

Effects of Energy Consumption and Economic Growth on Carbon Dioxide Emissions

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Abstract

This paper investigated the relationship between carbon dioxide(CO₂) emissions, energy use and real economic output based on the panel data for 37 Asian countries over the period 1996 to 2013. Firstly, we analyzed the tendencies of indicators at both Aisa level and region level. Next, we tested the data via pooled OLS model, fixed effects model and random effects model respectively. After taking LM test and Hausman test for all the models above, we chose fixed effects model for our panel data. The estimation results show that economic growth, energy consumption and population density are the most important factors that affect carbon dioxide emission at Aisa level. Specifically, economic growth, energy use and population density positively and significantly affect CO₂ emissions, and forest area negatively affects CO₂ emissions. The results at region level are slightly different from thoes at Aisa level. The results of South East Aisa are similar, while those of West and South Aisa show that output per capita and energy use positively affect CO₂ emissions. The results of Central and East Aisa show that output per capita have the same scenario with Aisa level; nevertheless, the coefficient of forest area(% of land area) is negative.

Keywords: Energy consumption, Economic growth, Carbon dioxide emission

1. Introduction

Since the beginning of the industrial revolution, human activities have produced 40% increase in the temperature concert-rain of carbon dioxide from 280 ppm in 1750[2] to 400 ppm in 2015[3]. The Intergovernmental

Panel on Climate Change (IPCC) Report of 2007 reveals that over the last three decades, greenhouse gas (GHG) emissions have increased by an average of 1.6% per year with carbon dioxide emissions. The consumption of energy leads to the large amounts of CO₂ emissions in newly industrialized countries (NICs), and NICs include a lot of Asian countries, namely China, India, Malaysia, Philippines, Thailand, and Turkey etc. Thus global warming draws people's attentions increasingly. The relationship between energy consumption and economic growth, which is studied by many authors using various methodologies for different time periods since the pioneering work of Kraft and Kraft (1978)[10], has become a key and hot topic in environmental science, climatology and other relative academic fields. Recent researches of Shafik and Bandyopadhyay (1992)[14] and Shafik (1994)[13] found that per capita CO₂ emissions increase monotonically with income growth. Galeotti and Lanza(1999)[9] also found that CO₂ emissions go up as a result of faster per capita income growth in developing countries. PK Narayan and S Narayan (2009)[12] pointed out that the long-run relationship between CO₂ emissions and income has a positive effect. Yu and Choi (1985)[17] examined the relationship between most Asian developing countries. As the economy grows, the pressure on the environment increases and thus environmental quality cannot be improved.

We collected 37 Asian countries data cross the period from 1996 to 2013, in order to learn more about the relationship between carbon dioxide emissions, energy use, economic growth, population density and forest area in Asia. The main motivation for testing the relationship between CO₂ emissions and economic growth is that it gives policy makers or relevant departments of government to judge the response of the carbon dioxide emissions to economic growth. This response is crucial since the objective function of any economy is to maximize economic growth.

The paper is organized as follows. In Section 2 we present a review of the literature on four different parts, focusing mainly on issues related to econometric specifications. Section 3 presents the indicator tendency in Asia. Data description, methodology, and estimation results are covered in Section 4.

2. Literature review

The existing literature on modeling Asian CO₂ emissions mainly falls into two categories from methodological perspectives. The first category is the in-

index decomposition analysis based on national level panel data, including Lee and Chang(2008)[11], Wang and Zhou (2011)[16], Asafu-Adjaye (2000)[5], etc. A variety of index decomposition methods were used in these previous studies according to the usage of the decomposition formulations and index numbers. Typically, CO₂ emissions are decomposed into population size, GDP per capita, energy use and forest area. Almost all of the index decomposition analyses found that energy intensity and economic activity are the main contributors to the decrease and increase of Asian CO₂ emissions.

The second category is the methodology for panel data. Kurt Schmidheiny (2016) introduced two basic models for the analysis of panel data, namely the fixed effects model and random effects model, which are also explained by Croissant and Millo (2008)[8], Arellano (2003)[4], and Andrew and Kelvyn[7].

From the literature review above, we found that almost all previous researches are based on time series or panel data. Following Auffhammer and Carson (2008)[6], this paper constructs a panel data set to investigate the determinants, evolution trends and reduction potential of Asian CO₂ emissions, in order to reap the benefits of panel econometric models. This panel data set not only considers that the economic growth affects carbon dioxide emissions, but also includes the data of population density. Our analysis provides new insights by using a new data set.

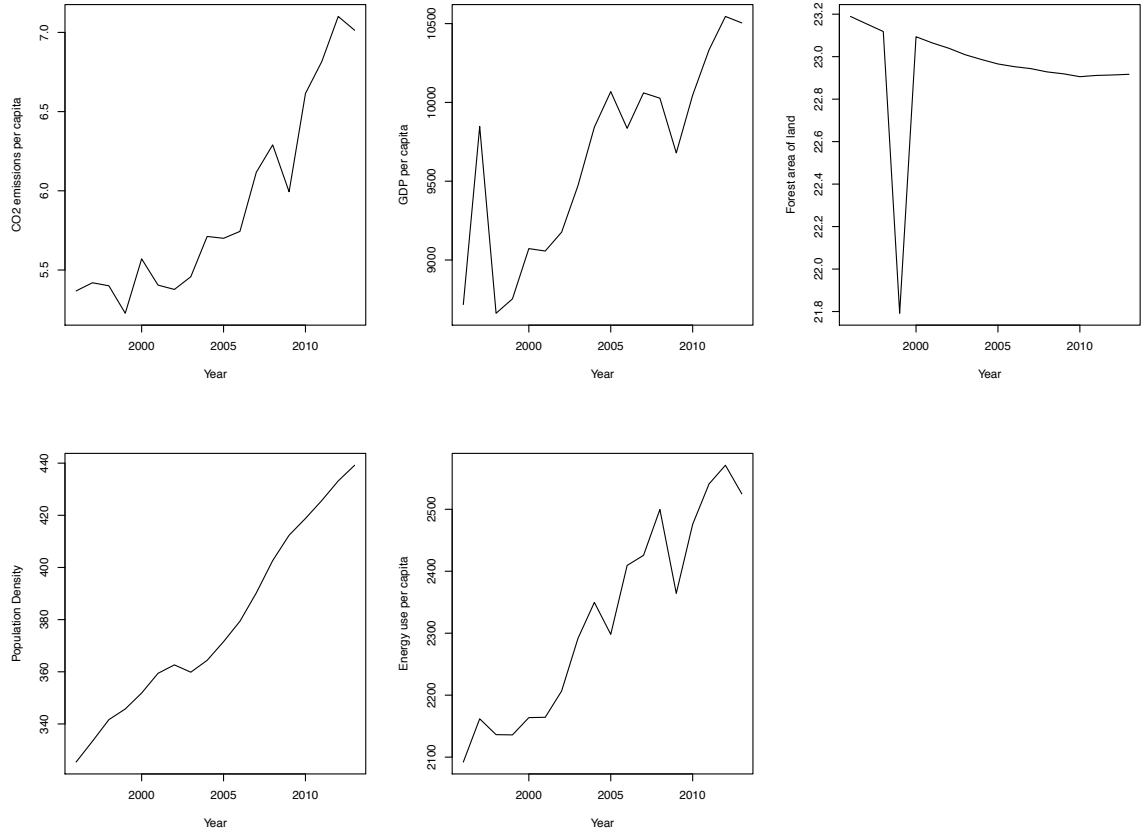
3. An overview of indicator tendency

3.1. Indicator tendency at Asia level

From Figure 1, we are able to observe that carbon dioxide emission per capita goes up slowly before 2000, but increased significantly and continuously after 2000. Generally, it has risen from 5.44 (metric tons per capita) in 1996 to 7.06 (metric tons per capita) in 2013 (close to 31 %). The trend of GDP per capita rapidly went up 20.5% during those years. Obviously, there is a huge decline from 1997 to 1998, due to financial crisis of Asia. Considering forest area, it can be seen that the forest area has a slight downward trend. Van der Werf and Morton (2009)[15] etc. investigated the relationship between CO₂ and forest loss, and declared that deforestation is the second largest anthropogenic source of CO₂ emission. From a global perspective, approximately 20% of anthropogenic CO₂ emission is from deforestation and forest degradation. Thus, the reduction of forest area is a vital factor of CO₂ emission. Finally, the population density and energy use increased 35%

and 20% respectively from 1996 and 2013. Except forest area , all the other variables have upward tendency.

Figure 1: Indicators' tendencies of Asia from 1996 to 2013

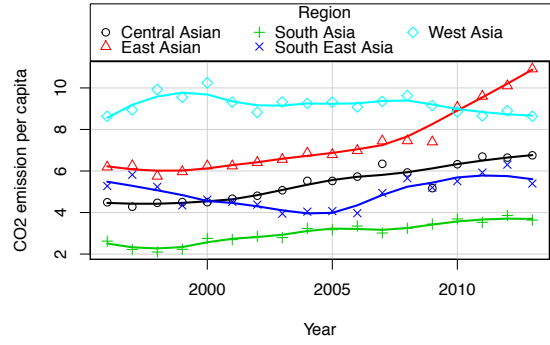


3.2. Indicator tendency at region level

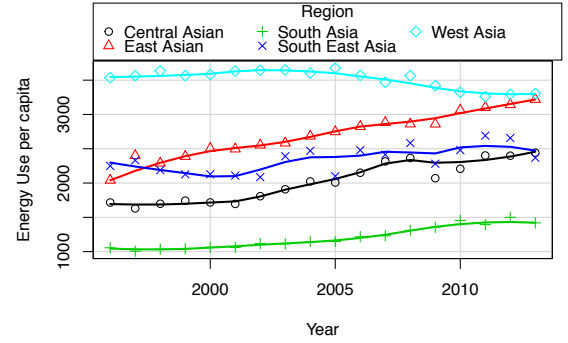
East Asia, Central Asia and South Asia have upward CO₂ emissions per capita tendencies. The emissions of West Asian and South East Asian also have a slight increase from 1993 to 2013 with some fluctuations. The average CO₂ emission per capita in East Asia increased much faster than other regions since 2007. The emissions of West Asia is remarkably higher than those of others with a stable trend. South Asia and Central Asia have slightly upward tendency, and rose about 39% and 50% respectively. The emissions of South East Asia are totally different. The emissions of South East decreased

gradually and reached the lowest point in 2006. After that it rose slowly after 2006. In respect of energy use, the mean energy use is highest for West area before 2012 followed by East, South East, Central, and South Asia. Based on energy use per capita, East Asia is the highest volatility area, and the trend went up with a high speed. Surprisingly, after 2005, the trend of West Asia was decreasing, and had an intersection with that of East Asia in 2012. Thus the mean energy use in East is the highest after 2012. Based on GDP per capita, there are two regions have similar and high trend - East and West Asia. The rank of GDP per capita is the following - South East, South, and Central Asia. Both Central and South Asia rise slowly from 2006 to 2013 with similar tendency. South Asia has the largest forest area, followed by East, South, West and Central Asia. Except Central Asia, others have downward tendency during given years. Besides, the mean of population density of South East Asia has the highest volatility, and that of Central Asia has the lowest volatility. The trends of population density of others are going up gradually.

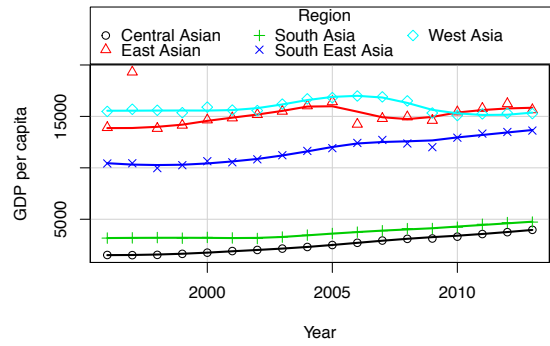
Figure 2: Indicators' tendencies of Asia from 1996 to 2013 by region



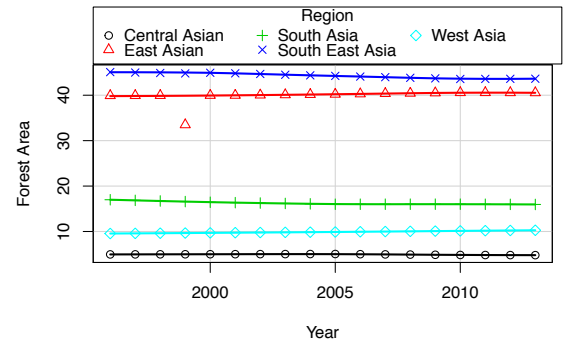
(a) carbon dioxide emission per capita from 1993-2013



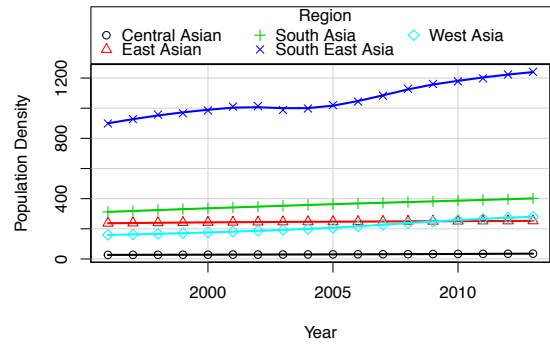
(b) energy use per capita from 1993-2013



(c) GDP per capita



(d) forest area % of total land from 1993-2013



(e) population density per capita from 1993-2013

4. Data description and methodology

This study uses data from World Bank Development Indicators (WDI). We collected annual data on the five variables, which are Gross Domestic Product per capita (GDP per capita), energy use, carbon dioxide emissions, the percentage of forest area of total land, and population density, for 37 Asian countries from 1996 to 2013. For the model examining Asia level (Model 1), we converted all variables into their natural logarithms so that the coefficients measure the expected percentage in the dependent variable when the independent variables increase or decrease by a fixed percentage. For the model examining each region (Model 2), we use first difference method. In order to find the relationship between CO₂ emissions, energy use, GDP per capita, forest area, and population density for the panel data, the following models are proposed:

Model 1 for Asia

$$\log(C_{i,t}) = \alpha + \beta_{i,t}^1 \log(Y_{i,t}) + \beta_{i,t}^2 \log(E_{i,t}) + \beta_{i,t}^3 \log(X_{i,t}) + \beta_{i,t}^4 \log(PD_{i,t}) + \mu_i + \epsilon_{i,t} \quad (1)$$

Model 2 for regions

$$\Delta(C_{i,t}) = \alpha + \beta_{i,t}^1 \Delta Y_{i,t} + \beta_{i,t}^2 \Delta E_{i,t} + \beta_{i,t}^3 \Delta X_{i,t} + \beta_{i,t}^4 \Delta PD_{i,t} + \mu_i + \epsilon_{i,t} \quad (2)$$

where $i = 1, 2, \dots, N$ represents each country in Asia in the panel, $t = 1, 2, \dots, T$ refers to the time period. As Table 1 presents, C denotes CO₂ emissions (measured in metric tons per capita), E denotes energy consumption (measured in kg of standard coal equivalent per capita), Y denotes per capita real GDP (measured in thousand constant 2010 USD), X denotes forest area of total land and PD denotes population density. The parameters β s represent the elasticity estimates of $\log(C)$ with $\log(Y)$, $\log(E)$, $\log(X)$, and $\log(PD)$ respectively, as well as for country (μ) and trend-effects (ϵ). These trend-effects are intended to capture any disturbances that are common across different members of the panel, such as global disturbances and international business cycles. In this paper we discuss two different region levels - Asia as a whole and the countries of Asia in five different regions. We selected 37 Asian countries and separate them into five categories: a panel of 4 East Asian countries, a panel of 9 South East Asian countries, a panel of 13 West Asian countries, a panel of 5 Central Asian countries and a panel of 6 South Asian countries. Table 2 shows the summary of five categories of those countries.

We omit unit root test in our study because we have 37 countries while our variables cover a period of only 18 years. We use our models to analyze the causalities assuming $\{T_i\}$ is fixed and allow $\{N_i\}$ to go to infinity.

Table 1: Statistics summary

Statistic	N	Mean	St. Dev.	Min	Max
C	684	6.824	7.430	0.098	36.904
E	684	2,687.317	2,939.023	132.199	12,674.140
X	684	22.029	22.436	0.006	76.546
Y	684	11,129.610	14,337.680	349.954	65,885.400
PD	684	356.235	1,044.005	1.491	7,636.721

Table 2: Asian countries by region

East	South East	South	West	Central
China	Brunei Darussalam	Bangladesh	Armenia	Kazakhstan
Korea	Cambodia	India	Azerbaijan	Kyrgyz Republic
Japan	Indonesia	Nepal	Bahrain	Tajikistan
Mongolia	Singapore	Saudia Arabia	Georgia	Turkmenistan
	Thailand	Sri Lanka	Iran, Islamic Rep.	Uzbekistan
	Vietnam	Pakistan	Isreal	
	Philippines		Jordan	
	Malaysia		Kuwait	
	Oman		Lebanon	
			Turkey	
			United Arab Emirates	
			Yemen,Rep.	
			Cyprus	

Table 3: Descriptive statistic of the variables by region

Region	Variable	N	Mean	St. Dev.	Min	Max
Central	C	90	5.413	4.694	0.294	15.651
	E	90	2,016.653	1,555.448	281.431	5,011.619
	X	90	4.946	2.863	1.226	8.782
	Y	90	2,516.108	2,662.752	364.650	10,310.120
	PD	90	30.669	22.101	5.504	71.094
East	C	72	7.345	3.166	2.649	14.547
	E	72	2,718.287	1,497.743	869.111	5,269.031
	X	72	40.216	26.874	7.279	68.484
	Y	72	16,262.420	16,235.900	1,328.595	44,327.940
	PD	72	246.261	191.575	1.491	515.253
West	C	234	9.199	9.730	0.725	36.904
	E	234	3,516.820	3,901.592	220.349	12,674.140
	X	234	9.892	10.445	0.241	40.616
	Y	234	15,865.380	16,763.050	1,080.731	65,885.400
	PD	234	211.694	326.206	29.518	1,752.503
South	C	108	3.024	5.542	0.098	19.189
	E	108	1,204.088	1,872.838	132.199	6,792.394
	X	108	16.247	12.544	0.454	35.541
	Y	108	3,699.173	5,988.017	414.717	20,753.120
	PD	108	358.986	346.082	8.993	1,207.324
South East	C	162	5.983	6.172	0.136	24.273
	E	162	2,631.413	2,613.350	250.377	9,695.714
	X	162	41.767	22.933	0.006	76.546
	Y	162	12,026.890	14,016.800	349.954	50,467.840
	PD	162	831.530	2,009.460	7.172	7,636.721

5. Empirical results and discussion

5.1. The results at Asian level

We used R to estimate our panel data. Based on Croissant and Millo (2008)[8], we downloaded the "plm" package and reorganized the data. Table 4 presents the result for model 1 using three different methods - Pooled OLS Model, Fixed Effects Model, and Random Effects Model. It is interesting to compare those three models via F test, LM test and Hausman test, in order to find the best model for our panel data. Breusch-Pagan Lagrange multiplier (LM) tests for Random Effects Model versus Pooled OLS Model. F test is the test for individual and/or time effects based on the comparison of the fixed effects model and the pooled OLS model. The F test showed that the fixed model is better here. For the LM test, the null hypothesis (H_0) is: there is no panel effect (i.e. Pooled Effects Model is better). The result of LM test shows that we failed to reject the null and conclude that Pooled OLS Model is not appropriate. Hausman test is help us to decide between Fixed Effects Model or Random Effects Model. The null hypothesis is that the preferred model is Random effects versus the alternative the Fixed effects (Green, 2008, Chapter 9). Basically, it tests whether the unique errors are correlated with the regressions, the null hypothesis is that they are not. Based one the result from Huasman test, the ρ is smaller than 0.05 (i.e. significant), thus we chose Fixed Effects Model in this paper.

The results from Fixed Effects Model shows that energy use has a positive effect on the increase in carbon dioxide emission with coefficient 1.000 with statistically significant at level 0.01, which implies that there is strong relationship between energy use and CO₂ emissions. We also observe that GDP per capita is statistically significant at the 1% level, and positively affects CO₂. The more GDP per capita grows, the more CO₂ emits . Generally, the coefficients of forest area is negative, which means the less forest area there is, the more CO₂ emission there will be. As we know there a huge number of population in Asia, for example China and India, in 2013 there are 1.375 billion people in China and 1.252 billion in India, which implies that with fixed land area, the number of people is increasing over time, thus population density is the best proxy to measure the relationship between CO₂ and population. The coefficient of population density is 0.149 and statistically significant at the 0.05 level, which means along with the growth of population density, CO₂ emission increases accordingly.

Table 4: Estimation results and model selection

Variable	<i>Pooled OLS Model</i>	<i>Fixed Effects Model</i>	<i>Random Effects Model</i>
	log(C)	log(C)	log(C)
log(E)	0.949*** (0.030)	1.000*** (0.040)	1.000*** (0.037)
log(Y)	0.186*** (0.024)	0.143*** (0.026)	0.149*** (0.026)
log(X)	-0.020** (0.008)	-0.192** (0.096)	-0.057** (0.032)
log(PD)	-0.083*** (0.009)	0.149** (0.041)	0.034 (0.031)
Constant	-6.882*** (0.111)	- -	-7.399*** (0.246)
Observations	684	684	684
R ²	0.929	0.682	0.727
Adjusted R ²	0.922	0.640	0.722
F Statistic	2,213.986*** (df = 4; 679)	344.115*** (df = 4; 642)	451.919*** (df = 4; 679)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

Table 5: Comparison between selected models

Lagrange Multiplier Test - (Breusch-Pagan)
chisq = 4465.3, df = 1, p-value < 2.2e-16
F test for individual effects
F = 138.89, df1 = 37, df2 = 642, p-value < 2.2e-16
Hausman Test
chisq = 16.203, df = 4, p-value = 0.002758

5.2. The analysis at region level

Table 6 provides the results of the first differences tests region by region, where the dependent variable is CO₂ emission. The panel estimators are shown at the bottom of Table 6. In general, the result for each region is consistent with the result of Asian level. The relationships between GDP per capita and CO₂ emissions are positive in all five regions. The coefficients of GDP per capita in Central, East and West Asia are statistically significant at the 1% level. In Central Asia and East Asia, 1% increase in GDP per capita will lead to a 0.04% increase in CO₂ emission. The coefficient of South East Asia is statistically significant at the 5% level.

The coefficients of energy use in those five regions are positively statistically significant at 1% level. The results show that an 1% increase in energy use leads to 0.3% increase in CO₂ emissions in Central, East, South and South East Asia, and 0.2% increase in West Asia.

Population density has negative effect on CO₂ emissions in East, West, and South Asia, with negative coefficients of -0.049, -0.002 and -0.001 respectively. Considering forest area (% of land area), the coefficients of West, South, and South East Asia are negative and for both West and South Asia, they are significant at 5% and 1% level respectively. We also found that the relationship between forest area and CO₂ emissions in East Asia is positive and significant at 1% level. This abnormality may be caused by a large increase of forest area in China since 1990 from 16.7% to 22.2% [1].

Table 6: First Difference Model for regions

	Central Asia	East Asia	West Asia	South Asia	South East Asia
ΔY	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0001*** (0.00001)	0.00004 (0.0001)	0.0001** (0.0004)
ΔE	0.003*** (0.0003)	0.003*** (0.0004)	0.002*** (0.0001)	0.003*** (0.0003)	0.003*** (0.0002)
ΔPD	0.016 (0.012)	-0.049*** (0.007)	-0.002*** (0.0005)	-0.001** (0.0004)	0.0001 (0.0001)
ΔX	0.015 (0.071)	0.445*** (0.063)	-0.029** (0.015)	-0.025*** (0.007)	-0.010 (0.007)
Constant	-0.402 (0.285)	-0.103 (0.203)	0.210 (0.183)	-0.317*** (0.109)	-0.053 (0.200)
Observations	72	54	234	90	144
R ²	0.992	0.922	0.969	0.991	0.939
Adjusted R ²	0.924	0.836	0.947	0.936	0.906
F Statistic	2,202.936*** (df = 4; 67)	144.430*** (df = 4; 49)	1,667.345*** (df = 4; 211)	2,245.909*** (df = 4; 85)	278.677*** (df = 4; 139)

Note: *p<0.1; **p<0.05; ***p<0.01

6. Conclusion

This paper analyzed the major determinants of CO₂ emissions for 37 Asian countries using annual data from the period 1996-2013. We also analyzed the relationship based on 5 regions of these countries, which are East Asia, West Asia, Central Asia, South Asia and South East Asia. The relationship among CO₂ emissions, energy consumption and economic growth has been found in our empirical results. Fixed effect model is used to examine the energy use and real output sensitivity on CO₂ emissions.

Our results show that GDP growth has a negative significant effect on CO₂ emissions in East Asia. One possible explanation is that as GDP increases, citizens' awareness rises. Producers are aware about the environmental degradation that is caused by GHG and trying to reduce CO₂ emissions. It is not surprising to find that energy consumption has a positive significant effect on CO₂ emissions across all the regions in Asia. The expansion of output requires additional energy usage which generates more emissions. We also found negative significant effect of population density on CO₂ emissions. One possible reason is that in the area with high population density, people rely more on the public transportation services and walking accessibility, instead of vehicular population. It is also not surprising to expect a negative relationship between forest area and CO₂ emissions. Deforestation can be considered to be the second largest anthropogenic source of CO₂ emissions after fossil fuel usage.

As we can see from the results, the relevant emission reduction variable is energy consumption. Countries should consider environmental policies that reduce energy consumption but do not harm long term economic growth. Exploiting renewable and environmental friendly energy sources is one of the efficient strategies with respect to energy consumption. Countries should also find a smart way to grow the urban residential densities depend on local conditions so that it may reduce CO₂ emissions. Besides, countries should be urged to develop policies to manage forest area in a sustainable way.

Reference

- [1] Forest area . <http://data.worldbank.org/indicator/AG.LND.FRST.ZS?locations=CN>. [Online].
- [2] Modern Records of Atmospheric Carbon Dioxide (CO₂) and a 2000-year Ice-core Record from Law Dome, Antarctica.

- http://cdiac.ornl.gov/trends/co2/modern_co2.htmlhttp://cdiac.ornl.gov/trends/co2/modern_co2.html. [Online].
- [3] Trends in Atmospheric Carbon Dioxide. <http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html>. [Online].
 - [4] Manuel Arellano. *Panel data econometrics*. Oxford University Press, 2003.
 - [5] John Asafu-Adjaye. The relationship between energy consumption, energy prices and economic growth: time series evidence from asian developing countries. *Energy economics*, 22(6):615–625, 2000.
 - [6] Maximilian Auffhammer and Richard T Carson. Forecasting the path of china’s co 2 emissions using province-level information. *Journal of Environmental Economics and Management*, 55(3):229–247, 2008.
 - [7] Andrew Bell and Kelvyn Jones. Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data. *Political Science Research and Methods*, 3(01):133–153, 2015.
 - [8] Yves Croissant, Giovanni Millo, et al. Panel data econometrics in r: The plm package. *Journal of Statistical Software*, 27(2):1–43, 2008.
 - [9] Marzio Galeotti and Alessandro Lanza. Richer and cleaner? a study on carbon dioxide emissions in developing countries. *Energy Policy*, 27(10):565–573, 1999.
 - [10] John Kraft and Arthur Kraft. Relationship between energy and gnp. *J. Energy Dev.:(United States)*, 3(2), 1978.
 - [11] Chien-Chiang Lee and Chun-Ping Chang. Energy consumption and economic growth in asian economies: a more comprehensive analysis using panel data. *Resource and energy Economics*, 30(1):50–65, 2008.
 - [12] Paresh Kumar Narayan, Seema Narayan, and Russell Smyth. Understanding the inflation–output nexus for china. *China Economic Review*, 20(1):82–90, 2009.
 - [13] Nemat Shafik. Economic development and environmental quality: an econometric analysis. *Oxford economic papers*, pages 757–773, 1994.

- [14] Nemat Shafik and Sushenjit Bandyopadhyay. *Economic growth and environmental quality: time-series and cross-country evidence*, volume 904. World Bank Publications, 1992.
- [15] Guido R Van der Werf, Douglas C Morton, Ruth S DeFries, Jos GJ Olivier, Prasad S Kasibhatla, Robert B Jackson, G James Collatz, and James T Randerson. Co2 emissions from forest loss. *Nature geoscience*, 2(11):737–738, 2009.
- [16] SS Wang, DQ Zhou, P Zhou, and QW Wang. Co 2 emissions, energy consumption and economic growth in china: a panel data analysis. *Energy Policy*, 39(9):4870–4875, 2011.
- [17] Eden SH Yu and Jai-Young Choi. Causal relationship between energy and gnp: an international comparison. *J. Energy Dev.;(United States)*, 10(2), 1985.