PANOECONOMICUS, 2019, Vol. 66, Issue 2, pp. 257-271
Received: 04 May 2016; Accepted: 02 December 2017.

UDC 338.43(510):504.5
https://doi.org/10.2298/PAN160504030D
Original scientific paper

Nezahat Doğan

Final International University,
Department of International Finance,
Turkey

✉ nezahat.dogan@final.edu.tr

The Impact of Agriculture on CO_2 Emissions in China

Summary: This study empirically analyses the long-term relationship between agricultural production and carbon dioxide (CO_2) emissions in China by using annual data covering1971-2010. In estimating the relationship between agriculture and CO_2 emissions, the study also includes real income and energy consumption as variables in the model, in line with the Environmental Kuznet Curves (EKC) hypothesis. To identify the existence of a long-term relationship between CO_2 emissions and agriculture, the bounds test approach for cointegration and autoregressive distributed lag (ARDL) methods are used. To determine the robustness of the results, other single-equation cointegration methods such as fully modified least squares (FMOLS), dynamic ordinary least squares (DOLS) and canonical cointegration regression (CCR) are also estimated. The results confirm cointegration among variables and the presence of an inverse U-shaped agriculture-induced EKC curve for China. Agriculture increases a country's long-term CO_2 emissions. The government, policymakers, and agricultural producers should set strategies covering energy-intensive economic activities, including agriculture, to solve environmental problems.

Key words: Agriculture, CO_2 emissions, Cointegration, China.

JEL: O13, O44, Q53.

Environmental issues have recently become major global concerns as a result of increasing demands of energy, industrialization, and climate change (V. G. R. Chandran Govindaraju and Chor Foon Tang 2013; Jyrki Luukkanen et al. 2015; Toshiyuki Sueyoshi, Yan Yuan, and Mika Goto 2017; Sofien Tiba and Anis Omri 2017). Global warming has been widely recognized as one of the main problems that will be faced in the future, and carbon dioxide (CO_2) emissions levels are known to be the main driver of pollution and global warming (Koji Tokimatsu, Rieko Yasuoka, and Masahiro Nishio 2015; Chengxi Liu, Yusak O. Susilo, and Anders Karlström 2016; Besma Talbi 2017). According to the World Resource Institute's (WRI) climate data explorer (CAIT)[1], China ranked as the world's largest producer of greenhouse gases (GHG) emissions in 2012. In addition to these figures, according to the Food and Agriculture Organization of The United Nations (FAO) report published recently (OECD and Food and Agriculture Organization of the United Nations 2015), China has the world's

[1] WRI is a global research organization that organizes their works at the nexus of environment, economic opportunity and human well-being. More detailed information is available at: http://www.wri.org and http://www.cait.wri.org.

largest agricultural economy. While China is a major producer of meat, vegetables, and cereal grains, it is also a major importer of feed grains, oil seeds, and cotton. Given the population of China, agriculture is an essential sector. Therefore, the impact of China's agricultural sector on pollution and the environment can have important outcomes for its citizens' living standards.

Briefly, China needs to increase its agricultural production to feed its population, however, environmental pollution is becoming worse every year due to the increase in its production levels. Therefore, this study focuses on the answers to the following questions in line with the Environmental Kuznet Curves (EKC) hypothesis as it relates to China: (i) Does growth (real income) have a positive impact on CO_2 emissions? (ii) Does a higher level of growth negatively impact CO_2 emissions? (iii) Does China's agricultural production have a positive (or negative) impact on its CO_2 emissions? Ultimately, the results of this study can be of interest to researchers, practitioners, and both agricultural and environmental policymakers for their future work on agriculture, energy, and the environment in China. Use of individual country regarding a specific sector will be a novel contribution of the study. Another contribution of the study to the literature is its use of a single equation of cointegration methods to determine whether results gathered using the autoregressive distributed lag (ARDL) method are robust.

1. Literature Review

The aim of this study is to determine how EKC, which examine the relationship between pollution (CO_2 emissions) and economic development, are affected by the agricultural sector in China. According to the EKC hypothesis, countries with lower income levels produce higher emissions at the beginning of their transition process from primarily agriculture-based to industrialized, but after a certain period of time, as they become higher income level economies with higher standards of living and improved rules and regulations regarding the environment, decreases in the level of CO_2 emissions can be observed.

The literature reveals two different approaches to analyzing the link between CO_2 emissions and economic growth using the EKC hypothesis. The first group of studies focuses on the economic growth and pollution nexus and draws different conclusions from consistent results, displaying an inverted U-shaped (Tao Song, Tingguo Zheng, and Lianjun Tong 2008; Fei Li et al. 2011; Halimahton Binti Borhan et al. 2012; Govindaraju and Tang 2013; Yu Benjamin Fu, Sophie Xuefei Wang, and Zhe George Zhang 2014; Linna Chen and Shiyi Chen 2015; Muhammad Shahbaz et al. 2015; Jianhua Yin, Mingzheng Zheng, and Jian Chen 2015) as well as a U- and N-shaped EKC curves for China (Gendi Wen and Zhe Cao 2009; Eunho Choi, Almas Heshmati, and Yongsung Cho 2010; Chuanqi Fan and Xiaojun Zheng 2013; Yan-Qing Kang, Tao Zhao, and Ya-Yun Yang 2016). For example, Song, Zheng, and Tong (2008) used waste water, solid waste, and waste gas as environmental indicators and gross domestic product (GDP) as the economic indicator, covering data from 1985-2005. They used a panel cointegration method, and their results show that China has a U-shaped EKC for all pollutants. Li et al. (2011) applied a panel-based dynamic ordinary least squares (DOLS) and heterogeneous panel cointegration for 30 provinces in

China covering 1985-2007 and posit a long-term cointegration between growth and energy consumption with the existence of a U-shaped EKC. Borhan et al. (2012) analyze the EKC for Malaysia and China from 1965 to 2010 by using a two-stage least square method and the results again support the inverted U-shaped EKC. However, Fan and Zheng (2013) estimated the EKC in China's Sichuan Province covering 1985-2010 and concluded there is an inverted N-shaped relationship or a U-shaped EKC, which indicates an invalid EKC for Sichuan Province. Govindaraju and Tang (2013) employed cointegration tests to examine CO_2 emissions, growth, and coal consumption in India and China. Results of the Granger causality test for China show strong evidence of unidirectional causality from GDP to CO_2. Another study by Chen and Chen (2015) estimated industrial CO_2 emissions and applied the EKC hypothesis to 31 provincial regions in China covering 1985-2010 and analyzed nonlinear relationships among variables based on nonparametric methods. Their results support the inverted U-shaped EKC hypothesis. Shahbaz et al. (2015) used the Bayer and Hanck cointegration test with the ARDL bounds test for the period of 1970-2012 and affirmed the presence of cointegration among variables and the validity of the EKC hypothesis in China both in the short- and long-term. Wen and Cao (2009) examined the EKC hypothesis for China during 1989-2008 using sulfur dioxide (SO_2), waste water, solid waste, and waste gas as pollution indicators. The regression results reveal that China's data form a U-shaped curve, which is not in line with the EKC hypothesis. Choi, Heshmati, and Cho (2010) used a simple ordinary least square (OLS) regression analysis with time series data covering the years 1971-2006 to investigate the EKC for China, Korea, and Japan. According to the results, while Japan has a U-shaped curve, China has an N-shaped EKC and Korea contradicts the EKC. Kang, Zhao, and Yang (2016) used spatial panel data to investigate the EKC shape for CO_2 emissions in China by using time series data for 1997-2012 and concluded that China has an inverted N-shaped EKC. Heterogeneity among the results can be explained by differences in the pollution proxies, economic models, and the period they used.

The second group of studies focused on the link between the energy consumption nexus with growth and China's CO_2 emissions (Abdul Jalil and Syed F. Mahmud 2009; Xing-Ping Zhang and Xiao-Mei Cheng 2009; Li et al. 2011; Sisi Wang et al. 2011; Govindaraju and Tang 2013; Luukkanen et al. 2015) and emphasized that energy usage is the main driver of CO_2 emissions in China. Jalil and Mahmud (2009) used the ARDL method to examine long-term relationships between energy, growth, and the CO_2 emissions nexus for China by employing time series data collected between 1975 and 2005. The results are in line with the EKC hypothesis. According to Zhang and Cheng (2009), there is a unidirectional Granger causality from GDP to energy consumption, and from energy consumption to long-term carbon emissions for China during 1960-2007. Wang et al. (2011) conducted another study of China's 28 provinces, using panel cointegration and panel vector error correction model (VECM) over the 1995-2007 period and concluded that variables are cointegrated and GDP and energy consumption are the causes of CO_2 emissions in the long-term. The common conclusion of these studies is that China needs to implement some carbon dioxide emission reduction policies.

Briefly, all these studies examine whether the EKC hypothesis is valid for China. However, the relationship between these variables with a specific sector in an economy, as seen in the agricultural sector, has not received enough attention in the literature. The agricultural sector plays a crucial role not only for economic reasons such as providing job opportunities and increasing income but also by providing food to societies in both developing and developed countries. It is also very important regarding its environmental impacts. According to Mustafa Önder, Ercan Ceyhan, and Ali Kahraman (2011), agriculture's expected environmental impacts can be classified into negative effects and positive effects; negative effects come from increased energy consumption due to using machinery and equipment during production and transportation processes, electrical lighting on farms, heating and cooling of farm buildings, increased demand for raw materials and land use, and using pesticides, chemicals, and fertilizers. The positive effects of agriculture come from providing different kinds of natural life and increasing oxygen production in the atmosphere through photosynthesis. Another study conducted by Matthias Stolze et al. (2000) emphasized the positive impact of agriculture from organic farming by eliminating pesticides, using fertilizers at lower rates, and decreasing the rate of using high-energy feedstuffs. Among other studies of the Chinese economy, Yongfu Huang and Jingjing He (2012) analyzed the effects of agricultural machinery, fertilizer consumption, and different energy types on GHG emissions with regional data covering the years 1995-2007 from 31 provinces of China by using the spatial error model and found that fertilizer and pesticide consumption, using machinery, and investment are the main driving factors of pollution in China. Recently, Boquiang Lin and Rilong Fei (2015) analyzed the CO_2 emissions performance of China's agricultural sector by using a Malmquist index approach covering the period 2003-2010 in 30 provincial regions and suggested that the state should apply different policies to reduce emissions based on actual conditions in the different regions. Another group of studies conducted by Rui-li Li and Shu Geng (2013) and Shuai Chen, Xiaoguang Chen, and Jintao Xu (2016) examined the impact of climate change on agriculture in China and concluded that global warming has caused economic loss in China's agricultural sector.

This paper concentrates on the impact of the agricultural sector on CO_2 emissions levels in China within the framework of the EKC hypothesis by using four different single-equation cointegration methods, namely ARDL, fully modified least squares (FMOLS), DOLS, and canonical cointegration regression (CCR), to check the robustness of the results. Therefore, to our knowledge, this study may be unique as well as important for policymakers in China by providing a new approach based on the agriculture induced EKC hypothesis.

The remainder of the paper is organized as follows: In the next section, the theoretical setting will be presented, then methodology will be discussed, and in last part, the empirical results and conclusions will be elaborated.

2. Theoretical Setting

In the literature, carbon dioxide is considered the main driver of air pollution and environmental quality. The main aim of this study is to test the hypothesis that the agricultural sector could contribute to air pollution (carbon dioxide emission level) in

China. From the literature, in addition to real income as a measure of development, energy consumption is regarded as another determinant of CO_2 emissions to test the EKC hypothesis in this study.

It is commonly expected that expansion in the agricultural sector increases real income and the amount of energy used through different stages of agricultural activities due to industrialization and modern agriculture. Whilst direct energy needs in agriculture come from activities such as harvesting, transporting of agricultural inputs and products, irrigation, lighting, and indirect energy needs result from fertilizing and pesticides, which, in turn, affect a country's environmental quality. On the other hand, as mentioned in the literature, positive effects of agriculture on air pollution come from increasing oxygen production in the atmosphere through photosynthesis and elimination of pesticides, as well as using fertilizers at lower rates.

From this point of view, the following EKC model is suggested in this study:

$$CO2 = f(GDP, GDP2, E, A), \tag{1}$$

where $CO2$ denotes carbon dioxide emissions (kt), E represents energy consumption (kt of oil equivalent), GDP is real income, $GDP2$ is the square of real income, and A stands for the agricultural proxy.

The agricultural-induced EKC model in Equation (1) can be expressed in logarithmic form to capture its long-term impacts as shown below:

$$LCO2_t = \beta_0 + \beta_1 LGDP_t + \beta_2 LGDP2_t + \beta_3 LE_t + \beta_4 LA_t + \varepsilon_t, \tag{2}$$

where at period t, $LCO2$ is the natural log of carbon dioxide emissions, LE is the natural log of energy consumption, $LGDP$ is the natural log of real income, $LGDP2$ is the square of natural log real income, LA is the natural log of the agriculture proxy, and ε is the error-disturbance.

Drawing from previous research and theories, especially considering the EKC, the following hypotheses were tested empirically in this study: (a) increase in real income increases CO_2 emissions at early stages of growth (the coefficient of GDP is expected to be positive); (b) after some point in time, an increase in real income decreases the CO_2 emissions due to changes in environmental procedures and changes in production processes (the coefficient of $GDP2$ is expected to be negative); (c) higher energy consumption causes higher CO_2 emissions levels (the coefficient of E is expected to be positive); and finally (d) agricultural production as a share of real income may negatively or positively affect CO_2 emissions depending on agricultural policies.

The dependent variable in Equation (2) may not immediately adjust to its long-term equilibrium level following a change in its determinants. Therefore, estimating the following error correction model (ECM) can capture the speed of adjustment between the short- and long-term levels of the dependent variable:

$$\Delta LCO2_t = \phi_0 + \textstyle\sum_{i=1}^{n} \phi_1 \Delta LCO2_{t-j} + \sum_{i=0}^{n} \phi_2 \Delta LGDP_{t-j} + \sum_{i=0}^{n} \phi_3 \Delta LGDP2_{t-j} + \sum_{i=0}^{n} \phi_4 \Delta LE_{t-j} + \sum_{i=0}^{n} \phi_5 \Delta LA_{t-j} + \phi_6 \varepsilon_{t-1} + u_t, \tag{3}$$

where Δ represents changes in $CO2$, E, GDP, and $GDP2$, and ε_{t-1} is the one period lagged error correction term (ECT), which is estimated from Equation (2). The ECT in Equation (3) shows how quickly disequilibrium between the short-term and long-term values of the dependent variable ($CO2$) is eliminated in each period. The expected sign of ECT is negative.

This empirical paper uses annual data covering 1971-2010. Carbon dioxide emissions ($CO2$) (kt) are used as an environmental indicator in the model. As explanatory variables, energy use (E) (kt of oil equivalent), real GDP with 2005 as the base year (2005 = 100) (GDP) and squared constant GDP (2005 = 100) ($GDP2$) are taken into account. Additionally, the volume of agriculture (A) in China is included in the model. The agriculture variable in the present study was proxied by real income from agriculture due to data availability. Data were obtained from Thomson Reuters Datastream (2015)[2] logarithmic forms of the variables are used in the analyses. To investigate the long-term relationship between the variables, the bound test for cointegration with ARDL modeling approach is adopted in this study.

3. Methodology

In the study, the bound test for cointegration with ARDL modelling approach developed by M. Hashem Pesaran, Yongcheol Shin, and Richard J. Smith (2001) is used due to some advantages it provides in application: firstly, it can be applicable whether the regressors are integrated of order 1 or 0, or both; secondly, it is good model to prefer even in small samples; thirdly, endogeneity is not a big problem in ARDL because it is free of residual correlation, and finally, it simultaneously provides both short- and long-term estimates. However, the primary focus of this paper is analyzing the agricultural sector's long-term impact on China's CO_2 emission levels.

The ARDL approach has two stages. To begin, the long-term relationships among variables should be determined by using the bound test developed by Shin and Pesaran (1999). When information is available regarding the direction of the relationships between variables, the unrestricted conditional error correction model (UECM) is incorporated in the bound test approach. While doing this, each variable is taken as a dependent variable and the UECM is defined as:

$$\Delta Y_t = \mu_0 + \mu_1 t + \lambda_1 Y_{t-1} + \sum_{i=0}^{4} \theta_i V_{it-1} + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \sum_{i=1}^{4} \sum_{j=0}^{p} \omega_{ij} \Delta V_{it-j} + \psi D_t + \varepsilon_t. \tag{4}$$

In Equation (4), V_t is the vector defined as $V_t = (LGDP, LGDP2, LE, LA)$, D_t is the vector including exogenous variables such as structural break dummies. Here, according to the Wald test, the null hypothesis asserts there is no cointegration (H_0: $\lambda_1 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$, while the alternative hypothesis asserts a long-term relationship between variables (H_1: $\lambda_1 \neq \theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq 0$). While testing the null hypothesis, the critical values provided by Pesaran, Shin, and Smith (2001) are used. They provide three different scenarios in their paper about the conclusions of test results. When calculated F-statistics exceed the upper bound critical value at a given significance level, a null hypothesis is rejected, and we can conclude that variables have a long-term relationship (are cointegrated). In the light of the results, the ARDL approach to the estimation of level relations is adopted as below.

[2] **Thomson Reuters Datastream.** 2015. https://infobase.thomsonreuters.com/infobase/login/?next=/infobase/ (accessed November 15, 2015).

$$Y_t = \mu_0 + \sum_{j=1}^{p_i} \beta_j Y_{t-j} + \sum_{i=1}^{4} \sum_{j=0}^{q_i} \emptyset_{ij} V_{it-j} + \psi D_t + u_t. \quad (5)$$

Here, in the Equation (5), all variables are defined as above with the maximum lags determined by Akaike Information Criteria (AIC) and Schwartz Information Criteria (SIC) to determine the optimal ARDL specification. The next step in the ARDL procedure is the estimation of short-term coefficients by using the conditional ECM as defined below:

$$\Delta Y_t = \mu + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \sum_{i=1}^{4} \sum_{j=0}^{p} \omega_{ij} \Delta V_{it-j} + \vartheta ECM_{t-1} + \psi D_t + \varepsilon_t. \quad (6)$$

In the Equation (6), while y_j and ω_{ij} are short-term parameters, ϑ shows the speed of adjustment through the long-term equilibrium after a shock. The value of speed of adjustment ranges between 0 (no convergence after a shock) and -1 (perfect convergence after a shock). The error correction term (ECM_t) is defined in the following format:

$$ECM = Y_t - \hat{\beta}_0 - \hat{\beta}_1 LGDP - \hat{\beta}_2 LGDP2 - \hat{\beta}_3 LE - \hat{\beta}_4 LA. \quad (7)$$

In Equation (7), ECM_{t-1} is the error correction term and its sign must be negative and significant to ensure convergence. To ascertain the ARDL model's goodness of fit, diagnostic tests are also conducted to examine heteroscedasticity, autocorrelation, and functional form associated with the model. Diagnostic tests for serial correlation, functional form, and heteroscedasticity were also conducted and the results are reported in Tables 4 and 5. These tests include the Breusch-Godfrey serial correlation Lagrange multiplier (LM) test (H_0: No serial correlation in the residuals) (p-values are 0.3015 and 0.3000 for the models with constant and the model with constant and trend, respectively), Breusch-Pagan-Godfrey Heteroskedasticity test (H_0: Homoskedasticity) (p-values are 0.0230 and 0.2907, respectively), and Ramsey RESET test ($H_0: \varepsilon - N(0, \sigma^2 I), H_1: \varepsilon - N(\mu, \sigma^2 I), \mu \neq 0$) ($p$-values are 0.1524 and 0.1142, respectively). None of the statistics reject the null hypothesizes in the respective tests which means the results show that the models are well specified, and there is no autocorrelation or heteroscedasticity. All these results confirm that all necessary conditions for the short-term ECM model are met. Also, the cumulative sum (CUSUM) procedure suggested by Pesaran and Bahram Pesaran (1997) was employed to test the stability of long-term estimates. It indicates that residuals fall within the 5% critical boundaries, which means the estimated coefficients are stable at a level of 5%. To check the robustness of the ARDL test results of Equation (2), the long-term relationship was also estimated for the same period with three single equation cointegration techniques, namely, FMOLS, DOLS, and CCR.

4. Empirical Results

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit roots tests were conducted to ensure that none of the variables are integrated of order 2. The results are provided in Table 1. Based on the unit root test results, all variables are non-stationary at their levels but become stationary at their first differences, which means that they are integrated of order 1.

Table 1 Unit Root Test Results

	Variables	Level		First differences	
		Intercept	Intercept & trend	Intercept	Intercept & trend
ADF	*LCO2*	0.223327 (1)	-2.374595 (1)	-3.796404*** (0)	-3.799168** (0)
	LGDP	1.185731 (2)	-4.679220** (4)	-4.324102*** (4)	-4.097642* (4)
	LGDP2	2.033687 (2)	-2.464867 (2)	-2.448239 (1)	-3.988317* (4)
	LE	1.252891 (1)	-0.723829 (1)	-3.822744** (0)	-4.096739* (0)
	LA	-1.346874 (7)	-2.689078 (9)	-2.750231* (9)	-4.660501*** (9)
PP	*LCO2*	0.343750	-1.813636	-3.833298***	-3.838031**
	LGDP	2.475117	-3.098135	-4.159287***	-4.159287***
	LGDP2	4.658005	-2.144950	-3.211056**	-4.068528**
	LE	1.377667	-0.445228	-3.809086***	-4.096739**
	LA	0.200887	-2.334021	-5.220749***	-5.131815***

Notes: *, ** and *** denote rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

Source: Authors' results.

Next, the bound test was employed to check if there was a long-term relationship between variables. Table 2 presents the bound test results for cointegration between *LGDP*, *LGDP2*, *LE*, *LA*, and *LCO2* under three different scenarios suggested by Pesaran, Shin, and Smith (2001). The scenarios include a model without deterministic trends (F_{iii}), a model with restricted deterministic trends (F_{iv}), and a model with unrestricted deterministic trends (F_v). This procedure begins with determining the appropriate lag order. Maximum lag order (p) is determined as 1 according to both AIC results and SIC results. Therefore, maximum lag length is set to 1. Then, by using F-statistics suggested by Shin and Pesaran (1999), the presence of a long-term relationship in the model is tested. Since $k = 4$ (number of independent variables), the 0.05 critical value bounds are (2.86, 4.01), (-2.86, -3.99), (3.05, 3.97), (3.47, 4.57) (-3.41, -4.36) for F_{iii}, t_{iii}, F_{iv}, F_v, and t_v, respectively. For $p = 1$, tests lie outside the 0.05 critical value bounds, except the F_{iii} model without deterministic trends, and reject the null hypothesis that there exists no level equation in both cases with or without a deterministic trend. Hence, it can be concluded that there is cointegration between CO_2 emissions and the independent variables.

Table 2 Bound Test Results

Without deterministic trends			
k = 4		I(0)	I(1)
F_{iii}	3.700720	2.86	4.01
t_{iii}	3.700720	-2.86	-3.99
With deterministic trends			
k = 4		I(0)	I(1)
F_{iv}	4.569368	3.05	3.97
F_v	5.258553	3.47	4.57
t_v	-4.636368	-3.41	-4.36

Source: Authors' calculations.

Table 3 shows the results of level equations (long-term estimation) for the agriculture-induced EKC hypothesis. The coefficients of all the variables in the equation have the expected sign and they are highly significant, except *LGDP* in the level equation with constant. Although *LGDP* has the correct expected sign, it seems insignificant. However, according to the ARDL level equation with constant and trend, the coefficient of all variables, including $LGDP$, has the correct sign and is highly significant. Coefficients in the long-term equation also represent the estimated long-term elasticities of the respective variables. According to the EKC hypothesis, we expect higher CO_2 emissions at the lower levels of GDP, and then after the attainment of a certain level of living standards, such as an increase in *per capita* income, a decrease, not only due to improvement in environmental policies, rules and regulations, but also due to the availability of more environmentally friendly technologies used in production and transportation, and increased funds available to pay for these. Therefore, in line with the EKC hypothesis, whilst the expected sign for GDP is positive, the expected sign for $GDP2$ is negative. From Table 3, the coefficients of these variables have a highly significant correct sign, and the results support the EKC hypothesis. While the coefficient of GDP is inelastic (0.36) in the level equation with constant and insignificant ($p = 0.21$), its coefficient seems elastic (1.26) and statistically significant ($p < 0.01$) in constant with the trend model. Further, the coefficient of $GDP2$ is negative (-0.04 and -0.06, respectively) and highly significant ($p < 0.01$) as well as on both constant and constant with trend models. These results are consistent with the inverted U-shaped EKC hypothesis. Meanwhile, the energy-used variable (LE) has the correct sign, which is positive (1.26 and 1.44, respectively) and significant ($p < 0.10$) in both models. This shows that energy consumption has a long-term relationship with carbon dioxide emissions at a 1% significance level. The positive coefficient sign of energy consumption reveals that an increase in energy used in the long-term will increase carbon dioxide emissions in China, as discussed in the introduction. The long-term ARDL estimation results confirm that CO_2 emissions have an inverted U relationship with economic growth in line with the EKC hypothesis and energy consumption leads to higher-level CO_2 emissions. Therefore, China should promote the use of energy-saving technologies in all sectors, including agriculture, to improve environmental quality. They may also increase the amounts of research and development investment in cleaner energies.

The key variable in this study that determines CO_2 emissions ($CO2$) in China is agriculture. It has a positive impact on carbon dioxide emission with a coefficient of 0.53 ($p < 0.05$) in the level equation with constant model, which suggests that a 10% increase in agricultural production would lead to a 5.3% change in carbon emissions in the same direction and 0.30 ($p < 0.05$) in the level equation with constant and trend model, which suggests that a 10% increase in agricultural production would lead to a 3% change in carbon emissions in the same direction. This means an increase in agricultural production in China will lead to higher CO_2 level and pollution in turn. However, this study does not explain the reasons for the relationship between agricultural production and CO_2 emissions. It might be due to agricultural production volume and crops which lead to higher levels of CO_2, higher amounts of use of high energy consuming feed stuffs, increased use of mineral fertilizers, and use of pesticides, among others. These reasons and their impacts should be examined in future studies. However, the estimated results indicate that agricultural production in China increases carbon dioxide emissions. Based on the empirical findings, this study provides several policy implications for the Chinese government and policymakers, as well as local farmers. First, the agricultural sector should adopt cleaner production practices such as using new energy-saving technologies in production. Next, the government should support producers using organic fertilizers by exempting them from taxes or providing some subsidies for them to prevent environmental pollution. Finally, the government should increase investments in research and development to build energy saving, modern, environmentally friendly, and sustainable agricultural systems in the sector. Public awareness regarding the environment should be improved as well through education. Farmers should also be informed about the benefits of using energy saving lighting and irrigation systems.

Table 3 ARDL Level Equations

Level equation with constant				
Dependent variable: *LCO2*				
Variable	Coefficient	Std. error	*t*-statistic	Prob.
LGDP	0.3613	0.2847	1.2689	0.2128
LGDP2	-0.0361	0.0124	-2.9083	0.0063
LE	1.2626	0.1147	11.0039	0.0000
LA	0.5302	0.2272	2.3327	0.0255
C	-10.4079	2.5956	-4.0098	0.0003
Level equation with constant and trend				
Variable	Coefficient	Std. error	*t*-statistic	Prob.
LGDP	1.2684	0.2767	4.5831	0.0001
LGDP2	-0.0635	0.0099	-6.3763	0.0000
LE	1.4479	0.0692	20.9193	0.0000
LA	0.2994	0.1297	2.3081	0.0270
C	-14.7684	1.8004	-8.2024	0.0000

Source: Authors' estimation results.

In addition to the results of the ARDL estimation, FMOLS, DOLS, and CCR estimations are also presented to check the robustness of results in Table 4. The FMOLS estimation assumes the existence of a single cointegration and employs a semiparametric correction to avoid estimation problems caused by the long-term correlation between the cointegrating equation and stochastic regressors. The CCR estimation is similar to FMOLS but instead employs stationary transformations of the data to avoid the cointegration problems. The DOLS estimation uses lags and leads to eliminate the long-term correlation problems. The FMOLS and CCR methods use a Barlet kernel and Newey-West fixed bandwidth of 4.0000 and both also include the trend as an additional deterministic regressor in computing the results. The DOLS uses 1 as leads and lags, and its long-term variance estimates are also calculated using the Newey-West. Overall, using these methods, this study calculates similar coefficient estimates with the same expected signs.

The results from all three cointegration equations support the hypothesis that China has an inverted U-shaped EKC and is consistent with the results gathered from the ARDL equations. In all three cointegration equations, the estimated sign of GDP is positive (0.46 in all) and significant in the FMOLS and CCR estimations. According to the DOLS, even if it seems insignificant, it has the positive expected sign as well. This can be explained by the DOLS method's use of leads and lags, which may lead to results displaying the wrong sign or not indicating significance for small sample periods. The results indicate that a 10% increase in China's GDP will lead to a 4.6%

change in the same direction in CO_2 emissions in the country. As expected, the estimated sign of $GDP2$ also produced a negative sign (-0.04, -0.05, -0.04 with $p < 0.001$, respectively) in the estimation results of FMOLS, DOLS, and CCR.

Table 4 Estimation Results of FMOLS, DOLS, and CCR

Variable	Coefficient	Std. error	*t*-statistic	Prob.		
Method: FMOLS						
LGDP	0.4640	0.1815	2.5568	0.0152	R^2 = 0.9978	Adj. R^2 = 0.9975
LGDP2	-0.0375	0.0078	-4.7773	0.0000	S.E. of reg. = 0.0300	*DW* = 1.0780
LE	1.2522	0.0682	18.3550	0.0000	Mean dep. var. = 14.7695	S. D. dep. var. = 0.6097
LA	0.4219	0.1442	2.9257	0.0061	Sum squared resid. = 0.0307	Long-run variance = 0.0008
C	-9.4754	1.5301	-6.1925	0.0000		
Method: DOLS						
LGDP	0.4616	0.3094	1.4917	0.1514	R^2 = 0.9989	Adj. R^2 = 0.9981
LGDP2	-0.0464	0.0146	-3.1693	0.0048	S. E. of reg. = 0.0247	*DW* = 1.3020
LE	1.3439	0.0981	13.6867	0.0000	Mean dep. var. = 14.7658	S. D. dep. var. = 0.5708
LA	0.5669	0.2163	2.6202	0.0164	Sum squared resid. = 0.0122	Long-run variance = 0.0006
C	-12.0988	2.2361	-5.4105	0.0000		
Method: CCR						
LGDP	0.4614	0.1904	2.4237	0.0208	R^2 = 0.9978	Adj. R^2 = 0.9975
LGDP2	-0.0372	0.0076	-4.8666	0.0000	S. E. of reg. = 0.0300	*DW* = 1.0748
LE	1.2466	0.0616	20.220	0.0000	Mean dep. var. = 14.7695	S. D. dep. var. = 0.6097
LA	0.4210	0.1461	2.8800	0.0068	Sum squared resid. = 0.0307	Long-run variance = 0.0008
C	-9.3891	1.4844	-6.3249	0.0000		

Source: Authors' estimation results.

The long-term coefficient of energy used also has the expected positive sign (1.25, 1.34, and 1.24, respectively in FMOLS, DOLS, and CCR, with $p < 0.01$ in all estimations), which is the same as those derived from ARDL level estimations. Finally, the coefficient of agricultural proxy is also positive (0.4 in FMOLS with $p < 0.001$ and in CCR with $p < 0.05$, and 0.6 in DOLS with $p < 0.001$), which is consistent with the results gathered from ARDL estimations.

5. Conclusion

The primary objective of this study was to test the impact of the Chinese agricultural sector and existence of EKC over the period covering 1971-2010. A bound test and an ARDL model estimation were used to test cointegration between variables. Other single equation methods and cointegration techniques were also employed in this study such as FMOLS, DOLS, and CCR to check the results' robustness. All results suggest the empirical existence of a long-term relationship between the variables and confirm the existence of an inverse U-shaped EKC hypothesis with a positive sign for income and a negative sign for the square of income. Additionally, the results also confirm that an increase in energy demand leads to higher levels of CO_2 emissions. The results also indicate that China's agricultural sector is a significant determinant of CO_2 emissions.

The results prove that agricultural activities in China should be redesigned to decrease CO_2 emissions in the future. Furthermore, the paper shows that the government of China should pay greater attention to its pollution levels and considers the agricultural sector as one of the main drivers of this pollution. As a policy suggestion, the government should promote projects such as organic farming through using new environmentally friendly technologies, reasonable use of pesticides and chemical fertilizers to reduce the country's pollution level and CO_2 emissions. Also, more attention should be paid to using energy saving lighting and irrigation systems in farmlands to reduce energy consumption. Furthermore, public awareness regarding air pollution caused by different sectors should be improved, because inadequate education and ignoring the potential risks of pollution can be reasons for the pollution.

Finally, the effects of agricultural production on CO_2 might be different in different countries and in different regions depending on crop diversification or agricultural policies, or both. Therefore, further studies should be conducted on these differences and different types of GHG emissions from agricultural sectors such as nitrous oxide (N_2O) and methane (CH_4) to understand how to minimize the negative impact of agriculture on the environment while maximizing the agricultural share of income.

References

Borhan, Halimahton Binti, Mizan Bin Hitam, Rozita Naina Mohamed, and Mazzini Muda. 2012. "Income and CO2 in China and Malaysia from Environmental Kuznets Curve (EKC) Perspective." Paper presented at Cambridge Business & Economics Conference, Murray Edwards College, Cambridge.

Chen, Linna, and Shiyi Chen. 2015. "The Estimation of Environmental Kuznets Curve in China: Nonparametric Panel Approach." *Computational Economics*, 46(3): 405-420. http://dx.doi.org/10.1007/s10614-015-9486-7

Chen, Shuai, Xiaoguang Chen, and Jintao Xu. 2016. "Impacts of Climate Change on Agriculture: Evidence from China." *Journal of Environmental Economics and Management*, 76(2): 105-124. http://dx.doi.org/10.1016/j.jeem.2015.01.005

Choi, Eunho, Almas Heshmati, and Yongsung Cho. 2010. "An Emprical Study of the Relationship between CO2 Emissions, Economic Growth and Openness." Institute for the Study of Labor Discussion Paper 5304.

Fan, Chuanqi, and Xiaojun Zheng. 2013. "An Emprical Study of the Environmental Kuznets Curve in Sichuan Province, China." *Environment and Pollution*, 2(3): 107-115. http://dx.doi.org/10.5539/ep.v2n3p107

Fu, Yu Benjamin, Sophie Xuefei Wang, and Zhe George Zhang. 2014. "Population Growth and the Environmental Kuznets Curve." http://pdfs.semanticscholar.org/b524/476da5de0da7401b2fa25bbc66cc078a8215.pdf.

Govindaraju, V. G. R. Chandran, and Chor Foon Tang. 2013. "The Dynamic Links between CO_2 Emissions, Economic Growth and Coal Consumption in China and India." *Applied Energy*, 104(C): 310-318. http://dx.doi.org/10.1016/j.apenergy.2012.10.042

Huang, Yongfu, and Jingjing He. 2012. "The Carbonization of China's Agriculture." United Nations University, World Institute for Development Economic Research Working Paper 2012/74.

Jalil, Abdul, and Syed F. Mahmud. 2009. "Environment Kuznets Curve for CO_2 Emissions: A Cointegration Analysis for China." *Energy Policy*, 37(12): 5167-5172. http://dx.doi.org/10.1016/j.enpol.2009.07.044

Kang, Yan-Qing, Tao Zhao, and Ya-Yun Yang. 2016. "Environmental Kuznets Curve for CO_2 Emissions in China: A Spatial Panel Data Approach." *Ecological Indicators*, 63: 231-239. http://dx.doi.org/10.1016/j.ecolind.2015.12.011

Li, Fei, Suocheng Dong, Xue Li, Quanxi Liang, and Wangzhou Yang. 2011. "Energy Consumption-Economic Growth Relationship and Carbon Dioxide Emissions in China." *Energy Policy*, 39(2): 568-574. http://dx.doi.org/10.1016/j.enpol.2010.10.025

Li, Rui-li, and Shu Geng. 2013. "Impacts of Climate Change on Agriculture and Adaptive Strategies in China." *Journal of Integrative Agriculture*, 12(8): 1402-1408. http://dx.doi.org/10.1016/S2095-3119(13)60552-3

Lin, Boquiang, and Rilong Fei. 2015. "Regional Differences of CO_2 Emissions Performance in China's Agricultural Sector: A Malmquist Index Approach." *European Journal of Agronomy*, 70: 33-40. http://dx.doi.org/10.1016/j.eja.2015.06.009

Liu, Chengxi, Yusak O. Susilo, and Anders Karlström. 2016. "Estimating Changes in Transport CO_2 Emissions due to Changes in Weather and Climate in Sweden." *Transportation Research Part D: Transport and Environment*, 49(C): 172-187. http://dx.doi.org/10.1016/j.trd.2016.09.004

Luukkanen, Jyrki, Juha Panula-Ontto, Jarmo Vehmas, Liu Liyong, Jari Kaivo-oja, Laura Häyhä, and Burkhard Auffermann. 2015. "Structural Change in Chinese Economy: Impacts on Energy Use and CO_2 Emissions in the Period 2013-2030." *Technological Forecasting and Social Change*, 94(C): 303-317. http://dx.doi.org/10.1016/j.techfore.2014.10.016

OECD, and Food and Agriculture Organization of the United Nations. 2015. *OECD-FAO Agricultural Outlook 2015-2024*. Paris: OECD Publishing. http://dx.doi.org/10.1787/19991142

Önder, Mustafa, Ercan Ceyhan, and Ali Kahraman. 2011. "Effects of Agricultural Practices on Environment." Paper presented at the International Conference on Biology, Environment and Chemistry, Singapore.

Pesaran, M. Hashem, and Bahram Pesaran. 1997. *Working with Microfit 4.0: Interactive Econometric Analysis*. Oxford: Oxford University Press.

Pesaran, M. Hashem, Yongcheol Shin, and Richard J. Smith. 2001. "Bounds Testing Approaches to the Analysis of Level Relationships." *Journal of Applied Econometrics*, 16(3): 289-326. http://dx.doi.org/10.1002/jae.616

Shahbaz, Muhammad, Saleheen Khan, Amjad Ali, and Mita Bhattacharya. 2015. "The Impact of Globalization on CO2 Emissions in China." Munich Personal RePEc Archive Paper 64450.

Shin, Yongcheol, and M. Hashem Pesaran. 1999. "An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis." In *Econometrics and Economic Theory in the 20th Century*, ed. Steinar Strøm, 371-413. Cambridge: Cambridge University Press.

Song, Tao, Tingguo Zheng, and Lianjun Tong. 2008. "An Emprical Test of the Environmental Kuznets Curve in China: A Panel Cointegration Approach." *China Economic Review*, 19(3): 381-392. http://dx.doi.org/10.1016/j.chieco.2007.10.001

Stolze, Matthias, Annette Piorr, Anna Häring, and Stephan Dabbert. 2000. *The Environmental Impacts of Organic Farming in Europe - Organic Farming in Europe: Economics and Policy*. Vol. 6. Stuttgart-Hohenheim: University of Hohenheim.

Sueyoshi, Toshiyuki, Yan Yuan, and Mika Goto. 2017. "A Literature Study for DEA Applied to Energy and Environment." *Energy Economics*, 62(C): 104-124. http://dx.doi.org/10.1016/j.eneco.2016.11.006

Talbi, Besma. 2017. "CO2 Emissions Reduction in Road Transport Sector in Tunisia." *Renewable and Sustainable Energy Reviews*, 69(C): 232-238. http://dx.doi.org/10.1016/j.rser.2016.11.208

Tiba, Sofien, and Anis Omri. 2017. "Literature Survey on the Relationships between Energy, Environment and Economic Growth." *Renewable and Sustainable Energy Reviews*, 69(C): 1129-1146. http://dx.doi.org/10.1016/j.rser.2016.09.113

Tokimatsu, Koji, Rieko Yasuoka, and Masahiro Nishio. 2015. "Global Zero Emissions Scenarios: Assessment of Climate Change Mitigations and Their Costs." *Energy Procedia*, 75: 2211-2214. http://dx.doi.org/10.1016/j.egypro.2015.07.383

Wang, Sisi, Dequn Zhou, Peng Zhou, and Qunwei Wang. 2011. "CO_2 Emissions, Energy Consumption and Economic Growth in China: A Panel Data Analysis." *Energy Policy*, 39(9): 4870-4875. http://dx.doi.org/10.1016/j.enpol.2011.06.032

Wen, Gendi, and Zhe Cao. 2009. "An Empirical Study on the Relationship between China's Economic Development and Environmental Quality - Testing China's Environmental Kuznets Curves." *Journal of Sustainable Development*, 2(2): 65-72. http://dx.doi.org/10.5539/jsd.v2n2p65

Yin, Jianhua, Mingzheng Zheng, and Jian Chen. 2015. "The Effects of Environmental Regulation and Technical Progress on CO_2 Kuznets Curve: An Evidence from China." *Energy Policy*, 77(C): 97-108. http://dx.doi.org/10.1016/j.enpol.2014.11.008

Zhang, Xing-Ping, and Xiao-Mei Cheng. 2009. "Energy Consumption, Carbon Emissions, and Economic Growth in China." *Ecological Economics*, 68(10): 2706-2712. http://dx.doi.org/10.1016/j.ecolecon.2009.05.011

THIS PAGE INTENTIONALLY LEFT BLANK