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Firm-level climate change risk and adoption of ESG practices: a machine learning prediction

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Abstract

Purpose – By combining the notion of prospect theory with advanced machine learning algorithms, this study aims to predict whether financial institutions (FIs) adopt a reactive stance when they perceive climate change as a risk, consequently leading to the adoption of environmental, social and governance (ESG) practices to avoid this risk. Prospect theory assumes that decision-makers react quickly when decisions are framed as a risk or threat rather than as an opportunity.

Design/methodology/approach – We used a sample of 168 FIs across 27 countries and seven regions over the period 2003–2020. To conduct our empirical investigation, we compared the prediction accuracy of various machine learning algorithms.

Findings – Our findings suggest that out of 12 machine learning algorithms, AdaBoost, Gradient Boosting and XGBoost have the most precision in predicting whether FIs react to climate change risk in adopting ESG practices. This study also tested the overall climate change risk and risks associated with physical, opportunity and regulatory shocks of climate change. We observed that risks associated with physical and regulatory shocks significantly impact the adoption of ESG practices, supporting prospect theory predictions.

Practical implications – The insights of this study provide important implications for policymakers. Specifically, policymakers must take into account the risk posed by climate change in the corporate decision-making process, as it directly influences a firm's adoption of corporate actions (ESG practices).

Originality/value – To the best of our knowledge, this is the first study to investigate the firm-level climate change risk and adoption of ESG practices from a prospect theory perspective using novel machine learning algorithms.

Keywords Adoption of ESG practices, Climate change risk, Machine learning algorithms, Prospect theory

Paper type Research paper

1. Introduction

The extent to which a firm's corporate actions combat climate change-related issues has received increasing attention among practitioners and academicians. The core corporate action in this arena is often referred to as environmental, social and governance (hereafter, ESG) practices. According to the International Finance Corporation (June 2004), the acronym ESG was introduced in the year 2004 by 20 financial institutions following a call from Kofi Annan, the Secretary General of the United Nations. ESG is defined as "how corporations and investors integrate environmental, social, and governance concerns into their business models" (Gillan *et al.*, 2021, p. 2).

In recent decades, climate change has emerged as a significant social and financial concern, as evidenced by prevailing regulatory reforms driven by various groups of stakeholders (Haque, 2017). Climate change not only causes a substantial risk for human health and societal and economic advancement but also for the growth of businesses (Boubaker *et al.*, 2024; Kong *et al.*, 2022). Thus, it is imperative for companies to devise business strategies that harmonize economic efficiency and sustainable development goals

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while striving for profit maximization as well as actively integrating ESG practices (Rojo-Suárez and Alonso-Conde, 2023; Yin *et al.*, 2023). ESG involves the incorporation of environmental, social and corporate governance factors into financial and operational decision-making processes (Ziolo and Spoz, 2022; Yu and Van Luu, 2021; Esch *et al.*, 2019). These practices also provide an important framework for companies to monitor and regulate their performance and serve as a critical gauge for investors assessing a firm's dedication to sustainable development (Fu *et al.*, 2024). In addition, policymakers and investors are increasingly integrating ESG considerations into regulatory frameworks and investment choices, recognizing their vital role in managing firm risks and determining valuation (Li *et al.*, 2023a, b; Zhang and Lucey, 2022).

As evidenced by the recent Global Sustainable Investment Alliance [1] report, ESG investment in major financial markets worldwide reached approximately $30.3tn in 2023. Consequently, an escalating number of firms are publishing ESG reports and embedding ESG elements into their day-to-day operations. There is an increasing onus on firms to enhance their environmental strategies, leading them to give greater priority to their climate change strategy within their overall business strategy (Lewandowski, 2017). Moreover, institutional investors and other stakeholders are showing a remarkable surge of interest in firm risks associated with climate change, including regulatory and market influences (Matsumura *et al.*, 2014). This mounting pressure is compelling corporate managers to give priority to assessing and combating such risks and the corresponding opportunities (Alsaifi *et al.*, 2022). Climate change risk, also referred to as carbon risk, is a component of the overall financial risk and is defined as "any corporate risk associated with climate change or the utilization of fossil fuels" (Hoffmann and Busch, 2008, p. 514). Moreover, Sautner *et al.* (2023) further categorized the climate change risk at the firm level and documented that climate change risk is associated with opportunity, physical and regulatory shocks related to climate change.

By integrating the notion of prospect theory with advanced machine learning algorithms, this paper seeks to predict the extent to which financial institutions (FIs) respond to the risks associated with climate change by implementing ESG practices. Particularly, this paper attempts to answer two important research questions. First, do FIs respond to climate change risk by adopting ESG practices? Prospect theory posits that decision-makers tend to respond more promptly when choices are framed in terms of potential risks or threats rather than opportunities (Cantarella *et al.*, 2023). We anticipate that FIs tend to adopt a reactive stance (characterised by risk-averse behaviour) when they perceive climate change as a threat. This perception, in turn, shapes their corporate actions, particularly the adoption of ESG practices to avoid such risk. In other words, if decision-makers choose not to adopt ESG practices, there could be a potential loss from such inaction, and individuals generally tend to avoid losses. Therefore, the loss-aversion effect among decision-makers could also contribute to the intention to adopt ESG practices.

Second, do FIs react differently to climate change risks related to opportunity, physical and regulatory shocks? To answer this question is also important because, as suggested by Elijido-Ten and Clarkson (2019), countering to the exposures and opportunities related to climate change represents a moral challenge for firms. Elijido-Ten and Clarkson (2019) further documented that in the past, firms could simply externalize the costs of their carbon emissions; however, evolving societal norms and stakeholder expectations have propelled climate change to a pivotal position within a firm's business strategy. The increasing corporate focus on climate change stems from the recognition that while firms have an economic obligation to generate profits, they also have the legal and ethical responsibilities to comply with laws and societal norms (Harjoto *et al.*, 2015; Eberlein and Matten, 2009). To the best of our knowledge, this is the first study that uses the prospect theory lens to explain the link between climate change risk and the adoption of a firm's ESG practices by employing modern machine learning algorithms.

This paper contributes to the literature in two ways. First, this paper uses a prospect theory lens to further understand the topical corporate governance issue of a firm's adoption of ESG practices as a reactive or proactive business strategy. Hence, this paper extends the existing work contributing to the growing literature on the climate change risk-corporate governance nexus (Huang and Lin, 2022; Mbanyele and Muchenje, 2022; Ozkan *et al.*, 2022; Gillan *et al.*, 2021; Elijido-Ten and Clarkson, 2019; Elijido-Ten, 2017, among others). Second, existing studies on ESG practices have predominantly used classical models. For instance, the ordinary least square regression model (Nirino *et al.*, 2021; Shakil, 2021; He *et al.*, 2023; Shaddady and Alnori, 2024), the generalized method of moments approach (Taddeo *et al.*, 2024; Galletta *et al.*, 2023; Chen and Xie, 2022; Azmi *et al.*, 2021), and probit model (Abudy *et al.*, 2023), among others. However, this paper employs advanced machine learning algorithms to make valuable predictions about corporate actions (ESG practices) under uncertainty and risk situations. Since our dependent variable is dichotomous (adoption of ESG practices), classical regression-based models such as the logistic regression model fail to address the classification problem (De Caigny *et al.*, 2018; Wang *et al.*, 2018). Another potential drawback of classical models is their limited ability to capture out-of-sample properties through in-sample static estimates. However, machine learning algorithms combine the power of tuning functional forms and implementing robust protection against overfitting, such as regularisation and cross-validation (Choudhury *et al.*, 2021; Abu-Mostafa *et al.*, 2012), in order to improve prediction accuracy. In other words, the robustness of machine learning models has enabled algorithms to conduct thorough model searches and identify optimal functional forms for predictions that demonstrate superior performance in out-of-sample scenarios. Machine learning models have the ability to unveil intricate yet interpretable patterns in data, surpassing the current limits of human imagination and intuition, in a reliable and replicable manner (Choudhury *et al.*, 2021; Shrestha *et al.*, 2021). Once these relationships are identified, researchers can then develop inductive theorizing, aiming to generate an intuitive understanding and interpretation of the results. Moreover, such theories are more likely to align with empirical evidence observed in other samples (Thompson and Buertey, 2023).

The rest of the study is organised in the following manner. Section 2 provides the theory and review of recent literature. Section 3 provides the data, choice of machine learning algorithms, and the empirical strategy. Section 4 reports the empirical results. Section 5 provides the discussion of the results and finally, section 6 concludes.

2. Theoretical background and hypotheses development

2.1 Prospect theory

Uncertainty and risk play significant roles in nearly all decision-making within business contexts, including, for instance, the choice to adopt ESG practices. Prospect theory, a well-supported model of decision-making, elucidates how individuals, such as decision-makers and top management teams, make choices and decisions amidst uncertainty. Prospect theory, proposed by psychologists Kahneman and Tversky (1979), continues to be widely employed for understanding decision-making processes. One key insight of prospect theory is that individuals' risk preferences are influenced by whether they perceive potential outcomes as losses or gains. As outlined by Barberis *et al.* (2021), prospect theory suggests that individuals assess outcomes by considering changes perceived as either "gains" or "losses" from a specific reference point rather than focusing on total value. Additionally, prospect theory posits that individuals are more responsive to losses compared to equivalent gains. Consequently, they tend to consider the impact of losses more than equivalent gains, prioritizing the avoidance of losses over the pursuit of gains, a phenomenon known as "loss aversion" (Tversky and Kahneman, 1992). For instance, most individuals perceive it as preferable not to lose money rather than to gain the same amount (Chen *et al.*, 2024a, b; Piancharoenwong and Badir, 2024; Ogunmokun *et al.*, 2023).

Existing research studies suggest that losses have approximately twice the psychological impact of gains, indicating that individuals place higher value on possessions they already have compared to equivalent possessions they do not possess (Giannikos *et al.*, 2023; Li *et al.*, 2023a, b; Hastie and Dawes, 2009). Numerous empirical studies have confirmed the existence of this phenomenon of loss aversion (Sanders *et al.*, 2021; Zhang *et al.*, 2021; Gal and Rucker, 2018; Xie *et al.*, 2018). Furthermore, individuals tend to approach gains and losses differently. While they exhibit risk aversion with gains, they become risk-seeking with losses. In simpler terms, when dealing with gains, people tend to avoid risks in decision-making; however, when dealing with losses, they tend to take risks (Lin *et al.*, 2024). This differing response to gains and losses underscores the significant influence of how outcomes are framed in terms of a positive or negative connotation from a particular reference point, a phenomenon described in prospect theory as the "framing effect" (Takemura and Takemura, 2021; Okder, 2012; Tversky and Kahneman, 1981).

2.2 Hypotheses development

Drawing on the prospect theory (Kahneman and Tversky, 1979) and recognizing the importance of climate change risk, our paper contributes to the debate by exploring whether firms frame their corporate actions, such as ESG practices, based on climate change risk. Prospect theory suggests that decision-makers react quickly when decisions are framed as a risk or threat rather than as an opportunity (Kahneman and Tversky, 1979, 2000). While prospect theory was developed to explain how individual investors frame their decisions under uncertainty, it has also been subsequently applied to decision-making at the firm level (Bahadar *et al.*, 2022; Chen *et al.*, 2018; Elijido-Ten, 2017).

This paper extends the latter stream of research that uses prospect theory to examine the framing of corporate strategic decisions at the firm level. We argue that firms take a reactive position (risk-averse behaviour) when they perceive climate change as a threat, which, in turn, frames their corporate actions (ESG practices) to combat such risks. In this regard, there is a growing stakeholder expectation for businesses to adopt socially responsible practices, particularly concerning the detrimental impacts that firms can have on the environment. These effects possess the potential to damage a firm's reputation and, in extreme cases, lead to the revocation of its operating license (Zaman *et al.*, 2022). As a result, risk-averse firms typically prioritize safeguarding their corporate reputation and tend to opt for corporate strategies that address environmental concerns arising from their business operations (Bahadar *et al.*, 2022).

Recently, Ozkan *et al.* (2022) examined the impact of climate change risk on firm performance and the moderating role of corporate social responsibility. They found that firms operating in countries with increased climate risk are associated with higher levels of corporate social responsibility initiatives. Their finding potentially implies that firms react to climate risks by actively participating in more corporate social responsibility activities. Elijido-Ten (2017) investigated the recognition of risks related to climate change for the sustainable performance of the world's largest 500 firms under the prospect theory perspective. They found that recognition of climate change as a risk is significant and adversely impacts sustainability performance, thereby aligning with the predictions of prospect theory. In the same research stream, Huang and Lin (2022) explored whether climate change risk beliefs shape a firm's corporate social responsibility-related decisions. They found a significant and positive association between climate change risk and corporate social responsibility initiatives. Likewise, Hossain and Masum (2022) explored the resilience of corporate social responsibility activities towards climate change risk for a large sample of US firms over the period of 2002–2018. They noted that corporate social responsibility activities play a buffering role against climate change risk. Based on these studies, this paper conjectures that:

H0. There is no impact of climate change risk on financial institution's adoption of ESG practices.

H1. Climate change risk significantly influences the financial institution's adoption of ESG practices.

3. Data, machine learning algorithms and empirical strategy

3.1 Data and choice of sample

The ESG practices, also known as the Equator Principles (EP), are a set of environmental and social principles that offer a risk management structure for banks (financial institutions) involved in financing large-scale infrastructure and industrial investment projects. The establishment of the EP took place on the 4th of June 2003, as a private initiative within the financial sector, aiming to foster global collaboration in promoting environmental responsibility. On its inception, eight financial institutions from developed countries signed the EP's membership and recently, 138 financial institutions from 38 countries are members of the Equator Principles [2].

We used the following selection criteria for the choice of our sample. Initially all 138 financial institutions (henceforth, FIs) from 38 countries adopting ESG practices were considered in the sample. In the next step, we manually matched the FIs adopting ESG practices with the climate change risk database using International Securities Identification Numbering system (ISINs) provided by Sautner *et al.* (2023) [3]. By matching FIs from both databases, a sample of 94 FIs were selected. Moreover, FIs from the same countries were also taken that do not adopting the ESG practices. Our final sample contained 168 FIs from 27 countries across seven regions over the period of 2003–2020.

The target variable was adoption of ESG practices; we used a binary variable for adoption of ESG practices that takes value 1 if the financial institution adopted the ESG practices and 0 otherwise. The features information we used includes the firm-level climate change risk and different components of firm-level climate change risk. These selected features were measured in the following manner: Overall firm-level climate change *risk* (*cc_risk_ew*) variable was adopted from Sautner *et al.* (2023), who recently developed a firm-level time-varying measure of climate change risk using social media data on earnings conference calls for selected firms. Specifically, Sautner *et al.* (2023) used the following formula to compute the climate change risk:

$$cc\_risk\_ew_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} (1[b \in C]) \tag{1}$$

where $b = 0, 1, \ldots, B_{it}$ are bigrams in the earning call transcripts of firm i in the year t and $1[.]$ is the indicator function. Overall firm-level climate change *risk* is a relative frequency with which bigrams are associated with climate change based on the word "risk" or "uncertainty" on social media earnings conference calls. We also considered overall firm-level climate change *exposure* (*cc_expo_ew*), a relative frequency with which bigrams associated with climate change on earnings conference calls, and overall firm-level climate change *sentiment* (*cc_sent_ew*), a relative frequency with which bigrams associated to climate change based on the negative or positive tone words on social media regarding earnings conference calls. Sautner *et al.* (2023) further categorized climate change risk into three categories: physical, regulatory and opportunity components. Physical *risk* (*ph_risk_ew*) and *exposure* (*ph_expo_ew*) are variables that capture physical shocks for firms related to climate change. Regulatory *risk* (*rg_risk_ew*) and *exposure* (*rg_expo_ew*) are variables that capture regulatory shocks for firms related to climate change. Finally, opportunity *exposure* (*op_expo_ew*) is a variable that captures opportunities for firms related to climate change.

3.2 Machine learning algorithms for classification issue

Since our target variable was binary (dichotomous), hence this study addressed the classification issue in the case of firms adopting ESG practices. Existing studies have extensively used machine learning models to address the classification issue in the discipline of business and management (Thompson and Buertey, 2023; Lin *et al.*, 2022; Yu *et al.*, 2022; Pang *et al.*, 2021; Zhu *et al.*, 2019; Tsai *et al.*, 2014, among others). Classification is a machine learning approach used for predicting the class or category applicable to the data. Like any other machine learning algorithm, the accuracy of a classification model depends a lot on the quality of the data. Any unwanted measurement noise or uncertainties within data can jeopardize the prediction power of even a robust classification algorithm. Until the advancement of computational powers, traditional classification models such as decision tree, logistic regression, etc. were more popular. However, in recent years, the ensemble approach and deep neural network have occupied the centre stage while dealing with a typical classification problem. A deep neural network, though it offers a more robust prediction capability, is often underused because of the lack of sufficient data samples corresponding to the given domain. To avoid model overfitting and reliable prediction, the ratio of the size of training and testing data is very important. For a fair training, we first trained the models on a training set (80% of the sample), and the remaining observations (20% of the sample) were used as the test set.

Machine learning models have proven their utility in the domain of management and finance literature (Gan *et al.*, 2020) and, specifically, for default risk (Pang *et al.*, 2021; Li *et al.*, 2020; Zhu *et al.*, 2019; Tsai *et al.*, 2014), credit ratings (Chen *et al.*, 2024a, b; Sharma *et al.*, 2024; Yu *et al.*, 2022), corporate social responsibility assurance (Thompson and Buertey, 2023), business intelligence (Hamzehi and Hosseini, 2022), supply chain management and business process (Lin *et al.*, 2022; Mehdiyev *et al.*, 2020), among others. This study involved altogether twelve classification algorithms. Table 1 outlines the main attributes of these machine learning models [4]. However, the best three algorithms, namely, the Adaptive Boosting (AdaBoost) algorithm, the Gradient Boosting algorithm and the Extreme Gradient Boosting (XGBoost) algorithm, were finally chosen based on their accuracy measures.

3.3 Empirical strategy

This study is primarily based on data-driven classification algorithms. However, the selection of the most optimal classification algorithm is often the trickiest step in such kinds of problems. Therefore, the design of the empirical strategy considers all the basic elements of data pre-processing along with a rigorous mechanism to figure out the best-performing classification algorithms on the given data. The major steps are as follows:

Step 1: Performing exploratory data analysis (EDA) to reveal some important features from the data which otherwise would be nearly impossible.

Algorithm	Characteristics
Adaptive Boosting (AdaBoost)	• AdaBoost classifier is a meta-estimator which first fits a classifier on the original dataset, then fits additional copies of the classifier on the same dataset by adjusting the weights of instances that are not correctly classified • AdaBoost is considered as a robust algorithm when it comes to working with data containing missing values
Bagging classifier	• Bagging is a sort of ensemble learning which involves training several base models concurrently and independently on various subsets of the training data • The bagger classifier frequently performs better than a single classifier because it decreases overfitting and boosts predictive accuracy. It can more effectively generalise to unknown data by integrating various base models • Bagging aggregates predictions from several models to minimise the effect of noise and outliers in the data. This improves the model's robustness
Bernoulli Naïve Bayes (BNB)	• BNB belongs to the family of Naïve Bayes classifier family • It works well with data distributed using multivariate Bernoulli distributions, meaning that even though a feature may have several values, each one is taken to be a binary variable • The use cases of BNB could be, spam detection, credit card fraud detection etc.
Decision tree (DT)	• DT models are easy to visualise and hence easy to implement and interpret. • DT works with both numerical and categorical data • The data preparation steps are simpler compared to many other classification algorithms • Chances of overfitting are high by creating very complex trees incapable of generalising the data satisfactorily
Gaussian Naïve Bayes (GNB)	• GNB is based on probabilistic framework and Gaussian Distribution • GNB predicts the probability of a dependent variable in each class • An assumption that variables are distributed according to Gaussian distribution sometimes acts as major limitation in realistic classification problems
Gradient Boosting	• Gradient Boosting is a generalisation of boosting to arbitrary differentiable loss functions • Gradient Boosting is typically a better option for small sample numbers, as binning could produce split points that are too close together
K-nearest neighbour classifier (KNN)	• Neighbours-based classification simply maintains instances of the training data rather than attempting to build an internal model • The closest neighbours of each point vote with a simple majority to determine the classification • K neighbours Classifier applies learning based on each query point's closest neighbours, where K is an integer number that the user specifies • The optimal value for K depends largely on the available data. Greater K often reduces the impact of noise however it causes the weakening of classification boundaries
Logistic regression	• Logistic regression is very simple to implement as well as interpret • A logistic function is used to model the probability describing the probable outcomes of a single trial • It can easily be extended to multiple classes • It assumes a linear relation between dependent and independent variables which limits its applications in real-world classification problems

(*continued*)

Table 1. Characteristics of various machine learning classification algorithms

Algorithm	Characteristics
Quadratic discriminant analysis (QDA)	• QDA involves quadratic decision surface • It generates closed-form solutions which are easy to compute • QDA works well with multiclass • There are no hyperparameters to tune in QDA
Random Forest	• Every tree in an ensemble in a random forest is constructed using a sample taken with replacement from the training set • Random Forest is robust against noisy data since it aggregates the predictions from multiple decision trees • Random Forest reduces the variation that comes with individual trees, leading to more accurate predictions by voting on the associated trees' forecasts
Stochastic gradient descent (SGD)	• SGD belongs to the family of optimisation techniques • SGD fits linear classifiers with a convex loss function • SGD is popular in text classification and natural language processing • SGD requires some hyperparameters. Such as for regularisation and iterations • SGD can be sensitive to feature scaling
Extreme gradient boosting (XGBoost)	• XGBoost is an ensemble approach that enhances prediction accuracy by combining several decision trees • XGBoost is made to operate quickly and effectively, even with big datasets • Regularisation techniques are included in XGBoost to help prevent overfitting • Memory usage with XGBoost can be high, particularly with large datasets • XGBoost lacks the transparency making it difficult to analyse the prediction process

Table 1. **Source(s):** Authors' computations

Step 2: Splitting the given data into parts – training set and testing set. The models were trained using the training set and the testing set was used to test the accuracy of the various candidate models.

Step 3: Altogether 12 classification models were trained and subsequently ranked based on their accuracy measures.

Step 4: Until step number 3, all the eight variables enlisted in Table 2 were employed in modelling.

Step 5: The top three performing classification models were trained on an incremental basis; starting with one variable then adding one more variable and so on. This step allows assessing the respective contributions of each variable in predicting the correct label.

4. Results

4.1 Exploratory data analysis

In data science and statistics, the EDA method is used to investigate and summarise data sets (e.g. Indrakumari *et al.*, 2020; Song and Zhu, 2016). EDA is also used in business and management literature in the context of inductive research (Kazemi *et al.*, 2019; Jebb *et al.*, 2017; Flood *et al.*, 2016), among others. EDA, as the name suggests, is more like acquaintance with the data with the help of suitable plots, maps, charts, etc. Often, EDA helps to detect the

Table 2. Summary statistics

	Count	Mean	Std	Min	25%	50%	75%	Max
ESG practices	2,252	0.501391	0.476450	0.000000	0.000000	0.000000	1.000000	1.000000
cc_expo_ew	2,252	0.000834	0.002278	0.000000	0.000089	0.000261	0.000652	0.034995
cc_risk_ew	2,252	0.000041	0.000156	0.000000	0.000000	0.000000	0.000000	0.003890
cc_sent_ew	2,252	0.000151	0.000579	−0.002871	0.000000	0.000000	0.000152	0.006744
op_expo_ew	2,252	0.000002	0.000019	0.000000	0.000000	0.000000	0.000000	0.000443
ph_expo_ew	2,252	0.000011	0.000095	0.000000	0.000000	0.000000	0.000000	0.002090
ph_risk_ew	2,252	0.000001	0.000019	0.000000	0.000000	0.000000	0.000000	0.000678
rg_expo_ew	2,252	0.000045	0.000280	0.000000	0.000000	0.000000	0.000000	0.009129
rg_risk_ew	2,252	0.000009	0.000088	−0.000577	0.000000	0.000000	0.000000	0.001613

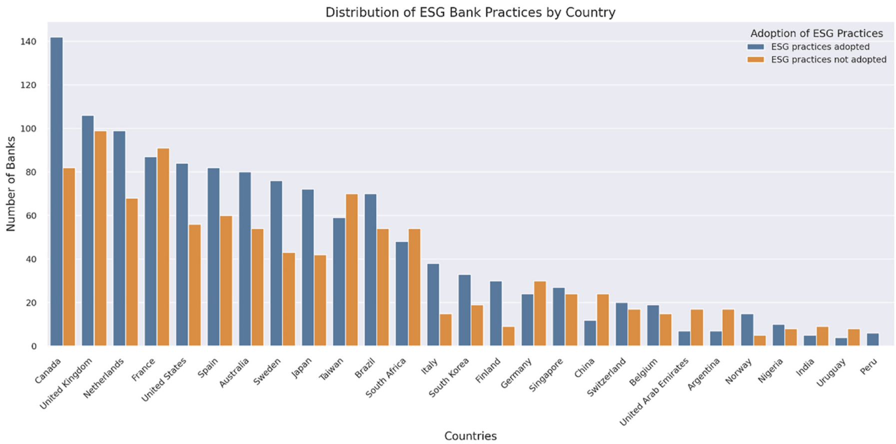
Note(s): ESG is a binary variable for the adoption of ESG practices that takes value 1 if the financial institution adopted the ESG practices and 0 otherwise. Furthermore, *cc_risk_ew*, *cc_expo_ew*, *cc_sent_ew*, *op_expo_ew*, *ph_expo_ew*, *ph_risk_ew*, *rg_expo_ew* and *rg_risk_ew* are variables that capture overall, opportunity, physical and regulatory shocks for firms related to climate change
Source(s): Authors' computations

appropriate type of data processing and machine learning algorithms that could be applied to the given data.

Figure 1 presents the grouping of the dataset by country name and adoption of ESG practices to visualise the frequency distribution observations of banks in a country. It is clear from the data that Canada has the largest number of observations for financial institutions that follow the ESG practices, while the lowest observations are for Uruguay and India.

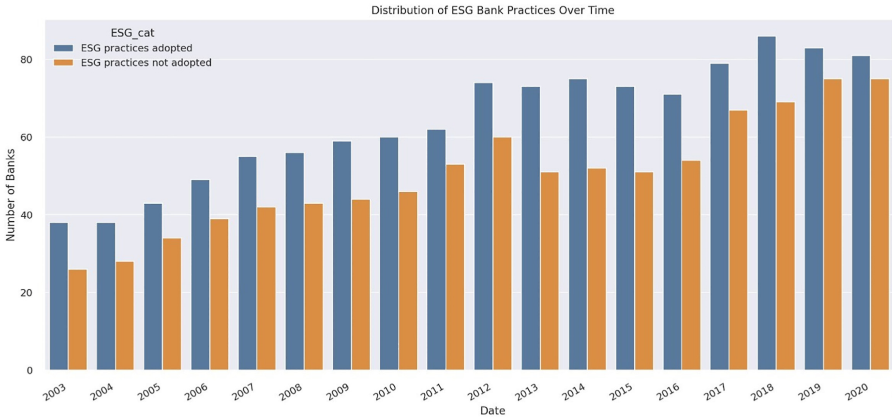
In addition, Figure A1 in the Appendix illustrates the distribution of ESG practice adoption by banks across regions. Our findings indicate that banks in the European region exhibit the highest adoption of ESG practices.

Similarly, Figure 2 presents the grouping of the dataset by year and adoption of ESG practices to the frequency distribution of banks. A significant increase in the adoption of ESG practices is observed over the period. Likewise, Figure A2 in the Appendix depicts the distribution of banks adopting and not adopting ESG practices. Moreover, Table 2 reports the descriptive statistics of the data. About 50% of financial institutions in the sample are following the ESG practices.



Source(s): Authors' computations

Figure 1. Number of financial institutions (banks) adopting ESG practice across sampled countries

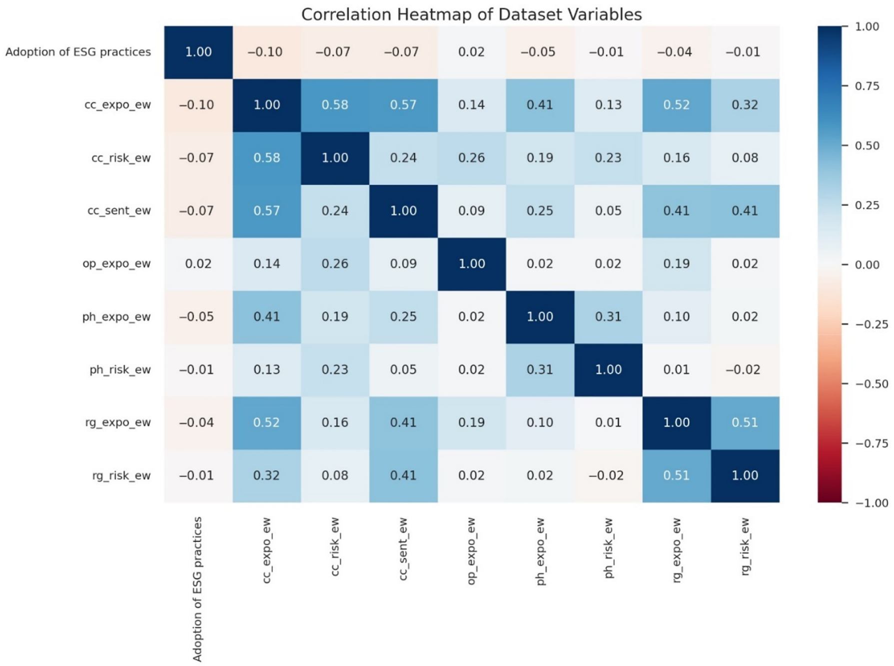


Source(s): Authors' computations

Figure 2.
The frequency of adoption of ESG practice over the period of time

4.2 Correlation analysis

Besides, correlation analysis was carried out to test the direction and strength of the relationship among different features. Figure 3 presents the correlation matrix. Correlation analysis is one of the most common steps of a typical data pre-processing step. It allows measurement of any kind of correlation present among the variables but often fails to reveal the correct relationship if the data are highly nonlinear. In a simple sense, correlation analysis



Source(s): Authors' computations

Figure 3.
Correlation analysis results corresponding to all the variables

can be performed by a simple visualization plot of the two variables, but that does not reveal any quantitative relationship. Moreover, if the number of variables is high, like in this study, then the visualization approach fails to provide any clear insight about the correlation. Therefore, a correlation matrix is used to measure the connectedness among the variables of interest. The correlation coefficient, typically represented as "r" varies between −1 and 1. The neutral point for "r" is 0 which indicates zero correlation. Negative values indicate negative correlation, whereas positive values represent positive correlation among the variables.

Figure 3 presents the findings related to correlation analysis performed on all the available variables. Our results indicate no multicollinearity issue among the feature variables, as all correlation coefficients are below the cutoff point of 0.7 (Khan *et al.*, 2023). Interestingly, the coefficient of *op_expo_ew* is positively linked with the adoption of ESG practices, suggesting that banks consider ESG practices as a means to exploit climate-related opportunities.

4.3 Identification of the top-performing models based on forecasting accuracy

In the next step, to test the accuracy of different machine learning algorithms, altogether, AdaBoost, Bagging classifier, Bernoulli Naive Bayes, Decision tree, Gaussian Naive Bayes, Gradient Boosting, k-nearest neighbours, Logistic regression, Quadratic discriminant analysis, Random Forest, Stochastic gradient descent and XGBoost classification algorithms were trained and tested using the full sample. At this stage, all eight variables (*cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew, rg_expo_ew* and *rg_risk_ew*) were considered in the modelling phase.

The model accuracy results corresponding to all the candidate models are summarised in Table 3 and Figure 4. According to the performance of the candidate algorithms (Table 3 and Figure 4 based on a full sample), the top three, namely, AdaBoost, Gradient Boosting and XGBoost classification, were chosen for the next stage of modelling. For further details, the confusion matrix corresponding to each model is given in Figure A3 in Appendix.

4.4 Baseline analysis: performance of top three algorithms using full sample

To move one step forward, we also explored the accuracy of the top three selected models for the full sample by introducing the risk features in a hierarchical manner. This helps to answer the two important research questions: do FIs respond to climate change risk in adopting ESG practices? And do FIs react differently to climate change risks related to opportunity, physical and regulatory shocks? Table 4 and Figure 5 present the results for AdaBoost algorithm performance. In this model, eight different measures of climate change risk were

Models	Precision	Recall	Balanced F-score	Support
AdaBoost	*0.66*	*0.66*	*0.66*	505
Bagging classifier	0.60	0.59	0.58	505
Bernoulli Naive Bayes	0.60	0.59	0.58	505
Decision tree	0.57	0.57	0.56	505
Gaussian Naive Bayes	0.60	0.54	0.47	505
Gradient Boosting	*0.64*	*0.64*	*0.64*	505
k-nearest neighbours	0.60	0.59	0.59	505
Logistic regression	0.58	0.54	0.50	505
Quadratic discriminant analysis	0.57	0.53	0.46	505
Random Forest	0.60	0.60	0.59	505
Stochastic gradient descent	0.55	0.53	0.49	505
XGBoost	*0.63*	*0.62*	*0.62*	505

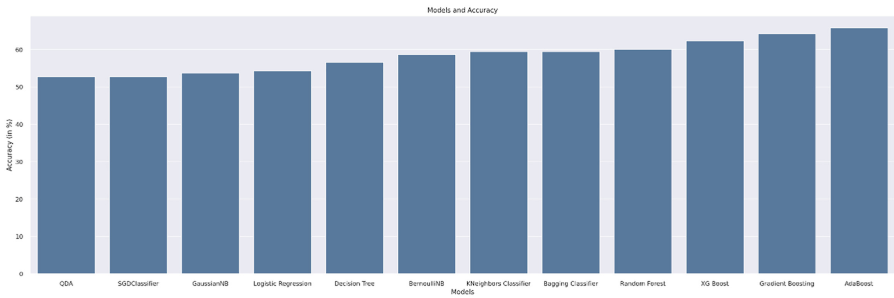
Source(s): Authors' computations

Table 3. Model summaries based on full sample

introduced, namely, *cc_risk_ew* (the relative frequency of bigrams related to climate change containing the words "risk" or "uncertainty" on social media earnings conference calls). *cc_expo_ew* (the relative frequency of bigrams related to climate change discussed during earnings conference calls). *cc_sent_ew* (the relative frequency of bigrams associated with climate change, categorized by the presence of negative or positive tone words on social media in relation to earnings conference calls). *op_expo_ew* (the exposure to opportunities that firms have in relation to climate change). *ph_expo_ew* and *ph_risk_ew* (variables that measure the physical impacts experienced by firms due to climate change). Lastly, *rg_expo_ew* and *rg_risk_ew* (variables that quantify the regulatory impacts experienced by firms as a result of climate change).

It is clearly observed that the inclusion of overall climate risk (*cc_risk_ew*), sentiment component (*cc_sent_ew*) and regulatory component of climate risk (*rg_expo_ew*) improve the algorithm accuracy, suggesting that overall climate risk as well as the sentiment and regulatory aspects related to climate change risk impact the adoption of ESG practices.

Likewise, Table 5 and Figure 6 present the model accuracy results regarding the Gradient Boosting algorithm. The results suggest that in addition to overall climate risk (*cc_risk_ew*), sentiment component (*cc_sent_ew*) and regulatory component of climate risk (*rg_expo_ew*), physical risk components also improve the algorithm accuracy, implying that physical aspects related to climate change risk also impact the adoption of ESG practices.



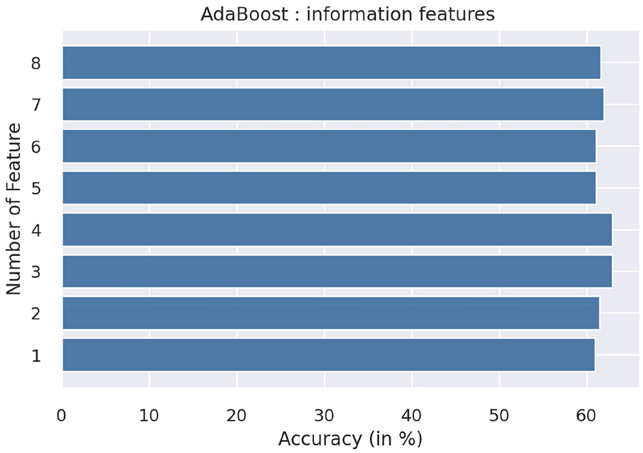
Source(s): Authors' computations

Figure 4.
The accuracy of models based on all features

Table 4.
AdaBoost algorithm performance

No. of features	Variables	Model accuracy (%)
1	cc_expo_ew	60.949
2	cc_expo_ew, *cc_risk_ew*	*61.477*
3	cc_expo_ew, cc_risk_ew, *cc_sent_ew*	*62.928*
4	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew	62.928
5	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew	61.081
6	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew	61.081
7	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew, *rg_expo_ew*	*62.005*
8	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew, rg_expo_ew, rg_risk_ew	61.609

Note(s): Our target variable, ESG, is a binary variable representing the adoption of ESG practices. It takes a value of 1 if the financial institution adopted the ESG practices and 0 otherwise. Furthermore, *cc_risk_ew*, *cc_expo_ew*, *cc_sent_ew*, *op_expo_ew*, *ph_expo_ew*, *ph_risk_ew*, *rg_expo_ew* and *rg_risk_ew* are variables that capture overall, opportunity, physical and regulatory shocks for firms related to climate change
Source(s): Authors' computations



Note(s): 1 = cc_expo_ew, 2 = cc_risk_ew, 3 = cc_sent_ew, 4 = op_expo_ew, 5 = ph_expo_ew, 6 = ph_risk_ew, 7 = rg_expo_ew, and 8 = rg_risk_ew

Source(s): Authors' computations

Figure 5. AdaBoost algorithm performance by adding features

No. of features	Variables	Model accuracy (%)
1	cc_expo_ew	54.353
2	cc_expo_ew, *cc_risk_ew*	*56.860*
3	cc_expo_ew, cc_risk_ew, *cc_sent_ew*	*59.762*
4	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew	58.575
5	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, *ph_expo_ew*	*59.234*
6	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, *ph_risk_ew*	*59.762*
7	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew, *rg_expo_ew*	*60.02*
8	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew, rg_expo_ew, rg_risk_ew	59.894

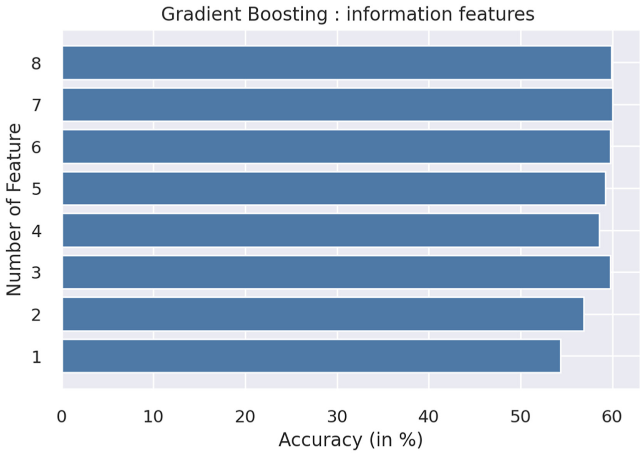
Note(s): Our target variable, ESG, is a binary variable representing the adoption of ESG practices. It takes a value of 1 if the financial institution adopted the ESG practices and 0 otherwise. Furthermore, *cc_risk_ew*, *cc_expo_ew*, *cc_sent_ew*, *op_expo_ew*, *ph_expo_ew*, *ph_risk_ew*, *rg_expo_ew* and *rg_risk_ew* are variables that capture overall, opportunity, physical and regulatory shocks for firms related to climate change
Source(s): Authors' computations

Table 5. Gradient Boosting algorithm performance

Finally, Table 6 and Figure 7 provide the model accuracy results regarding the XGBoost algorithm. The results are qualitatively similar to the findings of the Gradient Boosting algorithm. Overall, our results suggest that financial institutions respond to climate change risk and frame their ESG practices.

4.5 Performance of top three algorithms: region-wise analysis based on sub-samples

To delve deeper, we also explored how firms respond to climate change risk through the adoption of ESG practices by utilizing sub-samples across different regions. Figure 8



Note(s): 1 = cc_expo_ew, 2 = cc_risk_ew, 3 = cc_sent_ew, 4 = op_expo_ew, 5 = ph_expo_ew, 6 = ph_risk_ew, 7 = rg_expo_ew, and 8 = rg_risk_ew

Source(s): Authors' computations

Figure 6. Gradient Boosting algorithm performance by adding features

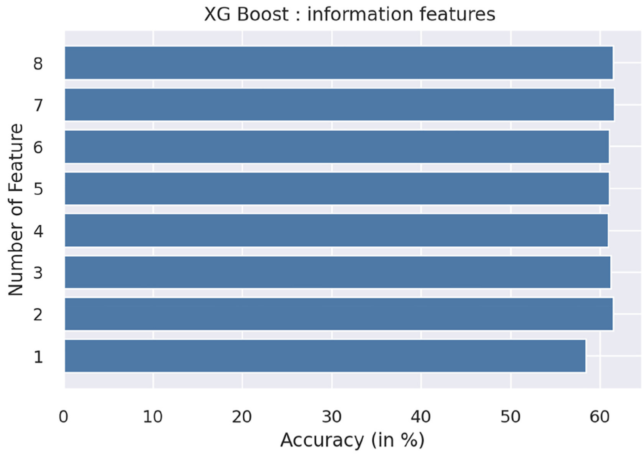
No. of features	Variables	Model accuracy (%)
1	cc_expo_ew	58.443
2	cc_expo_ew, *cc_risk_ew*	*61.477*
3	cc_expo_ew, cc_risk_ew, cc_sent_ew	61.213
4	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew	60.949
5	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, *ph_expo_ew*	*61.081*
6	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew	61.081
7	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew, *rg_expo_ew*	*61.609*
8	cc_expo_ew, cc_risk_ew, cc_sent_ew, op_expo_ew, ph_expo_ew, ph_risk_ew, rg_expo_ew, rg_risk_ew	61.477

Note(s): Our target variable, ESG, is a binary variable representing the adoption of ESG practices. It takes a value of 1 if the financial institution adopted the ESG practices and 0 otherwise. Furthermore, *cc_risk_ew*, *cc_expo_ew*, *cc_sent_ew*, *op_expo_ew*, *ph_expo_ew*, *ph_risk_ew*, *rg_expo_ew* and *rg_risk_ew* are variables that capture overall, opportunity, physical and regulatory shocks for firms related to climate change
Source(s): Authors' computations

Table 6. XGBoost algorithm performance

presents the results regarding model accuracy results corresponding to all the candidate models across different regions.

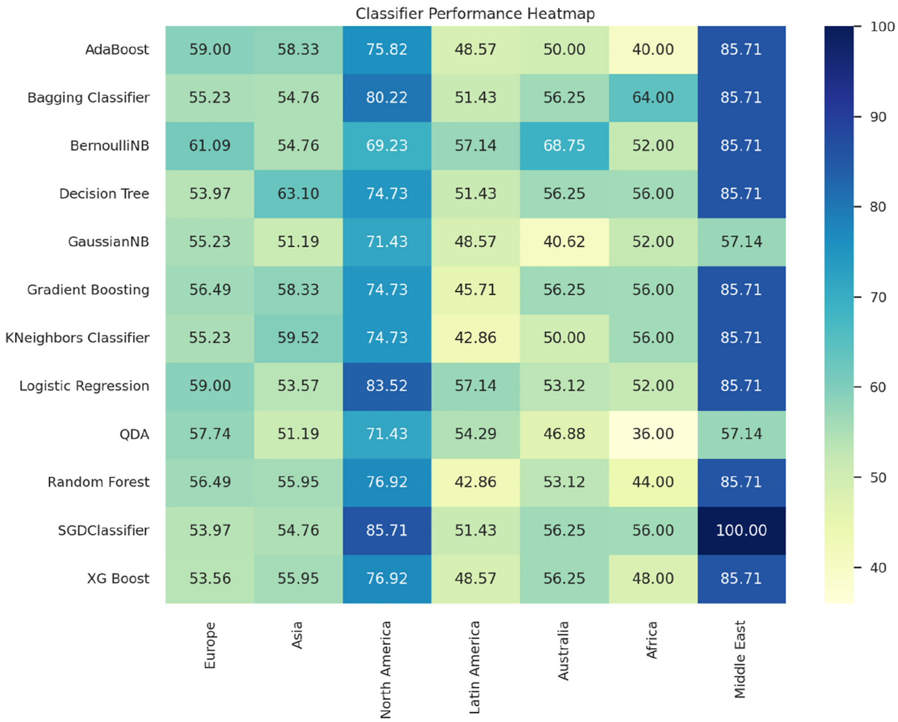
Figure 8 clearly depicts heterogeneity among model accuracies across the subsamples. Specifically, the BernoulliNB algorithm in the context of Europe, Latin America and Australia, the bagging classifier in the context of Africa, the decision tree in the Asian context, SGD classifier in the context of North America and Middle East and the logistic regression in the Latin American context are the best performing algorithms. For further details, the confusion matrix corresponding to each model across African, Asian, Australian,



Note(s): 1 = cc_expo_ew, 2 = cc_risk_ew, 3 = cc_sent_ew, 4 = op _expo_ew, 5 = ph_expo_ew, 6 = ph_risk_ew, 7 = rg_expo_ew, and 8 = rg_risk_ew

Source(s): Authors' computations

Figure 7.
XGBoost algorithm performance by adding features



Source(s): Authors' computations

Figure 8.
Model summaries based on sub-samples across different regions

Latin American, Middle Eastern, North American and European regions is given in Figures A4–A10 in the Appendix. The variation in model accuracies among sub-samples may stem from differences in the adoption of ESG practices by firms across geographical regions. For example, Singhania and Saini (2023) observed that differences in a country's social and governance disclosures could result from voluntary or mandatory codes concerning ESG practices.

Moreover, we also examined the accuracy of the best-performing models across regions selected by introducing the risk features in a hierarchical manner. Figure 9 presents the results.

We observed intriguing findings regarding the relationship between climate change risk and the adoption of ESG practices by firms across various regions. For instance, in Europe, Australia and North America, regulatory aspects of climate change risk (*rg_expo_ew* and *rg_risk_ew*) significantly influence ESG adoption. Similarly, in the African region, overall climate change risk as well as physical and regulatory components (*cc_risk_ew, ph_expo_ew* and *rg_risk_ew*), play a pivotal role in ESG practice adoption. However, in the Middle Eastern region, firms do not respond to climate change risk as a driver for adopting ESG practices.

5. Discussion

The aim of this study was to investigate if financial institutions adopt a reactive approach when they view climate change as a risk, which in turn prompts them to implement ESG

Figure 9.
Performance of best model from each region by adding features

Note(s): 1 = cc_expo_ew, 2 = cc_risk_ew, 3 = cc_sent_ew, 4 = op_expo_ew, 5 = ph_expo_ew, 6 = ph_risk_ew, 7 = rg_expo_ew, and 8 = rg_risk_ew

Source(s): Authors' computations

practices to mitigate this risk. Particularly, we answered two research questions: Do FIs respond to climate change risk in adopting ESG practices? And do FIs react differently to climate change risks related to opportunity, physical and regulatory shocks.

In the first step, we introduced the climate change risk and exposure features related to opportunity, physical and regulatory shocks in a hierarchical manner for the full sample using the top three performing algorithms. In sum, our findings suggested that the forecasting accuracy of the machine learning algorithms improved with the inclusion of different climate change risk factors, implying that climate change risk significantly impacts firms' adoption of ESG practices. These findings are consistent with the premise of prospect theory that firms in our sample are more likely to react quickly to climate change when they consider it a risk or threat (Lin *et al.*, 2024; Cantarella *et al.*, 2023; Barberis *et al.*, 2021; Kahneman and Tversky, 1979, 2000). The findings are also in line with Elijido-Ten (2017), who found that recognition of climate change as a risk is significant and adversely impacts sustainability performance.

In the next step, we also examined the said association using sub-samples across different regions. Qualitatively, our results are consistent with the findings from the full sample. In simple words, firms often react defensively when they see climate change as a threat, leading them to adopt ESG practices to reduce this risk. If decision-makers do not adopt these practices, they might face potential losses. Since decision-makers usually try to avoid losses, this fear of losing could also motivate them to implement ESG practices. Thus, our findings in the context of corporate sustainability practices support the notion of prospect theory.

6. Concluding remarks

Confronting climate change presents firms with both substantial risks and significant opportunities. The growing recognition of these risks and opportunities is evident from both professional and academic literature. Hence, this study combined the prospect theory perspective with advanced machine learning algorithms to predict whether financial institutions react to climate change risk by adopting ESG practices. We gathered data from a sample of 168 financial institutions across 27 countries over the period 2003–2020. For an empirical strategy, various machine learning algorithms are compared regarding prediction accuracy.

Our findings revealed that out of 12 machine learning algorithms, AdaBoost, Gradient Boosting and XGBoost have the most precision in predicting whether financial institutions react to climate change risk in adopting ESG practices. Moreover, consistent with prospect theory predictions, our results suggested that physical and regulatory risks from climate change significantly influence the adoption of ESG practices.

Our study provides twofold policy implications for managers and regulators. On the one hand, managers must consider the climate change risk in corporate actions because it determines a firm's adoption of ESG practices. On the other hand, regulators and governments need to craft effective enforcing mechanisms regarding climate change activities, such as carbon emissions trading schemes and promote environmentally friendly alternative investment projects. Importantly, the regulatory aspect of climate change risk was a common feature across all models in the full sample. These findings remain consistent even when the analysis is extended to sub-samples, emphasizing the need to strengthen "command-and-control" regulations in other sectors as well, such as manufacturing, mining and oil and gas, which are particularly vulnerable to climate risks due to high carbon emissions. Therefore, mandating the implementation of carbon tax-related regulations can further incentivize firms to adopt ESG practices.

Our study also contributes on the theoretical front. In our study, we extend the discussion of prospect theory to better understand a topical corporate governance issue: how firms decide to adopt ESG practices and the critical role of climate change within a firm's business strategy. We examine whether the adoption of ESG practices is driven by reactive or proactive business strategies when choices are framed in terms of potential risks or threats rather than opportunities.

Our study has two potential limitations that can be addressed by future research studies. First, our research was exploratory in nature, and the insights from this exploratory research can serve as a useful springboard for future studies. For instance, future research could employ machine learning-based panel data methods to explore the impact of firm-level climate change risk on firm performance, considering the moderating role of ESG practices. Second, our study used a dichotomous variable to measure ESG practices. However, future research could refine our findings by using ESG scores, environmental scores, social scores, governance scores and environmental innovation scores of firms across different industries. We leave these issues for future research.

Notes

1. https://www.gsi-alliance.org/members-resources/gsir2022/
2. https://equator-principles.com/members-reporting/
3. https://osf.io/fd6jq/
4. *Scikit-learn Machine Learning in Python*. (n.d.). https://scikit-learn.org/stable/

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Further reading

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Appendix

The supplementary material for this article can be found online.

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