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 trade-off. 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.

Section 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 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, 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 trade-off 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), have fully participated in Climate change initiatives, 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 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 9th 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, Fatima, and Rahman, 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 reduced. However, there 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 pre-determined 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 to the study and Section 2 conceptualized Climate
Change and COVID-19 scenario. Section 3 review the recent literature on the theme while Section 4 delves into the neural network analysis. The study concludes in Section 5.

Section 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 to the living. The Intergovernmental Panel on Climate Change (IPCC) estimates that till the end of 21\textsuperscript{st} century there will be an average rise in temperature between 2.5 to 7.8 degrees Celsius. 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 land mass may even vanish. There are around seven prominent theories of Climate Change presented in Figure 1.

![Climate Change Theories](image.png)

**Figure 1. Climate Change Theories**

**Source:** Climate Change issues in BRICS countries

All these theories attempt to identify the cause and suggests 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 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 25\textsuperscript{th} February 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 31\textsuperscript{st} January after which preventive measures were imposed. However, as the cases started to rise in end February and March, lockdown was imposed on April 17 2020. However, in the end of March it was already implemented on the Russian borders. On 24\textsuperscript{th} March 2020, a nationwide lockdown was imposed in India for 21 days which was later extended. He 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 23\textsuperscript{rd} January 2020. Lockdown was followed by quarantine measures, follow up checks, and travel history analysis for possible carrier of virus. On 5\textsuperscript{th} March 2020 officially it was reported in South Africa that cases have started spreading rapidly. As a breakdown strategy, nationwide lockdown was imposed on 27\textsuperscript{th} March 2020. BRICS economies responded quickly to the COVID-19 pandemic except Brazil that was late. This lockdown resulted in almost total lockdown of industrial and economic activities. This has resulted in reduction in the carbon emissions for BRICS countries. However, no official statistics has been released by any of the multilateral agencies. In absence of any official statistics, it can only remain conjecture on the carbon emissions.
In figure 2, the study conceptualizes Covid10 lockdown and Climate Change with the help of 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 were at minimum in the BRICS economies for the first time in history. This reduced the carbon emissions as well as gave time to ecosystem to rejuvenate. The second quadrant (+, -) captures the positive role of COVID-19 lockdown but still 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 digital economy, it is expected that digital waste has gone up which further leads to degradation of 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 negative impact 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 have gone up as people were locked in their homes. The economic cost in the form job loss cannot be ignored which will have a long-term consequence 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 et cetera. Figure 2 shows the Stringency Index for BRICS economies.
Figure 3. Stringency Index for BRICS (1st January to 30th April 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 it is trend is opposite. Initially in the month of 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 Chinese government to tackle the spread of COVID-19. India has witnessed the highest level of stringency index in the month of March and there was not 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 to their highest in the month of April 2020.

Section 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 towards climate change has remained unchanged during COVID-19 (Chen, de Rubens, Xu, and Li, 2020). A study conducted on the province of Ontario identified that the electricity consumption in the month of April 2020 declined by 14%. The pattern of highest electricity demand has changed after the COVID-19. In pre-covid1, Mon-Fri were the days with highest electricity demand. However, in the post COVID-19, Mon-Tue 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 set 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 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 ecosystem, evidence suggests that a strong association of biodiversity conservation with coronavirus (Corlett, et al. 2020). Using a multi-regional macro-economic model, researchers have attempted to identify the spill over 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 PM$_{2.5}$, and 5.1Mt of SO$_2$ and NO$_x$. 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, Rogers, and Samandari, 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 economic impact of climate change. There will be lower output when savings rate is constant in the presence of climate change, this has a spill over effect on the investment (Fankhauser, and Tol, 2005). SMEs also are influenced by government policies pertaining to climate change (Iqbal and Rahman, 2015). Evidence from last 50 years on the relationship between climate change and economic growth suggest that higher temperature substantially
reduces 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, Jones, and Olken, 2008). With the help of an integrated assessment model for economic growth and climate change, it was found that economic growth has substantial effect on climate change and vice-versa particularly for the developing countries (Roson, and Van der Mensbrugghe, 2012).

Section 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 has 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, 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 brain functioning. Neural network analysis has an advantage over traditional regression models. Regression models are based on Ordinary Least Squares (along with finite sample properties) and store judgemental 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 output layer, 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 of 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 iteration of the data to make it a possible probabilistic model based on the Bayesian mathematics. The power of 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 means the corresponding year figure as the data is a panel. For Training purposes (Step 2 of the figure), 70% cases are used (357 observations), and for testing purposes (Step 3-5 of the figure 2) 30% cases are used (153 observations). The network, with its internal dynamics, is presented in Table 2.

Table 2: Network Information

|                |                |      |
|----------------|----------------|------|
| Input Layer    |                |      |
| Covariates     | 1: CAB         | 6    |
| 2: CPI         |                |      |
| 3: FDI         |                |      |
| 4: GDP         |                |      |
| 5: RER         |                |      |
| 6: TOP         |                |      |
| Number of Units |                | 6    |
| Rescaling Method for Covariates | Standardized |      |
| Number of Hidden Layers | 1 |      |
| Hidden Layer(s) | Number of Units in Hidden Layer 1 | 5 |
| Activation Function | Hyperbolic tangent |      |
| Dependent Variables | 1 CO2 |      |
| Number of Units | 1 |      |
| Output Layer   | 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 (CO2) (target output). The standardized method for covariates and scale dependents is applied to make the output parsimonious. 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 CO2 for the panel of BRICS Economies are Current Account Balance (CAB) via hidden Layer 1:2, Inflation (CPI) via hidden layer 1:1 and 1:4; Gross Domestic Product (GDP) via hidden layer 1:1 and 1:2; Foreign Direct Investment Inflows (FDI) via hidden Layer 1:2, 1:3 and 1:4, Real Effective Exchange Rate (RER) via hidden Layer 1:2, 1:4 and 1:5; and Trade Openness (TOP) via hidden layer 1:1 and 1:2. The hidden layer 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) have a stronger relationship with the Carbon Emissions of BRICS Economies, indicating CPI, FDI, GDP, RER, 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).
The normalized importance of the predictors suggests the order of predictors in importance with respect to carbon emissions. The most important predictor is the Trade Openness followed by GDP of the country. Next comes the Current Account Balance and Real Effective Exchange Rate of the BRICS economies. However, FDI and Inflation plays a pity role in the climate change economics of BRICS economies. Table 4 captures the summarized results of neural network analysis for the BRICS Economies.

### Table 3: Neural Network Summary

| Variable | Relationship | Hidden Layers | Impact on CO2 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                              |
| RER      | Strong       | H (1:2)       | Significant                              |
| TOP      | Strong       | H (1:1); H (1:2) | Significant                              |

Source: Output generated through Neural Network by the researchers
Section 5: Conclusion

Climate Change challenges are worth discussing for a post covid10 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 Current Account Balance, Inflation, Gross Domestic Product, Foreign Direct Investment Inflows, Real Effective Exchange Rate and Trade Openness have significant relationship for BRICS economies by applying the neural network approach. Time and again BRICS economies have reiterated their commitment towards 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 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.

References

Abu-Rayash, A., and Dincer, I. (2020). Analysis of the electricity demand trends amidst the COVID-19 coronavirus pandemic. *Energy Research and Social Science, 68*, 101682. Doi: https://doi.org/10.1016/j.erss.2020.101682

Bekhet, H. A., and Othman, N. S. (2018). The role of renewable energy to validate dynamic interaction between CO2 emissions and GDP toward sustainable development in Malaysia. *Energy economics, 72*, 47-61. Doi: https://doi.org/10.1016/j.eneco.2018.03.028

Birol, F. (2020). Put clean energy at the heart of stimulus plans to counter the coronavirus crisis. *International Energy Agency, 14*, https://www.bmjgerard.nl/wp-content/uploads/2020/04/put-clean-energy-at-heart-of-stimulus-plans-after-corona-%E2%80%93-analysis-IEA-removal-subsidies_14mrt2020.pdf

Chen, C. F., de Rubens, G. Z., Xu, X., and Li, J. (2020). Coronavirus comes home? Energy use, home energy management, and the psychological factors of COVID-19. *Energy research and social science, 68*, 101688. Doi: https://doi.org/10.1016/j.erss.2020.101688

Corlett, R. T., Primack, R. B., Devictor, V., Maas, B., Goswami, V. R., Bates, A. E., ... and Cumming, G. S. (2020). Impacts of the coronavirus pandemic on biodiversity conservation. *Biological Conservation, 246*, 108571. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7139249/

Dell, M., Jones, B. F., and Olken, B. A. (2008). *Climate change and economic growth: Evidence from the last half century* (No. w14132). National Bureau of Economic Research. Doi: 10.3386/w14132

Doda, B. (2014). Evidence on business cycles and CO2 emissions. *Journal of Macroeconomics, 40*, 214-227. Doi: https://doi.org/10.1016/j.jmacro.2014.01.003

Dogan, E., and Asian, A. (2017). Exploring the relationship among CO2 emissions, real GDP, energy consumption and tourism in the EU and candidate countries: Evidence from panel models robust to heterogeneity and cross-sectional dependence. *Renewable and Sustainable Energy Reviews, 77*, 239-245. Doi: https://doi.org/10.1016/j.rser.2017.03.111

Fankhauser, S., and Tol, R. S. (2005). On climate change and economic growth. *Resource and Energy Economics, 27*(1), 1-17. Doi: https://doi.org/10.1016/j.reseneeco.2004.03.003

Heil, M. T., and Selden, T. M. (1999). Panel stationarity with structural breaks: carbon emissions and GDP. *Applied Economics Letters, 6*(4), 223-225. Doi: https://doi.org/10.1080/135048599353384

Helm, D. (2020). The environmental impacts of the coronavirus. *Environmental and Resource Economics, 1*. Retrieved from https://link.springer.com/content/pdf/10.1007/s10640-020-00426-z.pdf?andcasa_token=r-GuFSrP5OgAAAA:qvldoZygXvhbTVstrPQVSB7etye2G8oLY_OMTGIL6YEvvBLU8U1w55P581pS4qFybJRC0SFbc9rUlg7ex

Hossain, M. S. (2011). Panel estimation for CO2 emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries. *Energy Policy, 39*(11), 6991-6999. Doi: https://doi.org/10.1016/j.enpol.2011.07.042
Hussain, S., Ahmad, W., Qamar, Y., and Akram, M. S. (2019). Impact of Inflation, CO2 Emissions and Foreign Investment on Economic Growth: A Case of Pakistan. *Asian Development Policy Review, 7*(4), 307-317. Retrieved from http://www.aessweb.com/pdf-files/ADPR-2019-7(4)-307-317.pdf

Iqbal, B. A., and Rahman, M. N. (2015). Contribution of ASEAN-6 SMEs to economic growth of ASEAN. *Economics World, 3*(11-12), 258-269. DOI: 10.17265/2328-7144/2015.1112.002

Iqbal, B. A., and Rahman, M. N. (2016). BRIC (S) as an Emerging Block?. In *The challenge of BRIC multinationals*. Emerald Group Publishing Limited. DOI: 10.1108/S1745-886220160000011012

Lenzen, M., Li, M., Malik, A., Pomponi, F., Sun, Y. Y., Wiedmann, T., ... and Gómez-Paredes, J. (2020). Global socio-economic losses and environmental gains from the Coronavirus pandemic. *PloS one, 15*(7), e0235654. Doi: https://doi.org/10.1371/journal.pone.0235654

Lozano, S., and Gutierrez, E. (2008). Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO2 emissions. *Ecological Economics, 66*(4), 687-699. Doi: https://doi.org/10.1016/j.ecolecon.2007.11.003

Mair, S. (2020). How will coronavirus change the world?. *BBC Future, 31*. Retrieved from https://www.counsellingresources.co.nz/uploads/3/9/8/5/3985535/how_will_coronavirus_change_the_world.pdf

McGregor, P. G., Swales, J. K., and Turner, K. (2008). The CO2 ‘trade balance’ between Scotland and the rest of the UK: performing a multi-region environmental input–output analysis with limited data. *Ecological Economics, 66*(4), 662-673. Doi: https://doi.org/10.1016/j.ecolecon.2007.11.001

Pao, H. T., and Tsai, C. M. (2011). Multivariate Granger causality between CO2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. *Energy, 36*(1), 685-693. Doi: https://doi.org/10.1016/j.energy.2010.09.041

Pinner, D., Rogers, M., and Samandari, H. (2020). Addressing climate change in post-pandemic world. *McKinsey Quarterly April*. Retrieved from http://acdc2007.free.fr/mckclimate420.pdf

Rahman, M. N. (2016). Role of WTO in promoting merchandise trade of BRICS. *Transnational Corporations Review, 8*(2), 138-150. DOI: 10.1080/19186444.2016.1196867

Rahman, M. N. (2020). Editorial Note-Special Issue on “BRICS: The Emerging Block”. *Manag Econ Res J, 6*(S5), 18791.

Rahman, M. N., and Grewal, H. S. (2017). Foreign direct investment and international trade in BIMSTEC: panel causality analysis. *Transnational Corporations Review, 9*(2), 112-121. DOI: 10.1080/19186444.2017.1326720

Rahman, M. N., and Iqbal, B. A. (2019). Public policies for providing cloud computing services to SMEs of Latin America. In *Advanced Methodologies and Technologies in Government and Society* (pp. 365-376). IGI Global. DOI: 10.4018/978-1-5225-7661-7.ch029

Rahman, M. N., and Turay, A. M. (2018). Climate change issues in BRICS countries. *Manag Econ Res J, 4*(2018), 6790. Retrieved from https://merj.scholasticahq.com/article/6790.pdf

Rahman, M. N., Fatima, Z., and Rahman, N. (2020). Quantitative dynamics of intra-BRICS trade. *BRICS Journal of Economics, 1*(4), 6-23. DOI: 10.38050/2712-7508-2020-1-4-2

Roson, R., and Van der Mensbrugghe, D. (2012). Climate change and economic growth: impacts and interactions. *International Journal of Sustainable Economy, 4*(3), 270-285. Doi: https://doi.org/10.1504/IJSE.2012.047933

Sebri, M., and Ben-Salha, O. (2014). On the causal dynamics between economic growth, renewable energy consumption, CO2 emissions and trade openness: Fresh evidence from BRICS countries. *Renewable and Sustainable Energy Reviews, 39*, 14-23. Doi: https://doi.org/10.1016/j.rser.2014.07.033

Shahbaz, M., Tiwari, A. K., and Nasir, M. (2013). The effects of financial development, economic growth, coal consumption and trade openness on CO2 emissions in South Africa. *Energy Policy, 61*, 1452-1459. Doi: https://doi.org/10.1016/j.enpol.2013.07.006
Zhang, S., Liu, X., and Bae, J. (2017). Does trade openness affect CO2 emissions: evidence from ten newly industrialized countries. *Environmental Science and Pollution Research*, 24(21), 17616-17625. Doi: 10.1007/s11356-017-9392-8

Zhang, Y., and Zhang, S. (2018). The impacts of GDP, trade structure, exchange rate and FDI inflows on China's carbon emissions. *Energy Policy*, 120, 347-353. Doi: https://doi.org/10.1016/j.enpol.2018.05.056

**Annexures**

### Annexure I: Variables Description

| Type            | Variable                              | Measure (Source)                      | Symbol |
|-----------------|---------------------------------------|---------------------------------------|--------|
| Target Output   | Carbon Emissions                      | Kt -Annual (UNCTAD Statistics)       | CO2    |
| Predictor       | Current Account Balance               | US Dollars Millions (UNCTAD Statistics)| CAB    |
| Predictor       | Inflation                             | Consumer Price Indices; Index Base 2010 (UNCTAD Statistics) | CPI    |
| 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 Statistics)| RER    |
| Predictor       | Trade Openness                        | Average of Exports and Imports in US Dollars Millions (UNCTAD Statistics)| TOP    |

Source: Compiled by Researchers

### Annexure II: Data Description

| Symbol | Sample Period | Sample Countries | Justification from Climate Change Economics Literature |
|--------|---------------|------------------|-------------------------------------------------------|
| CO2    | 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     | Brazil           | McGregor, Swales, and Turner, (2008).                |
| CPI    | 2005-2019     | Brazil, Russia   | Hussain, Ahmad, Qamar, and Akram, (2019).            |
| FDI    | 2005-2019     | India, China, South Africa | Pao and Tsai (2011). |
| GDP    | 2005-2019     | Brazil, Russia   | 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). |
| RER    | 2005-2016     | Brazil, Russia   | Zhang and Zhang (2018).                              |
| TOP    | 2005-2019     | Brazil, Russia   | Sebri and Ben-Salha (2014); Hossain, (2011); Shahbaz, Tiwari, and Nasir (2013); Zhang, Liu, and Bae (2017). |

Source: Compiled by Researchers
**Annexure III: Neural Network Causal Nodes**

![Diagram of causal nodes](diagram.png)

Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

Source: Output generated through Neural Network by the researchers.

**Annexure IV: Model Summary**

|        | Sum of Squares Error | Relative Error |
|--------|----------------------|----------------|
| Training | .373                 | .018           |
| Testing  | .128                 | .007           |

Dependent Variable: CO2

a. Error computations are based on the testing sample.

Source: Output generated through Neural Network by the researchers.

**Annexure V: Independent Variable Importance**

| Variable | Importance | Normalized Importance |
|----------|------------|-----------------------|
| CAB      | .136       | 24.1%                 |
| CPI      | .042       | 7.5%                  |
| FDI      | .025       | 4.5%                  |
| GDP      | .136       | 24.1%                 |
| RER      | .095       | 16.8%                 |
| TOP      | .565       | 100.0%                |

Source: Output generated through Neural Network by the researchers.