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Comparative Analysis of the Relationship between Renewable Energy Adoption, Fossil Fuel Energy Consumption, and CO_2 Emission in the United States and China

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Abstract

This study addresses the critical issue of carbon dioxide (CO_2) emissions, focusing on understanding the intricate interplay between four major variables Gross Domestic Product per capita (GDPC), Renewal Energy (RE), Fossil Fuel energy consumption (FF), and Patent application (PTS). This research is crucial due to the emerging negative impacts of climate change, which will create a disastrous future for human beings. It focuses on three decades from 1990 to 2020 and compares the results between the United States and China. Underlying long-run relationships and unit root characteristics of the variables are analyzed with the help of unit root tests, cointegration analysis, descriptive statistics, and an autoregressive distributed lag (ARDL) model. The analysis shows that the examined variables are strongly related and significantly impact CO_2 emission. For example, GDPC and PTS have a positive relationship with CO_2 emissions, Whereas wider use of RE has a negative effect on emissions. The findings, therefore, emphasize the need for country-specific emission reduction policies because of the differences between the Chinese and the American systems. In conclusion, this study detects that the interaction between economic growth and technology and energy utilization are major influential factors that need to be incorporated in developing efficient policies to minimize the emission of CO_2. It is helpful for policymakers and those interested in environmental conservation as it stresses that combating climate change requires differentiated approaches in distinct countries. This research moves beyond extant literature by adopting a novel comparative methodology to analyze the shifts in the process of CO_2 emission in two of the world's largest economies. Hence, it captures the interaction of GDPC, RE adoption, FF consumption, and PTS on CO_2 emissions, which is crucial for formulating environmental policies and future emission control strategies.

Keywords
CO_2 emission; GDP per capita; energy adoption; technological innovation

1. Introduction

Global integration has risen substantially, and therefore, the nexus between technology, development, energy, and environmental impacts has emerged as a matter of debate and discussion on both policy and research fronts [1]. However, the study to be conducted in this paper shall compare the United States of America and China, two of the world's most significant economies. With the conditions that the world has witnessed drastic changes due to economic liberalization, new inventions in the field of technology, and increasing consciousness towards the environment, it becomes essential to study how these factors are interconnected and affect sustainable development [2, 3].

Hence, this research aims to investigate and compare the main determinants of sustainable development in China and the United States. Thereby, this study intends to examine the relationship between the five macro variables, including GDP per capita, renewable energy (RE), fossil fuel (FF) consumption, and patents (PTS), as well as CO_2 emissions in these top economies of the world. The rationale for this study derives from the fact that China and, especially, the United States, as two leading influential economies, determine the trends in SD future evolution [4, 5].

It is crucial to comprehend the importance of each variable in the doubt. By definition, GDPC gives information on the economic health of a nation's people [6]. RE and consumption of FF bear witness to a nation's practices on sustainable energy. PTS can be seen as a proxy for innovation and the level of technology, and the indicators of environmental developments are given by CO_2 emissions [7]. Thus, the four variables comprise an accurate framework for measuring the general advancement of such countries as China and the United States in the SD context. This research seeks to answer several core questions: What are the trends of GDPC, CO_2 emissions, PTS, adoption of RE, and FF consumption in the US and China from 1990-2020? In the context of the generally defined sustainable development, what links can be identified between these factors? It is essential to know how this comparative study can help provide ways to navigate global strategies, innovations, and policies for sustainable development.

Thus, to compare trends, differences, and/or challenges and opportunities seen on the international level, this study seeks to contribute towards enhancing the understanding of the international community's pursuit of sustainable development. Thus, in contrast to the previous works focusing on specific aspects of economic growth, energy consumption, and ecological characteristics [8-11], this paper improves the methodological approach to the comparative analysis of several factors over a long period. Therefore, this research will strive to support literature studies by presenting a comprehensive and comparative evaluation of the linkage between CO_2 emission, RE, GDPC, and PTS. This study's significance revolves around giving policymakers in China, the United States of America, and any other country with similar issues clues on the way forward. The progress of these countries within the world economy may serve as an example of the transition from the approach where the economy and, thus, the population's well-being are the main priorities. At the same time, the environment is considered a subordinate factor in an innovative economy that thoroughly takes into consideration the efforts needed for environmental protection. This research aims to identify the efficiency of the strategies undertaken and reveal the prospects for further development. Furthermore, the study establishes this analysis to discuss the relationship between GDP economic growth, environmental management, and technological advancement [12, 13]. The strategies of the United States and China in the sphere of sustainable development present examples of effective cooperation in responding to global issues.

The introduction sets the stage for the study, which will continue with a literature review summarizing key concepts related to the topic. Following the literature review, the methods section will detail the statistical tests and econometric modeling used to explore the relationships between the variables. The findings section will outline the patterns and trends observed systematically and then explain them further in the discussion section in light of current global sustainable development. Lastly, the discussion section will bring together the key results, underscore the research's contribution, and advise on the potential for future research. By adopting this structured approach, this study aims to provide a comprehensive understanding of the intricate relationships influencing the sustainable development paths of China and the United States.

2. Literature Review

After the world economy began to change and environmental concerns grew, researchers began focusing on the complex relationships between economic indicators, energy consumption patterns, technological innovation, and ecological impacts. Concerning the links between GDPC, RE, FF, PTS, and CO_2, this literature review attempts to summarize the research that has already been done. Through a comparative analysis, we hope to understand better the intricate dynamics impacting CO_2 emissions. We focus on the two largest global economies, China and the United States, with different regulatory contexts.

2.1 Sustainable Development and Technological Innovation

Researchers have focused on the complex interaction between technological innovation and sustainable development. [14] claims that technical innovation gives countries the tools to increase productivity and competitiveness, catalyzing economic growth. Fostering innovation, according to [15], is crucial for solving environmental issues and preserving economic momentum. But [16] stresses that innovation must align with ecological ideals. The author advocates a complete paradigm that merges innovation and sustainability and argues that unbridled technological advancement can have unexpected environmental implications [17].

Furthermore, according to [18], "sustainable innovation" has become more well-known recently. Seen from this perspective, innovation is, therefore, considered to play an important role in social and environmental health, along with economic development. Change is called for a new way of thinking where inventiveness is directed toward solutions that increase the stability of ecosystems.

Such a point of view is reiterated and emphasizes how instrumental sustainable practices are when implementing innovation [19, 20]. Thus, based on [21, 22]. This paper posits that technology innovation should coincide with environmental goals by incorporating sustainability as one of the chief goals in technology development and deployment.

Sustainable development, therefore, seeks to balance the profit, growth, and demand of the present to not impede future generations from getting theirs. It focuses on the rational use of the earth's resources when it concerns economic development. Therefore, competent operations in the landscape, where modeling and geo-visualization of GTCs are focused, are crucial to sustainable development [23]. These tools enable great potential for change conditions to be recognized and evaluate probable orders of environmental influence, which in turn assist regional organizers and decision-makers in strategies to preserve susceptible ecosystems and minimize the ecological effects [24-27].

There is a close relationship between technology advancement and the management of environmental issues related to economic development. Indeed, incorporating RS data and applying machine learning, namely the Random Forest classifier, has enhanced the determination of accurate LULC outcomes [28]. These advancements enable the quantitative analysis of landscape dynamics, providing valuable insights into spatial patterns and changes over time. Such information is crucial for developing sustainable policies and interventions to manage natural resources. Integrating technological innovations, such as smart metering, with non-technological innovations, such as active demand response participation, can help reduce CO_2 emissions by improving energy efficiency and promoting sustainable consumption patterns [29].

Sustainable development seeks to balance economic growth with environmental protection and social well-being. Technological innovation is critical in this context, driving the transformation processes necessary for sustainable development. However, the COVID-19 pandemic has shown that technological advancements alone are insufficient; they must be accompanied by policies that promote social well-being and support Sustainable Development Goals (SDGs) [30-33]. The emerging policy rationale of "transformative research and innovation policy" emphasizes the need for research and innovation (R&I) to address grand challenges and foster socio-technical system transformations [30, 34-36].

In conclusion, a balanced and sustainable approach to technological advancement is advocated, while others see innovation as a catalyst for economic growth [37-39]. The literature on technological innovation and sustainable development reflects this diversity of viewpoints. As a prelude to the thorough comparative research carried out in this study, this literature provides a fundamental framework for comprehending the relationships between innovation, economic progress, and environmental sustainability.

2.2 The Impact of Economic Growth on the Environment

There has been a lot of discussion among academics about the complex relationship between GDPC, which measures economic growth, and the environment. According to [40], there could be negative repercussions on ecosystems and natural resources if GDP development is pursued narrowly without considering the environment. Promoting environmental sustainability and economic prosperity calls for a paradigm shift in economic growth and urges politicians to adopt these techniques.

However, [41] has a more optimistic view that some forms of economic growth can coexist with ecological sustainability. The research illustrates green technologies and behaviors whose innovation supports economic prosperity and environmental preservation. This intricate position emphasizes the fact of choosing sustainable paths for economic development. Further [42, 43] dwells on "green growth," arguing that business expansion does not always conflict with environmental conservation. To separate economic advancement from natural resource exhaustion and environmental degradation, the report suggests pro-efficient policies that are innovation-oriented, resource-based, and use renewable sources.

Increased industrialization, urbanization, energy consumption and population increase due to economic growth often overstretch natural resources, thus leading to environmental deterioration [44]. Other studies have shown that uncontrolled economic activities cause rapid land use changes, resulting in loss of forest cover, water bodies, and agricultural lands. This upsets the equilibrium in ecosystems but also increases land surface temperatures, resulting in climate change [45]. The relation between economic growth and environmental degradation illustrates why sustainable development practices need to be implemented to strike a balance between economic progress and environmental preservation. The use of energy, changes in land use, and consumption patterns by humans have been major drivers of greenhouse gas emissions, which have approximately doubled over the last six decades [46]. Consequently, this has led to ecological imbalances and climate destabilization with more severe threats to the global public's well-being [47, 48]. It would appear evident that we are running out of time for global emission reduction, but anthropogenic emissions are still rising, thereby igniting the call for more effective environmental policies and sustainable practices [49].

All research suggests that any effort toward achieving economic growth must consider social and environmental externalities and incorporate sustainable practices within its central framework. This understanding forms the basis for evaluating China's and America's economic progress regarding their respective environmental impacts.

2.3 Adoption of Renewable Energy and Use of Fossil Fuels

Achieving sustainable development requires both the use of RE sources and a simultaneous decrease in the use of FF. To lessen the adverse effects of energy production on the environment, [3, 50] emphasizes the significance of switching to RE sources. The report cites prosperous cases of countries aggressively adopting RE sources and drastically decreasing their carbon footprint.

However, [51, 52], based on this literature and arguments, directs a note of caution as to the challenges and trade-offs associated with the rapid shift towards RE. As the research shows, it is necessary to shift from FF, but the social and economic consequences that this process impacts must be considered. The author fosters planning by considering the big picture of the socio-economic context.

In addition, [53] discusses different aspects of the RE policy, arguing that technological advancement, appropriate and friendly policies, and social relevance of the methods must be addressed for adoption strategies to work. Therefore, the study provides an understanding of the factors that shape national energy architecture and contributes to understanding the factors influencing the effectiveness of RE programs.

The shift from FFs to RE sources is vital insofar as the negative environmental influence of economic activities. Carbon dioxide emissions result from using fossil fuels, and ecological changes from this product catalyze climate change. This means the increased use of RE sources like solar, wind, and hydroelectric power helps reduce these emissions and encourages sustainable development. Studies show that the expansion of the proportion of RE in the energy portfolio causes a decrease in the emission of greenhouse gases and the pollution of the environment [44].

This is evident since the energy sector is always in demand due to the unceasing human need for energy, and this puts pressure on the emission of CO_2. Thus, managing such emissions calls for systemic transitions of the existing socio-technical systems and the need for coherent and comprehensive energy policies to address both the technological and social aspects. To enhance the speed of the planned decarbonization of the energy systems, innovation policies that encourage the development of energy-related technologies, require an educated workforce, and engage public/private sector funding will be necessary [47, 54, 55]. Integrating RE sources like the sun, wind energy, and electricity for new energy sources is crucial to decrease the use of FFs and solve climate change problems [56].

The literature review on the adoption of RE and the usage of FF highlights the significance of having a thorough grasp of the potential and problems related to switching to sustainable energy sources. This prepares the ground for comparing the US and China's energy dynamics and policy strategies.

2.4 Carbon Dioxide Emissions as an Environmental Indicator

This relationship is a much-researched area in environmental economics because of the interaction between economic activities or energy consumption and CO_2 emissions. In light of the previous scholarly post, the following literature can be quoted: [57, 58] CO_2 emissions are often regarded as a function of growth and industrialization. The paper focuses on the relationship between, on the one hand, the increasing demand for energy, to an extent met by FFs, and, on the other hand, the rise in carbon dioxide content in the atmosphere. This accords prominence to understanding the relationship between economic growth patterns and their environmental effects.

Traditionally, CO_2 emissions measure environmental pressure and are connected with economic activity and energy usage. They include industries, transport, and the utilization of FFs, and the levels of CO_2 emissions are high. Through the reduction of CO_2 emissions, the effects of climate change and the attainment of sustainable development goals and objectives are enabled. Landscape conversion by humans, as represented by deforestation and urbanization, is also known to have implications for the extent of C-sinks and, subsequently, higher levels of CO_2 in the atmosphere [59]. Subsequently, the land use dynamics must be well understood and properly managed to regulate the discharge of CO_2 and soothe the environment.

However, [3, 60] perceive the chances of decoupling the growth of carbon emissions from economic development, as Historically has been seen, and they believe that that is required for future sustainability. The paper is centered on the potentiality of breaking the provision of continuous pollution in pursuit of growth through an analysis of the select countries that have scaled down their CO_2 emissions and, at the same time, strode forward on the economic growth front.

Some other studies related to the topic also deserve attention as they discuss the function of legislative endeavors in regulating CO_2 emissions [61, 62]. Their study emphasizes how important international agreements, emissions reduction goals, and regulatory frameworks are in determining the course of sustainable development. The research highlights that although economic expansion might be a factor in CO_2 emissions, deliberate policy choices can change the course of events and lead to a scenario in which environmental protection and economic growth coexist.

As addressed by [11, 63-65], the literature on CO_2 emissions as an environmental indicator highlights the complex relationship between energy use, economic growth, and ecological effects. Comprehending this correlation is crucial for assessing the sustainability paths of countries, such as the United States and China, concerning their CO_2 emissions within the time frame examined in this research.

Examining the entire body of research on sustainable development, it is clear that although individual studies offer insightful information, there is an apparent deficiency in the thorough comparative evaluation of several variables over a prolonged period. Previous research has focused on analyzing specific aspects of GDPC, adopting RE, and consuming FF, PTS, and CO_2 emissions. Still, no effort has been made to determine the interrelation between these variables. For instance, [66, 67] has done a commendable previous study that enunciates the relationship between RE and environmental sustainability in detail with details about the strategies adopted by a few counties in depth. However, this means that no composite perspective encompasses multiple factors in the study and hinders one from understanding the whole picture of sustainable development. Similarly, [68] examines linkages between environmental depletion and growth, including potential tensions and challenges. However, the study exclusively focuses on a single aspect and thus cannot provide comparative values that would disclose more complex patterns or differences between countries.

Therefore, the specificity of the current work is defined by its response to the apparent need of the existing literature. To fill the existing gaps, this paper analyzes the coincidence of GDPC using RE, FF, PTS, and CO_2 emissions in the US and China through a comparative analysis. Apart from the limitations of prior singular-focus research, the study will strive to effectuate this complete vision that is supposed to offer a complex comprehension of the processes underlining the availability of sustainable development paths.

Therefore, the justification of the current study can be derived from the perspective that both China and the US are among the largest economies in the world today. Such countries always play a critical role in defining the directions of further development and trends in the world because most are members of the global economy. To analyze international policies and programs, it is necessary to know the policy-making, the history of the formation of specific policy, and the distinguishing features of the policy between the development and conservation of the environment. Therefore, the current study fills this crucial gap by offering a thorough analysis that captures the various facets of sustainable development in two significant global economies.

3. Methodology and Data

3.1 Data Sources and Variables

Data retrieval was conducted systematically from the World Bank Data repository. Which is a reliable and extensive source of economic and demographic statistics. Data was retrieved for the chosen nations (USA and China) from 1990 to 2020. The World Bank offers an extensive collection of information and metrics that are pertinent to this research, such as CO_2 emissions, GDPC (gross domestic product per capita), RE (renewable energy consumption), FF (fossil fuel consumption), and PTS (patent application).

This study employed a logarithmic model to examine CO_2 emissions, GDP per Capita, and PTS. Using logarithmic form helps simplify the complexity of the resulting estimate after applying the natural logarithm to the variables. Equation 1 represents the regression form.

$$CO_2 = f(GDPC, RE, FF, PTS) \qquad \text{(Equation 1)}$$

Table 1 displays the variables, their respective units, and the sources from which they were obtained. This study aims to compare the correlation between GDPC, RE, FF, PTS, and CO_2 emissions in the United States and China. The analysis will be based on annual time series data from 1990 to 2020. The dependent variable is the level of CO_2 emissions, whereas the independent variables include GDPC, RE, FF, and PTS.

Table 1 Data sources.

Symbol	Variables	Description	Source	URL
CE	CO_2 emissions	metric tons per capita	World Development Indicators	World Development Indicators - CO_2 emissions https://data.worldbank.org/indicator/EN.ATM.CO2E.PC
RNEC	Renewable energy consumption	% of total final energy consumption	World Development Indicators	World Development Indicators - Renewable energy consumption https://data.worldbank.org/indicator/EG.FEC.RNEW.ZS
FF	Fossil fuel energy consumption	(% of total)	World Development Indicators	World Development Indicators - Fossil fuel energy consumption https://data.worldbank.org/indicator/EG.USE.COMM.FO.ZS
GDPC	GDP per capital	(Current US$)	World Development Indicators	World Development Indicators - GDP per capita https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
PTS	Patent Application,	Total patent, Residents	World Intellectual Property Organization (WIPO)	World Development Indicators - Patent applications https://data.worldbank.org/indicator/IP.PAT.RESD

3.2 Methodology

The goal of this paper is to examine the complex relationship between different variables, such as GDP per capital, renewable energy, fossil fuel energy, patent application, and CO_2 emission in the United States of America and the People’s Republic of China This research will seek to use a rather wide range of statistical methods. These include a range of econometric models that can be categorized by what analytical requirement they have been designed to meet. In the wealth of the possible models for adoption in this task, the one suitable for this investigation is the Autoregressive Distributed Lag (ARDL) model.

3.2.1 ARDL Model

The ARDL model was developed by Pesaran, Shin, and Smith in 1997 and extended in 1999 and in 2001. The prominent uniqueness of the ARDL model is its ability to estimate models and the variables used in them, ordered by the first and zero degrees of integration. Further, it has the flexibility needed to deal with the datasets indicated by restricted samples, an aspect explained further by Pesaran, Shin, and Smith (1999).

3.2.2 Unit Root

However, it must be emphasized that using the ARDL model only depends on the integration order of the examined variables. Thus, this study begins with a comprehensive unit root test to ensure that the employed model is correctly specified for the analysis and to check the exact integration order of each of the variables incorporated into the model. To validate the presence or absence of a unit root, this study administers two prominent tests: two of the most commonly used statistical tests for assessing the first difference in a time series data: the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. These much-used tests developed by Dickey & Fuller (1979) and Phillips & Perron (1988) provide relevant information on the stationarity characteristics in the variables.

3.2.3 ARDL Bound Test

Afterward, the analysis proceeds to use the ARDL bounds test model, a technique suggested by Pesaran, Shin, and Smith (2001). This test is used as a long-run cointegration pars test of potential existence among the tested variables. However, a long-term relationship can be tested through the F-statistic and t-statistic by comparing these variables to predetermined lower and upper bounds. Identifying any such relation calls for using the Error Correction Model (ECM) to investigate such a relation further. Suppose the variables are not co-integrated and long-run relationships are not established. In that case, the study flawlessly employs the short-run co-integrated ARDL model coupled with the ARDL bounds test model. Equation 2 unveils the paradigm of the tangled statistical structure embodied in the ARDL model.

3.2.4 Statistical Representation

The statistical framework of the ARDL model is represented as follows:

$$\begin{aligned}\Delta lnCO_{2_t} = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta lnCO_{2_{t-i}} \\ + \sum_{i=1}^{q} \beta_{2i} \Delta lnGDPC_{t-i} + \sum_{i=1}^{q} \beta_{3i} \Delta RE_{t-i} + \sum_{i=1}^{q} \beta_{4i} \Delta FF_{t-i} + \sum_{i=1}^{q} \beta_{5i} \Delta\, ln\, PTS_{t-i} \\ + \beta_{6i} lnCO_{2_{t-1}} + \beta_{7i} lnGDPC_{t-1} + \beta_{8i} RE_{t-1} + \beta_{9i} FF_{t-1} \\ + \beta_{10i} lnPTS_{t-1} + \varepsilon_t \qquad \text{(Equation 2)}\end{aligned}$$

The long-term dynamics of the variables are shown in Equation (2). Furthermore, the demonstration of the short-run error correction is shown in the equation below:

$$\begin{aligned}\Delta lnCO_{2_t} = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta lnCO_{2_{t-i}} \\ + \sum_{i=1}^{q} \beta_{2i} \Delta lnGDPC_{t-i} + \sum_{i=1}^{q} \beta_{3i} \Delta RE_{t-i} + \sum_{i=1}^{q} \beta_{4i} \Delta FF_{t-i} + \sum_{i=1}^{q} \beta_{5i} \Delta\, ln\, PTS_{t-i} \\ + \beta_{6i} lnCO_{2_{t-1}} + \beta_{7i} lnGDPC_{t-1} + \beta_{8i} RE_{t-1} + \beta_{9i} FF_{t-1} + \beta_{10i} lnPTS_{t-1} \\ + \beta_{11i} ECT_{t-1} + \varepsilon_t \qquad \text{(Equation 3)}\end{aligned}$$

Where:

t = Represents the time from 1990 to 2020.

ε = Represents the Error term, and

β_0 is the consant term.

β_1 to $\beta_5$are short-term parameters.

β_6 to β_{10} are long-term parameters.

β_{11} are the error correction term (ECT) parameters.

ln is the log of a variable.

Δ shows that a variable has been differenced.

In the first instance, we offer an account of the descriptive statistics of the variables of interest. Next, the ADF and PP tests establish the integration orders for these variables. The applied method is the ARDL Bound Test, which establishes a potentially permanent connection between our variables, and the results are significant for ARDL. This step enables the expansion of long-term relationships within the obtained dataset.

3.2.5 Diagnostic and Stability Tests

Also, the key to our method is a series of diagnostic and stability tests that help build the face validity of our model and enhance its credibility. These diagnostic tests are the Breusch–Godfrey LM test for serial correlation, the Jarque-Bera Statistic normality test, the Breusch–Pagan–Godfrey test for heteroskedasticity, the test for linearity known as the Ramsey Reset test and the CUSUM stability test. These evaluations establish the model's robustness and ability to regulate and monitor its operations under different circumstances. Thus, this multifaceted research method not only increases the credibility of the analysis but also provides a methodological base for the empirical study, guaranteeing that our results are credible and reliable.

4. Empirical Results

In this study, Table 2 analyses and presents the descriptive statistics of several critical variables, namely GDP. For this aim, Table 2 applies and reports the descriptive statistics of several core factors, which include GDP per capita, the incidence of renewable energy, fossil fuel energy use, patent application, and CO_2 emission. Our data cover both the US and China and the years 1990 to 2020.

Table 2 Descriptive statistics results.

VARIABLES	CE	FF	GDPC	RE	PTS
CHINA					
Mean	6185670	84.34176	3612.395	21.17645	363609.5
Median	5824625	85.87274	1753.414	17.44000	93485.00
Maximum	10944686	94.06131	10408.72	33.91000	1393815
Minimum	2173364	74.83197	317.8847	11.34000	5832.000
Std. Dev.	3191762	5.975574	3484.519	8.550465	482147.5
Skewness	0.184775	-0.044668	0.738382	0.193545	1.117651
Kurtosis	1.382961	1.679626	2.004904	1.267064	2.653988
Sum	1.92E+08	2614.595	111984.2	656.4700	11271893
Sum Sq. Dev.	3.06E+14	1071.225	3.64E+08	2193.313	6.97E+12
Observations	31	31	31	31	31
UNITED STATES					
Mean	5246397	84.92310	43131.01	199793.1	6.693548
Median	5156425	85.57482	44123.41	207867.0	5.840000
Maximum	5775807	86.45649	65120.39	295327.0	11.16000
Minimum	4320533	82.42783	23888.60	87955.00	4.090000
Std. Dev.	383498.4	1.322922	12689.83	72425.91	2.220660
Skewness	-0.189882	-0.465482	0.074683	-0.180317	0.522892
Kurtosis	2.174742	1.594691	1.818129	1.604399	1.829836
Sum	1.63E+08	2632.616	1337061	6193587	207.5000
Sum Sq. Dev.	4.41E+12	52.50370	4.83E+09	1.57E+11	147.9399
Observations	31	31	31	31	31

Regarding these variables, other relevant essential statistics were ascertained, encompassing the mean, median, standard deviation, and range of values. These measures were computed separately for each country (the United States and China) and the entire dataset.

Unit root tests were used to evaluate the stationarity characteristics of the major variables, such as the LCE, FF, LGDPC, RE, and LPTS. The ADF and PP tests were performed to determine whether a unit root, which indicates non-stationarity, is present. Table 3 reports the results of the unit root tests applied in China and the United States. This gives statistics of the t-statistic and their associated p-value for each variable. When the null hypothesis of a unit root is rejected, the result obtained signifies that the time series is stationary. The findings thereby show that for the model concerning China, the variables of LCE, FF, LGDPC, and RE are non-stationary with the result of the ADF test; in contrast, the results from the PP test on variable LGDPC and RE are inconsistent. This difference emphasizes that one should consider several tests' outcomes and possibly employ other types of examinations. ADF and PP tests establish non-stationarities for the variables LCE, FF, RE, and LPTS in the United States. At the same time, the LGDPC data shows a mixed picture of the outcomes, which requires more cautious treatment of the methodology for further diagnostic possibilities.

Table 3 Unit Root.

VAR	**ADF**				**PP**			
	LV		**FD**		**LV**		**FD**	
	t-statistics	**p-value**	**t-statistics**	**p-value**	**t-statistics**	**p-value**	**t-statistics**	**p-value**
CHINA								
LCE	-1.117	0.695	-2.715	0.083*	-1.126	0.907	-2.811	0.069*
FF	-2.346	0.398	-4.856	0.002***	-2.346	0.398	-4.875	0.002***
LGDPC	-3.947	0.026**	-2.790	0.0720	-1.336	0.858	-2.864	0.061*
RE	-1.521	0.118	-2.203	0.028**	-0.759	0.958	-2.164	0.031**
LPTS	-1.007	0.927	-3.529	0.014**	-1.560	0.784	-3.587	0.012**
UNITED STATE								
LCE	-1.042	0.921	-5.693	0.000***	-0.465	0.979	-5.032	0.001***
FF	-1.764	0.696	-6.100	0.000***	-1.734	0.710	-6.100	0.000***
GDPC	1.333	0.859	-3.540	0.054**	-0.314	0.986	-2.647	0.095*
RE	-1.682	0.734	-6.786	0.000***	-1.287	0.871	-8.423	0.000***
PTS	-0.315	0.986	-6.021	0.000***	0.386	0.998	-6.021	0.000***

Note: ***; **, * represents 1%, 5% and 10% level of significant

In this research paper, we utilized the ARDL bounds testing for cointegration analysis, developed by Pesaran et al. (2001), as presented in Table 4. The ARDL Bound Test was utilized to examine a long-term association between the main variables in both China and the United States. This test is crucial in ascertaining whether the variables demonstrate cointegration, indicating a durable and consistent long-term relationship. The approach outlined in this paper applies to the annual sampling period from 1990-2020. This study selected the ARDL model based on the Akaike information criterion (AIC) lag selection criteria. The parameters for China were (1,0,1,0,1), and for the United States, they were (1,1,1,0,0). Results of the bound test procedure for analysis between dependent (CO_2) and all the independent (GDPC, RE, FF, PTS) variables are presented in Table 4 below. The tests under ARDL involve the comparison of the F-statistics against critical values.

Table 4 ARDL Bound Test.

Test Statistic	**Value**	**Significant**	**I(0)**	**I(1)**
CHINA				
F-statistics	1.276	10%	2.450	3.520
		5%	2.860	4.010
		1%	3.740	5.060
United State				
F-statistics	3.075	10%	2.450	3.520
		5%	2.860	4.010

	1%	3.740	5.060

The test provides valuable insights into the integration properties of these variables, helping us understand whether they are integrated of order 0 (I(0)) or order 1 (I(1)). The F-statistics for China, which examine the combined significance of the lagged levels and differences of the variables, suggest that there is not enough evidence to reject the null hypothesis of no cointegration (I(0)) or cointegration (I(1)). The calculated F-statistic of 1.276975 is lower than the critical values for all significance levels (10%, 5%, 1%).

The current sample size of 30 observations in both datasets shows that the observed values are lower than the critical values for both I(0) and I(1) at all significance levels. The findings from the ARDL Bound Test conducted in both nations indicate scant support for cointegration. The conflicting F-statistic indications suggest possible variations in the integration orders of particular variables. These findings require careful interpretation in future analyses. Conducting more research, such as exploring different model specifications or accounting for possible changes in the underlying structure, could strengthen the reliability of the findings about the long-term relationships among the variables under study.

The findings for the ARDL long-run estimation for China and the US are shown in Table 5, together with the coefficients, standard errors, t-statistics, and related probabilities. These coefficients show how the dependent variable and the designated lagged values of the independent variables are related throughout the long run.

Table 5 ARDL Long Run Estimation for China and the United States.

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
China				
FF	0.019	0.017	1.154	0.258
LGDPC(-1)	0.013	0.197	0.068	0.946
LPTS	0.125	0.105	1.189	0.245
RE(-1)	-0.024	0.008	-2.771	0.010
FF	0.019	0.017	1.154	0.258
LGDPC(-1)	0.013	0.197	0.068	0.946
United State				
FF(-1)	-0.033	0.042	-0.789	0.437
LGDPC(-1)	0.275	0.331	0.831	0.413
LPTS	0.116	0.176	0.659	0.515
RE	-0.094	0.040	-2.349	0.026

The ARDL long-run estimation for China reveals vital insights into the relationships among our variables. According to the positive coefficient in FF, a 1% rise in FF use over time is thought to be linked to an increase in the dependent variable of about 0.0199%. Nevertheless, the t-statistic p-value 0.2586 does not reach conventional significance, suggesting that the statistical robustness of this association may be questionable. The LGDPC lagged by one period, showing that although the p-value 0.9462 is large, the t-statistic is low, and the coefficient is positive. This indicates that there may not be a long-term, statistically significant relationship between the LGDPC and the dependent variable. According to the positive coefficient for LPTS, there is a long-term correlation between a 1% rise in PTS and an increase in the dependent variable of about 0.1259%. However, like FF, the resulting p-value of 0.2451 is not statistically significant at conventional levels. While RE lags by one period, the negative coefficient indicates that a 1% increase in lagged RE adoption is long-term associated with a 0.0242% decrease in the dependent variable. A potentially strong negative link is shown by the t-statistic, which is statistically significant at the 1% level (p-value = 0.0102).

For the United States, the ARDL long-run estimation offers more information. According to the negative coefficient, over an extended period, a 1% rise in LFF in the United States is linked to a 0.0337% decrease in the dependent variable. Nevertheless, the outcome p-value of 0.4370 is not statistically significant at standard levels. A 1% increase in the LGDPC is linked to an increase in the dependent variable of roughly 0.2752%, according to the LGDPC-1 positive coefficient. However, with a p-value of 0.4134, the outcome is not statistically significant. The positive coefficient LPTS shows the long-term association between a 1% increase in PTS and an approximate 0.1161% growth in the dependent variable. Like FF and LGDPC, the conclusion is not statistically significant, with a p-value of 0.5155. Moreover, according to the negative coefficient of RE, there is a long-term correlation between a 1% increase in RE and a 0.0941% decrease in the dependent variable. At the 5% level, the t-statistic p-value 0.0267 is statistically significant, suggesting a potentially strong negative connection.

The coefficients represent the long-run estimated effects of each variable on the dependent variable. A significant long-term influence of the related variables on the dependent variable is indicated by statistically significant coefficients (low p-values). The non-significant coefficients prompt further exploration. Future analyses may involve addressing potential econometric issues to enhance the robustness of our conclusions.

Table 6 presents the short-run estimation findings for China and the United States using ARDL. These results shed light on the factors' immediate influence on the dependent variable. In China, A 1% increase in the lagged log of CO_2 emissions is associated with a 0.781986% increase in the dependent variable in the short run. The result is statistically significant at the 0.05% level. A 1% increase in FF is associated with a 0.004339% increase in the dependent variable. However, this relationship is not statistically significant. A 1% increase in log GDPC is associated with a 0.088915% increase in the dependent variable. This relationship is not statistically significant. The lagged log of GDPC shows a negative association, but it is not statistically significant. A 1% increase in PTS is associated with a 0.027444% increase in the dependent variable in the short run. While the relationship is positive, it is not statistically significant at conventional levels at a 10% significance level. A 1% increase in RE is associated with a significant -0.030246% decrease in the dependent variable. A 1% increase in the LRE is associated with a 0.024962% increase in the dependent variable. This relationship is statistically significant. The constant term is not statistically significant, suggesting that it may not significantly impact the dependent variable in the short run.

Table 6 ARDL Short Run Estimation for China and The United States.

VARIABLE	COEFFICIENT	STD. ERROR	T-STATISTIC	PROB.
CHINA				
LCE(-1)	0.781	0.172	4.520	0.000
FF	0.004	0.003	1.202	0.241

LGDPC	0.088	0.079	1.112	0.277
LGDPC(-1)	-0.085	0.069	-1.234	0.230
LPTS	0.027	0.015	1.765	0.091
RE	-0.030	0.004	-6.997	0.000
RE(-1)	0.024	0.007	3.272	0.003
C	2.802	2.311	1.212	0.238
COINTEQ*	-0.218	0.079	-2.746	0.010
UNITED STATE				
LCE(-1)	0.661	0.151	4.355	0.000
FF	0.001	0.011	0.093	0.926
FF(-1)	-0.012	0.009	-1.269	0.217
LGDPC	1.112	0.224	4.952	0.000
LGDPC(-1)	-1.018	0.204	-4.988	0.000
LPTS	0.039	0.063	0.620	0.541
RE	-0.031	0.012	-2.613	0.015
C	4.917	1.605	3.063	0.005
COINTEQ*	-0.338	0.079	-4.262	0.000

In the United States, A 1% increase in LCO_2 emissions is associated with a 0.661585% increase in the dependent variable in the short run. The result is statistically significant at the 0.05% level. The relationship between FF and the dependent variable is not statistically significant. A 1% increase in the lagged FF is associated with a -0.012449% decrease in the dependent variable. However, this relationship is not statistically significant. A 1% increase in log GDPC is associated with a 1.112048% increase in the dependent variable in the short run. The result is statistically significant at the 0.05% level. The lagged log of GDPC is negatively associated with the dependent variable and is statistically significant. The relationship between PTS and the dependent variable is not statistically significant. A 1% increase in RE is associated with a significant -0.031844% decrease in the dependent variable in the short run. However, the co-integration equation term for both countries is negatively associated with the dependent variable and is statistically significant.

Table 7 contains results from various diagnostic tests conducted on two datasets: "China" and "The United States. These tests play a vital role in assessing the models' robustness and reliability, the quality and assumptions of regression models, including the Breusch–Godfrey LM test for serial correlation, the Jarque-Bera Statistic normality test, the Breusch–Pagan–Godfrey test for heteroskedasticity, the Ramsey Reset test for linearity as well as the CUSUM stability tests to ensure the validity of our econometric analysis. Below is a concise interpretation of the results for each dataset. In China, the results of the Breusch-Godfrey LM test for serial correlation in the residuals showed a non-significant p-value of 0.4449, indicating that serial correlation was not present throughout time. The variance of the residuals is constant across observations, according to the non-significant p-value of 0.8094 obtained from the Breusch-Pagan-Godfrey test for heteroskedasticity. A non-significant p-value of 0.164921, which indicates that the residuals are roughly normally distributed, was obtained using the Jarque-Bera statistic used to test for normality. With a non-significant p-value of 0.2042, the linearity assumption was found to be accurate by the Ramsey Reset test. According to the CUSUM test, there is no indication of instability in the model, which verified the coefficients' stability over time. Similar diagnostic tests were carried out on the model in the

United States. The results of the Breusch-Godfrey LM test for serial correlation in the residuals showed a non-significant p-value of 0.1399, indicating no proof of serial correlation across time. The non-significant p-value of 0.2214 from the Breusch-Pagan-Godfrey test for heteroskedasticity indicated continuous residual variance. The residuals are roughly normally distributed, as indicated by the non-significant p-value of 0.739017 obtained from the Jarque-Bera statistic assessing normality. The linearity assumption was not broken, as demonstrated by the non-significant p-value of 0.3558 obtained from the Ramsey Reset test. Overall, the diagnostic tests indicate that the models for China and the US are valid and satisfy critical presumptions. The non-significant results in serial correlation, heteroskedasticity, normality, and linearity confirm the desirable qualities of the residuals. Stability tests further validate the long-term constancy of coefficients, adding to the estimated models' legitimacy for both nations.

Table 7 Result of Diagnostic Test Statistics.

DIAGNOSTIC TEST	TEST TYPE	F-STATISTIC	PROB
CHINA			
Serial Correlation	Breusch-Godfrey LM	0.843	0.444
Heteroskedasticity	Breusch-Pagan-Godfrey	0.520	0.809
Normality	Jarque-Bera statistic	3.604	0.164
Linearity	Ramsey Reset	1.717	0.204
Stability	CUSUM	Stable	
UNITED STATES			
Serial Correlation	Breusch-Godfrey LM	2.173	0.139
Heteroskedasticity	Breusch-Pagan-Godfrey	1.492	0.221
Normality	Jarque-Bera statistic	0.604	0.739
Linearity	Ramsey Reset	0.891	0.355
Stability	CUSTOM	Stable	

In addition, the CUSUM is used to check the stability of the model. These tests are vital in assessing the reliability of the ARDL-bound test model utilized in this research. As depicted in Figure 1 and Figure 2, there is no evidence of instability in the model coefficients over time. Both graphs fall within the 5% significant bands, signifying the robustness and stability of the model adopted for this investigation. These results enhance the overall credibility and integrity of this research findings.

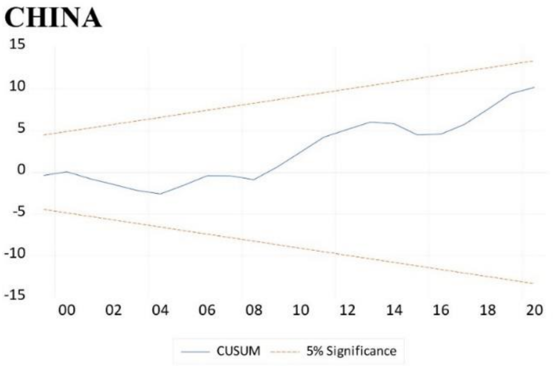
CHINA

Figure 1 CUSUM test graph.

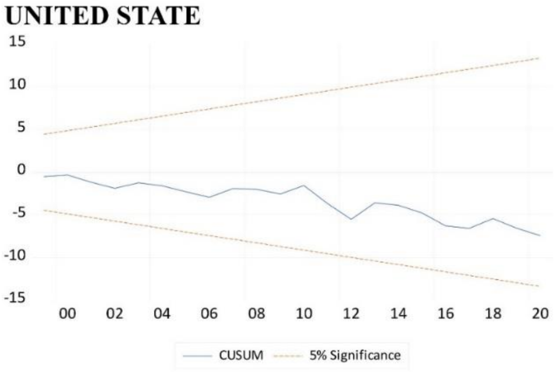

Figure 2 CUSUM test graph.

5. Discussion

The findings of this study align with the Environmental Kuznets Curve (EKC) hypothesis, suggesting varying relationships between economic growth and CO_2 emissions across different countries. Azam et al. [69] identified a significant positive correlation between economic growth and CO_2 emissions in China, Japan, and the USA, contrasting with a negative correlation in India from 1971 to 2013. In China and the USA, our results show positive coefficients for GDP growth (LGDPC), although statistically insignificant, similar to findings by Zhang et al. [70] and Davis et al. [71]. These studies suggest a nuanced relationship, indicating that while economic growth may not always directly increase emissions, its impact varies by sector and over time. Conversely, Narayan & Narayan [72] highlight that economic activities in these nations still heavily rely on carbon-intensive processes, emphasizing the need for early adoption of sustainable practices to prevent long-term environmental degradation. Furthermore, Yousefi-Sahzabi et al. [73] and Dogan & Inglesi-Lotz [74] argue for a complex relationship, suggesting an inverted U-shaped curve between GDP per capita and CO_2 emissions, implying that initial economic growth increases emissions before plateauing or declining with development maturity.

Our analysis supports a significant negative correlation between adopting renewable energy (RE) and CO_2 emissions. Zhou et al. [75] and Sovacool et al. [76] find that increased RE adoption in China and the USA leads to long-term reductions in CO_2 emissions, echoing our findings of negative coefficients for RE adoption in both countries. This aligns with the rapid mitigation effects observed in short-run estimations [77, 78], underscoring the immediate environmental benefits of integrating renewable sources into energy policies. However, Marques [79] notes the complexity of RE adoption's impact on overall energy demands, suggesting careful planning to capitalize on its potential benefits [80] entirely. Studies by Bilan et al. [81] and Mehmood et al. [82] further emphasize the variability in results across different methodologies and contexts, indicating that the effectiveness of RE in reducing emissions depends on local conditions and policy frameworks.

Our findings indicate a nuanced relationship between fossil fuel (FF) efficiency and CO_2 emissions. While fuel efficiency improvements show positive coefficients in short-term estimations for China and the USA, the long-term impacts are statistically insignificant [83, 84]. This suggests that while technological advancements may temporarily mitigate emissions, their sustained impact on long-term environmental sustainability remains uncertain [85, 86]. Lin & Xu [87] highlight regional disparities in China, where FF consumption exhibits a nonlinear impact on CO_2 emissions due to varied development stages and energy mix compositions. Similar studies in Pakistan [88, 89] and globally [90, 91] underscore the detrimental effect of FF consumption on environmental quality, necessitating stringent regulations and technological innovations to mitigate its environmental impact.

Patent counts serve as proxies for technological innovation, indicating mixed impacts on CO_2 emissions across different countries. Studies by Acemoglu et al. [92] and Popp et al. [93] suggest that while innovation can drive economic growth, its environmental impacts depend on the type and deployment of technologies. The findings of Wang et al. [94] and Jiao et al. [95] support the localized benefits of green technologies in reducing carbon intensity, albeit with varying degrees of effectiveness across sectors and regions. Policies promoting innovation, as highlighted by Buonanno et al. [96] and Popp et al. [97], can play a crucial role in accelerating the adoption of sustainable technologies, thereby mitigating emissions while fostering economic growth.

In conclusion, the drivers of CO_2 emissions are multifaceted and vary significantly across different economic contexts. Economic growth, renewable energy adoption, fossil fuel efficiency, and technological innovation interact complexly to shape emissions trajectories. Tailored policy approaches are essential to harnessing the potential of these drivers effectively in mitigating climate change impacts globally.

6. Conclusion

This study has investigated the intricate interplay between GDP per capita, CO_2 emissions, PTS, adoption of RE, and FF consumption in the United States and China from 1990 to 2020. By employing the Autoregressive Distributed Lag (ARDL) model and various statistical tests, the research has provided significant insights into these relationships, addressing the research questions posed at the outset. In the Main Findings, the US and China experienced substantial growth in GDPC, with China showing a more rapid increase than the US. CO_2 emissions increased in both countries, with a more pronounced rise in China due to rapid industrialization. PTS increased significantly in both countries, especially China, reflecting a strong focus on technological advancement. Adoption of RE increased in both countries, with China exhibiting a significant surge. FF consumption remained substantial in both countries, though efforts to reduce dependency were more evident in the US. In Relationships and Connections Among Variables during the Long-term Relationships China, A 1% increase in FF consumption is associated with a 0.0199% increase in CO_2 emissions. However, this relationship is not statistically significant (p-value 0.2586).GDPC did not show a statistically significant long-term relationship with CO_2 emissions (p-value 0.9462).PTS showed a positive but not statistically significant long-term relationship with CO_2 emissions (p-value 0.2451).RE had a significant negative impact on CO_2 emissions, with a 1% increase in RE associated with a 0.0242% decrease in CO_2 emissions (p-value 0.0102).In the US, A 1% increase in FF consumption is linked to a 0.0337% decrease in CO_2 emissions, but this relationship is not statistically significant (p-value 0.4370). A 1% increase in GDPC is associated with a 0.2752% increase in CO_2 emissions, though this is not statistically significant (p-value 0.4134). PTS showed a positive but not statistically significant relationship with CO_2 emissions (p-value 0.5155).RE had a significant negative impact on CO_2 emissions, with a 1% increase in RE associated with a 0.0941% decrease in CO_2 emissions (p-value 0.0267).

Conversely, in Short-term Relationships, China's 1% increase in the lagged log of CO_2 emissions is associated with a 0.781986% increase in CO_2 emissions in the short run, which is statistically significant (p-value 0.0002). FF showed a positive but not statistically significant short-term relationship with CO_2 emissions, with a 1% increase in FF associated with a 0.004339% increase in CO_2 emissions (p-value 0.2418). A 1% increase in GDPC is associated with a 0.088915% increase in CO_2 emissions, but this relationship is not statistically significant (p-value 0.2779). The lagged GDPC is negatively associated with CO2 emissions but is not statistically significant (p-value 0.2301). A 1% increase in PTS is associated with a 0.027444% increase in CO_2 emissions in the short run, though this relationship is not statistically significant (p-value 0.0914). A 1% increase in RE is associated with a significant -0.030246% decrease in CO_2 emissions in the short run (p-value 0.0000), and the lagged RE also had a significant positive impact (p-value 0.0035). In the US, a 1% increase in the lagged log of CO_2 emissions is associated with a 0.661585% increase in CO_2 emissions in the short run, which is statistically significant (p-value 0.0003). FF showed a negative but not statistically significant short-term relationship with CO_2 emissions, with a 1% increase in the lagged FF associated with a -0.012449% decrease in CO_2 emissions (p-value 0.2177). A 1% increase in GDPC is associated with a 1.112048% increase in CO_2 emissions in the short run, which is statistically significant (p-value 0.0001). The lagged GDPC is negatively associated with CO_2 emissions and is statistically significant (p-value 0.0001). PTS showed a positive but not statistically significant short-term relationship with CO_2 emissions (p-value 0.5412). A 1% increase in RE is associated with a significant -0.031844% decrease in CO_2 emissions in the short run (p-value 0.0159).

6.1 Policy Recommendations

- Financial Incentives for Renewable Energy: The viewpoint of the economic incentives that governments should offer and encourage various investments into RE business through concessions in either tax rebates or subventions. This can also go a long way in reducing the emission of CO_2 and promoting the use of renewable energy.
- Reducing Fossil Fuel Dependency: Measures that will assist in the reduction of the usage of fossil fuels have to be well articulated. This consists of enhancing energy utilization, promoting innovation in the creation of power, and being bound by the intergovernmental wildlife and climate accords.
- Promoting Innovation: The government embarked on policies on forced innovation, subsidies for research and development, and the collaboration of the government, schools, and industries, which are how technological advancement will foster the economy and the environment.
- Cross-border Partnerships: The US and China should formulate Cross-border collaboration partnerships to combat environmental issues because they have what it takes to share good practices. Thus, cooperation of this kind might enhance the efficiency of the international approaches to sustainable development.
- Policy Integration: Thus, it is necessary to synchronize the policies based on the directions to be followed in the economy, technology, and environment to sustain development. It also provides a means of managing development for monetary growth while attending to environmental issues.

6.2 Research Limitations

- Data Limitations: The analysis relies on the availability and accuracy of historical data, which may vary in quality and completeness.
- Model Limitations: The ARDL model, while robust, has limitations in capturing all dynamic interactions and external shocks that could affect the variables.
- Scope of Variables: The study focuses on specific variables related to sustainable development. Future research could include other relevant factors such as policy changes, socio-economic variables, and international trade impacts.
- Temporal Scope: The study covers the period from 1990 to 2020. Ongoing and future trends, especially rapidly evolving technologies and global climate policies, need continuous monitoring and analysis.

Author Contributions

Christiana Chioma Efe-Onakpojeruo: Software, writing – original draft, formal analysis, methodology, analysis. Mehdi Seraj: Conceptualization, writing – review and editing the final draft, analysis, supervising. Huseyin Ozdeser: Supervising. All authors have read and approved the published version of the manuscript.

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Competing Interests

The authors declare that they have no competing interests.

Data Availability Statement

Data retrieval was conducted systematically from the World Bank Data repository. a trusted and comprehensive source of economic and demographic information. The data were accessed for the selected countries (USA and China) and for the specified time frame of 1990 to 2020.

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