E ISSN : 3024 - 9961
JOURNAL OF CLIMATE CHANGE SOCIETY
JCCS
https://jccs.ppj.unp.ac.id rccc.lp2m.unp.ac.id

An Econometric Analysis of the Impact of Contemporary Climate Smart Technologies on Global Carbon Dioxide Emissions

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ARTICLE INFORMATION

DOI: 10.24036/jccs/Vol3-iss1/45
Page: 01-21

Received: Janary 25, 2025
Revised: May 28, 2025
Accepted: May 29, 2025

ABSTRACT

This paper provides an econometric analysis of the impact of climate smart technologies on global carbon dioxide emissions. It considers carbon dioxide due to the observation that it is the most significant greenhouse gas whose emissions currently stand at 37 gigatons per annum. Making use of graphite, zinc, silver global production annual trends, global land use changes and the changing trends of global forest area cover of global data running from 1990 to 2023 to generate the formula, **$Log(co2) = \beta_0 + \beta_1 Logforest + \beta_2 Log(graphite) + \beta_3 Log(landuse) + \beta_4 log(silver) + \beta_5 dlog(zinc) + \varepsilon$,** in EViews 7, the study found that a 1% increase in forest, graphite, landuse, silver and zinc technologies yields a 95% reduction in carbon dioxide emission. There is positive progress in attempts at reducing carbon dioxide emissions. The study therefore recommends nation-states to increase and gear-up their climate smart efforts to achieve net-zero GHGs emissions by 2050.

KEYWORDS: carbon dioxide reduction, climate change, climate smart technologies, global efforts and progress

INTRODUCTION

Climate smart technologies, which refer to the sustainable, processing and reutilization of natural resources to create a low carbon global economy (World Bank, 2024), are part and parcel of the low-carbon technological climate change package, which has entered the arena for climate policy discussions since the 1980s (Planete Energies, 2024). Past efforts at tackling climate change have been around since 1980 firstly with the launching of the First International Climate Programme, the 1988 creation of the Intergovernmental Panel on Climate Change (IPCC), the 1992 Rio Earth Summit, the 1997 Kyoto Protocol, the 2005 European Union Emissions Trading system up to the 2019 European Green Deal. All these global efforts were meant to harness human actions that would address one of the greatest enemies of our times and probably one of the extreme encounters that the whole human race is facing at the moment. The need to address the problem of climate change is a top priority to make the planet earth hospitable both to human beings and the whole global ecosystem.

In view of these efforts, the need to produce climate smart solutions (Ekins-Daukes, 2009; Huisiningh et al., 2015) has recently flooded the discussions on how to get rid of the greenhouse gas emissions to our common atmosphere. Adopting and embracing advanced battery technology to power modern engines including the locomotives, investing in renewable sources of energy and taking social responsibility in land use and land use change have been touted as particularly necessary in reducing greenhouse gas (GHG) emissions (Nunes, 2023; Parry, 2019). The use of membrane technologies that encompass the use of discerning membranes to capture gases such as carbon dioxide from gas streams generated in the power plants of fossil fuels, is aimed at separating carbon dioxide from other gases. This allows more than 90% of the carbon being emitted into the atmosphere to be captured (Nunes, 2023). In the area of land use and land use change, reduction in the use of artificial fertilisers have also been recognised as excellent mechanisms in reducing greenhouse gases including nitrous oxide (Nabuurs et al., 2015; Nunes, 2023).

Notwithstanding, human beings are a unique creation possessing the ability to fundamentally change the ecological environment for the better through the prudent utilisation of resources supplied by the earth system (Nunes, 2023). The convening of the 2015 Paris Agreement was aimed at reducing global temperatures by 2˚C (Lin, 2019; World Bank, 2020) through various Carbon Dioxide Removal (CDR) technologies that include, but not limited to Bioenergy with Carbon Capture and Storage (BECCS), Direct Air Capture (DAC), Biochar, enhanced weathering and ocean fertilisation. These technologies have generated a lot of global policies and projects that were aimed at reducing the concentration of greenhouse gases into the atmosphere. Classic examples of these policies include the carbon tax global policy as well as other numerous projects that include the AISI Carbon dioxide Breakthrough programme in North America, the Australian Carbon Dioxide Breakthrough programme, The Japanese COURSE50 programme, the European ULCOs programme (Hollapa, 2020) including the afforestation and reforestation programmes in both the Economically Advanced Regions of the World and the Emerging Economies.

While a considerable array of academic work and policy discussions have been carried out with particular reference to the above policies and programmes, the need to quantitatively evaluate the progress of these actions in reducing carbon dioxide emissions on a global scale to date has received little attention. Following these observations, critical minerals such as zinc, silver, graphite, cobalt, copper, lithium and other prudent climate smart farming technologies have become increasingly important in restoring the ecosystem's well-being to its original form (New Scientist, 2024; Saleem et al., 2024; World Bank, 2024). The need to trace progress by individual countries collectively in climate change mitigation is absolutely necessary considering that we are only two and a half decades away from the net-zero emissions 2050 global deadline.

Global efforts at addressing climate change

The need to address the climate change conundrum of our time did not start with the 2015 Paris Agreement discussions. Other global actions predate these attempts. In 1980, the First International

Climate Change Programme was established (Planète Energies, 2024). This was the effort by the World Meteorological Organisation in Switzerland's capital, Geneva alongside the International Council of Scientific Unions (Planète Energies, 2024). This action critically boosted climate science, especially with reference to the mathematical simulation of oceanic and atmospheric phenomena (Planète Energies, 2024).

In 1988 in November, the Intergovernmental Panel on Climate Change (IPCC) was created (Planète Energies, 2024). IPCC was established because world leaders and academics wanted to understand the causes, challenges and consequences of climate change. In June of 1992, the Rio Earth Summit was also convened in Brazil marking the second Earth Summit, which led to the establishment and ratification of the United Nations Framework Convention on Climate Change, initially endorsed by 166 countries. The summit acknowledged that human beings are responsible for global warming. Similarly, the summit led to the establishment of the Conference of Parties (COP), which now brings together all the nations globally to discuss on the way forward on climate change. In 1997, a global consensus on international emissions came in and effected the Kyoto Protocol of December 1997 (Planète Energies, 2024). The major objective was to drastically reduce the emissions of greenhouse gases by approximately 5.2% versus 1990 levels between 2008 and 2012 (Lutsey and Sperling, 2008; Planète Energies, 2024).

In 2005, a European Union emissions Trading system was launched. Under this initiative, firms that were highly responsible for the emission of greenhouse gases were awarded a certain number of emission allowances and they were expected to buy these allowances from other companies if they exceed their limits (Planète Energies, 2024).

In 2009, global nations met in Copenhagen for a conference to discuss the maximum possible or acceptable increase in global temperatures. Additionally, the nations also met in 2010 for the Cancun Climate Change Conference and Green Climate Fund. At this conference, the parties agreed to establish the Green Climate Fund (Planète Energies, 2024).

In 2015, the countries of the globe also met in Paris under the auspices of the COP21 summit (Planète Energies, 2024). At this conference, the major goal was to limit global warming to less than 2°c. In 2019 in December, the European Green Deal was also signed. The conference encouraged European Union member states to adopt a net-zero emission of greenhouse gases. The above global conferences and initiatives have generated some positive results in the reduction of greenhouse gas emissions though the world still has a long way to go; for example, the European Union reached a significantly low level of GHG emissions this year in 2024 while the United Kingdom has already closed its last remaining coal power station in September 2024 (Crownhart, 2024), signifying a global positive attitude to the green climate smart new deal.

Technologies for reducing atmospheric carbon dioxide

Global governments and research institutions have proposed several Carbon Dioxide Removal (CDR) technologies. The idea behind is to create a clean atmosphere in which the balance of gases goes back to their original form. This section details briefly the various technologies that have been advanced to deal with greenhouse gases, but with particular reference to carbon dioxide. The discussion is centred on carbon dioxide removal technologies revolving around Direct Air Capture (DACs), Bioenergy with carbon capture and storage (BECCS) and other technologies that include but not limited to afforestation, reforestation, biochar, ocean fertilisation and enhancing the weathering process.

One of the Carbon Dioxide Removal technologies that have been proposed by Atmospheric experts is the Direct Air Capture technology (DACs). This technology makes use of chemical processes to remove carbon dioxide from the air (Lin, 2019). The type of material that is used to extract the carbon dioxide or substrate must then be regenerated (Lin, 2019). The carbon dioxide that is released in the process of regeneration is then stored in the ocean or in the soil (Lin, 2019). However, this technology is very expensive since it requires more than US$250 to remove a tonne of carbon dioxide (Lin, 2019, p.9). Climeworks, a company that is found in Zurich, has recently developed a new Direct Air Capture Technology, which is capable of removing millions of tonnes of carbon dioxide from the atmosphere by the end of this decade (Mendelsohn, 2024). With this technology, Climeworks argues that the facility is able to remove about 36 000 tonnes of carbon dioxide from the atmosphere (Mendelsohn, 2024).

Another form of Carbon Dioxide Removal technology that has been advanced in climate policy discussions is the Bioenergy with carbon capture and storage (BECCS). This form of technology involves the cultivation of biological energy crops which are deemed to remove carbon dioxide from the air during the process of photosynthesis (Lin, 2019). The second stage for this process involves the burning of the subsequent biomass at power stations which will yield energy and carbon dioxide, which is then captured, crushed and kept in geological reservoirs in liquid form or possibly in the deep sea (Lin, 2019). However, this Renewable Energy Technology (RET) has been faced with quite a number of challenges that include land shortages (Fawzy et al., 2029; Lin, 2019).

Other Carbon dioxide removal technologies that have been proposed include afforestation and reforestation in which the planted trees would act as carbon sinks. However, some scholars have argued that this technology provides a temporary measure of carbon dioxide storage since the process is deemed to increase global warming through reducing the effect of albedo, particularly in regions that are susceptible to seasonal snow cover (Lin, 2019). Other technologies such as biochar, which encompasses the combustion of biomass in the absence of oxygen to give charcoal and then ploughed into the earth, improves the soil’s nutrient content and simultaneously stores carbon (Lin, 2019).

Other carbon dioxide removal technologies that have been advanced as solutions to the problem of atmospheric carbon dioxide concentration relates to the enhancement of the process of weathering. This process includes the addition of ground-up silicate rocks to the ocean or the soils to induce chemical reactions that would eventually absorb carbon dioxide from the atmosphere (Lin, 2019). Whilst this process can remove about 4 gigatons of carbon dioxide per annum from the atmosphere, the harnessing of this technology has thus far been challenged as inefficient as it has been restricted to laboratory level experiments (Lin, 2019; Suman, 2021).

Ocean fertilisation has similarly been proposed as one of the Carbon dioxide removal technologies. This method involves the addition of iron (Fe) or other nutrient forms to the seas or oceans to arouse biological activities (Lin, 2019). Theoretically, enhanced microorganism populations would extract carbon from the atmosphere and subsequently transport the carbon to the ocean depths when they die (Lin, 2019). However, this technology has the disadvantage of giving a complete alteration of the oceans' chemistry and their respective ecosystems thereby disrupting food chains, food webs, availability of oxygen as well as harming algae blooms (Lin, 2019; Song, 2006).

Climate Smart technologies

Critical minerals such as silver, graphite, cobalt, lithium, copper, zinc and other smart forms of land use and agriculture have been proposed as top-notch methods in restoring balance to the global ecosystem (Ekins-Daukes, 2009). These proposals have soared significantly as efforts at protecting the Anthropocene have gathered global momentum (World Bank, 2024). The climate smart technologies are being used in generating a climate smart environment world-wide and have undergone serious global experiments with the overall aim of creating a low carbon global economy (Calderon et al., 2023; Zanoletti et al., 2024).

With the need to address the problem of climate change, metal technologies, land use changes and technologies have since been harnessed as important strategies to restore the balance of the global ecosystem (World Bank, 2019). These technologies, especially the metal technologies, have been exploited in the powering of Electric Vehicles; ensuring their competent release and storage of energy (World Bank, 2019). Similarly, cobalt has been used in battery cathodes considering that scientifically, it has been proven to enhance the density of energy including the longevity of battery lives (World Bank, 2019). Copper has also been used extensively in electrical grids through transmitting, connecting and distributing energy (World Bank, 2019). Copper has been used in solar panels due to its ability in connecting photovoltaic cells (World Bank, 2018; 2019).

Global Projects at atmospheric Carbon dioxide reduction and their impacts

Quite a number of projects and programmes have been adopted and harnessed globally to create a carbon dioxide free atmosphere. The purpose of this section is to provide a review of these projects and programmes including their impact on reducing atmospheric carbon dioxide.

Carbon Capture and Storage technologies have been proposed and practiced in some countries as part of Carbon Dioxide Removal technologies (Lin, 2019; Hollapa, 2020). Oil producing companies in the United States of America and in other oil producing countries have used Carbon Dioxide Capture and Storage technologies to get rid of atmospheric carbon dioxide concentration by using cryogenic distillation/membrane, physical absorption and chemical absorption-based separation technologies. LanzaTech, an Illinois United States-based company has also developed microbial bioreactor systems with the ability of direct gas fermentation to generate ethanol from carbon-holding gases like integrated iron and steel plant off gases (Hollapa, 2020). Another demonstration plant has also been set up in Shouqang in China while another one was similarly constructed in Belgium at Arcelor Mittal Ghent (Hollapa, 2020). These CCS technologies were said to have been able to reduce atmospheric carbon dioxide concentration by 9% (Hollapa, 2020, p.9).

Globally, national governments have advanced their technologies to minimise the emission of greenhouse gases into the atmosphere. Notable examples are the Japanese COURSE50 programme, the European ULCOs programme, the Australian Carbon dioxide Breakthrough programme and the

North American AISI Carbon dioxide Breakthrough programme. Similarly aligned programmes have been implemented in Taiwan, India and China (Hollapa, 2020). These global technologies consisting of heat recovery, optimised internal recycling as well as the replacement of air using oxygen have especially been found to be impactful in reducing greenhouse gas emissions (Hollapa, 2020). With these technologies, "the reductions in carbon dioxide emissions were estimated to be in the range of 10% to 25%" (Hollapa, 2020, p. 7).

Low carbon dioxide emissions have similarly been reduced through the harnessing of renewable technologies such as wind, solar, nuclear and hydro-power. With an increase in the use of climate smart technologies, global economic giants like China, which is the greatest producer of global steel, have been able to reduce carbon dioxide emissions to 620g co2/kwh (Hollapa, 2020). Similarly, the United States of America was able to reduce carbon dioxide emissions by 420gco2/kwh, while the European Union was able to reduce its carbon emissions by 282gco2/kwh (Hollapa, 2020). With these technologies, global emissions of carbon dioxide are at 10% for the past three decades (Hollapa, 2020, p. 11).

In Nepal, Renewable Energy Technologies (RETs) have also been implemented. Technologies such as the National Energy Crisis Mitigation and Energy Development Decade have been in operation since 2016, whilst the Nationally Determined Contributions have been effected in the past 5 years (Suman, 2021). With these climate smart technologies, a total of 86 803 tco2e were reduced (Suman, 2021, p. 10). Additionally, global countries have attempted to reduce the emission of greenhouse gases into the atmosphere through the reduction of their energy requirements (Hollapa, 2020). Along these recommendations, China has similarly reduced its energy consumption patterns by approximately 15% in the years between 2006 and 2017. These efforts have indirectly reduced the emission of carbon dioxide since demand was curtailed; hence its respective production (Hollapa, 2020).

Even in African countries, projects and programmes that have been implemented to drastically reduce the carbon dioxide emissions have been noticed. The implementation of the 300MW Bui Hydro project in western Ghana above the Volta Dam has significantly contributed to the reduction of greenhouse gas emissions (Ahinsah-Wobil, 2024). In view of these past evaluated programmes and projects, the need to provide an econometric analysis of the Impact of contemporary climate smart metal technologies on global carbon dioxide emissions through hypothesis testing has never adequately featured in global literature. In that regard, the purpose of this paper is to provide a quantitative analysis of the impact of climate smart metal technologies on carbon dioxide emissions.

METHODS

This study was a global study and was grounded on quantitative world data collected from 1990 to 2023. The major variables of particular concern were carbon dioxide and climate smart technologies (forest, graphite, land use, silver and zinc). Some variables like lithium, rare earth, fertiliser consumption including others like magnesium and aluminium were dropped as they depicted higher levels of multicollinearity. All these data were accessed from the World Bank databases (http://ourworldindata.org/metals-minerals; https://data.worldbank,org/indicator/AG.LND.FRSTZS? https://ourworldindata.org/co2-emissions from fossil fuels and land use change, world) . In table 1 below, I provide a summary of the definitions of the variables in question including how they were measured and utilized.

Table 1. Definitions of variables and their measurements

Variable	**description of variable**	**measurement**
Co2	Carbon dioxide	Global emissions in billion tonnes/year
Graphite	graphite	global production in thousand tonnes per/year
Landuse	land use	global changes on uses of land in percentage/year
Forest	forest area	global percentage of area covered by forests/year
Solver	Silver	global production in thousand tonnes/year
Zinc	Zinc	global production in thousand tonnes per/year

Before the computation of the regression model on the impact of climate smart technologies on carbon dioxide emissions, several pretests were carried out to ensure that the results of the analysis were far from spuriosity. Firstly, I downloaded the required data from the above-mentioned websites. Initially, many variables were included for the study (See appendix). However, some of them were dropped after finding out that they depicted high levels of multicollinearity and autocorrelation and so could not qualify for this analysis. Others like lithium were dropped considering that data on lithium production only appears from the year 2000 onwards and so could do not qualify the specified criteria. I also decided to start the statistical analysis from 1990 owing to the observation that other variables of interest especially the dynamics and statistics of the area covered by the world forests were not available prior to 1990. With these data specification criterions, global area covered by the world forests (forest), land use, silver, graphite and zinc were found to meet my data selection criterion. The encouragement of nation-states to bring deforestation to an end to protect the world's diversity (Ritchie, Spooner and Roser 2021) and create carbon sinks (Chiba, 2024) have also been among the climate smart technologies to reduce carbon dioxide emissions. Similarly, governments have also been encouraged to reduce their land use to leave more land for wildlife (Ritchie and Roser, 2013); thus, being part and parcel of climate smart technologies. Critical minerals such as silver, graphite and zinc have widely been used to create climate smart energy requirements (Jennifer, 2024; Salas and Dunn, 2024; World Economic Forum, 2022).

I provided the descriptive statistics for the data. In doing this, the idea was to familiarise myself with an understanding of the data; which is a prerequisite in statistical analysis. The unit root tests were conducted with the sole aim of avoiding spurious regression as well as ensuring the stationarity of the data that was in use. To do this, EViews implements quite a number of tests for panel data stationarity/unit root, which include Ng-Perron, Kwiatkowski-Phillips-Schmidt-Shin, Augmented Dickey Fuller, Dickey-Fuller and Phillips-Perron and they have the Null Hypothesis that all panel data carry with them a unit root. However, in this analysis, I utilised the Augmented Dickey-Fuller test to ensure data stationarity. One major condition of statistical analysis is that the data used for regression analysis should display a higher level of stationarity (Newey and Powell, 1987; Silverman, 1986). This guards against the dangers of getting misleading results.

I similarly engaged the VAR Order Selection Criterion test to determine the optimal lag length of the model to enhance the interpretation of the model (Koenker and Hallock, 2001; Welsh, 1988). In doing this, I used the unrestricted VAR at the lag length of 2. Additionally, I also conducted Granger-causality tests. The Granger Causality concept is not new in econometrics. It has been used elsewhere. Quite a number of studies have utilized panel Granger causality in their attempt to examine causality between the variables of interest; for example, Hartwig (2010) and Podrecca and Carmeci (2001). Drawing from the Granger causality definition, a time series cross-sectional variable that is stationary (Climate smart technologies) is considered to affect stationary variable (Carbon dioxide) given that the lagged variable demonstrates any statistically significant information about a variable; which is Carbon dioxide in the current of lagged Climate Smart technologies. The Null Hypothesis for this paper is stated below:

$H_0 : \beta_1 \ ,1 = \beta_{2,} \ 2 = \ldots\ldots = \beta_2 , \mathrm{k} = 0$

I test whether Climate smart technologies have a forecasting power for carbon dioxide emissions as stated below for the null hypothesis:

$H_0 : \alpha_1 \ , 1 = \alpha_2 \ 2 = \ldots\ldots = \alpha_2 \ , k = 0$

In this paper, the technique of Vector Autoregression (VAR) provides tests for the lagged coefficients of Climate smart technologies and checks their forecasting level on carbon dioxide emissions or vice versa. Before conducting the causality tests, a proper lag length choice was provided to prevent spurious regression results. In both cases, the Schwartz Information Criteria and the Akaike Information Criterion must demonstrate an ideal lag length. In view of the above, a Var approach in Least Squares method in EViews 7 was utilized in which an application of the Pair-Wise Granger-causality test was utilised.

It was similarly necessary to carry out residual tests for this analysis since the tests entirely seek to test for the stability of the data residuals. These tests included multicollinearity, heteroscedasticity, normality tests and autocorrelation. Multicollinearity, a statistical phenomenon in which two or more variables in a regression model demonstrate higher levels of correlation (Kocherginsky et al., 2005; Roger and Hallock, 2001), was another test that was carried out. I utilised the Variance Inflation Factor for these tests, possibly owing to their widespread utility in statistics.

Heteroscedasticity tests, which refers to a statistical condition in which errors or residuals in a regression model are not constant across all the levels of the independent variables, were similarly carried out. I used the Breusch-Pagan-Godfrey heteroscedasticity test owing to its widespread utility in regression analysis (Xuming and Hu, 2002). One condition that is also required in statistical analysis is to understand if the data being worked upon follows a normal distribution specification. Similarly, I applied the Histogram-Normality test where the Jarque-Bera statistic and the probability value were used to interpret the level of normality. Checking for normality is important because it helps us to verify linear regression assumptions as well as checking for outliers (He and Hu, 2002; Jack and DiNardo, 1997). Autocorrelation, a condition in which the current value of a variable is correlated to its past value, was also carried out. The idea was to prevent spurious regression (Whitney and Powel, 1987). The statistic was thus conducted using the Breusch-Godfrey Serial Correlation LM Test.

I also applied the Ramsey RESET test to check for the misspecification of the model. It checks if inappropriate purposeful forms or omitted variables carry significant influences on the results of the regression output.

After performing the above tests, I then computed the equation using the formula log(co2) c log(forest) log(graphite) log(landuse) log(silver) dlog(zinc) using the LS-Least Squares (NLS and ARMA) method. The use of the Least Squares approach motivated me because of a variety of reasons that include its ability to deal with probable endogenous dealings between carbon dioxide emissions and climate smart technologies. With this approach, I was able to find the lagged effects of climate smart technologies on carbon dioxide emissions and establish whether the carbon dioxide-climate smart technological change feedback was present. Resultantly, the model I utilized is stated below:

$$\mathbf{Log(co2) = \beta_0 + \beta_1 Logforest + \beta_2 Log(graphite) + \beta_3 Log(landuse) + \beta_4 log(silver) + \beta_5 dlog(zinc) + \varepsilon}$$

; where Log(co2) was the logarithm of carbon dioxide; β_0 is a constant and β_1; β_2; β_3; β_4 and β_5 are the parameters to be estimated. Log(forest); Log(graphite); Log(landuse); log(silver) and dlog(zinc) are the logarithms for the values of forest technologies, graphite technologies, landuse technologies, silver technologies and zinc technologies respectively.

RESULTS AND DISCUSSION

Results

Table 2 below provides a summary of the descriptive parameters of the variables in this paper. The mean of the variables is given. For most of the variables, the median is close to the mean and this shows a relatively symmetric distribution. The table also consists of the minimum and maximum values which demonstrate variable range; for example, graphite ranges from 517000 to 1680000. Standard deviation measures data dispersion. For example, co2 has a standard deviation of 5.52. This shows significant variation among its values. Skewness is a measure of the distribution asymmetry. A negative figure demonstrates a longer left tail, while a positive figure shows a longer right tail. This means that -0.102455 for carbon dioxide demonstrates a longer left tail, while the land use value of 2.525337 shows a longer right tail. Kurtosis is a statistical measure of the distribution tailedness. Figures that are greater than 3 demonstrate heavier tails; for example, zinc, which has a figure of 3. 446345.The Jarque Bera test is a test for normality in which a higher value demonstrates a deviation from normality. In this case, the probability value of landuse shows a significant deviation from normality, whereas others like forest do not vary significantly from normality. This analysis of the descriptive parameters is particularly significant as it provides a foundational comprehension of the characteristics of the data; thus, providing a guide for further statistical exploration.

Table 2. Summary of descriptive parameters (2000-2024)

	CO2	FOREST	GRAPHITE	LANDUSE	SILVER	ZINC
Mean	3.01E+10	0.317235	965352.9	0.372059	21176.47	10139412
Median	3.11E+10	0.320000	939000.0	0.370000	21000.00	10150000
Maximum	3.78E+10	0.330000	1680000.	0.390000	29000.00	13800000
Minimum	2.24E+10	0.310000	517000.0	0.370000	14000.00	1200000.
Std. Dev.	5.52E+09	0.005630	298058.4	0.005382	4562.499	2933094.
Skewness	-0.102455	0.066369	0.710207	2.525337	0.055101	-0.713648
Kurtosis	1.412501	2.619493	2.960304	8.174211	1.764349	3.446345
Jarque-Bera	3.629700	0.230074	2.860465	74.06582	2.180219	3.168232
Probability	0.162862	0.891333	0.239253	0.000000	0.336180	0.205129
Sum	1.02E+12	10.78600	32822000	12.65000	720000.0	3.45E+08
Sum Sq. Dev.	1.01E+21	0.001046	2.93E+12	0.000956	6.87E+08	2.84E+14
Observations	34	34	34	34	34	34

One essential condition for analysing time series data is the determination of the data stationarity. Time series data that do have variables with a unit root generate biased results (Wu, 2016). In this analysis, I used the Augmented Dickey-Fuller test for time series unit root considering its robustness and acceptance among statisticians. The Augmented Dickey-Fuller bias adjusted t-statistic was found to be significant at all typical variable levels (carbon dioxide, forest, graphite, landuse, silver and zinc). The Null Hypothesis of a unit root is therefore rejected in favour of the Alternative hypothesis that the series is stationary.

Table 3. Time series unit root tests

Variable	**unadjusted t-statistics**	**Adjusted t-statistics**	**p-values**
Carbon dioxide	-5.061186	-5.956500	0.0000
forest	-5.904264	-11.54110	0.0000
graphite	-2.991878	-6.152998	0.0000
landuse	-3.102548	-7.358365	0.0000
silver	-4.992385	-6.867339	0.0000
zinc	1.320811	-5.444771	0.0001

Augmented Dickey-Fuller test for time series unit root

H0: There is a unit root in the series

F-Statistic =93.94253

Prob>F= 0.000000

The model selection criteria were proposed by Andrews and Lu (2001) and in this study, the model selection criteria were used to determine the overall coefficients. The results demonstrate that the smallest figures of Akaike Information Criterion (AIC), The Schwarz Information Criterion (SC) and the Hannan-Quinn Information criterion (HQ) are found in order 1, hence, the first order VAR model is preferred.

Table 4. VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1690.820	NA	4.60e+38	106.0512	106.3261	106.1423
1	-1576.966	177.8974*	3.70e+36*	101.1853*	103.1091*	101.8230*
2	-1547.257	35.27885	7.08e+36	101.5786	105.1513	102.7628

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Granger-causality Results

One of the tests that was particularly important was the Granger-causality test. The idea was to establish the direction of causality; being bi-directional or mono-directional. The results are presented on table 5 below:

Table 5a. Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.
FOREST does not Granger Cause CO2	32	0.30758	0.7378
CO2 does not Granger Cause FOREST		3.79979	0.0352
GRAPHITE does not Granger Cause CO2	32	0.18442	0.8326
CO2 does not Granger Cause GRAPHITE		4.42445	0.0218
LANDUSE does not Granger Cause CO2	32	0.84281	0.4415
CO2 does not Granger Cause LANDUSE		2.11355	0.1404
SILVER does not Granger Cause CO2	32	0.11614	0.8908
CO2 does not Granger Cause SILVER		2.84805	0.0755

ZINC does not Granger Cause CO2	32	1.08086	0.3535
CO2 does not Granger Cause ZINC		5.93284	0.0073

Table 5b. Pairwise Granger Causality Tests (cont'd)

GRAPHITE does not Granger Cause FOREST	32	2.39694	0.1101
FOREST does not Granger Cause GRAPHITE		3.42095	0.0474
LANDUSE does not Granger Cause FOREST	32	2.65148	0.0888
FOREST does not Granger Cause LANDUSE		0.27478	0.7618
SILVER does not Granger Cause FOREST	32	4.61010	0.0189
FOREST does not Granger Cause SILVER		0.08459	0.9191
ZINC does not Granger Cause FOREST	32	3.29640	0.0524
FOREST does not Granger Cause ZINC		0.89447	0.4206
LANDUSE does not Granger Cause GRAPHITE	32	0.30813	0.7374
GRAPHITE does not Granger Cause LANDUSE		1.50861	0.2393

Table 5c. Pairwise Granger Causality Tests (*continued)*

Null Hypothesis:	Obs	F-Statistic	Prob.
SILVER does not Granger Cause GRAPHITE	32	3.83843	0.0341
GRAPHITE does not Granger Cause SILVER		0.51644	0.6024
ZINC does not Granger Cause GRAPHITE	32	4.29100	0.0241
GRAPHITE does not Granger Cause ZINC		7.71248	0.0022
SILVER does not Granger Cause LANDUSE	32	0.79525	0.4618
LANDUSE does not Granger Cause SILVER		1.89149	0.1703
ZINC does not Granger Cause LANDUSE	32	1.53574	0.2335
LANDUSE does not Granger Cause ZINC		0.03285	0.9677
ZINC does not Granger Cause SILVER	32	3.83904	0.0341
SILVER does not Granger Cause ZINC		0.47898	0.6246

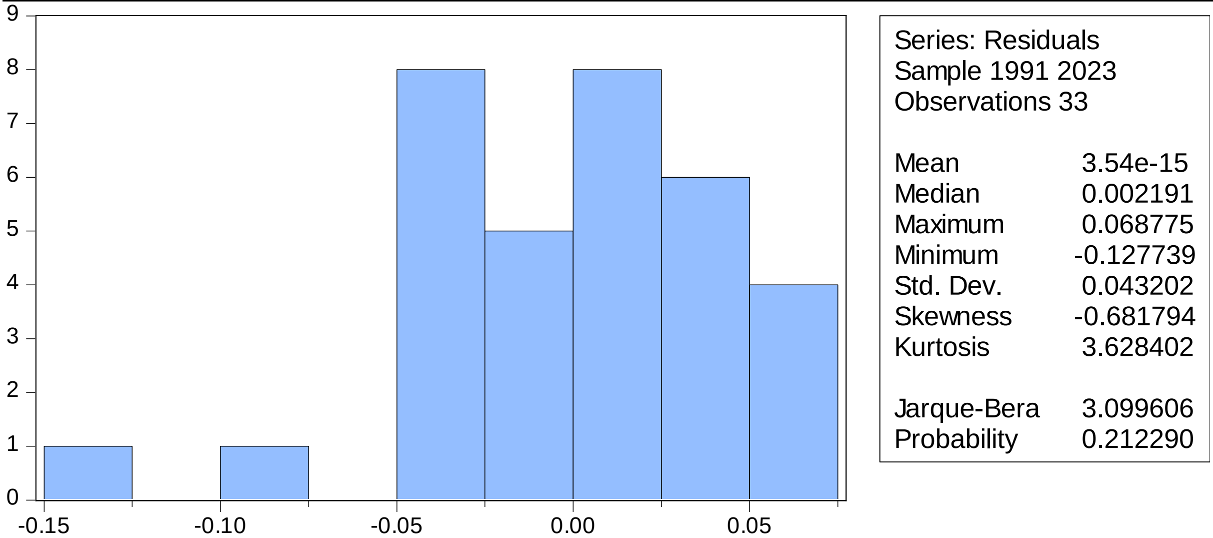
H0: Excluded variable does not granger cause Equation variable
Ha: Excluded variable Granger causes Equation variable

Tables 5a-c above demonstrate that carbon dioxide Granger causes forest, but not the other way round. Carbon dioxide similarly Granger causes graphite, but not the other way round. There is also evidence that landuse and carbon dioxide do not Granger cause one another and so is silver and carbon dioxide. Carbon dioxide Granger causes zinc, but not the other way. Similarly, forest Granger causes graphite and not the other way. There is no granger causality between land use and forest. Silver Granger causes forest, but not the other way. However, there is bi-directional causality between zinc and gravity, while there is no causality between silver and landuse, but uni-directional causality between zinc and land use. Zinc granger causes silver, but not the other way round. Table 5 depicts that most causality is uni-directional though there is bi-directional causality between zinc and graphite.

There was also need to carry out further tests to ensure that the results of this research were not grounded on spurious regression. In that regard, I went further in carrying out statistical diagnostic tests which include normality tests, autocorrelation, multicollinearity and heteroscedasticity tests. The outputs and interpretation of these tests are shown below.

The normality case

Figure 1. Time series normality tests



In the above output, the p-Value of 0.438514 is greater than 0.05, the assumption was that normality is present. This is also confirmed by the Jarque-Bera statistic, which is also closer to 2.

Autocorrelation

I also tested the data for autocorrelation using the following Null and Alternative Hypotheses:

H0: ƒ=0 (No autocorrelation)

Ha: ƒ#0 (autocorrelation present)

Table 6. Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.783806	Prob. F(2,25)	0.1887
Obs*R-squared	4.121143	Prob. Chi-Square(2)	0.1274

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.145361	0.795895	0.182638	0.8566
LOG(FOREST)	-0.140882	0.920971	-0.152971	0.8796

LOG(GRAPHITE)	0.008380	0.042657	0.196440	0.8459
LOG(LANDUSE)	0.236113	0.847757	0.278515	0.7829
LOG(SILVER)	-0.018945	0.080199	-0.236223	0.8152
DLOG(ZINC)	0.003944	0.023300	0.169253	0.8670
RESID(-1)	0.321692	0.201252	1.598454	0.1225
RESID(-2)	0.088702	0.227091	0.390602	0.6994

R-squared	0.124883	Mean dependent var	3.54E-15
Adjusted R-squared	-0.120150	S.D. dependent var	0.043202
S.E. of regression	0.045724	Akaike info criterion	-3.125164
Sum squared resid	0.052267	Schwarz criterion	-2.762374
Log likelihood	59.56520	Hannan-Quinn criter.	-3.003096
F-statistic	0.509659	Durbin-Watson stat	1.948360
Prob(F-statistic)	0.818479		

In the output above, I fail to reject the Null Hypothesis of no autocorrelation considering that all the P-values in this output are greater than 0.05. This demonstrates that spurious regression results have been avoided.

Multicollinearity

One other important test that was carried out to ensure that the results are not biased were multicollinearity tests. The hypotheses that guided this analysis was based on the Null and Alternative hypothesis: Ho: ∧=0 (no multicollinearity); Ha: ∧#0(multicollinearity present). Considering that I applied the Variance Inflation Factor (VIF) to test the presence or absence of multicollinearity in these data series, I was guided by the following hypothesis: H0: VIF≤5 (No multicollinearity) Ha: ≥5 (multicollinearity present). The output for this test is provided in table 7 below:

Table 7. Variance Inflation Factors

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.656450	9792.973	NA
LOG(FOREST)	0.866533	17083.47	3.436887
LOG(GRAPHITE)	0.001811	5097.916	2.480871
LOG(LANDUSE)	0.675802	9887.021	1.335591
LOG(SILVER)	0.006493	9581.664	4.622045
DLOG(ZINC)	0.000486	1.220946	1.199746

The above output also shows that all the variables are stable. The Null Hypothesis of no multicollinearity is failed to be rejected. This state of affairs demonstrated that the data was stable and so produced unbiased results considering that all the centred Variance Inflation Factors are less than 5.

Heteroscedasticity

The test was guided by these hypotheses:

H0: Ꝺ^2=constant (homoscedasticity)[1]

Ha: Ꝺ^2#constant(heteroscedasticity)[2]

Table 8. Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.790075	Prob. F (5,27)	0.5661
Obs*R-squared	4.211979	Prob. Chi-Square (5)	0.5193
Scaled explained SS	3.705507	Prob. Chi-Square (5)	0.5925

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.013131	0.052194	-0.251576	0.8033
LOG(FOREST)	-0.005960	0.059967	-0.099393	0.9216
LOG(GRAPHITE)	-0.002124	0.002741	-0.774972	0.4451
LOG(LANDUSE)	-0.057642	0.052958	-1.088449	0.2860
LOG(SILVER)	-0.001992	0.005191	-0.383649	0.7042
DLOG(ZINC)	0.000187	0.001420	0.131840	0.8961

R-squared	0.127636	Mean dependent var	0.001810
Adjusted R-squared	-0.033913	S.D. dependent var	0.002980
S.E. of regression	0.003030	Akaike info criterion	-8.597642
Sum squared resid	0.000248	Schwarz criterion	-8.325550
Log likelihood	147.8611	Hannan-Quinn criter.	-8.506091
F-statistic	0.790075	Durbin-Watson stat	2.029618
Prob(F-statistic)	0.566075		

The above output also showed that the Null Hypothesis should be failed to be rejected considering that all the p-values are greater than 0.05. This shows that the data was stable thus being able to give us reliable results.

Table 9. Ramsey RESET Test

Ramsey RESET Test

Equation: EQ01

Specification: LOG(CO2) C LOG(FOREST) LOG(SILVER) LOG(GRAPHITE) LOG(LANDUSE) DLOG(ZINC)

Omitted Variables: Squares of fitted values

	Value	Df	Probability
t-statistic	1.290606	26	0.2082

[1] The residuals' variance is constant across all levels of the independent variables

[2] The variance of the residuals are not constant across all the levels of the independent variables

F-statistic	1.665663	(1, 26)	0.2082
Likelihood ratio	2.049151	1	0.1523

F-test summary:

	Sum of Sq.	Df	Mean Squares
Test SSR	0.003596	1	0.003596
Restricted SSR	0.059726	27	0.002212
Unrestricted SSR	0.056130	26	0.002159
Unrestricted SSR	0.056130	26	0.002159

LR test summary:

	Value	Df
Restricted LogL	57.36414	27
Unrestricted LogL	58.38872	26

Unrestricted Test Equation:
Dependent Variable: LOG(CO2)
Method: Least Squares
Date: 01/08/25 Time: 15:53
Sample: 1991 2023
Included observations: 33

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-41.80416	43.48731	-0.961296	0.3453
LOG(FOREST)	-5.824074	4.815848	-1.209356	0.2374
LOG(SILVER)	-15.61559	12.60899	-1.238448	0.2266
LOG(GRAPHITE)	-2.892842	2.335990	-1.238379	0.2266
LOG(LANDUSE)	45.88210	37.06274	1.237958	0.2268
DLOG(ZINC)	0.233428	0.189513	1.231721	0.2291
FITTED^2	0.515115	0.399127	1.290605	0.2082

R-squared	0.948915	Mean dependent var	24.11925
Adjusted R-squared	0.937127	S.D. dependent var	0.185301
S.E. of regression	0.046464	Akaike info criterion	-3.114468
Sum squared resid	0.056130	Schwarz criterion	-2.797027
Log likelihood	58.38872	Hannan-Quinn criter.	-3.007658
F-statistic	80.49311	Durbin-Watson stat	1.395387
Prob(F-statistic)	0.000000		

Considering that the p-values are greater than the significance level of 0.05%, I fail to reject the Null Hypothesis that the model is accurately specified and that the residuals follow a random distribution.

The final regression model

After engaging a series of the above coefficient, residual and stability diagnostic tests, I then computed the final regression and the output is given below:

Table 10. The impact of Climate smart technologies on carbon dioxide emissions

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.31129	0.810216	17.66355	0.0000
LOG(FOREST)	0.276916	0.930877	0.297479	0.7684
LOG(GRAPHITE)	0.121512	0.042551	2.855656	0.0082
LOG(LANDUSE)	-1.939786	0.822072	-2.359631	0.0258
LOG(SILVER)	0.657323	0.080580	8.157370	0.0000
DLOG(ZINC)	-0.009540	0.022041	-0.432805	0.6686

R-squared	0.945643	Mean dependent var	24.11925
Adjusted R-squared	0.935576	S.D. dependent var	0.185301
S.E. of regression	0.047033	Akaike info criterion	-3.112978
Sum squared resid	0.059726	Schwarz criterion	-2.840886
Log likelihood	57.36414	Hannan-Quinn criter.	-3.021427
F-statistic	93.94253	Durbin-Watson stat	1.303366
Prob(F-statistic)	0.000000		

Table 10 above is an output of a study that was carried out to test if the current climate smart technologies on a global scale are making significant strides towards a low global carbon economy. The constant (c)'s coefficient 14.31129 is statistically significant and this suggests that when forest, graphite, landuse, silver and zinc increase by 1%, carbon dioxide emissions will be reduced by 14%.

The coefficient of the forest variable is 0.276916 and the probability value is 0.7684. The coefficient shows that a 1% increase in forest area of the global land results in 0.27% reduction in carbon dioxide emissions. However, in this model, the p-value is greater than 0.05. This is because of a lot of current deforestation that is taking place in the different parts of the world particularly in the emerging economies. On the other hand, the graphite coefficient is 0.121512 and the p-value is 0.0082. This variable is statistically significant demonstrating that graphite technologies have a significant impact on carbon dioxide emissions. This means that a 1% increase in graphite technologies will result in 0.12% reduction in carbon dioxide emissions.

The land use coefficient is -1.939786 and the p-value is 0.0258 is approaching a level of significance; suggesting that landuse technologies have a positive influence on carbon dioxide emission reduction, though currently its impact is mild (not strong). Silver has a coefficient of 0.657323 and the p-value is 0.0000. The variable is statistically significant showing that silver technologies have a significant impact on carbon dioxide emissions. A 1% increase in silver technologies significantly yields a 0.68% reduction in carbon dioxide emissions. Additionally, zinc has a coefficient of -0.009540 and the probability value is 0.6686 and is greater than 0.05. This shows that zinc technologies are not yet significant in reducing carbon dioxide emissions; but a continuous harnessing of this technology will finally result in a low carbon economy in the future.

In terms of model fit, the R-Squared value of 0.945643 indicates that a 1% increase in forest, graphite, landuse, silver and zinc technologies yield 95% of carbon dioxide emission reduction. The F-statistic 93.94253 and a p-value of 0.000000 demonstrates that the overall model is statistically significant, demonstrating that at least one of the regressors in the model is significantly related to atmospheric carbon dioxide reduction. In this case, the model is robust and demonstrate that the global nations' efforts aimed at reducing the emissions of carbon dioxide in the atmosphere are moving in the right direction; meaning that the deadline of the 2050 net-zero emission might be achieved if progress is maintained or even enhanced.

Discussion

The findings in this study have demonstrated that an increase in metal technologies is associated with a subsequent decline in atmospheric carbon dioxide emissions. These findings are in line with previous findings; for example, Lin (2019) and Hollapa (2020) found that oil producing companies in the United States of America and in other oil producing companies have used Carbon Dioxide Capture and Storage technologies to get rid of atmospheric carbon dioxide concentration by using cryogenic distillation/membrane, physical absorption and chemical absorption-based separation technologies. LanzaTech, an Illinois United States-based company has also developed microbial bioreactor systems with the ability of direct gas fermentation to generate ethanol from carbon-holding gases like integrated iron and steel plant off gases (Hollapa, 2020). Another demonstration plant has also been set up in Shouqang in China while another one was similarly constructed in Belgium at Arcelor Mittal Ghent (Hollapa, 2020). These CCS technologies were said to have been able to reduce atmospheric carbon dioxide concentration by 9% (Hollapa, 2020, p.9).

Similarly, the Japanese COURSE50 programme, the European ULCOs programme, the Australian Carbon dioxide Breakthrough programme and the North American AISI Carbon dioxide Breakthrough programmes impactfully reduced greenhouse gas emissions (Hollapa, 2020). With these technologies, "the reductions in carbon dioxide emissions were estimated to be in the range of 10% to 25% (Hollapa, 2020, p. 7). Even the harnessing of renewable technologies such as wind, solar, nuclear and hydro-power have been found to be important in carbon dioxide emission reductions. With an increase in the use of climate smart technologies, global economic giants like China, which is the greatest producer of global steel, have been able to reduce carbon dioxide emissions to 620g co2/kwh. Similarly, the United States of America was able to reduce carbon dioxide emissions by 420gco2/kwh, while the European Union was able to reduce its carbon emissions by 282gco2/kwh (Hollapa, 2020). With these technologies, global emissions of carbon dioxide are at 10% for the past three decades (Hollapa, 2020, p. 11). Even in Nepal, Renewable Energy Technologies (RETs) have also been implemented. Technologies such as the National Energy Crisis Mitigation and Energy Development Decade have been in operation since 2016, whilst the Nationally Determined Contributions have been effected in the past 5 years (Suman, 2021). With these climate smart technologies, a total of 86 803 tco2e were reduced (Suman, 2021, p. 10).

Even in African countries, projects and programmes that have been implemented to drastically reduce the carbon dioxide emissions have been noticed. The implementation of the 300MW Bui Hydro project in western Ghana above the Volta Dam has significantly contributed to the reduction of greenhouse gas emissions (Ahinsah-Wobil, 2024). The results for this study are similarly consistent with the observations that the emissions of GHGs have been reduced when world governments came together to form international agreements to deal with greenhouse gas emissions since 1980 (Ritchie et al., 2023).

CONCLUSION

The study has shown that climate smart technologies are part and parcel of the low-carbon technological climate change package, which have entered the arena for climate policy discussions since the 1980s. Past efforts at tackling climate change have been around since 1980 and the need to create a low carbon economy has been at the forefront of climate change global discussions. Against this background, the paper provided an econometric analysis of the impact of climate smart technologies on global carbon dioxide emissions. It quantitatively traced the progress that has been made globally in reducing carbon dioxide emissions considering that the 2050 net-zero emissions deadline is only two and a half decades away. The paper considered carbon dioxide due to the observation that it is the most significant greenhouse gas whose emissions currently stand at 37 gigatons per annum. The study has made use of graphite, zinc, silver global production annual trends, global land use changes and the changing trends of global forest area cover of global data running from 1990 to 2023 and found that a 1% increase in forest, graphite, landuse, silver and zinc technologies yield 95% of carbon dioxide emission reduction. A positive association between carbon dioxide emissions and climate smart technologies have been found. The study therefore recommends nation-states to increase and gear-up their climate smart efforts to achieve net-zero GHGs emissions by 2050.

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