Does educational attainment matter for Environmental Kuznets Curve? Evidence from aggregated and disaggregated time series data of China

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Research Article

Keywords: Education. Environmental Kuznets Curve. China

Posted Date: November 23rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-1004802/v1

Abstract

The primary focus of this study is to evaluate the impact of various levels of education on CO_2 emissions in China. Moreover, the study also tested the EKC hypothesis for different levels of education and economic development. The analysis employed disaggregate and aggregate data for education that included enrollment at primary, secondary, and tertiary levels and the average year of schooling. For empirical analysis, we employed an error correction model and bounds testing approach to cointegration. The results of the study provided some useful information both in the short and long run. All the proxies of education positively impact CO_2 emissions at the initial level both in the short and long run; however, when we take the square of these variables, the effects of education on CO_2 emissions become negative. Similarly, the impact of economic growth on CO_2 emissions is positive in the short and long run, and the square of economic growth on CO_2 emissions is negative, supporting the EKC hypothesis.

Introduction

Many policymakers, governments, and economists view sustained development and the worldwide impact of China as both alarming and impressive. China raised almost half of its deprived population above the poverty line in a very short period (Shen et al. 2018). Apart from several regional disparities, economic, and social issues, this change occurs at the cost of severe environmental issues. OECD (2018) highlighted that although leading worldwide rankings in various groups, including exports and imports, FDI, China is also at front-runner position for production and consumption of energy, carbon emissions, and greenhouse gas emissions. Nonetheless, China is very much committed to making efforts for attaining the Sustainable Development Goals (SDGs). In the United Nations General Assembly conference of 2015, the member states vowed to eradicate poverty and hunger, provision of quality-based and equal education opportunities, reduction in carbon emissions, nitrogen gas, and certain other detrimental pollutants. Modifications in economic and social factors such as knowledge, innovation, income, and FDI can enhance the environmental quality during the path of economic development (Aslam et al. 2021; Jafri et al. 2021; Ullah et al. 2021).

In the view of researchers, education may contribute significantly to solving various ecological, economic, and social issues (Yin et al. 2021). As a social paradigm, education works as an influential instrument for altering lives, as it helps in improving innovation capabilities, skills, and knowledge of the economies (Bangay, 2016). Meanwhile, education helps in enhancing the quality of the environment by creating consciousness about pollutants and environmental issues and helps in circulating compulsory wisdom mandatory for the enactment of green standards of living, green production, eco-innovation, carbon decline policies for attainment of viable future, particularly for developing economies (Khatak et al. 2020).

The policymakers and researchers argue that higher education and economic growth are closely related due to several implications for technological development and knowledge. But there is an insufficiency of empirical literature on the nexus between environmental pollution and higher education, revealing that economists and environmentalists have paid diminutive consideration to this imperative issue (Uddin 2014). The available literature on this issue represents two strands of research. The first strand infers that education plays a significant positive role in reducing CO_2 emissions, and the second strand of literature demonstrates on-campus accomplishments for higher CO_2 emissions.

The followers of the first-strand claim that education increases CO_2 emissions through numerous educational activities that happen in the higher education system. For example, the study done by Caird et al. (2015) investigated the education-carbon footprint nexus for 15 higher educational institutions in UK. The findings of the study reveal that on-campus educational activities result in increasing carbon emissions, however, online educational activities result in reducing CO_2 emissions. The study highlighted some factors that are linked with on-campus educational activities, such as, consumption of energy at dormitories, consumption of fuel, construction, and certain other campus-related operation. For Japan, Parra et al. (2018) reported that teaching activities, studies, and on-campus miscellaneous work contributed significantly to raising CO_2 emissions. Versteijlen et al. (2017) study for Netherland highlighted that frequent traveling by students and staff are the main source of high carbon emissions and online educational setup tend to reduce global and regional CO_2 footprint. The literature highlighted some other determinants of carbon emissions that are directly linked with on-campus educational activities such as air transportation (staff and students sometimes travel through long-distances), food, housing activities, consumption, and mobility (Sippel et al. 2018).

The second strand of literature argues that education exerts a significant positive impact on carbon emissions through various techniques and methods for different economies. Li and Zhou (2019) examined that how demographic structure and higher education affect carbon emissions at a national and provincial levels in China. The study reported negative interaction between higher education and CO_2 emissions in case of East China. Uddin (2014) study examined the linkage between economic growth, pollution emissions, and educational expenditures for Bangladesh. The study concluded that an increase in educational expenditures augment economic growth and mitigate carbon emissions through increased consciousness. In the case of United States, literature found that education offers improved substitutes to govern human activities to subside carbon emissions (Mirsa and Verma, 2015). A bulk of literature infers that improvement in the education sector mitigates carbon emissions (for example, Sarwar et al. 2019; Subramaniam and Masron 2020). Conversely, the study done by Balaguer and Cantavella (2018) investigated the linkage between environmental quality and education in the context of environmental kuznet curve framework. The study reported harmful impacts of higher education on environmental quality in the early stages but afterward when the education level achieves a certain threshold it starts improving the quality of the environment.

China has taken several initiatives in its higher education field in terms of higher education institutes, quality of education, and student enrollment. An extraordinary increase has been observed in both number of student enrollments and number of higher education institutions from the time period 2000 to 2019. Such as, the number of students has increased from 9.398 million to 40.02 million and number of institutes has increased from 1813 to 2688 during this period. Furthermore, the expenditures on the education sector have increased up to 26 percent of the GDP in this period.

Regardless of the anticipated theoretical importance of education, the CO_2 emission and education association remains widely unexplored in the literature of environmental economics. The empirical findings from available studies provide mixed evidence on the linkage between education and CO_2 emissions. Some scholars reported a positive impact of education on CO_2 emissions and others demonstrated the negative impact of education on CO_2 emissions (for instance, Balaguer and Cantavella 2018; Sippel et al. 2018; Li and Zhou 2019). In case of China, there is only one study available that investigated the impact of higher education on CO_2 emissions for East China by using total student enrollments in thirteen higher education institutes as a proxy for measuring higher education and reported a negative impact of higher education on CO_2 emissions. The primary objective of the study is to fill the knowledge gap in pollution research and environmental economics by examining the potential impact of higher education in determining environmental quality in China.

Model And Method

The theoretical base of the model is derived from the EKC model. The EKC model was first presented by Grossman and Kreuger (1995), which confirmed the inverted U-shaped relationship between GDP and CO2 emissions. According to the EKC hypothesis, at the initial level of economic development, CO2 emissions rises, and at the later stage of the economic development, CO2 emissions decline. Balaguer and Cantavella (2018) augmented the EKC model for Australia with the variables of education. Following them, we also have augmented the EKC model of China with different variables of education. Hence, the baseline looks as follows:

$$CO2_t = \beta_0 + \beta_1 X_t + \beta_2 LnY^2{}_t + \beta_3 LnZ_t + \varepsilon_t \quad \text{--------} \ (1)$$

Where the dependent variable is CO2 emissions, a proxy of environmental degradation. X is a set of main variables that include primary education (PE), secondary education (SE), tertiary education (TE), the average total years of schooling (AE), and economic growth (GDP). Then, Y^2 is a set of variables where we have taken the square of each of the main variables such as square of primary education (PE^2), square of secondary education (SE^2), square of tertiary education (TE^2), square of average total years of schooling (AE^2), and economic growth (GDP^2). Lastly, Z_t is a set of control variables that include energy consumption (EC), individuals using the internet (Internet), and government expenditure (GE). The above model (1) is a long-run model and only provides the long run estimates. To obtain the short-run results, we need to reformulate the above model in an error correction specification as shown below:

$$\Delta CO2_t = \beta_0 + \sum_{k=1}^{n1} \beta_{1k} \Delta CO2_{t-k} + \sum_{k=0}^{n2} \beta_{2k} \Delta X_{t-k} + \sum_{k=0}^{n3} \beta_{3k} Y^2{}_{t-k} + \sum_{k=0}^{n4} \beta_{4k} Z_{t-k} + \gamma_1 CO2_{t-1} + \gamma_2 X_{t-1} + \gamma_3 X^2{}_{t-1} + \gamma_4 Z_{t-1} + \varepsilon_t \qquad (2)$$

Specification (2) has now taken the form of ARDL model of Pesaran et al. (2001). This method is considered superior as compared to most of the other techniques. First of all, it provides short and long-run estimates only by estimating a single equation (2). Certainly, short-run results are revealed in the coefficient estimates linked to the Δ variables. The long-run results are represented from approximations of γ_2 - γ_4 normalized on γ_1. In order to prove the validity of the long-run estimates, Pesaran et al. (2001) suggest a co-integration test that confirms the combined significance of lagged level variables (Bahmani-Oskooee et al. 2020). The process is similar to the procedure of the F-test; however, Pesaran et al. (2001) developed new critical values for this test. Another advantage of this method is that we don't need to worry about the pre-unit root testing because this method can account for the integrating properties of the variables, i.e., we can include a mixture of I(0) and I(1) variables. Moreover, the technique provides efficient results even if the sample size is small. Lastly, the inclusion of a short-run dynamic process provides feedback effects among the variables, consequently control the endogeneity and multicollinearity (Pesaran et al. 2001).

Data

The study aims to investigate the role of educational activities in determining the environmental Kuznets Curve (EKC) in case of China for time horizon 1991 to 2019. The dependent variable EKC is measured by carbon dioxide emissions in kilotons. The study utilizes four proxies to measure the role of educational activities in China such as primary education, secondary education, tertiary education, and average education. These education levels are measured as school enrollments at gross percentage of primary, secondary, and tertiary levels, however, average education is measured as average total years of schooling. Some other variables namely GDP per capita measured at constant 2010US$, energy consumption in kg of oil equivalent per capita, use of internet in the percentage of the population, and general government final consumption expenditures in the percentage of GDP are taken as control variables. Table 1 gives us information about variables and definitions. Data for all variables have been sourced from the World Bank and the human development index.

Table 1
Variables and definitions

Variables	Symbol	Definitions
CO2 emissions	CO2	CO2 emissions (kt)
Primary education	PE	School enrollment, primary (% gross)
Secondary education	SE	School enrollment, secondary (% gross)
Tertiary education	TE	School enrollment, tertiary (% gross)
Average years of schooling	AE	Average total years of schooling
GDP per capita	GDP	GDP per capita (constant 2010 US$)
Energy consumption	EC	Energy use (kg of oil equivalent per capita)
Internet users	Internet	Individuals using the Internet (% of population)
Government expenditure	GE	General government final consumption expenditure (% of GDP)

Results And Discussion

Our aim in this study is to investigate the role of school enrollment at various levels in the formation of the EKC in China. To get estimates of the variables, we employ the ARDL model. ARDL has various advantages over other techniques, but the foremost advantage of this technique is that it performs well even if the variables are a mixture of I(0) and I(1). However, we can’t include the variables of I(2) in the analysis. Therefore, to confirm that none of the included variables is I(2), we employ two unit root tests, one without a structural break and another with a structural break. Table 2 provides the findings of both the unit root tests. From the results, we can deduce that most of the variables are I(1) and some are I(0) by using either of the tests; however, none of the variables in the analysis is I(2). These findings give us a positive signal that we can apply the ARDL model. Another important thing that needs to be decided before starting our formal discussion is selecting the appropriate lag. Our data is annual, and we apply a maximum of two lags and to choose the correct number of lags, we use Akaike Information Criterion (AIC).

Table 2
Unit root testing

	Unit root without break test			Unit root with break test				
	I(0)	**I(1)**	**Decision**	**I(0)**	**Break date**	**I(1)**	**Break date**	**Decision**
CO2	-0.898	-4.689***	I(1)	-5.025***	2002			I(0)
PE	-2.654*		I(0)	-4.452**	2001			I(0)
SE	-0.325	-4.965***	I(1)	-4.332	2006			I(0)
TE	-0.356	-2.887*	I(1)	-0.897	2012	-6.231	2014	I(1)
AE	-1.789	-7.654	I(1)	-3.323	2018	-6.689	2002	I(1)
GDP	-0.875	-2.635*	I(1)	-3.201	2002	-4.356*	2007	I(1)
EC	-0.456	-3.678*	I(1)	-4.821**	2002			I(0)
Internet	-0.623	-2.658*	I(1)	5.398***	2006			I(0)
GE	-2.671*		I(0)	-5.164	2015			I(0)
Note: ***p<0.01; **p<0.05; and *p<0.10								

We have used four different proxies for education for empirical analysis: enrollment at primary, secondary, and tertiary levels. Moreover, we also include the average total years of schooling to get the accumulative impact of education on the CO2 emissions. First, we discuss the short-run estimates, and after that, we discuss the ones in the long run.

Table 3 illustrates the short-run and long-run results of the ARDL model. In short run, the estimated coefficient of D(PE) is positively significant, and the estimate of D(PE^2) is negatively significant. Similarly, the estimate attached to D(SE) is positive, and the estimate attached to D(SE^2) is negative and significant. Then the estimate attached to D(TE) is positively significant, whereas the estimate attached to D(TE^2) is negatively significant. Lastly, the estimates attached D(AE) is positive at first lag, and the estimate attached to D(AE^2) is negatively significant at first lag. These findings confer that increased enrollment at all levels does increase the CO2 emissions; however, at the later stage, increased enrollment at all levels decreases the CO2 emissions. The estimated coefficients of D(GDP) are positively significant in all models, and the estimates attached to D(GDP^2) are negatively significant, confirming the presence of EKC in the short run. Given the importance of long-run results, we now pay attention to the long-run estimates provided in Table 3. The validity of the long-run results depends on the confirmation of cointegration between them. To that end, we rely on two tests of cointegration, i.e., F-test and ECM_{t-1} and the results of both the tests are provided in Table 3, which confirm that cointegration exists among the CO2, SE, PE, TE, AE, GDP, EC, Internet, and GE.

The long-run estimates attached to PE, SE, TE, and AE are positively significant, or more precisely, we can say that a 1% rise in primary, secondary, tertiary, and aggregate enrollment increases the CO2 emissions by 1.570%, 1.218%, 0.008%, and 0.580%. Conversely, the estimates attached to PE^2, SE^2, TE^2, and AE^2 are negatively significant or in terms of elasticity, we can say that a 1% rise in PE^2, SE^2, TE^2, and AE^2 causes the CO2 emissions to decline by 2.058%, 0.171%, 0.023%, and 0.580%. Generally, our findings imply that an increase in educational activities at all levels increases the CO2 emissions at the early stages; however, later on education help reduces the CO2 emissions.

In other words, the relationship between CO2 emissions and all levels of education follows an inverted U-shaped path, implying that CO2 emissions increase in the early parts of increased educational activities and decline at the later stages. As the demand for education in the country increases, on one side, more educational infrastructure such as schools, colleges, universities, and hostels are required; on the other side, demand for transportation facilities, laundry, dry cleaning, and saloon services will also increase (Becken et al. 2001, 2003; Gossling, 2002). As a result, the energy demand rises, which is a primary driver of CO2 emissions. However, the positive effects of education on the environment may come later once the education sector starts producing more trained, skilled, capable and efficient human resources that can replace the more energy-intensive inputs in the production process and ultimately reduce CO2 emissions.

Social and economic activities performed by humans cause emissions, and education is an important source that can positively alter human behavior (Jian et al. 2021). Moreover, education help raise the technical skills and capabilities that will improve human efficiency in all walks of life and contribute to economic development (Usman et al. 2021). Experts of economics strongly agree that human capital is essential for the economic growth of a country in the long run. They also agree that human capital is a by-product of formal education, trained and experienced labor, research and development, which are fundamental parts of the inputs used in the production function (Barro, 1991). Most developing economies have replaced their labor-intensive production techniques with human-capital intensive ones and achieved the economic goals with a more clean environment. However, the evidence suggests that education may pollute the environment in developing and emerging economies due to energy-intensive infrastructure and low economic development (Mahalik, 2021). The energy consumed by educational activities at various levels may differ at different stages of economic development (Inglesi-Lotz and Morales, 2017), which may form an inverted U-shaped relationship between education and CO2 emissions.

As far as the long-run relationship between economic development and environmental quality is concerned, we can see that the estimates attached to GDP are positive but insignificant in most models. However, the estimates attached to GDP^2 are negatively significant in all models confirming the presence of an inverted U-shaped relationship between economic development and CO2 emissions in China. Such an inverted U-shape relationship is known as the EKC of Grossman and Kreuger (1995), which implies that the early part of economic growth pollutes the environment and later improves it. This result also implies that China is heading towards sustainable development, i.e., achieving economic growth without polluting the environment further.

The estimate of the control variable of EC suggests that increased energy consumption causes the CO2 emissions to rise; however, the estimates of Internet and GE are significant and negative, implying that increased internet subscriptions and government expenditures cause the CO2 emissions to decline in China.

Finally, to confirm the efficiency of our estimates, some diagnostic tests are also outlined in Table 3. Firstly, Langrage Multiplier (LM) test confirms that our residuals are free from first-order serial correlation. Secondly, the Ramsey RESET test confirms that no misspecification is found in our model. Thirdly, Breusch Pagan (BP) test approves that the variance of the error terms is homoscedastic. Finally, the CUSUM and CUSUMSQ confirm the parametric stability of the models where ‘U’ represents the stable parameters and ‘US’ represents the unstable parameters.

Table 3
ARDL estimates of CO2 emissions

	Primary education		Secondary education		Tertiary education		Average education	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
Short-run								
D(PE)	2.618***	2.763						
D(PE(-1))	-1.561	1.482						
D(PE^2)	-3.229***	2.782						
D(PE^2(-1))	2.021	1.432						
D(SE)			3.371	0.435				
D(SE(-1))			9.660*	1.832				
D(SE^2)			-0.515	0.540				
D(SE^2(-1))			-1.210*	1.835				
D(TE)					0.010*	1.772		
D(TE(-1))					0.003	1.043		
D(TE^2)					-0.039*	1.885		
D(AE)							0.429	0.783
D(AE(-1))							2.449***	3.070
D(AE^2)							0.032	0.853
D(AE^2(-1))							-0.177***	3.019
D(GDP)	1.153**	2.133	1.894***	3.406	1.045**	1.989	1.825***	3.032
D(GDP(-1))	0.479	0.822			0.567	1.172	0.866	1.578
D(GDP^2)	1.376*	1.760	2.169**	2.879***	2.310	3.512***	1.289**	1.981
D(EC)	0.859***	2.783	1.255***	5.846	1.105***	5.135	1.527***	5.892
D(EC(-1))	0.447	1.444					-0.429	1.275
D(Internet)	-0.002	0.510	-0.003*	1.828	-0.005*	1.843	-0.011**	2.150
D(Internet(-1))	0.008***	2.756			-0.009**	2.414	-0.019*	1.752
D(GE)	0.008	0.466	-0.013	1.070	-0.004	0.426	0.233	0.123
D(GE(-1))	0.036*	1.699						
Long-run								
Note: ***p<0.01; **p<0.05; and *p<0.10								

	Primary education		Secondary education		Tertiary education		Average education	
PE	1.570**	2.182						
PE^2	-2.058**	2.164						
SE			1.218*	1.755				
SE^2			-0.171**	1.986				
TE					-0.008***	2.983		
TE^2					0.023*	1.921		
AE							0.580***	3.436
AE^2							-0.039***	3.266
GDP	0.270	0.196	0.353	0.318	0.002	0.022	0.386**	2.330
GDP^2	-0.879**	2.065	-0.456*	1.867	-0.231*	1.661	-0.776**	2.101
EC	1.194***	5.733	1.431***	3.599	1.174***	9.466	1.568***	4.218
Internet	0.001	0.118	-0.002*	1.835	-0.001*	1.880	-0.002*	1.952
GE	-0.002	0.123	-0.019***	2.823	-0.017***	3.181	-0.012*	1.840
C	-5.114	2.071	3.334***	2.301	7.299	2.245	5.401***	7.866
Diagnostics								
F-test	13.12		12.10		13.12		9.789	
ECM(-1)	-0.471***	6.729	-0.592***	9.563	-0.652***	9.521	-0.578***	7.307
LM	1.298		1.023		0.398		1.785	
BP	0.325		0.875		0.795		1.035	
RESET	0.689		1.487		0.980		2.033	
CUSUM	S		S		S		S	
CUSUM-sq	S		S		S		S	
Note: ***p<0.01; **p<0.05; and *p<0.10								

Conclusion And Implications

Human capital is a by-product of education, and it serves as an input in the production function. Many advanced economies have moved from labor-intensive production methods to human-capital intensive, which has transformed their economies and helped them achieve sustainable development. Following the footprint of many developed economies, emerging markets and developing economies started to develop human capital through education, technical training, and skill development programs. As a result, even the production techniques in the emerging economies are now becoming more environmentally friendly and emitting fewer carbons. Education provides the base for human capital development; however, investment in education infrastructure may hurt the environmental quality at the earlier stages and improve at the later stages. Empirics also have linked the positive impact of education on the environmental quality with the level of economic development, i.e., the positive effects of education on the environment are visible at a higher level of economic development.

China is an emerging economy growing fast, and the role of human capital is on a high in China's economic development. However, the role of different levels of education in the formation of EKC in China is underexplored. Therefore, the primary focus of this study is to evaluate the impact of various levels of education on the CO2 emissions in China. Moreover, the study also tested the EKC hypothesis for different levels of education and economic development. The analysis employed disaggregate and aggregate data for education that included enrollment at primary, secondary, and tertiary levels and the average year of schooling. For empirical analysis, we employed an error correction model and bounds testing approach to cointegration. The results of the study provided some useful information both in the short and long run. All the proxies of education positively impact CO2 emissions at the initial level both in the short and long run; however, when we take the square of these variables, the effects of education on CO2 emissions become negative. Similarly, the impact of economic growth on CO2 emissions is positive in the short and long run, and the square of economic growth on CO2 emissions is negative, supporting the EKC hypothesis. These findings imply that both education and economic growth follow an inverted U-shaped path while affecting the CO2 emissions, i.e., both education and economic growth degrades the environmental quality at the initial stages and improves at the later stages.

Based on the findings, we also provide some practical policy implications. Both education and development are interconnected, and both can affect the environmental quality via increased energy demand. Economic growth requires energy, which deteriorates the environmental quality at the initial stage due to energy-intensive infrastructure in the developing economies. Energy conservation policy may reduce CO2 emissions, but it can also deter China's economic growth because China heavily relies on non-renewable energy consumption for its economic development. This problem can be addressed by depending more on renewable energy projects and increasing the amount of renewable energy in the total energy mix. On the other side, an increase in educational infrastructure also pushes the energy demand upward, which may deteriorate the environmental quality at the initial stages. Energy is an essential demand of educational institutions; therefore, a prudent energy policy is required to improve energy performance and efficiency in educational institutions. In this regard, an energy policy should mainly focus on evaluating energy performance and conservation, attaining decreases in fossil fuel expenses, investing more in renewable energy projects, and installing clean and green energy sources for educational institutions and projects.

Declarations

Ethical Approval: Not applicable

Consent to Participate: I am free to contact any of the people involved in the research to seek further clarification and information

Consent to Publish: Not applicable

Author's Contributions: This idea was given by Yuanpei Cui. Yuanpei Cui, Zikun Wei, and Qinglin Xue, analyzed the data and wrote the complete paper. While Sidra Sohail read and approved the final version.

Funding: Not applicable

Competing Interests: The authors declare that they have no conflict of interest.

Availability of data and materials: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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