The Impacts of Non-Renewable Energy Consumption and Education Expenditure on CO2 Emission Intensity of Real GDP in China

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Abstract

Background

With the economic development, China has become the world's largest CO2 emitter. Given that climate warming has increasingly become the focus of the international community, Chinese government committed to reducing its CO2 emission intensity substantially. Prior studies find that the evolution of economic structure and technological progress can reduce CO2 emissions, but lack of considering CO2 emissions and output as a whole. In addition, the role of education expenditure is relatively overlooked. This paper contributes to the literature by examining the link of CO2 emission intensity, non-renewable energy consumption and education expenditure in China during 1971-2014.

Results

We use the ARDL approach and find that in the long run, every 1% increase in non-renewable energy consumption results in a 0.92% increase in CO2 intensity, while every 1% increase in operational education expenditure reduces the CO2 intensity by 0.86%. In the short term, 36% of the deviation from the long run equilibrium is corrected in the next period.

Conclusions

We draw out two important conclusions and make important policy recommendations. First and foremost, as long as the increase in operational educational expenditure exceeds the increase in non-renewable energy consumption, CO2 intensity of real GDP will decrease in the long run. This means that in the development stage when economic activities are still highly dependent on non-renewable energy sources, the Chinese government should continue to vigorously increase expenditures on public education. Second, the increase in non-renewable energy consumption will result in an increase in CO2 intensity of real GDP. Therefore, gradually increasing the proportion of clean energy consumption in the energy nexus is another powerful starting point for China to achieve its goal of reducing CO2 intensity of real GDP.

JEL Classification

C32. I2. Q4. Q53. Q56.

1. Introduction

It has reached a common consensus that carbon dioxide emissions (CO2) are the main cause of global warming. Burning fossil fuels (no-renewable energy) and producing cement are the two primary sources of CO2 emissions. The United Nations General Assembly adopted the "United Nations Framework Convention on Climate Change" (UNFCCC) on May 9, 1992. The goal of the convention is to maintain the concentration of greenhouse gases in the earth's atmosphere at a level that "human activities do not interfere with systemic hazards in the climate". According to its principle of "common but differentiated

responsibilities", different obligations and fulfilling procedures are stipulated for developed and developing countries, as well as for the least developed countries.

Economic growth and CO2 emissions are the two inseparable sides of the coin of human economic activities. Thus, limiting CO2 emissions will inevitably have a negative impact on economic growth in the historical stage where human economic activities still rely mainly on burning fossil fuels to generate energy. This has led to fierce controversies between the developing countries such as China and the developed countries such as the United States, based on their respective economic and political considerations. A central question is what indicators should be used to measure the reduction of CO2 emissions. Gross CO2 emissions, total historical CO2 emissions, CO2 emissions per capita and historical CO2 emissions per capita are the common indicators proposed by each party respectively. With the economic success, China has become the world's largest CO2 emitter regardless of how emission is measured, imposing China under enormous international pressure in the climate change negotiations. However, according to the World Bank's classification of countries by income level, China is a country of middle-high income since 2019 On the one hand, China needs to keep prioritizing economic growth to increase national income. On the other hand, it also needs to pay more attention to the quality of living, which might be deteriorated by CO2 emissions. Therefore, Chinese government attaches great importance to promoting the work of CO2 emissions reduction.

CO2 intensity of real GDP is arguably a better index than other indicators since it can take production and CO2 emission as a whole to reflect the nature of human economic activities. In fact, Chinese government has promised to cut it by 60-65% of 2005 level by 2030 (Yang, Xia, Zhang & Yuan, 2018). Many economic variables have effects on the formation of real GDP, such as physical capital, education expenditure, energy consumption, population, foreign trade, industrial structure and the level of urbanization. Among these variables, energy consumption, foreign trade, industrial structure and the level of urbanization have effects on CO2 emissions as well, and were studied by researchers repeatedly. However, the impact of education expenditure or closely related human capital on CO2 emissions has not attracted enough attention from the academic community. Education expenditure might at least take the upgrading of industrial structure as a carrier among other mechanisms to impact on CO2 emissions. To fill this literature gap, we employ the ARDL approach to study the possible long-run and short-run relationship among CO2 intensity of real GDP, non-renewable energy consumption and education expenditure.

2. Literature Review

A seminal study on the relationship between economic growth and environmental pollution is Forster (1972), which pioneer the introduction of pollution stock in the production function of the neoclassical economic growth model, and proposes that the cause of pollution is the use of capital. Grossman & Krueger (1991) find that there is an inverted U-shaped relationship between the three air quality indicators of sulfur dioxide, dust and suspended particles and income, using data from 42 countries. Arrow, Bolin, Costanza, Dasgupta, Folke & Holling, et al. (1995) further believes that there is an inverted U-shaped relationship between environmental pollution and economic growth. Since the famous Kuznets curve

also exhibits an inverted U-shape in economic theory, the inverted U-shaped relationship between environmental pollution and economic growth is called the environmental Kuznets curve (EKC), which argues that with the economic development of a country, the level of environmental pollution increases first, and then begins to decline after the economy reaches a certain critical level.

The empirical research based on EKC is very rich, most of which focus on testing whether it exists or whether it shows an inverted U-shaped relationship. Selden & Song (1994) use cross-country panel data to study the relationship between four important air pollutants and GDP per capita, and the results show that the inverted U-curve relationship holds between them. Fodha & Zaghdoub (2010) use sulfur dioxide as an indicator of environmental pollution and find that the turning point of EKC in Tunisia occurs when the per capita income reaches 1,200 US dollars (constant prices in 2000).

With the intensification of global warming, the emission of greenhouse gases, especially CO2, has become the focus of environmental pollution. Therefore, studies on EKC are increasingly using CO2 emissions as a proxy for environmental pollution. The increase in non-renewable energy consumption directly causes the increase in CO2 emissions (Huang, Hwang & Yang, 2008; Lapinskienė, Peleckis & Nedelko, 2017; Lapinskienė, Peleckis & Slavinskaitė, 2017; Belke, Dobnik & Dreger, 2011; Wu, Xu, Ren, Hao & Yan, 2020). The explanation of this fact from a chemical view is straightforward: the carbon component of non-renewable energy is converted into carbon dioxide during the combustion process. In this context, other scholars have found that the industry structure and technological level can reduce the CO2 emissions from non-renewable energy consumption (Al-mulali, Lee, Mohammed & Sheau-Ting, 2013; Han & Chatterjee, 1997; Lantz & Feng, 2006; Hogan & Jorgenson, 1991; Sohn, 2007; Deng, Alvarado, Toledo & Caraguay, 2020). The former findings of industry structure and CO2 emissions are also confirmed in studies using China as a context (Zhou, Zhang & Li, 2013; Zhang, Liu, Zhang & Tan, 2014; Wang, Wu, Sun, Shi, Sun &Zhang, 2019; Guan, Meng, Reiner, Zhang, Shan & Mi et al., 2018), as well as technological level and CO2 emissions (Ang, 2009; Wang, Zeng & Liu, 2019; Yunfeng & Laike, 2010). Some scholars suggest that education plays a key role in the evolution of industry structure and technological progress (Keep, 2012; He, Zheng, Cheng, Lau & Cheng, 2019; Hansmann, 2012; Atkinson & Mayo, 2010; Adams & Demaiter, 2018). Following this reasoning, education should also play an important role in reducing CO2 emissions.

However, there are very scarce studies that integrate education and CO2 emissions into a unified framework. Li & Ouyang (2019) is the research that most directly related to our paper, which studies the dynamic impacts of financial development, human capital, and economic growth on CO2 emission intensity in China for the period of 1978–2015 using the ARDL approach. Yet, Li & Ouyang (2019) does not take into consideration non-renewable energy consumption as a key factor in affecting both CO2 emissions and real GDP. Our study adds to the understanding of the literature by including non-renewable energy consumption in the framework.

3. Methodology And Data

3.1. Methodology

In this article, the approach of autoregressive distributed model (ARDL) is used to capture the long-run and short-run relationship among our concerning variables since it has the following advantages (Pesaran & Shin, 1998; Pesaran, Shin & Smith, 2001): First, this approach can be used to test if there exists a level or co-integrating relationship among the variables irrespective of whether the regressors are purely I(0), purely I(1) or mutually cointegrated. Second, the coefficient can be easily estimated by the ordinary least square method (OLS). Third, it can estimate the long-run and short-run relationship simultaneously thought a simple linear transformation of the coefficient estimated from the OLS method. Last but not least, consistent and unbiased estimations of the underlying regressors for a small sample can be obtained, which is particularly suitable for our research (44 observations).

Similar to the research that has considered the impact of financial development and human capital on CO2 intensity in China (Li & Ouyang, 2019), the ARDL models of this paper are as follow:

$$LnCO2\_PG_t = a_0 + \sum_{i=1}^{p} \alpha_i LnCO2\_PG_{t-i} + \sum_{j=1}^{q_1} \beta_j LnEN\_PC_{t-j} + \varepsilon_t \qquad (1)$$

$$LnCO2\_PG_t = a_0 + \sum_{i=1}^{p} \alpha_i LnCO2\_PG_{t-i} + \sum_{j=1}^{q_1} \beta_j LnEN\_PC_{t-j} + \sum_{k=1}^{q_2} \beta_k LnEDU\_PC_{t-1} + \varepsilon_t \qquad (2)$$

Where notation Ln stands for the logarithm of relevant variables; a_0 is the intercept term; CO2_PG (CO2 PER GDP) represents CO2 emission intensity of real GDP, p stands for the maximum lags of it, and α_i is the coefficient for its each lagged term; EN_PC (ENERGY PER CAPITA) represents non-renewable energy consumption per capita, q_1 stands for the maximum lag of it, and β_j is the coefficient for its each lagged term; EDU_PC (EDUCATION EXPENDITURE PER CAPITA) represents education expenditure per capita, q_2 stands for the maximum lag of it, and β_k is the coefficient for its each lagged term; ε_t is an error term of covariance stationary and is not serial correlated.

To begin with, we test the long-run relationship between CO2 emission intensity of real GDP and non-renewable energy consumption per capita. Afterwards the LnEDU_PC term is included in equation (2) to test if there is a long-run relationship among the three variables.

Pesaran et al. (2001) have proposed an F-bounds test to check the possible long-run relationship in levels for an ARDL model. The null hypothesis is that there is no level relationship between a dependent variable and the regressors, under this null hypothesis, the asymptotic distributions of the statistics are non-standard. They provided two sets of asymptotic critical values, one is for the situation that all regressors are purely I(0) named lower bound, and the other is for the situation of purely I(1) named upper bound. The test results are classified into three cases: First, if the F-statistic exceeds the upper bound, then the

null hypothesis can be rejected, which means there is a level relationship. Second, if the F-statistic is smaller than the lower bound, the null hypothesis cannot be rejected. Third, if the F-statistic is between the upper and lower bounds, the conclusion will be indefinite.

3.2. Data

The data used in this research are extracted from the World Development Indicators (WDI) provided by World Bank (2020). CO_2 emissions intensity of real GDP (CO_2_PG) measured by kilograms per US dollar, is original in WDI.[1] Non-renewable energy consumption per capita (EN_PC) measured by kg of oil equivalent per capita, is also original in WDI.[2] Education expenditure per capital (EDU_PC) measured by US dollars per capita, is not original in WDI. Since only the total educational expenditure is provided and measured by current US dollar,[3] therefore, we first convert it to be measure by constant 2010 US dollar using a GDP deflator generated through dividing the GDP (current US dollar) by GDP (constant 2010 US dollar), and then divide it by the corresponding population.

According to the metadata provided by WDI, it is important to emphasize the data caliber of the variables used in this research as follow:

CO_2 emissions refers specifically to anthropogenic CO_2 emissions. They result primarily from fossil fuel combustion and cement manufacturing. In combustion, different fossil fuels release different amounts of CO_2 for the same level of non-renewable energy use: oil releases about 50 percent more CO_2 than natural gas, and coal releases about twice as much. Cement manufacturing releases about half a metric ton of CO_2 for each metric ton of cement produced. Data of CO_2 emissions in WDI includes gases from the burning of fossil fuels and cement manufacture, but excludes emissions from land use such as deforestation. They are often calculated and reported as elemental carbon, and were converted to actual CO_2 mass through multiplying them by 3.667 (the ratio of the mass of carbon to that of CO_2).

Non-renewable energy consumption refers to the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport.

Education expenditure refers to the current operating expenditures in education, including wages and salaries but excluding capital investments in buildings and equipment.

4. Results And Discussion

4.1. Unit root tests

To apply the ARDL approach, it has to ensure that the integrating orders of all the variables included in the model are less than two. Therefore, the ADF (Dickey & Fuller, 1981), PP (Phillips & Perron, 1988) and KPSS (Kwiatkowski, Phillips, Schmidt & Shin, 1992) unit root tests are employed to examine the stationarity of the variables.

Table 1 ADF unit test

variables	none	Intercept	intercept and trend
LnCO2_PG	-1.72*	0.09	-2.88
LnEN_PC	2.60	0.69	-1.32
LnEDU_PC	2.43	1.93	-2.57
D.LnCO2_PG	-2.17**	-3.28**	-3.31*
D.LnEN_PC	-2.53**	-3.70***	-3.89**
D.LnEDU_PC	-0.98	-3.59**	-4.17**

Note: The hypothesis of ADF unit test is that the serial has an unite root.

*, **, and *** means that the hypothesis can be rejected at 10%, 5% and 1% level respectively.

Prefix D. means the first difference of a corresponding variable

Before the ADF unit root testing, the maximum lags of the serials have to be selected. We determine the maximum lag orders of the sequences according to the principle of minimizing AIC information criteria. In addition, whether the intercept or trend term are included in the testing equation will also affect the test results. Table 1 summarizes the results of ADF unit root tests of variables LnCO2_PG, LnEN_PC and LnEDU_PC in their levels and 1st differences.

LnCO2_PG is stationary at the significance level of 10% if the intercept term and the trend term are both excluded from the testing equation but non-stationary in the other two cases, which implies that the stationarity of LnCO2_PG might depend on whether its data generating process includes a deterministic term. However, it is stationary in its 1st difference under all the situations, which makes it meet the prerequisites of ARDL approach. LnEN_PC is a differential stationary process under all the situations. LnEDU_PC is non-stationary in its level, but stationary in its 1st difference except for the situation that both the intercept and trend term are excluded from the testing equation.

Because the power of the ADF unit root test is relatively weak, these results require us to further test the stationarity of the first-order difference form of the variable LnEDU_PC. In addition, if all the variables of interest are differential stationary processes, the conventional approach of Johansen (1991) can be employed to verify the co-integrating relationship among them, which makes the ARDL approach not the unique option. Therefore, the KPSS unit root test is used to check the stationarity of LnCO2_PG in its level form.

Table 2 PP unit root test

variables	none	intercept	intercept and trend
LnEDU_PC	8.60	0.93	-2.75
D.LnEDU_PC	0.00***	-7.09***	-7.21***

Note: The hypothesis of PP unit test is that the serial has an unite root.

*** means that the hypothesis can be rejected at 1% level.

Prefix D. means the first difference of a corresponding variable

Table 2 reports the results of PP unit test for LnEDU_PC, which implies that LnEDU_PC is a differential stationary process under all the situations.

Table 3 KPSS unit test

variables	intercept	intercept and trend
LnCO2_PG	0.81**	0.10
D.LnCO2_PG	0.14	0.12

Note: The hypothesis of KPSS unit test is that the serial is stationary.

*, **, and *** means that the hypothesis can be rejected at 10%, 5% and 1% level respectively.

Prefix D. means the first difference of a corresponding variable

Tables 3 shows the KPSS unit test results of variable LnCO2_PG, which confirms that it is not clear whether the variable is stationary in its level form but consistently stationary in its first-order difference form. This suggests the necessity of applying ARDL approach to examine the co-integrating relationship among the variables.

4.2. F-bounds test and long-run relationship

Intuitively, there might be a co-integrating relationship between the variables of LnCO2_PG and LnEN_PC. Therefore, the ARDL approach is applied to equation (1) to verify if there exists a long-run relationship between them at first. The optimal lag structure is selected using the AIC criterion, which results in an ARDL(3,2) model.

Table 4 F-bounds test results of an ARDL(3,2) model

		Asymptotic Sample Size (n=1000)			Actual Sample Size (n=41)		
Test Statistic	Value	Signifi.	I(0)	I(1)	Signifi.	I(0)	I(1)
F-Statistic	2.18	10%	4.04	4.78	10%	4.24	5.00
		5%	4.94	5.73	5%	5.26	6.16
		1%	6.84	7.84	1%	7.63	8.83

Table 4 reports the results of F-bounds test applying to equation (1). The F-statistic is below the critical value of I(0) even at the significance level of 10%, regardless of asymptotic sample size or the actual sample size, which means that there is no co-integrating relationship between the two variables, and implies that attempting to decrease the CO2 intensity of real GDP simply by reducing the consumption of non-renewable energy is futile. Although reducing non-renewable energy consumption can reduce CO2 emissions, it will also reduce economic output. Therefore, the impact of just reducing non-renewable energy consumption on CO2 intensity depends on the relative degree of the above two reductions. However, the effect of non-renewable energy consumption on the two also depends on many other factors, such as industrial structure, technological level, etc., and education has played a key role in the changes of these other factors. Under the condition that the average education level of society remains unchanged, these factors will not change much. Then, the CO2 emissions and output changes caused by the changes in non-renewable energy consumption will be relatively fixed, so that there is no co-integration relationship only between CO2 intensity of real GDP and non-renewable energy consumption

Therefore, we proceed to examine whether there is a long-run relationship among the three variables of LnCO2_PG, LnEN_PC and LnEDU_PC. The AIC criterion is used to determine the optimal lag structure again, and selects an ARDL(3,2,2) model.

Table 5 F-bounds test results of an ARDL(3,2,2) model

		Asymptotic Sample Size (n=1000)			Actual Sample Size (n=41)		
Test Statistic	Value	Signifi.	I(0)	I(1)	Signifi.	I(0)	I(1)
F-Statistic	16.56	10%	3.17	4.14	10%	3.73	4.38
		5%	3.79	4.85	5%	4.13	5.26
		1%	5.15	6.36	1%	5.89	7.34

Table 5 shows the results of F-bounds test applying to equation (2). The value of F-statistic is 16.56, which exceeds the critical value of I(1) at the 1% level under both the asymptotic and actual sample sizes.

This implies that there exists a co-integrating relationship among them in the long term, which confirms our explanation for the results of the former ARDL(3,2) model.

Table 6 Levels Equation derived from an ARDL(3,2,2) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LnEN_PC	0.92	0.09	10.54	0.00
LnEDU_PC	-0.86	0.04	-19.33	0.00
EC = LnCO2_PG – (0.92LnEN_PC – 0.86LnEDU_PC)				

Table 6 presents the result of the co-integrating equation with three variables. The coefficients of LnEN_PC and LnEDU_PC are 0.92 and -0.86 respectively, which means that in the long run when the operational education expenditure remains hold, every 1% increase of non-renewable energy consumption per capita will lead to a 0.92% increase in CO2 intensity of real GDP, while operational education expenditure has a negative impact of 0.86% on CO2 intensity of real GDP. Generally, the coefficients are both statistically and economically significant, and have the expected signs.

Furthermore, the relative larger coefficient of LnEN_PC means that reducing CO2 intensity of real GDP in the long run needs the percentage increase in operational education expenditure per capita exceed it in non-renewable energy consumption per capita. This is consistent with the data used in this paper, that is, during the sample period, the former increased by 4.81 times, while the latter increased by 32.87 times. It might be an important reason for the decrease in CO2 intensity of real GDP in China over time.

4.3. T-bounds test and short-run relationship

After the long-run co-integrating relationship is examined by F-bounds test, Pesaran et al. (2001) proposed a t- bounds test, and suggest to apply it to further confirm the level relationship among the variables.

Table 7 Error correction regression of an ARDL(3,2,2) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-1.07	0.14	-7.45	0.00
D(LNCO2_PG(-1))	0.31	0.12	2.70	0.01
D(LNCO2_PG(-2))	-0.26	0.09	-2.86	0.01
D(LNEN_PC)	0.46	0.10	4.84	0.00
D(LNEN_PC(-1))	0.28	0.11	2.49	0.02
D(LNEDU_PC)	-0.17	0.05	-3.53	0.00
D(LNEDU_PC(-1))	0.11	0.05	2.06	0.05
CointEq(-1)*	-0.36	0.05	-7.27	0.00

Note: * means that the p-value is incompatible with the standard t-distribution.

Prefix D. means the first difference of a corresponding variable, and suffix (-1) means the first lag term of a corresponding variable.

Table 7 reports the results of an error correction regression (ECM) derived from the ARDL(3,2,2) model. It shows that most coefficients are statistically significant at 1% level, with the coefficients of D(LnEN_PC(-1)) and D(LnEDU_PC(-1)) are statistically significant at 2% and 5% level respectively. However, the statistical significance of the coefficient of the first order lagged error correction term CoinEq(-1) cannot be inferred by the standard t-distribution.

Table 8 t-bounds test of the ARDL(3,2,2) model

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-7.27	0.10	-2.57	-3.21
		0.05	-2.86	-3.53
		0.03	-3.13	-3.80
		0.01	-3.43	-4.10

Table 8 shows the critical values of the t-statistic for the coefficient of the first order lagged error correction term CoinEq(-1). Pesaran et al. (2001) use an example to demonstrates that if the absolute value of the t-statistic exceeds the absolute value of I(1) critical value, it can be confirmed that there is a level relationship among the variable include in the ARDL model and the coefficient of the first order lagged error correction term is significant at the corresponding significant level. Therefore, it can be confirmed that the term CoinEq(-1) in our results is statistically significant at 1% level. The coefficient of the error correction term -0.36 is also very significant economically, and means that any deviation of the

cointegration relationship among the three in the short term will be corrected by 36% in the next period, which is a fast correction speed.

4.3. Residual diagnostic and stability test

To further check the stability of the long run co-integrating relationship and the short run error correction term parameters, three conventional methods are used, which are Breusch-Godfrey serial correlation LM test, Cumulative Sum Recursive Residuals (CUSUM) test, and Cumulative Sum of Squares of Recursive Residuals (CUSMSQ).

Table 9 Breusch-Godfrey serial correlation LM test

Test Statistic	Value	p value
F-statistic	1.38	0.27
Chi-square	5.29	0.15

Note: the null hypothesis is that there is no serial correlation in the residual

Table 9 reports the results of Breusch-Godfrey serial correlation LM test, since the p values of the F-statistic and Chi square-statistic are 0.27 and 0.15 respectively, it can be inferred that the residuals are not serial correlated, which means that our ARDL model is well specified.

5. Conclusion And Policy Implications

This paper examines the relationship among CO2 intensity of real GDP, non-renewable energy consumption, and operational education expenditure. Our results show that there is no co-integration relationship between CO2 intensity of real GDP and non-renewable energy consumption, while after the introduction of operational education expenditure, a co-integration relationship appears among the three variables. In the long run, every 1% increase in non-renewable energy consumption results in a 0.92% increase in CO2 intensity of real GDP. In contrast, every 1% increase in operational education expenditure reduces the CO2 intensity of real GDP by 0.86%. In the short term, 36% of the deviation from the long run equilibrium is corrected in the next period. Based on the results of the empirical research, we can draw several important conclusions and make important policy recommendations as follow:

First and foremost, as long as the increase in operational educational expenditure exceeds the increase in non-renewable energy consumption, CO2 intensity of real GDP will decrease in the long run. This means that in the development stage when economic activities are still highly dependent on non-renewable energy sources, the Chinese government should continue to vigorously increase expenditures on public education, particularly improving the salary of teachers.

Second, the increase in non-renewable energy consumption will result in an increase in CO2 intensity of real GDP. Therefore, gradually increasing the proportion of clean energy consumption in the energy nexus

is another powerful starting point for China to achieve its goal of reducing CO2 intensity of real GDP.

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets generated and/or analysed during the current study are available in the World Development Indicators repository, https://databank.worldbank.org/source/world-development-indicators.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

He Huang: Conceptualization, Literature review, Writing. Qiushi Deng: Data, Estimates, Methodology. Liang Li: Editing.

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Figures

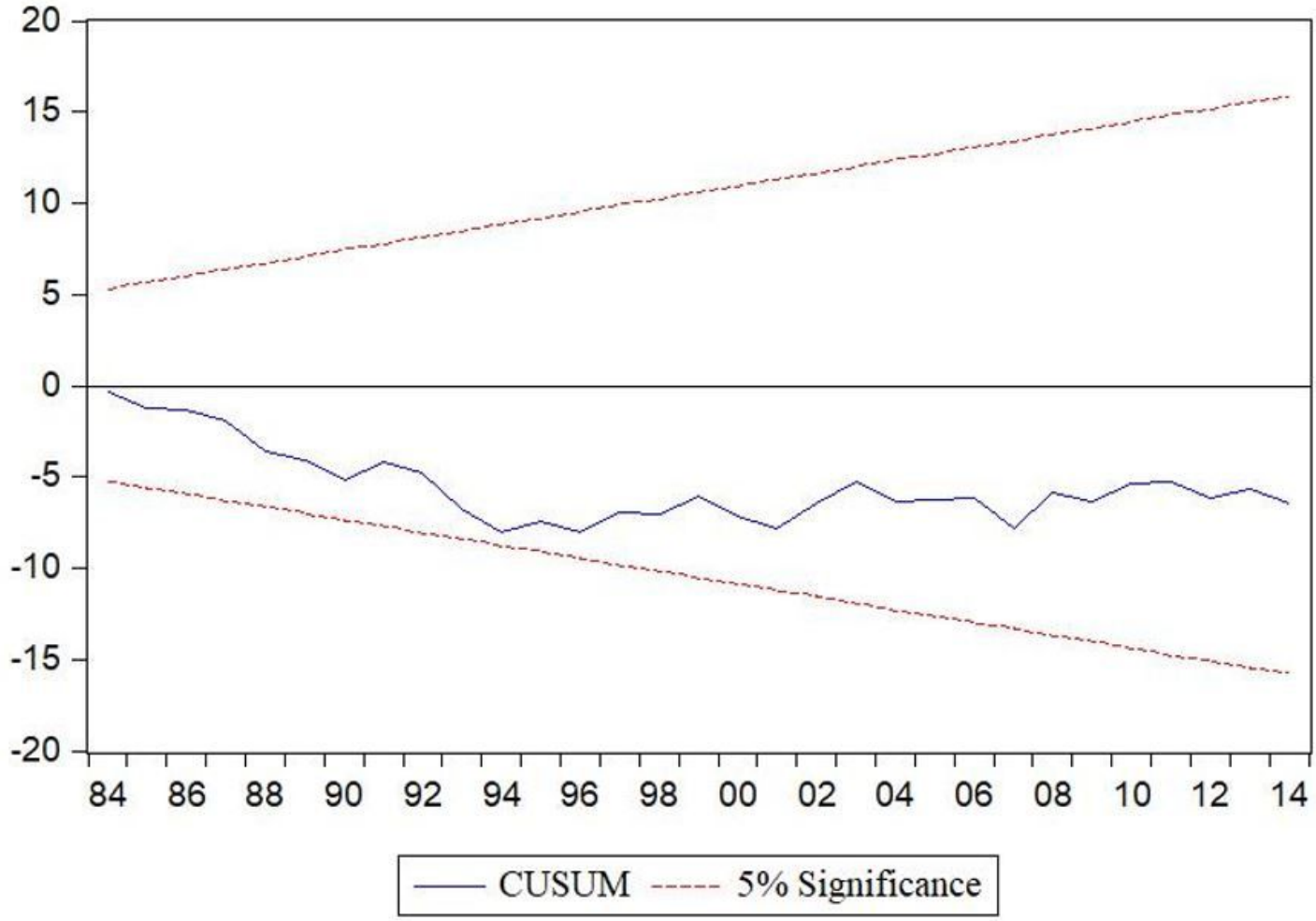

Figure 1

Plot of Cumulative Sum of Recursive Residuals

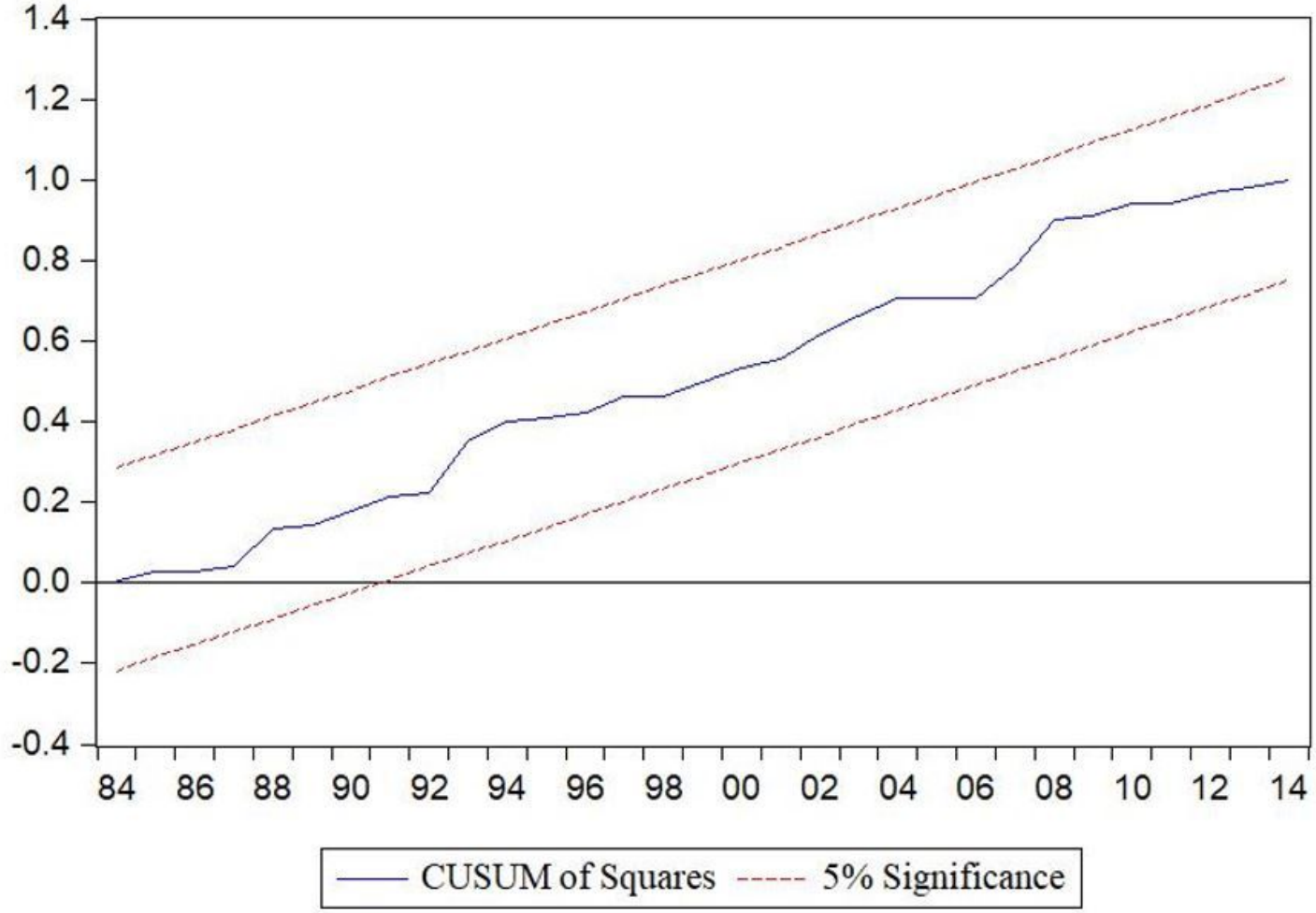

Figure 2

Plot of Cumulative Sum of Squares of Recursive Residuals