How does Climate Policy Uncertainty predict the BSE 100 ESG? An Application of Artificial Neural Network

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Abstract

This study uses monthly data on the climate policy uncertainty (CPU) index along with BSE 100 ESG to study the prediction of CPU on BSE 100 ESG in the light of ESG reporting under sustainability. The multilayer perceptron (MLP) model under Artificial Neural Network (ANN) is used to study the prediction. The period of the study begins in December 2017 and continues up to August 2023 with 68 observations. The descriptive test indicates that the data are non-normal in nature with high kurtosis values indicating non-linear features. The model is found to be valid. The accuracy in training is 80.9% and the accuracy in testing is 19.1%. The model's training accuracy is typically greater than its testing accuracy. The study also provides the predicted values of the multilayer perceptron (MLP) model.

Keywords: climate policy uncertainty, BSE 100 ESG, Artificial Neural Network, multilayer perceptron, prediction

JEL Classifications: B22, C45, C87, D53, E37, E44

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1. Background of the Study

Our environment is evolving. Very little is known about the cost of transitioning to a world with fewer greenhouse gas emissions, the onset and extent of climate change, and other related issues. The negative effects of climate change are expected to intensify in the absence of significant action to reduce greenhouse gas (GHG) emissions, increasing the likelihood of uncontrollable, catastrophic events. It is anticipated that the impoverished members of society will be most impacted by climate change, particularly in developing countries because of their heightened susceptibility. Limited resources for mitigation, adaptation, and recovery from climate-related catastrophes. Consequently, a substantial level of policy uncertainty exists because a large number of initiatives and strategies are still in the planning stages. (IEA, 2017).

Major investments have been made by the Indian government in hydroelectric, wind, and solar energy. This has made it possible for the nation to transition to renewable energy and lessen its dependency on pricey fossil fuels. Additionally, it is attempting to increase the amount of forest cover and has made efforts to safeguard its woods from deforestation and degradation. To aid firms in converting to green technology and improving their sustainability, the government has also established several subsidies and incentives. This comprises, among others, the Low Carbon Technologies Fund, the Patents Facilitation Fund, and the National Adaptation Fund on Climate Change. Among its latest efforts in that domain is the ESG structure, which comprises standards for ESG investing, grading, and disclosures/reporting. (Mondaq, 2023). Examining the kinds of disclosures corporations make in SEBI-BRR, Reports was thought to be essential in light of global trends, as a way to make businesses more accountable and responsible to society. In 2020, MCA adopted the National Guidelines for Responsible Business Conduct (the "NGRBC") based on internationally recognized standards. The Business

Responsibility and Sustainability Reporting (BRSR), developed by an MCA committee on BRR, later took the position of BRR under SEBI (Gulati and Manaktala, 2023).

Keeping in mind such a scenario with developments in the business sector and implementations of such a framework, the industry craves some valuable empirical inputs as to how the ESG indices perform as a result of any effect from such uncertainties arising out of climate policy changes.

The remaining sections of the paper are structured as follows: Section 2 summarizes the findings of previous research along with the study's goals and research gaps; Section 3 addresses the research methodology; Section 4 covers data analysis and related discussions; and Section 5 offers closing remarks.

2. Past Studies

The authors have meticulously studied the existing studies within the relevant field and the pertinent works are summarised and highlighted below for identification of the research gaps and the goals of the present topic that are also discussed within this section.

Malik and Yadav (2020) evaluated sustainability indices, which reflect a group of businesses that take a socially responsible approach to their business practices, in terms of anticipating both the return and the volatility of these returns. The ARIMA findings of the three indices indicate that AR (1) is used to forecast Carbonex, MA (3) is used to forecast ESG, and AR (3) MA (3) is used to forecast Greenex. Variances are dynamic and dependent on prior behavior, as demonstrated by the GARCH (1,1) process for Carbonex and Greenex. However, in the case of ESG, GARCH (1,1) is unable to account for the residual variation, which may be caused by the existence of additional exogenous components in the time series.

Mukherjee et al. (2023) applied deep learning methodology where the CNN model has an accuracy of 98.92% compared to the ANN model's accuracy of 97.66%. On the basis of 2-D histograms generated from the quantized information over a predetermined amount of time, the CNN model generated predictions.

Loh et al. (2017) using Singapore-listed corporations as a reference, look into the link between sustainability reporting and company value. Empirical findings indicate a favourable association between sustainability reporting and a company's market value that holds regardless of industry or firm type, such as family-owned or government-affiliated organizations.

Sudha, S. (2014) thinks that during that time, the ESG India Index was less erratic than the Nifty. These findings have ramifications for businesses that want to take advantage of the stock markets' sensitivity to ESG factors. It also reflects on the willingness of investors to make such investments and the possibility for growth in India.

Based on the above summary of the existing studies, it needs to be mentioned that some research gaps have been identified and noted below. Firstly, it is difficult to locate studies that predict the BSE 100 ESG index based on climate policy uncertainty. Secondly, the available studies either use simple econometric tests to achieve their goals or do not use artificial intelligence to monitor the BSE 100 ESG index. Lastly, the majority of the studies are theoretical discussions and analyses of ESG funds and BRSR from an Indian perspective, with a focus on the legal framework. The above-mentioned research gaps offer us the prospect of additionally carrying out extensive studies in this field which guides the authors to confirm the objective of the study i.e., to study the predictability of the BSE 100 ESG index by the climate policy uncertainty in the Indian framework.

3. Research Methodology

This study considers the monthly closing data of the CPU index in addition to the BSE 100 ESG index. The Gavriilidis (2021) database is the source of the climate policy uncertainty index, which is regarded as a stand-in for climate policy uncertainty. The BSE 100 ESG index data is gathered from the investing.com database. The first adoption of ESG reporting in India occurred after the Ministry of Corporate Affairs (MCA) of the Government of India published optional suggestions on corporate social responsibility (MCS, 2011). Nonetheless, SEBI required BRR submissions from the top 100 listed businesses based on market capitalization and imposed ESG reporting in 2012 (MCA, 2020). Due to the lack of data from 2012, the author purposefully chose to take into account the monthly data of the S&P BSE 100 ESG from December 2017 to August 2023. All the data are converted into corresponding natural logarithmic returns.

To address the objective of the study, the MLP model under ANN is used alongside descriptive statistics. For the analysis work, IBM SPSS 21.0 is used.

3.1 Artificial Neural Network (ANN) – Concepts and Critical Appraisal

ANN represents a subfield of artificial intelligence that draws inspiration from biology and is designed to mimic human brain function. Computer networks called artificial neural networks are derived from evolutionary neural networks, which are the fundamental units of the human brain. Artificial neural networks are made up of neurons that are connected to one another at different layers of the network, just like neurons in a real brain. Nodes are the name given to these neurons. As a subset of artificial intelligence, artificial neural networks (ANNs) seek to mimic the neuronal network that gives rise to the human brain, enabling computers to understand ideas and form opinions in a manner that is comparable to that of humans. Artificial neural networks are created by programming computers to behave similarly to a network of interconnected brain cells.

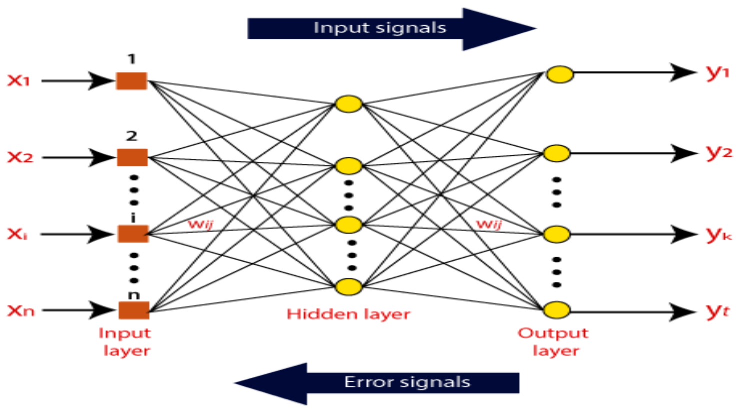

Figure 3.1: Structure of ANN

(Source: Javapoint)

For research using paradigms for comparable computing that involve strongly connected adaptive processing units, an ANN is a superior tool. Conventional programming stores data throughout the network rather than in a database. Even if some data momentarily vanishes from one place, the network still works. Furthermore, even with limited data, the data may still produce output after ANN training. The reason for the performance loss in this case is the significance of the misplaced data. Furthermore, for an ANN to be able to adapt, it is essential to identify the instances and motivate the network based on the desired output.

Since the network's recurrence is directly linked to the selected occurrences, the network's output may be inaccurate if the episode cannot be accurately depicted by the system in all of its properties.

3.2 Multilayer Perceptron (MLP) Model

One of the neural network topologies that are most frequently used is the multilayer perceptron. According to the mapping capabilities, the MLP is thought to be able to approximate any function. Principe, Euliano, and Lefebvre (1999) have proven crucial in the investigation of various function mapping issues as well as nonlinear dynamics.

The logistic function and the hyperbolic tangent are the most frequently used nonlinear processing elements (PEs) in the multilayer perceptron, and they both have important properties such as massive interconnectivity, which means that any element of one layer feeds all the elements of the subsequent layer (Principe et al., 1999).

In most cases, the back-propagation technique is used to train MLPs (Principe et al., 1999). The backpropagation rule spreads faults throughout the network and enables concealed PEs to adjust. Since the multilayer perceptron is trained via error corrective learning, it is necessary to comprehend the intended response of the system.

The process of error corrective learning is as follows: An instantaneous error $\mathcal{E}_i(n)$ is defined by the system reaction at PE *i* at iteration n, $y_i(n)$, and the desired response $d_i(n)$ for a certain input pattern.

$$\varepsilon_i(n) = d_i(n) - y_i(n) \ldots\ldots.(1)$$

Each weight in the network may be adjusted using the principle of gradient descent learning by correcting its current value with a term that is proportionate to the current input and error at the weight, i.e.

$$w_{ij}(n+1) = w_{ij}(n) + n\delta_i(n)x_j(n) \ldots\ldots(2)$$

At the output PE, the local error $\delta_i(n)$ can be calculated directly from *Ɛi(n)*, or it can be calculated as a weighted sum of errors at the internal PEs. The step size, often known as the learning rate, is constant *n*. The backpropagation algorithm is the process in question.

Each weight in the network is updated proportionally to the sensitivity via backpropagation, which calculates the sensitivity of a cost function with respect to individual weights in the network. The procedure's efficiency and ability to be used with local data make it beautiful. It also only necessitates a small number of weight-specific multiplications. This process employs only local information because it is a gradient descent method, allowing it to be captured at local minima. Additionally, because we are utilizing a subpar estimate of the gradient, the technique is inherently noisy and converges slowly (Principe et al., 1999).

In that a memory tenure (the previous increase to the weight) is employed to accelerate and stabilize convergence, momentum learning is an enhancement over direct gradient descent. The equation to apprise the loads in momentum learning becomes

$$w_{ij}(n+1) = w_{ij}(n) + n\delta_i(n)x_j(n) + \alpha(w_{ij}(n) - w_{ij}(n-1)) \text{.....(3)}$$

Where α is the momentum. Usually, α ranges between 0.1 and 0.9.

Training can be carried out in one of two ways: either by presenting a pattern and modifying the weights (online training), or by presenting all patterns in the input file at once (an epoch), accumulating weight updates, and updating the weights with the mean weight update.

Batch learning refers to this. Backpropagation must begin by loading a starting value for the individual weight (often a tiny random number), and it must continue until a stopping requirement is satisfied. The three most popular ones are cross-validation, thresholding output means square inaccuracy, and capping the number of rounds. Since it ends training at the moment of greatest generalization (i.e., when performance in the test set is reached), cross-validation is the supreme operative of the three techniques (Principe et al., 1999). To conduct cross-validation, one must set sideways a tiny portion of the training data and apply it to test the trained network with a validation set, for example, every 100 training epochs. Training should be discontinued when the performance in the validation set begins to deteriorate (Alpaydn, 2004; Haykin, 1999; Principe et al., 1999).

On the other hand, the step size ought to be reduced when the learning curve equivocates up and down. In the extreme, the mistake may increase consistently, demonstrating the instability of learning. The network should be restarted at this point. It is time to reconsider the network topology (either adding additional hidden PEs or hidden layers or switching to a new topology entirely) or the training strategy when the learning curve stabilizes after several rounds at an error level that is not acceptable (other additional erudite gradient exploration procedures).

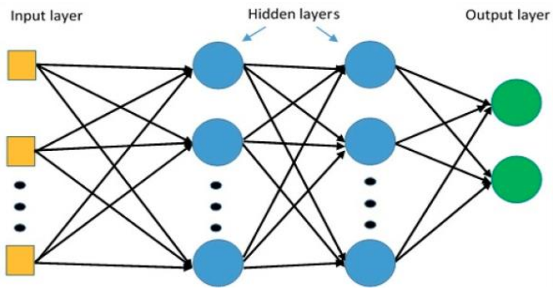

Figure 3.2: Arrangement of The Multilayer Perceptron (MLP) Model
(Source: tutorials point, 2024)

4. Results and Discussions

The authors decide to select 80:20 as the ratio for splitting the data into training and testing sets (https://www.baeldung.com/cs/train-test-datasets-ratio) under the Multilayer Perceptron (MLP) Model. Continuous data from the CPU index which is the controlled variable and the S&P BSE 100 ESG index which is the predicted variable are considered.

4.1 Descriptive Statistics

	BSE 100 ESG	CPU
Mean	1.0105	1.0733
Median	1.0083	0.9995
Maximum	1.1641	3.4304
Minimum	0.7663	0.3891
Std. Dev.	0.0554	0.452
Skewness	-0.9869	2.442
Kurtosis	8.244	13.4241
Jarque-Bera	78.4923	331.294
Probability	0.00*	0.00*

Sum	60.6338	64.3989
Sum Sq. Dev.	0.1815	12.0569
Observations	68	68

(* indicates significance at 1% level)

Table 4.1: Results of descriptive statistics

The above table denotes the result of the descriptive statistics with 68 observations. A significant p-value of Jarque-Bera test at 1% level indicates that the data are non-normal in nature. BSE 100 ESG increases to 1.1641 highest and decreases to 0.7663 lowest. Likewise, CPU index rises to 3.4304 highest and comes down to 0.3891 lowest. However, both the variables suffer from high kurtosis values.

4.2 Case Processing Summary

BSE 100 ESG			
		N	**Percent**
Sample	**Training**	55	80.9%
	Testing	13	19.1%
Valid		68	100.0%
Excluded		0	
Total		68	

Figure 4.2: Case Processing Summary of BSE 100 ESG

The above figure explains the results of the case processing summary of the dependent variable BSE 100 ESG with 68 observations. The total observations are bifurcated into a training sample with 55 observations and a testing sample with 13 observations. The "N" indicates the observations in each subset, and the "Percent" indicates the proportion of the total dataset represented by each subset. All the samples are valid with 80.9% in training and 19.1% in testing.

4.3 Network Information

BSE 100 ESG			
Input Layer	Covariates	1	CPU
	Number of Units[a]		1

	Rescaling Methods for Covariates		Standardized
Hidden Layer (s)	Number of Hidden Layers		1
	Number of Units in Hidden Layers 1[a]		1
	Activation Function		Hyperbolic tangent
Out Layers	Dependent Variables	1	ESG
	Number of Units		1
	Rescaling Methods for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares
a. Excluding the bias unit			

Figure 4.3: Network Information of BSE 100 ESG

The above figure represents the result of the Network Information where CPU is the independent variable and BSE 100 ESG is the dependent variable. There is 1 hidden layer with 1 unit in the input stratum. 1 unit is generated in the output stratum.

4.4 Neural Network

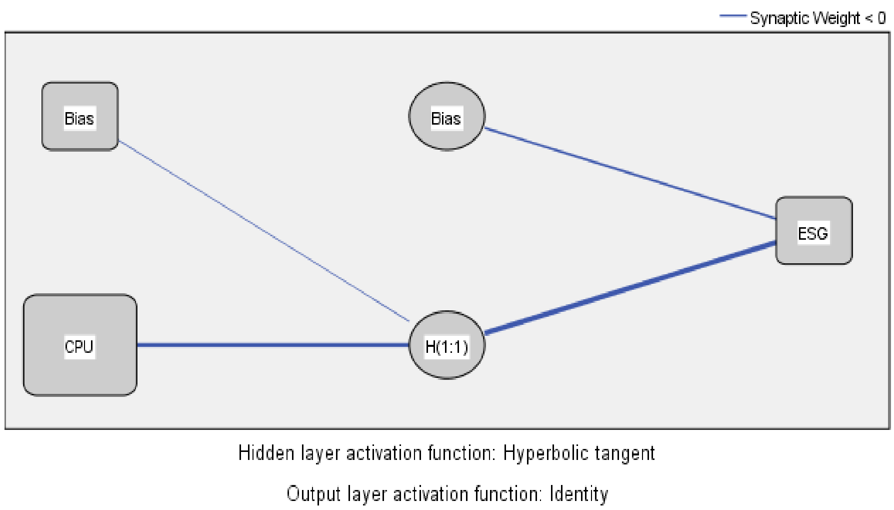

Figure 4.4: Neural Network of BSE 100 ESG

Above figure 4.4 represents the network of the neural where CPU is the independent variable and ESG is the dependent variable. The CPU is the input layer, H(1:1) is the hidden stratum and ESG is the output layer. After passing through the neurons in the hidden stratum, the output is predicted. However, it should be mentioned that the authors decided to consider only 1 hidden layer.

4.5 Model Summary

BSE 100 ESG		
Training	Sum of Squares Error	27.086
	Relative Error	0.030
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	2.461
	Relative Error	0.010
Dependent Variable: ESG		
a. Error computations are based on the testing sample.		

Table 4.5: Model summary of BSE 100 ESG

The above table delivers the goodness of fit of the model, where it is observed that only a 3% error exists in the training and 1% in the testing part of the networking for BSE 100 ESG. The sum of squares error for the training sample is 27.086 which embodies the total squared difference between the projected and real values of BSE 100 ESG in the training sample. The stopping regulation used is 1 uninterrupted step(s) with no reduction in error, which denotes that the training procedure would halt if the model's presentation does not progress after one iteration. The sum of squares error for the testing sample is 2.461 which signifies the total squared variance between the predicted and real values of BSE 100 ESG in the testing sample.

4.6 Parameter Estimates

Predictor	Predicted	
	Hidden Layer 1	**Output Layer**
	H(1:1)	BSE 100 ESG

Input Layer	(Bias)	.361	
	CPU	-.596	
Hidden Layer 1	(Bias)		.035
	H(1:1)		-.021

Table 4.6: Parameter Estimates under MLP

Table 4.6 shows the parameter estimates for a neural network with one hidden layer and an output layer. The neural network has one input node, one hidden node in the first layer, and one output node. The second row lists the predicted values for the weights connecting the input layer to the first hidden layer. The weight connecting the CPU to the first node in the first hidden layer is -.596. The output layer column lists the predicted values for the weights connecting the first hidden layer to the output layer. On the basis of the synaptic weights, the above table represents the results of the output layer where BSE 100 ESG is predicted. It can be observed that all H(1:1), H(1:2), and H(1:3) have synaptic weights of .035, and -.021 respectively which are less than 1.

5. Concluding Notes

It is possible to forecast and gain insight into how climate policy uncertainty affects ESG performance within the BSE 100 index by using an ANN to simulate the link between the CPU index and the BSE 100 ESG. Successful prediction of the index can lead to enticing advantages for both investors as well as policymakers. The case processing summary confirms the validity of the model. The accuracy in training is 80.9% and the accuracy in testing is 19.1%. The model's training accuracy is typically greater than its testing accuracy, suggesting that the model may have overfitted to the training set of data. It is worth mentioning that any ANN best fits in the context of a non-linear relationship which is evident in our study. Moreover, any elusive pattern is difficult to capture using any other old-fashioned model. Furthermore, since ANN is exposed to training and testing, it can continuously filter the result on the basis of the budding background. For investors, decision-makers, and organizations looking to line up their investments with sustainable and responsible practices, accurate projections of the BSE 100 ESG index based on climate policy uncertainties might be useful.

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Declaration of Competing Interest

The author declare that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability Statement

The data of this present study is available on reasonable request

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Appendix

Predicted Values of BSE 100 ESG under Multilayer Perceptron (MLP) Model

Month	MLP Predicted Values	Month	MLP Predicted Values	Month	MLP Predicted Values	Month	MLP Predicted Values
Jan-18	1.0089	Sep-19	1.013	May-21	1.0121	Jan-23	1.0098
Feb-18	1.0094	Oct-19	1.0077	Jun-21	1.0097	Feb-23	1.0101
Mar-18	1.0106	Nov-19	1.0089	Jul-21	1.0111	Mar-23	1.0103
Apr-18	1.0101	Dec-19	1.0113	Aug-21	1.0069	Apr-23	1.0086
May-18	1.0096	Jan-20	1.0089	Sep-21	1.0189	May-23	1.0095
Jun-18	1.0089	Feb-20	1.0094	Oct-21	1.0086	Jun-23	1.0093
Jul-18	1.0108	Mar-20	1.011	Nov-21	1.012	Jul-23	1.0098
Aug-18	1.0084	Apr-20	1.009	Dec-21	1.008	Aug-23	1.0081
Sep-18	1.0076	May-20	1.0091	Jan-22	1.0086		
Oct-18	1.0108	Jun-20	1.0079	Feb-22	1.0097		
Nov-18	1.0116	Jul-20	1.0093	Mar-22	1.0096		
Dec-18	1.0095	Aug-20	1.0117	Apr-22	1.0094		
Jan-19	1.011	Sep-20	1.0091	May-22	1.0097		
Feb-19	1.0105	Oct-20	1.0115	Jun-22	1.0087		
Mar-19	1.0079	Nov-20	1.0089	Jul-22	1.0128		
Apr-19	1.0077	Dec-20	1.0107	Aug-22	1.0085		
May-19	1.0105	Jan-21	1.0078	Sep-22	1.0082		

Jun-19	1.0116	Feb-21	1.0101	Oct-22	1.0101	
Jul-19	1.0085	Mar-21	1.0082	Nov-22	1.0098	
Aug-19	1.0113	Apr-21	1.0083	Dec-22	1.0091	