Economic Indicators and Climate Change for BRICS Economies in the Post–COVID-19 World: Neural Network Approach

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ABSTRACT
Climate change has emerged as one of the challenges of the global economy. Climate change economics has focused on the economic aspects of climate tradeoff. Studies have been conducted on the causal association of economic indicators and climate change indicators. However, for the sample of BRICS countries, that are important participants of global climate change, no study has attempted to identify whether causal connections apply to them. The study is an endeavor to identify the underlying causal connections between economic indicators and carbon emissions for BRICS economies. Six economic indicators, current account balance, inflation, foreign direct investment inflows, gross domestic product, real effective exchange rate, and trade openness, are selected for the sample period 2005–2019. Neural network analysis as a method of computational economics is applied for the superior methodology over standard statistical techniques. The outcome suggests that for BRICS economies, economic indicators have a significant relationship with carbon emissions, differing in intensity as per node strength of the neural network.

KEYWORDS: Climate Change, BRICS, Neural Network, Economic Indicators.

1. INTRODUCTION

Climate is part and parcel of human civilization; it has determined the course of humans and humans have also determined the course of climate. Changes in climate can be due to natural factors or due to human interventions known as anthropomorphic factors. Climate change as a policy term refers to changes due to anthropomorphic factors such as industrial production, deforestation, fire, and pollution, all leading to, in one or the other manner, carbon emissions. Thus, carbon emissions have emerged as the factor or indicator of climate change. The tradeoff between economic growth and climate change is the subject matter of climate change economics. Climate change policies target minimizing carbon emissions but its implementation is a bone of contention between developed and developing countries. Developing countries over the years have been arguing against the imposition of carbon policies, as they cannot curtail their growth challenges amid carbon minimization. BRICS economies as the composition of developing economies (Iqbal and Rahman, 2016; Rahman, 2020; Rahman and Iqbal, 2019) have fully participated in climate change imitative, including Kyoto Protocol and COP21. However, they have not ratified the agreements. This does not mean that they are not ready to engage in climate change issues. Over the years in the BRICS summit, climate change has remained an important objective, and the official statements have always been in favor of minimizing climate change in BRICS economies. In the ninth BRICS summit held in China (2017), BRICS economies invited all the countries over the world to participate and follow the UNFCC climate change principles (Rahman and Turay, 2018). COVID-19, the novel coronavirus, had a significant economic and social impact on the global as well as BRICS economies (Rahman *et al*., 2020). It has been hypothesized that due to COVID-19 lockdown all over the world, there would be a positive impact on the climate. Already due to lockdown, industrial operations have slowed down and carbon emissions have been reduced. However, there is not much time when the industrial pace would come back to its normal or rather may be aggravated to add to the climate change and carbon emissions. As developing economies, BRICS has to develop economic policies for the post–COVID-19, and having an understanding of the causal linkages between economic indicators and climate indicators is a necessity. Public policy for climate change in absence of causal linkages for BRICS will collapse and will fail to give predetermined results. The present study is an endeavor to find evidence for the causal linkages between economic and climate indicators for BRICS economies. The evidence can be used to formulate policies in the post–COVID-19 era. The study is divided into five sections. Section 1 introduces the study and Section 2 conceptualizes climate change and COVID-19 scenario. Section 3 reviews the recent literature on the theme, while Section 4 delves into the neural network analysis. The study concludes in Section 5.

2. CONCEPTUALIZING CLIMATE CHANGE IN THE POST–COVID-19 WORLD

The study revolves around three concepts, climate change, economic indicators, and COVID-19. Climate change is best understood not by definition but with the outcomes it is associated with. Climate change is characterized by rising sea levels, extreme droughts, weather anomalies, heavy rains, coastal erosions, to name a few. There are economic and geopolitical costs of climate change apart from the primary social cost of living. The Intergovernmental Panel on Climate Change estimates that till the end of the 21st century, there will be an average rise in temperature between 2.5°C and 7.8°C. This will have a devastating consequence on the world environment and may result in a rise in sea level beyond 80 cm, which may be problematic and alarming for coastal islands and regions. Partially, their landmass may even vanish. There are around seven prominent theories of climate change presented in Figure 1.

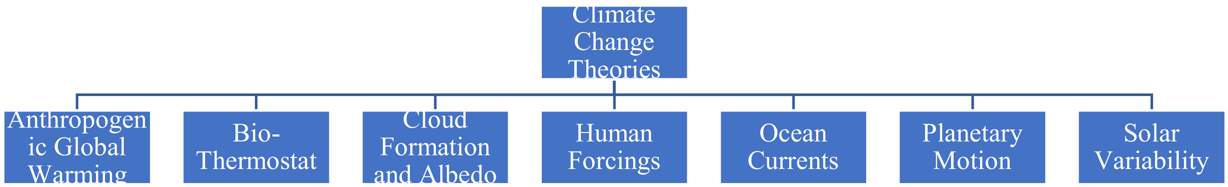

Figure 1. Climate change theories.
Source: Climate change issues in BRICS countries.

All these theories attempt to identify the cause and suggest controlling the cause may reduce climate change. The anthropogenic theory is the most important for our study. This theory states that human causes are the primary causes responsible for altering climate change. Other theories are more subtle and complex. Due to the popularity of anthropogenic theory, in general, climate change is understood as the changes in human factors including the carbon emissions due to production activities of humans. COVID-19 as a pandemic entered the world creating havoc and chaos, shutting down the physical activities, countries went for the nationwide lockdown. BRICS economies also responded to the global pandemic and implemented nationwide lockdown in 2020. Brazil was one of the countries to implement the lockdown with delay. The first case of COVID-19 was reported on February 25, 2020. However, due to the reluctance of the President, the lockdown was implemented on May 7 in several states when the cases started rising rapidly. The first case of COVID-19 was reported on January 31 after which preventive measures were imposed. However, as the cases started to rise at end of February and March, a lockdown was imposed on April 17, 2020. However, at the end of March, it was already implemented on the Russian borders. On March 24, 2020, a nationwide lockdown was imposed in India for 21 days which was later extended. The cases were already rising, and this created a total shutdown of economic and industrial activities. China was the destination for the origination of the COVID-19 virus. It all started from Wuhan and a lockdown was implemented in Wuhan on January 23, 2020. Lockdown was followed by quarantine measures, follow-up checks, and travel history analysis for a possible carrier of the virus. On March 5, 2020, officially, it was reported in South Africa that cases have started spreading rapidly. As a breakdown strategy, a nationwide lockdown was imposed on March 27, 2020. BRICS economies responded quickly to the COVID-19 pandemic except for Brazil which was late. This lockdown resulted in an almost total lockdown of industrial and economic activities. This has resulted in a reduction in the carbon emissions for BRICS countries. However, no official statistics have been released by any of the multilateral agencies. In absence of any official statistics, it can only remain conjecture on the carbon emissions.

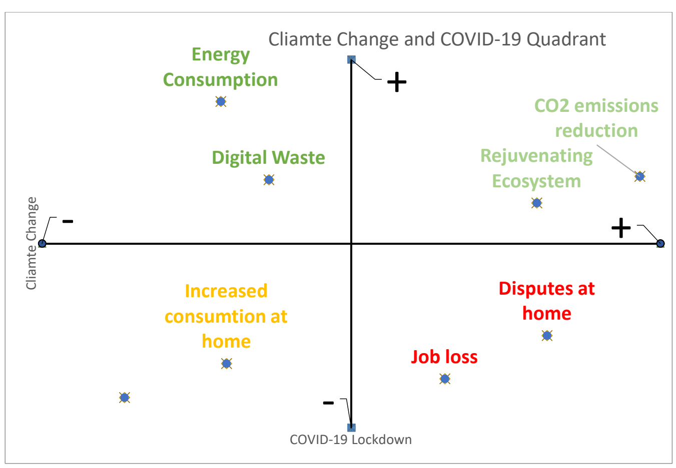

Figure 2. Conceptualized climate change economics.
Source: Developed by the researchers.

In Figure 2, the study conceptualizes COVID-19 lockdown and climate change with the help of a quadrant. The first quadrant (+, +) denotes the positive impact of climate change and COVID-19 lockdown resulting in reduced carbon emissions and a protected ecosystem. Due to lockdown, the movement of humans was at a minimum in the BRICS economies for the first time in history. This reduced the carbon emissions as well as gave time to the ecosystem to rejuvenate. The second quadrant (+, -) captures the positive role of COVID-19 lockdown but still has a negative impact on climate change. Energy consumption was still high due to home consumption rather the home consumption of energy went up as people were locked in their homes. Also due to the pressure on the digital economy, it is expected that digital waste has gone up which further leads to degradation of the environment in the form of toxic waste. The third quadrant (-, -) presents the negative role of COVID-19 as well as a negative impact on climate change. Again, the increased consumption at home of food items including meat consumption (it leads to carbon content) will in the long term impact negative on the climate change. Finally, the fourth quadrant (-, +) indicated a negative impact of COVID-19 lockdown but a positive impact on climate change. It has been reported that the number of home disputes has gone up as people were locked in their homes. The economic cost in the form of job loss cannot be ignored which will have long-term consequences for the people. In this quadrant, no negative impact on climate change is to be identified. It is imperative to highlight the stringency index of COVID-19 lock for the initial months to assess the intensity of the shutdown of the BRICS economies. Stringency index is a comprehensive index of 17 indicators of COVID-19 lockdown including containment at schools, workplace, public events, commute services, etc. Figure 2 shows the stringency index for BRICS economies.

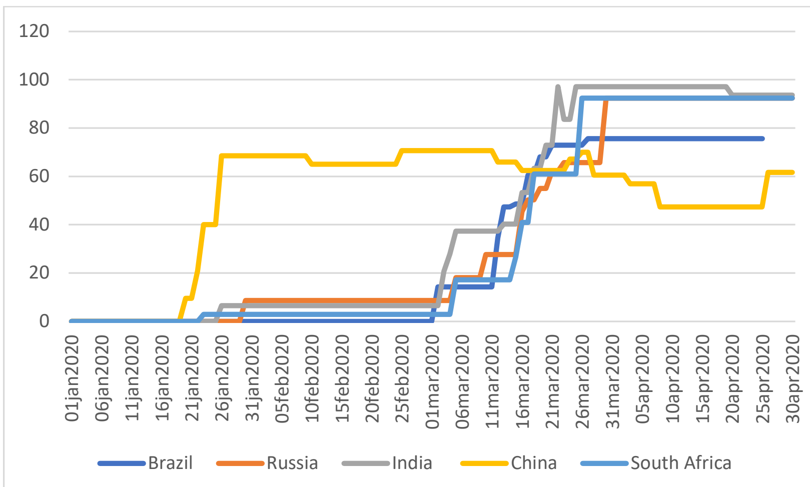

Figure 3. Stringency index for BRICS (January 1 to April 30, 2020).
Source: Oxford Stringency Index.

Figure 3 shows the pattern of lockdown intensity on a scale of 100. For Brazil, the intensity of containment went up in the last months of the sample period. However, for China, this trend is the opposite. Initially, in January, it went up rapidly and became stable in February and March and started falling in April. This is due to the effective policies of the Chinese government to tackle the spread of COVID-19. India has witnessed the highest level of stringency index in March, and there was no relaxation even at the end of April. It remained near about 100 in April 2020. For China and Russia, the trend is quite similar both reaching their highest in April 2020.

3. REVIEW OF LITERATURE

Studies have started pouring in on the subject of COVID-19 and climate change. A survey of New York residents identified that electricity consumption has become much higher due to work from home. The perception of the respondents toward climate change has remained unchanged during COVID-19 (Chen *et al*., 2020). A study conducted in the province of Ontario identified that the electricity consumption in April 2020 declined by 14%. The pattern of highest electricity demand has changed after the COVID-19. In pre–COVID-19, Monday–Friday were the days with highest electricity demand. However, in the post–COVID-19, Monday and Tuesday became the days with the highest electricity demand. The hourly electricity demand curve also flattened during the lockdown period (Abu-Rayash and Dincer, 2020). The wave of coronavirus has given an opportunity to think about the way of life in the context of climate change. There are lessons to be drawn on sustainability for the future world (Mair, 2020). The COVID-19 pandemic poses five sets of issues with respect to climate change such as impacts on emissions, environmental policy, investment in green deals, deglobalizing climate change policies, and intergenerational environmental impacts. The study argued that the positive consequences of the COVID-19 on the environment will be short term and the world should not dump the environmental concerns (Helm, 2020). Thus, for future environmental policies, it is important to put clean energy at the front of the stimulus package (Birol, 2020). As we have conceptualized the rejuvenation of the ecosystem, evidence suggests a strong association of biodiversity conservation with coronavirus (Corlett *et al*., 2020). Using a multiregional macroeconomic model, researchers have attempted to identify the spillover effects of lockdown and other containments during the COVID-19. It was identified that global atmospheric emissions are reduced by 2.5Gt of greenhouse gases, 0.6Mt of PM2.5, and 5.1Mt of SO2 and NO2. This is remarkable in absence of any specific endeavor. However, the study also suggests socio-economic challenges for the global economy including unsustainable global patterns (Lenzen *et al*., 2020). The post pandemic world requires stringent planning to tackle climate change issues. The public policy for climate change must incorporate the lessons drawn from the COVID-19 crisis (Pinner *et al*., 2020). With respect to the relationship between climate change and economic indicators, most of the studies focus on carbon emissions and economic growth. Evidence is available with dynamic effects model on saving and capital accumulation for the economic impact of climate change. There will be lower output when the savings rate is constant in the presence of climate change; this has a spillover effect on the investment (Fankhauser and Tol, 2005). SMEs are also influenced by government policies pertaining to climate change (Iqbal and Rahman, 2015). Evidence from the last 50 years on the relationship between climate change and economic growth suggests that higher temperatures substantially reduce economic growth in poor countries reducing agricultural and industrial output. Thus, poor countries feel more burn of the climate change on their economic growth (Dell *et al*., 2008). With the help of an integrated assessment model for economic growth and climate change, it was found that economic growth has a substantial effect on climate change and vice-versa particularly for the developing countries (Roson and Van der Mensbrugghe, 2012).

4. NEURAL NETWORK ANALYSIS FOR ECONOMIC INDICATORS AND CARBON EMISSIONS

The plausible question in climate change economics has remained the causal linkages between economic indicators and indicators of climate change. Carbon emissions have remained the single most important indicator of climate change due to two factors; the evidence of the significant impact of carbon emissions on climate and the data availability of carbon emissions. The recent techniques of computational economics have the potential to identify causal linkages; the neural network approach is one of such endeavors.

A neural network is a computational family of models with ample parameter space, independent of hypothesis, flexible structure, developed resembling, and brain functioning. Neural network analysis has an advantage over traditional regression models. Regression models are based on ordinary least squares (Rahman and Grewal, 2016) (along with finite sample properties) and store judgmental knowledge in the regression coefficients. Regression analysis is just one type of neural network, but neural network analysis is far more than ordinary least squares. Another superiority of a neural network is that it is dynamic rather than static (regression). We use the multilayer perceptron method for a model with one dependent variable (target output) and several predictive variables. The variable description is presented in Annexure I, and the data description with justification is presented in Annexure II.

The analysis employs three layers, namely the output layer, the input layer, and the unobserved layer. Step 1 initializes the analysis of the feedforward structure, while Step 2 trains the data for revealing the internal dynamics. Step 3 is the critical step of creating forward propagation for the data set fed in Step 2. Step 4 goes with the backward propagation where all reliability and validity are tested, and if now appropriate, the model collapses without giving node results. The final step of the cycle is an iteration of the data to make it a possible probabilistic model based on Bayesian mathematics (Figure 4). The power of the neural network approach in such a feedforward structure is incredible and has a multitude of benefits over standard statistical procedures. The most prominent being no application of hypothesis formulation as it is imbibed in the methodology. The normalized importance output becomes the evidence of variables to be associated with the target out, whether due to mediating or moderating role.

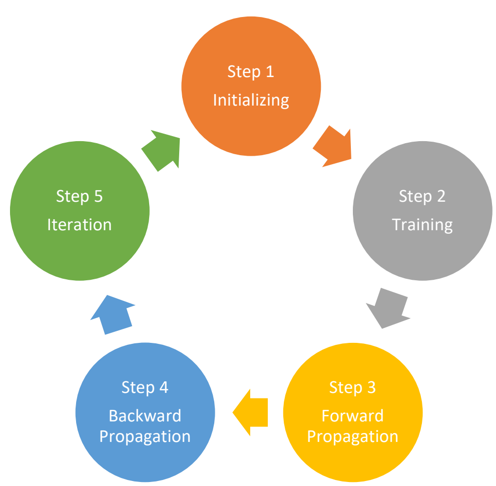

Figure 4. Steps in the algorithm propagation of the neural network.
Source: Developed by the researchers.

The neural analysis is run in a single command for the full dataset to minimize the training time and generate overall results for BRICS economies. All predictors are fed as covariates due to close linkages between economic indicators. Table 1 shows the case processing summary for the multilayer perceptron.

Table 1. Case processing summary.

		N	Percent
Sample	Training	42	70.0%
	Testing	18	30.0%
Valid		178	100.0%
Excluded		2	NA
Total		75	

Source: Output generated through neural network by the researchers.

The total cases in Table 1 are 75, while the total number of observations in the dataset is 510. Cases here mean the corresponding year figure as the data is a panel. For training purposes (Step 2 of the figure), 70% of cases are used (357 observations), and for testing purposes (Steps 3–5 of Figure 2), 30% of cases are used (153 observations). The network, with its internal dynamics, is presented in Table 2.

Table 2. Network information.

Input layer		1	CAB
		2	CPI
	Covariates	3	FDI
		4	GDP
		5	REER
		6	TOP
Hidden layer(s)	Number of units[a]		6
	Rescaling method for covariates		Standardized
	Number of hidden layers		1
	Number of units in hidden layer 1[a]		5
	Activation function		Hyperbolic tangent
Output layer	Dependent variables	1	CO_2
	Number of units		1
	Rescaling method for scale dependents		Standardized
	Activation function		Identity
	Error function		Sum of squares
[a]Excluding the bias unit.			

Source: Output generated through neural network by the researchers.

Six input layers denote the predictors (covariates) and one hidden layer with a hyperbolic tangent for carbon emissions (CO_2) (target output). The standardized method for covariates and scale dependents is applied to make the output parsimonious (See Annexure IV). The network structure is selected to make the model robust and reliable. Annexure III shows the network nodes and the outcome of the analysis. The blue lines in the hidden layer activation function suggest a causal relationship, while the dull lines indicate a weak relationship (meaning thereby insignificant relationship). The significant variables affecting the CO_2 for the panel of BRICS economies are current account balance (CAB) via hidden layer 1:2; inflation (CPI) via hidden layers 1:1 and 1:4; gross domestic product (GDP) via hidden layers 1:1 and 1:2; foreign direct investment (FDI) inflows via hidden layers 1:2, 1:3, and 1:4; real effective exchange rate (REER) via hidden layers 1:2, 1:4, and 1:5; and trade openness (TOP) via hidden layers 1:1 and 1:2. The hidden layers H(1:1) and H(1:2) have a stronger relationship with the carbon emissions of the BRICS economies. The network suggests that variables having an association with H(1:1) and H(1:2) are having a significant relationship with the carbon emissions of BRICS economies, indicating CPI, FDI, GDP, REER, and TOP. The neural analysis suggests that bias (omitted variables) does play an essential role in impacting the carbon emissions of the BRICS economies, which is natural. However, it also suggests that the economic indicators are having a significant impact on the carbon emissions of BRICS economies. The relative importance of the predictors is shown in Figure 5 (for statistics, see Annexure V).

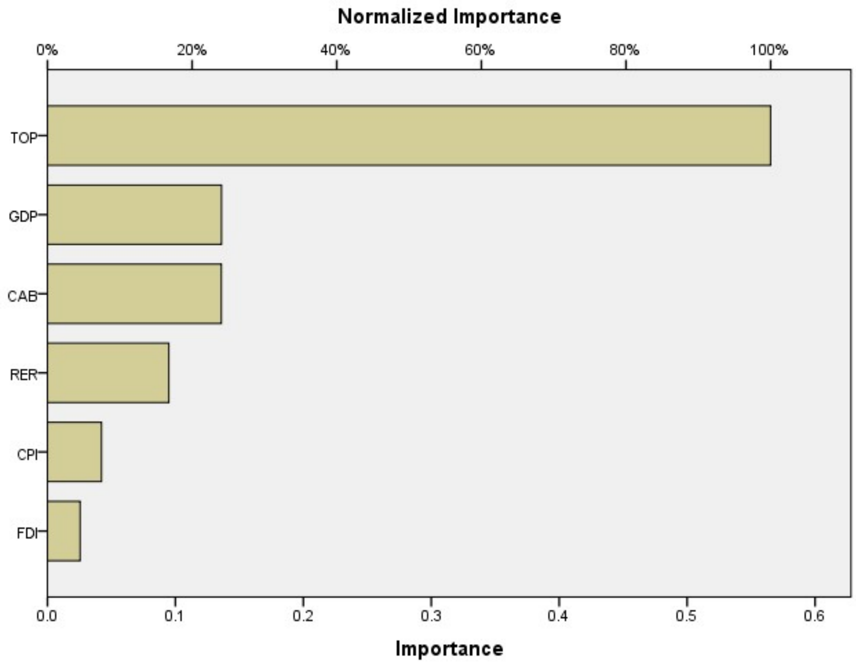

Figure 5. Normalized importance of predictors based on multilayer perceptron.
Source: Developed by the researchers.

The normalized importance of the predictors suggests the order of predictors in importance with respect to carbon emissions. The most important predictor is the TOP followed by the GDP of the country. Next comes the CAB and REER of the BRICS economies. However, FDI and CPI play a pity role in the climate change economics of BRICS economies. Table 3 captures the summarized results of neural network analysis for the BRICS economies.

Table 3. Neural network summary.

Variable	Relationship	Hidden layers	Impact on CO_2 through H (1:1) and H (1:2)
CAB	Strong	H (1:2)	Significant
CPI	Strong	H (1:1); H (1:2)	Significant
FDI	Strong	H (1:2)	Significant
GDP	Strong	H (1:1); H (1:2)	Significant
REER	Strong	H (1:2)	Significant
TOP	Strong	H (1:1); H (1:2)	Significant

Source: Output generated through neural network by the researchers.

5. CONCLUSION

Climate change challenges are worth discussing for a post–COVID-19 world with socio-economic shocks. Future climate change policies cannot be framed without having an understanding of the causal relationship between economic indicators and carbon emissions. The study has identified that economic indicators such as CAB, CPI, GDP, FDI inflows, REER, and TOP have a significant relationship for BRICS economies by applying the neural network approach. Time and again, BRICS economies have reiterated their commitment toward climate change principles, particularly the UNFCC principles. During COVID-19 lockdown in BRICS economies, except Brazil, all economies were quick to implement lockdown as a preventive strategy. The stringency index for BRICS economies suggests the shutdown of the economy and social institutions during March and April. The study has proposed a conceptual model for COVID-19 and climate change as well based on quadrant.

CONFLICT OF INTEREST

None.

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ANNEXURES

Annexure I. Variables description.

Type	Variable	Measure (source)	Symbol
Target Output	Carbon emissions	Kt-Annual (UNCTAD Statistics)	CO_2
Predictor	Current account balance	US Dollars Millions (UNCTAD Statistics)	CAB
Predictor	Inflation	Consumer Price Indices; Index Base 2010	CPI
		(UNCTAD Statistics)	
Predictor	Foreign direct investment inflows	US Dollars Millions (UNCTAD Statistics)	FDI
Predictor	Gross domestic product	US Dollars Millions (UNCTAD Statistics)	GDP
Predictor	Real effective exchange rate	CPI Based; Base Year 2005 (UNCTAD	REER
		Statistics)	
Predictor	Trade openness	Average of Exports and Imports in US Dollars	TOP
Millions (UNCTAD Statistics)			

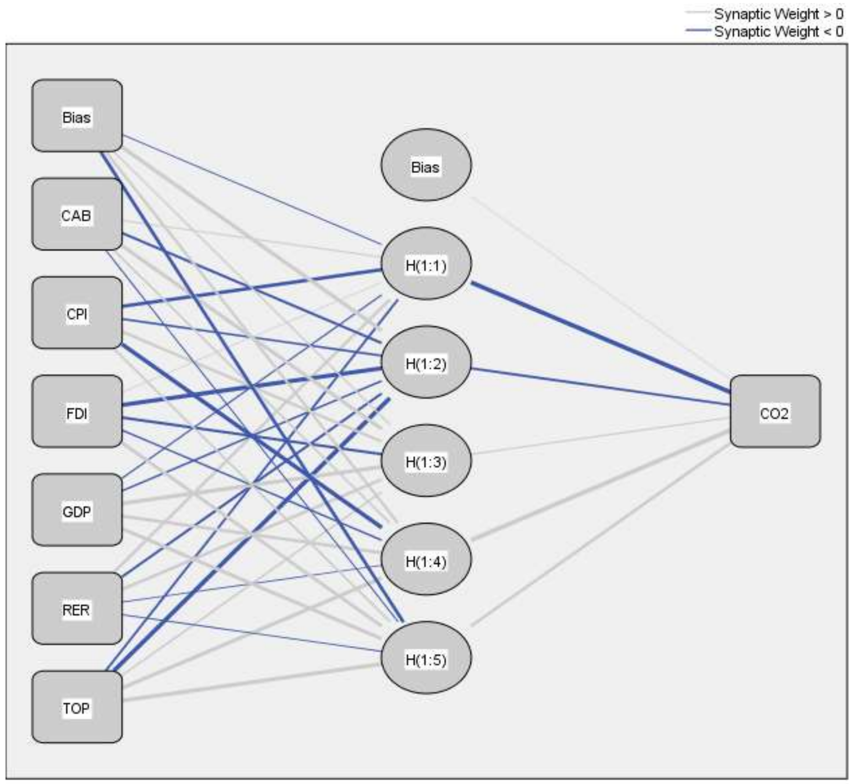
Source: Compiled by researchers.

Annexure II. Data description.

Symbol	Sample period	Sample countries	Justification from Climate Change Economics Literature
CO_2	2005–2019		Heil and Selden (1999); Dogan and Aslan (2017); Pao and Tsai (2011); Bekhet and Othman, (2018); Lozano and Gutierrez (2008); McGregor, Swales, and Turner, (2008).
CAB	2005–2019		McGregor, Swales, and Turner, (2008).
CPI	2005–2019	Brazil	Hussain, Ahmad, Qamar, and Akram, (2019).
FDI	2005–2019	Russia	Pao and Tsai (2011).
GDP	2005–2019	India	Heil and Selden (1999); Doda (2014); Dogan and Aslan (2017); Pao and Tsai (2011); Bekhet and Othman (2018); Lozano and Gutierrez (2008); Hossain (2011); Shahbaz, Tiwari, and Nasir (2013).
		China	
		South Africa	
REER	2005–2016		Zhang and Zhang (2018).
TOP	2005–2019		Sebri and Ben-Salha (2014); Hossain, (2011); Shahbaz *et al*. (2013); Zhang *et al*. (2017).

Source: Compiled by researchers.

Annexure III. Neural network causal nodes.



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Annexure IV. Model summary.

Training	Sum of squares error	0.373
	Relative error	0.018
Testing	Sum of squares error	0.128
	Relative error	0.007
Dependent variable: CO_2		
a. Error computations are based on the testing sample.		

Source: Output generated through Neural Network by the researchers.

Annexure V. Independent variable importance.

	Importance	**Normalized importance**
CAB	0.136	24.1%
CPI	0.042	7.5%
FDI	0.025	4.5%
GDP	0.136	24.1%
REER	0.095	16.8%
TOP	0.565	100.0%

Source: Output generated through neural network by the researchers.