THE IMPACT OF AGRICULTURE ON CO2 EMISSIONS IN CHINA

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Abstract:

This study empirically analyses the long-term relationship between agricultural production and carbon dioxide emissions in China by using annual data covering 1971–2010. In estimating the relationship between agriculture and CO2 emissions, the study also includes real income and energy consumption as variables in the model, in line with the EKC hypothesis. To identify the existence of a long-term relationship between CO2 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 FMOLS, DOLS, and 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 CO2 emissions. The government, policymakers, and agricultural producers should set strategies covering energy-intensive economic activities, including agriculture, to solve environmental problems.

Keywords: Agriculture, CO2 emissions, Cointegration, China

Jel Classification: O13, Q53, O44

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1. INTRODUCTION

Environmental issues have recently become major global concerns as a result of increasing demands of energy, industrialization, and climate change (Chandran Govindaraju and Chor Foon Tang 2013; Jyrki Luukkanen et al. 2015; Sofien Tiba and Anis Omri 2017; S. E. Elias 2017; Toshiyuki Sueyoshi, Yan Yuan, and Mika Goto, 2017; Koji Tokimatsu, Rieko Yasuoka, and Masahiro Nishio 2015; Chengxi Liu, Yusak O. Susilo, and Anders Karlstrom 2016; Besma Talbi 2017). Global warming has been widely recognized as one of the main problems that will be faced in the future, and CO2 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 Karlstrom 2016; Besma Talbi 2017). According to the World Resource Institute’s (WRI) climate data explorer (CAIT), China ranked as the world’s largest producer of GHG emissions in 2012. In addition to these figures, according to the Food and Agriculture Organization of The United Nations (FAO) report published recently (2015), China has the world’s largest agricultural economy. While China is a major producer of meat, vegetables, and cereal grains, it is also a major importer of feed grains, oilseeds, 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 EKC hypothesis as it relates to China: a) Does growth (real income) have a positive impact on CO2 emissions? b) Does a higher level of growth negatively impact CO2 emissions? c) Does China’s agricultural production have a positive (or negative) impact on its CO2 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 data 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 ARDL method are robust.

2. LITERATURE REVIEW

The aim of this study is to determine how Environmental Kuznet Curves (EKC), which examine the relationship between pollution (CO2 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 CO2 emissions can be observed.

The literature reveals two different approaches to analyzing the link between CO2 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, Suocheng Dong, Xue Lia, Quanxi Liang, and Wangzhou Yang 2011; Halimahton Binti Borhan, Mizan Bin Hitam, Rozita Naina Mohamed, and Mazzini Muda 2012; Chandran Govindaraju and Tang 2013; Yu Benjamin Fu, Sophie Xuefei Wang, and Zhe George Zhang 2014; Linna Chen and Shiyi Chen 2015; Muhammad Shahbaz Khan Saleheen, Ali Amjad, and Bhattacharya Mita 2015; Jianhua
Yin, Mingzheng Zheng, and Jian Chen (2015) as well as 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 et al. (2008) used wastewater, solid waste, and waste gas as environmental indicators and 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 OLS 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 CO2 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 CO2. Another study by Chen and Chen (2015) estimated industrial CO2 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 SO2, wastewater, 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 et al. (2010) used a simple 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 et al. (2016) used spatial panel data to investigate the EKC shape for CO2 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 CO2 emissions (Abdul Jalil and Syed F. Mahmud 2009; Xing-Ping Zhang and Xiao-Mei Cheng 2009; Li et al., 2011; S. S. Wang, D. Q. Zhou, Peng Zhou, and Kunwei Wang 2011; Govindaraju and Tang 2013; Luukkanen et al. 2015) and emphasized that energy usage is the main driver of CO2 emissions in China. Jalil and Mahmud (2009) used the ARDL method to examine long-term relationships between energy, growth, and the CO2 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 VECM over the 1995-2007 period and concluded that variables are cointegrated and GDP and energy consumption are the causes of CO2 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 Onder, 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, Annette Piorr, Anna Haring, and Stephan Dabbert (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 CO2 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 Shuai Chen, Xiaoguang Chen, and Jintao Xu (2015) and Rui-li Li and Shu Geng (2013) 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 CO2 emissions levels in China within the framework of the EKC hypothesis by using four different single-equation cointegration methods, namely ARDL, DOLS, FMOLS, and 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.

3. 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 CO2 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:

\[ CO_2 = f(GDP, GDP^2, E, A) \]  

where \( CO_2 \) denotes carbon dioxide emissions (kt), \( E \) represents energy consumption (kt of oil equivalent), \( GDP \) is real income, \( GDP^2 \) 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:

\[ \ln(CO_2_t) = \beta_0 + \beta_1 \ln(GDP_t) + \beta_2 \ln(GDP^2_t) + \beta_3 \ln(E_t) + \beta_4 \ln(A_t) + \varepsilon_t \]  

where at period \( t \), \( \ln(CO_2) \) is the natural log of carbon dioxide emissions, \( \ln(E) \) is the natural log of energy consumption, \( \ln(GDP) \) is the natural log of real income, \( \ln(GDP^2) \) is the square of natural log real income, \( \ln(A) \) is the natural log of the agriculture proxy, and \( \varepsilon \) is the error-disturbance.

Drawing from previous research and theories, especially considering the EKC, the following hypotheses were tested empirically in this study: i) increase in real income increases \( CO_2 \) emissions at early stages of growth (the coefficient of \( GDP \) is expected to be positive), then ii) 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 \( GDP^2 \) is expected to be negative), iii) higher energy consumption causes higher \( CO_2 \) emissions levels (the coefficient of \( E \) is expected to be positive), and finally, iv) 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 can capture the speed of adjustment between the short- and long-term levels of the dependent variable:

\[ \Delta \ln(CO_2_t) = \phi_0 + \sum_{i=1}^{n} \phi_1 \Delta \ln(CO_2_{t-i}) + \sum_{i=1}^{n} \phi_2 \Delta \ln(GDP_{t-i}) + \sum_{i=1}^{n} \phi_3 \Delta \ln(GDP^2_{t-i}) \\
+ \sum_{i=0}^{\infty} \phi_4 \Delta \ln(E_{t-i}) + \sum_{i=0}^{\infty} \phi_5 \Delta \ln(A_{t-i}) + \phi_6 \varepsilon_{t-1} + u_t \]  

where \( \Delta \) represents changes in \( CO_2 \), \( E \), \( GDP \), and \( GDP^2 \), and \( \varepsilon_{t-1} \) is the one period lagged error correction term (ECT), which is estimated from equation (2). The ECT (error correction
term) 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 DataStream and logarithmic forms of the variables are used in the analyses. To investigate the long-term relationship between the variables, the bound test for co-integration with ARDL modeling approach is adopted in this study.

4. METHODOLOGY

In the study, the bound test for co-integration with ARDL modelling approach developed by M. Hashem Pesaran, Yongcheol Shin, and Richard 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 CO2 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 Pesaran and Shin (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:

\[ \Delta Y_t = \mu_0 + \mu_t + \lambda_1 Y_{t-1} + \sum_{i=1}^{4} \theta_i V_{it-1} + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \sum_{i=1}^{4} \sum_{j=0}^{p} \omega_{ij} \Delta V_{it-j} + \psi D_t + \epsilon_t \]  

In this equation, \( V_t \) is the vector defined as \( V_t = (LGD, LGDP2, LE, LA) \), \( D_t \) is the vector including exogenous variables such as structural break dummies. Here, according to the Wald test, the null hypothesis asserts there is no co-integration \((H_0: \lambda_1 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = 0)\), 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 et al. (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.

\[ Y_t = \mu_0 + \sum_{j=1}^{p} \beta_j Y_{t-j} + \sum_{i=1}^{4} \sum_{j=0}^{p} \phi_{ij} V_{it-j} + \psi D_t + u_t \]
Here, 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 error correction model (ECM) as defined below:

\[
\Delta Y_t = \mu + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \sum_{j=1}^{q} \omega_{ij} \Delta V_{a-j} + \vartheta ECM_{t-1} + \psi 'D_t + \epsilon_t
\]  

(6)

In this equation, while \( \gamma_j \) and \( \omega_{ij} \) are short-term parameters, \( \vartheta \) 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) is defined in the following format:

\[
ECM = Y_t - \hat{\beta}_0 - \hat{\beta}_1 LGDP - \hat{\beta}_2 LGDP^2 - \hat{\beta}_3 LE - \hat{\beta}_4 LA
\]  

(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 Table 4 and Table 5. These tests include the Breusch-Godfrey serial correlation 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\(_0\): \( \epsilon \sim N(0, \sigma^2 I) \), H\(_1\): \( \epsilon \sim N(\mu, \sigma^2 I) \), \( \mu \neq 0 \)) (p values are 0.1524 and 0.1142 respectively). None of the statistics reject the null hypotheses 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 M. Hashem 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 Eq 2, the long-term relationship was also estimated for the same period with three single equation cointegration techniques, namely, fully modified least squares (FMOLS), dynamic ordinary least squares (DOLS), and canonical cointegration regression (CCR).

5. 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>
<thead>
<tr>
<th>Variables</th>
<th>Intercept</th>
<th>Intercept &amp; trend</th>
<th>Intercept</th>
<th>Intercept &amp; trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCO2</td>
<td>0.223327</td>
<td>-2.374595</td>
<td>-3.796404</td>
<td>-3.799168</td>
</tr>
<tr>
<td>LGDP</td>
<td>1.185731</td>
<td>-4.679220</td>
<td>-4.324102</td>
<td>-4.097642</td>
</tr>
<tr>
<td>LGDP(^2)</td>
<td>2.033687</td>
<td>-2.464867</td>
<td>-2.448239</td>
<td>-3.988317</td>
</tr>
</tbody>
</table>

Table 1. Unit Root Test 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 co-integration between LGDP, LGDP2, LE, LA, and LCO2 under three different scenarios suggested by Pesaran et al. (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 Akaike information criteria (AIC) results and Schwartz information criteria (SIC) results. Therefore, maximum lag length is set to 1. Then, by using F statistics suggested by Pesaran and Shin (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 CO2 emissions and the independent variables.

Table 2. Bound Test Results

<table>
<thead>
<tr>
<th>Scenario</th>
<th>k=4</th>
<th>I(0)</th>
<th>I(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Deterministic Trends</td>
<td>F_{iii}</td>
<td>3.700720</td>
<td>2.86</td>
</tr>
<tr>
<td></td>
<td>t_{iii}</td>
<td>3.700720</td>
<td>-2.86</td>
</tr>
<tr>
<td>With Deterministic Trends</td>
<td>F_{iv}</td>
<td>4.569368</td>
<td>3.05</td>
</tr>
<tr>
<td></td>
<td>F_v</td>
<td>5.258553</td>
<td>3.47</td>
</tr>
<tr>
<td></td>
<td>t_v</td>
<td>-4.636368</td>
<td>-3.41</td>
</tr>
</tbody>
</table>

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 CO2 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 GDP square 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 section. The long-term ARDL estimation results confirm that CO2 emissions have an inverted U relationship with economic growth in line with the EKC hypothesis and energy consumption leads to higher-level CO2 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 CO2 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 CO2 level and pollution in turn. However, this study does not explain the reasons for the relationship between agricultural production and CO2 emissions. It might be due to agricultural production volume and crops which lead to higher levels of CO2, higher amounts of use of high energy consuming feedstuffs, 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**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LGDP</td>
<td>0.3613</td>
<td>0.2847</td>
<td>1.2689</td>
<td>0.2128</td>
</tr>
<tr>
<td>LGDP^2</td>
<td>-0.0361</td>
<td>0.0124</td>
<td>-2.9083</td>
<td>0.0063</td>
</tr>
<tr>
<td>LE</td>
<td>1.2626</td>
<td>0.1147</td>
<td>11.0039</td>
<td>0.0000</td>
</tr>
<tr>
<td>LA</td>
<td>0.5302</td>
<td>0.2272</td>
<td>2.3327</td>
<td>0.0255</td>
</tr>
</tbody>
</table>
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 CO2 emissions in the country. As expected, the GDP square’s estimated sign 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

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>LGDP</td>
<td>0.4640</td>
<td>0.1815</td>
<td>2.5568</td>
<td>0.0152</td>
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<tr>
<td>LGDP²</td>
<td>-0.0375</td>
<td>0.0078</td>
<td>-4.7773</td>
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<tr>
<td>LE</td>
<td>1.2522</td>
<td>0.0682</td>
<td>18.3550</td>
<td>0.0000</td>
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<tr>
<td>LA</td>
<td>0.4219</td>
<td>0.1442</td>
<td>2.9257</td>
<td>0.0061</td>
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<tr>
<td>C</td>
<td>-9.4754</td>
<td>1.5301</td>
<td>-6.1925</td>
<td>0.0000</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Method: Dynamic Least Squares (DOLS)</th>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LGDP</td>
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<td>0.3094</td>
<td>1.4917</td>
<td>0.1514</td>
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<tr>
<td>LGDP²</td>
<td>-0.0464</td>
<td>0.0146</td>
<td>-3.1693</td>
<td>0.0048</td>
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<tr>
<td>LE</td>
<td>1.3439</td>
<td>0.0981</td>
<td>13.6867</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>LA</td>
<td>0.5669</td>
<td>0.2163</td>
<td>2.6202</td>
<td>0.0164</td>
<td></td>
</tr>
</tbody>
</table>
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.

6. 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 CO2 emissions. The results also indicate that China’s agricultural sector is a significant determinant of CO2 emissions.

The results prove that agricultural activities in China should be redesigned to decrease CO2 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 CO2 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 CO2 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


World Resources Institute. 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
