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RESEARCH ARTICLE

En route to attaining a clean sustainable ecosystem: a nexus between solar energy technology, economic expansion and carbon emissions in China

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Abstract
This paper probes the nexus between solar energy technology, carbon intensity of energy structures, economic expansion, and carbon emissions (CO_2) throughout 1990–2017 in China. The study utilized the vector auto-regressive (VAR) approach to co-integration testing and vector error-correction models to identify the most effective method for reducing CO_2 emissions. Results from the Granger causality (GC) suggest a unidirectional causality between the variables. The test of impulse response function (IRF) constituted in the VAR technique was also applied in this study. The results indicate that energy structure intensity and economic expansion positively affect carbon emissions, while solar energy technology negatively affects carbon emissions. Simultaneous IRF analysis demonstrated that solar energy technology, energy structure carbon intensity, and economic expansion all have long-term effects on carbon emissions. The study concluded that when the economy expands, it influences CO_2 emissions. Also, there exists a positive impact on CO_2 emissions from the number of solar patents, but was seen to be decreasing gradually. The policy implications were also stated.

Keywords Carbon emissions · Solar technology · Economic expansion · VAR model · Impulse response function · China

Introduction

Energy conservation and reduction of carbon dioxide emissions in China have become important issues. China is currently in the midst of swift suburbanization and industrialization, which is resulting in expeditious growth in energy usage. Whether for human survival, economic expansion, or social progress, energy is indispensable. Energy is one of the basic elements that promote economic expansion and an irreplaceable component in human survival and development (Smil 2019). Energy consumption is inevitably accompanied by carbon dioxide (CO_2) emissions. In other words, economic expansion always causes CO_2 emissions in places where conventional energy sources persist due to rapid industrialization and suburbanization (Appiah et al. 2019b). The leading contributors to total global CO_2 emissions are developed and

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developing countries with high levels of industrialization (Appiah et al. 2019a; Đan et al. 2019).

Since China's economic transformation and opening-up of trade as a populous country, its economic expansion and energy consumption have increased tremendously, making China among the biggest CO_2 emitters in the world (Xie et al. 2019). There has been an increasing international focus on China's efforts to reduce CO_2 emissions (Y. Huang and Matsumoto 2019). By 2000, China exhibited the largest increase in global energy usage out of all countries (Wang et al. 2005). In 2006, China's carbon emissions soared to 6.2 billion tons, surpassing the United States and attaining the title, "the world's largest carbon discharger" (Shi et al. 2019; Xie et al. 2019).

In addition, according to the BP Statistical Review of World Energy (2018), the carbon emissions generated by global energy consumption in 2017 rebounded after a 3-year growth between 2014 and 2016 (an increase of 1.6%). The reason, according to the review, was the intensification of natural gas use, and the sharp increase in the desire for natural gas in China caused a rise in global usage of natural gas. Therefore, there has been increased international pressure on China to strategically reduce emissions of CO_2 in the face of global warming.

Energy conservancy and CO_2 emission reduction have therefore become urgent tasks, and their effective implementation is inseparable from the necessary technical support, especially renewable energy technologies (Guo et al. 2018; Zhang et al. 2015).

In order to gain a leading edge in the future energy market, some companies actively participate in the solar energy patent "grab land" campaign (Li 2018; Zhao et al. 2015). The International Energy Agency has announced the possibility of reducing CO_2 emissions by adopting 17 top strategic renewable energy technologies, where 3 out of the 17 are solar energy technologies. This underscores the fundamental importance of solar energy technologies in reducing CO_2 emissions (Prăvălie et al. 2019; Serrano-Jiménez et al. 2019).

Our study is therefore driven by the reawakened interest in identifying the best method for reducing carbon emissions for a sustainable cleaner environment, both in China and worldwide. This study contributes to the literature by exploring the dynamic nexus between solar energy technology, economic expansion, and carbon emissions, the importance of adopting solar energy technologies for a cleaner environment and analyzing how economic expansion influences carbon emissions.

China was selected as the subject of this study for numerous reasons. Its economic expansion rates over the preceding two decades have been spectacular. Furthermore, as the globe's most populous country with an estimated 1.4 billion inhabitants, it is a useful case study area for examining the environment-development nexus. There has been controversy over the use of non-renewable energy sources (such as oil, coal, and natural gas) to promote economic growth, and this has instigated research into renewable energy sources, including solar technology and wind technology.

The outcomes of this paper suggest further valuable and pertinent information for policymakers in the field of solar energy technology and the reduction of carbon emissions in China and worldwide. The impulse response of economic expansion (GDP), solar patent technology, and energy structure carbon intensity fluctuate with diverse time horizons, whether with positive or negative impacts on CO_2. This study's findings offer a significant understanding of carbon emission policies from non-renewable energy sources and the need for a sustainable clean environment.

The remainder of the paper is arranged in the following manner: "Literature review" briefly reviews the literature; "Research methods and variable selection" presents the research methods and selection of variables; "Empirical analysis" discusses the empirical analysis; and "Conclusions and policy implications" draws conclusions and discusses policy implications.

Literature review

From all human activities such as breathing, walking, driving, and cooking that create CO_2 emissions, the academic community has carried out in-depth analyses of many factors influencing CO_2 emissions. These may be defined under the following broad categories.

Economic expansion

Economic burgeoning is inseparable from the consumption of energy, especially fossil fuels, which will inexorably lead to an upsurge in carbon emissions. For example, studies have pointed out that economic expansion, fixed asset investment, total import and export, service industry added value, fossil fuels, alternative energy, and nuclear technology have all been positively affecting carbon emissions (Anser 2019; Kahia et al. 2019; Karasoy 2019).

Peng et al. (2018) found that urban carbon emissions demonstrate an initial upward trend and decrease as the economic scale is increased, i.e., the relationship between urban CO_2 emissions and scale of economic activities has an inverse U-shape.

Xiao and Zhang (2019) conducted a comprehensive study of the influence of renewable energy usage and financial scale on carbon emissions and found that the state of economic development affects the impact of low carbon emissions from renewable energy consumption. When the state of the economy is poor, renewable energy consumption associates positively with carbon emissions, and vice versa. Therefore, in view of the carbon emissions from economic expansion, research suggests that improving the structures of energy consumption (Ji and Zhang 2019) and transforming and upgrading industrial structures (Guo and Feng 2019; Lin 2019) are important measures for reducing CO_2 emissions.

Urban development

As urbanization accelerates, the urban population begins to grow; hence, problems such as those associated with urban housing and transportation also begin to deepen, in turn influencing the continued increase in CO_2 emissions. Studies have shown that urbanization is inevitably accompanied by high carbon emissions (Asaduzzaman et al. 2019; Khoshnevis Yazdi and Dariani 2019; Kwakwa and Alhassan 2018; Wang et al. 2019c). The growth rate of carbon emissions is higher than that of the urbanization that causes it (Du and Lin 2019).

By contrast, new inner-city construction considers many factors, such as the residential population, employment rate of the inner-city population, and inner-city and rural structures; it has a low-carbon green development policy, which has a substantial effect on controlling the carbon intensity of energy use (Han et al. 2018; Wang et al. 2019b). For example, urban planning's effects on carbon emissions are a major factor in global climate change (Salahuddin et al. 2019b; Wang and Han 2019; Wang et al. 2019a, 2018). Through urban planning, innovative urban forms, which encourage residents to walk, ride bicycles and use public transport, can effectively reduce carbon emissions (Stojanovski 2019). Salahuddin et al. (2019a) also point out that urbanization in the future is the area with the greatest potential for energy conservation after industrialization.

Technological advances

Clean energy technology can reduce carbon releases from energy consumption, compared to hydrocarbon energy sources. Technological advances are, therefore, an effective measure of reducing carbon emissions (Ismael et al. 2018; Lu et al. 2019), and discouraging carbon emissions is more effective than promoting carbon efficiency by energy grants, while the two approaches form a positive interaction and ultimately contribute to reducing carbon emissions (Huang et al. 2018; Oliver and Upton 2019).

However, there is regional heterogeneity in the effects of technological innovation on carbon emissions; carbon emissions from energy consumption in high-carbon areas are more affected by technological innovation (Ren and Zhao 2018). Du et al. (2019) concluded that the role played by energy technology innovation is vital in reducing carbon emissions for economies with high income levels.

Policy perspectives

Hailemariam et al. (2019) found that implementing policies aimed at reducing income inequality can reduce carbon emissions and improve environmental quality. He and Fan (2019) pointed out that domestic waste incineration energy generation is imperative for reducing carbon emissions, but the effect may not be significant due to the small amount of waste treated in this way.

In summary, many scholars have studied the factors affecting carbon emissions. These include not only factors that lead to increased carbon emissions, such as those related to economic expansion and urbanization, but also those that reduce carbon emissions, such as improving the energy consumption structure, upgrading the industrial structure, implementing new urbanization, vigorously pursuing technological progress, and introducing relevant policies. However, there has recently been little research on the bearing of solar technology on carbon emissions. Consequently, situated in the discourse of the relevant literature, this paper intends to use the autoregressive model to reveal the inherent logical nexus between China's carbon emissions and its economic expansion and solar patent technology to describe the effects of solar energy technology and economic expansion on carbon emissions and provide a viable policy basis for reducing them.

Research methods and variable selection

Research methods

There have been studies on the nexus between technological progress, economic expansion, and greenhouse gas emissions using many quantitative research paradigms. These began in 1989 when the Japanese scholar Kaya proposed the "Kaya identities," based on the factorization method. More recently, there has been a tendency toward the use of Vector Auto-Regression (VAR) models.

The advantage of this model is that it considers the conversion of scientific and technological achievements and the failure of economic benefits. It can also predict time series with correlation and long-term equilibrium and possesses the ability to examine the dynamic effects of turbulence conditions on the variables.

VAR, one of the most suitable models to envisage and analyze multiple interrelated economic indicators, is constructed on statistical physiognomies of data, and it uses information on multiple variables expansively. Each endogenous variable in the VAR model found in the systems is seen to be the lagged value for the entirety of the endogenous variables, and there is a generalization of the auto-regressive univariate model to the "vector" auto-regressive model entailing multivariate variables in the time series.

The VAR model uses a single time series and thus covers abundant information more efficiently than other models. When used in projections, it is able to deliver more accurate predicted values. Sims (1980) introduced the VAR model into the field of economics and used it extensively in dynamic studies of economic structure.

Charfeddine and Kahia (2019) applied a vector autoregressive model to observe the key factors behind the upsurge of CO_2 emissions in the industrial sector; Sinha and Shahbaz (2018) also used this method to scrutinize the effects of renewable energy technologies on carbon emissions. Kahia et al. (2019) also employed the VAR method to measure the effects of economic expansion and renewable energy use on carbon dioxide emissions in 12 MENA states. Kang et al. (2019) used the VAR model to analyze the dynamic connections between growth of GDP, the use of renewable or non-renewable energy sources, and CO_2 emissions. Khoshnevis Yazdi and Shakouri (2018) also analyzed CO_2 emissions, economic expansion and consumption of energy during the period between 1975 and 2014 in Germany using VAR.

Kaya's identity is based primarily on fixed angle analysis, while the VAR model is relatively complex. The VAR model can construct a variable to model the lag period of all other variables; it is able to analyze the symmetric association between variables through the assessment of co-integration and analyze the underlying relationships between variables and can also avoid the use of subjective or arbitrary divisions between dependent and independent variables. Therefore, the vector autoregressive model was used to empirically study the impact of China's solar energy technology and the effects of economic expansion on carbon emissions.

The mathematical expression for the vector autoregressive model is constructed as follows:

$$y_t = \alpha_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + \varepsilon_t,\ t = 1, \ldots T \tag{1}$$

such that, $y_t$denotes a $k * 1$vector of endogenous variable, $\varphi_t$signifies the co-efficient matrices of $k * k$, $\varepsilon_t$symbolizes the estimate error with variance/covariance matrixΣ, the intercept is represented by α_0, and the lag length is p.

$$y_t = \alpha_1 + \sum_i^p \beta_i y_{t-i} + \sum_j^q \gamma_j x_{t-j} + \sum_k^r \eta_k z_{t-k} + \sum_l^m \varpi_l h_{t-l} + \mu_t \tag{2}$$

Equation (2) is an autoregressive vector model with the four variables (y, x, z, h). $\sum_i^p \beta_i y_{t-i}$, $\sum_j^q \gamma_j x_{t-j}$, $\sum_k^r \eta_k z_{t-k}$, $\sum_l^m \varpi_l h_{t-l}$ represent the variables y, x, z, h, lag p, q, r, m and time period t. The entire model in Eq. (2), however, represents the effects of$y_t$on the four variables.

Impulse response function analysis

The impulse response analysis simulates the effect of any endogenous variable on other variables in the system and comprehensively mirrors the nexus between various variables. It explicitly demonstrates effects on a recent or forthcoming value when an arbitrary error term from outside or within the system is added. Equation (1) contains a 'steadiness provision', which elucidates the VAR model as an infinite vector process if, and only if, the roots of the elements are not within the unit circle; thus, Eq. (1) can be revised as

$$y_t = \Xi(W)\mu_t \tag{3}$$

Such that W characterizes the lag operator. The conditioning random variables, when y_t is offered a unit of impulse in the foundation period: μ_{1t}=1, $t = 0$. $\mu_{1t} = 0$. t= *others*, $\mu_{2t} = 0$, $t = 0, 1, 2, 3, \ldots$,which is dubbed the impulse response function of y_2 triggered via y_1 and which can be designated as

$$t = 0,\ y_{20} = \psi_{21}^{(0)}; t = 1,\ y_{21} = \psi_{21}^{(1)}; t = 2,\ y_{22} = \psi_{21}^{(2)}; t = 3,\ y_{23} = \psi_{21}^{3}, \ldots, \tag{4}$$

Variables and data selection

Economic expansion and energy consumption are inseparable, and energy consumption inevitably produces carbon emissions; thus, economic expansion is thoroughly related to carbon emissions. In countries or regions experiencing economic growth, rapid economic expansion will be accompanied by environmental problems, given the difficulties of balancing economic expansion and environmental protection.

As the economy evolves to a certain stage, innovative technologies are used to protect the environment, increasing the use of emerging energy sources and minimizing carbon emissions. Therefore, this paper selects carbon emissions, energy structure carbon intensity, level of economic expansion, and solar energy technology as the principal analytical variables.

(1) Carbon emissions (CO_2): Carbon emissions refer to the average greenhouse gas emissions generated during production, transportation, use, and recycling of products. We obtained China's per capita carbon emissions data from 1990 to 2017 from the WDI database and the China Statistical Yearbook. Both sources were used to obtain the final carbon emissions over the years.

(2) Energy structure carbon intensity (ESCI): Energy structure carbon intensity is the ratio of carbon emissions to total energy consumption for the various energy sources, thus reflecting the impact of energy

structure on carbon emissions. We calculated the energy structure carbon intensity over the years based on the formula $ESCI = \left(\sum_i^n E_i\beta_i/\alpha_i\right)/Q$, where i refers to coal, oil, and natural gas; E_i represents the first type of energy consumption i, which is the product of the total energy consumption and the share of different classes of energy consumption; β_i is the coefficient of the first type of energy carbon emission; α_i indicates the energy conversion rate; Q indicates the type of energy carbon emission factor. The total energy consumption and the consumption, conversion factor, and carbon emission co-efficient of the three types of energy are taken from the China Statistical Yearbook and the Carbon Dioxide Information Analysis Center.

(3) Level of economic expansion (GDP): This paper expresses the level of economic expansion by gross domestic product (GDP), because GDP reflects the overall economic expansion of a nation or region's economy. At the same time, to avoid any impacts from price changes, this paper examines the GDP data from China's Statistical Yearbook, primarily based on real GDP in constant 2005 US dollars.

(4) Solar Patented Technology (SPT): We measured solar energy technology by the number of patents in the field.

Given that the logarithm does not change the co-integration association amidst the variables, and that this could eliminate the potential heterogeneity that may exist in the time series to some extent, the above four variables underwent a logarithmic conversion (base 10) to create a new series of variables: $lgCO_2$, lgESCI, lgGDP, and lgSPT. The names, symbols, and meanings of the above variables are summarized in Table 1.

Table 2 displays the descriptive statistics demonstrating that $lgCO_2$ had a higher average, and lgESCI had the lowest. In addition, lgESCI had the highest standard deviation (unpredictability). Moreover, the skewness and kurtosis tests indicate fairly asymmetrical and leptokurtic distributions, respectively. The Jarque-Bera assessment indicated that the distributions were not normal.

Table 2 Descriptive statistics

Variables	$lgCO_2$	lgESCI	lgGDP	lgSPT
Mean	5.719	2.279	4.852	2.928
Median	5.689	2.277	4.841	2.808
Maximum	6.049	2.307	5.359	4.285
Minimum	5.391	2.236	4.276	1.580
Std. Dev.	0.230	0.018	0.334	0.931
Skewness	0.126	− 0.471	− 0.082	0.075
Kurtosis	1.423	2.736	1.784	1.503
Jarque-Bera	2.977	1.114	1.757	2.640
Observations	28	28	28	28

Source: authors own compilation

Empirical analysis

Stationarity test of variables

In an economic time-series, it is necessary that the great majority of econometric models are stationary. Since most economic variables are non-stationary in the sequence, a method of differentiation is frequently adopted with the intention of eliminating the trend of non-stationarity, so as to construct a realistic model. In addition, if two non-stationary time series are regressed, the results are meaningless even if a higher coefficient is obtained. Therefore, when performing the model for analysis, it is indispensable to perform a unit root test on the variables to check their stationarity. Whether a random time series (such as the time series $[X_t]$ (= 1, 2, 3...)) is stable or not, it needs to agree with the following conditions: mean $E(X_t)$, variance$Var(X_t)$, and covariance $Cov(X_t, X_{t+k})$ are constants that are independent of time.

In the sequence of economic variables, the null hypothesis consistently stipulates that a unit root exists, and the alternate hypothesis implies that a unit root does not exist in a time series. Usually, if the time series turns out to be stationary either at levels, first-difference or at second difference, the meaning is that the original time series are all integrating at the same order, which is recorded as $I(n)$. Therefore, this paper first employs the Augmented Dickey Fuller (ADF) test to

Table 1 Summary of variables

Variable name	Symbol	Logarithmic symbol	Variable meaning
Carbon emission	CO_2	$lgCO_2$	Total carbon emissions over the years = per capita carbon emissions * population
Energy structure carbon intensity	ESCI	lgESCI	Energy structure carbon intensity = total carbon emissions of various energy consumption/total energy consumption Carbon emissions from various energy consumption = $\sum_i^n E, \beta, i, \alpha$
Gross domestic product	GDP	lgGDP	Real GDP obtained after the nominal GDP and GDP real growth index are deflated
Solar patented technology	SPT	lgSPT	Amount of patents invention in the discipline of solar energy

Source: authors own compilation

perform a unit root test on the variables to determine their stationarity. From the test results shown in Table 3, the ADF statistics at levels and first-order difference of the variables $lg\mathrm{CO}_2$, lgESCI, lgGDP, and lgSPT with significance levels 1%, 5%, and 10% are seen to be greater than the p values, suggesting that they are non-stationary; thus, a unit root exists among the four variables. However, in their second-order difference, all four variables became stationary at a significant level of 1%; hence, we reject the hypothesis that a unit root exists at the second-order difference, which is denoted as $I(2)$.

Formation of VAR model

Since all the variables are integrated at the same order, it is necessary to construct a VAR model, which is expressed as

$$\lg(C0_2)_t = \alpha_1 + \sum_i^p \beta_{ij}\lg(C0_2)_{t-i} + \sum_j^q \gamma_{1j}\lg(ESCI)_{t-j} + \sum_k^r \eta_{1k}\lg(GDP)_{t-k} + \sum_l^m \varpi_{1l}\lg(SPT) + ^{t-l}\mu_{1t} \quad (3)$$

In order to observe the long-term relationships among the variables in this study, we determined the lag order based on five indicators: LR, FPE, AIC, SC, and HQ. As shown in Table 4, the optimal lag order length of (4) is set for the VAR model. In addition, the evenness of the model is further tested. From Fig. 1, all the eigenvalues are found inside the unit circle, indicating that the proposed VAR model with a lag order of 4 is stable. To test for co-integration, the GC and IRF were employed.

Table 3 ADF test results

Variable	Test form (c, t, l)	ADF statistics	p value
Levels			
lg (CO_2)	(c, 1, 1)	− 0.707	0.828
lg (ESCI)	(c, 1, 2)	− 1.219	0.650
lg (GDP)	(c, 1, 1)	− 2.023	0.276
lg (SPT)	(c, 1, 0)	− 0.126	0.937
First difference			
D (lg (CO_2), 1)	(c, 1, 0)	− 1.947	0.307
D (lg (ESCI), 1)	(c, 1, l)	− 1.888	0.332
D (lg (GDP), 1)	(c, 1, 0)	− 1.629	0.454
D (lg (SPT), 1)	(c, 1, l)	− 2.076	0.255
Second difference			
D (lg (CO_2), 2)	(c, 1, 0)	− 4.123***	0.004
D (lg (ESCI), 2)	(c, 1, 0)	− 10.68***	0.000
D (lg (GDP), 2)	(c, 1, 0)	− 5.809***	0.000
D (lg (SPT), 2)	(c, 1, 0)	− 9.588***	0.000

Note: c, t, and l (c, t, l) C represent the intercept, t is the time trend, and l is the lag order, respectively, contained in the unit root test. The statistical significance is at ***($p < 0.01$ or 1%), **($p < 0.05$ or 5%), *($p < 0.1$ or 10%)

Johansen co-integration test

In order to construct a satisfactory model, a differencing methodology is usually assumed that eradicates the non-stationary order trend, since most times series of economic variables are non-stationary. The results of the unit root test in Table 3 demonstrate that the four variables in the VAR model were not stationary at their first-order difference, but became stationary at their second-order difference, thus satisfying the necessary conditions for proposing the co-integration equation.

Therefore, a long-term co-integration analysis was performed between the four variables. The most commonly used co-integration test methodology includes the two-step Engle-Granger (E-G) co-integration analysis and Johansen co-integration test based on regression coefficients. The former (E-G two-step) is mostly used to test co-integration of bivariate models, while the latter is mostly used to test co-integration of multivariate models.

Therefore, to locate the possible co-integration relationship that exists between the variables as stated in Eq. (3), we primarily applied the Johansen co-integration test. According to the results of the Johansen co-integration test, shown in Table 5, the trace statistic (t-statistics) value and the maximum eigenvalue are larger than the 5% critical value. Thus, the results in Table 5 confirm that the variables are co-integrated, as there are four co-integration equations found, and hence no causality in any direction. Therefore, there may be a long-term equilibrium relationship between the variables $lg\mathrm{CO}_2$, lgESCI, lgGDP, and lgSPT. As in the presence of co-integrating relationship among variables, the VAR model may mislead the statistical inference. We therefore adopted the vector error correction model (VECM), which is able to confine long-term conduct of the endogenous variables and be confluent to their co-integration relation.

Vector error correction model

The Johansen co-integration test showed that the variables were co-integrating and do possess a long-term equilibrium relationship; nonetheless, in the short term, there is disequilibrium in the variables, hence providing feasibility for establishing a VECM.

So far as there is the presence of a co-integration relationship between the variables, the model for the error correction is derivative from the distributed autoregressive lag model. Note that the equation for the VAR model is a distributed auto-regressive lag model; hence, the VEC model is thought-out to be a VAR model with co-integration impediments. Owing to the fact that there is a co-integration relationship in the VEC model, in a situation where there is a large

Table 4 Optimal lag order selection criteria for the VAR model

Lag	LogL	LR	FPE	AIC	SC	HQ
1	287.1247	NA	1.83E-15	− 22.59372	− 21.80835	− 22.38536
2	311.9693	33.12623	9.63E-16	− 23.33078	− 21.76004	− 22.91406
3	326.6655	14.69615	1.43E-15	− 23.22212	− 20.86602	− 22.59705
4	373.3166	31.10076*	2.27e-16*	− 25.77639*	− 22.63491*	− 24.94295*

*Designates lag order chosen by the criterion at 5% significance level

series of active fluctuations in the short term, the short-term imbalance and active structure can be stated as the VECM. Since the VAR lag order is 4, the lag order for the VECMs would be 3.

The third co-integration equation indicates that there is no relationship between ESCI, GDP, and SPT, which is not consistent with the general circumstances. Hence, with the first equation regarded as the co-integration equation of VECM, the equation's outputs are displayed as in Table 6.

The co-integration equation is

$$\lg CO_{2t} = 1.3839 \lg \mathrm{ESCI}_t + 1.4245 \lg \mathrm{GDP}_t - 0.2367 \lg \mathrm{SPT}_t - 3.6658 \quad (4)$$
$$(0.66527) \quad (0.18032) \quad (0.05792)$$

The co-integration equation of the above formula exhibits a stable long-term equilibrium relationship existing between the total carbon emissions in China and the energy structure carbon intensity, the number of solar patents and GDP from 1990 to 2017. The detailed analysis is as follows.

(1) A positive correlation exists between energy structure carbon intensity (ESCI) and carbon emissions (CO_2): when the energy structure strength logarithm (*lg*ESCI) increases by 1 unit, the total carbon emissions logarithm (*lg*CO_2) increases by 1.3839, indicating that China's energy structure carbon intensity is higher. In other words, the high consumption of coal, oil, natural gas and other mineral resources has a significant impact on China's carbon emissions.

(2) A positive relationship exists between economic expansion (GDP) and carbon emissions: for every unit of change in the logarithm of economic expansion (*lg*GDP), the logarithm of total carbon emissions (*lg*CO_2) increases by 1.4245 and vice versa. In other words, the rapid development of China's economy is indeed led by an upsurge in carbon emissions.

(3) A positive correlation exists between solar energy patents (SPT) and carbon emissions: a one-unit change of the solar energy patent (*lg*SPT) logarithm decreases the total carbon emissions logarithm (*lg*CO_2) by 0.2367, indicating that solar energy technology can perform an important function in reducing carbon emissions. In other words, with the extensive application of solar technology, solar energy consumption will increase, and will reduce the carbon emissions caused by fossil fuel consumption.

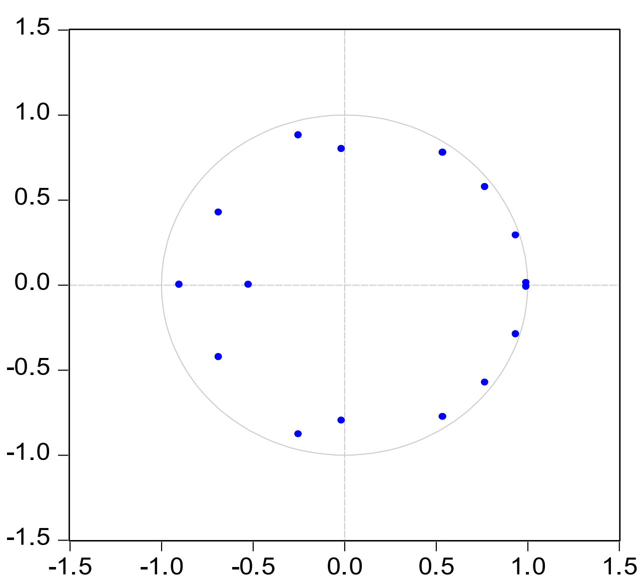

Fig. 1 VAR model stability test

Of the three variables, the most important factor affecting carbon emissions is the level of economic expansion, followed by energy structure carbon intensity, and finally the number of solar patents. The number of solar patents plays an important role in reducing carbon emissions.

The coefficients of each variable corresponding to CointEq1 in the estimation of the VECM in Table 7 are mostly negative, indicating that the model has an error correction mechanism, further demonstrating the existence of a long-term equilibrium relationship between the variables.

Granger causality test

The co-integration test suggests a long-term equilibrium relationship between the variables, in terms of a causal relationship; however, additional testing is required. In order to further investigate the causal relationship between the variables, we used the Granger causality (GC) test.

Table 5 Johansen cointegration test results

Hypothesized no. of CE(s)	Eigenvalues	*t*-statistics	0.05 critical value	Prob.**
Unrestricted co-integration rank test (Trace)				
None*	0.937	135.2	47.86	0.000
At most 1*	0.796	68.79	29.80	0.000
At most 2*	0.674	30.70	15.49	0.000
At most 3*	0.146	3.783	3.842	0.052
Unrestricted co-integration rank test (maximum eigenvalues)				
None*	0.937	66.37	27.58	0.000
At most 1*	0.796	38.09	21.13	0.000
At most 2*	0.674	26.92	14.26	0.000
At most 3*	0.146	3.783	3.842	0.052

Note: Trace test indicates 4 co-integration equations at the 0.05 level; Max-eigenvalue test suggests 4 co-integration equations at the 0.05 level

*Rejection of the hypothesis at the 0.05 level

**MacKinnon et al. (1999) *p* values

Source: Author's calculation

In the GC test, if a variable *Q* is supportive in forecasting a variable *Z*, where the regression of variable *Z* is grounded on previous values of variable *Z* and previous values of variable *Q* are included, this has the ability to greatly augment the explanatory strength of the regression. The variable *Q* can then be termed a Granger cause of variable *Z*; if not, it will be termed a non-Granger cause. A *p* value that is less than the 5% (0.05) significance level indicates an acceptance of the null hypothesis, namely the presence of a Granger cause.

The results displayed in Table 8 show a rejection of the hypothesis that *lg*GDP and *lg*SPT do not influence $lgCO_2$, i.e. that GDP and SPT have an impact on CO_2 emissions. This implies that the level of economic expansion and the number of solar patents affect China's total carbon emissions. In addition, a rejection of the hypothesis that *lg*GDP does not constitute a Granger cause of *lg*SPT indicates that GDP has an influence on SPT, suggesting that the level of economic expansion affects the number of solar patents. However, accepting the hypothesis that *lg*ESCI does not constitute a Granger cause of $lgCO_2$, i.e. that ESCI does not influence CO_2, suggests that the energy structure carbon intensity cannot directly affect China's carbon emissions in the short term. Nonetheless, according to the co-integration test, the energy structure carbon intensity positively affects carbon emissions under long-term conditions.

Table 6 Results of co-integration equation

Co-integrating Eq:	CointEq1
$lgCO_2$ (− 1)	1
*lg*ESCI (− 1)	1.3839 [0.0025]
*lg*GDP (− 1)	1.4245 [0.0854]
*lg*SPT (− 1)	− 0.2367 [− 0.0016]
C	− 3.665

Impulse response function analysis

The feedback of any dynamic system in response to some exterior change is termed an impulse response function (IRF). Since all the frequencies are embodied in the impulse function, the response of the linear time-invariant system for all frequencies is defined by the impulse response (Perpetuini et al. 2019).

Founded on the Johansen co-integration assessment, an IRF is constructed to analyze the shock from the standard deviation (referred to as "pulse") of a random disturbance term (also called "new interest") of a variable to another variable or its own current value and the impact of future values.

For this paper, the generalized pulse methodology is employed to analyze the IRF, in order to avoid the influence of different input orders of the variables on the pulse output. The energy structure carbon intensity, the level of economic expansion, the IRF of the number of solar patents to carbon emissions, and the results of the IRF analysis of the number of solar patents to the level of economic expansion are shown in Fig. 2. The lag period of the impact effect (unit: years) is represented on the horizontal axis, the change of the interpreted variable on the vertical axis; the solid middle line characterizes the IRF, and the upper and lower dashed lines represent the standard deviation band.

From Fig. 2, the impact of energy structure carbon intensity on carbon emissions has an inconsistent effect. From the current period (i.e., periods 1 and 2), the effect that the energy structure carbon intensity has on carbon emissions is almost zero, even though positive and rising very slowly to the 5th

Table 7 Vector error correction model estimation results

Error correction	D($lgCO_2$)	D(lgESCI)	D(lgGDP1)	D(lgSPT1)
CointEq1	− 0.171593 [− 0.95017]	− 0.144637 [− 3.00767]	0.011336 [0.22813]	− 1.094469 [− 1.87889]
D($lgCO_2$ (− 1))	0.798977 [1.91342]	0.249975 [2.24814]	− 0.033726 [− 0.29353]	1.367261 [1.01514]
D($lgCO_2$ (− 2))	0.015942 [0.03350]	0.218983 [1.72812]	− 0.079381 [− 0.60624]	0.117808 [0.07675]
D($lgCO_2$ (− 3))	0.00443 [0.01011]	0.196576 [1.68534]	0.054223 [0.44989]	0.746665 [0.52848]
D (lgESCI (− 1))	− 0.09536 [− 0.07374]	− 0.938026 [− 2.72386]	0.530275 [1.49017]	− 1.860128 [− 0.44592]
D (lgESCI (− 2))	− 0.735567 [− 0.52407]	− 0.865707 [− 2.31628]	0.495209 [1.28226]	2.123507 [0.46905]
D (lgESCI (− 3))	− 0.747958 [− 0.72245]	− 0.59854 [− 2.17106]	− 0.237398 [− 0.83334]	1.17236 [0.35106]
D(lgGDP1 (− 1))	0.9235 [0.86983]	0.366603 [1.29672]	0.600943 [2.05706]	− 0.329634 [− 0.09626]
D(lgGDP1 (− 2))	− 0.647555 [− 0.62236]	0.214695 [0.77488]	− 0.038535 [− 0.13460]	− 0.166691 [− 0.04967]
D(lgGDP1 (− 3))	0.149947 [0.21494]	− 0.411158 [− 2.21330]	− 0.013593 [− 0.07081]	2.503859 [1.11273]
D(lgSPT1 (− 1))	0.04215 [0.47997]	0.012248 [0.52378]	0.033457 [1.38460]	− 0.15044 [− 0.53110]
D(lgSPT1 (− 2))	0.022233 [0.28535]	0.002427 [0.11700]	− 0.003396 [− 0.15841]	0.192036 [0.76412]
D(lgSPT1 (− 3))	0.036917 [0.42712]	0.04269 [1.85479]	− 0.033625 [− 1.41385]	− 0.102681 [− 0.36830]
C	0.006484 [0.00321]	0.665272 [0.04941]	0.18032 [0.09628]	0.05792 [0.26471]

period. The maximum positive impact indicates that the energy structure carbon intensity positively impacts on carbon emissions in the short term, but is not rapid. After the 6th period, the impact falls to zero, then to a negative before rising to zero again. From the sample interval selected in this paper, the energy structure carbon intensity has an inadequate impact on carbon emissions.

Regarding the effects of economic expansion on carbon emissions, a positive change in economic expansion has a strong effect on carbon emissions, and this effect is moderately prolonged. The 1st period of economic expansion had a rapid positive impact on carbon emissions and began to gradually increase until it reached the highest value in the 4th period. However, the impact gradually weakened until the 8th period, when it stabilized. This shows that the increase in economic expansion will lead to an increase in carbon emissions, which in turn affects the ecological environment.

Lastly, the impact of the number of solar patents on carbon emissions in the 1st to 7th periods was positive, and rose slowly. The decline in impact towards zero can be explained to mean that an increase in the number of solar patents fails to effectively reduce carbon emissions. The possible reason behind this is that, although the patented solar technology is increasing in quantity, the conversion rate of results and the proportion widely used in the market are small, which leads to no significant reduction in carbon emissions.

Based on the above discussions, we conclude firstly that the energy structure carbon intensity has a positive effect on the increase of carbon emissions in the short term, but in the long run, a reasonable energy consumption structure will help reduce carbon emissions. Second, economic expansion also has a positive effect (causing a rapid and continuous increase) on carbon emissions, indicating that the repercussions from economic expansion include an upsurge in carbon emissions. Additionally, the number of solar patents positively affect carbon emissions (though this effect gradually weakens), indicating that the number of solar patents is yet play a momentous role in reducing carbon emissions (limited to the sample interval selected in this paper).

Table 8 Grange-causality test results

Null hypothesis	F statistics	Probability	Remarks	Directions
lgESCI does not cause $lgCO_2$	0.7049	0.6008	Accept	Unidirectional causality
$lgCO_2$ does not cause lgESCI	4.0411	0.0203	Reject	
lgGDP does not cause $lgCO_2$	3.0724	0.0492	Reject	Unidirectional causality
$lgCO_2$ does not cause lgGDP	1.9896	0.1479	Accept	
lgSPT does not cause $lgCO_2$	2.6593	0.0738	Reject	Unidirectional causality
$lgCO_2$ does not cause lgSPT	0.5300	0.7156	Accept	
lgSPT does not cause lgGDP	0.4531	0.7688	Accept	Unidirectional causality
lgGDP does not cause lgSPT	4.4570	0.0143	Reject	

Note: maximum lag selection is 4

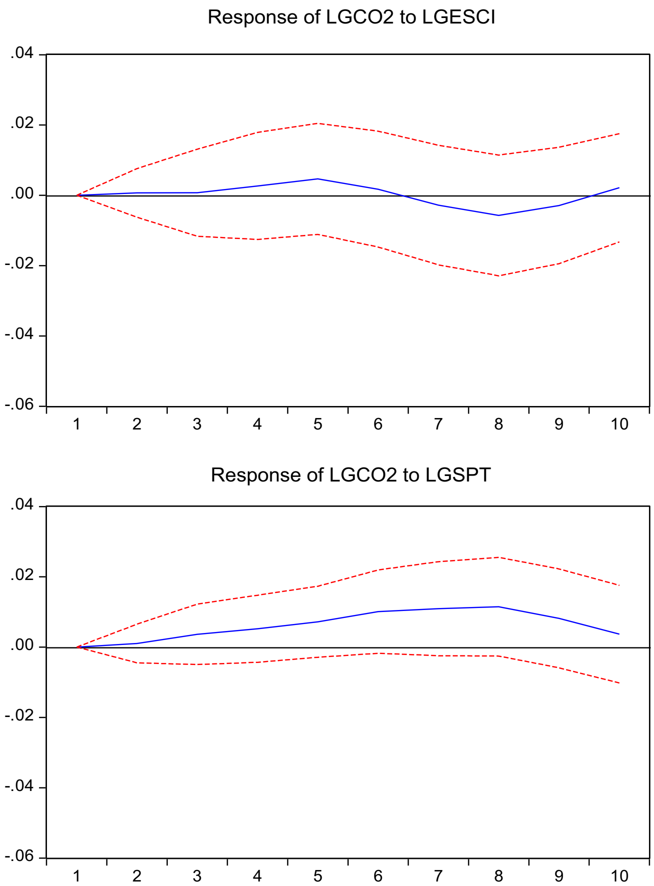

Fig. 2 Findings from the impulse response function

Conclusions and policy implications

The reliance on non-renewable energy sources in recent years has diminished owing to increasing understanding of environmental matters. This has led to the reinvigoration of energy generation worldwide, focusing on the generation of energy via renewable energy sources. This situation is a result of both internal factors (i.e., by accepting the fact that environmental dilapidation has a negative effect on humanity) and external factors (i.e., international bodies putting pressure on nations to cut down on their carbon emissions). This paper explores the relationship between solar energy technology, energy structure carbon intensity, economic expansion and carbon emissions from China from 1990 to 2017. The Vector Autoregressive (VAR) model adopted for this study reveals that the relationship between the above-mentioned variables is as follows.

The co-integration test and the VECM indicate a long-term stable relationship between China's carbon emissions, energy structure strength, economic expansion and solar energy patents. This means that the impacts of energy structure carbon intensity, economic expansion and the number of solar patents on carbon emissions in China are a long-term one.

China's carbon emissions intensify with the increase of energy structure strength and economic expansion, and decrease with the increase in number of solar patents. In terms of the degree of impact on carbon emissions, the order (from large to small) is (1) economic expansion, (2) energy structure carbon intensity, and (3) number of solar energy patents.

According to the Granger causality test, the level of economic expansion and the number of solar patents have substantial effects on China's carbon emissions. At the same time, the level of economic expansion has significantly affected the improvement of solar patent technology. The energy structure carbon intensity did not significantly affect carbon emissions, indicating that the effect of energy structure carbon intensity on China's carbon emissions is not significant in the short term. However, according to the co-integration test, the carbon intensity of the energy structure in the long term positively affects carbon emissions, i.e., the irrational structure of energy consumption is expected to spearhead the increase in carbon emissions.

According to the IRF test, the energy structure carbon intensity positively impacts on carbon emissions in the short-term, but this effect is not rapid. Also, a positive change in economic expansion exerts a stronger effect on carbon emissions, which suggests that the upsurge in economic expansion will lead to a long-term increase in carbon emissions. There is a positive impact on carbon emissions from the number of solar patents, but it is gradually decreasing, which may be due to the transformation and application of solar technology.

The Chinese government has recently adopted a policy of leaving "no stone unturned" in a bid to unravel the "resource headache" problem, and handle the huge CO_2 emissions from energy consumption, which is increasingly becoming a severe environmental issue. This study has the potential to inform development strategy, to resolve the imbalanced, uncoordinated, and unsustainable nature of current development. Built on the conclusions of our study, this paper proposes the following policy ideas:

(1) Strengthen environmental protection publicity and implement energy conservancy and emission reduction policies

With accelerated industrialization and urbanization, energy consumption and carbon emissions are increasing, so reducing carbon emissions needs to start from small things, and start from the source. On one hand, whether it is for individual or industrial enterprises, the government needs to strengthen the concept of protecting the environment and reducing carbon emissions through various platforms such as the Internet, television, and radio broadcasting, so that more individuals, families, and organizations can understand the need to reduce carbon emissions. The government also needs both economic and environmental protection strategies to reduce carbon emissions while ensuring stable and swift economic expansion (Appiah et al. 2018). Therefore, the government needs to formulate and enforce energy conservancy and emission reduction policies and attach corresponding incentives and punishment measures to encourage industrial enterprises that implement production activities in accordance with the energy conservancy and emission reduction policies, and severely punish those who violate them.

(2) Strengthen technology research and development, and increase capital investment

According to the BP World Energy Statistical Yearbook (2018), China's natural gas demand increased sharply in 2017 and may continue to do so for a long time, which will make it difficult to adjust the energy consumption structure in the short term. Therefore, in order to minimize carbon emissions, first of all, we must improve energy efficiency by increasing the use of effective energy and reduce the actual energy consumption by adopting to strategies aimed at reducing energy consumption. Second, we must strengthen the research and development of technologies related to carbon emission reduction. Finally, we must increase the usage of alternative energy sources, such as solar energy, which is universally available, harmless, capable of large-scale deployment, and sustainable. The widespread use of renewable resources such as solar energy can effectively reduce carbon emissions (Attari et al. 2019).

(3) Strengthening the collaborative innovation and integration alliance between industry, universities and research institutes

Soon, with the widespread use of alternative energy technologies, the construction of safe and environmentally-friendly energy consumption structures will continue to be realized. It will become possible to reduce the dependence of economic expansion on fossil fuels such as natural gas, and achieve fundamental reductions in emissions. To achieve this, it is extremely important to hasten the widespread use of alternative energy sources. Studies have shown that collaborative innovations between industry and academia can help propagate the transformation of scientific and technological achievements into real productivity (Zheng and Liu 2017). Therefore, it is necessary to fortify the links between universities, research institutes, and the business community, which will not only contribute to the transformation of scientific and technological achievements, but also help enterprises to continuously absorb and utilize the results of scientific research. This will be valuable according to market demand, especially through the application of intellectual property rights that help support industrial upgrading and optimize the industrial structure (Li et al. 2013).

Study limitations and future research

This research concentrated only on China which makes the conclusions and findings limited. The study also espoused variables for the period 1990–2017 to ascertain the nexus of solar energy technology, economic expansion and carbon emissions of China in the fight against CO_2 emissions. The methodology adopted was also limited since the study made use of only econometric methodologies.

It is, therefore, our hope that further studies with different variables, time frame, and other robust methodology covering other manufacturing dependent countries are adopted for the study that will at the end help decrease the emission of CO_2 worldwide. It is also our hope that other research works could be done on the nexus between other renewable energy sources like wind energy technology, economic expansion, and carbon emissions of China and other emerging economies. We would finally want to see further studies on the relationship between renewable energy and carbon emissions and how they can influence rapid economic expansions in less developed economies.

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References

Anser MK (2019) Impact of energy consumption and human activities on carbon emissions in Pakistan: application of STIRPAT model. Environ Sci Pollut Res 26(13):13453–13463

Appiah K, Du J, Poku J (2018) Causal relationship between agricultural production and carbon dioxide emissions in selected emerging economies. Environ Sci Pollut Res 25(25):24764–24777

Appiah K, Du J, Yeboah M, Appiah R (2019a) Causal correlation between energy use and carbon emissions in selected emerging economies—panel model approach. Environ Sci Pollut Res 26(8): 7896–7912

Appiah K, Du J, Yeboah M, Appiah R (2019b) Causal relationship between industrialization, energy intensity, economic growth and carbon dioxide emissions: recent evidence from Uganda. Int J Energy Econ Policy 9(2):237–245

Asaduzzaman M, Tsutsumi J-IG, Nakamatsu R, Majumder MSI (2019) Heat and carbon emission due to vehicle traffic in Dhaka City. Transylvanian Rev 1(5)

Attari SZ, Krantz DH, Weber EU (2019) Climate change communicators' carbon footprints affect their audience's policy support. Clim Chang:1–17

BP Statistical Review of World Energy (2018) BP statistical review of world energy 2018. Retrieved from UK

Charfeddine L, Kahia M (2019) Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: a panel vector autoregressive (PVAR) analysis. Renew Energy 139:198–213

Du Z, Lin B (2019) Changes in automobile energy consumption during urbanization: evidence from 279 cities in China. Energy Policy 132: 309–317

Du K, Li P, Yan Z (2019) Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. Technol Forecast Soc Chang 146:297–303

Guo P, Feng L (2019) Biased technological progress, factor substitution and carbon emission intensity-threshold regression based on factor-enhanced CES production function. Econ Issues (07):95–103

Guo J, Zhang Y-J, Zhang K-B (2018) The key sectors for energy conservation and carbon emissions reduction in China: evidence from the input-output method. J Clean Prod 179:180–190

Hailemariam A, Dzhumashev R, Shahbaz M (2019) Carbon emissions, income inequality and economic development. Empir Econ:1–21

Han X, Sun T, Gao M (2018) Research on new urbanization construction, energy consumption growth and carbon emission intensity control. Soft Sci 32(09):90–93

He Z, Fan Q (2019) Evaluation of the impact of domestic waste incineration power generation on regional carbon emissions: a case study of Chongqing City. Northwest Popul 40(04):79–90

Huang Y, Matsumoto KI (2019) Impact of urbanization on changes in CO 2 emissions in China: analysis of 30 provincial administrative units. Available at SSRN 3414208

Huang X, Bian N, Shi X (2018) The influence of energy endowment and industrial technology Progress on carbon emission intensity-evidence from the Yangtze River Economic Belt. Sci Technol Prog Policy 35(19):59–64

Ismael M, Srouji F, Boutabba MA (2018) Agricultural technologies and carbon emissions: evidence from Jordanian economy. Environ Sci Pollut Res 25(11):10867–10877

Ji Q, Zhang D (2019) How much does financial development contribute to renewable energy growth and upgrading of energy structure in China? Energy Policy 128:114–124

Kahia M, Jebli MB, Belloumi M (2019) Analysis of the impact of renewable energy consumption and economic growth on carbon dioxide emissions in 12 MENA countries. Clean Techn Environ Policy 21(4):871–885

Kang SH, Islam F, Tiwari AK (2019) The dynamic relationships among CO2 emissions, renewable and non-renewable energy sources, and economic growth in India: evidence from time-varying Bayesian VAR model. Struct Chang Econ Dyn

Karasoy A (2019) Drivers of carbon emissions in Turkey: considering asymmetric impacts. Environ Sci Pollut Res 26(9):9219–9231

Khoshnevis Yazdi S, Dariani AG (2019) CO2 emissions, urbanisation and economic growth: evidence from Asian countries. Econ Res Ekonomska Istraživanja 32(1):510–530

Khoshnevis Yazdi S, Shakouri B (2018) The renewable energy, CO2 emissions, and economic growth: VAR model. Energy Sources Part B Econ Plan Policy 13(1):53–59

Kwakwa PA, Alhassan H (2018) The effect of energy and urbanisation on carbon dioxide emissions: evidence from Ghana. OPEC Energy Rev 42(4):301–330

Li Y (2018) Analysis on patent intelligence of solar energy Technology in China in the aspect of global competition. China Management Science 17(03): 115–120

Li M, He W, Zhang W, Tai X (2013) Empirical research on intellectual property promotion of strategic emerging industry development: taking Jiangsu Province as an example. Sci Technol Prog Policy 30(09):54–59

Lin F (2019) Dynamic study on carbon emission, industrial structure and economic development level of Fujian: based on VAR model and granger test. J Zhongyuan Inst Technol 30(02):36–44

Lu N, Wang W, Wang W, Zhang C, Lu H (2019) Breakthrough low carbon technology innovation and carbon emissions: direct impact and spatial spillover. China Popul Resour Environ 29(05):30–39

MacKinnon JG, Haug AA, Michelis L (1999) Numerical distribution functions of likelihood ratio tests for cointegration. J Appl Econom 14:563–577

Oliver M, Upton G (2019) Energy endowments and economic growth. USAEE Working Paper No. 19-414, 2019. Available at SSRN: https://doi.org/10.2139/ssrn.3414528

Peng Z, Xiang N, Xia K (2018) Relationship between financial development and carbon emission in prefecture-level cities in the Yangtze River Economic Belt. Hubei Social Sciences 11:32–38

Perpetuini D, Cardone D, Filippini C, Chiarelli AM, Merla A (2019) Modelling impulse response function of functional infrared imaging for general linear model analysis of autonomic activity. Sensors 19(4):849

Prăvălie R, Patriche C, Bandoc G (2019) Spatial assessment of solar energy potential at global scale. A geographical approach. J Clean Prod 209:692–721

Ren H, Zhao J (2018) The impact of technological innovation and structural adjustment on energy consumption-an empirical analysis of PVAR based on carbon emission grouping. Soft Science 32(07): 30–34

Salahuddin M, Ali MI, Vink N, Gow J (2019a) The effects of urbanization and globalization on CO 2 emissions: evidence from the Sub-Saharan Africa (SSA) countries. Environ Sci Pollut Res 26(3): 2699–2709

Salahuddin M, Gow J, Ali MI, Hossain MR, Al-Azami KS, Akbar D, Gedikli A (2019b) Urbanization-globalization-CO2 emissions nexus revisited: empirical evidence from South Africa. Heliyon 5(6): e01974

Serrano-Jiménez A, Lizana J, Molina-Huelva M, Barrios-Padura Á (2019) Decision-support method for profitable residential energy retrofitting based on energy-related occupant behaviour. J Clean Prod 222:622–632

Shi J, Li H, An H, Guan J, Arif A (2019) Tracing carbon emissions embodied in 2012 Chinese supply chains. J Clean Prod 226:28–36

Sims CA (1980) Macroeconomics and reality. Econometrica:1–48

Sinha A, Shahbaz M (2018) Estimation of environmental Kuznets curve for CO2 emission: role of renewable energy generation in India. Renew Energy 119:703–711

Smil V (2019) Energy in world history. Routledge, Abingdon

Stojanovski T (2019) Urban form and mobility choices: informing about sustainable travel alternatives, carbon emissions and energy use from transportation in Swedish Neighbourhoods. Sustainability 11(2):548

Wang G, Han Q (2019) Assessment of the relation between land use and carbon emission in Eindhoven, the Netherlands. J Environ Manag 247:413–424

Wang C, Chen J, Zou J (2005) Decomposition of energy-related CO2 emission in China: 1957–2000. Energy 30(1):73–83

Wang S, Zeng J, Huang Y, Shi C, Zhan P (2018) The effects of urbanization on CO2 emissions in the Pearl River Delta: a comprehensive assessment and panel data analysis. Appl Energy 228:1693–1706

Wang S, Wang J, Fang C, Li S (2019a) Estimating the impacts of urban form on CO2 emission efficiency in the Pearl River Delta, China. Cities 85:117–129

Wang Z, Cui C, Peng S (2019b) How do urbanization and consumption patterns affect carbon emissions in China? A decomposition analysis. J Clean Prod 211:1201–1208

Wang Z, Sun Y, Wang B (2019c) How does the new-type urbanisation affect CO2 emissions in China? An empirical analysis from the perspective of technological progress. Energy Econ 80:917–927

Xiao D, Zhang Y (2019) Statistical test of the impact of renewable energy consumption on carbon dioxide emissions. Stat Decis 35(10):87–90

Xie R, Huang L, Tian B, Fang J (2019) Differences in changes in carbon dioxide emissions among China's transportation subsectors: a structural decomposition analysis. Emerg Mark Financ Trade 55(6): 1294–1311

Zhang J, Yan Y, Guan J (2015) Scientific relatedness in solar energy: a comparative study between the USA and China. Scientometrics 102(2):1595–1613

Zhao R, Zhao L, Deng S, Zheng N (2015) Trends in patents for solar thermal utilization in China. Renew Sust Energ Rev 52:852–862

Zheng W, Liu M (2017) The relationship between industry, university and research synergy innovation and technology production. Sci Technol Prog Countermeasures 34(24):13–17