPlanations (SHAP) values for model analysis. The results show that high GER and ESG values lead to lower crude oil prices, promoting climate change mitigation and economic prosperity through green energy resources.

Rubtsov and Shen (2024) examine the impact of the investment horizon on the optimal equity-bond-liquid portfolio in a dynamic model with climate change uncertainty. The equity risk premium is assumed to be an affine function of the global mean temperature and an unobserved factor estimated by Bayesian learning. The optimal investment strategy was found to be sensitive to climate uncertainty, with potentially significant welfare losses.

The impacts of climate change and water availability on corporate operational performance pose significant risks to investors, shareholders, and capital

markets. The Task Force on Climate-Related Disclosures (TCFD) obliges companies to disclose their exposures to financial risks, with the aim of incentivizing investments in climate resilience through the management of natural resources. Tian (2023) develops quantitative approaches to understand the financial relevance of water risk for corporate accounting and market performance. Indicators such as water intensity relative to turnover, operating profit and net fixed assets were assessed for companies representing nine industry sectors. It has shown that low water intensity results in better returns than the benchmark, return on equity and long-term valuation. An imputation methodology was developed that combines econometric models and machine learning techniques to predict water intensity parameters for companies that do not disclose water use risks. The results show that markets are rewarding waterintensive companies with higher yields, although the effect is attenuated after the implementation of TCFD.

Mohsin and Jamaani (2023) present a new method for estimating crude oil prices based on socio-political and economic factors in the context of green finance. They use the LASSO (Least Absolute Shrinkage and Selection Operator) model, evaluating six factors and green finance. The model outperforms other models and provides insights into the temporal association between socio-political factors, green finance, and crude oil. The study finds that global steel production, the Kilian index, the green finance index, the value of the dollar, and terrorist attacks are important drivers of demand.

Yu et al. (2022) study ML models for predicting the credit rating of eco-friendly companies. They use 355 Eurozone companies ranked by climate change score from 2010 to 2019. The results show that classification and regression trees have the highest accuracy for credit rating predictions, even in investment grade or predefined categories. A set of random forests can also be used to predict predefined assessments. These findings are crucial for assessing the credit risk of pro-green firms.

The financial sector is incorporating sustainability into risk assessment models, using machine learning concepts to predict the likelihood of default. Sufian and Levesley (2023) use regression and classification models, including Linear Regression, Decision Tree Regression, Support Vector Regression, Logistic Regression, Random Forest, Decision Tree Classifier, XGBoost Classifier, and Bagging Classifier. Label encoding converts categorical characteristics to numeric ones. The XGBoost classifier performs best in identifying defaulting companies, while the decision tree regressor predicts defaults. The authors explore the impact of machine learning on investment decisions, the potential benefits, limitations, and role in identifying sustainability-related risks and opportunities for sustainable growth.

Machine learning literature focus also on analysing text data. Text analysis (TA) is the process of transforming unstructured text into a structured format to identify meaningful patterns and new insights (Blei et al. (2003), Gentzkow et al. (2019)). The main advantage of this approach is the possibility to evaluate

the existence of climate risk premium for physical and transition risks, jointly. The first paper in this stream of literature is Engle et al. (2020). Focusing on the United States, they create an index based on climate news from The Wall Street Journal (WSJ) and another from Crimson Hexagon (CH), which gathers a vast corpus of news articles and social media posts, filtering for climate change relevance. They use E scores (from both MSCI and Sustainalytics) to measure each firm's climate risk exposure and construct a hedge portfolio for innovations in climate news.

3. Machine Learning and Climate Finance: Towards a New Era of Risk Analysis and Forecasting

We see that collaboration across disciplines, such as economics, environmental science, and data science, improves understanding of climate risks and sustainable investment opportunities. Therefore, starting from the vast body of literature concerning climate risk, uncertainty, and the financial dynamics of related assets, we propose possible lines of theoretical research to be developed in the future. We note, at least to the best of our knowledge, that based on the above information, a possible specific and not widely explored area of research could be the integration of machine learning models for assessing climate risk exposure into real-time investment portfolios. We observe, to the best of our knowledge, that a potentially particular and underexplored research field may involve the use of machine learning models for evaluating climate risk exposure inside real-time investment portfolios. This research can concentrate on gathering real-time data from diverse sources, such as climatic, financial, and business information, to achieve a more precise understanding of climate risk exposure in investment portfolios.

The application of machine learning techniques (neural networks, decision trees, or ensemble models) to develop advanced predictive models helps assess the climate risk exposure of investment portfolios. This line of research could offer valuable insights for investors, allowing them to better assess and manage climate risk exposure in their portfolios in real-time. It could also contribute to the development of more sustainable and resilient investment practices.

An alternative avenue for research could explore the interplay between climate change and financial resilience.

The idea is to study how extreme weather events and uncertainty affect the financial resilience of institutions and investment portfolios. A particular focus could be on how investors and portfolio managers can develop strategies to manage the risks associated with such events and then examine the role of portfolio diversification in mitigating the impact of these risks. The use of ML and Deep Learning techniques to predict climate change risks and their influence on companies' financial performance represents a new area of research that can be discussed. Such techniques can improve risk mitigation strategies, such as the adoption of clean technologies or sustainable practices. In fact,

company-level climate risk assessment investigates the impact of climate change on companies' business models, particularly in carbon-intensive sectors, and analyzes how companies can adapt their operational strategies to mitigate climate risk and improve sustainability.

Climate finance is a fast-growing industry that combines the world of finance with environmental sustainability goals. In this context, innovation plays a crucial role in opening new avenues to finance green projects and support the transition to a low-carbon economy. In addition, climate finance and innovation explore how new financial instruments (e.g. green bonds or ESG funds) can contribute to the transition to a low-carbon economy. In particular, the role of emerging technologies (Blockchain, Fintech and Artificial Intelligence Algorithms) in climate finance could be studied. Blockchain offers transparency and traceability in financial transactions, making it particularly useful for tracking the use of funds intended for green projects. For example, it can ensure that funds raised through green bonds are used for the stated purposes. While Fintech tools and Artificial Intelligence algorithms can accelerate the analysis of climate risks and ESG data, helping investors make more informed decisions and better manage their portfolios. Therefore, the aim is to examine the role of these technologies in climate finance and investigate how these technologies are improving transparency and efficiency in the management of sustainable investments? And what are the possible associated risks? To answer these questions, one can examine how blockchain is being used for the traceability of carbon transactions or how Artificial Intelligence is improving efficiency in the management of sustainable investments. Conducting interviews with industry experts, such as consultants, researchers, business executives, and regulators, can help gain insights into current trends and challenges related to the use of blockchain and Artificial Intelligence in climate finance.

4. Supply Chain Finance a new frontier of investigation

In correlation with climate finance and the use of emerging technologies such as blockchain and Artificial Intelligence, Supply Chain Finance (SCF) can play an important role in promoting more sustainable and responsible practices along the supply chain. In fact, SCF is a set of financial solutions that optimize the flow of capital along the supply chain, from the supplier to the end customer. It offers the opportunity to integrate sustainability practices along the supply chain using emerging technologies. This can lead to improved transparency, efficiency, and risk management, contributing to the transition to a low-carbon economy. Therefore, the use of blockchain in SCF allows for greater transparency and traceability of transactions along the supply chain. This allows companies to verify the origin of products, monitor carbon emissions, and ensure that suppliers comply with environmental and social standards. Artificial Intelligence can be used to optimize SCF processes such as payment management, demand forecasting, and data analysis to identify opportunities for improvement. This can lead to increased efficiency and reduced waste. In addition, the SCF can be used to incentivize suppliers to adopt sustainable practices by offering them more favorable financing terms in exchange for environmental and social commitments. For example, suppliers who reduce carbon emissions or use recycled materials may benefit from lower interest rates. Emerging technologies can help identify and mitigate risks along the supply chain, such as environmental or social risks associated with suppliers. This can help businesses maintain continuity of operations and protect their reputation. Blockchain-based SCF can facilitate collaboration between different parties in the supply chain, such as suppliers, manufacturers, and lenders. This can lead to increased information sharing and a better understanding of common needs and goals. One possible analysis, in our view, is the integration of climate risks into the management of the SCF. This involves analyzing how climate risks can be integrated into SCF management models to ensure greater resilience and sustainability.

How can companies use emerging technologies to monitor and mitigate climate risks across the supply chain? What innovative approaches can be taken to optimize financial management in conditions of climate uncertainty? To answer these questions, we believe it is useful to analyze how the integration of climate risks into SCF management models affects environmental sustainability and the valuation of financial assets, and to propose solutions to optimize the resilience and sustainability of supply chains. We also ask how the integration of climate risks into SCF management models improves the resilience and environmental sustainability of supply chain? What is the impact of ESG adoption on the valuation of financial assets along the supply chain? What innovative strategies can be adopted to optimize the financial management of supply chains under conditions of climate uncertainty? Therefore, it is crucial to understand the role of climate risks in SCF and their impact on environmental sustainability and the valuation of financial assets, but at the same time, it is crucial to identify innovative strategies and solutions to optimize the financial management of supply chains in conditions of climate uncertainty. Providing recommendations for companies interested in improving the resilience and sustainability of their supply chains through effective climate risk management is another aspect to focus on. Therefore, this line of research could help provide new perspectives on the financial management of supply chain in relation to climate risks, helping companies become more resilient and sustainable.

5. Conclusions

We have proposed several lines of future research, including the integration of machine learning models to assess climate risk exposure in investment portfolios in real-time. Highlighting how the use of real-time data and machine learning and deep learning techniques can help develop advanced predictive models to manage climate risk exposure and improve investment strategies. Emerging technologies such as blockchain and artificial intelligence are seen as promising for improving transparency, efficiency, and climate risk analysis in

sustainable investing. It highlights the importance of understanding the role of these technologies in climate finance and investigating the possible associated risks. In fact, we have highlighted how the role of Supply Chain Finance (SCF) is crucial in promoting more sustainable and responsible practices along the supply chain, in relation to climate finance and emerging technologies such as blockchain and artificial intelligence. This improves transparency, efficiency, and risk management, contributing to the transition to a low-carbon economy. Therefore, we have highlighted how the integration of climate risks into the management of the SCF improves the resilience and sustainability of supply chains. Emerging technologies can help monitor and mitigate climate risks along the supply chain, facilitating collaboration between different parties and contributing to environmental sustainability and the valuation of financial assets. This line of research can lead to new perspectives on the financial management of supply chains, helping companies become more resilient and sustainable in conditions of climate uncertainty.









Funding

This work was funded by European Union under the NextGeneration EU Programme within the Plan "PNRR - Missione 4 "Istruzione e Ricerca" - Componente C2 Investimento 1.1 "Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale (PRIN)" by the Italian Ministry of University and Research (MUR), Project title: "Climate risk and uncertainty: environmental sustainability and asset pricing". Project code "P20225MJW8" (CUP: E53D23016470001), MUR D.D. financing decree n. 1409 of 14/09/2022.

The work was supported also by the University of Modena and Reggio Emilia for the FAR2022 project.

Conflict of interest

The authors declare that they have no conflict of interest.

Availability of data and materials

Not applicable

Code availability

Not applicable

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