energies

Article

Dynamic Linkages among Carbon Emissions, Artificial Intelligence, Economic Policy Uncertainty, and Renewable Energy Consumption: Evidence from East Asia and Pacific Countries

Salman Ali Shah [1], Xingyi Ye [1,*], Bo Wang [2] and Xiangjun Wu [1]

[1] Academy of China-ASEAN International and Regional Studies, Guangxi Minzu University, Nanning 530006, China; salmanali.eco@gmail.com (S.A.S.); wxjsuede@163.com (X.W.)
[2] School of Politics and Public Administration, Guangxi Minzu University, Nanning 530006, China; 16677119006@163.com
* Correspondence: yexingyi@vip.163.com or 20180004@gxmzu.edu.cn

Abstract: A growing number of countries are concerned about the reliability of environmental indicators; as a result, there is a pressing need to find ways to improve ecological welfare on a global scale. This study investigates the dynamic linkages among CO_2 emissions, AI, economic policy uncertainty (EPU), and renewable energy consumption. To analyze these relationships empirically, this study used panel data for East Asian and Pacific countries from 2000 to 2023. This study used fully modified ordinary least squares (FMOLSs), dynamic ordinary least squares (DOLSs), Hausman fixed effects (FEs) and random effects (REs), the generalized method of moments (GMM), and variance decomposition tests. This study's results show that AI has a positive relationship with CO_2 emissions in terms of the benchmark regression, while it shows minimal impact on CO_2 emissions according to the variance decomposition test. Similarly, economic policy uncertainty shows a strong positive relationship with CO_2 emissions through benchmark regression FEs and REs, GMM, and the variance decomposition test. An increase in EPU will positively affect CO_2 emissions. Renewable energy consumption has a strong negative impact on CO_2 emissions in East Asian and Pacific countries. These findings reveal that a unit increase in renewable energy consumption will decrease CO_2 emissions. Based on the results of this study, it is suggested that policy certainty and an upsurge in renewable energy consumption are essential for environmental upgrading. In contrast, adopting AI has no robust effect on ecological degradation (CO_2 emissions). East Asian and Pacific countries need to focus on the adoption of renewables, as well as the control of economic policy uncertainty. While AI in East Asian and Pacific countries is still in the initial stage of adoption, policy formation is essential to overcome the possible carbon footprint of AI in the short term.

Keywords: CO_2 emissions; AI; economic policy uncertainty; renewable energy consumption; variance decomposition

Citation: Shah, S.A.; Ye, X.; Wang, B.; Wu, X. Dynamic Linkages among Carbon Emissions, Artificial Intelligence, Economic Policy Uncertainty, and Renewable Energy Consumption: Evidence from East Asia and Pacific Countries. *Energies* **2024**, *17*, 4011. https://doi.org/10.3390/en17164011

Academic Editor: Peter V. Schaeffer

Received: 13 May 2024
Revised: 29 July 2024
Accepted: 1 August 2024
Published: 13 August 2024

1. Introduction

Climate change-related devastation is still progressing, even though the economy has slowed down because of the COVID-19 pandemic and its aftermath. Emissions temporarily decreased as a result of a reduction in human activity during the pandemic. Around 95% of pollution emissions come from greenhouse gases that are generated by humans, which condense in the atmosphere [1] As sustainable development aims to meet "the needs of the present without comprising the ability of future generations to meet their needs", it is a critical global concern. According to the 17 sustainable development goals (SDGs) set out by the United Nations (UN) as part of the 2030 agenda, a better world must be created. The primary focus of all 17 objectives is prosperity and well-being, with 169 targets and subgoals set out to achieve these objectives. The UN SDGs demand significant action in all spheres of life, including all possible applications of technological innovation [2]. The other objectives cannot be attained without industry, innovation, and infrastructure, which are emphasized in SDG 9. Similarly, the Paris Agreement clarifies how crucial cutting-edge climate technology is to a sustainable future. A solution to climate change that might aid in promoting economic growth and easing environmental burdens is to accelerate and encourage innovation; however, it is difficult to achieve sustainable development in the early stages of growth and development. When meeting basic human needs is prioritized over the environment, there appears to be a clear tradeoff between economic development and environmental security.

Ref. [3] explained the fourth industrial revolution, in which technological dependence is crucial. Still, it also requires a dual shift to digital and green practices. This dual shift will impact every facet of people's lives. For instance, to promote growth and development, industries with low energy efficiency must increasingly rely on green energy and energy-efficient technologies, as detailed by [4]. Given the essential roles that green growth, connectivity, infrastructure, digitalization, and the Internet of Things play in the twin transition, this shift is key to decarbonizing the economy. In recent years, researchers have advanced the research in this field, adding a new Industry 5.0 phase centered on sustainability, the green economy, and the human–technology partnership [5]. One study explored the concept of Industry 5.0, which connects environmentally friendly practices and sustainability. According to the authors, collaboration between many economic sectors should be improved for the greater good [6].

Ref. [7] stated that green trade and investment are essential to supporting successful energy transitions and the implementation of nationally determined contributions (NDCs) in developing countries. The increasing need for energy has created a problematic tradeoff between environmental security and economic development. The pursuit of carbon neutrality exacerbates environmental corrosion and climate change. Greenhouse gas emissions (GHGs) and energy preservation are only two of the difficulties posed by this exceptional situation. Therefore, most recent energy- and environment-related studies aim to examine the connection between CO_2 emissions, environmental quality and advanced technology.

Since the Industrial Revolution, human activity has increased the quantity of greenhouse gases in the atmosphere and has caused significant global warming. Computer technology has been steadily improving since the 1990s, and numerous new economic models, including the digital economy, have been made possible by advances in artificial intelligence, blockchain technology, and 5G technology. In a digital economy, massive amounts of data are created, selected, filtered, stored, and used in a way that quickly and optimally allocates and regenerates resources, leading to high-quality economic development [6].

The current study adds fresh information that bridges separate streams of thought in the existing literature. In particular, CO_2 emissions, AI, EPU, and RENE are all investigated. As noted by [8], enhancing domestic energy-saving and emissions-reducing technologies depends on highly trained human resources. Developed countries with high levels of human capital are more likely to create cutting-edge technology, as detailed by [8].

A weak economy caused by EPU encourages companies to use more conventional, polluting, and less-expensive energy sources for production, such as coal and oil, which increases CO_2 emissions. Ref. [9] used U.S. sector data to conduct a new parametric test involving Granger causality, which was used to investigate the effect of EPU on CO_2 emissions; they determined the Granger causality between the two variables. In their study, ref. Ref. [10] used a bootstrap panel Granger causality test to examine the causative connection between EPU and both energy consumption and CO_2 emissions in the G7 countries. They stated that EPU had negative impacts on reducing emissions and conserving energy. Furthermore, ref. [11] reported strong correlations among geopolitical risk, economic policy uncertainty, energy consumption, economic growth, and CO_2 emissions in the long term, based on data from nations that are wealthy in resources yet prone to crises. These results show that higher EPU harms carbon abatement. This observation aligns with the outcome reported by [12]. Meanwhile, ref. [13] concluded that EPU reduces China's CO_2 emissions economically. Ref. [14] proposed that the degree of economic policy uncertainty in China's provinces substantially affects the carbon emission intensity of manufacturing enterprises. The second research stream indicates that EPU has a mitigating effect on CO_2 emissions.

According to the economic growth model proposed in Solow's foundational 1956 book, technological advancement comes from outside the economy. Ref. [15] created a growth model to supplement natural technical progress. Romer's model states that creating new goods through research and development by profit-maximizing corporate firms drives technological evolution. Various ideas and metrics have been used to assess the effects of globalization and technological advancements. Ref. [16] stated that technology is the repeatable use of scientific knowledge to achieve concrete goals. Finding knowledge outside of a company and incorporating it into the open innovation framework is one tactic that can lead to increased success. It may be possible to reduce barriers to the circular economy through open innovation. At the same time, we need to improve our understanding of how these fields may collaborate or how open innovation can contribute to developing a more sustainable economy. As noted previously, studies benefit from adopting multiple methodologies and ways of studying these issues. Nevertheless, more research is needed that investigates the connections among CO_2 emissions, cutting-edge (AI) technological adaptation, economic policy uncertainty, and renewable energy consumption in East Asian and Pacific countries. The literature indicates that there are relatively few studies on the effects of AI on the intensity of pollution emissions, suggesting that studies need to discuss the specific mechanisms and heterogeneity in AI's impact on pollution emission intensity. With its capacity for deep learning, AI can be rapidly and broadly applied across various economic and social fields [17]. This capability can alter traditional production models, unlock economic growth potential, promote industrial structure upgrades, produce systemic effects on the economic system, and create new opportunities to overcome the bottleneck in emissions reduction.

This study investigates the extent of AI's impact on CO_2 emission intensity and its mechanism of action by conducting a theoretical analysis and empirical tests. The significance and novelty of this article are as follows. First, this study uses East Asia and the Pacific as a case study to examine the impact of AI on carbon emissions intensity, based on the rapid growth of the intelligent market and the demand for green transformation. This serves as a model for developing green economies in other nations. Second, based on the fundamental properties of AI, this study provides an economic framework for analyzing the effects of artificial intelligence on CO_2 emissions. Third, this study improves the mechanism underlying the effect of economic policy uncertainty (EPU) on CO_2 emissions in the selected sample of countries. As noted in earlier studies, higher levels of EPU affect various macroeconomic indicators, including innovations, financial development, capital investment at the company level, the tourism sector, economic growth, and working capital and profits [3]. By analyzing the correlations between the two, this study concludes that renewable energy is the best method to combat environmental deterioration and increasing CO_2 emissions.

The rest of this paper is structured as follows. Section 2 provides an overview of the existing literature and a detailed study of the relevant theoretical concepts. Sections 3 and 4 describes the data sources and the specific methodologies employed in this study. Section 5, represent the empirical results and discussion. Section 6 concludes the results of this study.

2. Literature Review and Hypothesis Development

2.1. AI Technology and CO_2 Emissions

The connection between new technologies and increases in carbon emissions has been the subject of many academic studies. Ref. [18] examined how patent technology affects pollution levels. To shed further light on this association, the authors applied the cluster method to panel data from many provinces in China; their study determined the importance of technical progress in reducing CO_2 emissions. It was also determined that Eastern China is more likely to embrace environmental innovations and technology than other parts of the country. Across OECD member countries, adopting RENE regulations has a positive effect on the development of environmentally sustainable technology, which is in line with the findings of [19]. The authors also point out that enabling competition that may favor poor green solutions is counterproductive and that passing RENE laws effectively improves environmental standards. Likewise, ref. [20] examined the relationship between R&D spending and carbon emissions in a panel of Mediterranean economies during the period 1990–2016, using the generalized method of moments (GMM) empirical technique. The data analysis showed a negative correlation between R&D spending and greenhouse gas output. The analysis indicated that research and development spending appeared to have a unidirectional causal relationship with CO_2. The study's results provided strong evidence for the claim that promoting energy-efficient technology might significantly aid in reducing environmental damage.

According to [21], technological improvement is the primary means to decrease CO_2 emissions. Improvements in efficiency and scale expansion had a "double-edged sword effect". Ref. [22] found that technical advancement had an unpredictable effect on pollutant emissions.

Technological advancements reduce environmental pollution by increasing the industrial sector's efficiency in using multiple productive resources and lowering energy consumption per output unit [23]. The counterargument is that technological progress might cause production scales to rise, leading to more significant pollution and negating the benefits of higher efficiency in reducing emissions [24]. Emerging technologies, such as digitalization and AI, are thriving in China's developing economy, which is presently approaching the era of Industry 4.0. An emerging area of study is the possibility that these technologies might lessen the amount of pollution released into the atmosphere.

According to [24], the development of the digital economy has an "industrial pollution reduction effect", with the application of digital technology reducing industrial pollution emissions without causing yield loss. Ref. [25] concluded that the Internet reduced environmental pollution in the studied region and surrounding areas. Their model test of mediating effects demonstrated that encouraging industrial upgrading was the primary route through which the Internet affects environmental pollution. Using heavy metal enterprises as an example, ref. [26] proposed that the digital transformation of enterprises can achieve pollution reduction. However, under the agglomeration effect, there was a U-curve relationship between the digital transformation of enterprises and pollution reduction, with the final effect constrained by external scale. [23] examined the digital transformation of enterprises at the micro level and demonstrated that the use of digital equipment triggered economic scale expansion, leading to increased energy consumption. Simultaneously, the resulting technological and structural changes improved production efficiency and decreased energy consumption per output unit, significantly reducing pollution emissions. Ref. [27] showed that AI technologies had the potential to revolutionize several climate-friendly initiatives, such as the detection of greenhouse gas (GHG) leakage from pipelines, the monitoring of deforestation, and the invention of new materials with lower carbon footprints. However, statistics showing the environmental impact of AI are few or non-existent. AI businesses, such as OpenAI, should enhance their transparency regarding the expenses associated with system development, deep learning algorithm processing, and the training of their large language models (LLMs). It is critically important that complete transparency be afforded a higher priority as various nations tackle the task of AI regulation, especially in relation to the carbon emissions linked to the business.

By next year, the vast number of internet-connected devices might account for as much as 3.5% of worldwide carbon emissions. Computers and servers at data centers would quickly overheat if not for the constant, heavy usage of air conditioners, which contribute significantly to the overall energy consumption of these facilities. The AI industry significantly relies on data centers. If its usage and distribution continue to grow, it will inevitably result in increased carbon emissions from data centers in the coming years.

Hypothesis 1: *AI leads to an increase in CO_2 in East Asia and the Pacific.*

2.2. Economic Policy Uncertainty and CO_2

Ref. [28] found both an overestimation and an underestimation of the implications of economic policy uncertainty for environmental policymaking. Ref. [29] assessed two strategies to provide a roadmap for Japan to achieve its challenging ecological and energy-related objectives. Their study's conclusions indicated that, while air travel had a short-term effect, carbon dioxide emissions had a long-term relationship with GDP growth, renewable energy, and the economic complexity index.

It is assumed that uncertainty in economic policy significantly impacts the financial policies, investment plans, and consumer purchasing power of firms. According to [30], monetary policy uncertainty also has a nonlinear effect on inflation expectations and economic growth. These results suggest that it would be worthwhile to estimate the impact of EPU on environmental quality. As expected, relatively high EPU affects energy consumption, CO_2 emissions, and economic growth, all of which affect the sustainability and competitiveness of the environment [31].

As [32] explained, variations in production are the primary cause of wealth inequality among countries. It is impossible to overstate the significance of technological transfers in determining a country's productivity. In most countries, foreign sources of technology transfer account for up to 90% of the improvement in domestic productivity [33]. Rapid efforts are required to decarbonize the energy sector because of global warming and environmental damage. According to [34], energy efficiency and technological improvement are the primary drivers of a seamless transition from fossil fuels to renewable sources. Although most technology is generated in wealthier countries, it is still possible for technical progress to affect climate change patterns in developing countries through the transfer of knowledge. Refs. [2,35] used the spillover and feedback effects model to examine the impacts of CO_2 emissions in seven BRI zones from 2000 to 2015. According to their research, CO_2 emissions ratios increased over time in North Africa, Northeast Asia, and Western Asia, but dropped in Central Asia. The impact of technological changes such as regional technology transfer, foreign technology imports, and local innovation on CO_2 emissions in China was evaluated using panel data from 2008 to 2017 [36]. Ref. [37] used the generalized Divisia index approach (GDIM) to examine the influence of RENE on CO_2 emissions for a panel of 25 BRI countries between 2005 and 2019. Their innovative study showed that the growth in RENE sources was a significant factor in CO_2 emissions in most BRI countries. Long-term financial development had an M-shaped influence on CO_2 emissions in the United States, Japan, and Canada; an inverted N-shaped effect in the United Kingdom, France, and Italy; and a W-shaped impact in Germany [38]. Similar variability was revealed in [36] empirical investigation of the influence of advances in green technology across 264 Chinese prefecture-level cities from 2006 to 2017.

Hypothesis 2: *Economic policy and CO_2 emissions have a positive relationship.*

2.3. Renewable Energy Consumption and CO_2 Emissions

Ref. [39] thoroughly analyzed the relationship between RENE sources and CO_2 emissions in 128 countries between 1990 and 2014. Their study results indicated that switching to RENE might drastically reduce carbon emissions. On the other hand, CO_2 emissions in Europe were drastically different from those in the other five areas studied. According to the results of econometric research conducted by [40], carbon emissions decreased significantly across 16 EU countries when the pool mean group (PMG) approach was used for the data analysis. The use of alternative energy sources was credited for this decrease. Ref. [40] followed a methodology similar to that of [41]. Their study compared results from

24 African countries using data collected between 1985 and 2015. The data available in the African context supported the environmental Kuznets curve (EKC) hypothesis. According to the advocates, the availability of investments that emphasized ecological issues was crucial to the success of sustainable urban growth. The researchers were confident that using environmentally friendly forms of energy would allow them to meet their sustainable development goals.

Similar work was carried out by [42] in order to assess the role of renewable and non-renewable sources in mitigating greenhouse gas emissions. Ref. [43] used a panel dataset that included the years 1996–2012 for their analysis. Furthermore, the research conducted by [44] examined how imports and exports influenced carbon emissions in seven countries using a panel quantile regression approach. Their results demonstrated a strong connection among imports, exports, and carbon emissions. Recent research by [45] indicated that there is a strong correlation between rising CO_2 emissions in Asian countries and the unpredictability of their economic strategies. In addition, the pollution halo theory, based on a large body of prior academic research, offers an alternative explanation.

Policymakers and environmental economists worldwide are actively seeking strategies and solutions to address these pressing ecological difficulties due to the recent growth of global environmental concerns [46]. These studies consider factors such as international trade, knowledge transfer, and RENE use when examining the increase in CO_2 [47–49] (Researchers have examined how using renewable vs. non-RENE sources affects carbon emissions. As previously indicated, such research has been conducted in various countries using various econometric methods, techniques, and outcomes. Recent research by showed that reducing political risk and using ICT hold promise for effectively addressing CO_2 emissions in Morocco. Ref. [47] examined 42 countries in Sub-Saharan Africa to determine whether there was a connection between their utilization of RENE and their CO_2 emissions. The researchers included healthcare spending as a separate variable in their analysis, and the research covered a wide range of years, from 1995 through 2011. According to the available statistics, RENE use was linked to lower carbon CO_2 emissions.

Hypothesis 3: *Renewable energy consumption decreases CO_2 emissions in East Asia and Pacific countries.*

3. Methodology and Data Sample

This section explains the econometric techniques employed in our study, including unit root tests, cross-sectional dependency tests, panel co-integration estimates, the Granger causality test, two-stage least squares, and the two-step generalized method of moments (GMM). Figure 1 shows the overall conceptual framework if the study. This study compiled its findings using data for 14 East Asian and Pacific countries from the World Development Indicators (WDI) and the Our World by Oxford University database.

Model of this study

$$\boldsymbol{CO_2 = \beta_0 + \beta_1\, AI_{ij} + \beta_2\, EPU_{ij} + \beta_3\, RENE_{ij} + CV_{ij} + \mu} \quad (1)$$

where:

CO_2: carbon dioxide emissions.
AI: artificial intelligence.
EPU: economic policy uncertainty.
$RENE$: renewable energy.
β: coefficient.
CV: control variables.
μ: error term.

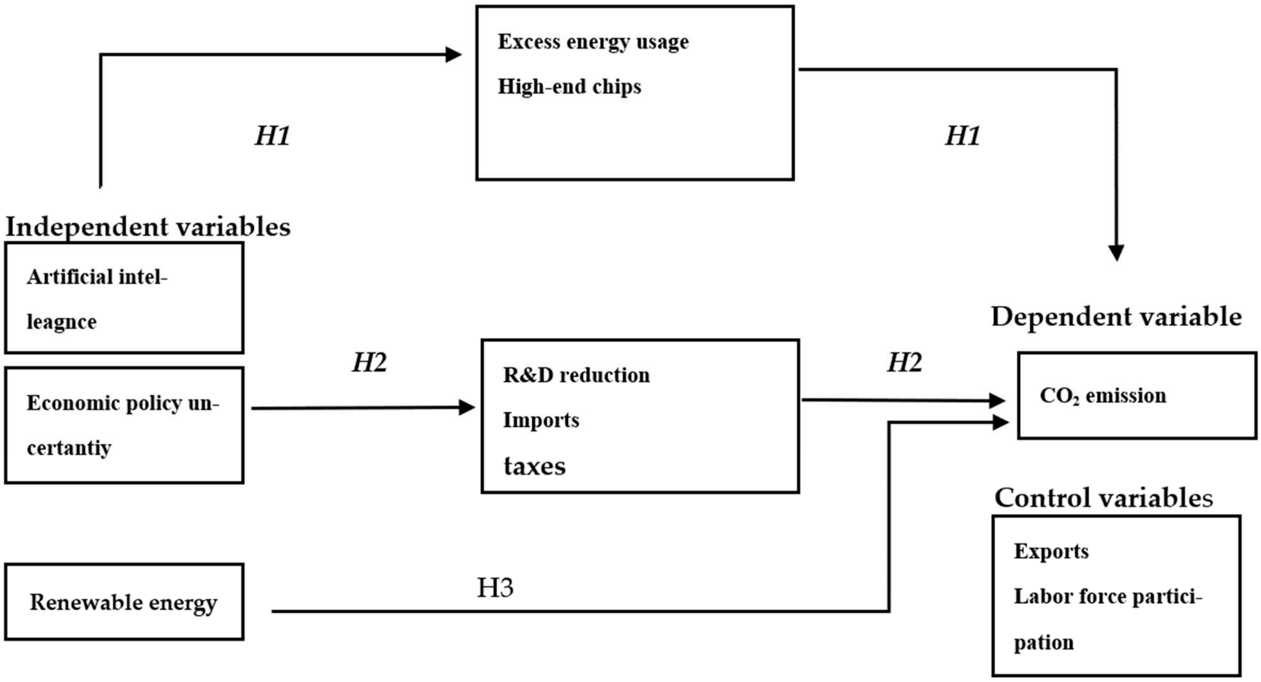

Figure 1. Conceptual framework. Source: made by the authors.

Description of Variables

CO_2: Emissions of carbon dioxide, abbreviated as CO_2, are byproducts of many industrial processes, including but not limited to the combustion of fossil fuels, the production of cement, and the use of gas as a fuel source. To measure CO_2 emissions, we used CO_2 emissions in metric tons per year. The data were collected from the World Bank World Development Indicators [50].

Artificial intelligence (AI): There are several academic and commercial uses of AI. AI is a multipurpose, all-purpose technology, similar to electricity or computers. Even though AI and the cloud operate virtually, they have many real-world impacts. In addition to increasing energy consumption and resource demands, they amplify emissions of greenhouse gases. One manifestation of this issue is increased energy use. This study's main econometric analytical problem involves finding data in the format of a cross-country panel dataset that can quantify the degree of AI. A variety of proxies, including high-tech specialists, patent filings, and AI investments in AI research, have been used in previous studies to quantify AI. This study used AI research publications as a proxy for evaluating AI, as there are variable amounts of data for each country. Similarly, this proxy shows the intentions and processes of each country moving toward the adoption of AI in our panel [51].

Economic policy uncertainty (EPU): Uncertainty concerning government policies and regulatory frameworks for the near future is known as economic policy uncertainty. A rise in EPU may lower CO_2 emissions by causing decreases in investment, consumption, and output. However, it may also impact innovation, R&D methods, and the usage of renewable energy sources, which might eventually result in increased CO_2 emissions. EPU can, therefore, either lessen or increase the impacts of environmental deterioration [52].

Renewable energy consumption: Renewable energy comes from sources that are naturally renewing yet limited in terms of flow. Renewable resources are almost endless in terms of length, but they are restricted in terms of the quantity of energy that is accessible per unit of time. We used per capita data for this variable (renewable energy consumption), as demonstrated by [53].

Exports: Concerns regarding the relationship between commerce and environmental degradation have arisen in response to the growing number of international trade agreements and the tightening of global value chains. This raises the question of the environmental consequences of trading. The liberalization of trade and investment might encourage businesses to embrace stricter environmental regulations. An increasing degree of international economic integration exposes a nation's export industry to ecological regulations enforced by major importers [54].

Labor force participation: Although it is impossible to overstate human capital's role in promoting sustainable development, there needs to be more discussion in the literature about whether or not labor force participation supports environmental sustainability. However, ecological quality has declined over time because of the ongoing increases in greenhouse gas (GHG) emissions worldwide. Climate change and other socioeconomic issues related to the dynamics of the labor market are caused by rising GHG emissions. Designing strategies to ensure social fairness through the creation of good jobs and to improve environmental quality is a growing priority for development organizations and governments.

Estimation

To analyze the data collected, this study used the following estimation tests.

Cross-sectional dependence

As a crucial component of panel data models, cross-sectional dependence (CD) may be influenced by the cultural, economic, and geographical links among the sampled nations. The cross-sectional dependency of East Asia and Pacific economies is a natural consequence of their close economic relationship. Ref. [55] noted that it is imperative to assess the likelihood of CD; failing to do so would lead to inaccurate and inconsistent estimates of stationarity and co-integrating traits.

Therefore, following [56], the CD test was employed in our investigation, considering its capacity to handle data with more constrained time frames and smaller cross-sectional units. The generalized method of moments (GMM) estimator accounts for the possibility of cross-sectional dependency in the data, eliminating endogeneity concerns in the regressors [57]. Unlike other estimation methods, such as least-squares regressions, GMM accounts for country-specific heterogeneities, eliminating dynamic panel bias. It is essential to conduct the GMM analysis after the cross-sectional dependence, unit root, and cointegration investigations. First, we use the Pesaran CD test, as described by [58], to determine whether there is a cross-sectional dependency problem. To reject the null hypothesis of cross-sectional independence, this technique estimates a test statistic that forecasts CD difficulties for each variable (or series). We used the CD estimate method proposed by Breusch and Pagan (1980), which takes into account a null hypothesis of cross-sectional independence, similar to that proposed by [59], for the robustness check.

Long-run estimation test

Popular panel data estimation methods, such as FE, RE, DOLS, FMOLS, and GMM, all rely on slope homogeneity across cross-sections, which could significantly impact the results.

$$\beta^*_{NT} = N^{-1}\sum_{i=1}^{N}\left[\sum_{i=1}^{T}\left(X_{it}-\overline{X}_i\right)^2\right]^{-1}\sum_{i=1}^{T}\left(X_{it}-\overline{X}_i\right)\gamma_{it-T_{\tau l}}$$

$$\gamma^*_{it} = (\gamma_{it}-\overline{\gamma}_i) - \frac{L_{21l}}{L_{22l}}\Delta X_{it}, \hat{\tau}_l = \hat{\Gamma}_{21l} + \hat{\Omega}^0_{21l} - \frac{L_{21l}}{L_{22l}}\left(\hat{\Gamma}_{22l} + \hat{\Omega}^0_{22l}\right)$$

The DOLS is written as follows:

$$\gamma_{it} = \alpha_i + \beta_i X_{it} + \sum_{j=-ji}^{jl}\theta_{ij}\Delta X_{it-j} + \varepsilon_{it}{}^*$$

$$\beta *_{DOLS} = N^{-1}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} Z_{it}Z^i_{it}\right)^{-1}\left(\sum_{t=1}^{T} Z_{it}\gamma^*_{it}\right)$$

$$Z_{it} = \left(X_{it}-\overline{X}_l, \Delta X_{it-j}, \ldots, \Delta X_{it+k}\right) \qquad 2(K+1)$$

$$Y_t = \sum_{j=0}^{k} \phi_i y_{t-i} + \varepsilon_t$$

$$\phi_i = \begin{cases} I_k, i = 0 \\ \sum\limits_{j=1}^{i} \phi_{t-j} A_j,\ i = 1,\ 2, \ldots \end{cases}$$

$$y_{it+h} - E[y_{it+h}] = \sum_{i=0}^{h-1} \varepsilon_i (t + h - 1) \phi_i$$

$$\sum_{i=0}^{hl} \theta_{nm}^2 = \sum_{i=0}^{hl} \left(i'_m K \phi_{in} \right)^2$$

4. Data Analysis

This study investigated the impact of AI, economic policy uncertainty, and renewable energy use on environmental quality in a panel of 14 East Asian and Pacific economies from 2000 to 2023. The summary statistics and correlation matrix are presented in Tables 1 and 2.

Table 1. Summary statistics.

	CO_2	AI	EPU	RENC	EXP	BFP
Mean	1.144614	−6.752220	4.808009	2.219551	3.912695	3.825545
Median	1.360290	−6.354429	4.794594	3.114838	3.933426	3.841317
Maximum	3.077580	−1.551640	5.787578	4.401584	5.433695	4.223207
Minimum	−1.820287	−12.92531	4.164067	−4.605170	2.852507	3.135320
Std. Dev.	1.156430	2.502786	0.430687	2.013087	0.589109	0.256398
Observations	254	254	254	254	254	254

Table 2. Pairwise correlations.

Variables	CO_2	AI	EPU	RENC	EXP	BFP
CO_2	1.000					
AI	0.492	1.000				
EPU	0.155	0.151	1.000			
RENC	−0.475	−0.232	−0.105	1.000		
EXP	0.249	−0.129	−0.064	−0.447	1.000	
BFP	−0.568	−0.193	−0.223	0.629	−0.233	1.000

Source: authors' calculations.

This study incorporated various variables. As the summary statistics indicate, all variables exhibit significant variability in their minimum and maximum values. Similarly, the matrix reveals a negative association between renewable energy and economic policy uncertainty and a positive correlation between the dimensions of AI and CO_2 emissions.

Before examining the presence of unit root and cointegration among the variables, we assessed the cross-sectional dependence among the nations included in the sample with the rise of liberalization and globalization. During this period, there has been growing economic and social interconnectedness across nations. Consequently, the actions implemented in one country can have an impact on another nation as well. Following [56], the cross-sectional dependence test was utilized to ascertain the presence of CD within the chosen East Asia and Pacific countries. The findings displayed in Table 3 validate the presence of a correlation among CO_2 emissions, AI, renewable energy consumption, time, and economic policy uncertainty in the sample nations. This suggests that any alteration in these factors in East Asian–Pacific countries can also impact the other Asian andPacific countries. Table 3 presents the findings of the slope homogeneity test introduced by [56] for all three regression models in this study.

Table 3. Cross-sectional dependence tests.

Variables	Breusch–Pagan LM	Pesaran Scaled LM	Pesaran CD
CO_2	1076.1676 (0.0000)	73.0254 (0.0000)	14.8976 (0.0000)
EPU	467.6181 (0.0000)	31.19442 (0.0000)	2.93362 (0.0034)
AI	468.8277 (0.0000)	31.29126 (0.0000)	−0.611140 (0.5411)
RENE	494.2888 (0.0000)	33.32978 (0.0000)	3.515709 (0.0000)
EXP	394.2699 (0.0000)	25.3218 (0.0000)	14.8976 (0.0000)
LBFP	838.0242 (0.0000)	55.3731 (0.0000)	22.9312 (0.0000)

Source: authors' calculations.

Both the constant term only and constant term and trend term versions of the three-unit root test techniques used in this study are shown in Table 4. Except for the LLC trial, every one of the discovered variables in the five trials rejected the null hypothesis at the 1% significance level. As a result, we examined the data using a first-order differential. We found that at the crucial 1% level, no hypotheses were rejected for each variable's unit root. However, this indicates the possibility of spurious regression; thus, the KAO test for cointegration is required.

Table 4. Panel unit root tests.

Variable	Level		First Difference	
	With Constant	**Constant and Trend**	**With Constant**	**Constant and Trend**
Levin, Lin, and Chu				
CO_2	1.14929	0.40833 *	−2.74790 **	−2.24790 ***
AI	−2.4150	−3.6099 **	−7.5668 ***	−5.4556 ***
EPU	1.9604	−4.2088 ***	−9.1004 ***	−9.6434 ***
RENE	0.128158	1.271932	−0.5498	0.047541 *
Im, Pesaran, and Shin test				
CO_2	2.30494	1.68899	−4.4875 ***	−3.3289 ***
AI	−0.7038	−4.2729 ***	−10.880 ***	−8.0240 ***
EPU	4.3012	−3.4030 ***	−8.7916 ***	−7.0831 ***
RENE	2.9665	1.97422	−4.3652 ***	−3.84803 ***
ADF-Fisher Chi-square test				
CO_2	23.5113	22.2661	72.0801 ***	59.4662 ***
AI	49.89272	72.3376 ***	164.1347 ***	115.6323 ***
EPU	3.32278	52.1911 **	126.2833 **	97.14846 ***
RENE	15.49658	11.82574	65.02550 **	58.6137 ***

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: authors' calculations.

Table 5 presents the findings of the cointegration test for CO_2 emissions, AI, economic policy uncertainty, and renewable energy. All three model groups rejected the initial hypothesis, suggesting that the panel data exhibit a cointegration relationship. The findings validate the existence of a long-term equilibrium cause-and-effect association among the variables, thus facilitating further investigation of this relationship.

The estimation results for the FMOLS and DOLS panel models are presented in Table 6. According to the parameters, DOLS provides a more accurate match. It may be inferred that a 1% increase in AI is associated with a corresponding 0.1665% increase in CO_2 emissions. Likewise, a 1% rise in economic policy uncertainty will result in a 0.237% increase in CO_2 emissions, leading to environmental damage. Additionally, CO_2 emissions will fall by −0.3658 if renewable energy usage increases. Policy ambiguity and adopting digitalization/AI will generally impact environmental degradation, but renewable energy consumption will exacerbate the ecological situation. Similarly, to check the robustness of the data, we incorporated the Hausman fixed effect and generalized method of moment to confirm the relationship. Tables 7 and 8 show the results of the Hausman test and GMM. The relationship between CO_2 emissions and AI and economic policy uncertainty was positive, whereas the result for renewable energy consumption was the opposite. This means that a unit increase in AI adoption and monetary policy uncertainty will contribute 1.316 and 0.867% to environmental degradation, respectively. The same results were found in the GMM.

Table 5. Kao test for cointegration.

		Null Hypothesis	***t*-Statistics**	**Probability**
1	ADF	No-cointegration	1.599509	0.0549
2	ADF	No-cointegration	−1.860175	0.0314
3	ADF	No-cointegration	−1.525220	0.0636

Source: authors' calculations.

Table 6. Benchmark results for CO_2, AI, EPU, and RENE (FMOLS and DOLS).

Variables	**CO_2**	**CO_2**	**CO_2**
FMOLS			
AI	1.316716 *		
	(0.699672)		
EPU		0.867909 **	
		(0.392765)	
RENE			−2.328345 **
			(1.058345)
DOLS			
AI	0.166554 ***		
	(0.066719)		
EPU		0.237011 **	
		(0.099588)	
RENE			−0.365873 **
			(0.117710)

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: authors' calculations.

Table 7. Hausman fixed effect.

Variables	**CO_2**	**CO_2**	**CO_2**
AI	0.195 ***		
	(0.0234)		
EPU		0.00191 *	
		(0.00103)	
REN			−0.431 ***
			(0.0337)
LEXP	0.386 ***	0.323 ***	−0.249 ***
	(0.104)	(0.114)	(0.0947)
LBFP	−1.794 ***	−2.149 ***	−0.515 **
	(0.244)	(0.267)	(0.244)
Constant	7.908 ***	7.882 ***	5.018 ***
	(1.102)	(1.253)	(0.962)
Observations	265	269	258
Number of years	22	22	22
R-squared	0.48	0.63	0.59

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8. GMM.

Variables	CO_2	CO_2	CO_2
AI	0.214 ***		
	(0.0241)		
EPU		0.595 **	
		(0.230)	
REN			−0.455 ***
			(0.0358)
LEXP	0.382 ***	0.352 ***	−0.276 ***
	(0.103)	(0.120)	(0.0979)
LBFP	−1.788 ***	−2.028 ***	−0.427 *
	(0.239)	(0.285)	(0.253)
Constant	8.021 ***	4.696 **	4.841 ***
	(1.068)	(1.955)	(0.992)
Observations	265	269	258
Number of years	22	22	22
Arellano–Bond test for AR(1) in first differences: z = −3.47 Pr > z = 0.001			
Arellano–Bond test for AR(2) in first differences: z = 0.80 Pr > z = 0.421			
Sargan test of overid. restrictions: chi2(14) = 238.35 Prob > chi2 = 0.000			

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Impulse response and variance decomposition

Before analyzing the pulse effect and variance decomposition as endogenous variables in VAR systems, defining the best lag order for mechanization, rainfall, and agricultural carbon emissions is recommended. This study presents the following five approaches for comprehensive judgment: the LR test statistic (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan–Quinn Information Criterion (HQ). We found that lag order 2 is the best lag term, as indicated in Table 9. Figure 2 was created following this order, which clearly shows that all the roots fall inside the unit circle, meaning this VAR model meets the requirements for variance decomposition and impulse response analysis.

Table 9. Optimal lag period selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−1078.181	NA	4.996539	12.96025	13.03494	12.99057
1	136.9475	2357.495	0.0000029	−1.400569	−1.027156	−1.249009
2	159.4494	42.57845	0.00000268	−1.478436	−0.806294 *	−1.205628
3	175.6993	29.96996	0.00000267	−1.481429	−0.510557	−1.087374
4	181.8982	11.13563	0.00000301	−1.364050	−0.094448	−0.848746
5	206.4746	42.97200	0.00000273	−1.466762	0.101570	−0.830211
6	239.9958	57.00601	0.00000222	−1.676596	0.190466	−0.918797
7	318.4096	129.5942	0.00000106	−2.424067	−0.258275	−1.545020
8	353.1120	55.69001	0.00000085	−2.648048	−0.183526	−1.647753

Source: authors' calculations. * Shows the lag period.

The VAR model of a standard deviation of the random disturbance impact on the trajectories of other variables and the influence of current and future values may be visually represented using the impulse response function. Thus, using an impulse response function diagram, we further examined how AI and EXP affect the other CO_2 emissions [29]. We set a reaction time of twenty years. In Figure 3, the range of the potential impulse response is indicated by dotted lines on either side of the solid lines; the abscissa shows the lag length of the effect, and the longitudinal coordinates show the degree of reaction. Table 9 shows the optimal lag period selection.

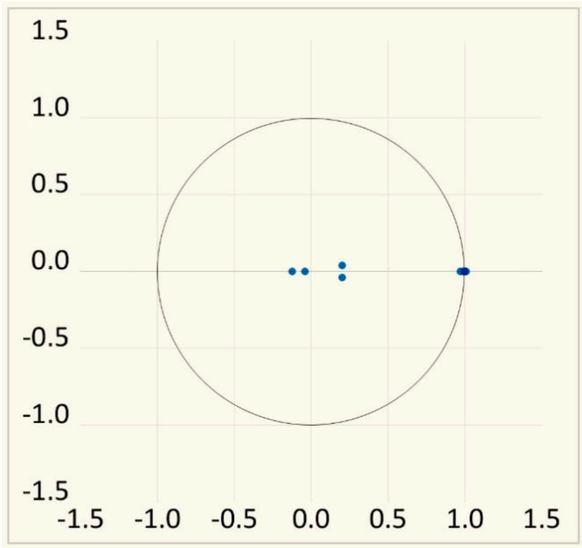

Figure 2. Inverse roots of PVAR characteristic polynomial.

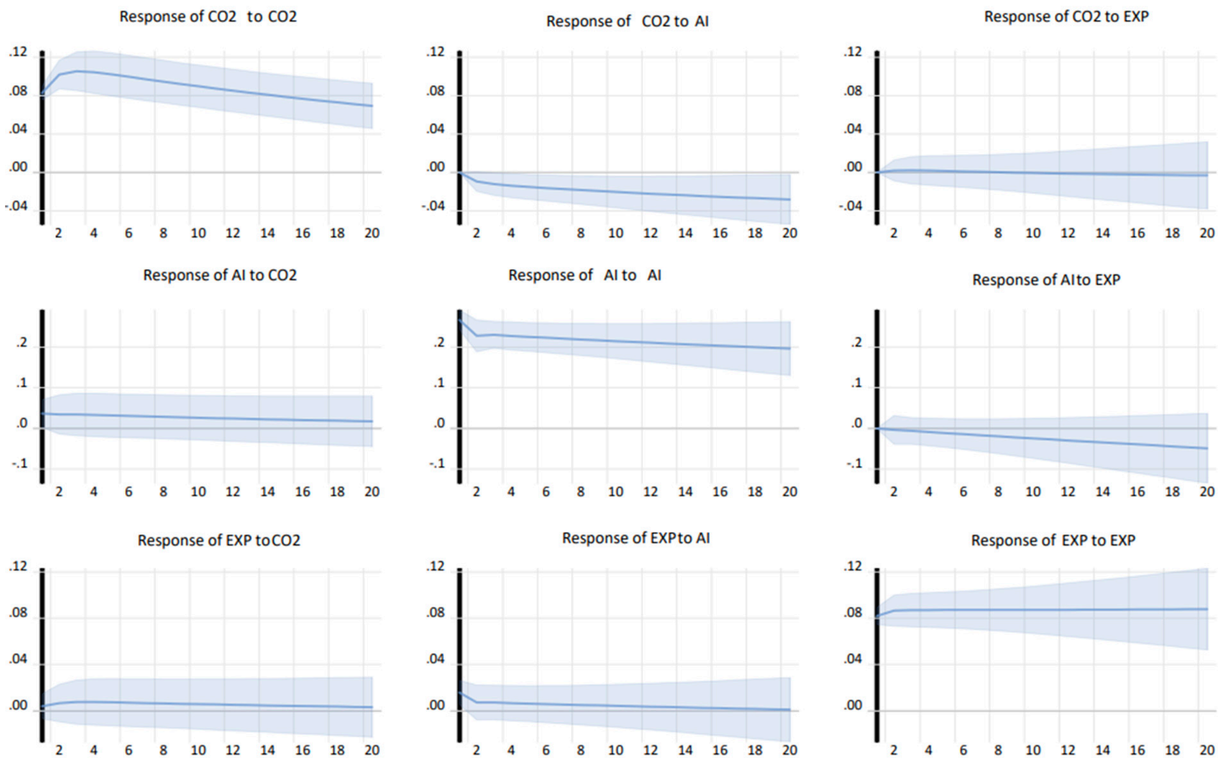

Figure 3. Impulse response for CO_2 and AI.

Table 10 represents the results of the variance decomposition analysis of CO_2 emissions, AI, and exports. The results show that the variation in CO_2 emissions is self-generated in the short term. Similarly, in the short term, AI adoption has minimal impact on variations in CO_2 emissions. Our study's results align with the previous research conducted by [60], and we can see that the value for period 20 is 5.208, compared with 94.751. This minimal variation is because AI is an emerging cutting-edge technology, and most countries are in line to adopt it. It is also the case that AI has not yet been embraced fully. Figure 3 shows the impulse response between AI and CO_2 emission. In addition, the environmental concerns of AI are relatively understudied at present, compared to other phenomena.

Table 10. Variance decomposition.

Variance Decomposition of CO_2				
Period	**S.E.**	**CO_2**	**AI**	**EXP**
1	0.083	100.000	0.000	0.000
2	0.132	99.456	0.521	0.023
3	0.169	99.146	0.822	0.032
4	0.199	98.899	1.068	0.034
5	0.225	98.678	1.290	0.031
6	0.246	98.465	1.507	0.028
7	0.265	98.251	1.724	0.025
8	0.282	98.032	1.946	0.022
9	0.298	97.806	2.174	0.020
10	0.312	97.572	2.410	0.018
11	0.324	97.328	2.654	0.018
12	0.336	97.076	2.906	0.018
13	0.347	96.815	3.167	0.019
14	0.357	96.544	3.435	0.020
15	0.367	96.265	3.712	0.023
16	0.375	95.978	3.997	0.025
17	0.384	95.683	4.289	0.029
18	0.392	95.379	4.588	0.032
19	0.399	95.069	4.895	0.037
20	0.406	94.751	5.208	0.041
Variance Decomposition of AI:				
Period	**S.E.**	**CO_2**	**AI**	**EXP**
1	0.2694	1.8192	98.1808	0.0000
2	0.3544	1.9866	98.0029	0.0105
3	0.4239	2.0386	97.9330	0.0284
4	0.4821	2.0457	97.8986	0.0557
5	0.5331	2.0302	97.8775	0.0923
6	0.5788	2.0030	97.8587	0.1383
7	0.6204	1.9694	97.8368	0.1938
8	0.6586	1.9323	97.8089	0.2588
9	0.6942	1.8934	97.7733	0.3333
10	0.7275	1.8537	97.7290	0.4173
11	0.7588	1.8137	97.6755	0.5108
12	0.7884	1.7739	97.6124	0.6138
13	0.8165	1.7345	97.5393	0.7262
14	0.8433	1.6957	97.4561	0.8482
15	0.8690	1.6577	97.3627	0.9795
16	0.8935	1.6205	97.2592	1.1203
17	0.9171	1.5842	97.1453	1.2705
18	0.9398	1.5488	97.0213	1.4300
19	0.9617	1.5143	96.8870	1.5987
20	0.9830	1.4807	96.7426	1.7767
Variance Decomposition of EXP:				
Period	**S.E.**	**CO_2**	**AI**	**EXP**
1	0.083	0.230	3.641	96.128
2	0.121	0.422	2.108	97.470
3	0.149	0.540	1.618	97.843
4	0.173	0.596	1.351	98.053
5	0.194	0.620	1.179	98.201
6	0.213	0.625	1.055	98.319
7	0.230	0.621	0.959	98.420
8	0.246	0.611	0.881	98.508
9	0.261	0.598	0.815	98.588
10	0.275	0.582	0.757	98.660
11	0.289	0.566	0.707	98.727
12	0.302	0.549	0.662	98.789

Table 10. *Cont.*

Variance Decomposition of EXP: Period	**S.E.**	**CO_2**	**AI**	**EXP**
13	0.314	0.531	0.622	98.847
14	0.326	0.514	0.586	98.900
15	0.338	0.497	0.552	98.951
16	0.349	0.480	0.522	98.998
17	0.360	0.463	0.494	99.042
18	0.370	0.448	0.468	99.084
19	0.381	0.432	0.445	99.123
20	0.391	0.417	0.423	99.160

Source: authors' calculations.

Figures 4 and 5 represent the impulse response of the relationship between CO_2 emissions and economic policy uncertainty (EPU). The graph shows that the reaction of CO_2 to CO_2 declines over a certain period, while, in the second graph, the relationship between CO_2 emissions and EPU is initially positive. In contrast, in the later stages, it becomes damaging. Table 11 shows the variance decomposition between CO_2 emissions and EPU. In the short term, the variation in CO_2 is self-generated while, in the long term, the variation in CO_2 arises from EPU. The results show that the value of EPU in year 20 was recorded at 65.2376, which is higher than 34.3352. Our study's results support those of [61].

Table 11. VDC of CO_2 and EPU.

		Variance Decomposition of CO_2		
Period	**S.E.**	**CO_2**	**EPU**	**EXP**
1	0.0830	100.0000	0.0000	0.0000
2	0.1330	99.4992	0.4993	0.0015
3	0.1705	99.0061	0.9855	0.0083
4	0.2001	98.5239	1.4605	0.0156
5	0.2247	97.9988	1.9785	0.0228
6	0.2457	97.3764	2.5932	0.0304
7	0.2642	96.6016	3.3595	0.0389
8	0.2808	95.6112	4.3398	0.0489
9	0.2960	94.3278	5.6112	0.0609
10	0.3103	92.6547	7.2698	0.0755
11	0.3243	90.4728	9.4338	0.0934
12	0.3384	87.6418	12.2430	0.1152
13	0.3534	84.0075	15.8509	0.1416
14	0.3701	79.4213	20.4055	0.1732
15	0.3895	73.7756	26.0143	0.2101
16	0.4131	67.0531	32.6951	0.2517
17	0.4424	59.3802	40.3230	0.2968
18	0.4795	51.0567	48.6004	0.3429
19	0.5267	42.5350	57.0777	0.3873
20	0.5868	34.3352	65.2376	0.4272
		Variance Decomposition of EPU:		
Period	**S.E.**	**CO_2**	**EPU**	**EXP**
1	26.5331	0.3259	99.6741	0.0000
2	42.7444	1.6824	98.0691	0.2485
3	58.8412	2.5311	97.1289	0.3400
4	76.1302	3.0476	96.5675	0.3850
5	95.5157	3.3739	96.2154	0.4107
6	117.7649	3.5928	95.9799	0.4273
7	143.6526	3.7476	95.8135	0.4389

Table 11. *Cont.*

Period	S.E.	CO_2	EPU	EXP
Variance Decomposition of EPU:				
8	174.0314	3.8616	95.6911	0.4473
9	209.8775	3.9480	95.5983	0.4538
10	252.3306	4.0148	95.5264	0.4588
11	302.7338	4.0673	95.4700	0.4627
12	362.6776	4.1090	95.4251	0.4659
13	434.0518	4.1423	95.3893	0.4684
14	519.1052	4.1691	95.3604	0.4705
15	620.5170	4.1906	95.3371	0.4723
16	741.4812	4.2081	95.3182	0.4737
17	885.8076	4.2223	95.3029	0.4748
18	1058.0415	4.2337	95.2904	0.4758
19	1263.6072	4.2431	95.2803	0.4766
20	1508.9786	4.2507	95.2720	0.4773
Variance Decomposition of EXP:				
Period	**S.E.**	**CO_2**	**EPU**	**EXP**
1	0.0826	0.1527	0.0734	99.7739
2	0.1199	0.2353	3.5233	96.2414
3	0.1497	0.1782	5.4266	94.3952
4	0.1753	0.1321	6.9265	92.9414
5	0.1983	0.1043	8.3646	91.5311
6	0.2199	0.0943	9.9084	89.9973
7	0.2407	0.1032	11.6607	88.2362
8	0.2612	0.1335	13.7039	86.1625
9	0.2820	0.1890	16.1145	83.6965
10	0.3037	0.2738	18.9651	80.7611
11	0.3268	0.3921	22.3208	77.2870
12	0.3522	0.5479	26.2306	73.2216
13	0.3806	0.7435	30.7145	68.5420
14	0.4132	0.9791	35.7503	63.2706
15	0.4512	1.2514	41.2615	57.4871
16	0.4964	1.5535	47.1131	51.3334
17	0.5505	1.8749	53.1205	45.0045
18	0.6158	2.2029	59.0703	38.7268
19	0.6949	2.5237	64.7511	32.7252
20	0.7908	2.8254	69.9840	27.1906

Table 12. VDC for CO_2 and RENE.

Variance Decomposition of CO_2: Period	S.E.	CO_2	RENE	EXP
1	0.07788329	100	0	0
2	0.1312	99.9869	0.0036	0.0095
3	0.1736	99.9831	0.0048	0.0122
4	0.2078	99.9846	0.0040	0.0114
5	0.2360	99.9872	0.0031	0.0096
6	0.2597	99.9889	0.0031	0.0080
7	0.2800	99.9885	0.0045	0.0070
8	0.2976	99.9854	0.0077	0.0069
9	0.3131	99.9794	0.0128	0.0079
10	0.3267	99.9703	0.0198	0.0099
11	0.3389	99.9583	0.0287	0.0130
12	0.3498	99.9431	0.0397	0.0172
13	0.3596	99.9250	0.0525	0.0225
14	0.3685	99.9039	0.0673	0.0288

Table 12. *Cont.*

Variance Decomposition of CO_2:				
Period	**S.E.**	**CO_2**	**RENE**	**EXP**
15	0.3766	99.8799	0.0839	0.0362
16	0.3839	99.8530	0.1024	0.0446
17	0.3906	99.8235	0.1226	0.0539
18	0.3967	99.7912	0.1446	0.0642
19	0.4023	99.7565	0.1682	0.0754
20	0.4074	99.7192	0.1934	0.0874
Variance Decomposition of RENC:				
Period	**S.E.**	**CO_2**	**RENE**	**EXP**
1	0.077906609	10.17802357	89.82197643	0
2	0.1205	10.4838	89.3727	0.1435
3	0.1527	10.5850	89.1621	0.2529
4	0.1790	10.5266	89.1335	0.3399
5	0.2016	10.3687	89.2130	0.4183
6	0.2214	10.1536	89.3519	0.4946
7	0.2392	9.9071	89.5212	0.5717
8	0.2555	9.6447	89.7041	0.6512
9	0.2705	9.3756	89.8904	0.7340
10	0.2845	9.1056	90.0739	0.8206
11	0.2976	8.8380	90.2507	0.9112
12	0.3099	8.5751	90.4186	1.0063
13	0.3215	8.3183	90.5759	1.1058
14	0.3325	8.0684	90.7217	1.2099
15	0.3430	7.8260	90.8552	1.3187
16	0.3530	7.5914	90.9763	1.4323
17	0.3626	7.3647	91.0846	1.5507
18	0.3718	7.1461	91.1800	1.6739
19	0.3807	6.9354	91.2627	1.8019
20	0.3892	6.7326	91.3326	1.9347
Variance Decomposition of EXP:				
Period	**S.E.**	**CO_2**	**RENE**	**EXP**
1	0.0858	0.0665	0.0012	99.9323
2	0.1237	0.3678	0.0085	99.6237
3	0.1523	0.5565	0.0108	99.4328
4	0.1762	0.6368	0.0096	99.3536
5	0.1970	0.6503	0.0078	99.3419
6	0.2156	0.6278	0.0067	99.3654
7	0.2325	0.5880	0.0069	99.4051
8	0.2481	0.5415	0.0088	99.4497
9	0.2627	0.4946	0.0123	99.4931
10	0.2764	0.4507	0.0176	99.5317
11	0.2893	0.4118	0.0246	99.5636
12	0.3016	0.3791	0.0333	99.5876
13	0.3133	0.3531	0.0436	99.6033
14	0.3245	0.3339	0.0554	99.6106
15	0.3353	0.3217	0.0688	99.6095
16	0.3456	0.3161	0.0836	99.6003
17	0.3557	0.3170	0.0998	99.5832
18	0.3654	0.3241	0.1172	99.5587
19	0.3748	0.3370	0.1359	99.5271
20	0.3839	0.3554	0.1557	99.4888

Source: authors' calculations.

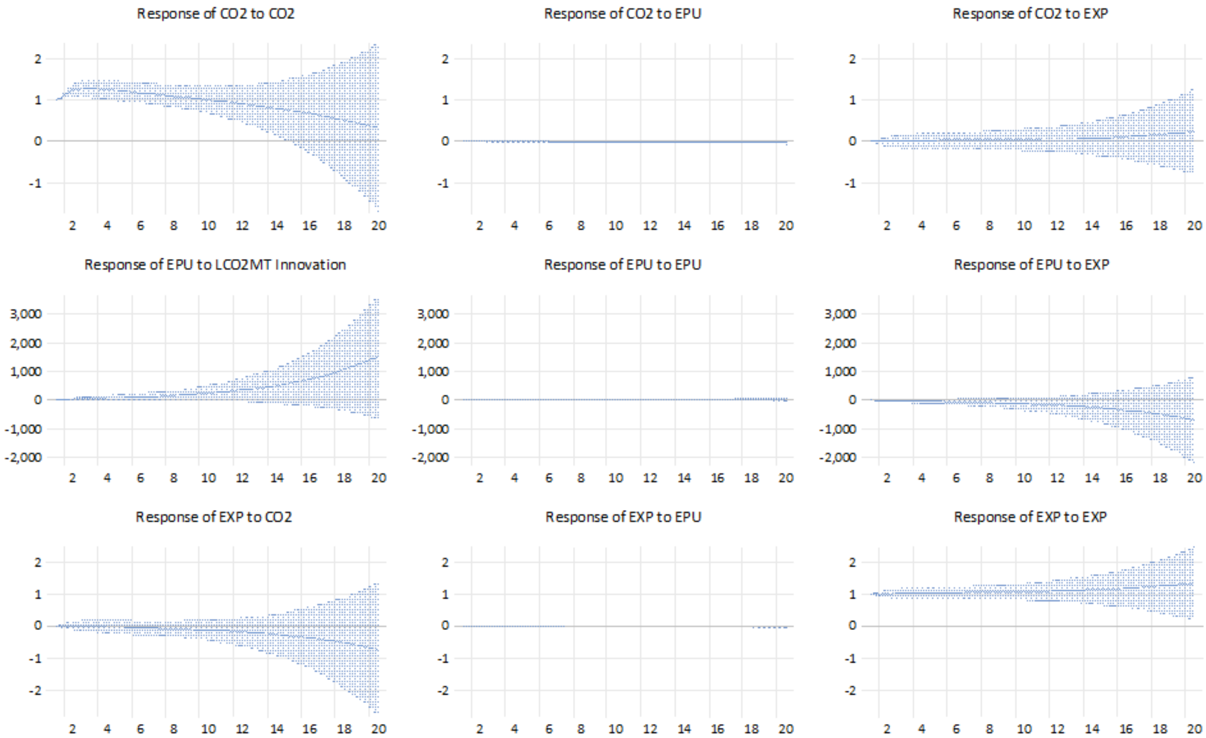

Figure 4. Impulse response for CO_2 and EPU.

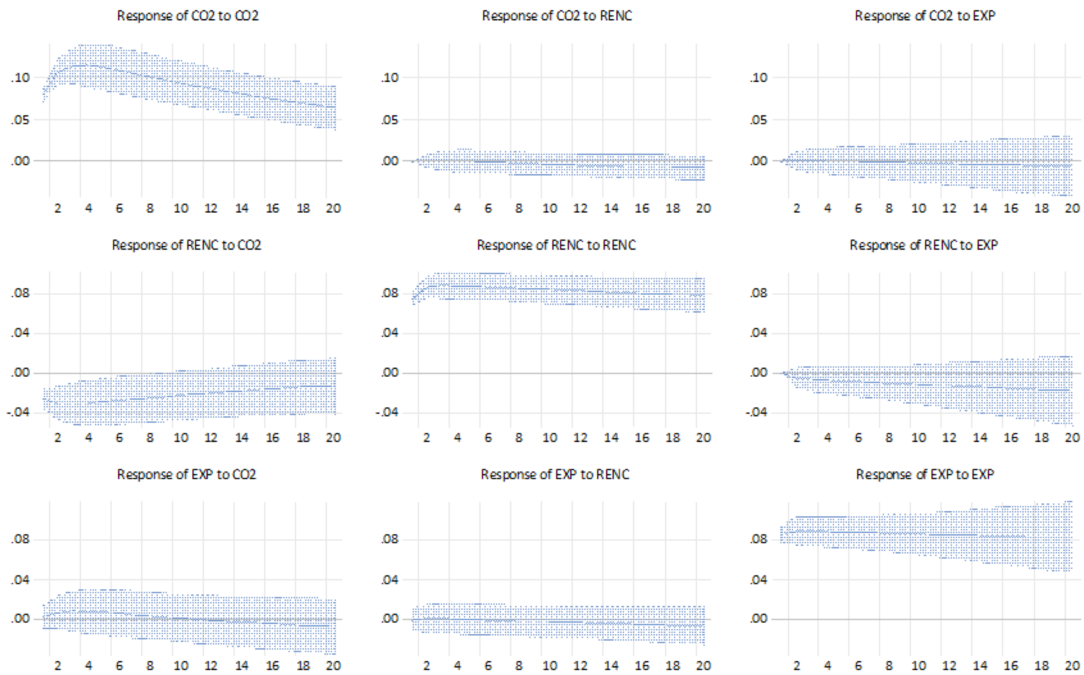

Figure 5. Impulse response for EXP and RENE.

Table 12 reports the variance decomposition results between CO_2 emissions and renewable energy. The variation in CO_2 emissions in the case of renewable energy consumption is slightly different from the relationship with AI. The variation in the short-term is totally self-generated while, in the long-term, the variance decomposition for CO_2 arises from renewable energy consumption. As noted in an earlier study by [62], adopting renewable energy production and consumption sources will decrease CO_2 emissions in East Asia and Pacific countries. Figure 6 shows the CO_2 emission trend in the selected countries.

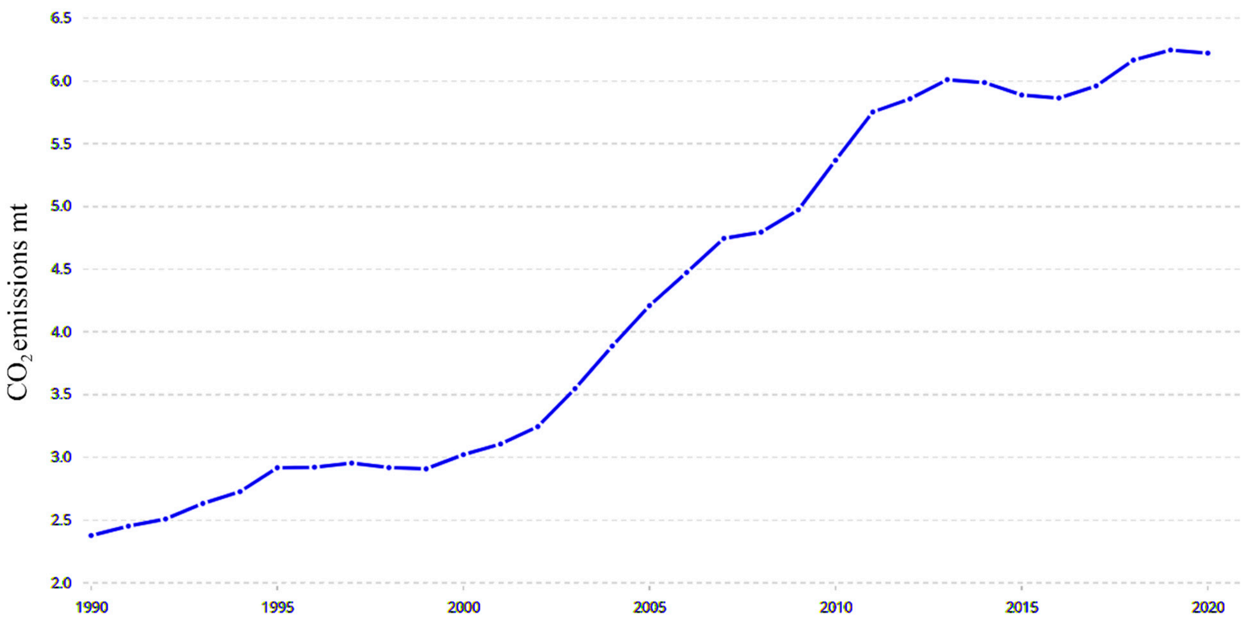

Figure 6. East Asia and Pacific CO_2 emissions (metric tons per capita), Source: World Bank. World development indicators.

5. Results and Discussion

Global warming is a serious environmental issue that affects every nation on the planet and is related to the long-term viability of human life. Furthermore, there is a strong link between agricultural carbon emissions and climate change. Thus, we sought to build an empirical framework to study the influences of AI, economic policy uncertainty, and renewable energy consumption on CO_2 emissions. Our approach produced empirical findings. First, the association among the variables was confirmed using a cross-sectional correlation test. We used the ADF, Im, Pesaran and Shin, and LLC tests to evaluate the stability of the unit root of panel data. According to the results, each variable is an integrated sequence of the same order and may be employed in the PVAR model. This also reveals that the variable after the first-order difference is stable. Additionally, we used the Kao test to confirm the long-term cointegration connection among the variables. The findings indicate that these three variables have a long-term integration connection. The link among the variables was then empirically studied using the Hausman test, the generalized method of moments, and VAR-based impulse response techniques. The findings demonstrate that the impulse response function more accurately captures the dynamic interaction among the examined factors. The FMOLS and DOLS test results confirm the robustness of the long-term findings. The causal link among the variables was also analyzed. We found that digitalization—for which we took AI as a proxy—showed a positive relationship with environmental degradation. Therefore, the more that AI is integrated into a country, the more vulnerable the environment is. It is worth noting that the impact of digitalization is twofold; on one hand, it can contribute to the economy by boosting production and the transparency of different projects, while, on the other hand, it can cause damage to the environment, leading to increases in CSR costs. Similarly, economic policy uncertainty also showed a positive relationship for the following reasons. First, the danger posed by EPU is uncertain because of its unexpected nature [6,63]. Second, since 1997, several financial crises have affected the world's economies and financial markets [64]. Regrettably, the size, rate of spread, and complexity of EPU have all risen with each global economic crisis. Thus, the literature has demonstrated that EPU is significantly correlated with economic recessions [64], increased unemployment, and volatile exchange rates. On the other hand, it is unclear how EPU affects carbon emissions globally. Hence, an empirical study is necessary. Third, research indicates that a firm's financial performance, investment choices, and business competitiveness are all impacted by EPU. Thus, we conclude that

EPU impacts a firm's carbon emissions. Real options and prospect theories provide the foundation of our argument. Fourth, earlier research indicated that the extraordinary global economic expansion over the last 25 years has come at the price of a clean and sustainable environment for future generations. The leading cause of environmental deterioration and the threat of climate change is global CO_2 emissions [35]. Similarly, the relationship between renewable energy consumption and CO_2 emissions is harmful, as many earlier studies have pointed out. In their foundational study, ref. [65] established what is now known as the Environmental Kuznets Curve (EKC) framework, which is the primary theory used to explain global CO_2 emissions trends over the long term. found a non-linear (inverted U-shaped) relationship between per capita GDP and environmental outcomes including CO_2 emissions. Multiple review studies have demonstrated the validity of the EKC hypothesis [66,67]. "Strong evidence in support of EKC" was found by [68], who completed a revised meta-analysis of 101 papers. The results of our study align with previous studies in the case of East Asia and Pacific countries.

6. Conclusions and Recommendations

Global warming and climate change are global issues that have gained tremendous momentum in spheres ranging from politics to the public domain and academia. At the same time, uncertainty in the economy, the emergence of AI, and the demand for renewable energy exacerbate these environmental concerns. This study focused on the relationships among these factors. Notably, earlier studies have examined similar factors for different countries. A significant contributor to climate change is the human-caused emission of gases into the atmosphere, including carbon dioxide. Energy consumption from renewable sources, EPU, AI, and CO_2 emissions are the subjects of this study's dynamic interconnections. In this study, panel data for East Asian and Pacific nations from 2000 to 2023 were collected to facilitate an empirical analysis of the links among these factors. The variance decomposition test indicates that AI does not affect CO_2 emissions, whereas the benchmark regression indicates a positive link between AI and CO_2 emissions. To similar extents, the variance decomposition test and benchmark regression FE, RE, and GMM tests all demonstrate a robust positive correlation between economic policy uncertainty and CO_2 emissions. Carbon dioxide emissions are positively affected by an increase in EPU. Renewable energy significantly reduces CO_2 emissions in East Asian and Pacific nations. The findings show that a unit increase in the use of renewable energy results in a unit decrease in CO_2 emissions.

Policy recommendations

Based on the results of this study and by investigating the components of environmental degradation via an increase in CO_2 emissions, this study suggests the following policy recommendations, which will help to reduce CO_2 emissions. The first concerns the use of fossil fuels and inducement towards renewables overall. The most effective, efficient, and cost-effective tool for encouraging investments in clean technology is carbon pricing laws, which include emission trading systems and carbon taxes. Investments in environmentally friendly goods, regulations that promote a greener economy, and sustainable development projects are also important factors. Second, machine learning researchers should be incentivized to create more effective machine learning (ML) models to disclose their energy use and carbon footprints. An innovative model that incorporates these aspects from the outset has the potential to decrease emissions.

Third, to help their customers understand and lower their energy usage and carbon footprint, data center providers should be incentivized to share information regarding data center efficiency and the cleanliness of the energy supply by location. Cloud data centers use 30% less energy than the typical local data centers, and they have cooling and power delivery overheads of less than 10%. Finally, experts in machine learning (ML) deserve recognition for training models in the most environmentally friendly data centers, which are now frequently located in the cloud. They can produce 5 to 10 times fewer emissions for the same work, even in the same place.

Author Contributions: All authors contributed to this study's conception and design. S.A.S. and X.Y. performed the material preparation, data collection, and analysis. The first draft of this manuscript was written by S.A.S., X.Y., B.W. and X.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science and Technology Partnership Program, the Ministry of Science and Technology of China Developing China–ASEAN Public Health Research and Development Collaborating Center Project No.: KY202101004.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: All authors confirm that they have no conflicts of interest.

Abbreviations

CO_2	carbon dioxide emissions
AI	artificial intelligence
EPU	economic policy uncertainty
RENE	renewable energy
FMOLS	fully modified ordinary least squares
DOLS	dynamic ordinary least squares
CD	cross-sectional dependency
GMM	generalized method of moments
NDCs	nationally determined contributions
GHGs	greenhouse gases
SDGs	sustainable development goals
LLMs	large language models

References

1. Acharyya, J. FDI, growth and the environment: Evidence from India on CO_2 emission during the last two decades. *J. Econ. Dev.* **2009**, *34*, 43. [CrossRef]
2. Adams, S.; Adedoyin, F.; Olaniran, E.; Bekun, F.V. Energy consumption, economic policy uncertainty and carbon emissions; causality evidence from resource rich economies. *Econ. Anal. Policy* **2020**, *68*, 179–190. [CrossRef]
3. Ai, H.; Deng, Z.; Yang, X. The effect estimation and channel testing of the technological progress on China's regional environmental performance. *Ecol. Ind.* **2015**, *51*, 67–78. [CrossRef]
4. Akyildirim, E.; Corbet, S.; Lucey, B.; Sensoy, A.; Yarovaya, L. The relationship between implied volatility and cryptocurrency returns. *Financ. Res. Lett.* **2020**, *33*, 101212. [CrossRef]
5. Anser, M.K.; Apergis, N.; Syed, Q.R. Impact of economic policy uncertainty on CO_2 emissions: Evidence from top ten carbon emitter countries. *Environ. Sci. Pollut. R* **2021**, *28*, 29369–29378. [CrossRef] [PubMed]
6. Apergis, N.; Jebli, M.B.; Youssef, S.B. Does RENE consumption and health expenditures decrease CO_2? Evidence for sub-Saharan African countries. *Renew. Energy* **2018**, *127*, 1011–1016. [CrossRef]
7. Apergis, N.; Payne, J.E. Energy consumption and economic growth in Central America: Evidence from a panel co-integration and error correction model. *Energy Econ.* **2009**, *31*, 211–216. [CrossRef]
8. Arellano, M.; Bond, S. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [CrossRef]
9. Azka, A.; Eyup, D. The role of economic policy uncertainty in the energy-environment nexus for China: Evidence from the novel dynamic simulations method. *J. Environ. Manag.* **2021**, *292*, 112865.
10. Bartleet, M.; Gounder, R. Energy consumption and economic growth in New Zealand: Results of trivariate and multivariate models. *Energy Policy* **2010**, *38*, 3508–3517. [CrossRef]
11. Baker, S.R.; Bloom, N.; Davis, S.J. Measuring economic policy uncertainty. *Q. J. Econ.* **2016**, *131*, 1593–1636. [CrossRef]
12. Bekun, F.V.; Emir, F.; Sarkodie, S.A. Another look at the relationship between energy consumption, CO_2, and economic growth in South Africa. *Sci. Total Environ.* **2019**, *655*, 759–765. [CrossRef] [PubMed]
13. Borhan, H.; Ahmed, E.M.; Hitam, M. The impact of CO_2 on economic growth in ASEAN 8. *Procedia Soc. Behav. Sci.* **2012**, *35*, 389–397. [CrossRef]
14. Cai, J.; Li, X.; Liu, L.; Chen, Y.; Wang, X.; Lu, S. Coupling and coordinated development of new urbanization and agro-ecological environment in China. *Sci. Total Environ.* **2021**, *776*, 145837. [CrossRef] [PubMed]
15. Chen, Y.; Wang, Z.; Zhong, Z. CO_2 emissions, economic growth, renewable and non-RENE production and foreign trade in China. *Renew. Energy* **2019**, *131*, 208–216. [CrossRef]

16. Deng, X.; Du, L. Estimating the environmental efficiency, productivity, and shadow price of CO_2 for the BRI countries. *J. Clean. Prod.* **2020**, *277*, 123808. [CrossRef]
17. Durani, F.; Bhowmik, R.; Sharif, A.; Anwar, A.; Syed, Q.R. Role of economic uncertainty, financial development, natural resources, technology, and renewable energy in the environmental Phillips curve framework. *J. Clean. Prod.* **2023**, *420*, 138334. [CrossRef]
18. Fagerberg, J. Technology and international differences in growth rates. *J. Econ. Lit.* **1994**, *32*, 1147–1175.
19. Ferreira, J.J.; Fernandes, C.I.; Ferreira, F.A. Technology transfer, climate change mitigation, and environmental patent impact on sustainability and economic growth: A comparison of European countries. *Technol. Forecast. Soc. Chang.* **2020**, *150*, 119770. [CrossRef]
20. Gyamfi, B.A.; Agozie, D.Q.; Bekun, F.V. Can technological innovation, foreign direct investment and natural resources ease some burden for the BRICS economies within the current industrial era? *Technol. Soc.* **2022**, *70*, 102037. [CrossRef]
21. Gorus, M.S.; Aydin, M. The relationship between energy consumption, economic growth, and CO_2 emission in MENA countries: Causality analysis in the frequency domain. *Energy* **2019**, *168*, 815–822. [CrossRef]
22. Han, M.; Lao, J.; Yao, Q.; Zhang, B.; Meng, J. Carbon inequality and economic development across the BRI regions. *J. Environ. Manag.* **2020**, *262*, 110250. [CrossRef] [PubMed]
23. Hassan, T.; Song, H.; Khan, Y.; Kirikkaleli, D. Energy efficiency a source of low carbon energy sources? Evidence from 16 high-income OECD economies. *Energy* **2022**, *243*, 123063. [CrossRef]
24. Hassan, T.; Song, H.; Kirikkaleli, D. International trade and consumption-based carbon emissions: Evaluating the role of composite risk for RCEP economies. *Environ. Sci. Pollut. Res.* **2022**, *29*, 3417–3437. [CrossRef] [PubMed]
25. Hu, H.; Xie, N.; Fang, D.; Zhang, X. The role of RENE consumption and commercial services trade in carbon dioxide reduction: Evidence from 25 developing countries. *Appl. Energy* **2018**, *211*, 1229–1244. [CrossRef]
26. Huang, J.; Wu, Z. Impact of Environmental Regulations on Export Trade-Empirical Analysis Based on Zhejiang Province. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12569. [CrossRef] [PubMed]
27. Houssam, N.; Ibrahiem, D.M.; Sucharita, S.; El-Aasar, K.M.; Esily, R.R.; Sethi, N. Assessing the role of green economy on sustainable development in developing countries. *Heliyon* **2023**, *9*, e17306. [CrossRef] [PubMed]
28. Hussain, J.; Zhou, K.; Muhammad, F.; Khan, D.; Khan, A.; Ali, N.; Akhtar, R. RENE investment and governance in countries along the Belt & road: Does trade openness matter? *Renew. Energy* **2021**, *180*, 1278–1289.
29. Inglesi-Lotz, R.; Dogan, E. The role of renewable versus non-RENE to the level of CO_2 emissions a panel analysis of sub-Saharan Africa's Big 10 electricity generators. *Renew. Energy* **2018**, *123*, 36–43. [CrossRef]
30. Jebli, M.B.; Farhani, S.; Guesmi, K. RENE, CO_2 emissions and value-added: Empirical evidence from countries with different income levels. *Struct. Chang. Econ. Dyn.* **2020**, *53*, 402–410. [CrossRef]
31. Jesus, G.M.K.; Jugend, D.; Paes, L.A.B.; Siqueira, R.M.; Leandrin, M.A. Barriers to the adoption of the circular economy in the Brazilian sugarcane ethanol sector. *Clean Technol. Environ. Policy* **2023**, *25*, 381–395. [CrossRef]
32. Jiang, Y.; Zhou, Z.; Liu, C. Does economic policy uncertainty matter for carbon emission? Evidence from US sector-level data. *Environ. Sci. Pollut. Res. Int.* **2019**, *26*, 24380–24394. [CrossRef] [PubMed]
33. Kahouli, B. The causality link between energy electricity consumption, CO_2 emissions, R&D stocks and economic growth in Mediterranean countries (MCs). *Energy* **2018**, *145*, 388–399.
34. Kannadhasan, M.; Das, D. Do Asian emerging stock markets react to international economic policy uncertainty and geopolitical risk alike? A quantile regression approach. *Financ. Res. Lett.* **2020**, *34*, 101276. [CrossRef]
35. Khan, M. CO_2 emissions and sustainable economic development: New evidence on the role of human capital. *Sustain. Dev.* **2020**, *28*, 1279–1288. [CrossRef]
36. Khan, Y.; Bin, Q. The environmental Kuznets curve for CO_2 and trade on BRI countries: A spatial panel data approach. *Singap. Econ. Rev.* **2020**, *65*, 1099–1126. [CrossRef]
37. Khan, Y.; Bin, Q.; Hassan, T. The impact of climate changes on agriculture export trade in Pakistan: Evidence from time-series analysis. *Growth Chang.* **2019**, *50*, 1568–1589. [CrossRef]
38. Khan, Y.; Hassan, T.; Kirikkaleli, D.; Xiuqin, Z.; Shukai, C. The impact of economic policy uncertainty on carbon emissions: Evaluating the role of foreign capital investment and RENE in East Asian economies. *Environ. Sci. Pollut. Res.* **2022**, *29*, 18527–18545. [CrossRef] [PubMed]
39. Khan, Y.; Oubaih, H.; Elgourrami, F.Z. The role of private investment in ICT in CO_2 mitigation: Do RENE and political risk matter in Morocco? *Environ. Sci. Pollut. Res.* **2022**, *29*, 52885–52899. [CrossRef]
40. KhoshnevisYazdi, S.; GhorchiBeygi, E. The dynamic impact of RENE consumption and financial development on CO_2 emissions: For selected African countries. *Energy Sources Part B* **2018**, *13*, 13–20. [CrossRef]
41. Lin, B.; Ma, R. Green technology innovations, urban innovation environment and CO_2 emission reduction in China: Fresh evidence from a partially linear functional-coefficient panel model. *Technol. Forecast. Soc. Chang.* **2022**, *176*, 121434. [CrossRef]
42. Mahadevan, R.; Sun, Y. Effects of foreign direct investment on carbon emissions: Evidence from China and its BRI countries. *J. Environ. Manag.* **2020**, *276*, 111321. [CrossRef] [PubMed]
43. Mahmood, H.; Alkhateeb, T.T.Y.; Furqan, M. Exports, imports, foreign direct investment and CO_2 emissions in North Africa: A spatial analysis. *Energy Rep.* **2020**, *6*, 2403–2409. [CrossRef]
44. Melane-Lavado, A.; Álvarez-Herranz, A.; González-González, I. Foreign direct investment as a way to guide the innovative process towards sustainability. *J. Clean. Prod.* **2018**, *172*, 3578–3590. [CrossRef]

45. Michieka, N.M.; Fletcher, J.; Burnett, W. An empirical analysis of the role of China's exports on CO_2 emissions. *Appl. Energy* **2013**, *104*, 258–267. [CrossRef]
46. Naseem, S.; Hu, X.; Sarfraz, M.; Mohsin, M. Strategic assessment of energy resources, economic growth, and CO_2 emissions in G-20 countries for a sustainable future. *Energy Strategy Rev.* **2024**, *52*, 101301. [CrossRef]
47. Nesta, L.; Vona, F.; Nicolli, F. Environmental policies, competition and innovation in RENE. *J. Environ. Econ. Manag.* **2014**, *67*, 396–411. [CrossRef]
48. Ockwell, D.; Mallett, A. Low carbon innovation and technology transfer. In *Low Carbon Development: Key Issues*; Routledge: London, UK, 2013; pp. 109–128.
49. ECD.AI. Visualization Powered by JSI, Using Data from OpenAlex. 2024. Available online: www.oecd.ai (accessed on 16 July 2024).
50. Pata, U.K.; Caglar, A.E.; Kartal, M.T.; Depren, S.K. Evaluation of the role of clean energy technologies, human capital, urbanization, and income on the environmental quality in the United States. *J. Clean. Prod.* **2023**, *402*, 136802. [CrossRef]
51. Patterson, D.; Gonzalez, J.; Le, Q.; Liang, C.; Munguia, L.M.; Rothchild, D.; So, D.; Texier, M.; Dean, J. Carbon emissions and large neural network training. *arXiv* **2021**, arXiv:2104.10350.
52. Pesaran, M.H.; Yamagata, T. Testing slope homogeneity in large panels. *J. Econom.* **2008**, *142*, 50–93. [CrossRef]
53. Pesaran, M.H. General diagnostic tests for cross-sectional dependence in panels. *Empir. Econ.* **2021**, *60*, 13–50. [CrossRef]
54. Pirgaip, B.; Dincergok, B. Economic policy uncertainty, energy consumption and carbon emissions in G7 countries: Evidence from a panel Granger causality analysis. *Environ. Sci. Pollut. Res. Int.* **2020**, *27*, 30050–30066. [CrossRef] [PubMed]
55. Qingquan, J.; Khattak, S.I.; Ahmad, M.; Ping, L. A new approach to environmental sustainability: Assessing the impact of monetary policy on CO_2 emissions in Asian economies. *Sustain. Dev.* **2020**, *28*, 1331–1346. [CrossRef]
56. Rauter, R.; Globocnik, D.; Perl-Vorbach, E.; Baumgartner, R.J. Open innovation and its effects on economic and sustainability innovation performance. *J. Innov. Knowl.* **2019**, *4*, 226–233. [CrossRef]
57. Ren, X.; Zhang, X.; Yan, C.; Gozgor, G. Climate policy uncertainty and firm-level total factor productivity: Evidence from China. *Energy Econ.* **2022**, *113*, 106209. [CrossRef]
58. Salman, M.; Long, X.; Dauda, L.; Mensah, C.N. The impact of institutional quality on economic growth and carbon emissions: Evidence from Indonesia, South Korea and Thailand. *J. Clean. Prod.* **2019**, *241*, 118331. [CrossRef]
59. Sebri, M.; Ben-Salha, O. On the causal dynamics between economic growth, RENE consumption, CO_2 emissions, and trade openness: Fresh evidence from BRICS countries. *Renew. Sustain. Energy Rev.* **2014**, *39*, 14–23. [CrossRef]
60. Selmey, M.G.; Elamer, A.A. Economic policy uncertainty, renewable energy, and environmental degradation: Evidence from Egypt. *Environ. Sci. Pollut. Res. Int.* **2023**, *30*, 58603–58617. [CrossRef]
61. Shah, S.A.; Ali, S.; Wang, T.; He, C. Does energy conversion contribute to economic development in emerging and growth leading economies (EAGLE's): Evidence from panel ARDL approach. *Environ. Sci. Pollut. Res.* **2023**, *30*, 64472–64485. [CrossRef] [PubMed]
62. Tee, C.M.; Wong, W.Y.; Hooy, C.W. Economic policy uncertainty and carbon footprint: International evidence. *J. Multinatl. Financ. Manag.* **2023**, *67*, 100785. [CrossRef]
63. Tu, Z.; Feng, C.; Zhao, X. Revisiting energy efficiency and energy related CO_2 emissions: Evidence from RCEP economies. *Econ. Res.* **2022**, *35*, 5858–5878.
64. Tufail, M.; Song, L.; Adebayo, T.S.; Kirikkaleli, D.; Khan, S. Do fiscal decentralization and natural resources rent curb carbon emissions? Evidence from developed countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 49179–49190. [CrossRef] [PubMed]
65. Wang, J.; Dong, K.; Dong, X.; Taghizadeh-Hesary, F. Assessing the digital economy and its carbon-mitigation effects: The case of China. *Energy Econ.* **2022**, *113*, 106198. [CrossRef]
66. Wang, J.; Dong, X.; Dong, K. How does ICT agglomeration affect carbon emissions? The case of Yangtze River Delta urban agglomeration in China. *Energy Econ.* **2022**, *111*, 106107. [CrossRef]
67. Wang, J.; Wang, B.; Dong, K.; Dong, X. How does the digital economy improve high-quality energy development? The case of China. *Technol. Forecast. Soc. Chang.* **2022**, *184*, 121960. [CrossRef]
68. Yu, J.; Shi, X.; Guo, D.; Yang, L. Economic policy uncertainty (EPU) and firm carbon emissions: Evidence using a China provincial EPU index. *Energy Econ.* **2021**, *94*, 105071. [CrossRef]