energies

Article

The Interplay of Green Technology and Energy Consumption: A Study of China's Carbon Neutrality and Sustainable Digital Economy

Isbat Alam [1], Shichang Lu [1], Muddassar Sarfraz [2,*] and Muhammad Mohsin [3,*]

1 College of Business Administration, Liaoning Technical University, Huludao 125105, China
2 School of Management, Zhejiang Shuren University, Hangzhou 310015, China
3 School of Business, Hunan University of Humanities, Science and Technology, Loudi 417000, China
* Correspondence: muddassar.sarfraz@gmail.com (M.S.); mohsinlatifntu@gmail.com (M.M.); Tel.: +86-18-751-861-057 (M.S.)

Abstract: In light of the carbon neutrality goals set post-Paris Climate Conference (COP21), this study delves into the relationship between green technology innovations, energy consumption, and CO_2 emissions in China, spanning the period of 1990 to 2021. The objective of this paper is to creatively present the idea of a low-carbon digital economy from the viewpoint of digital technology. Utilizing the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, we scrutinize this relationship, employing unit-root testing to verify the integrative attributes of the variables, inclusive of structural break data. Further analysis using the bootstrap Autoregressive Distributed Lag (ARDL) bound testing method corroborates the relationship between these key variables. The study reveals unidirectional co-integration over time among green technology innovations, renewable and non-renewable energy, per capita income, population, and CO_2 emissions as per the Granger causality test. Interestingly, our findings suggest that while green technology innovation, per capita income, and renewable energy contribute to the reduction of CO_2 emissions, non-renewable energy consumption and population growth exacerbate them. These insights offer valuable guidance for policymakers in formulating comprehensive strategies to enhance environmental quality through the promotion of renewable energy and green technology innovations, with a specific emphasis on the Chinese context.

Keywords: energy consumption; green technology; CO_2 emissions; BARDL; China

Citation: Alam, I.; Lu, S.; Sarfraz, M.; Mohsin, M. The Interplay of Green Technology and Energy Consumption: A Study of China's Carbon Neutrality and Sustainable Digital Economy. *Energies* **2023**, *16*, 6184. https://doi.org/10.3390/en16176184

Academic Editor: Bert Scholtens

Received: 15 June 2023
Revised: 10 August 2023
Accepted: 21 August 2023
Published: 25 August 2023

1. Introduction

Every country must consistently allocate energy resources and develop socially fair technology with the least negative environmental impact [1]. However, the unacceptable natural environmental degradation brought on by the burning of fossil fuels can only be stopped by slowing down both economic expansion and fossil fuel consumption [2]. Su et al. [3] have been educated on various economic choices about energy technology and resources to achieve low-level carbon green economic development. In addition, the world economy experienced a catastrophic economic shutdown as a result of unsafe lending practices by US banks [4,5]. The recession's repercussions cause a considerable decline in foreign trade and a drop in pricing [6]. Almost all countries were desperate to escape recession [6]. Since then, implementing green technology has presented a win-win situation because not only are they green, but most of them are not utilized [7]. They provide a valuable argument on combining green technology innovation, energy production policies, and policy incentive timing for countries based on their socio-economic and biological conditions.

Advances in Green technology are critical to meeting sustainable development goals while having the least harmful impact on the normal environment [8,9]. Carbon neutrality, or achieving net-zero CO_2 emissions, is a hot topic among legislators, researchers, and other environmental sectors. The phrase CO_2 emissions, on the other hand, refers to the discharge of carbon into the environment from various types of energy consumption and trade-associated sources. At the moment, there is a series of conversations regarding green innovation technology (GTIs) in which the phrase "environmental sound technologies (ESTs)" is regarded to be the first conception [10]. But the traditional green technology concept has been transformed into completely sustainable solutions considering the economy, the environment, and society.

Different countries have implemented various techniques to promote green development. For example, the Chinese government has proposed that Green Technology appropriately be implemented according to the United Nations (UN) 2030 agenda [11]. The Chinese government and commercial banks provide unconditional financial loans for green investment and environmentally friendly industries [12]. The idea of green technologies was first introduced by Braun and Wield [13], believing it has to include ecological treatment, pollution management, recycling, monitoring, purification, and other evaluation procedures. Moreover, environmental considerations should be considered during the invention of the manufacturing process; hence a novel GTIs system established on the classic linear model technological innovations has been established. The necessity for GTIs is seen in every country worldwide. As a result, the transformation of green technology is critical for environmental conservation. This is because developing countries continue to struggle to gain access to modern green technology. Approximately 66.7% of countries still seek appropriate green technology to stabilize their economy and environment [14]. The UN Framework Agreement on Climate Change (UNFCC) has initiated a program concentrating on climate-changing technologies, with the participation of 85 nations [15]. The success and efficiency of GTI in terms of green economy development can decrease air pollution and preserve energy sources.

According to some researchers, the GTI's performance is the association between input and output during all operations of GTIs. Three basic methods for estimating the efficiency of local GTIs have been observed [16,17]. The first method utilizes the patent indications for green technology innovation, particularly based on GTI accomplishments. Given an instance of such practices, show the number of patent applications received by firms, and analyze when the stock of green and global green technology knowledge influenced technological development. But one of the major drawbacks of this technique is that GTI is a broad concept that a single indication cannot present. The second way to assess GTI performance is through main element analysis across many locations, organizations, and economies [18]. This strategy was evaluated by the people who created GTI's index system. A third strategy uses parametric and non-parametric techniques to determine GTI input and output proficiencies [19].

With expanding financial and economic demands, emerging economies confront numerous issues since increased economic activity increases energy demand, primarily from conventional resources such as coal, gas, and oil [20]. Renewable energy sources (RE) are strategic energy services for long-term development [2]. Solar energy, waste, wind, and biomass are considered environmentally friendly and cost-effective because they reduce pollution, improve energy safety, reduce the harmful effects of climate changes, and ultimately, provide low costs energy to remote areas [21,22]. Most of the previous literature outcomes about the renewable energy role in the environment are significant and positive [23]. In the evaluation, some research shows that renewable energy has little effect on energy production or CO_2 emissions concentration [24,25]. On the other side, the lack of green technology innovations and inefficient gearing structures are among the elements that prove the harmful effect of renewable energy on environmental quality [26]. This will propose that such technological developments can limit REC's harmful environmental effects [17].

The Chinese economy is the fastest-growing economy globally, and greenhouse gas (GHGs) emissions are increasing rapidly. Its economy is disconnected from energy consumption, air pollution, water usage, and garbage production. However, due to the Chinese economy's high resource intensity and fossil fuels dependence, environmental pressures will increase in absolute terms [27,28]. Currently, the results of the GHG inventory show that total GHG emissions as CO_2 equivalent increased by 0.34% in 2021 relative to the previous year; with the energy sector accounting for GHG emissions it is a big part. Furthermore, total GHGs emission per capita were found to be 1.9 metric tons CO_2 eq. in 1990-, 8.39- and 8.73-tons CO_2 eq. in 2020 and 2021, respectively (see Figure 1). Fined particulate matter emissions from the power sector and transportation pose major health risks currently. Around 660 major Chinese cities generate solid waste, approximately 190 million tons each year; 29% of the world's MSW is generated each year. Environmental protection, energy savings, pollution control, water conservation, recycling, low carbon, emission reduction, environmental protection, and ecology are also examples of inventions. All the numbers above provide sufficient justification for examining the Chinese's economy while monitoring trends in CO_2 emissions based on factors of interest such as green technology innovation, energy consumptions, and numerous other macro-economic dynamic forces.

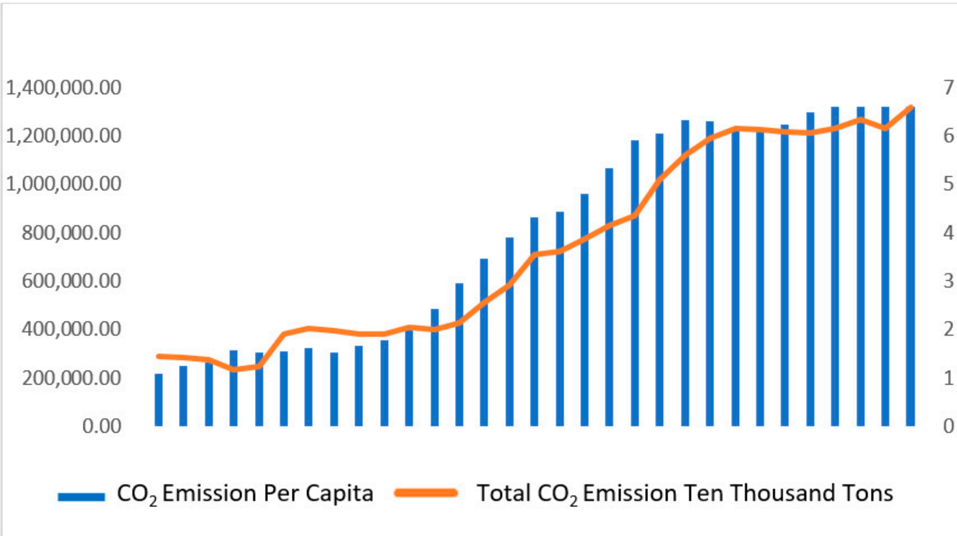

Figure 1. Per capita and total CO_2 emission during 1990–2021.

The objective of this paper is to add the existing literature in the following ways: (1) Its concept uses annual data on the Chinese economy from 1990 to 2021 to compare CO_2 emissions, GTI, NREC, REC, POP and PI with the significance of GTIs. (2) This present study explores the characteristics of unit root all variables such as GTIs, NREC, REC, POP, PI, and CO_2 emissions using ADF and ZA tests. (3) The bootstrapping ARDL bound analysis approach is used in this work to validate co-integration association aimed variables for co-integration analysis. Several advantages have been noticed in the present literature when using the BARDL technique for data analysis. For example, the BARDL test increases the lagged values significance of selected variables, indicating a better understanding of the model's Co-integration status than some classic models such as OLS and the basic ARDL test. Other advantages of utilizing BARDL include the absence of inconclusive intervention with a bound test. Furthermore, there is strong evidence about the indigeneity difficulties with the size of the ARDL bound testing structure and its small effect on power dynamics when utilizing the bootstrap ARDL test.

In addition, we used the Granger causality method to investigate the causality relationship between the research variables. Pragmatic evidence suggests that developments in green technology and energy reduce both long-run and short-run CO_2 emissions. However, China's CO_2 emissions are increasing due to an increase in energy consumption and population. The causality test indicates a significant relationship between GTIs and CO_2

emissions, NREC and CO_2 emission, REC and CO_2 emissions, POP and CO_2 emissions, and PI and CO_2 emissions.

The remaining part of the paper is organized as follows: Section 2 examines the pertinent literature. The data, technique, and models are all described in Section 3. Section 4 contains the findings and discussion, while Section 5 has the conclusion and policy recommendations.

2. Literature Review

2.1. Green Technological Innovations and Environmental Quality

Numerous studies have investigated the pragmatic relationships between green technology innovations and environmental Quality [29,30]. Ali et al. [31], for example, studied the association between urbanization, income level, technological innovation, and CO_2 emissions. According to the study's outcomes, technological innovation, growing urbanization, and money per capita significantly impact environmental quality. Their study determined that technological innovation introduces innovative technology in the country, which inclines to lower CO_2 emissions [6,8]. The negative association between green technology advancement and environmental quality was demonstrated. The study determined that technological innovation progress results in energy production and efficient technology, which are less harmful to the environment.

Ganda [32] investigated the association between technological development, REC, and environmental pollution and determined that REC and technological progress significantly reduce pollution, finally improving environmental quality. Simultaneously, several other studies contended that technological innovation did not help much to decrease CO_2 emissions in emerging nations. For example, Bai et al. [33] concluded that technological advancement increases energy consumption, increasing greenhouse gas emissions. The study also indicated that emerging countries primarily rely on traditional energy sources, significantly contributing to environmental quality. Thus, rather than CO_2 emissions, technical improvements in developing economies tend to increase them. Similarly, Ganda [32] found that green technology innovation increases pollution in low-income nations. With these contradicting outcomes in mind, scholars have begun working on green technology breakthroughs [2].

Töbelmann et al. [34] examine the relationship between GTIs and environmental degradation in N11 economies from 1995 to 2017. Their research re-examined chosen economies' technological policies, environmental quality, economic development, and clean, inexpensive energy production. Based on the Environmental Kuznets Curve, they studied the influence of technological advancement, renewable energy, and other macroeconomic dynamics on pollution using bootstrap regression analysis [34]. Using the generalized method of moments and panel settings, they examined the remarkable impact of carbon emissions on environmental quality in EU-27 member states from 1990 to 2014. Environmental innovations are thought to have contributed to lower carbon dioxide emissions, although general innovation does not affect such CO_2 emissions. GTIs are synonymous with environmental innovation, an effective technique that minimizes pollution while positively contributing to economic growth [35]. Many researchers have claimed that GTIs favor lowering CO_2 emissions or improving environmental quality [36]. For example, Miao et al. [37] investigated the impact of green technology research and development on environmental quality and determined that green technology research and development is useful for environmental quality. The role of green technology in improving environmental quality has also been mentioned [38]. Lee and Min [39] investigate the impact of green innovations, REC, and economic growth in reducing carbon emissions in the Chinese economy from 1990 to 2018. The QARDL technique reveals that technological innovation, renewable energy, and economic growth have a major impact on Chinese CO_2 emissions [11].

For the COP 21 agreements, we examined the relationship between financial development, renewable energy, technological innovations, and CO_2 emissions. The unit root test improved the mean groups, and commonly correlation impact mean group approaches were used for data analysis [40]. The researcher's finding shows a significant positive connection between financial development and CO_2 emissions. Furthermore, a negative relationship exists between CO_2 emissions and green technological innovations [1]. Consider using a panel model with slope heterogeneity and a cross-sectional test to examine the intensity reduction in CO_2 emission and technological innovation in China from 2001 to 2016. According to the data, when technological innovations increase one percent, the renewable energy reduces carbon intensity by 0.051 percent. Other studies have also found a trend in CO_2 emissions in many economies [41]. Kone and Buke [27] have examined the GTIs on the Turkish environment while keeping an eye on trends in GTI. They go on to say that green technology has a bright future. As a result, the Turkish economy has seized the lead in producing electrical automobiles for the international market. Lee and Min [39] have investigated the influence of clean energy, GTIs, and militarization on economic growth in China's green perspective.

According to the study's conclusions, clean energy is an essential dynamic force in developing a green economy in the Chinese economy. On the other hand, technological innovations promote green economic development in the selected country [42]. In defining the green construction industry, the Chinese economy was also considered to study the environmental valuation based on social, economic, political, and green technological considerations. According to the study, the impact of macro-environmental factor industries was determined to be medium to high. According to the above mentioned materials, the resulting hypothesis was proposed:

H1. *Green technology innovation (GTI) is important in determining China's* CO_2 *emissions.*

2.2. Energy Consumptions and Environmental Quality

2.2.1. Non-Renewable Energy Consumption (NREC) and Environmental Quality

Previous research has focused on the energy and environmental nexus. Numerous studies have investigated the impact of traditional energy sources on environmental quality. Simultaneously, others investigated the contribution of renewable energy sources to environmental quality. Previous research has shown that NREC resources increase carbon emissions. According to Saboori and Sulaiman [43], the impact of energy use on Malaysian environmental pollution was that NREC increases environmental degradation. As a result, environmental degradation occurs. The researchers conducted the same research for SAARC countries and discovered a positive association between traditional energy usage and environmental quality [44]. Research also demonstrated the positive benefits of traditional energy sources to environmental quality reduction in Pakistan [31]. In the same way, the research of Sharif and Raza [45] shows that conventional energy plays a positive impact on worsening the environment quality. Liu et al. [46] investigated the impact of home energy consumption on environmental quality and demonstrated the relevant relationships between such factors. Because energy sources are the most important engine of every nation's economic growth, this hopeful association between traditional energy and the environment is becoming a threat to the economy. As a result, researchers have been looking for an alternative measurement of traditional energy to develop environmental quality and boost green economic growth. The next hypothesis is proposed based on the above literature.

H2. *Non-renewable energy consumption (NREC) is essential in determining China's* CO_2 *emissions.*

2.2.2. Renewable Energy Consumption (REC) and Environmental Quality

Consumption of renewable energy is an alternative approach that recovers environmental quality while contributing considerably to green economic growth [47]. By consuming renewable energy sources, total energy can be produced to meet household energy needs. These forms of energy can generate electricity without compromising environmental quality. Experts have been exploring the relationship between unconventional energy sources and environmental quality while considering renewable energy sources.

The impact of REC and NREC sources on the reduction of CO_2 emission was investigated in South Africa and revealed a strong connection among the factors. According to the study, increasing NREC by 1% also increased CO_2 emissions by 10,235 kt. A 1% increase in REC decreased carbon emissions by 2855 kt. According to the study, NREC is less strongly associated with CO_2 emissions [48]. From 2000 to 2011, the effect of Chinese economic growth and poor air quality are studied, counting the production and utilization of REC. The study also found that although renewable energy production and consumption can positively contribute to economic growth, they are not significantly associated with water and air pollution in the selected country.

In the study conducted by Wang and Wang [49], "renewable energy resources" were explored as "cleaner energy sources" and suggested their beneficial role in enhancing the efficiency of the environment. Wind energy was considered an important source and production of renewable energy [50]. As a result, the author examined wind energy's contribution to environmental pollution and discovered that energy generated from renewable sources of wind has a beneficial effect on environmental quality. Tsoutsos et al. [51] noticed that solar energy has been proven to impact environmental quality directly. Sharif et al. [52] have re-examined the environmental footprints of REC and NREC in Turkey. From 1965 until 2017, they used the QARDL method for this purpose. Under all of the study quantiles, it is seen that the REC function effectively reduces the environmental footprint. In the meantime, the study's results have approved the existence of the environmental Kuznets curve (EKC). Kalmaz and Kirikkaleli [53], using innovative quantile modelling, attempted to examine the association between REC and environmental quality from 1990 to 2019. The study results show a two-way connection between REC and environmental quality. This contributes empirically to estimating CO_2 emissions in emerging economies using energy use, economic development, and other macroeconomic parameters. Findings from Sharif et al. [54] suggest that CO_2 emissions, energy consumption, and other macroeconomic factors have long-term equilibrium relationships.

Based on the discussion so far, it is possible to conclude that the literature has effectively explored the relationship between GTIs, REC, NREC, and environmental quality. However, according to the authors, there is a widespread lack of agreement when it comes to investigating the role of GTIs, REC, NREC, and environmental quality within the framework of the STIRPAT model. Given this study's theoretical and empirical value, it would be reasonable to support its inclusion in the existing literature. Another methodological gap occurs, as we have learned that the researcher provides limited literature when using the BARDL technique to determine tendencies in environmental sustainability, particularly in the environment of China. As a result, the current work has addressed methodological and theoretical gaps in the literature. Alola and Kririkkaleli [55], used wavelet quantile and gradual-shift causality techniques to study the relationship between REC and environmental quality in the immigration and healthcare sector in the United States. The 1999–2008 study outcomes revealed a significant feedback connection between REC and CO_2 emissions at various scales. Short-run estimates show a favorable association between the research variables.

H3a. *Renewable energy consumption is important in deciding China's CO_2 emissions. In addition, the following assumptions were investigated in our study.*

H3b. *per capita income plays a key effect in influencing China's CO_2 emissions.*

H3c. *China's population plays a crucial effect in determining CO_2 emissions.*

3. Materials and Methods

Earlier studies offered support for the IPAT model in calculating CO_2 emission variables [33,56]. More work has been added to the IPAT concept by Dietz and Rosa [57]. Recently, the model has been adapted to a stochastic variation known as stochastic effects Regression on Population, Affluence, and Technology. An important advantage of the

STIRPAT model is that it can empirically test hypotheses. As a result, we formulate the following equation for empirical investigation:

$$CO_2EM_{it} = f(POP_{it}, NREC_{it}, PI_{it}, REC_{it}, GTI_{it}) \quad (1)$$

In this Equation (1), CO_2EM is the function of population, non-renewable energy consumption, income per capita, renewable energy consumption, and Green Technology Innovation, respectively. The model was derived from the study contributions of Alam et al. [58] and Paramati et al. [40]. The model has recently been transformed into a stochastic variant called the Stochastic Impacts by Regression on Population, Affluence, and Technology. The STIRPAT model has the advantage of being able to test assumptions empirically. As a result, for the pragmatic inquiry, we constructed the following equation:

Data and Empirical Modelling

From 1990 to 2021, data on the role of GTI, REC, NREC, POP, PI, and CO_2 emissions in China were collected for empirical study. CO_2 emissions are quantified per capita, while the number of registered environmental patents assesses green technical innovation; data for both variables are obtained from the OECD statistics website. Moreover, renewable energy includes geothermal, hydro, sun, wind, and tide, whereas non-renewable energy includes using petroleum, gas, coal, and other fossil fuels to generate energy. Figure 2 exhibits the methodology flowchart of this study.

In conclusion, REC and NREC data were obtained from an Energy Information Administration (EIA) databank. The data are logarithmically transformed to produce a more accurate estimate. According to McNown et al. [59] and Sohag et al. [60], the current study makes use of "The Bootstrapping ARDL Co-integration method" to assess the Co-integrating relationship between the intended set of selected variables. Furthermore, when compared to the previous ARDL approaches of Pesaran et al. [61] and Perron [62], one of the primary benefits of using the bootstrap ARDL method is the capability to deal with power attributes and the low side. According to the most recent Co-integration test, its bootstrapping ARDL Co-integration can strengthen both the "T-test" and the "F-test." According to this viewpoint, Pesaran et al. [61] provide two criteria for identifying a similar Co-integration system, the first which describes their major outcomes with an error-correction co-efficient. On the other hand, the second criterion requires the coefficients of variables with significant lagged values. More specifically, Pesaran et al. [61] state that for the other case, "the upper and lower critical limitation should be utilized during co-integration". However, for initial possible examples, the bound test and their limitation are not required. This test can also address the first requirement mentioned previously (coefficient for error terms and their significant outcomes), provided that the dimensions 1 model incorporates research factors. However, as stated by Goh et al. [63], common "unit-root" tests can be confusing due to low specificity and strength characteristics. The problem is handled fairly [64]. ARDL performs a bound test while providing a bootstrap. The superiority of its bootstrapping bound ARDL test may be seen due to its vulnerability in order of "parameters integration properties." For the time being, it is an appropriate solution in the situation of " time-series complex analysis," determining such problems as ample examples related to usual ARDL bound estimation [42]. An alternative advantage of bootstrap ARDL bound analysis is generating "measured values" by eliminating the possibility of unknown areas and cases (which exist in traditional bound testing techniques). Figure 3 exhibits the dependent and independent variable of the study. Also, it shows how these variables have positive and negative relationships in the previous literature.

$$y_t = \sum_{i=1}^{p} a_i y_{t-i} + \sum_{j=0}^{q} \beta_J x_{t-j} + \sum_{k=0}^{r} \gamma_k Z_{t-k} + \sum_{j=1}^{s} \tau_j D_{t,1} + \mu_t \quad (2)$$

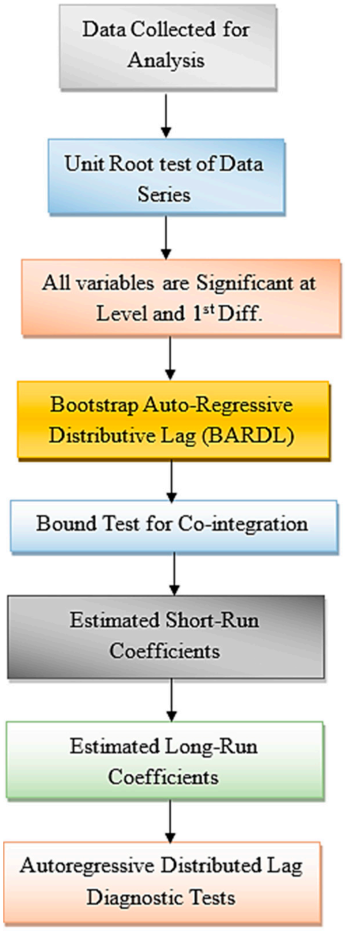

Figure 2. Methodology Flowchart.

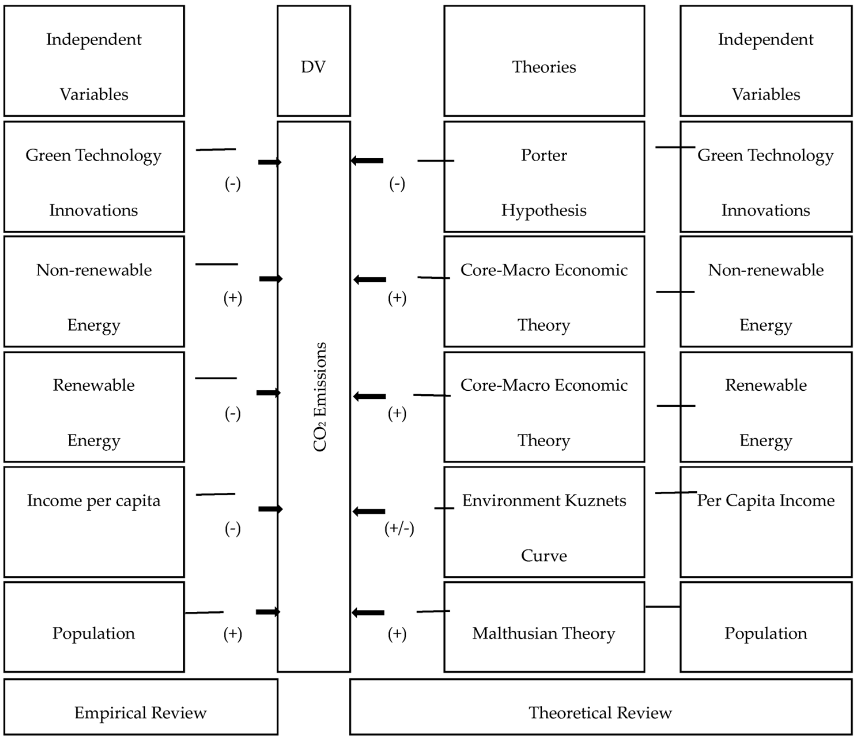

Figure 3. Theoretical and Conceptual Model.

Equation (2) above shows the mathematical technique for the conventional bootstraps ARDL bound test. In the 1st Equation, representations like i, j, k, l are identified as lag terms. For example, i = 1, 2 . . . p; j = 0, 1, 2 . . ... q; k= 0, 1, 2, R; l = 0, 1, 2 . . .. s and t denote the time. Furthermore, yt is a responsible variable, while xt and zt are defining factors in the study. The parameters of the lagged descriptive variables are denoted by Coefficient in the model. In addition, t represents the zero (0) mean error term with determinate variance. In the model above, the error-correction form is represented by Equation (3), which is as follows:

$$\Delta \mathrm{y_t} = \varphi \mathrm{y_{t-1}} + \gamma_{\mathrm{x1}} + \Psi \mathrm{z_{t-1}} + \sum_{\mathrm{i=1}}^{\mathrm{p-1}} \pi_{\mathrm{i}} \mathrm{y_{t-i}} + \sum_{j=1}^{q-1} \delta_j x_{t-j} + \sum_{\mathrm{i=1}}^{r-1} \pi_{kz-k} + \sum_{\mathrm{i=1}}^{s} \omega_i D_{t,1l} + \mu_t \quad (3)$$

In the preceding Equation (2)

$$\varnothing = \sum_{\mathrm{i=1}}^{\mathrm{p}} \mathrm{ai}, \gamma = \sum_{\mathrm{i=1}}^{\mathrm{q}} \beta \mathrm{i}, \text{and } \Psi = \sum_{\mathrm{i=0}}^{\mathrm{r}} \gamma \mathrm{i}$$

At this stage, the symbols i, j, k, and I denote the functions associatied with Equation (2). Equation (3) is approximated. In the following model, a constant term designated by the letter c is used:

$$\Delta y_t = \widetilde{c} + \varphi y_{t-1} + \widetilde{\gamma_{x1}} + \Psi \widetilde{_{zt-1}} + \sum_{i=1}^{p-1} \widetilde{\lambda}_i y_{t-i} + \sum_{j=1}^{q-1} \widetilde{\delta}_i x_{t-j} + \sum_{i=1}^{r-1} \widetilde{\pi}_i z_{t-k} + \sum_{i=1}^{s} \widetilde{\omega}_i D_{t,1l} + \widetilde{\mu_t} \quad (4)$$

To confirm Co-integration among the variables of the analysis "yt, tx, and zt," Equation (4) has three null hypotheses to be rejected, which can be addressed below:

I. The F1 test, as related to all appropriate error-correcting terms.

$$\mathrm{H0} : \varnothing = \Psi = 0 \text{ Compare to } \mathrm{H1} : \varnothing \neq \mathrm{Y} \neq \Psi$$

$\neq$0, which is notice that any of ∅,y, and ψ are not equal to zero.

II. The quality of F2 based on the response of variable settings.

$$\mathrm{H0} : \varnothing = \Psi = 0 \text{ alongside } \mathrm{H1} : \varnothing \neq \mathrm{y} \neq \Psi$$

= 0 denotes that either y or Ψ is not equivalent to zero.

III. A T-test with an emphasis on lagged forecaster variable estimations

$$\mathrm{H0} : \varnothing = 0 \text{ in contradiction of } \mathrm{H1} : \varnothing \neq 0, \text{meaning that } \Psi \text{ is not equal to zero}$$

An important assumption is that the general ARDL model produces significant bound test values in the F1 and T-tests. Nonetheless, it rejects the test score based on the irregular variables, The F2 examination. It is possible to have critical values for all three metrics by using the BARDL approach given by McNown et al. [59]. Finally, we used the key values that they tabulated to produce some robust logical results. Furthermore, all Co-integration tests require a static test. However, previous research used the ADF unit root technique to check the data aspect, which is inappropriate for data with structural breaks that significantly impact the study outcomes. As a result, Zivot and Andrews [65] have significantly supported the current literature by allowing the possibility of structural hypothesis breakdowns in data without specifying a breakpoint time. This technique allows the structural breakpoint to be correctly identified; leaving aside the breakpoint issue. In addition, this can support the idea that the choice of the endogenous breakpoint greatly affects the yield of the unit root. As a result, the current study also used the ZA and ADF unit root test for better comparison. Figure A1 shows the recursive estimation of all variables. The study data soureces are mentioned in the Table A1.

4. Results and Discussion

Table 1 displays descriptive statistics for the findings. Regarding mean scores, we discovered that POP is the most valuable, followed by PI, NREC, and REC. This would support the claim that the targeted economy's average POP is higher, but Personal Income trends are higher than Renewable Energy. Furthermore, we find that CO_2 emissions are more volatile than NREC. Conversely, PI has a higher deviation than REC, GTI, CO_2 emissions, NREC, and POP. In the current literature, Jarq-B is the direct measurement of goodness-of-fits used to determine whether or not the data confirm a normal distribution, as indicated by skewness and kurtosis. However, the Jarq-B results are positive, with the value remote from zero indicating that the variables of interest have a normal distribution. The same findings were discovered using [66]. The Jarq-B results reveal that CO_2, GTI, PI, REC, NREC, and POP are normally distributed.

Table 1. Descriptive statistic.

	LNCO$_2$	LNGTI	LNNREC	LNPI	LNPOP	LNREC
Mean	0.533575	0.960359	1.829364	3.42743	6.11876	2.717955
Med	0.640506	0.965996	1.868094	3.485112	6.120149	2.664451
Max	0.819934	1.075912	2.126988	4.098828	6.15444	3.37328
Min	0.031709	0.808886	1.493179	2.562841	6.068364	2.089905
Std. Dev.	0.283756	0.075208	0.225783	0.510382	0.026513	0.423897
Skew	−0.40931	−0.40732	−0.14323	−0.17038	−0.24013	0.144333
Kurt	1.493327	2.032314	1.389685	1.582919	1.871102	1.602751
Jarq-Bera	3.920268	2.133407	3.566899	2.832308	2.006749	2.714178
Prob	0.14084	0.344141	0.168057	0.242645	0.36664	0.257409

Note: CO_2: CO_2 emissions, GTI: green technology innovation, REC: renewable energy consumption, NREC: non-renewable energy consumption, PI: personal income. POP: population. Source: Author Estimation.

The pragmatic results of pair-wise correlations in (Table 2) show significant associations between CO_2 emissions and REC, population and CO_2 emissions, CO_2 emissions, and PI. CO_2 emissions and POP, on the other hand, are found to be adversely associated with GTIs and NREC. In addition, REC, PI, and pop are positively connected. During the study period, there was a substantial relationship "between the variables" and a negligible link between "population and RE." in the Chinese region. The variables variance inflation factor (VIF) and threshold as 1/VIF are shown in Table 2. The singular value and Mean of VIF for the variables of interest is less than 5, indicating that multi-collinearity is not an issue. The variable's values are more than 0.10, indicating the variables are connected within an acceptable range.

Table 2. Estimations of correlation analysis.

	LNCO$_2$	LNGTI	LNNREC	LNPI	LNPOP	LNREC
LNCO$_2$	1					
LNGTI	−0.77401 ***	1				
LNNREC	−0.58173 ***	0.216973	1			
LNPI	0.38751 **	0.453051 ***	0.288723	1		
LNPOP	0.687239 ***	0.352844 **	0.489001 ***	0.494725 ***	1	
LNREC	0.986504 ***	0.75523 ***	0.987168 ***	0.398992 ***	0.21927	1
Variables			VIF			1/VIF
LNGTI			1.849523			0.024096
LNNREC			1.232772			0.048118
LNPI			1.384842			0.029397
LNPOP			1.599988			0.528927
LNREC			1.371023			0.00484
Means VIF			1.61734			

Note: Whereas: *** $p < 1\%$, ** $p < 5\%$.

The unit root test applies to the small data size. In the same way, as demonstrated by Phillip and Perron [67] and Dickey and Fuller [68], due to insufficient explanatory power, typical unit root tests might reject the null hypothesis issues. On the other hand, the ADF unit root reflects these problems through its better explanatory control and provides some stable pragmatic evidence about the existence of structural breaks. Table 3 shows unit root test results with structural breaks. CO_2 emissions, GTI, REC, NREC, POP, and PI, have all been discovered to have the unit root problem at a level. As previously indicated, reliable tests for unit roots in structural breakdowns may provide misleading results, particularly in time-series data. The ZA test, which takes into account one structural break as suggested by Zivot and Andrews [65]—ZA after this—solves this problem. Table 3 also includes the results of the ZA tests. Furthermore, ADF (Δ) and ZA (Δ) demonstrate variables are stationary at 1st difference.

Table 3. Unit-root test.

Variables	ADF (Level)	ADF (Δ)	ZA (Level)	Break Year	ZA (Δ)	Break Year
$LNCO_2$	−1.296433	−2.940861	−5.266215	2009 Q3	−8.095561	2000 Q2
LnGTI	−1.440102	−6.434796	−3.425299	2005 Q2	−7.523634	1995 Q1
LNNREC	−1.144383	−5.481820	−3.878664	2001 Q1	−6.997140	2015 Q2
LNPI	−0.872587	−3.577986	−4.410252	2002 Q2	−6.163395	2013 Q3
LNPOP	0.980725	−5.760702	−3.301945	2016 Q2	−6.079257	1993 Q1
LNREC	0.079889	−6.440344	−2.877119	2002 Q1	−7.492728	2002 Q4

The ADF and ZA test statistics.

Table 4 shows the results of the Bootstrapped ARDL Co-integration analysis. The F-test values and T-test show that ARDL rejected the H0 of Co-integration between the variables. We also reject the H0 because CO_2 emissions are a significant dependent variable. The Reciprocal F-test and T-test will be used on multiple lagged values of all variables to verify the presence of co-integration vectors in the Chinese CO_2 emission system. Moreover, distinctive CO_2 concentrations, GTIs, REC, NREC, POP, and PI, have a long-run association in China from 1990 to 2021. The value of R^2 is 0.967, indicating that all variables describe CO_2 emissions at the same time. In conclusion, the JB results demonstrate the existence of a normal residual distribution for the model.

Table 4. Co-integration based on ARDL.

Bootstraps ARDL Co-Integration Analysis						Diagnostic Tests			
Estimated Models	Lag Length Criteria	Break Year	FPSS	TDV	TIV	R2	Q-stat	LM(2)	JB
Model	1, 2, 2, 2, 2, 2	2007 Q2	7.750 ***	−2.932 *	7.946 ***	0.967	4.498	1.051	1.728

Model: CO_2t = f (GTI_t, $NREC_t$, RE_t, POP_t, PI_t). Nota bene: *** *p* 1%, and * *p* 10%.

The Akaike Information Criterion (AIC) was used to estimate the optimal lag time. The F-statistic is based on the bootstrap process's critical asymptotic bounds. The dependent variable TDV is the t-statistic, and the independent variable, the t-statistic, is TIV. LM measures the Langrage Multiplier test, and the approximation term for JB is the Jarq-B test. Table 5 depicts the long-run study findings, demonstrating that green technology innovation significantly and negatively influences CO_2 emissions.

The short-run empirical findings are shown in Table 6. We find that GTI considerably reduces CO_2 emissions. This will support the claim that increased advancement in green technology will cut carbon dioxide emissions in the short run. At a 1% level of relevance, renewable energy is negatively and strongly associated with CO_2 emissions. This demonstrates how REC helps to shift the typical energy pattern, reducing CO_2 emissions in the Chinese economy. PI and REC are negative and significant with CO_2 emission; this is typically the pattern of personal income and energy sources reducing CO_2 emission. However, NREC and POP are positively related to CO_2 emissions by 1%, implying that these are key factors in increasing CO_2 emissions. The ECMt-1 estimation value is (−0.497), which is negatively significant at 1% at the level. The model short-run has also confirmed diagnostic tests that show normality, autoregressive heteroscedasticity, serial correlation, and homoscedastic variance in the study data. The short-run parameters' stability is confirmed by CUSUM and CUSUMsq, showing that the short-run dimension model is objectively designed.

Table 5. Bootstrapped ARDL co-integration (long-run) analysis.

Variables	Co-Efficient	Std. Error	t-Statistic	Prob
$LNGTI_t$	−0.475344 ***	0.131852	−3.60513	0.0014
$LNNREC_t$	0.326949 **	0.32653	1.920033	0.0428
$LNPI_t$	−0.44764 ***	0.144665	−3.094331	0.0050
$LNPOP_t$	0.021231 ***	1.960909	4.600536	0.0001
$LNRE_t$	−0.261724 **	0.105181	−2.488328	0.0202
C	−54.38687 ***	11.86316	−4.584516	0.0001
R^2	0.995435			
Adj-R^2	0.994294			
Durbin-Watson	1.732422			
Stability analysis Test		F-Stat		P-V
X^2 Normal		0.35341		0.7064
X^2 Serial		0.87322		0.6037
X^2 Arch		0.76858		0.8362
X^2 Hetero		0.74889		0.2473
X^2 Reset		0.36013		0.2687
CUSUM		Stable		
CUSUMsq		Stable		

Note: *** $p < 1\%$, ** $p < 5\%$.

Table 6. Bootstrapped ARDL co-integration (short-run) analysis.

Variable	Co-Efficient	Std. Error	t-Statistic	Prob.
C	−61.21319 ***	10.6776	−5.73286	0.0000
$LNGTI_t$	−0.409602 ***	0.117934	−3.473129	0.0021
$LNNREC_t$	0.956586 ***	0.308773	3.098024	0.0051
$LNPI_t$	−0.502818 ***	0.128371	−3.9169	0.0007
$LNPOP_t$	10.09867 ***	1.76105	5.734459	0.0000
$LNRE_t$	−0.272036 ***	0.092345	−2.945855	0.0073
ECMt-1	−0.497867	0.066471	−7.48995	0.0000
R^2	0.993575			
Adj-R^2	0.992339			
Durbin-Watson	1.335798			
Stability analysis Test		F-Statistics		*p*-Value
X^2 Normal		3.508969		0.0744
X^2 Serial		0.353413		0.7064
X^2 Arch		0.24356		0.8362
X^2 Hetero		1.360131		0.2687
X^2 Reset		0.508969		0.8291
CUSUM		Stable		
CUSUMsq		Stable		

Note: *** $p < 1\%$.

Finally, the VECM Granger causality method is used to investigate a causal association between the study variables, and the results exist in Table 7. The importance of Granger causality in time series analysis literature cannot be overstated as it helps decide whether the time series is suitable in anticipating others. Table 7 shows that the F-statistics value for the first null hypothesis is significant at 5%, indicating that GTI Granger causality is positively unimportant. CO_2 is positively caused by NREC but not by Granger, whereas NREC is positively caused by CO_2. The PI-CO_2 relationship shows significant evidence that PI does not cause CO_2 and CO_2 causes PI, with an F-statistic of 10.2084. Furthermore, the study's alternate theory is supported by the fact that the population does not produce CO_2, and CO_2 causes POP. Finally, we discover that REC does not cause CO_2 granger and that CO_2 granger causes REC significantly by 1% at the level.

Table 7. Granger causality.

H0	F-Statistic	Prob.
$\longrightarrow$ LNGTI $LNCO_2$	1.06075	0.2547
$\longrightarrow$ $LNCO_2$ LNGIT	4.71613 **	0.0183
$\longrightarrow$ LNNREC $LNCO_2$	1.32948	0.2827
$\longrightarrow$ $LNCO_2$ LNNREC	10.7987 ***	0.0004
$\longrightarrow$ LNPI $LNCO_2$	0.05266	0.9488
$\longrightarrow$ $LNCO_2$ LNPI	10.2084 ***	0.0006
$\longrightarrow$ LNPOP $LNCO_2$	0.57778	0.5685
$\longrightarrow$ $LNCO_2$ LNPOP	6.61566 ***	0.0049
$\longrightarrow$ LNREC $LNCO_2$	0.27418	0.7625
$\longrightarrow$ $LNCO_2$ LNREC	5.5917 ***	0.0098

Note: *** $p < 1\%$, ** $p < 5\%$. Source: Author Estimations.

5. Discussion

The results of this study indicate that a 1% increase in green technology is associated with a 0.47% decrease in g CO_2 emission, indicating their inverse relationship. These results are related to those of Umar et al. [69] and Jordaan et al. [70]. The NREC and CO_2 emissions are substantial and positive, implying that NREC is a boon for increasing CO_2 emissions in the Chinese region. All else being equal, a 1% increase in the value of NREC increases CO_2 emissions by 0.33%. This confirms the positive result of increased CO_2 emissions from NREC. This pragmatic finding is consistent with Adamas and Acheampong [71]. Similarly, even at a 1% at level, REC is highly positively associated with CO_2 emissions. This suggests that personal income is beneficial for China's low CO_2 emissions. If everything else remains constant, a -0.45% reduction in CO_2 emissions is accounted for by a 1% increase in personal income. This pragmatic result is dependable on the findings of Khan et al. [72]. The association between POP and CO_2 emissions is significant statistically, implying that POP frequently plays a vital role in hastening CO_2 emissions, such as energy consumption. By holding all variables constant, a 1% increase in labor increases the CO_2 emissions by 0.021%. These results are supported by Yeh and Liao [73].

Renewable energy has a tangible and negative link with CO_2 emissions, showing that renewable energy is a boon for reducing CO_2 emissions in China. Keeping everything else unchanged, a 1% change in REC reduces CO_2 emissions by 0.26%. This validates the positive result for rising CO_2 emissions from renewable energy during the period. Taiwan's population growth rate has a substantial impact on carbon emissions. At 5%, the impact of per capita CO_2 emissions is significant. This would indicate that the Chinese economy had higher per capita CO_2 emissions. According to historical data, China's per capita wealth has expanded dramatically over the last few decades, resulting in rising CO_2 emissions. The long-term explained variation in CO_2 emissions through all variables is 0.994%. Altogether, autocorrelation is identified using DW statistics and detected as no auto-correlation in the model data. The model approved all stability tests and had no problems in normality, serial Co-relation, heteroscedasticity, autoregressive conditional heteroscedasticity, or description. The Parameter constancy can be observed using CUSUM and CUSUMsq, which reflect long-run parameter stability. In a nutshell, all the hypotheses of this study are accepted. Table 8 shows the summary of hypothesis results:

Table 8. Hypotheses Summary.

	Hypothesis	Results
H1	Green technology innovation (GTI) is important in determining China's CO_2 emissions.	Supported
H2	Non-renewable energy consumption (NREC) is essential in determining China's CO_2 emissions.	Supported
H3a	Renewable energy consumption is important in deciding China's CO_2 emissions. In addition, the following assumptions were investigated in our study.	Supported
H3b	Per capita income plays a key effect in influencing China's CO_2 emissions	Supported
H3c	China's population plays a crucial effect in determining CO_2 emissions.	Supported

6. Conclusions

China begins to make progress toward its carbon neutrality objective following the Paris Climate Conference (Conference of the Paris COP: 21). The goal of this research was to examine the association between CO_2 emissions, GTI, NREC, REC, POP, and PI in the Chinese economy from 1990 to 2021. Co-integration can be seen in GTIs, NREC, REC, POP, PI, and CO_2 emissions. GTI, REC, and PI negatively influence CO_2 emissions, but NREC and POP have long-term positive impacts. Similarly, in the short run, REC, GTIs, and PI all negatively and significantly impact CO_2 emissions, while the remaining drivers have a positive impact.

The pragmatic results of the causality reveal unidirectional causation between GTI and CO_2 emissions, NREC and CO_2 emissions, REC and CO_2 emissions, population and CO_2 emissions, and PI and CO_2 emissions. GTI, REC, and PI negatively influence CO_2 emissions in terms of policy implications. This would mean that more policies should be devised to stimulate increased GTIs, PI, and the usage of REC while achieving long-term environmental development. Our findings show a link between GTI, PI, REC, and CO_2 emissions. Improved economic trends towards more GTIs advancements, REC, and PI will directly impact natural carbon emissions in such situations.

Policy Recommendation

The Chinese government must develop policies encouraging GTIs, REC, and the CO_2 emission triangle. In addition, our empirical data show that NREC, POP, and CO_2 levels are all rising. To get positive results, the local government should develop encouragement programs to promote REC sources. Appropriate measures are also required to limit the growing population expansion hazard, leading to increased carbon emissions. Furthermore, such empirical research has demonstrated that the government and policymakers confront extra challenges in implementing proper macroeconomic changes to address the direct association between REC, POP, and CO_2 emissions. Based on this distressing reality, our research highlights the significance of designing and implementing serious policies to control the direct and significant effect of elements more strategically such as REC, POP, and PI on CO_2 emissions.

Finally, this study has several drawbacks. The present study looks at tendencies in carbon neutrality and the role of GTIs and RECs in the Chinese economy. This means that the rest of the Asian countries are not considered in the analysis. Second, the economic expansion role in the influence of environmental quality is generally recognized in the present literature, according to the theoretical assumption known as the Environmental Kuznets Curve (EKC). However, the existing analysis needs to be refined to analyze this trend in CO_2 emissions on the EKC theoretical basis. Future studies should include these barriers to improve race and policy implications.

Author Contributions: Conceptualization, I.A. and S.L.; methodology, M.M. and M.S.; software, M.S.; validation, I.A., M.S. and M.M.; formal analysis, S.L.; investigation, M.S.; resources, S.L.; data curation, M.M.; writing—original draft preparation, M.S.; writing—review and editing, I.A.; visualization, M.M.; supervision, S.L.; project administration, I.A.; funding acquisition, S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been funded by Zhihui Yunan Province with Funding number 202203AM140003.

Data Availability Statement: REC and NREC data were obtained from an Energy Information Administration (EIA) databank (see Table A1).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

GTI	Green technology innovation
NREC	Non-Renewable Energy Consumption
REC	Renewable Energy Capital
POP	Population
PI	Per capita Income
CO_2	Carbon emission
EKC	Environmental Kuznets Curve
ARDL	Autoregressive Distributed Lag
BARDL	Bootstrap Autoregressive Distributed Lag
EIA	Energy Information Administration

Appendix A

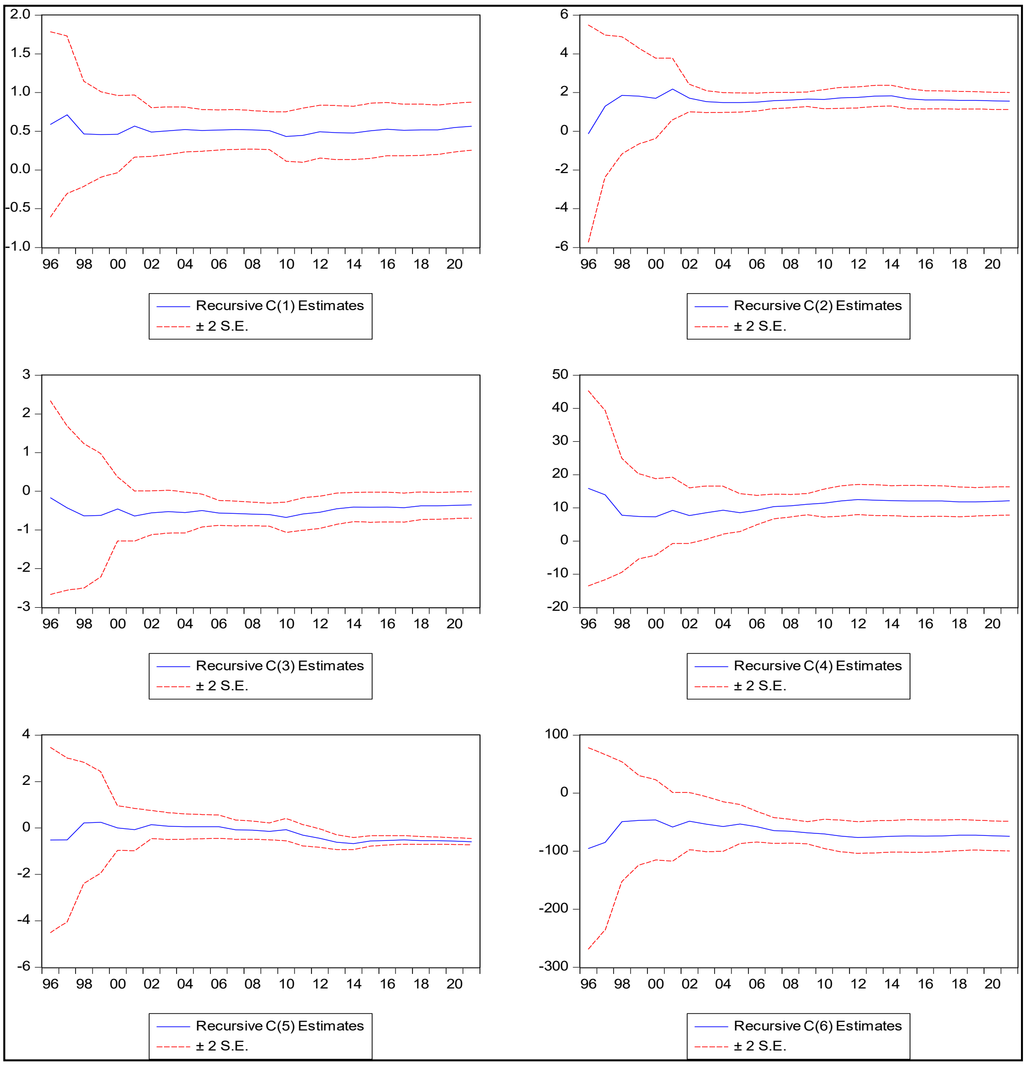

Figure A1. Recursive estimation of all variables.

Appendix B

Table A1. Data source.

Variables		Data Source
GTI	Green technology innovation	OECD
NREC	Non-Renewable Energy Consumption	EIA
REC	Renewable Energy Capital	EIA
POP	Population	World Bank Indicator
PI	Per capita Income	World Bank Indicator
CO_2	Carbon emission	World Bank Indicator

References

1. Cheng, Y.; Yao, X. Carbon intensity reduction assessment of renewable energy technology innovation in China: A panel data model with cross-section dependence and slope heterogeneity. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110157. [CrossRef]
2. Mahjabeen; Shah, S.Z.A.; Chughtai, S.; Simonetti, B. Renewable energy, institutional stability, environment and economic growth nexus of D-8 countries. *Energy Strateg. Rev.* **2020**, *29*, 100484. [CrossRef]
3. Su, M.R.; Chen, B.; Xing, T.; Chen, C.; Yang, Z.F. Development of low-carbon city in China: Where will it go? *Procedia Environ. Sci.* **2012**, *13*, 1143–1148. [CrossRef]
4. Abreu, J.F.; Alves, M.G.; Gulamhussen, M.A. State interventions to rescue banks during the global financial crisis. *Int. Rev. Econ. Financ.* **2019**, *62*, 213–229. [CrossRef]
5. Apergis, N.; Payne, J.E. CO_2 emissions, energy usage, and output in Central America. *Energy Policy* **2009**, *37*, 3282–3286. [CrossRef]
6. Feng, K.; Hubacek, K.; Guan, D. Lifestyles, technology and CO_2 emissions in China: A regional comparative analysis. *Ecol. Econ.* **2009**, *69*, 145–154. [CrossRef]
7. Lin, S.; Sun, J.; Marinova, D.; Zhao, D. Evaluation of the green technology innovation efficiency of China's manufacturing industries: DEA window analysis with ideal window width. *Technol. Anal. Strateg. Manag.* **2018**, *30*, 1166–1181. [CrossRef]
8. Aswathanarayana, U.; Harikrishnan, T.; Kadher-Mohien, T.S. *Green Energy*; CRC Press: Boca Raton, FL, USA, 2010; ISBN 978-0-20384-146-4.
9. Wu, Y.; Sun, C. A Research on the Green Technology Innovation of the Cemetery Industry. In Proceedings of the 2008 International Seminar on Business and Information Management, Wuhan, China, 19 December 2008; pp. 147–150.
10. Verhoosel, G. Beyond the unsustainable rhetoric of sustainable development: Transferring environmentally sound technologies. *Geo. Int, Envtl. L. Rev.* **1998**, *2*, 9.
11. Wang, R.; Mirza, N.; Vasbieva, D.G.; Abbas, Q.; Xiong, D. The nexus of carbon emissions, financial development, renewable energy consumption, and technological innovation: What should be the priorities in light of COP 21 Agreements? *J. Environ. Manag.* **2020**, *271*, 111027. [CrossRef]
12. Guo, H.; Yang, Z.; Huang, R.; Guo, A. The digitalization and public crisis responses of small and medium enterprises: Implications from a COVID-19 survey. *Front. Bus. Res. China* **2020**, *14*, 19. [CrossRef]
13. Braun, E.; Wield, D. Regulation as a means for the social control of technology. *Technol. Anal. Strateg. Manag.* **1994**, *6*, 259–272. [CrossRef]
14. Hasan, M.A. Does globalization accelerate economic growth? South Asian experience using panel data. *J. Econ. Struct.* **2019**, *8*, 26. [CrossRef]
15. Wu, H.; Li, Y.; Hao, Y.; Ren, S.; Zhang, P. Environmental decentralization, local government competition, and regional green development: Evidence from China. *Sci. Total Environ.* **2020**, *708*, 135085. [CrossRef] [PubMed]
16. Luo, L.; Liang, S. Study on the efficiency and regional disparity of green technology innovation in China's industrial companies. *Chin. J. Popul. Resour. Environ.* **2016**, *14*, 262–270. [CrossRef]
17. Jia, J.; Zhang, W. The path dependency of green technology innovation and environmental regulation analysis. *Sci. Sci. Manag. Sci. Technol.* **2014**, *5*, 44–52.
18. Li, C.; Liu, X.; Bai, X.; Umar, M. Financial Development and Environmental Regulations: The Two Pillars of Green Transformation in China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 9242. [CrossRef]
19. Zhong, Z.; Meng, F.; Zhu, Y.; Wang, G. Research on the Technological Innovation Efficiency of China's Strategic Emerging Industries Based on SBM: NDEA Model and Big Data. *Math. Probl. Eng.* **2020**, *2020*, 7069191. [CrossRef]
20. Umar, M.; Su, C.-W.; Rizvi, S.K.A.; Lobon, O.-R. Driven by fundamentals or exploded by emotions: Detecting bubbles in oil prices. *Energy* **2021**, *231*, 120873. [CrossRef]
21. Tareen, W.U.K.; Anjum, Z.; Yasin, N.; Siddiqui, L.; Farhat, I.; Malik, S.A.; Mekhilef, S.; Seyedmahmoudian, M.; Horan, B.; Darwish, M.; et al. The Prospective Non-Conventional Alternate and Renewable Energy Sources in Pakistan—A Focus on Biomass Energy for Power Generation, Transportation, and Industrial Fuel. *Energies* **2018**, *11*, 2431. [CrossRef]

22. Gielen, D.; Boshell, F.; Saygin, D.; Bazilian, M.D.; Wagner, N.; Gorini, R. The role of renewable energy in the global energy transformation. *Energy Strateg. Rev.* **2019**, *24*, 38–50. [CrossRef]
23. Mohsin, M.; Naseem, S.; Sarfraz, M.; Zia-Ur-Rehman, M.; Baig, S.A. Does energy use and economic growth allow for environmental sustainability? An empirical analysis of Pakistan. *Environ. Sci. Pollut. Res.* **2022**, *29*, 52873–52884. [CrossRef] [PubMed]
24. Irandoust, M. The renewable energy-growth nexus with carbon emissions and technological innovation: Evidence from the Nordic countries. *Ecol. Indic.* **2016**, *69*, 118–125. [CrossRef]
25. Bilgili, F.; Koçak, E.; Bulut, Ü. The dynamic impact of renewable energy consumption on CO_2 emissions: A revisited Environmental Kuznets Curve approach. *Renew. Sustain. Energy Rev.* **2016**, *54*, 838–845. [CrossRef]
26. Heal, G.M. Reflections—The Economics of Renewable Energy in the United States. *Rev. Environ. Econ. Policy* **2010**, *4*, 139–154. [CrossRef]
27. Köne, A.Ç.; Büke, T. Factor analysis of projected carbon dioxide emissions according to the IPCC based sustainable emission scenario in Turkey. *Renew. Energy* **2019**, *133*, 914–918. [CrossRef]
28. Mo, J. *How Is Students' Motivation Related to Their Performance and Anxiety?* OECD: Paris, France, 2019.
29. Xie, B.; Jones, P.; Dwivedi, R.; Bao, L.; Liang, R. Evaluation, comparison, and unique features of ecological security in southwest China: A case study of Yunnan Province. *Ecol. Indic.* **2023**, *153*, 110453. [CrossRef]
30. Dwivedi, P.; Dwivedi, R.; Yoshikuni, A.C.; Xie, B.; Naik, B. Role of Digitalization in Business Process to Reduce Manpower: A Case of Human Resource Management Process. *Int. J. Econ. Bus. Adm.* **2023**, *11*, 66–76. [CrossRef]
31. Ali, W.; Abdullah, A.; Azam, M. The Dynamic Linkage between Technological Innovation and carbon dioxide emissions in Malaysia: An Autoregressive Distributed Lagged Bound Approach. *Int. J. Energy Econ. Policy* **2016**, *6*, 389–400.
32. Ganda, F. The impact of innovation and technology investments on carbon emissions in selected organisation for economic Co-operation and development countries. *J. Clean. Prod.* **2019**, *217*, 469–483. [CrossRef]
33. Bai, C.; Feng, C.; Yan, H.; Yi, X.; Chen, Z.; Wei, W. Will income inequality influence the abatement effect of renewable energy technological innovation on carbon dioxide emissions? *J. Environ. Manag.* **2020**, *264*, 110482. [CrossRef]
34. Töbelmann, D.; Wendler, T. The impact of environmental innovation on carbon dioxide emissions. *J. Clean. Prod.* **2020**, *244*, 118787. [CrossRef]
35. Aggeri, F. Environmental policies and innovation: A knowledge-based perspective on cooperative approaches. *Res. Policy* **1999**, *28*, 699–717. [CrossRef]
36. Zhao, X.; Yin, H.; Zhao, Y. Impact of environmental regulations on the efficiency and CO_2 emissions of power plants in China. *Appl. Energy* **2015**, *149*, 238–247. [CrossRef]
37. Miao, C.; Fang, D.; Sun, L.; Luo, Q. Natural resources utilization efficiency under the influence of green technological innovation. *Resour. Conserv. Recycl.* **2017**, *126*, 153–161. [CrossRef]
38. Godil, D.I.; Yu, Z.; Sharif, A.; Usman, R.; Khan, S.A.R. Investigate the role of technology innovation and renewable energy in reducing transport sector CO_2 emission in China: A path toward sustainable development. *Sustain. Dev.* **2021**, *29*, 694–707. [CrossRef]
39. Ki-Hoon Lee, B.M. Green R&D for eco-innovation and its impact on carbon emissions and firm performance. *J. Clean. Prod.* **2015**, *108*, 534–542.
40. Paramati, S.R.; Sinha, A.; Dogan, E. The significance of renewable energy use for economic output and environmental protection: Evidence from the Next 11 developing economies. *Environ. Sci. Pollut. Res.* **2017**, *24*, 13546–13560. [CrossRef]
41. Mohsin, M.; Kamran, H.W.; Atif Nawaz, M.; Sajjad Hussain, M.; Dahri, A.S. Assessing the impact of transition from nonrenewable to renewable energy consumption on economic growth-environmental nexus from developing Asian economies. *J. Environ. Manag.* **2021**, *284*, 111999. [CrossRef]
42. Ulubeyli, S.; Kazanci, O. Holistic sustainability assessment of green building industry in Turkey. *J. Clean. Prod.* **2018**, *202*, 197–212. [CrossRef]
43. Saboori, B.; Sulaiman, J. Environmental degradation, economic growth and energy consumption: Evidence of the environmental Kuznets curve in Malaysia. *Energy Policy* **2013**, *60*, 892–905. [CrossRef]
44. Rehman, M.U.; Rashid, M. Energy consumption to environmental degradation, the growth appetite in SAARC nations. *Renew. Energy* **2017**, *111*, 284–294. [CrossRef]
45. Sharif, A.; Ali Raza, S. Dynamic Relationship between Urbanization, Energy Consumption and Environmental Degradation in Pakistan: Evidence from Structure Break Testing. *J. Manag. Sci.* **2016**, *3*, 3–23. [CrossRef]
46. Liu, G.; Lucas, M.; Shen, L. Rural household energy consumption and its impacts on eco-environment in Tibet: Taking Taktse county as an example. *Renew. Sustain. Energy Rev.* **2008**, *12*, 1890–1908. [CrossRef]
47. Sarkodie, S.A.; Adams, S. Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa. *Sci. Total Environ.* **2018**, *643*, 1590–1601. [CrossRef] [PubMed]
48. Hu, H.; Zhang, X.-H.; Lin, L.-L. The interactions between China's economic growth, energy production and consumption and the related air emissions during 2000–2011. *Ecol. Indic.* **2014**, *46*, 38–51. [CrossRef]
49. Wang, S.; Wang, S. Impacts of wind energy on environment: A review. *Renew. Sustain. Energy Rev.* **2015**, *49*, 437–443. [CrossRef]
50. Panwar, N.L.; Kaushik, S.C.; Kothari, S. Role of renewable energy sources in environmental protection: A review. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1513–1524. [CrossRef]

51. Tsoutsos, T.; Frantzeskaki, N.; Gekas, V. Environmental impacts from the solar energy technologies. *Energy Policy* **2005**, *33*, 289–296. [CrossRef]
52. Sharif, A.; Baris-Tuzemen, O.; Uzuner, G.; Ozturk, I.; Sinha, A. Revisiting the role of renewable and non-renewable energy consumption on Turkey's ecological footprint: Evidence from Quantile ARDL approach. *Sustain. Cities Soc.* **2020**, *57*, 102138. [CrossRef]
53. Kalmaz, D.B.; Kirikkaleli, D. Modeling CO_2 emissions in an emerging market: Empirical finding from ARDL-based bounds and wavelet coherence approaches. *Environ. Sci. Pollut. Res.* **2019**, *26*, 5210–5220. [CrossRef]
54. Sharif, A.; Mishra, S.; Sinha, A.; Jiao, Z.; Shahbaz, M.; Afshan, S. The renewable energy consumption-environmental degradation nexus in Top-10 polluted countries: Fresh insights from quantile-on-quantile regression approach. *Renew. Energy* **2020**, *150*, 670–690. [CrossRef]
55. Alola, A.A.; Kirikkaleli, D. The nexus of environmental quality with renewable consumption, immigration, and healthcare in the US: Wavelet and gradual-shift causality approaches. *Environ. Sci. Pollut. Res.* **2019**, *26*, 35208–35217. [CrossRef] [PubMed]
56. York, R.; Rosa, E.A.; Dietz, T. Bridging Environmental Science with Environmental Policy: Plasticity of Population, Affluence, and Technology. *Soc. Sci. Q.* **2002**, *83*, 18–34. [CrossRef]
57. Dietz, T.; Rosa, E. Rethinking the Environmental Impacts of Population, Affluence and Technology. *Hum. Ecol. Rev.* **1994**, *1*, 277–300.
58. Alam, I.; Mohsin, M.; Latif, K.; Zia-ur-Rehman, M. The Impact of Macroeconomic Factors on Stock Market: An Evidence from China and Pakistan. *NICE Res. J.* **2020**, *13*, 1–26. [CrossRef]
59. McNown, R.; Sam, C.Y.; Goh, S.K. Bootstrapping the autoregressive distributed lag test for cointegration. *Appl. Econ.* **2018**, *50*, 1509–1521. [CrossRef]
60. Sohag, K.; Taşkın, F.D.; Malik, M.N. Green economic growth, cleaner energy and militarization: Evidence from Turkey. *Resour. Policy* **2019**, *63*, 101407. [CrossRef]
61. Pesaran, M.H.; Shin, Y.; Smith, R.J. Bounds testing approaches to the analysis of level relationships. *J. Appl. Econom.* **2001**, *16*, 289–326. [CrossRef]
62. Perron, P. Testing for a Unit Root in a Time Series with a Changing Mean. *J. Bus. Econ. Stat.* **1990**, *8*, 153. [CrossRef]
63. Goh, S.K.; Sam, C.Y.; McNown, R. Re-examining foreign direct investment, exports, and economic growth in asian economies using a bootstrap ARDL test for cointegration. *J. Asian Econ.* **2017**, *51*, 12–22. [CrossRef]
64. Lannelongue, G.; Gonzalez-Benito, J.; Quiroz, I. Environmental management and labour productivity: The moderating role of capital intensity. *J. Environ. Manag.* **2017**, *190*, 158–169. [CrossRef]
65. Zivot, E.; Andrews, D.W.K. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *J. Bus. Econ. Stat.* **2002**, *2*, 25–44. [CrossRef]
66. Mohsin, M.; Naseem, S.; Sarfraz, M.; Ivascu, L.; Albasher, G. COVID-19 and greenhouse gas emission mitigation: Modeling the impact on environmental sustainability and policies. *Front. Environ. Sci.* **2021**, *9*, 764294. [CrossRef]
67. Phillips, P.C.B.; Perron, P. Testing for a Unit Root in Time Series Regression. *Biometrika* **1988**, *75*, 335–346. [CrossRef]
68. Dickey, D.A.; Fuller, W.A. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* **1981**, *49*, 1057. [CrossRef]
69. Umar, M.; Ji, X.; Kirikkaleli, D.; Shahbaz, M.; Zhou, X. Environmental cost of natural resources utilization and economic growth: Can China shift some burden through globalization for sustainable development? *Sustain. Dev.* **2020**, *28*, 1678–1688. [CrossRef]
70. Jordaan, S.M.; Romo-Rabago, E.; McLeary, R.; Reidy, L.; Nazari, J.; Herremans, I.M. The role of energy technology innovation in reducing greenhouse gas emissions: A case study of Canada. *Renew. Sustain. Energy Rev.* **2017**, *78*, 1397–1409. [CrossRef]
71. Silvestri, R.; Adamashvili, N.; Fiore, M.; Galati, A. How blockchain technology generates a trust-based competitive advantage in the wine industry: A resource based view perspective. *Eur. Bus. Rev.* **2023**, *35*, 713–736. [CrossRef]
72. Khan, H.; Khan, I.; Binh, T.T. The heterogeneity of renewable energy consumption, carbon emission and financial development in the globe: A panel quantile regression approach. *Energy Rep.* **2020**, *6*, 859–867. [CrossRef]
73. Yeh, J.-C.; Liao, C.-H. Impact of population and economic growth on carbon emissions in Taiwan using an analytic tool STIRPAT. *Sustain. Environ. Res.* **2017**, *27*, 41–48. [CrossRef]