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Do Industry 4.0 & Technology Affect Carbon Emission: Analyse with the STIRPAT Model?

Asha SHARMA[1]

Assistant Professor, Department of Accountancy and Business Statistics, University College of Commerce & Management Studies, Mohanlal Sukhadia University, Udaipur (Rajasthan), India.
E-mail: asha.sharma@mlsu.ac.in

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Abstract

Purpose – The main purpose of the paper is to examine the variables affecting carbon emissions in different nations around the world.

Research design, data, and methodology – To measure its impact on carbon emissions, secondary data has data of the top 50 Countries have been taken. The stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model have been used to quantify the factors that affect carbon emissions. A modified version using Industry 4.0 and region in fundamental STIRPAT model has been applied with the ordinary least square approach. The outcome has been measured using both the basic and extended STIRPAT models.

Result – Technology found a positive determinant as well as statistically significant at the alpha level of 0.001models indicating that technological innovation helps reduce carbon emissions. In total, 4 models have been derived to test the best fit and find the highest explaining capacity of variance. Model 3 is found best fit in explanatory power with the highest adjusted R2 (97.95%).

Conclusion – It can be concluded that the selected explanatory variables population and Industry 4.0 are found important indicators and causal factors for carbon emission and found constant with all four models for total CO2 and Co2 per capita.

Keywords: Carbon emission, Carbon per capita, Technology, Industry 4.0, STIRPAT Model

JEL Classification Code: O15, E24, D74,

1. Introduction

Industry 4.0 and increased energy use are causing environmental harm while promoting economic progress. Climate change is mostly the result of carbon emissions. On a worldwide scale, it is the most challenging issue of this century. The United Nations is now more aware of the need to move towards a target of zero carbon emissions. Climate Neutral is a recent UNFCC initiative. It was established in 2015 to encourage the voluntary use of carbon market mechanisms approved by the Convention. The Climate Neutral Now Initiative urges businesses and other interested parties to take immediate action to realize the Paris Agreement's goal of a climate-neutral world by 2050.

Global warming, climate change, and over-exploitation of natural resources have all had a detrimental effect on human life. Humans can employ technology to accomplish any task for their comfort in the era of industry 4.0, robotics, atomization, and machine learning, yet they are helpless to stop the excessive use of natural resources and greenhouse gas emissions. Due to its negative consequences on ecosystems, rapid climate change has become a prominent topic since the beginning of the 21st century (Malhi et al., 2020).

It has been a key topic and challenge to measure and control carbon emissions. Carbon emissions have continuously increased with the change in the global economy. Researchers are interested in investigating the linkage between CO2 emissions and economic growth to meet emission reduction goals (Dong et al., 2020).

High levels of carbon emissions may be caused by the increased use of fossil fuels in industrial production. Economic development can be a significant reason to increase in carbon emissions. Many academics have looked into and taken a keen interest in the research on how change and development in the economy affect carbon emissions (Gokmenoglu et al., 2015)

Scholars both domestically and internationally have conducted fruitful research about the variables that affect carbon emissions. Driving force analysis with the IPAT equation and driving factor analysis using the Kaya model are two relevant examples of the research knowledge that are representative. According to the IPAT equation proposed by Ehrlich et al., the combined impact of population density, economic development, and scientific and technical advancement is what are the influencing drives carbon emissions (Dietz & Rosa, 1994) created the STIRPAT model by combining stochastic theory with the IPAT model (York et al., 2003).

Existing STARPAT Model: The study is mainly focused on the impact factors of CO2 emissions, earlier IPAT model was popular. Dietz and Rosa analyzed and improved an adjusted IPAT model with the effects of P, A, and T on CO2 emissions at a global level that would eventually become STIRPAT (1997). According to their findings, the population affects the environment that is roughly inversely correlated with its size throughout a range of population sizes (1997). Consequently, a change in population correlates with a change in impact (York et al. 2003a).

Carbon emission= The Stochastic Impacts by Regression on P (pop.) x A (affluence) x T (technology).

Additional STIRPAT: Results on CO2 Using the STIRPAT model, Shi (2003) and Fan et al. (2006) extended the global analysis of CO2 emissions. They followed Dietz and Rosa's basic structure (1997) York et al. (2003b; 2003c) but separated the various stages of economic development into four groups, placing high-income economies at the top, upper-middle-income economies next, lower-middle-income economies next, and low-income economies at the bottom (Fan et al. 2006). According to the World Bank's classification system, countries are divided into four income tiers (Shi 2003). This model made it possible to examine the differences between various national economies. They discovered that at various stages of development, the effects of population, wealth, and technology on CO2 emissions do vary (Fan et al. 2006; Shi 2003).

2. Review of Literature

The literature on the topic of carbon emissions was reviewed. To understand the previous work, the research papers published in national and international journals, books, magazines, and websites of the World Bank have been examined. The following international literature has been examined:

2.1. Carbon Emission and Industry 4.0

The next study thoroughly examines the variables affecting the Chinese ISI's carbon emissions. It examines this problem from the viewpoint of the industrial chain. It offers fresh research directions for upcoming simulation model studies. (Z. Li et al., 2019)

The Beijing carbon trading market in China is used in the study to pinpoint the factors that influence carbon price variations and project future carbon prices. Using the grey correlation technique, it is determined whether the selected variables that affect variations in the price of carbon are fair. The GA-ELM model is found to have the best predictive impact (Yanmei Li & Song, 2022)

Domestic energy use and financial flexibility were the main focuses of the essay. The study's main factors were county income levels and carbon intensity. Through the effects of income on spending habits, the cross-country inverted-U relationship between per capita GDP and emissions intensity has been found (Caron & Fally, 2022)

The present research discusses the impact of changing wealth disparity on carbon dioxide (CO2) emissions in OECD countries. The link between economic growth and carbon emissions has been proven. Panel data estimation techniques using Gini coefficients have been used to measure relationships. A positive correlation exists between rising top-income inequality and carbon emissions (Hailemariam et al., 2020)

According to the study's findings, government expenditure on households, ships, and the environment does not have the same significant and favorable impact on environmental deterioration as manufacturing industries do (Azwardi et al. 2022).

2.2. Carbon Emission and technological innovation with Different Models

The paper's key idea is an investigation of the factors influencing CO2 emissions. Determining climate conditions based on socioeconomic factors is one of the most important factors in successfully reducing greenhouse gas emissions. The STIRPAT model has mainly been used to investigate the mechanism of emissions induced by the combination of natural and social factors. The main factors are urbanization rate, GDP per capita, population, energy intensity, trade openness, cooling degree days, mean temperature anomaly, and economic development (Yang et al., 2018).

Innovation in technology helps to reduce carbon emissions. The acquired results demonstrate that the EKC hypothesis is true for the top 10 carbon-emitting nations. To achieve sustainable development of the population, resources, and environment, the governments of these nations should implement policies to encourage environmental technology innovation and energy efficiency (Thio et al., 2022).

Although the STIRPAT model has many uses and great potential, there are still some unresolved issues and knowledge gaps, including geographical imbalances in study scope, an almost sole focus on carbon emissions, disagreements over the best data to use, additional explanatory variables, and regression models, disagreements over how to best approximation T, and a lack of explicit analyses of the (E) RE. Our findings are valuable to academics and policymakers for method development, more study, and policy review (Vélez-Henao et al., 2019)

Panel quantile regression and an extended Environmental Kuznets Curve, Population, Affluence, and Technology (STIRPAT) model were used to examine the factors that drove carbon emissions in the top 10 nations between 2000 and 2014. To determine the link between the variables and assess the EKC, we also performed panel quantile regression (Thio et al., 2022)

To look into the environmental Kuznets curve (EKC) hypothesis and driving variables for CO2 emissions in China, an extended-STIRPAT model and system dynamics model have been developed. At 1%, 5%, or 10% confidence levels, the panel regression findings demonstrate that all coefficients are significant. The STIRPAT model was used to verify emission peaking (D. Liu & Xiao, 2018).

Difference based on the stochastic impact by regression on population, affluence, and technology (STIRPAT) model, the generalized method of moments is used to evaluate the influence of energy patents on carbon emissions. The findings show that energy patents are not an effective tool for reducing carbon emissions. Energy patents from businesses and scientific institutions, however, have a good impact on lowering carbon emissions, while patents from higher education institutions have an even greater impact (Huang et al., 2021).

The primary contributing elements for energy-related carbon emissions in Xinjiang were identified using an enhanced STIRPAT model based on the traditional IPAT identification. In the three distinct stages of development, numerous elements have varying effects and influences on carbon emissions.

Before the Reform and Opening up (1952–1977), carbon intensity and population density were the two main drivers of increases in carbon emissions, whereas the structure of energy use had a significant impact on reducing emissions. Economic expansion and population growth are the two main drivers of increases in carbon emissions after the Reform and Opening up (1978–2000), while carbon intensity has a significant adverse impact on carbon emissions (C. Wang et al., 2017).

The primary contributing elements for energy-related carbon emissions in Xinjiang were identified using an enhanced STIRPAT model based on the traditional IPAT identification. The following things have an impact on and influence carbon emissions:

The empirical findings indicate that there were significant and varied effects of age structure on carbon emissions. To ascertain how many nations hit the carbon peak, the EKC hypothesis is further tested with the threshold model of per capita income on carbon emissions. This analysis demonstrated that the pattern of global carbon consumption and the evidence at the household level are consistent. Another noteworthy conclusion is that, in contrast to what certain household energy consumption models would anticipate, population aging may generally increase heat and electricity carbon emissions (W. Liu et al., 2022).

According to the empirical findings, the structure and trend of the carbon emissions in the four provinces of the Yangtze River Delta between 2005 and 2019 differed significantly from one another. The main influencing elements that affect each province differently, and the effects of the same factor on several locations vary dramatically. Last but not least, the policy recommendations for the provinces are specifically adapted to the various carbon emission-influencing elements to help them attain their peak carbon emissions and carbon neutrality targets (Guo et al., 2022).

(Ziyuan et al., 2022)

We compared estimated carbon emissions from the original STIRPAT model and the ISTIRPAT model for 17 cities and prefectures from 2012 to 2018 with actual emissions data. The outcomes demonstrate that when the province carbon emission inventory was scaled down using the ISTIRPAT model to the city level, the inversion accuracy reached 0.9, which was higher than that of the original model (Q. Wang et al., 2022)

Technology's potential impact on electrification is gradually losing its sway. When China's economic growth slows down, the potential for electrification will as well, however as technology advances, the trend of sluggish electrification potential growth will be reversed (Li & Lu, 2021).

The STIRPAT model has been applied to comprehend the variety and importance of the variables, scopes, assumptions, statistical methods, and the often-researched environmental consequences. The results show that despite the STIRPAT model's numerous applications and high potential, there are still unresolved issues and knowledge gaps, including a geographic imbalance in the scope of studies, an almost sole focus on carbon emissions, disagreements over the selection of data, additional explanatory factors, and regression models, disagreements over how to approximation T, and a lack of explicit analyses of the (E) (Vélez-Henao et al., 2019).

We, therefore, used panel quantile regression and an expanded Environmental Kuznets Curve, Population, Affluence, and Technology (STIRPAT) model to examine the factors that drove carbon emissions across the top 10 nations from 2000 to 2014. To determine the link between the variables and assess the EKC, we also performed panel quantile regression (Thio et al., 2022).

We compared estimated carbon emissions from the original STIRPAT model and the ISTIRPAT model for 17 cities and prefectures from 2012 to 2018 with actual emissions data. The outcomes demonstrate that when the province carbon emission inventory was scaled down using the ISTIRPAT model to the city level, the inversion accuracy reached 0.9, which was higher than that of the original model (Q. Wang et al., 2022).

2.3. Identification of Research Gap

Understanding the current research gaps requires a rigorous mapping of the literature. By reading the study, it appears that the majority of the research was done using the STIRPAT model, but the influence of industry 4.0 has not yet been quantified. So, the following is the hypothesis:

H1: There is no significant impact of the STIRPAT model on total carbon emission among selected global top 50 carbon emitting countries

H2: There is no significant impact of the STIRPAT model on carbon emission per capita among selected global top 50 carbon emitting countries

H3: There is no significant impact of extended the STIRPAT model on total carbon emission among selected global top 50 carbon emitting countries

H4: There is no significant impact of extended the STIRPAT model on carbon emission per capita among selected global top 50 carbon emitting

3. Research Methodology

Research work is based on secondary data. Data relating to carbon emission, income group, and region has been gathered through the World Bank website (data.worldbank.org). Carbon Emission Global share of the Top 50

Countries out of a total of 270 global countries for the financial year 2021 have been identified for further research purposes. Cross-sectional data has been used.

3.1. Application of the STARPAT Model

A modified version of the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model has been used to measure the factors that affect carbon emissions. Two models are applied using the OLS approach to determine their influence. Thus, the three variables P (population), A (affluence), and T (technology) are covered by the Basic STIRPAT Model.

$$Y_{it} = \beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3 + E_{it}$$

$$\text{Carbon Emission}_{it} = \beta_1 + \beta_2 (\text{Population}) + \beta_3 (\text{Affluence}) + \beta_4 (\text{Technology}) \text{-----Equation-1}$$

3.2. Proposed STIRPAD Model

With the change in industrial development, technological advancement and the economy expansion, there is an increasing need to reduce carbon emissions. Additionally, it is discovered that the USA tops the list of nations with the biggest carbon emissions. Therefore, it would seem that there is a pressing need to address the impact of such factors as industry, region, and technological change on carbon emissions. The outcomes demonstrate that when the province carbon emission inventory was scaled down using the ISTIRPAT model to the city level, the inversion accuracy reached 0.9, which was higher than that of the original model (Q. Wang et al., 2022). As result shows that by applying the advanced STIRPAT Model ISTIRPAT, the accuracy level has been improved to 0.9. Based on this review, it is tried to analyze whether there is any improvement in explained variance proportion possible by modifying the basic STIRPAD Model. While reviewing it is found that panel quintile regression and an expanded Environmental Kuznets Curve (Thio et al., 2022) have been added to improve the result. While reviewing, the fact is found that industry 4.0 and region are also important factors that have not been used for analysis. So, in addition to the basic STIRPAT model and expectation of improved results, the new model has been derived. In this proposed model, two additional new factors have been added two other models were used to further improve the results. New factors “Industry 4.0” and “region” have been added to the fundamental STIRPAT model (Population, Affluence, and Technology) and applied using the ordinary least square approach to examine their effects on carbon emissions.

$$Y_{it} = \beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3 + \beta_5 X_4 + \beta_6 X_5 + E_{it}$$

$$\text{Carbon Emission}_{it} = \beta_1 + \beta_2 (\text{Affluence}) + \beta_3 (\text{Population}) + \beta_4 (\text{Industry 4.0}) + \beta_5 (\text{Technology}) + \beta_6 (\text{Region}) + E_{it} \text{-------------Equation 2}$$

"I" is an indicator of the time series dimension and t denotes the time-series dimension, Yit represents the model's dependent variable, i.e. carbon emission or carbon emission per capita, β - contains the model's set of explanatory variables, β1 is the constant β2, β3, β4, β5, and β6 represents the coefficients.

3.3. Statistical Tools and Techniques

The basic analysis uses descriptive statistics. The theory has been supported by cross-section data analysis. The fitness of the model has been determined using the ordinary least square regression model with e-views software.

3.4. Objectives of the Study

- To understand the STIRPAT Model and its relationship to carbon emissions
- To find out the impact of the STIRPAT model on total carbon emission and per capita carbon emission among selected global top 50 carbon emitting countries
- To modify the existing STIRPAT Model to understand the impact on Industry 4.0 on total carbon emission and carbon emission per capita among selected global top 50 carbon emitting countries

• To find the best-fit model

4. Result Discussion

Descriptive statistics were measured to comprehend the frequency distribution in greater detail.

For the top 50 countries in the world, the population, affluence, and technology (STIRPAT) model and the ordinary least square regression technique have been used to analyze the driving variables of carbon emissions. The OLS regression method is also used to confirm the extended STIRPAT model.

Description regarding how variables have been measured is as follows:

Dependent variable like, 'per capita CO2 emissions', and 'total emission' data have been used as is available on the World Bank website (Financial year, 2021). Total 5 factors are considered as independent variables for influence carbon emission. (Affluence)-For measured on the income level based, categorized as high affluence, upper middle affluence, and lower middle affluence category. It was available from the World Bank site (level of income). (Population) -population data for the year 2021 has been taken. (Industry 4.0) - average of Industrial development (Technology)- countries have been divided into high and low technologically developed countries based on an adaption of technological development (Region)= The three geographical "Regions" of the 50 countries that were chosen are "East Asia & Pacific," "Europe & Central Asia," and "South Asia".

Table 1: Descriptive Analysis and Correlations

Variables	**Mean**	**Std. Deviation**	**co2 per Capita**	**population**	**Industry 4.0**	**Affluence**	**Region**	**Technology**	**Carbon Emission**
co2 per Capita	6.5228	4.4457	1						
population	424825035.2	1282224780	.571**	1					
Industry 4.0	470.46	1143.99677	.705**	.954**	1				
Affluence	1.8	0.857	0.202	0.167	0.205	1			
Region	1.76	0.591	-0.262	-0.197	-0.206	-0.016	1		
Technology	1.52	0.505	-.807**	-.295*	-.384**	-0.085	.290*	1	
Carbon Emission	661759.1922	1766800.19	.719**	.919**	.987**	0.182	-0.217	-.380**	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 1 depicts the descriptive statistics of the data. the mean values of the variables considered in the study—661759.19 for carbon emission, 6.52 for CO2 per capita, 424825035.24 for population, 470.46 for industry 4.0, 1.8 for Affluence, 1.76 for region, 1.52 for technology. The value of the standard deviation suggests a more accurate and detailed estimate of the dispersion. Moreover, standard deviations indicate the fluctuation of the time series in all the variables but there is a high variance found with population and carbon emission. The table shows Industry 4.0 has the highest positive correlation to population (.954) and CO2 Per capita (.571) at the same time CO2 per capita has the highest negative relationship to technology. The result are the same with carbon emission, it has the highest significant positive correlation to population (0.919) and industry 4.0 (0.987) at the same time CO2 per capita has the highest negative significance at a 5% level (-0.380) relationship to technology. It means technological changes reduce per capita CO2

4.1. Pooled OLS Model has been applied to prove the hypothesis

Certain hypotheses have been framed and to prove these, ordinary least square regression analysis with STARPAT Model has been applied. Hypotheses 1 and 2 have been framed to find the impact of STIRPAT variables on carbon emission. Hypotheses 3 and 4 have been framed to find the impact of extended STIRPAT variables on carbon emission. Total carbon emission has been applied as the dependent variable for hypotheses 1 and 3, but carbon emission per capita for hypotheses 2 and 4.

H1: There is no significant impact of the STIRPAT model on total carbon emission among selected global top 50 carbon emitting countries

H2: There is no significant impact of the STIRPAT model on carbon emission per capita among selected global top 50 carbon emitting countries

Table 2: Best-Fit the STIRPAT Model

Variables	Carbon emission level		Carbon emission level	
	Model 1		Model 2	
	coefficient	p-value	coefficient	p-value
C	689987.3	0.0905	1.2587	0.000
Population	0.0012	0	1.22E-09	0.000
Affluence	50657.64	0.6652	0.4352	0.2379
Technology	-417283	0.0463	-6.1372	0.0000
R^2	0.8579		0.7802	
Adj R^2	0.8486		0.7659	
F	92.5547		54.4278	
F Sig.	0.000		0.000	
D-W	1.2681		0.3594	

The variables in the STIRPAT Model are regressed using the least squares method. The population has a considerable positive impact on model 1 (where the dependent variable is total carbon output) and model 2 (where the dependent variable is C02 per capita), while technology has a negative impact. The conclusion that population growth raises carbon emissions can be changed by technology. It is under a lot of pressure to reduce its carbon emissions. The most important factor affecting the reduction of carbon emissions is technological advancement. In contrast to previous research, this study restricts technical advancement to the energy sector and focuses solely on energy patents (Huang et al., 2021).

Test outcomes for Model 1 have an adjustable coefficient R 2 of 0.8486, F is 92.5547, and p is 0.00000 0.05. Model 2 has an adjustable coefficient R 2 of 0.7659, F is 54.4278, and p is 0.00000 0.05.

As a result, it can be said that model 1 is much more effective at explaining the variable, as evidenced by the adjusted R2 of model 1 (84.86%) over model 2 (76.59%).

H3: There is no significant impact of extended the STIRPAT model on total carbon emission among selected global top 50 carbon emitting countries

H4: There is no significant impact of extended STIRPAT model on carbon emission per capita among selected global top 50 carbon emitting countries

Table 3: Best-Fit Extended the STIRPAT Model

Variables	Carbon emission level		Carbon emission level	
	Model 3		Model 4	
	coefficient	p-value	coefficient	p-value
C	-27990.56	0.8732	12.7734	0.000
Population	-0.000395	0.0002	-0.00000229	0.0009
Industry 4.0	1966.32	0	0.0043	0.000
Region	-57803.88	0.3736	0.0309	0.9422
Technology	95490.17	0.2541	-5.061	0.000
Affluence	-6.16E+04	0.1612	1.86E-01	0.5167
R^2	0.9816		0.874	
Adj R^2	0.9795		0.8597	
F	470.79		61.057	
F Sig.	0		0	
D-W	2.54		0.837	

Higher levels of carbon emissions are determined to be most impacted by population growth and Industry 4.0. Innovation in technology helps to reduce carbon emissions, nevertheless. To test the outcome, the primary Ordinary least square analysis through cross sectional data was utilized.

The test results are shown in a table. Model 1 has the adjustable coefficient R 2 = 0.9795, F = 470.79, and p = 0.00000 0.05; model 2 contains the adjustable coefficient R 2 = 0.8597, F = 61.057, and p = 0.00000 0.05.

As a result, it can be said that model 1 is far more effective at explaining the variable, as evidenced by the adjusted R2 of model 1 (97.95%) over model 2 (85.97%). Model 3 accounts for 97.95% of the variance in the data. Model 3 is thus determined to be the best match model overall.

5. Conclusion

One of the biggest issues in the current situation is carbon emissions. It is crucial to control this issue on a worldwide scale. It is necessary to occasionally make efforts to reduce greenhouse gases.

The study's primary goal is to identify the variables that affect the level of carbon emissions. Out of a total of 270 countries worldwide, the Top 50 Countries' Global Carbon Emission Share has been identified for future research.

Two models are applied using the OLS approach to determine their influence. Thus, the three variables P (population), A (affluence), and T (technology) are covered by the Basic STIRPAT Model.

Then a new model with an enhanced STIRPAT model was used to further improve the results. Industry 4.0 and region are added to the fundamental STIRPAT model (Population, Affluence, and Technology) and applied using the ordinary least square approach to examine their effects on carbon emissions.

To assess the impact and choose the model with the best fit using the ordinary least square technique, two distinct models with two distinct dependent variables have been created.

It can be concluded that Industry 4.0 is a significant indicator and contributor to carbon emissions. Among a few worldwide nations, there is a considerable correlation between Industry 4.0 and carbon emissions. Among the top 50 countries, there is no evidence of a substantial correlation between location and wealth, and carbon emission. There, one of the most significant causes of carbon emissions has been identified as Industry 4.0. The findings suggest that industrial expansion is directly to blame for and linked to a rise in carbon emissions.

Except for geography and wealth, all of the explanatory factors and the constant are significant in the models for total CO2 and CO2 per capita. The population is a positive determinant and statistically significant at the alpha level of 0.001 in all four models. Further investigation reveals an antagonistic relationship between technology and carbon emissions. However, according to models 1, 2, and 4, technology innovation is also helpful in each model for reducing carbon emissions. Population growth, technology development and Industry 4.0 are the important factors influencing the carbon emission.

To assess the best fit and determine which model has the highest variance explanatory capacity, a total of 4 models have been developed. With the greatest adjusted R2, model 3 is found to have the best fit in terms of explanatory power. Models 1, 4, and 2 are ranked second, third, and fourth, respectively.

The study has academic importance. Carbon emission is one of the most challenging issues around the world. In searching for the best model presenting the highest describing influencing factors, the study sounds quite academically significant. Different models have been applied to measure combinations of highly affecting carbon emission whether improving or reducing CO2.

The government is also concerned about the reduction of carbon emissions around the world. This research tries to identify the factors that determine carbon emissions and help shed light on policy implications. This paper explored how technological innovation helps reduce carbon emissions. Population growth, economic development, and Industrialization have been found the important factors that influence carbon emissions. The more the economy and industry grow, the more carbon emission grows. These factors can be taken care of while designing the policy and its implementation.

The study is limited to the top 50 carbon emission countries. The number of countries can be increased for better results. Also, the study is concerned with one financial year. It could have taken more than one year to use a panel data study.

The study opens the direction for new researchers. Modification in the STIRPAT model leads to the application of new models to measure carbon emission and to reduce and control it.

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