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Analysis of carbon dioxide emissions, energy consumption, and economic growth in China

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Abstract: This study examines the nexus of carbon dioxide (CO_2) emissions, energy consumption (EC) and gross domestic products (GDP), using an Autoregressive Distributed Lag (ARDL) bounds test approach of co-integration and error-correction model (ECM) for the period 1971–2015. The aim of the research is to i) examine the relationship between CO_2 and GDP as "cross-coupling, relative decoupling, or absolute decoupling," and validate the existence of the Environmental Kuznets Curve (EKC) hypothesis; ii) detect causality between CO_2 emissions, EC, and GDP, and scrutinize their impacts. The ARDL results confirm a long-run and short-run co-integration relationship between the variables. The relationship between CO_2 emissions and GDP is "relatively decoupling," and the EKC exists in China. Its CO_2 emissions are more explained by EC and contribute twofold of GDP. In the long run, there was significant negative causality from CO_2 emission and GDP to EC. This indicates Chinese economic development structure should be re-designed towards energy-saving and decarbonized economic structure. Moreover, the central and provincial governments of China should synchronize optimal energy utilization and green economic structure to mitigate environmental deterioration and climate change.

Keywords: autoregressive distributed lag; causality; co-integration; Environmental Kuznets Curve; error-correction model

To achieve a win-win situation of sustainable development and environmental protection, energy-related environmental issues have become research hotspots reflecting global warming and climate change. In general, this research mainly analysed the regulation of CO_2 emissions (Gómez-Gener et al. 2016) and its determinants (Balogh and Jambor 2017) with the nexus of economic growth, CO_2 emissions and energy consumption (EC) (Acheampong 2018). As for studies of relationships between economic growth, environmental pollution, and EC, the achievements have been intensively analysed and three main findings of them have been presented. Focused on the link between environmental resembles and economic development, the first stand called the "pollution-growth" nexus is examined by the environmental Kuznets Curve (EKC) hypothesis and it asserts an inverted U-shape relationship. Since the first empirical EKC research proposed by Grossman and Krueger (1991), extensive studies employing several tests have been carried out in the literature. The second group of analysis addressing the "energy-growth" nexus dates back to the pioneering work of Kraft and Kraft (1978) who introduced the use of the Granger Causality test focusing on the link between EC and economic growth. As stronger economic development needs a higher level of EC, economic growth is closely related to EC (Halicioglu 2009). Finally, the "pollution-energy-growth" nexus concentrated on the combination of the preceding two nexuses. It investigates the dynamic relation-

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ships between economic growth, environmental pollution, and EC (Ang 2008).

Knowing that China is the world's largest coal producer, energy consumer, and one of the top five per capita CO_2 emitters, we used recently developed autoregressive distributed lag (ARDL) bounds testing of cointegration and error-correction model (ECM) based Granger causality models to examine the nexus of CO_2 emissions, EC, and GDP for the period between 1971 and 2015 with aggregated per capita econometric data. We specifically sought to: i) identify whether the relationship between CO_2 emissions and economic growth is cross-coupling, relative-coupling, or absolute-decoupling; ii) ascertain and validate the existence of the EKC hypothesis in China; iii) examine the impact of EC and per capita GDP on CO_2 emissions; and iv) investigate long-run and short-run stability and causality between CO_2 emissions, EC, and GDP.

MATERIAL AND METHOD

Variable description and expected sign. Using the online databases of World Development Indicators (WDI 2018) and World Energy Consumption (Enerdata 2018), we traced the annual per capita CO_2, EC, and GDP econometric time series data of China for the period 1971–2015 for this study. We adopted CO_2 emissions as a dependent variable, and EC and per capita GDP as explanatory variables, the nexus of those is to be investigated. All the variables were transformed into natural logarithm forms to reduce heteroscedasticity and obtain the growth rate of relevant variables (Figure 1).

We used aggregate per capita econometric variables of CO_2, EC, and GDP rather than dis-aggregated data to weigh and reflect the effect of individual variables. The functional form of our linear model is as follows:

$$CO_{2t} = f(EC_t, GDP_t) \tag{1}$$

Considering the work of Halicioglu (2009), Acaravci and Ozturk (2010), Sari and Soytas (2009) and Menyah and Wolde-Rufael Y. (2010) to specify the study model, we rewrote Equation (1), considering GDP-squared (GDP^2) in the contentions of the theoretical sense of Grossman and Krueger (1995) to check the robustness of that equation in regression form, using:

$$CO_{2t} = \alpha + \beta EC_t + \gamma GDP_t + \delta GDP_t^2 + \varepsilon_t \tag{2}$$

where: CO_{2t} – carbon dioxide emissions; EC_t – energy consumptions; GDP_t – gross domestic product; GDP_t^2 – GDP-squared after taking natural logarithms; α – a constant. The parameters to be estimated (β, γ, and δ) indicate the long-run and short-run elasticity of CO_2 emissions concerning EC, GDP, and GDP^2, respectively; t – the period and ε_t – the error term that is assumed to be independent and identically distributed, with zero mean and constant variance.

The expected sign of β (EC) concerning CO_2 emissions must be positive, because a higher level of EC may result in greater CO_2 emissions for greater economic growth. Under a valid EKC hypothesis, the sign of γ (GDP) is expected to be positive and significant, whereas the expected sign of δ (GDP^2) is negative and significant.

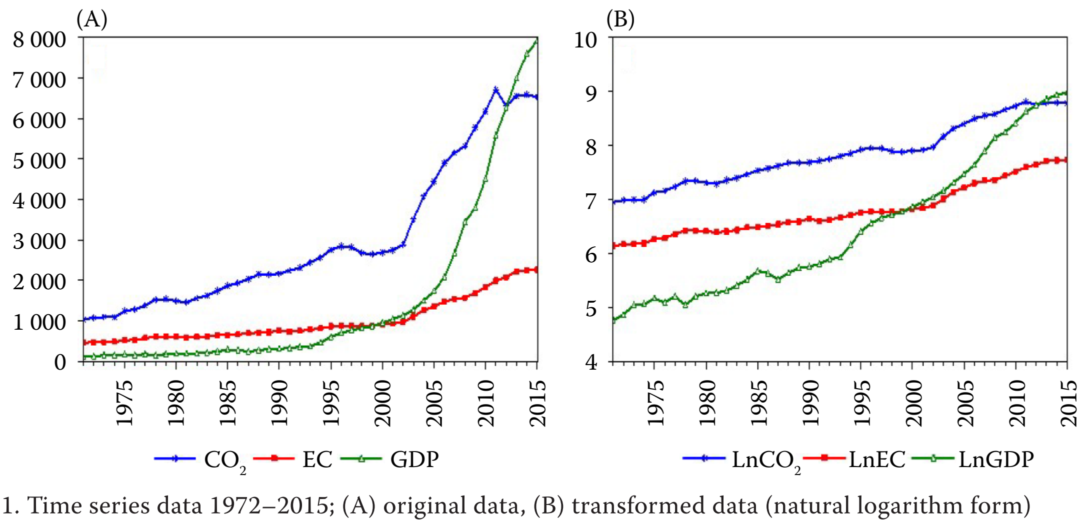

Figure 1. Time series data 1972–2015; (A) original data, (B) transformed data (natural logarithm form)

CO_2 – carbon dioxide emissions; *EC* – energy consumption; *GDP* – gross domestic product

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

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Autoregressive Distributed Lag (ARDL) bounds test for cointegration. The ARDL bounds test for examining the long-run and cointegration relationship between variables, which is applicable regardless of whether the underlying series are $I(0)$ or $I(1)$, is a standard least-squares regression containing lags of the dependent and independent (explanatory) variables and is usually denoted as ARDL ($p, k_1, k_2, k_3, ..., k_i$). Here, p is the number of lags of the dependent variable and k_i the number of lags of the i^{th} explanatory variable. Explanatory variables that have no lagged term in the model are called static or fixed regressors. Explanatory variables with at least one lagged term are called dynamic regressors.

The ARDL approach involves two basic steps for estimating long-run relationships. The first is to determine the existence of long-run relationships among all variables in the equation under investigation. The ARDL model for the standard linear functional model specification of a long-run relationship between carbon emissions, energy consumption, GDP, and the square of GDP is found through [Equation (3)]:

$$\begin{aligned}\Delta CO_{2t} = {} & \alpha_1' + \sum_{i=1}^{p}\theta_{1i}\,\Delta CO_{2t-1} + \sum_{i=1}^{k1}\beta_{1i}\,\Delta EC_{t-1} + \\ & + \sum_{i=1}^{k2}\gamma_{1i}\,\Delta GDP_{t-i} + \sum_{i=1}^{k3}\delta_{1i}\,\Delta GDP_{t-i}^2 + \\ & + \tau_1 CO_{2t-1} + \tau_2 EC_{t-1} + \tau_3 GDP_{t-1} + \\ & + \tau_4 GDP_{t-1}^2 + \varepsilon_{2t}\end{aligned} \tag{3}$$

where: Δ – the first difference operator; ε_t – the white noise term; p – the lag of the dependent variable; τ_i – the lag of independent variables.

The co-integration (τ) equation is defined as:

$$\tau_1 CO_{2t-1} - (\tau_2 EC_{t-1} + \tau_3 GDP_{t-1} + \tau_4 GDP_{t-1}^2 + \varepsilon_{2t}) = 0 \tag{4}$$

The bounds test method implies investigating the null hypothesis (H_0) of no co-integration through the joint significance test of lagged variables, based on Fisher (F-statistics) or Wald statistics, and is the first stage of the ARDL co-integration method. This should be performed using equation Equation (3) as H_0: $\tau_1 = \tau_2 = \tau_3 = \tau_4 = 0$ and the alternative hypothesis (H_1) is assumed positive, i.e. H_1: $\tau_1 \neq \tau_2 \neq \tau_3 \neq \tau_4 \neq 0$.

To specify an ARDL model and F-statistics, we selected the appropriate lag for each constructed variable (p, k_1, k_2 and k_3) based on the Akaike Information Criterion (AIC) and Schwarz Bayesian criterion (SBC) and the Eview 9 statistical package was used. The SBC selects the shortest possible lag whereas the AIC selects the maximum relevant lag. The long-run relationship between variables can be estimated after the selection of the ARDL model using the AIC or SBC criterion. Conditional upon the existence of cointegration between CO_2 emissions, EC and GDP is confirmed. In the second stage, the associated long-run and short-run estimates of ARDL are made using Equation (5) and Equation (6), respectively.

$$\begin{aligned}CO_{2t} = {} & \alpha_2 + \sum_{i=1}^{p}\theta_{2i}CO_{2t-1} + \sum_{i=1}^{k1}\beta_{2i}EC_{t-1} + \\ & + \sum_{i=1}^{k2}\gamma_{2i}GDP_{t-1} + \sum_{i=1}^{k3}\delta_{2i}GDP_{t-1}^2 + \varepsilon_{2t}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta CO_{2t} = {} & \alpha_3 + \sum_{i=1}^{p}\theta_{3i}\Delta CO_{2t-1}\sum_{i=0}^{k1}\beta_{3i}\Delta EC_{t-1} + \\ & + \sum_{i=0}^{k2}\gamma_{3i}\Delta GDP_{t-1} + \sum_{i=0}^{k3}\delta_{3i}\Delta GDP_{t-1}^2 + \\ & + \phi ECT_{t-1} + \varepsilon_{3t}\end{aligned} \tag{6}$$

where: p and k_i – the optimal lag lengths determined by AIC and SBC for dependent and independent constructed variables, respectively; ε – a serially un-correlated error term; ϕ – an error-correction term (ECT) coefficient defined via:

$$\begin{aligned}ECT_t = {} & CO_{2t} - \alpha_2 - \sum_{i=1}^{p}\theta_{2i}CO_{2t-i} - \sum_{i=1}^{k1}\beta_{2i}\Delta EC_{t-i} - \\ & - \sum_{i=1}^{k2}\gamma_{2i}\Delta GDP_{t-i} - \sum_{i=1}^{k3}\delta_{2i}\Delta GDP_{t-1}^2\end{aligned} \tag{7}$$

The ϕ coefficient is said to be the adjustment speed for any shock leading to a deviation from long-run equilibrium, and ECT_{t-1} is an ECT obtained from the estimated co-integration [Equation (3)]. It shows how quickly variables converge to equilibrium and should have a statistically significant coefficient with a negative sign.

However, before proceeding with ARDL estimation, it is necessary to test for unit root to ensure that all variables satisfy the underlying assumptions of the ARDL bounds testing cointegration method. Therefore, time-series properties of the variables were checked via the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root test procedures, by including an intercept.

Granger causality test. The Granger causality test based on the vector ECT model (VECM) was used to examine the causality relationship between the constructed variables in two steps. Once the long-run model was estimated by Equation (5), to estimate the residuals, the next step was to estimate the ECT-

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$$\begin{bmatrix}\Delta CO_{2t}\\ \Delta EC_t\\ \Delta GDP_t\\ \Delta GDP_t^2\end{bmatrix}=\begin{bmatrix}c_1\\ c_2\\ c_3\\ c_4\end{bmatrix}+\begin{bmatrix}\pi_{11,i} & \pi_{12,i} & \pi_{13,i} & \pi_{14,i}\\ \pi_{21,i} & \pi_{22,i} & \pi_{23,i} & \pi_{24,i}\\ \pi_{31,i} & \pi_{32,i} & \pi_{33,i} & \pi_{34,i}\\ \pi_{41,i} & \pi_{42,i} & \pi_{43,i} & \pi_{44,i}\end{bmatrix}\begin{bmatrix}\Delta CO_{2t-i}\\ \Delta EC_{t-i}\\ \Delta GDP_{t-i}\\ \Delta GDP_{t-i}^2\end{bmatrix}+\cdots+$$
$$+\begin{bmatrix}\pi_{11,k} & \pi_{12,k} & \pi_{13,k} & \pi_{14,k}\\ \pi_{21,k} & \pi_{22,k} & \pi_{23,k} & \pi_{24,k}\\ \pi_{31,k} & \pi_{32,k} & \pi_{33,k} & \pi_{34,k}\\ \pi_{41,k} & \pi_{42,k} & \pi_{43,k} & \pi_{44,k}\end{bmatrix}\begin{bmatrix}\Delta CO_{2t-k}\\ \Delta EC_{t-k}\\ \Delta GDP_{t-k}\\ \Delta GDP_{t-k}^2\end{bmatrix}+\begin{bmatrix}\phi_1\\ \phi_2\\ \phi_3\\ \phi_4\end{bmatrix}(ECT_{t-1})+\begin{bmatrix}\psi_{1t}\\ \psi_{2t}\\ \psi_{3t}\\ \psi_{4t}\end{bmatrix} \quad (8)$$

based Granger causality model. The direction of causality can be detected by the VECM of long-run cointegration. To this end, an augmented form of the Granger test involving the error correction term was formulated by a VECM using Equation (8), as shown in Acaravci and Ozturk (2010) [Equation (8) above].

In Equation (8), residual terms ψ_1, ψ_2, ψ_3, and ψ_4 are independently and normally distributed with zero mean and constant variance; π represents short-run elasticity parameters to be estimated, and other variables are as explained above. The causal relationships can be explained in two ways. First, significant t-statistics or Wald test for the significance of the relevant ψ coefficients in the lagged ECT indicate the significance of the long-run causal relationships, while the F-statistic or Wald test determine short-run or weak Granger causality through significant levels of the relevant π coefficients in the first difference series. The Granger causality null hypothesis test presented as (Table 1).

Model diagnostics and stability checking. To ensure goodness-of-fit (GoF) of the model, diagnostics and a stability test were conducted. The Ramsey test for function form, serial correlation test, heteroscedasticity test and normality tests for the residuals were determined by Jarque-Bera (JB) statistics for diagnostic checking. Additionally, to check long-run and short-run stability, the coefficient cumulative sum (CUSUM) and cumulative sum square (CUSUMSQ) were used as in Brown et al. (1975). CUSUM and CUSUMSQ were graphically represented by two straight lines bounded by the 5% significance level. If the plots of these statistics fall within the critical bounds of 5% significance, assuming that the coefficients of the given regression are stable, the null hypothesis is accepted. However, if any point lies beyond this 5% level, the null hypothesis of stable parameters is rejected.

EMPIRICAL RESULTS AND DISCUSSION

Unit root test. The ARDL bounds test is applicable irrespective of whether the underlying explanatory variables are integrated at $I(0)$ or $I(1)$ order; and importantly, none of the constructed variables was integrated at $I(2)$ order or above. Hence, it is crucial to test the univariate stationary property of the series. The concept of co-integration requires that the set of variables be integrated at the same order and that their linear combinations be stationary to do the co-integration test. If the econometric time-series data do not follow the same order of integration, the relationship between the variables can be meaningless. Therefore, in our study, unit root tests were weighted using ADF and PP tests (Table 2). The ADF

Table 1. Null hypothesis for the Granger causality test

	Short-run				Lon-run
	ΔCO_2	ΔEC	ΔGDP	ΔGDP^2	
ΔCO_2	–	$\pi_{12,1} = \cdots = \pi_{12,k} = 0$	$\pi_{13,1} = \cdots = \pi_{13,k} = 0$	$\pi_{14,1} = \cdots = \pi_{14,k} = 0$	ϕ_1
ΔEC	$\pi_{21,1} = \cdots = \pi_{21,k} = 0$	–	$\pi_{23,1} = \cdots = \pi_{23,k} = 0$	$\pi_{24,1} = \cdots = \pi_{24,k} = 0$	ϕ_2
ΔGDP	$\pi_{31,1} = \cdots = \pi_{31,k} = 0$	$\pi_{32,1} = \cdots = \pi_{32,k} = 0$	–	$\pi_{34,1} = \cdots = \pi_{34,k} = 0$	ϕ_3
ΔGDP^2	$\pi_{41,1} = \cdots = p_{41,k} = 0$	$\pi_{42,1} = \cdots = \pi_{32,k} = 0$	$\pi_{43,1} = \cdots = \pi_{43,k} = 0$	–	ϕ_4

Δ – the first difference operator; k – optimal lag; π and ϕ – short-run and long-run causality elasticity coefficients, respectively; CO_2 – carbon dioxide emissions; EC – energy consumption; GDP – gross domestic product; GDP^2 – squared gross domestic product

Source: Authors' model construction

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Table 2. Results of unit root test

Variables	ADF test				PP test				Conclusion
	level		1st differences		level		1st differences		
	test statistics	optimal lag length	test statistics	optimal lag length	adjusted *t*-statistics	bandwidth	adjusted *t*-statistics	bandwidth	
CO_2	–0.43	1	–4.23***	0	–0.21	3	–4.22***	1	stationary
EC	0.77	1	–4.01***	0	1.41	2	–4.01***	2	
GDP	1.93	1	–5.12***	0	2.35	0	–5.17***	2	
GDP^2	2.24	1	–3.87***	0	3.36	2	–3.89***	3	

***1% significance level at the first difference rejection of the null hypothesis; CO_2 – carbon dioxide emissions; *EC* – energy consumption; *GDP* – gross domestic product; GDP^2 – squared gross domestic product

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

Table 3. Autoregressive Distributive Lag (ARDL) bounds test of co-integration result of (1, 1, 0, 0) model

Variables	*F*-statistic value	*P*-value	Outcome
F_{CO2} (CO_2|*EC*, *GDP*, GDP^2)	4.398	***	co-integration
Critical value bounds	significance (%)	*I*(0) bound	*I*(1) bound
	10	2.37	3.2*
	5	2.79	3.67**
	1	3.65	4.66

*1o% significance level, **5% significance level, ***1% significance level; CO_2 – carbon dioxide emissions), *EC* – energy consumption; *GDP* – gross domestic product; GDP^2 – squared gross domestic product

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

test result shows that none of the constructed variables was stationary at their level form and confirmed a unit root problem. However, the time-series data of the constructed variables at their first difference became stationary, indicating that none of the variables was at *I*(2) order or above. The PP test was consistent with the ADF test. From the unit root test results, we found that the order of integration of all variables was stationary at either *I*(0) or *I*(1) and that there was no unit root problem. Hence, we could confidently endorse the use of the ARDL bounds test for co-integration instead of the Johansen or Engle and Granger approaches.

Analysis of ARDL bounds test co-integration result. The ARDL bounds test approach used *F*-statistics to confirm the existence of cointegration between the constructed variables such as CO_2 emissions, EC, GDP, and GDP^2. The results of cointegration (Table 3) show that the *F*-statistic is greater than its upper bound critical value (3.67) at the 5% significance level.

This showed that the null hypothesis of no cointegration was rejected at that level. This finding confirmed evidence of co-integration between CO_2 emissions, EC, GDP, and GDP^2 in China. The ARDL bounds co-integration equation (*Co*int*Eq.*) (Equation 4) can be rewritten as:

$$Co\operatorname{int}Eq. = CO_{2t} - (1.61EC_t + 0.766GDP_t - 0.068GDP_t^2 - 5.067) = 0 \tag{9}$$

Result of the long-run relationship. The results confirmed the existence of long-run co-integration between CO_2 emissions, EC, and GDP. Therefore; we can confidently use the ARDL long-run and short-run relationships between the variables. The first important step in investigating the long-run relationship using the ARDL approach is to estimate Equation (3), using an unrestricted error correction model. Because the ECM specification assumes that the disturbances are serially uncorrelated, the choice of appropriate lag order selection is important. The Vector Autoregression (VAR) order lag selection of the first difference variables was determined by employing the AIC, SBC, and Hannan-Quinn information criterion (HQC). Therefore, we set the maximum order of lag to three. However, the result of an appropriate lag order for the better ARDL model was identical for the AIC, Schwarz Bayesian Criterion (BSC), and HQC (Figure 2). Therefore, we only used the better ARDL model (1, 1, 0, 0) in further analysis.

Under the EKC hypothesis, the long-run and short-run elasticity estimates of CO_2 emissions concern-

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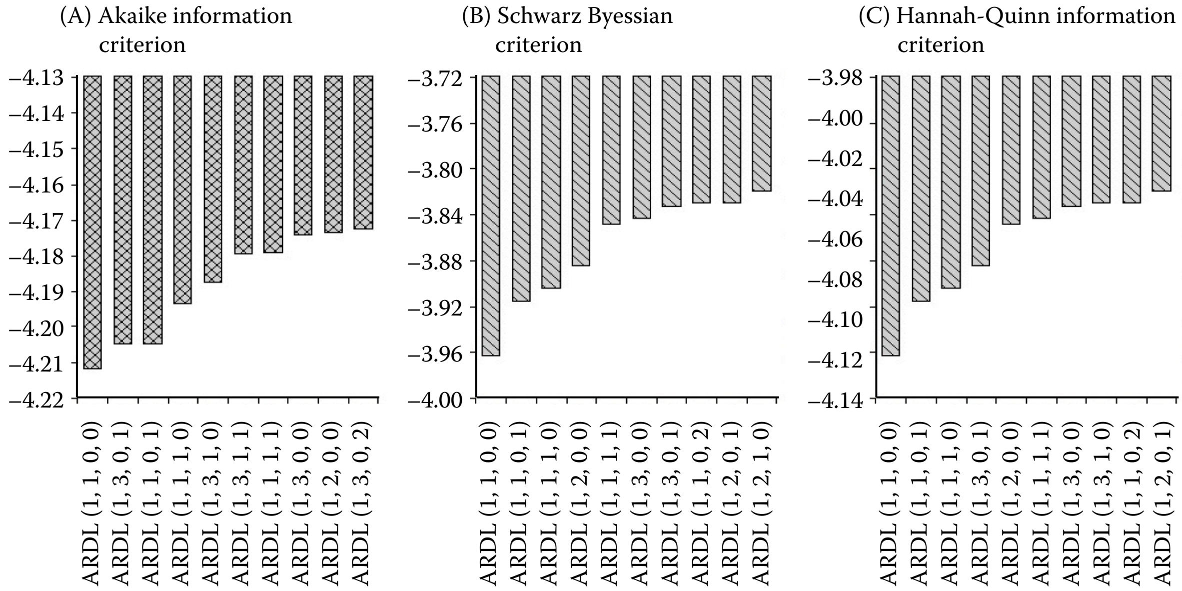

Figure 2. Lag selection criteria for Autoregressive Distributive Lag (ARDL) model using Akaike information criterion (AIC), Schwarz Bayssian criterion (SBC) and Hanna-quinn information criterion (HQC).

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

ing GDP and GDP^2 are expected to be $\gamma > 0$ and $\delta < 0$, respectively. Our result (Table 4) confirms that the long-run elasticity of GDP and GDP^2 are significantly positive and negative (0.766 and –0.068, respectively) coefficients concerning CO_2 emissions at the $P < 1\%$ significance level. The elasticity coefficient of GDP concerning CO_2 emissions is between 0 and 1, so we can say that the relationship is "relatively decoupling" (Wang 2011). In the long run, the growth rate of CO_2 emissions is 23.4% less than per capita income growth, which means that as per capita income increased by 1% the per capita CO_2 emissions rose by 0.766%.

This result also confirms that the EKC existed in China during the study period. The graphical result supports the EKC hypothesis that the level of CO_2 emissions increases with income growth, reaches the turning point, and stabilizes (Figure 3A). Therefore, beyond a threshold level of GDP, any increase in GDP is likely to reduce environmental degradation in the country.

The long-run elasticity estimate of CO_2 emissions concerning EC is expected to be $\beta > 0$. *F*-test bounds of the cointegration test of the long-run relationship of CO_2 emissions and EC are positive and significant at the $P < 1\%$ significance level, with an estimated coefficient of 1.61. This demonstrates that for each 1% increase in EC, there was a rise of 1.61% in CO_2 emissions. This reveals that the per capita EC had twice the CO_2 emissions contribution as per capita income (Figure 3B). This indicates that greater EC increases CO_2 emissions and may aggravate the environmental pollution problem in China.

The long-run co-integration is supported by the significant negative coefficient of the ECT, which shows

Table 4. Autoregressive Distributive Lag (ARDL) (1, 1, 0, 0) model long-run elasticity estimated coefficients

Variable	Coefficient	Standard error	*t*-statistics	*P*-values
EC	1.610	0.223	7.231	***
GDP	0.766	0.148	5.169	***
GDP^2	–0.068	0.012	–5.871	***
Constant	–5.067	1.271	–3.988	***
$EC_{(t-1)}$	–0.336	0.083	–4.029	***

***1% significance level; CO_2 – carbon dioxide emissions; *EC* – energy consumption; *GDP* – gross domestic product; *GDP*^{2} – squared gross domestic product; EC_{t-1} – error correction

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

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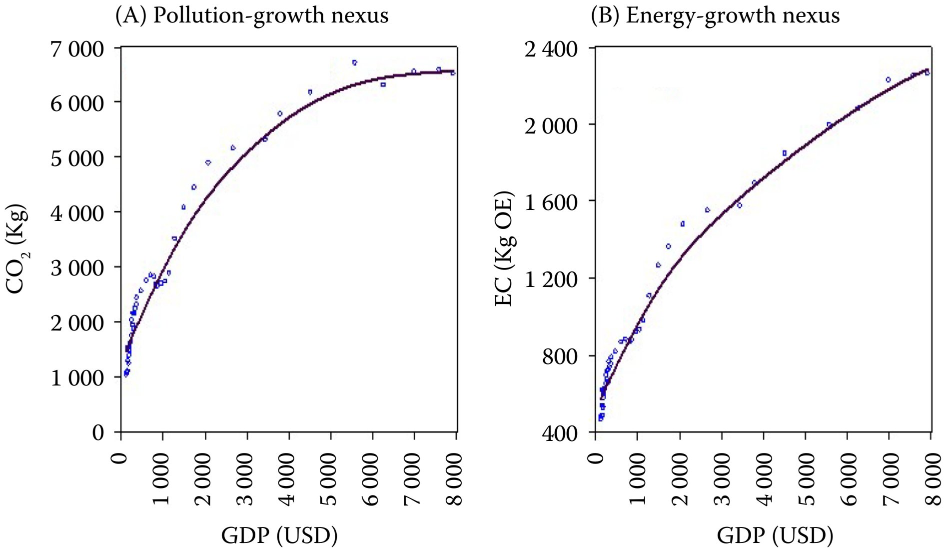

Figure 3. (A) Environmental Kuznets Curve EKC (Pollution-Growth) nexus and (B) Energy-Growth nexus for China from 1971–2015

The bold line shows the kernel fit; CO2 – carbon dioxide emissions; EC – energy consumption; GDP – gross domestic product; OE – oil equivalent

Source: Authors calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

the speed of the adjustment process to restore equilibrium (Kremers et al. 1992; Gutierrez 2003). The relatively large ECT coefficients imply a faster adjustment process toward long-run equilibrium following short-run shocks. Our ECT estimate is negative (–0.336) and statistically significant at the 1% confidence level (Table 4). The sign of the ECT is as expected. This result reveals that any deviation from the long-run equilibrium between variables is correlated at 33.6% for each period. That is, when CO_2 emissions are above or below their equilibrium level, they adjust by 33.6% within the first year.

Results of the short-run relationship. The ARDL short-run and long-run relationships between CO_2 emissions, EC, GDP, and GDP^2 are statistically significant and have expected signs (Table 5). As expected, the short-run elasticities of CO_2 emissions, EC, and GDP are less than their long-run elasticities. Hence, there are long-run and short-run relationships between CO_2 emissions, EC, GDP, and GDP^2 in China.

The short-run ARDL results also show that the estimated coefficients of GDP and GDP^2 are positive (0.227) and negative (–0.020) at a 1% significance level, respectively. These results support the validity of the EKC hypothesis and the "relatively coupling" relationship between GDP and CO_2 emissions in the short run in China. Additionally, the growth rate of CO_2 emissions was 76.4% lower than per capita income growth, which means that each 1% increase in per capita income led to a 0.227% increase in per capita CO_2. The EC elasticity concerning CO_2 emissions in the short run is also significant at the P < 1% significance level. This implies that in the short run, EC importantly increases environmental degradation in China. In general, the long-run elasticity of EC concerning CO_2 emissions is greater than its short-run elasticity. Similar findings were presented by Lin et al. (2014), Govindaraju and Tang (2013) and Chang (2010) for China. This indicates that CO_2 emissions from EC could increase in the future unless the Chinese government commits to the Montreal Protocol and reduce Greenhouse Gases (GHGs) emissions. This could lead to successful outcomes by adopting an ambitious approach to climate change and encouraging energy-saving and low-carbon-emitting technologies and industries, thus reducing CO_2 emissions.

Model diagnostic and stability test. The selected ARDL (1, 1, 0, 0) model passed several diagnostic tests as summarized in Table 6. Values of R^2 and adjusted R^2 are greater than 99%, indicating substantial GoF of the model. We confirmed a lack of spurious effect on the model which revealed an absence of serial correlation, functional form, and heteroscedasticity. Nonetheless, the JB test showed that residuals were not normally distributed.

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Table 5. Autoregressive Distributive Lag (ARDL) short-run elasticity estimated coefficients for ARDL (1, 1, 0, 0) model

Variable	Coefficient	Standard error	t-statistics	P-values
CO_2 (–1)	0.704	0.103	6.801	***
EC	1.211	0.123	9.813	***
EC (–1)	–0.734	0.192	–3.827	***
GDP	0.227	0.083	2.743	***
GDP^2	–0.020	0.007	–3.038	***
Constant	–1.501	0.564	–2.662	**

*** and ** indicates 1% and 5% significance levels respectively; CO_2 – carbon dioxide emissions; EC – energy consumption; GDP – gross domestic product; GDP^2 – squared gross domestic product

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

Table 6. Model diagnostic test result

Diagnostic tests	
R-square	0.998
Adjusted R-square	0.988
DW-statistics	1.976
F-statistic	3 729 (0.0000)
RSS	0.027
Ramsey's test	0.077 (0.782)
LM	0.048 (0.9762)
NORM	0.934 (0.627)
HET	2.417 (0.7889)
S.E.	0.027

LM – Lagrange Multiplier test for serial correlation, with a chi-square (χ^2) distribution and three degrees of freedom; NORM – test for normality of residuals in the JB test; HET – heteroscedasticity test, with a χ^2 distribution and 5 degrees of freedom; these statistics are distributed as χ^2 variants, with P-values in brackets; DW – Durbin Watson statistic; RSS – residual sum square; S.E. – standard error of regression

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

As suggested by Brown et al. (1975), the short-run and long-run coefficient stability were checked through the CUSUM and CUSUMSQ tests because the structural changes in macro-economic series data may be subject to one or more structural breaks. The stability of the CUSUM and CUSUMSQ test results are within two straight lines bound by the 5% significance level. The model diagnostics and stability test results (Figure 4) indicate that all long-run and short-run coefficients are within the ARDL bounds critical value at 5% significance. This means that the estimated model is stable during the study period in China. Therefore, we assume that the coefficients of given regression are stable.

Result of granger causality. The existence of a long-run relationship between carbon emissions, EC, and economic growth suggests Granger causality in at least one direction. The long-run and the short-run Granger causality relationship between CO_2 emissions, EC, GDP, and GDP^2 are estimated by the VECM.

The results (Table 7) reveal no evidence of causality of EC, GDP and GDP^2 to CO_2 emissions in either the long or short run. Therefore, it is difficult to forecast future levels of CO_2 emissions from past EC and economic growth data of China. However, there was uni-

Table 7. Long-run and short-run Granger causality results

Variables	Short-run Granger causality				Long-run Granger
	ΔCO_2	ΔEC	ΔGDP	ΔGDP^2	ϕ_i (i = 1, 2, 3, 4)
ΔCO_2	–	1.593 (0.6610)	0.534 (0.9112)	0.318 (0.9565)	–0.036 (0.8519)
ΔEC	2.33 (0.5062)	–	0.238 (0.9712)	0.074 (0.9948)	–0.625 (0.0386)**
ΔGDP	0.59 (0.8987)	7.36 (0.0612)*	–	8.521 (0.0364)**	0.402 (0.0251)
ΔGDP^2	0.791 (0.8517)	6.732 (0.0809)*	7.576 (0.0556)*	–	–0.606 (0.0220)**

* and ** represent Granger causality relationship at 10% and 5% significance levels, respectively; the null hypothesis is that there is no causal relationship between variables; values in brackets are P-values for Wald tests with F-distribution; CO_2 – carbon dioxide emissions; EC – energy consumption; GDP – gross domestic product; GDP^2 – squared gross domestic product

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

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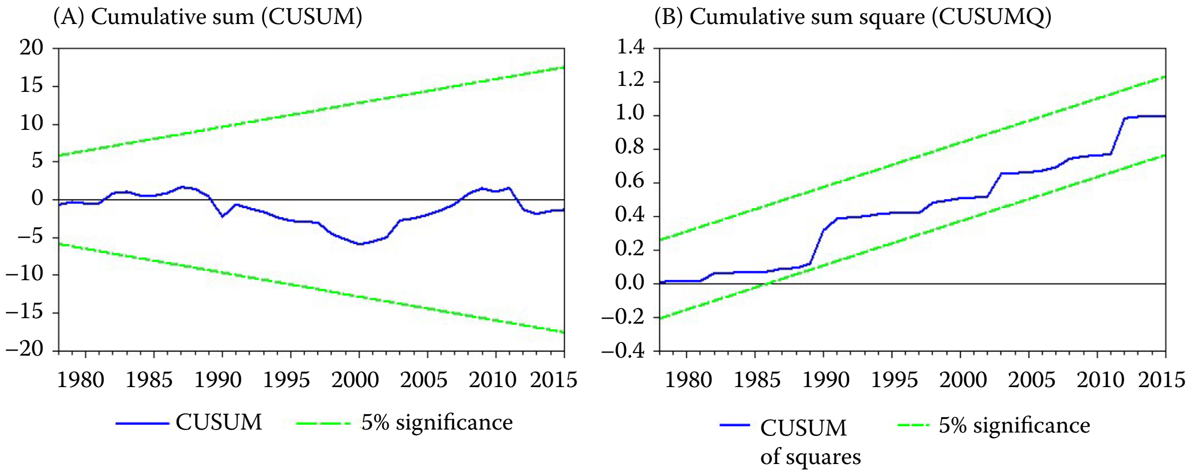

Figure 4. Autoregressive Distributive Lag (ARDL) model stability test result

Source: Authors' calculation from world development indicator (WDI 2018) and World Energy Consumption (Enerdata 2018)

directional causality from EC to GDP in the short run. This supports the growth hypothesis, which means that energy is the key to economic growth in China. This finding is in line with the studies of Shahbaz et al. (2013), Shiu and Lam (2004) in China.

Long-run causality from CO_2 emissions, GDP, and GDP^2 to EC is negative and statistically significant at the $P < 0.05$ significance level. This shows that rapid economic growth and associated carbon emissions could reduce the fossil-fuel EC in China in the long run. This may be attributable to: i) concentration of the Chinese economic development in construction and high-tech, low energy-consuming industries; ii) the replacement of the share of fossil-fuel energy sources by non-fossil-fuel energies such as nuclear, hydropower, wind, and geothermal, and iii) national commitment to the Paris Agreement, thereby achieving successful outcomes by adopting an ambitious amendment to the Montreal Protocol to tackle GHGs. These results contradict the findings of Wang et al. (2011) and Zhang and Cheng (2009).

CONCLUSIONS AND POLICY IMPLICATIONS

This study examined the ARDL bounds *F*-test and found evidence of long-run co-integration nexus of CO_2 emissions, EC, and per capita GDP using the ARDL bounds testing approach of cointegration and EC-based Granger causality over the period 1971–2015 in China. The CUSUM and CUSUMSQ tests supported ARDL long-run and short-run estimated coefficient stability throughout the study period. The long-run elasticity estimate of per capita income concerning CO_2 emissions is positive and statistically significant at $P < 1\%$, with an estimated coefficient of 0.776. This demonstrates that in the long run, the growth rate of CO_2 emissions has been 23.4% lower than the growth rate of per capita income. The nexus between CO_2 emissions and per capita income indicated a relatively decoupling relationship. This study also confirmed the existence of the EKC hypothesis in China, in both the short and long runs. This implies that the rapid economic growth in the country has not caused major environmental deterioration. In the short run, the growth of per capita CO_2 emissions has been 76.4% lower than per capita income growth. The long-run elasticity estimate of EC concerning CO_2 emissions is 1.61. This reveals that the contribution of energy consumption to carbon emissions is twice that of per capita economic growth in China. The speed of the adjustment (ECT) to return when CO_2 emissions are above or below their equilibrium level changed by 33.6% within the first year. There is no sgrowth to carbon emissions in long-run and short-run Granger causality tests over the period studied. Therefore, it is difficult to forecast future levels of CO_2 emissions from past EC and GDP data from China. However, there is a negative and statistically significant long-run causality from CO_2 emissions and GDP to EC. This shows that rapid economic growth and associated carbon emissions may reduce the consumption of fossil-fuel energy in China in the long run.

Energy is the main driver of both environmental deterioration and economic growth in China. The policymakers should, therefore, exercise caution in macroeconomic structural policy development and consider energy-saving and decarbonized economic structures.

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China should make environment-friendly and alternative energy such as hydropower, geothermal, wind, solar, and biofuel to reduce over-dependence on traditional (fossil fuel) energy. The Chinese government should be committed to the Paris Agreement to address GHGs. Moreover, the central and provincial governments should coordinate with each other on the design, implementation, and strengthening of the green economy to optimize energy utilization structures and further implement the transformation to a low-carbon economy. The country also needs to encourage energy-saving and low-carbon research innovations, energy-saving industries, green investment, and carbon-sequestration technologies, as well as foster public environmental awareness to mitigate environmental deterioration and climate change.

REFERENCES

Acaravci A., Ozturk I. (2010): On the relationship between energy consumption, CO_2 emissions and economic growth in Europe. Energy, 35: 5412–5420.

Acheampong A.O. (2018): Economic growth, CO_2 emissions and energy consumption: What causes what and where? Energy Economics, 74: 677–692.

Ang J.B. (2008): Economic development, pollutant emissions and energy consumption in Malaysia. Journal of Policy Modeling, 30: 271–278.

Balogh J.M., Jambor A. (2017): Determinants of CO_2 emission: A global evidence. International Journal of Energy Economics and Policy, 7: 217–226.

Brown R.L., Durbin J., Evans J.M. (1975): Techniques for testing the constancy of regression relationships over time. Journal of the Royal Statistical Society: Series B, 37: 149–163.

Chang C.C. (2010): A multivariate causality test of carbon dioxide emissions, energy consumption and economic growth in China. Applied Energy, 87: 3533–3537.

Govindaraju V.C., Tang C.F. (2013): The dynamic links between CO_2 emissions, economic growth and coal consumption in China and India. Applied Energy, 104: 310–318.

Gómez-Gener L., Obrador B., Marcé R., Acuña V., Catalán N., Casas-Ruiz J.P. (2016): When water vanishes: magnitude and regulation of carbon dioxide emissions from dry temporary streams. Ecosystems, 19: 710–723.

Grossman G., Krueger A. (1991): Environmental impacts of a North American free-trade agreement. National Bureau of Economic Research Working Paper Series, 3914: 1–57.

Grossman G.M., Krueger A.B. (1995): Economic growth and the environment. The Quarterly Journal of Economics, 110: 353–377.

Gutierrez L. (2003): On the power of panel cointegration tests: a Monte Carlo comparison. Economics Letters, 80: 105–111.

Halicioglu F. (2009): An econometric study of CO_2 emissions, energy consumption, income and foreign trade in Turkey. Energy Policy, 37: 1156–1164.

Kraft J., Kraft A. (1978): On the relationship between energy and GNP. The Journal of Energy and Development, 3: 401–403.

Kremers J.J.M., Ericsson N.R., Dolado J.J. (1992): The power of cointegration tests. Oxford Bulletin of Economics and Statistics, 54: 325–348.

Lin B., Moubarak M., Ouyang X. (2014): Carbon dioxide emissions and growth of the manufacturing sector: Evidence for China. Energy, 76: 830–837.

Menyah K., Wolde-Rufael Y. (2010): Energy consumption, pollutant emissions and economic growth in South Africa. Energy Economics: 32: 1374–1382.

Sari R., Soytas U. (2009): Are global warming and economic growth compatible? Evidence from five OPEC countries? Applied Energy: 86: 1887–1893.

Shahbaz M., Khan S., Tahir M.I. (2013): The dynamic links between energy consumption, economic growth, financial development and trade in China: Fresh evidence from multivariate framework analysis. Energy Economics, 40: 8–21.

Shiu A., Lam P.L. (2004): Electricity consumption and economic growth in China. Energy Policy, 32: 47–54.

Wang K.M. (2011): The relationship between carbon dioxide emissions and economic growth: quantile panel-type analysis. Quality and Quantity, 47: 1337–1366.

World Development Index (WDI) (2018): World Development Index Online Databases. Available at http://databank.worldbank.org. (accessed May 25, 2018).

World Energy Consumption (Enerdata) (2018): World Energy Consumption Online Databases. Available at http://yearbook.enerdata.net (accessed May 30, 2018).

Zhang X.P., Cheng X.M. (2009): Energy consumption, carbon emissions, and economic growth in China. Ecological Economics, 68: 2706–2712.

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