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Assessing the Long-Term Effectiveness of CO_2 Emission Reduction Policies: An Econometric Analysis of Major Global Emitters

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***Abstract*: This study investigates the dynamic relationship between CO_2 emissions excluding land use change and forestry (CO_2 excl. LUCF) and their potential drivers—greenhouse gas emissions (GGE excl. LUCF), population, GDP per capita, and international tourism—within the United States and China from 1990 to 2023. Using the ARDL (Autoregressive Distributed Lag) model, the analysis reveals that both countries exhibit a significant and stable long-term equilibrium relationship, with short-run adjustments occurring more rapidly in China than in the USA. The results show that GDP per capita significantly increases CO_2 emissions in the short run, underlining the environmental cost of economic expansion. In China, population growth seems to mitigate emissions in the long run, suggesting improved efficiency and demographic transition, whereas in the USA, both population and tourism continue to exert upward pressure on emissions.**

Given their technological, economic, and industrial leadership, both nations are uniquely positioned to turn their strengths into drivers of decarbonization. As top global actors in energy innovation, digital infrastructure, and scientific research, they possess the tools and influence necessary to pioneer low-carbon pathways. However, this dual capacity also presents a paradox: their power can either accelerate environmental solutions or deepen global emissions if not guided by responsible strategies. These findings highlight the urgent need for a nuanced policy approach that harnesses existing capacities while minimizing the unintended consequences of unchecked growth. In this context, aligning national strategies with the United Nations Sustainable Development Goals (SDGs) particularly Goal 13 is essential to reconciling economic ambition with ecological responsibility and ensuring long-term environmental resilience.

***Keywords*: CO_2 emissions, ARDL model, emission reduction policies, long-term effectiveness, economic-environmental and social factors.**

I. INTRODUCTION

ENVIRONMENTAL Environmental challenges such as global warming, rising sea levels, and extreme weather events are increasingly threatening human living conditions. Greenhouse gas emissions, particularly carbon dioxide (CO_2), are a key component of this crisis, contributing significantly to rising global temperatures and climate change [1]. In response, countries have implemented various policies aimed at mitigating these environmental threats, with the reduction of CO_2 emissions emerging as a key global priority. The urgency of this issue is underscored by the International Energy Agency (IEA), which reported a record 37.4 billion tons of global CO_2 emissions in 2023, highlighting the urgent need for effective emission mitigation strategies [2] [3]. Major economies, particularly the United States and China, play a pivotal role in global emissions due to their significant contributions to industrial production and energy consumption. These two countries are not only the largest emitters of carbon dioxide (CO_2), but they are also leaders in diverse industrial sectors, making their emission reduction strategies critical to global climate efforts. Studies indicate that the economic structures and energy consumption patterns in the United States and China differ significantly, affecting the effectiveness of their emission reduction policies [4]. This requires careful examination of their individual policies in the context of their unique industrial environments and development priorities. As the world's largest emitters, the United States and China play a pivotal role in shaping global CO_2 levels.

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Their massive industrial production and energy consumption patterns also significantly influence global climate strategies. Therefore, their emission reduction policies have far-reaching implications, not only for their economic and environmental futures, but also for achieving global sustainability goals [2]. Despite international agreements such as the Kyoto Protocol and the Paris Agreement, there remains considerable debate about the long-term effectiveness of emission reduction commitments, particularly in light of economic growth priorities and energy dependence [5]. Understanding the long-term effects of carbon dioxide reduction policies requires focusing on the structural characteristics of high-emitting economies. Economic fluctuations, technological advances, and policy reversals can lead to temporary reductions in emissions, but without lasting changes in energy consumption and industrial practices, these reductions may not be sustainable [3]. The need for a long-term perspective is evident in evaluating these policies, as short-term successes may mask more pressing systemic issues in the energy sectors and industrial structures [6]. Therefore, it is essential to assess the long-term performance of emission reduction policies in the United States and China, given their economic systems and energy needs. Based on the above discussion, the following question arises: **To what extent are the carbon dioxide emission reduction policies in the United States and China, the world's two largest economies, effective in the long term, using econometric analysis to assess the sustainability of these policies?** In 2023, the top 10 carbon-emitting countries released a record 24.5 billion metric tons of CO_2 from energy, driven mainly by China, India, and the U.S. China led with a sharp rise due to industrial rebound, while India's coal reliance pushed its emissions higher. The U.S., Japan, Germany, and others saw declines due to renewable adoption. Russia, Saudi Arabia, and Iran saw increases. Global energy emissions are expected to keep rising, especially in coal-dependent nations like China, India, and Indonesia [7]. According to [8] CO_2 and greenhouse gas emissions remain largely driven by fossil fuel use, particularly in energy and industry. The data stresses the historical responsibility of high-income nations, but also the growing share of emissions from developing economies. Reducing emissions equitably requires both major emitters and historically responsible countries to invest in cleaner energy, improve efficiency, and support global mitigation efforts.

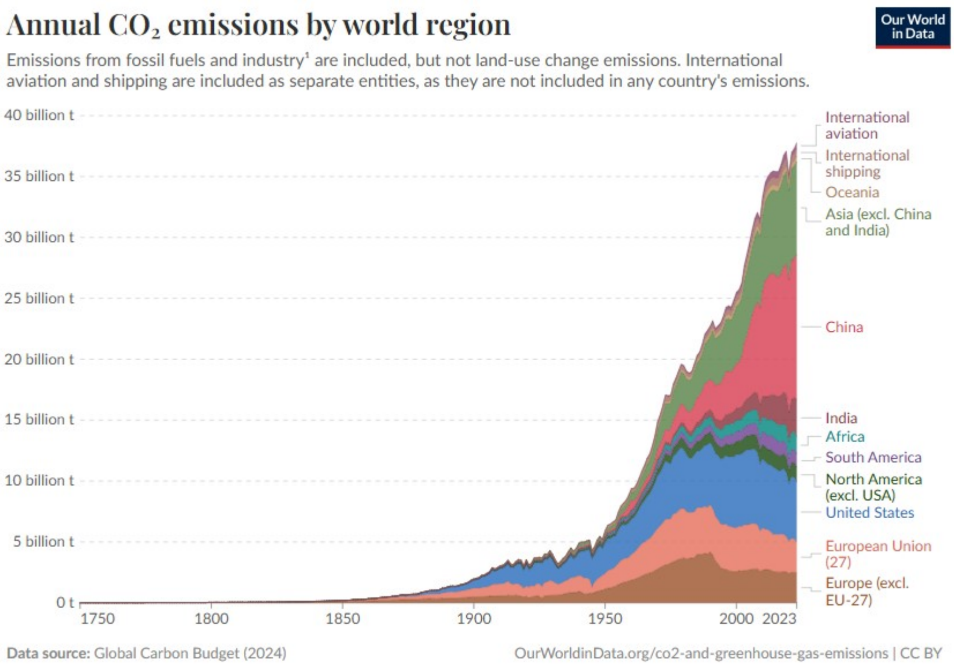

Figure 1: Our World in Data. (n.d.). CO_2 Emissions. [Online]. Available:https://ourworldindata.org/co2-emissions.

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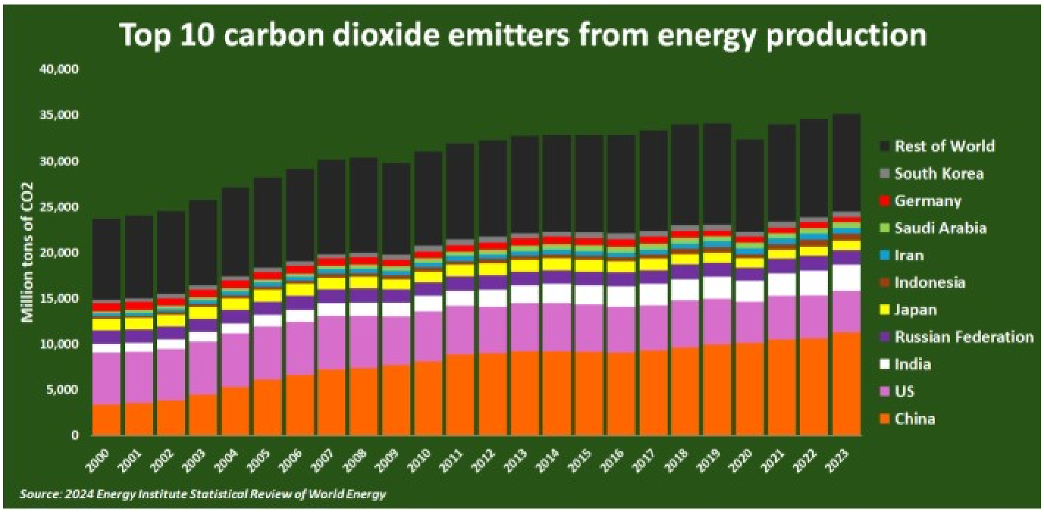

Figure2: D. Stanway and S. Twidale, "Top 10 country emitters discharged record amount of CO2 in 2023," *Reuters*, Jun. 21, 2024. [Online]. Available: https://www.reuters.com/markets/commodities/top-10-country-emitters-discharged-record-amount-co2-2023-2024-06-21/

This study focuses exclusively on the United States and China, two of the largest CO_2 emitters in the world, selected based on their economic size, industrial output, and historical emission levels. Given their prominent role in both emission levels and policy implementation, the effectiveness of their emission reduction policies warrants specific attention. Through econometric analysis, this research seeks to assess whether their CO_2 emission reduction strategies lead to sustainable, structural changes or merely short-term fluctuations. The analysis spans from 1990 to 2023, utilizing annual data for both countries, and employs a traditional ARDL model, focusing on the individual effectiveness of each country's policies over the long term. This study seeks to assess the long-term impact of CO_2 emission reduction policies in the United States and China using the ARDL model. It examines the relationship between policy interventions and CO_2 emissions, identifying key economic, industrial, and environmental drivers. The research also investigates which policy measures have been most effective in reducing CO_2 emissions over the long term in both countries. Additionally, the study aims to forecast future CO_2 emission trends in the United States and China based on current policy frameworks and evaluate the effectiveness of these policies in the context of global sustainability goals.

II. LI TERATUREREVIEW

Climate change, predominantly driven by rising carbon dioxide (CO_2) emissions, is widely recognized as one of the most pressing global challenges [9]. In response, a growing body of literature has emphasized the need for accurate forecasting models to better understand emissions dynamics and support the formulation of effective environmental policies. Within this context, the relationship between CO_2 emissions and economic growth has been extensively studied, particularly in light of sustainable development goals and decarbonization strategies. A central framework in this discourse is the Environmental Kuznets Curve (EKC) hypothesis, which posits an inverted U-shaped relationship between economic growth and environmental degradation. According to this theory, CO_2 emissions initially increase with rising income levels but eventually decline after surpassing a certain threshold [10]. However, empirical evidence remains mixed. For example, [11] reported a persistent positive correlation between GDP and CO_2 emissions in Azerbaijan, challenging the EKC framework. Similarly, [12] identified an N-shaped relationship in EU-5 countries, indicating that emissions may increase again in advanced development stages, thereby necessitating sustained regulatory interventions. In addition to economic factors, institutional quality and governance play a critical role in shaping environmental outcomes. Countries with robust regulatory frameworks tend to experience slower emissions growth, as demonstrated by [4] who underscored the mitigating role of governance quality. Moreover, trade openness has been shown to influence emissions, particularly in developing economies where trade expansion is often accompanied by increased industrial activity and energy consumption. The extent to

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which trade exacerbates or alleviates emissions is contingent upon a country's stage of economic development and its adherence to environmental standards [4]. Energy consumption patterns, particularly the reliance on fossil fuels, remain a dominant factor in CO_2 emissions. [13] noted that developing countries face significant challenges due to population growth and escalating energy demand, which contribute to higher per capita emissions. However, evidence from developed economies suggests that strong climate mitigation policies can offset these trends. For instance, [15] observed that countries with stringent environmental regulations often achieve reductions in per capita emissions despite high income levels. Similarly, [16] found a negative long-run relationship between GDP and CO_2 emissions in 18 EU countries, implying that technological advancements and structural changes in mature economies can lead to decoupling between economic growth and emissions.

In a recent study, [17] explored the relationship between CO_2 emissions and macroeconomic indicators in some of the most polluted regions globally, specifically the United States and the Asia-Pacific region. Using correlation and regression analysis over the period from 1970 to 2020, the study found that macroeconomic factors such as GDP, exports, imports, inflation, and unemployment significantly influenced CO_2 emissions. This provides valuable insights for governments to diagnose, monitor, and forecast macroeconomic outcomes that can reduce or stabilize CO_2 emissions. The study emphasizes the importance of econometric models in evaluating economic losses from environmental pollution, underscoring the need for balanced socioeconomic development and low-carbon energy transitions. Their findings revealed mixed decoupling patterns, with some economies achieving weak decoupling, while others, notably China and India, continued to exhibit growth-driven emissions. However, the study did not directly evaluate the effectiveness of specific environmental policy instruments over time. [18] utilized a panel ARDL approach to assess the impact of policy uncertainty on CO_2 emissions in BRICS nations, confirming a long-term relationship between uncertainty and emission levels. This study highlights how unstable policy environments can undermine environmental progress. However, it overlooked the structural characteristics of national energy systems and the influence of policy-specific variables.
Studies have consistently demonstrated the multifaceted relationship between economic growth and CO_2 emissions, emphasizing the roles of GDP per capita, tourism, population density, and technological innovation. For instance, Stern (2004), Cole & Neumayer (2004), and Pardoe (2011) show that while higher income levels initially lead to increased emissions, policy reforms and technological progress can reverse this trend. Similarly, Miller (2014) and Gössling & Peeters (2015) highlight the environmental burden of international tourism, especially in wealthy nations. Zhang & Cheng (2020) and Liu & Zhang (2015) further argue that urban population density correlates with higher energy consumption and emissions, calling for sustainable urban planning. Additionally, Zhao & Liu (2019) and Bai & Liu (2017) emphasize the importance of considering greenhouse gases like HFCs, PFCs, and SF_6, which indirectly contribute to CO_2 levels. Technological innovation, as explored by,[30] and [31] & is crucial in decoupling economic growth from environmental degradation. Recent studies highlight the complex relationship between economic development and CO_2 emissions. [31] found that globalization and institutional quality can mitigate emissions in OECD countries, although economic growth and electricity consumption still contribute to higher emissions. [32] demonstrated that in the United States, AI innovation, renewable energy usage, and the digital economy help reduce CO_2 emissions, while GDP growth and industrialization continue to drive them upward. Additionally, research by [33] supports the Environmental Kuznets Curve hypothesis, indicating that renewable energy adoption and energy efficiency improvements can lead to emission reductions in major manufacturing countries.

However, the literature has largely concentrated on either command-and-control or market-based regulatory instruments, overlooking the potential role of the Pollution Levy policy, which directly penalizes firms based on the level of emissions they produce. Notably, the 2007 adjustment to the pollution levy standard provides a unique opportunity to analyze its impact as a quasi-natural experiment. In parallel, there remains a gap in exploring how these variables interact with carbon emission efficiency, particularly in countries with higher levels of technological development, stronger trade exposure, and larger national revenues. Therefore, this paper attempts to fill this research gap by examining the causal impact of pollution levy standard adjustments

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on carbon emission efficiency, while also accounting for the roles of green technology adoption, economic structure, trade openness, population dynamics, tourism activity, and institutional governance quality

III. DATA AND METHODOLOGY

This study examines the long-term effectiveness of CO_2 emission reduction policies across major global emitters, focusing on the period from 1990 to 2023. The analysis centers on China and the United States, which are among the top industrial leaders in multiple sectors, contributing significantly to global greenhouse gas emissions. The dependent variable, Total CO_2 emissions from fossil fuels and cement production (excluding land use, land-use change, and forestry, or LULUCF), was sourced from the World Bank Group (WBG), providing a comprehensive measure of carbon output. The independent variables include Total greenhouse gas emissions (excluding LULUCF) and GDP per capita, both obtained from the WBG, offering insights into the broader environmental and economic impacts. Socio-economic variables such as total population and international tourism (number of arrivals) were derived from the World Development Indicators (WDI) database, capturing trends in population growth and international travel. The study also integrates a dummy variable to account for significant global events, particularly Technological Advancements, marked by key milestones in renewable energy and green innovation. Through econometric analysis, this methodology aims to explore the complex relationship between environmental policies, socio-economic factors, and CO_2 emissions over time, contributing to a nuanced understanding of sustainability dynamics.**Table 1.**

Table 1. Variables definition.

variables	Definition	Units of Measurement
Dependent Variable		
CO2 excl LUCF	Total CO_2 emissions from fossil fuels and cement production, excluding land use, land-use change, and forestry (LULUCF).	Metric tons of CO_2 equivalent (Mt CO_2e)
Independent Variables		
POP	Midyear estimate of the total number of residents.	Number of individuals (count)
GGE excl LUCF	Total greenhouse gas emissions excluding LULUCF	Metric tons of CO_2 equivalent (Mt CO_2e)
GDP PC	GDP in international dollars using PPP rates, reflecting purchasing power. Includes gross value added, taxes, and subsidies. Data are in constant 2021 international dollars.	Constant 2021 international $
D_TECH	Dummy variable indicating major technological milestones (1 = significant advancement, 0 = otherwise).	Binary (0 or 1)

Source: Own elaboration based on data from WDI and WBG

Excluding Land Use, Land-Use Change, and Forestry (LULUCF) from the dependent variable in CO_2 emissions studies is crucial for enhancing consistency and accuracy. LULUCF emissions are highly volatile due to natural factors such as wildfires and human activities like deforestation, leading to significant fluctuations that complicate trend analysis and international comparisons. In contrast, emissions from fossil fuel combustion and cement production are more stable and predictable, reflecting industrial and economic activity, thus offering a more reliable measure of human-induced emissions. Moreover, excluding LULUCF improves the reliability of economic models by reducing data uncertainty and relying on more stable datasets. Standardized reporting of fossil fuel and cement emissions further enhances international comparability, unlike LULUCF, where inconsistent accounting methods persist. Excluding LULUCF also avoids accounting complexities[34]. The European Union initially excluded LULUCF from its climate policies until 2020 due to "problems of uncertainty in the estimates of sequestered carbon, the lack of annually based LULUCF reporting cycles, and uncertainty over whether LULUCF should be incorporated into the EU's ETS or the

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commitment mechanism" . Despite efforts to standardize greenhouse gas accounting rules through the LULUCF Regulation (841/2018), inherent volatility continues to justify its exclusion for more consistent analysis [35]. Therefore, incorporating Total greenhouse gas emissions excluding LULUCF as an independent variable provides a clearer reflection of anthropogenic CO_2 sources. This approach minimizes uncertainties linked to land-use factors, improves predictive reliability, and strengthens the model's capacity to inform policy decisions effectively.

To achieve this, we employed a quantitative standard methodology using the autoregressive distributed lag (ARDL) co-integration technique. Initially proposed by [36] and later extended by[37], the ARDL test process yields effective results regardless of whether the variables are stationary I(0), integrated of order one I(1), or mutually cointegrated [37], Our study focused on a small sample size, and we identified a single long-run relationship between the underlying variables.

In the context of the Autoregressive Distributed Lag (ARDL) model, there are two fundamental steps. Initially, we conduct an F-bounds test to evaluate the presence of a long-term relationship among the variables. Subsequently, we construct an Error Correction Model (ECM) based on the ARDL framework [38]. The study model takes the following functional form:

CO2 excl LUCF =f (GGE excl LUCF, POP, GDP PC, ITN, D_TECH)

Building upon the previous methodology, we specify the Autoregressive Distributed Lag (ARDL) version of our model as:

$$\text{CO2 excl LUCF} = B_0 + B_1\,\text{CO2 excl LUCF}_{t-1} + B_2\,\text{GGE excl LUCF}_{t-1} + B_3\,\text{POP}_{t-1} + B_4\,\text{ITN}_{t-1} + B_5\,\text{D\_TECH} + \sum_{i=1}^{p} \Delta\text{CO2 excl LUCFt} - \text{p} + \sum_{i=1}^{p} \Delta\text{GGE excl LUCFt} - \text{p} + \sum_{i=1}^{p} \Delta\text{POPt} - \text{p} + \sum_{i=1}^{p} \Delta\text{ITNt} - \text{p} + \varepsilon_t$$

Where: • $\boldsymbol{\varepsilon}$: The error term. • $\boldsymbol{\Delta}$: The first difference.

IV. RESULTS AND DISCUSSION

In the investigation of time series stability and the degree of variable integration, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test were employed to assess the null hypothesis of a unit root (non-stationarity) against the alternative hypothesis of stationarity [39]. Using EViews 12, these tests were conducted on all-time series data, as summarized in Table 2 and Table 3. The results indicate that in China, all variables are integrated of order one, I(1), while in the USA, all variables are I(1) except for the population variable, which is integrated of order zero, I(0). Consequently, the bounds testing approach is applicable in this context.

Given the combination of I(0) and I(1) variables, the Autoregressive Distributed Lag (ARDL) model is the best option for the research question. The ARDL approach is particularly suitable for handling variables integrated of different orders, specifically I(0) and I(1), but not I(2) or higher. This model facilitates the estimation of both short-run and long-run dynamics without requiring all variables to exhibit the same order of integration. Therefore, for the period 1990–2023, the ARDL model is well-suited for examining the relationship between CO_2 emissions (excluding LUCF) and its potential determinants, including greenhouse gas emissions (excluding LUCF), international tourism arrivals, population, and GDP per capita.

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Table 2: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Test Results in USA

Variables	ADF			PP			Order of Integration
	T-Statistic	P-Value	Value 5%	T-Statistic	P-Value	Value 5%	
CO2 excl LUCF	- 6.290545	0.0001**	- 3.562882	-6.630845	0.0000**	-3.557759	I(1)
POP	- 10.89098	0.0000**	- 3.552973	- 10.89098	0.0000**	- 3.552973	I(0)
ITN	- 6.827383	0.0000**	- 3.557759	- 6.932540	0.0000**	- 3.212361	I(1)
GGE excl LUCF	- 5.877716	0.0002**	- 3.212361	- 6.302683	0.0001**	- 3.557759	I(1)
GDP PC	- 6.515560	0.0000**	- 3.562882	-6.727349	0.0000**	- 3.557759	I(1)

Source: Authors' computations using Eviews 12 software..

Table 3: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Test Results in CHINA

Variables	ADF			PP			Order of Integration
	T-Statistic	P-Value	Value 5%	T-Statistic	P-Value	Value 5%	
CO2 excl LUCF	-3.557759	0.0352**	-3.345282	-3.557759	0.0352**	-3.358113	I(1)
POP	- 3.870022	0.0292**	-3.603202	-3.557759	0.0104**	-1.167641	I(1)
ITN	-3.662167	0.04167**	-3.574244	-16.487281	0.0000**	-3.557759	I(1)
GGE excl LUCF	- 3.557759	0.0120**	-3.152268	-3.557759	0.0086**	-3.168820	I(1)
GDP PC	- 7.144505	0.0000**	- 3.557759	-6.946092	0.0000**	- 3.557759	I(1)

Source: Authors' computations using Eviews 12 software..

The analysis, illustrated in Figures 3 and 4, involved estimating 20 distinct model specifications for both the USA and China to determine the optimal lag structure for the variables under consideration. Utilizing standard information criteria, such as the Akaike Information Criterion (AIC), the optimal lag configuration for the USA was identified as (1,1,0,0,0). This configuration implies that a lag length of one period is appropriate for 'Total CO_2 emissions from fossil fuels and cement production, excluding LULUCF' and 'GDP in international dollars using PPP rates,' suggesting these variables exhibit significant autocorrelation or dynamic interdependencies warranting the inclusion of their first lag. Conversely, a lag length of zero was deemed sufficient for 'Total greenhouse gas emissions excluding LULUCF,' 'International tourism (number of arrivals),' and 'Population,' indicating that their current values are adequately explained without incorporating past values in the model.
In contrast, for China, the optimal lag configuration was determined to be (1,2,2,2,0). This suggests that 'Total CO_2 emissions from fossil fuels and cement production, excluding LULUCF' requires one lag, while 'GDP in international dollars using PPP rates,' 'Total greenhouse gas emissions excluding LULUCF,' and 'International tourism (number of arrivals)' each require two lags, reflecting more complex dynamic relationships. The 'Population' variable, similar to the USA, was adequately captured without lags.

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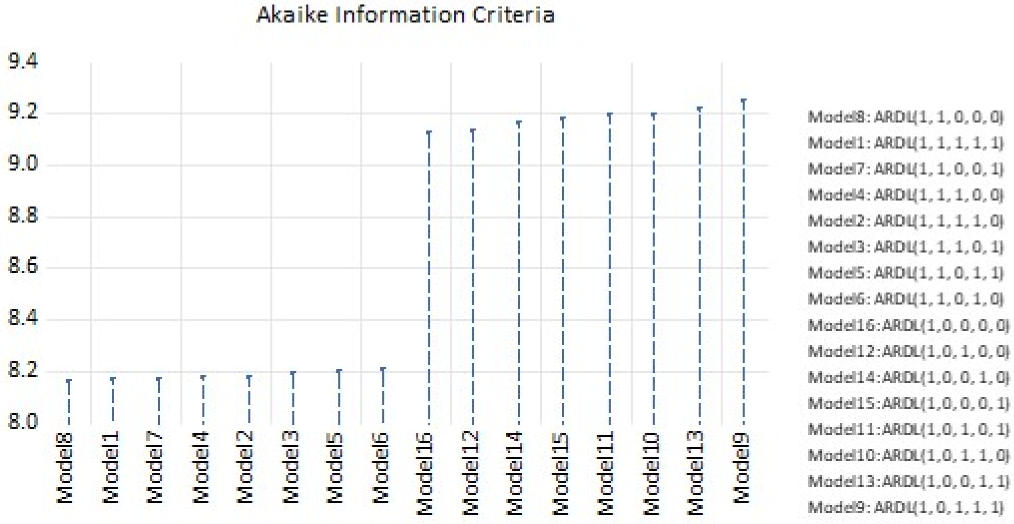

Figure 3: Optimal Lag Length Selection for USA

Source: Authors' computations using Eviews 12 software..

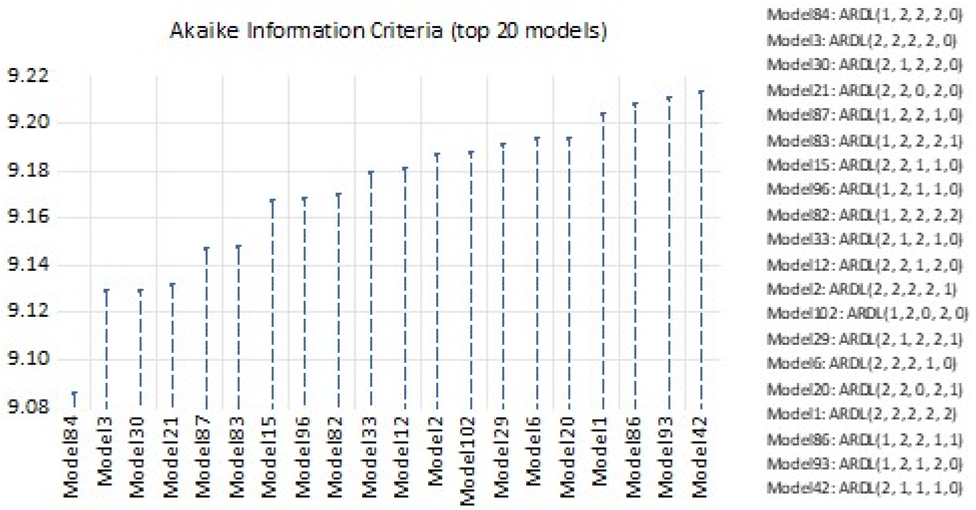

Figure 4: Optimal Lag Length Selection for China

Source: Authors' computations using Eviews 12 software..

To investigate the long-term equilibrium relationship between CO_2 emissions excluding land use change and forestry (LUCF) and its potential determinants—specifically, greenhouse gas emissions excluding LUCF (GGE excl. LUCF), international tourism arrivals (INT), and population (POP)—we apply the ARDL bounds testing approach. As shown in Table 4, the computed F-statistics for the United States and China are 5.986417 and 6.520321, respectively. These values exceed the critical bounds at the 1%, 5%, and 10% significance levels, leading to the rejection of the null hypothesis of no cointegration. This confirms the existence of a stable long-run relationship among the variables in both countries. Consequently, we proceed to estimate an error correction model (ECM) to analyze both the short-term dynamics and long-term effects of GGE excl. LUCF, INT, and POP on CO_2 emissions excluding LUCF. Table 4 and Table 5:

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Table 4: ARDL Bound Test Results

USA

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	5.986417	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	33	Finite Sample: n=35		
		10%	2.46	3.46
		5%	2.947	4.088
		1%	4.093	5.532
		Finite Sample: n=30		
		10%	2.525	3.56
		5%	3.058	4.223
		1%	4.28	5.84

Table 5: ARDL Bound Test Results

CHINA

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	6.520322	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	32	Finite Sample: n=35		
		10%	2.46	3.46
		5%	2.947	4.088
		1%	4.093	5.532
		Finite Sample: n=30		
		10%	2.525	3.56
		5%	3.058	4.223
		1%	4.28	5.84

Source: Authors' computations using Eviews 12 software..

A. Short-Run ARDL Model Estimation

The next phase entails the estimation of the Error Correction Model (ECM) and the examination of both the short-term and long-term interrelationships among the model variables. The results of this analysis are outlined in Table 6 as follows:

Table 6: Error Correction Model (ECM), Short-Run, for **USA**

ECM Regression Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP_PC)	1.078898	0.011848	91.06461	0.0000
D_TECH	-11.88976	12.84353	-0.925739	0.3634
CointEq(-1)*	-0.240883	0.046092	-5.226147	0.0000
R-squared	0.996449	Mean dependent var	-7.530009	
Adjusted R-squared	0.996212	S.D. dependent var	191.1337	
S.E. of regression	11.76378	Akaike info criterion	7.854436	
Sum squared resid	4151.596	Schwarz criterion	7.990482	
Log likelihood	-126.5982	Hannan-Quinn criter.	7.900211	
Durbin-Watson stat	1.992520			

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Table 7: Error Correction Model (ECM), Short-Run, for CHINA

ECM Regression
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GGE_EXCL_LUCF)	0.891865	0.016081	55.46174	0.0000
D(GGE_EXCL_LUCF(-1))	-0.078502	0.017551	-4.472665	0.0002
D(ITN)	1.71E-07	1.54E-07	1.106462	0.2817
D(ITN(-1))	-9.85E-07	2.90E-07	-3.390909	0.0029
D(GDP_PC)	0.039587	0.024025	1.647724	0.1150
D(GDP_PC(-1))	0.085581	0.032731	2.614663	0.0166
CointEq(-1)*	-0.665066	0.095104	-6.993026	0.0000

R-squared	0.997142	Mean dependent var	334.6700
Adjusted R-squared	0.996457	S.D. dependent var	288.2318
S.E. of regression	17.15741	Akaike info criterion	8.713377
Sum squared resid	7359.418	Schwarz criterion	9.034007
Log likelihood	-132.4140	Hannan-Quinn criter.	8.819657
Durbin-Watson stat	2.086784		

From the analysis presented in Table 6 and Table 7, we observe that the error correction coefficient is negative and statistically significant for both the USA and China. Specifically, in the USA, the coefficient is -0.240883, while in China, it is -0.665066, with both values being statistically significant at the 5% level. This indicates that if CO_2 emissions excluding land use change and forestry (CO_2 excl. LUCF) deviate from their long-run equilibrium, the system will adjust back towards equilibrium. In the case of the USA, this adjustment occurs at an annual rate of approximately 24.09%, whereas in China, the rate is 66.51%.

Additionally, the R-squared values for the USA and China are 0.996448 and 0.997142, respectively. These high R-squared values suggest that the explanatory variables—namely greenhouse gas emissions excluding LUCF (GGE excl. LUCF), population (POP), and international tourism arrivals (INT)—account for approximately 99.64% and 99.71% of the variations in CO_2 emissions excluding LUCF in the USA and China. This highlights a very strong relationship between these variables and CO_2 emissions in both countries, reinforcing the robustness of the model.

- United States**:** In the short-run estimation for the United States, only GDP per capita (GDP_pc) exhibits a statistically significant impact on CO_2 emissions excluding LULUCF, significant at the 5% level. The dummy variable representing technological advancement (D_Tech) is statistically insignificant, indicating that, within the short-run framework, technological changes do not have an immediate discernible effect on CO_2 emissions in the U.S.
- China: For China, the short-run ECM results indicate that current greenhouse gas emissions excluding LULUCF (GGE_excl_LULUCF), its first lag, and the first lag of international tourism arrivals (INTR(-1)) are significant at the 1% level, highlighting their immediate and lagged effects on CO_2 emissions. GDP per capita lagged by one period (GDP_pc(-1)) is significant at the 5% level, while its current value is significant at the 10% level, suggesting a delayed effect of economic growth on CO_2 emissions. The variables representing international tourism arrivals (INTR) and the technological advancement dummy (D_Tech) are not statistically significant, indicating limited short-run influence on CO_2 emissions.
  In the short term, the positive impact of higher GDP per capita on CO_2 emissions, excluding Land Use, Land-Use Change, and Forestry (LULUCF), can be understood in the context of economic expansion and industrialization. As both China and the USA experience growth in GDP per capita [10] [11] , this economic development often drives an increase in industrial output, energy consumption, and transportation activities. Industrial growth in these countries, as major economic powerhouses,

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contributes significantly to global CO_2 emissions, primarily due to reliance on fossil fuels for energy production and manufacturing. The expansion of industrial activities correlates with higher energy demand, and the subsequent increase in energy consumption, particularly from fossil fuel-based sources, further escalates CO_2 emissions.
The short-term positive effect of government economic activities (excluding LULUCF) on carbon dioxide emissions can be attributed to industrial activities and energy consumption. As China's economy expands, increased industrial output and energy demand—particularly from fossil fuels—lead to higher greenhouse gas emissions, thereby contributing to rising carbon dioxide levels. This pattern aligns with the Environmental Kuznets Curve (EKC) hypothesis [17] [33], which suggests that environmental degradation tends to increase in the early stages of economic growth before eventually declining as income levels rise. In contrast, the significant negative effect of lagged greenhouse gas emissions (excluding land use, land-use change, and forestry; GGE excluding LUCF) on current carbon dioxide emissions (CO_2 excluding LUCF) indicates that higher emissions in previous periods may have triggered policy responses and technological advancements aimed at emission reduction.[32] [33] [34] [35] This is further evidenced by the technology dummy variable, whose indirect effect was found to be statistically insignificant in the short term. In China, the introduction of stringent environmental regulations and the promotion of clean energy technologies [40] [41] have been integral to these efforts, although their short-term impact may be limited due to the slow pace of adoption and integration. The insignificant positive effect of international tourism (ITN) on CO_2 emissions excluding LUCF in the short term in China likely reflects the adoption of greener tourism infrastructure and policies that offset immediate emission increases [42]. The significant negative effect of lagged ITN suggests that past tourism growth appears to have spurred investments in low-carbon technologies and stricter environmental regulations, leading to reduced emissions in subsequent periods [43].

B. Long-Term ARDL Model Estimation

This section presents the long-term estimation results of the AutoRegressive Distributed Lag (ARDL) model, which is employed to examine the equilibrium relationship between the dependent and independent variables over time

Table 8: Long-Term ARDL Model Estimation for **USA**

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP PC	1.130641	0.056715	19.93565	0.0000
GGE excl LUCF	2.638070	3.440522	0.766764	0.4504
ITN	-3.339544	1.353789	-2.466813	0.0208
POP	0.244603	0.099546	2.457191	0.0213
C	-168721.0	69162.61	-2.439483	0.0221

CE = CO2 excl LUCF - (1.130641* GDP PC +2.638070* GGE excl LUCF - 3.339544* ITN + 0.244603* POP -168721)

Source: Authors' computations using EViews 12 software.

Understanding the long-term drivers of CO_2 emissions in the United States -Table 8- requires analyzing the significance of various structural and economic variables. The results reveal that population, GDP per capita, and international tourism have a statistically significant positive impact on CO_2 emissions, whereas greenhouse gas emissions excluding land use, land-use change, and forestry (GGE excl LUCF) are statistically insignificant.

The significant impact of population on CO_2 emissions aligns with the foundational findings of Dietz and [44] who demonstrated that population growth leads to increased environmental stress.[45], through the STIRPAT

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model, further confirmed that population size is a central driver of environmental impact, including emissions. Similarly, GDP per capita exerts a significant upward pressure on CO_2 emissions, consistent with the Environmental Kuznets Curve literature and studies such as [46], which found that economic growth initially increases emissions in the United States before potential long-term reductions. Moreover, international tourism also shows a significant impact on emissions. The carbon intensity of air travel and tourism-related consumption behaviors contribute to this effect, as highlighted by [47]and more recently by [48] who found that tourism expansion correlates with increased CO_2 emissions in both developed and developing nations. In contrast, the insignificance of GGE excl LUCF may reflect the growing decoupling between broader greenhouse gas trends and direct CO_2 emissions. This may be attributed to successful policy initiatives such as the EPA's Clean Power Plan [49] which aimed to reduce carbon intensity in the energy sector, and the broader critique of carbon pricing mechanisms. Furthermore, the increasing shift toward renewable energy sources, as emphasized by [50], and more recently forecasted by Keerthana et al. [51], may be mitigating the impact of other GHGs on overall CO_2 trends.

Table 9: Long-Term ARDL Model Estimation for **CHINA**

Source: Authors' computations using Eviews 12 software..

Variable	Coefficient	Std.Error	t-Statistic	Prob.
GDP PC	0.010783	0.007929	64.465190	0.1898
GGE excl LUCF	0.883251	0.013701	0.766764	0.0000
ITN	1.866941	7.276663	2.565656	0.0189
POP	-1.368214	5.373212	2.457191	0.0197
C	553.3882	616.9418	0.896986	0.3810

CE = CO2 excl LUCF - (0.010783 * GDP PC + 0.883251* GGE excl LUCF 1.866941* ITN - 1.368214* POP +553.3882)

In the long term, greenhouse gas emissions excluding land use, land-use change, and forestry (GGE excl. LUCF), international tourism (ITN), and population (POP) are found to have a significant impact on CO_2 emissions in China,- Table 9- while GDP per capita exerts an insignificant yet positive impact. First, GGE excl. LUCF significantly contributes to increasing CO_2 emissions. This result aligns with findings [27] [28] [34], who emphasized that industrial emissions, particularly from fully fluorinated greenhouse gases, remain key contributors to China's carbon footprint despite ongoing mitigation efforts. Likewise, the analysis by [52] report underscores the pivotal role of industrial processes and fossil fuel combustion in shaping emission trends, even excluding the LUCF component. Additionally, [53] offer accurate estimates of China's fossil fuel and cement-related emissions, reinforcing the robustness of this variable's long-term influence. Tourism, as measured by international tourist arrivals, shows a statistically significant positive impact on CO_2 emissions. This finding is consistent with the results of Le and Nguyen (2021), who analyzed data from 95 countries and concluded that increased tourism activity intensifies environmental pressure, particularly through transportation and infrastructure development. On the contrary, population demonstrates a significant but negative long-term effect on CO_2 emissions in China, a result that may be linked to urban demographic shifts and improvements in emission efficiency per capita. Zhu and Peng (2012) highlight that between 1978 and 2008, demographic changes in China contributed to decreasing emission intensity due to urbanization and lifestyle transformation. Regarding GDP per capita, the analysis reveals an insignificant positive impact on CO_2 emissions. This aligns with Caporale, Gil-Alana, and Plastun (2021), who found a nonlinear relationship between GDP and CO_2 emissions in China, supporting the Environmental Kuznets Curve hypothesis. Similarly, Hao, Huang, and Wu (2019) demonstrate that economic growth in China has increasingly decoupled from carbon emissions, especially due to the country's shift toward less carbon-intensive sectors.

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C. *Diagnostic Tests for Model Robustness*

To ensure the robustness and validity of the estimated model, a series of diagnostic tests were conducted to examine the statistical properties of the residuals. These tests evaluate key assumptions including heteroskedasticity, autocorrelation, normality, and model specification.

- **Inconsistency Test for Error Variance (ARCH Test):** This test examines the presence of autoregressive conditional heteroskedasticity (ARCH) in the residuals. The correlograms of the squared residuals were analyzed to assess ARCH. If no ARCH is detected, the autocorrelations and partial autocorrelations should be zero at all lags, and the Q-statistics should not be significant.
- **Autocorrelation Test Between Errors (Serial Correlation LM Test):** We investigated serial correlation in the residuals. The Durbin-Watson test is commonly used to detect AR(1) serial correlation, where autocorrelation might occur.
- **Normal Distribution Test for Random Errors:** We assessed the normality of the error terms. The outcomes of these tests are summarized in
- **The Ramsey RESET test**: is used to evaluate whether the functional form of the regression model is appropriate. It tests for potential misspecification by examining whether adding higher-order terms, such as squared fitted values, improves the model's fit. A failure to reject the null hypothesis suggests the model is correctly specified.

Table 10: ARCH Test and Serial Correlation LM Test Results for USA

Heteroskedasticity Test: ARCH			
F-statistic	0.206229	Prob. F(1,26)	0.6535
Obs*R-squared	0.220345	Prob. Chi- Square(1)	0.6388
Breusch-Godfrey Serial Correlation LM Test:			
Null hypothesis: No serial correlation at up to 2 lags			
F-statistic	1.048047	Prob. F(2,17)	0.3722
Obs*R-squared	3.183203	Prob. Chi- Square(2)	0.2036

Source: Authors' computations using Eviews 12 software.

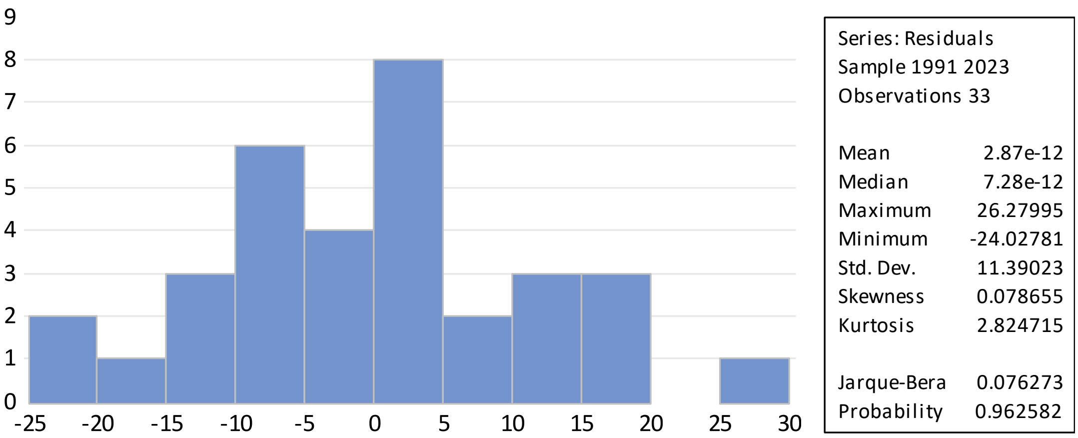

Figure 5: Normal Distribution Test for Random Errors

Source: Authors' computations using Eviews 12 software..

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Table 11: Ramsey RESET Test for USA

Unrestricted Test Equation:
Dependent Variable: CO2_EXCL_LUCF
Method: Least Squares
Date: 04/17/25 Time: 03:41
Sample: 1991 2023
Included observations: 33

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2_EXCL_LUCF(-1)	1.144249	0.269934	4.238988	0.0003
GDP_PC	1.576144	0.319778	4.928875	0.0000
GDP_PC(-1)	-1.205831	0.282039	-4.275406	0.0003
ITN	-1.22E-05	3.64E-06	-3.361598	0.0026
POP	0.091096	0.027226	3.345899	0.0027
GGE_EXCL_LUCF	6.18E-09	7.63E-08	0.080893	0.9362
D_TECH	-22.98029	16.45705	-1.396379	0.1754
C	-64477.05	19616.55	-3.286870	0.0031
FITTED^2	-3.53E-05	2.27E-05	-1.556485	0.1327

R-squared	0.999340	Mean dependent var	6571.740
Adjusted R-squared	0.999120	S.D. dependent var	422.5660
S.E. of regression	12.53486	Akaike info criterion	8.121905
Sum squared resid	3770.944	Schwarz criterion	8.530043
Log likelihood	-125.0114	Hannan-Quinn criter.	8.259231
F-statistic	4542.801	Durbin-Watson stat	2.012588
Prob(F-statistic)	0.000000		

Source: Authors' computations using Eviews 12 software..

•**Table 12:** ARCH Test and Serial Correlation LM Test Results for CHINA

Heteroskedasticity Test: ARCH			
F-statistic	0.255218	Prob. F (1,30)	0.6171
Obs*R-squared	0.269937	Prob. Chi-Square (1)	0.6034
Breusch-Godfrey Serial Correlation LM Test:			
Null hypothesis: No serial correlation at up to 2 lags			
F-statistic	0.726064	Prob. F (2,23)	0.4946
Obs*R-squared	1.959757	Prob. Chi-Square (1)	0.3754

•**Source:** Authors' computations using Eviews 12 software.

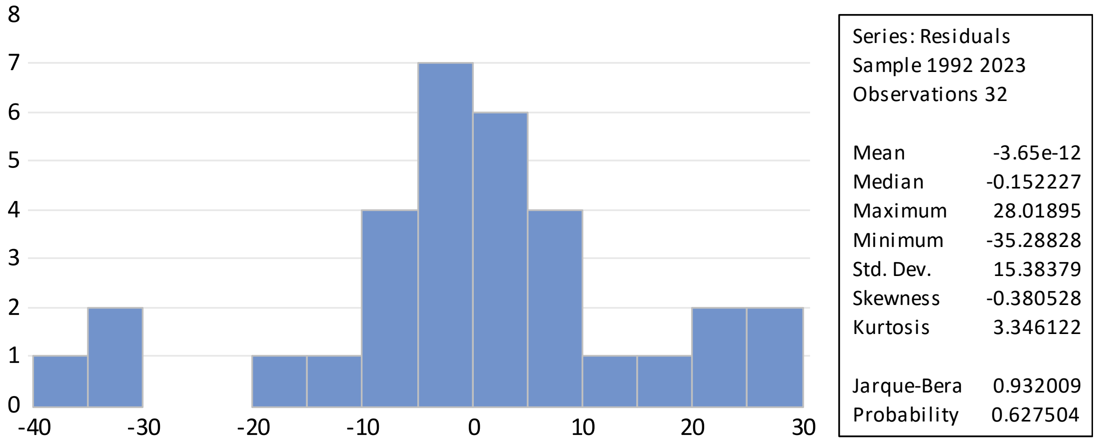

Figure 6: Normal Distribution Test for Random Errors

Source: Authors' computations using Eviews 12 software..

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Table 12: Ramsey RESET Test for CHINA

Date: 04/12/25 Time: 04:04
Sample: 1992 2023
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2_EXCL_LUCF(-1)	0.568350	0.136402	4.166730	0.0005
CO2_EXCL_LUCF(-2)	-0.283695	0.175067	-1.620496	0.1208
GGE_EXCL_LUCF	0.881445	0.022681	38.86355	0.0000
GGE_EXCL_LUCF(-1)	-0.558050	0.124644	-4.477158	0.0002
GGE_EXCL_LUCF(-2)	0.307944	0.152130	2.024221	0.0565
ITN	2.96E-07	1.92E-07	1.538938	0.1395
ITN(-1)	2.10E-07	1.92E-07	1.095031	0.2865
ITN(-2)	7.45E-07	2.17E-07	3.432413	0.0026
POP	-6.46E-07	2.28E-07	-2.831368	0.0103
D_TECH	6.405990	11.58178	0.553109	0.5863
C	31.60981	304.6840	0.103746	0.9184
FITTED^2	1.22E-06	1.12E-06	1.087694	0.2897

R-squared	0.999980	Mean dependent var	7568.684
Adjusted R-squared	0.999968	S.D. dependent var	3656.890
S.E. of regression	20.58867	Akaike info criterion	9.167355
Sum squared resid	8477.865	Schwarz criterion	9.717006
Log likelihood	-134.6777	Hannan-Quinn criter.	9.349549
F-statistic	88905.24	Durbin-Watson stat	2.492996
Prob(F-statistic)	0.000000		

Source: Authors' computations using Eviews 12 software..

❖ The diagnostic tests conducted for both China and the USA suggest that the regression models satisfy key assumptions, indicating reliable and robust estimations, specifically:

ARCH Test for Heteroscedasticity: In China, the ARCH test yielded an F-statistic of 0.26 with a p-value of 0.62, while in the USA, the F-statistic was 0.22 with a p-value of 0.64. Both p-values exceed the 5% significance level, leading to the acceptance of the null hypothesis of homoscedasticity. This implies that the variance of the error terms remains constant over time, indicating the absence of heteroscedasticity in both models.
Breusch-Godfrey Serial Correlation LM Test: For China, the Breusch-Godfrey test produced an F-statistic of 0.73 with a p-value of 0.49, and for the USA, an F-statistic of 1.04 with a p-value of 0.37. Since these p-values are greater than 0.05, we fail to reject the null hypothesis of no serial correlation. This suggests that the residuals are not autocorrelated, supporting the assumption of independence in the error terms. Normality Assessment via Jarque-Bera Test: The Jarque-Bera test for normality yielded a p-value of 0.6275 for China and 0.9626 for the USA. Both values surpass the 5% threshold, indicating that the residuals are normally distributed in each case. This satisfies the normality assumption necessary for valid inference in regression-analysis.-Table-10and-Table-12-
Normality-Assessment
Based on the Jarque-Bera statistic, the probability value is 0.96 for the USA and 0.62 for China, both exceeding the 5% significance level. Therefore, we fail to reject the null hypothesis, indicating that the residuals are normally distributed in both cases. Figure 5and 6
The Ramsey RESET test : In the case of the USA, the test statistic for $FITTED^2$ was 0.1327, and for China, it was 0.2897. Both p-values exceed the 0.05 significance level, indicating that we fail to reject the null hypothesis. This implies that the models' current functional forms are sufficient, and there is no need for additional higher-order terms. -Table 11 and Table 12-

V. CONCLUSION

To assess the extent to which CO_2 emission reduction policies in the United States and China are effective in the long term, we applied an econometric analysis that focused on the key variables influencing CO_2 emissions. This analysis considered the interactions between GDP per capita, population growth, international tourism, and greenhouse gas emissions (GGE), excluding land-use, land-use change, and forestry (LUCF). By

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utilizing Error Correction Models (ECM), we investigated the short-run and long-run dynamics that shape the countries' CO_2 emissions pathways.

In the long term, the analysis revealed that both countries face distinct challenges in balancing economic growth and emission reduction. The United States demonstrated a clear reliance on GDP per capita as the dominant factor driving CO_2 emissions. However, the insignificance of GGE excluding LUCF in the long run suggests that technological advances and policy shifts aimed at reducing greenhouse gas emissions could potentially decouple economic growth from CO_2 emissions. This suggests that while the USA's emission reduction policies have had some effect, the overall sustainability of these policies remains contingent on continuous advancements in clean energy technologies and strict environmental regulations. Thus, the policies show some effectiveness but require more substantial integration of green technologies to ensure long-term sustainability.

On the other hand, China's CO_2 emissions are more closely linked to industrial output, population growth, and international tourism. This reflects the country's ongoing industrialization and urbanization. The short-term dynamics suggest that while China has made strides in adjusting emissions to policy changes, significant emissions reduction has not yet been achieved. The high responsiveness of emissions in China to population growth and international tourism points to the heavy reliance on industrial growth as a key contributor to CO_2 emissions. Nevertheless, China's higher rate of adjustment to long-term equilibrium suggests that the country is more adaptable to policy changes, particularly in terms of emission reductions. The implication here is that while China's emission reduction policies are potentially more effective in the short run, the long-term sustainability of these policies will require structural shifts toward cleaner energy, efficient industries, and environmental regulation.

The effectiveness of both countries' emission reduction policies is, therefore, mixed. In the United States, the challenge lies in reconciling economic growth with sustained reductions in CO_2 emissions, while China's policy impact is still hampered by its heavy dependence on industrialization and tourism. Econometric results suggest that while these policies have had some impact on CO_2 emissions, the long-term sustainability of these policies is uncertain without deeper structural changes. For both countries, further advancements in technology and stricter environmental policies are required to meet long-term climate goals effectively.

Therefore, the extent to which CO_2 emission reduction policies in the United States and China are effective in the long term, as assessed through this econometric analysis, shows that while progress is being made, the sustainability of these policies remains contingent upon further technological innovations, shifts in industrial practices, and stricter implementation of climate regulations. In conclusion, both countries have made initial strides toward reducing CO_2 emissions, but the impact and sustainability of these policies will ultimately depend on their ability to integrate more comprehensive green technologies and regulations into their economic frameworks.

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