RESEARCH ON DRIVING FORCES OF CARBON DIOXIDE EMISSIONS FROM CEMENT PRODUCTION AND FOSSIL FUEL COMBUSTION IN CHINA

by

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Abstract

As China has become the biggest emitter of greenhouse gas in the world, it is important to investigate factors affecting CO_2 emissions and how these vary with growth in China. A Tier 1 IPCC method is used to estimate CO_2 emissions from cement production and fossil fuel combustion in China to construct a panel data set with 27 provinces over 15 years. The results suggest a global cubic relationship between per capita CO_2 emissions and per capita real GDP. Based on extrapolation, we expect a presence of the environmental Kuznets curve in the future of China. A model predicts that per capita CO_2 emissions will fall when per capita real GDP exceeds 60972.06 RMB (1995 currency). Then, separate estimation on three regions with different levels of economic development suggests that economic growth significantly affects per capita CO_2 emissions in the Eastern and Middle regions but not the Western region.

Key Words: Environmental Kuznets Curve; per capita CO_2 emissions; per capita real GDP; fixed-effects panel model

List of Abbreviations and Symbols Used

GHG	Greenhouse Gas
IPCC	Intergovernmental Panel on Climate Change
CO_2	Carbon Dioxide
WMO	World Meteorological Organization
UNEP	United Nations Environmental Programme
UNFCCC	United Nations Framework Convention on Climate Change
COPs	Committees of Parties
EIT	Economies in Transition
EKC	Environmental Kuznets Curve
LULUCF	Land Use, Land-Use Change and Forestry
NCV	Net Calorific Value
$CaCO_3$	Calcium Carbonate
CaO	Lime

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Chapter 1

Introduction

Human economic activities are causing greenhouse gas (GHG) emissions that are resulting in global warming and ocean acidification. According to the Intergovernmental Panel on Climate Change (IPCC), Fifth Assessment Report (Stocker, 2013)[37], the temperature of the atmosphere and oceans have increased and the sea level has risen. In addition, the amounts of ice and snow have fallen and the concentrations of GHGs have increased. Many of these observed changes are unprecedented over decades to thousand years. In terms of carbon dioxide (CO_2), the concentrations of CO_2 have increased by 40% since pre-industrial times. The main anthropogenic sources of CO_2 are fossil fuel and land use emissions. The IPCC 2013 Fifth Assessment Report reported that the average global surface temperature has increased by 0.9°C relative to pre-industrial times. Taking China as an example, the average temperature has increased by 0.4°C to 0.5°C over the past century, especially in winter.

The global warming will not only cause the temperature to rise, but will also melt glaciers, and cause the sea levels to rise. The Stern review explained that due to the global warming, people will increasingly suffer from hunger, flooding and water shortages. It is also reported to lead to a spread of infectious diseases.

Stern (2007)[36] concluded that the benefits of strong and early action far outweigh the economic costs of not acting. In order to mitigate global warming and avoid catastrophic effects on humans, the World Meteorological Organization (WMO) and United Nations Environment Programme (UNEP) established the IPCC to provide scientific and technological advice for problems caused by GHGs. As GHGs are global pollutants, damages are independent of the location of the source such that international cooperation is required to reduce emissions. As such, in June 1992, parties from each country in the United Nations put together the United Nations Framework Convention on Climate Change (UNFCCC) due to the need for international cooperation given that the GHGs are global pollutants. In December 11th, 1997, Committees of Parties (COPs) from each nation jointly signed the Kyoto Protocol, which came into effect on February 16th, 2005. Under the Protocol, the Early Industrialized Countries and Economies in Transition (EITs) set targets to jointly reduce GHG emissions, but other lower income and newly industrialized countries such as China were not required a target in the first commitment period under Kyoto Protocol (5% below 1990 level from 2008 to 2012). China has not agreed to abate GHG emissions in the second commitment period (18% below 1990 level from 2013 to 2020) under Copenhagen Accord.

However, by 2007, China had overtaken the United States as the biggest emitter of GHGs. As the largest emitter of GHGs and second nationally largest economy, China is facing increasing international pressure to reduce its GHG emissions and is responsible for GHGs reduction. Therefore, a most urgent task for Chinese government is to fully understand drivers and characteristics of Chinese CO_2 emissions such that they can formulate effective carbon reduction policies. China has set both a short-term goal for to reduce energy intensity from 2006 to 2010 and a longer-term goal for to reduce carbon intensity by 2020 (Zhou et al, 2011)[44]. Hence, it is important to study the drivers of per capita CO_2 emissions in order to not only help the Chinese government to participate in international climate negotiations, but also help the government develop realistic per capita CO_2 reduction policies.

CO_2 is the type of GHG responsible for most warming. According to the IPCC Forth Assessment Report (2007)[4], CO_2 emissions accounted for 76.6% of total global GHG emissions, and CO_2 emitted from the consumption of fossil energy accounted for 56.6% of total global GHG emissions. Moreover, fossil fuel combustion, cement, lime, calcium carbide, and steel production, and other industrial processes discharge CO_2 due to physical and chemical reactions. For CO_2 emissions created by industrial processes, cement accounts for 56.8%, lime for 33.7%, and the proportion of calcium carbide, steel production for less than 10%. Due to the rapid development of industrialization and urbanization in China in recent years, large amounts of roads, buildings, sidewalks and energy are required. Moreover, because China has the highest population in the world, dividing total GHG emissions by total population eliminates effects of population on total GHG emissions.

Therefore, to research the relationship between per capita GHG emissions and per capita income, this paper researches impacts of per capita real GDP, industrial structure, urbanization and technology on per capita CO_2 emissions from cement production and fossil fuel combustion. As a result, this paper estimates relationships between per capita CO_2 emissions from cement production and fossil fuel combustion and per capita real GDP in China as a whole, and three separate regions of China which differ relative to measures of economic development. This paper uses a panel data model with 27 provinces of China from 1995 to 2009, and uses Driscoll-Kraay[9] standard errors to account for the presence of heteroskedasticity and cross sectional dependence in a fixed-effects model for a sample of China as a whole. In addition, three regional panel-data models are estimated using clustered robust standard errors to accommodate heteroskedasticity and serial autocorrelation.

According to the research, there exists an inverted N-shaped curve in China, the Eastern and Middle regions. This suggests that per capit CO_2 emissions fall as per capita real GDP increases from low levels but then rises to fall again at higher levels of income. However, for the Western region, we find no relationship between per capita CO_2 emissions and per capita real GDP. In the future of China, we predict an EKC, and a turning point is 60972.06 RMB (1995 currency). Based on our extrapolation, we predict that when per capita real GDP exceeds 60972.06 RMB (1995 currency), per capita CO_2 emissions will decrease.

The paper is organized as follows. Chapter 2 is literature review on the EKC hypothesis and environmental and empirical models. Chapter 3 introduces features of CO_2 emissions in China compared with world levels. Chapter 4 is data description. Chapter 5 explains a method computing CO_2 emissions from cement production and fossil fuel combustion, and description of panel data models. Chapter 6 is an empirical analysis. And, Chapter 7 provides a conclusion and discussion for a future research.

Chapter 2

Literature Review

In this chapter, we review the Environmental Kuznets Curve (EKC) hypothesis. The EKC hypothesis predicts that GHG emissions are related to output due to a scale effect, composition effect and abatement effect. These can generate an inverted U-shaped relationship between CO_2 emissions and economic growth, which is referred to as the EKC. In addition, energy intensity and urbanization under the abatement effect may affect CO_2 emissions when income level is high. Although some empirical studies support the EKC hypothesis for a variety of pollutants including CO_2, others have questioned the existence of the EKC arguing that results have depended on poor econometric methods.

2.1 Environmental Kuznets Curve (EKC)

In 1955, the Nobel laureate Simon Kuznets firstly used the Kuznets curve to study a relationship between income distribution of inequality and economic growth. Because of the economic growth, income inequality may increase. After the per capita income reaches a certain level, the income inequality will decrease with the economic growth. Therefore, the Kuznets curve is an inverted U shape (Kuznets, 1955)[16]. Recently, the relationship between economic growth and environmental pollution has been paid much attention by environmental economists. Grossman and Kruger (1991)[12], in the study of potential impacts of North American Free Trade Agreement (NAFTA) on the environment, hypothesized and found empirical support for an inverted U-shaped curve between per capita GDP and a variety of environmental pollutants. In the early 1990s, the inverted U-shaped curve had become to be referred to as the EKC originally hypothesized by Kuznets.

The inverted U-shaped curve is derived from three effects, which are the scale effect, composition effect and abatement effect. The three effects were hypothesized to explain impacts of economic development on environmental quality (Pannayotou, 2003)[20].

2.1.1 Scale Effect

Income growth increases pollution monotonically because a larger scale of economic activities causes worse environmental quality. Friedl and Getzner (2003)[10] suggested that the relationship between CO_2 emissions and average income was positive. Therefore, the scale effect on CO_2 emissions, holding the composition and abatement effects constant, is a monotonically increasing function of the income. The larger scale of economic activities causes energy consumption to increase and, in turn, CO_2 emissions increase (Shi, 2003)[30].

2.1.2 Composition Effect

The composition effect refers to an inverted U-shaped curve between income and environmental pollution. When the income starts to increase from low levels, the share of GHGs emitted from an industrial sector rises. This composition effect causes CO_2 emissions to increase. However, as the income increases further, the shift from the industrial sector to the service sector causes a reduction in pollution intensity. This composition effect can potentially cause a reduction of CO_2 emissions if the composition effect outweighs the scale effect. Thereby, changing the share of GDP in the industrial sector, a representative of the structural changes, can potentially lead to an inverted U-shaped relationship between pollution and output (Pannayotou, 2003)[20].

The dynamic evolution of the industrial structure is dependent on a speed of economic growth. Panayotou (1993)[19] analyzed that if changes in the industrial structure went from labour-intensive, through capital (energy) intensive, and then on to technology intensive. Early industrialized regions are becoming more diversified with a larger share of GDP in the service sector, which reduces per capita GHG emissions per unit of GDP. Also, manufactures may be moving to cheaper areas. Parts of China may be

Table 2.1: Changes in Industrial Structure

Year	Industry sector (% of GDP)	Service sector (% of GDP)
1995	47.18	32.86
1996	47.54	32.77
1997	47.54	34.17
1998	46.21	36.23
1999	45.76	37.77
2000	45.92	39.02
2001	45.15	40.45
2002	44.79	41.47
2003	45.97	41.23
2004	46.23	40.38
2005	47.37	40.51
2006	47.95	40.49
2007	47.34	41.89
2008	47.44	41.82
2009	46.24	43.43

Data source: World Development Indicators Online Database, World Databank

experiencing what already happened in the USA. As a result, we can take a look at how the China's industrial structure has changed in recent years.

Since the reform and open policy, China has had stable economic growth, which has constantly improved its national economy, based on a variety of indicators including GDP. As shown in Table 2.1, the share of GDP in the industrial sector went upward after a fall from 1995 to 2009. It decreased from 47.18% in 1995 to 44.79% in 2002, to around 47% in recent years and fluctuated slightly around this number. The share of GDP in the service sector had an upward trend, which rose from 32.86% in 1995 to 43.42% in 2009. The industrial sector had a larger proportion of GDP. Although the share of GDP in the service sector were rising, the share of GDP in the service sector in 2009, 43.43%, was still far below the level of developed countries.

In general, it is assumed that the industrial sector emits more CO_2 than the agricultural and service sectors respectively. Because the dependence of the industrial sector on raw materials and energy is relatively high, the production process generates a large amount of CO_2. However, the dependence of the agricultural and service sectors is relatively low so that the two sectors produce less CO_2. [1] In contrast, the industrial sector, such as steel, cement and other raw materials production, consumes more energy and emits more CO_2, soot, sludge and waste water than that emitted from the service sector. The service sector includes information production, financial services and bio-pharmaceutical production. Given the lower GHG intensity of the service sector, an adjustment in the national structure towards a larger share of GDP in the service sector can reduce CO_2 emissions effectively and sustainably (Li et al, 2010)[17].

2.1.3 Abatement Effect

The abatement effect is due to demand for environmental quality depending on levels of per capita income. On the demand side, as income increases at low-income levels, this is not hypothesized to cause a large effect on the demand for environmental quality since income increases directly raise demand for food and shelters. However, at higher levels of income, income increases may raise the demand for environmental quality. At high levels of income, people are willing to spend more on pollution abatement and stricter environmental regulations leading to an increase in supply. As a result, the abatement effect is expected to be a monotonically decreasing function of income (Pannayotou, 2003)[20].

These three effects combined can result in the EKC relationship if the latter two effects come to dominate the scale effect at some income level. Also, there may be other factors affecting CO_2 emissions. Energy intensity and urbanization are the two factors, which have effects on CO_2 emissions when the income level is high.

2.2 Energy Intensity

Energy intensity is a component of the abatement effect. The energy intensity reflects

[1] If large-scale agriculture is more energy intensive than small scale agriculture, as GDP increases, agriculture can become more GHG intensive.

a degree of economic dependence on energy, and it is mainly affected by the nature of technology (Wei et.al, 2011)[40].

With an improvement of technology based on the high income levels, energy efficiency greatly improves such that less energy is used to make each unit of output causing CO_2 emissions to decrease, all else equal. In addition, due to the substitution of lower GHG technology, such as from coal, oil and other carbon fuels, to less GHG intensive energy (ex. hydrogen, renewable energy and nuclear), these two factors cause the GHG intensity to fall, which drives GHG emissions down all else equal. Although total GHGs can still rise due to the scale effect, whether the total GHG emissions rise or fall depends upon which effect dominates.

Table 2.2 shows that energy intensity of China was significantly higher than the world average level from 1995 to 2009. In 1995, energy intensity of China was 2.1 times higher than the world level and the USA, and was 2.9 times higher than in the EU, and 2.6 times higher than in OECD countries. However, by 2009, energy intensity of China has fallen to 1.5 times higher than the world average level, 1.75 times higher than in the USA, and 2.3 times higher than in the EU, and 2 times higher than in OECD countries. It was even 1.74 times higher in 1995 than in middle income countries but decreased to 1.27 times higher in 2009. As we can see, there exists a gap between energy intensity of China and the energy intensity of the world and developed countries' levels, but the gap has been greatly reduced. However, from 2002 to 2004, energy intensity of China increased, probably because China has entered into a new round of growing cycle and there exists a rapid growth of investment in fixed assets. There was a rapid expansion in production of iron, steel, cement and aluminium, that is to say high "energy-consuming" industries. After 2004, the energy intensity of China declined again because of economic development of China, inherent laws and strong governmental policies.

Table 2.2: International Comparison of Energy Intensity (kg oil equivalent per dollar, constant 2005 PPP)

Year	China	USA	EU	World	OECD	Middle-income
1995	0.47	0.22	0.16	0.22	0.18	0.27
1996	0.44	0.22	0.16	0.22	0.18	0.26
1997	0.40	0.21	0.15	0.21	0.17	0.26
1998	0.37	0.20	0.15	0.21	0.17	0.25
1999	0.35	0.20	0.15	0.21	0.17	0.25
2000	0.34	0.20	0.14	0.20	0.16	0.24
2001	0.33	0.19	0.14	0.20	0.16	0.24
2002	0.32	0.19	0.14	0.20	0.16	0.24
2003	0.33	0.19	0.14	0.20	0.16	0.24
2004	0.34	0.18	0.14	0.20	0.16	0.24
2005	0.33	0.18	0.13	0.19	0.15	0.24
2006	0.32	0.17	0.13	0.19	0.15	0.23
2007	0.30	0.17	0.12	0.18	0.15	0.22
2008	0.28	0.17	0.12	0.18	0.14	0.22
2009	0.28	0.16	0.12	0.18	0.14	0.22

Data source: World Development Indicators Online Database, World Databank[5]

2.3 Urbanization

As countries industrialize, people move from the country side to urban areas, which may lead to changes of GHG emissions. However, the relationship between urbanization and CO_2 emissions does not have an unanimous conclusion.

As shown in Figure 2.1, the urbanization rate of China, that is the proportion of urban population, increased from 29.04% in 1995 to 46.59% in 2009. It increased by 17.55 percentage points and the urbanization rate increased by 1.17 percentage points annually.

Table 2.3 shows that the current rate of urbanization and economic development in China is similar to that of middle-income countries. When a state's economic development is high, the urbanization rate is also relatively high. In 2008, the world average urbanization rate was 49.9%. The high-income countries had an average of

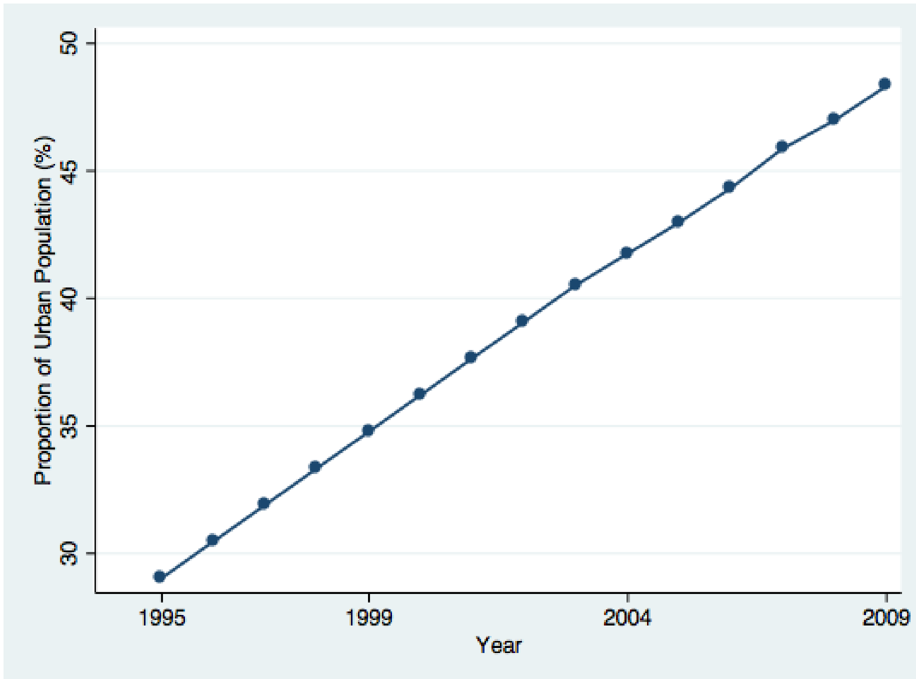

Figure 2.1: Changes in the Level of Urbanization

Table 2.3: Major Proportion of Urban Population and Per Capita GDP in 2008

Category	Proportion of urban population	Per capita GDP ($ U.S)
The World average	49.9	9054
High-income countries	77.7	40420
Middle-income countries	48.1	3618
Low-income countries	28.7	584
United States	81.7	46716
Japan	86.3	38443
China	45.7	3263

Japan's urbanization rate data from the Japan Statistical Yearbook[2]; Chinese data from China Statistical Yearbook[24]. Other countries' urbanization rate and per capita GDP data are from the World Bank database.

77.7%, middle-income countries were at 48.1%, and low-income countries were at 28.7%. In 2008, China's per capita GDP of 3,263 dollars was well below the world average of 9,054 dollars and relatively below the middle-income countries' average level of 3,618 dollars. The urbanization rate was correspondingly 4.3 percentage points lower than the world average level.

Urbanization can lead to economies of scale. For example, as the urban population becomes bigger, it may become cost effective to build roads, sidewalks or schools. In addition, economies of scale may lead to a shift in the mode of production and lifestyle. For instance, the household consumption of electric appliances may increase rapidly and automobiles may become more affordable for households (Wei et al, 2011)[40]. As urban centres grow, the scale can allow the development of the service and transport sectors as more banks, restaurants, roads and highways are required. Urbanization also impacts the energy demand, thereby affecting CO_2 emissions.

From the point of view of space, production activities move from rural areas to cities as people move to urban areas, such that the energy consumption is concentrated in the city as well. This leads to an increase in CO_2 emissions due to transformation from the agricultural sector to the industrial sector (Wei et al, 2011)[40].

According to Wei et al (2011)[40], the main factors due to urbanization, which affect lifestyle and CO_2 emissions are: 1) people migrate from rural to urban areas; 2) the share of household energy consumption in cities increases; 3) the agricultural population decreases; 4) the high demand for agricultural products requires increased agricultural productivity leading to the development of farming mechanization; in turn, causing more energy consumption to increase in the agricultural sector. This large scale of industrialized agriculture causes more CO_2 emissions along with other GHG emissions such as nitrous oxide from fertilizer and methane.

During the urbanization process, the impacts of industrial restructuring on CO_2 emissions are mainly from the industrial sector to the service sector (Wei et al, 2011)[40]. The impact of the industrial sector on CO_2 emissions is the largest, and the service sector has the second largest impact. In the early stage of urban development, a leading industry is a light industry, such as a manufacturing of shoes, clothing, furniture and home appliances. As the economy continues to develop, in the middle stage of urbanization, the industry gradually shifts from the light to heavy industries, such as steel making and energy production. With the development of urbanization, the share of GDP in the agricultural sector becomes smaller. The share of GDP in the industrial sector increases firstly but decreases later, and the share of GDP in the service sector rises steadily (Wei et al, 2011)[40].

Urbanization tends to decrease birth rates caused by delayed childbearing because people living in urban environments may give birth at older ages and they tend to be more receptive to governmental efforts to further childbearing (Yi and Vaupel, 1989)[42]. As a result, urbanization may lead to the reduction of population causing CO_2 emissions to decrease.

The above effects suggest that during the initial period of urbanization, energy consumption increases, but that later, net energy consumption declines with the development of urbanization as advanced technology promotes energy efficiency. With increases in the levels of urbanization, CO_2 emissions are expected to rise through changing lifestyles and consumption patterns. If further economic growth occurs, the high demand for environmental quality may then push the government to generate policies in some sectors to reduce CO_2 emissions.

In addition to CO_2 emissions, this paper predicts that the development of urbanization increases cement production because large amount of roads, buildings, sidewalks are required. Moreover, the cement production is an important source of global CO_2 emissions, and CO_2 emissions from the cement production account for about 2.4% of global CO_2 emissions from industrial and energy consumption (Marland et al, 1989)[18]. As such, in addition to considering CO_2 emissions from energy products, due to fossil fuel burning, this paper considers CO_2 emissions from cement production and fossil fuel combustion as a major indicator.

2.4 Environmental Models

In terms of the impacts of anthropogenic activities on climate change, York et al (2003)[43] pointed out two identities, the $IPAT$ identity and $ImPACT$ identity. Analyzing the impacts of human activities on the environment widely uses the $IPAT$ identity. This identity is a formula explained as $I = PAT$. On the formula's left-hand side, I refers to environmental impacts. On the right-hand side, P is population; A is affluence (per capita GDP); T is technology (impact per unit of GDP). According to this identity, environmental impacts are a multiplicative output of the three major driving forces (population, affluence and technology).

Waggoner and Ausbel (2002)[38] generated the $ImPACT$ identity. They conceptualized the $IPAT$ by decomposing T (technology) into C (consumption per unit of GDP) and T (impact per unit of consumption). $I = PACT(ImPACT)$ is a model focusing on estimating factors that can be altered to decrease impacts. Compared with $IPAT$, $ImPACT$ identity states that overall emissions equal products of population (P), per capita GDP (A), energy consumption per unit of GDP (C) and emissions per unit of energy consumption (T).

Based on $IPAT$ identity and $ImPACT$ identity, Dietz and Rosa (1994)[6] developed a $STIRPAT$ model as $IPAT$ and $ImPACT$ are limited for testing hypothesis given that the two accounting equations assume proportional relationship in a function between factors. Grossman and Krueger (1995)[13] explained that $IPAT$ and $ImPACT$ were not useful for testing the EKC hypothesis because affluence as measured by per capita GDP under the EKC hypothesis might have both non-monotonic and non-proportional environmental impacts.

The $STIRPAT$ model was introduced in order to investigate stochastic impacts by regression on population, affluence and technology (Dietz and Rosa, 1994)[6]. By reformulating $I = PAT$, Dietz and Rosa (1997)[7] added the subscript i referring to varying quantities of different observations. In the $STIRPAT$ model, technology (T) is considered as an error term (e). The technology term not only includes technology but also social organizations, institutions, culture and other factors affecting the environment except for population and affluence. So, the $STIRPAT$ model is shown as follows:

$$I_i = a \times P_i^b \times A_i^c \times e_i \tag{2.1}$$

where, i represents individuals, b and c are coefficients of population and affluence, a represents constants that determines scale of the model, and e represents the technology error term (Dietz and Rosa, 1997)[7]. Standard statistical techniques can be applied to estimate a, b, c and e.

Raupach et al (2007)[28] used the Kaya identity, a special case of the $ImPACT$ identity, to estimate CO_2 emissions from energy consumption at the global and regional levels. The Kaya identity is:

$$F \equiv P \times \left(\frac{G}{P}\right) \times \left(\frac{E}{G}\right) \times \left(\frac{F}{E}\right) \tag{2.2}$$

in which, F refers to global CO_2 emissions; G is global GDP and E represents global energy consumption. To simplify the identity, $\left(\frac{G}{P}\right)$ is replaced by g meaning per capita GDP. $\left(\frac{E}{G}\right)$ is energy intensity of GDP that is changed to e, and $\left(\frac{F}{E}\right)$ indicates carbon intensity of energy, which is replaced by f. The simplified formula is:

$$F \equiv P \times g \times e \times f \tag{2.3}$$

In terms of regional CO_2 emissions, subscript i represents different regions. Hence, the Kaya identity for regional CO_2 emissions is:

$$F_i \equiv P_i \times g_i \times e_i \times f_i \tag{2.4}$$

By summing up CO_2 emissions in each region over all regions (n), we obtain global CO_2 emissions.

$$F = \sum_{i=1}^{n} F_i \tag{2.5}$$

Both the $STIRPAT$ model and the Kaya identity can be used to estimate the relationship between environmental impacts and anthropogenic activities. The $STIRPAT$

and Kaya identity both account for impacts of population (P) and per capita GDP, with g in the Kaya identity corresponding to affluence (A) in the $ImPACT$ model. Even if the $STIRPAT$ does not include the energy intensity of GDP as in the Kaya identity, $ImPACT$ is the extended identity of $IPAT$ due to including the energy intensity of GDP and carbon intensity of energy consumption (technology term). The energy intensity in the Kaya identity corresponds to technology (e). The technology (e) is an error term in the $STIRPAT$ model. Even though energy intensity is not included in the $STIRPAT$ model, energy intensity should be considered because it impacts CO_2 emissions in terms of the Kaya identity.

2.5 Empirical Analysis on EKC

Some economists have tested the EKC hypothesis using econometric methods. Stern (2004)[33] showed that a standard EKC regression model fitted a quadratic form using a panel data model.

$$ln(E/P)_{it} = \alpha_i + \gamma_t + \beta_1 ln(GDP/P)_{it} + \beta_2 [ln(GDP/P)]^2_{it} + \varepsilon_{it} \tag{2.6}$$

E is emissions; P is population; α_i and γ_t are intercept parameters that respectively vary across countries or regions i and years t. In this model, it is assumed that the income elasticity of per capita emissions is the same in all regions at a given level of per capita income. This model can be estimated by a fixed-effects or random-effects model. The α_i and γ_t represent regression parameters in a fixed-effects model, and represent components of disturbances in a random-effects model. If the individual effects represented by α_i are correlated with independent variables, only parameters and statistical inferences in a fixed-effects model can be estimated consistently because a fixed-effects model allows independent variables to be correlated with time-invariant component of the error α_i. Independent variables have to be uncorrelated with ε_{it}. Therefore, a fixed-effects model can obtain consistent estimates of marginal effects of independent variables even if the independent variables are endogenous. Stern (2004)[33] explained that people could use a Hausman test to verify that random-effects specification was consistent by comparing coefficients between a fixed-effects and random-effects model. A significant difference indicates that random-effects estimates are inconsistent because independent variables are correlated to time-invariant components of residuals.

Model selection depends on properties of data because estimators are inconsistent and statistical inferences are invalid when a selected model does not fit the data properties. For instance, Perman and Stern (2003)[21] stated that a static EKC regression could be spurious if variables were integrated. Perman and Stern (2003)[21] found a U-shaped or monotonically increasing relationship between sulphur emissions and per capita income in a largish minority of 74 countries. This finding is against the EKC hypothesis.

An issue of heteroskedasticity may be important for regressions of grouped data (Stern et al, 1996)[35] because OLS estimation is inefficient even if it is consistent and unbiased. A GLS estimation, which adjusts for heteroskedasticity, can significantly improve goodness of fit (Stern, 2002)[31]. Moreover, using a heteroskedasticity-covariance matrix estimator introduced by White (1980)[41] can allow for the attainment of consistent and efficient parameter estimates in the presence of heteroskedasticity.

Stern and Common (2001)[34] estimated a logarithmic quadratic EKC for the world sample and subsamples of OECD and non-OECD. A turning point of income can be calculated by the formula

$$\tau = \exp(-\beta_1/(2\beta_2)). \tag{2.7}$$

Their random-effects and fixed-effects estimations found statistical support for a monotonic relationship between per capita sulphur emissions and per capita income in the global sample. The random-effects model could not be estimated consistently as the Hausman test indicated correlation between time-invariant effects and independent variables. However, the random-effects estimators in 23 OECD countries were consistent because the individual effects were not correlated with independent variables. The EKC was an inverted U shape in the OECD sample. In the case of non-OECD countries, the random-effects model could not be estimated consistently.

The EKC was monotonically increasing in income. The Hausman test showed significant differences between the parameters of the random-effects and fixed-effects model for both global and non-OECD samples, and the independent variables of the two samples were correlated with specific effects.

Stern and Common (2001)[34] also estimated the first difference model for the World, OECD and non-OECD separately by using OLS and fixed-effects estimations. The EKC was monotonic in each sample. The first differences reduced the serial correlation and eliminated the between effects, which were related to specification problem for level models. Stern and Common (2001)[34] realized that the relationship between sulphur emissions and income was monotonically increasing in income for both OECD and non-OECD countries. As a result, the reduction in sulphur emissions was time-related instead of income-related. This result is against the EKC hypothesis.

Friedl and Getzner (2003)[10] suggested that the EKC hypothesis was not reasonable. They found a cubic relationship between per capita real GDP and total CO_2 emissions. Dinda (2004)[8] provided an overview of literature on the EKC up to 2004 and existence of EKC is questioned from several dimensions. They suggested that different stages of economic growth had different relationships between pollutants and income, and that environmental pollution was a multifaceted problem. Dinda (2004)[8] used a reduced form model to test various relationships between pollution and income by using panel data.

$$y_{it} = \alpha_i + \beta_1 x_{it} + \beta_2 [x_{it}]^2 + \beta_3 [x_{it}]^3 + \beta_4 z_{it} + \varepsilon_{it} \tag{2.8}$$

y represents environmental indicators, x represents income, z represents other variables of influence on environmental degradation. i represents a country and t is time.

In terms of a peak point of the EKC, there is a misinterpretation on the EKC hypothesis that policies increasing GDP lead a country to peak on the curve as soon as possible. Panayotou (1993)[19] proposed that a deep and upward sloping part of the EKC indicated that quick economic development could lead to irreversible damages during early periods of development. Examples include tropical deforestation, and loss of biodiversity. To prevent this, developing countries may be able to flatten the EKC out by eliminating policy distortions. These are early ideas about the research of the EKC relationship between environmental quality and economic development. There are several situations as follows:

1. $\beta_1 = \beta_2 = \beta_3 = 0$ There is no relationship between environmental pollution and economic development.

2. $\beta_1 > 0$ and $\beta_2 = \beta_3 = 0$ A monotonic increasing relationship between x and y.

3. $\beta_1 < 0$ and $\beta_2 = \beta_3 = 0$ A monotonic decreasing relationship between x and y.

4. $\beta_1 > 0, \beta_2 < 0$ and $\beta_3 = 0$ An inverted U-shaped relationship, such as EKC.

5. $\beta_1 < 0, \beta_2 > 0$ and $\beta_3 = 0$ A U-shaped relationship between x and y.

6. $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 > 0$ A cubic polynomial or N-shaped figure.

7. $\beta_1 < 0$, $\beta_2 > 0$ and $\beta_3 < 0$ Opposite to the N-shaped curve.

Results from many studies cast doubt on the EKC hypothesis of inverted U-shaped curve. Researchers have found different relationships between environmental pollution and per capita income depending on different samples, different estimation methods and different properties of data. As a result, even though the EKC hypothesis is supported for some pollutants in developed countries, it need not indicate that the EKC hypothesis will occur in developing countries. Whether the EKC hypothesis holds is conditional upon many factors.

Based on the above review on the EKC hypothesis and factors affecting CO_2 emissions, many factors have an impact on CO_2 emissions and the results from some studies provide statistical evidence which do not support the EKC hypothesis. Different countries, different estimation methods and different properties of data may lead to different relationships between CO_2 emissions and economic growth. As such, this paper analyzes features of CO_2 emissions in China in order to determine factors which may affect CO_2 emissions in China. Also, specification analysis is necessary to select an appropriate model and to obtain consistent and valid estimates.

Chapter 3

Features of CO_2 Emissions in China

3.1 The Impacts of Economic Development on CO_2 Emissions

Chinese CO_2 emissions are mainly due to combustion of solid fuels (coal and wood), liquid fuels (gasoline, diesel and kerosene), gaseous fuels (methane) and cement production. As Figure 3.1 shows, share of CO_2 emissions from solid fuel combustion was dominant in 1995, 2005 and 2009. The share of CO_2 emissions from gaseous fuel combustion was lowest in 1995, 2005 and 2009. The share of CO_2 emissions from gaseous fuels in 1995 was lower than that in 2009. And the share of CO_2 emissions from solid fuels consumption decreased from 1995 to 2009. The Figure 3.1 shows that the CO_2 emissions from "other sources" increased steadily from 7.1% in 1995 to 10.7% in 2009. Cement production is an important component of the other categories. [1]

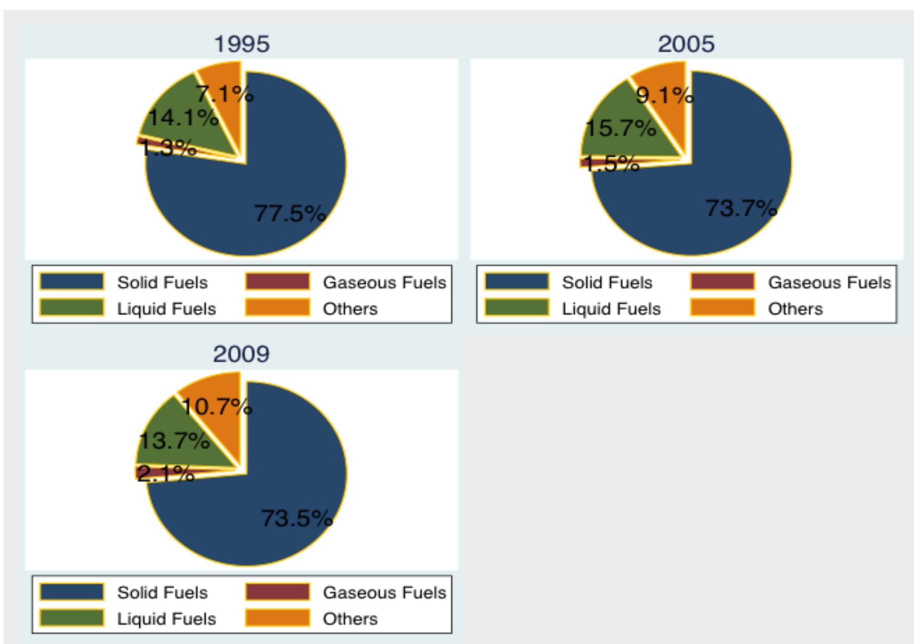

Figure 3.1: Share of CO_2 Emissions from Solid, Gaseous and Liquid Fuels in China

[1] World Development Indicators Online Database, World Databank.

As can been seen from Figure 3.2, the proportion of China's CO_2 emissions from cement production out of global CO_2 emissions from cement production has increased year by year. In 2008, it was 48.92% due to the rapid growth of China's cement production. Since 1990, it has been among the first in the world. And China's CO_2 emissions per unit of the cement production were significantly higher than the major developed countries if we used data (CDIAC) about CO_2 emissions to be divided by cement production. Therefore, CO_2 emissions from cement production may be an important contributor driving the total CO_2 emissions of China up. [2]

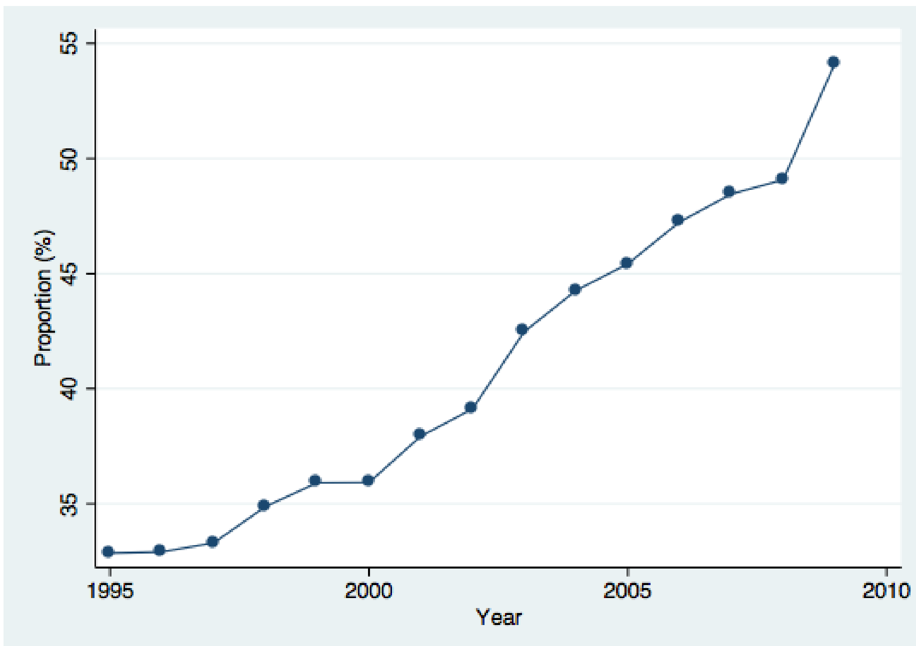

Figure 3.2: Ratio of China's to Global CO_2 Emissions from Cement Production

3.2 Rapid CO_2 Emissions Growth but Low Per Capita Emissions and Cumulative Emissions

Economic levels and energy consumption in China are growing rapidly. At the same time, the growth of CO_2 emissions from cement production and fossil fuel combustion has also accelerated (shown in Figure 3.3) and, overall, CO_2 emissions of China have

[2] Data resource: Carbon Dioxide Information Analysis Centre, CDIAC.

increased rapidly, growing from 3.35 to 7.55 billion tonnes between 1995 to 2008, an increase of 125%.

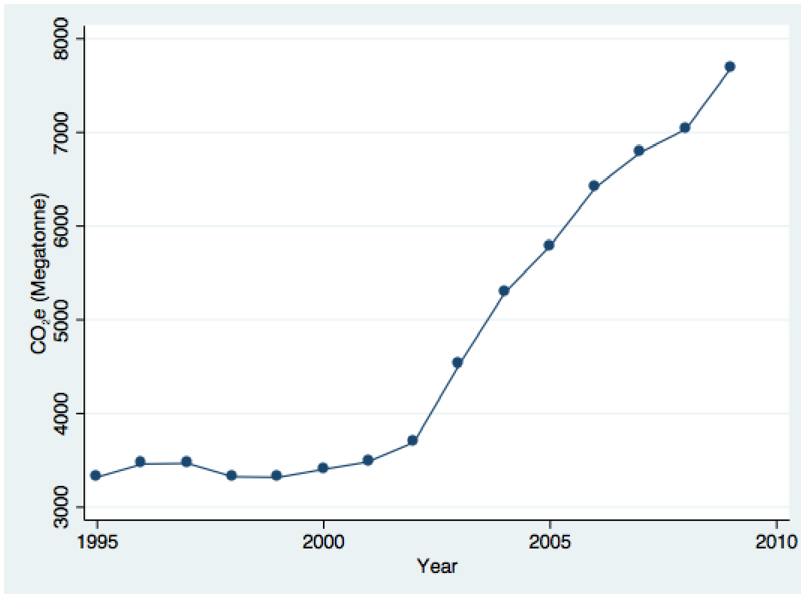

Figure 3.3: Changes in CO_2 Emissions from Cement Production and Fossil Fuel Combustion

In contrast to these yearly emissions, cumulative CO_2 emissions of China compared with industrialized countries are not high. From 1990 to 2004, cumulative CO_2 emissions of China accounted for only about 7.96% of the world cumulative emissions. The proportion was significantly lower than that of the USA, Western Europe and Central Europe. Cumulative emissions in the USA were the largest proportion at 28.02%; Central Europe at 17.01%; and Western Europe at 13.94%. Cumulative CO_2 emissions of China between 1999 and 2004 were only equivalent to 28.39% of the cumulative CO_2 emissions of the USA over the same period. [3]

Per capita CO_2 emissions in China are significantly lower than those in the major developed countries and also the world average level. Although total CO_2 emissions of China are large, the value becomes lower than the world average level when it is divided by population. In 2000, per capita mass CO_2 emissions of China were 2.7 metric tonnes that were equivalent to 65.85% of the world average level that was 4.1

[3]Data source: CO_2 Emissions from Fuel Combustion, 2010 edition, IEA, Paris

metric tonnes per capita. Moreover, it was equal to 13.37% of the USA's 20.2 metric tonnes CO_2e per capita, and was equal to 27.59% of Japan's 9.6 metric tonnes CO_2e per capita. In 2006, per capita CO_2 emissions of China first passed the average world level. Per capita CO_2 emissions of China were 4.9 metric tonnes, which was 104% of the world level (4.7 metric tonnes CO_2e per capita). By 2009, per capita CO_2 emissions of China had increased to 5.8 metric tonnes (123.4% of the world average level), which was 4.7 metric tonnes CO_2e per capita, and it was equivalent to 26.71% of the USA's 17.6 metric tonnes CO_2e per capita and 54.77% of Japan's 9.2 metric tonnes CO_2e per capita. [4]

3.3 Large Regional Differences in CO_2 Emissions of China

Figure 3.4 shows that during the period between 1995 and 2000, growth rates of CO_2 emissions in the Eastern, Central and Western regions were relatively low. The reasons may be because the levels of economic development and industrialization were relatively low. China also has mainly relied on labour intensive industries such that energy consumption and CO_2 emissions levels grew slowly. However, after 2000, with the development of industrialization, the CO_2 emissions of the three areas have grown rapidly.

Based on the above literature review and the features of CO_2 emissions in China, the EKC studies are discordant because there are many indicators affecting the environment. Most studies focus on estimating relationships between CO_2 emissions and the economic growth in developed countries. As CO_2 emitted from cement production is a major contributor of "other" category, the sum of CO_2 emissions from energy combustion and cement production would be pretty close to the mass CO_2 emissions in China excluding LULUCF. So this paper will use CO_2 emissions from cement production and fossil fuel combustion as total CO_2 emissions not including LULUCF. Also, the different features of regional CO_2 emissions make it necessary to estimate different relationships between per capita CO_2 emissions from cement production and fossil fuel combustion respectively in the Eastern, Middle and Western regions. But the EKC is a questionable hypothesis.

[4] Data source: World Development Indicators Online Database, World Databank

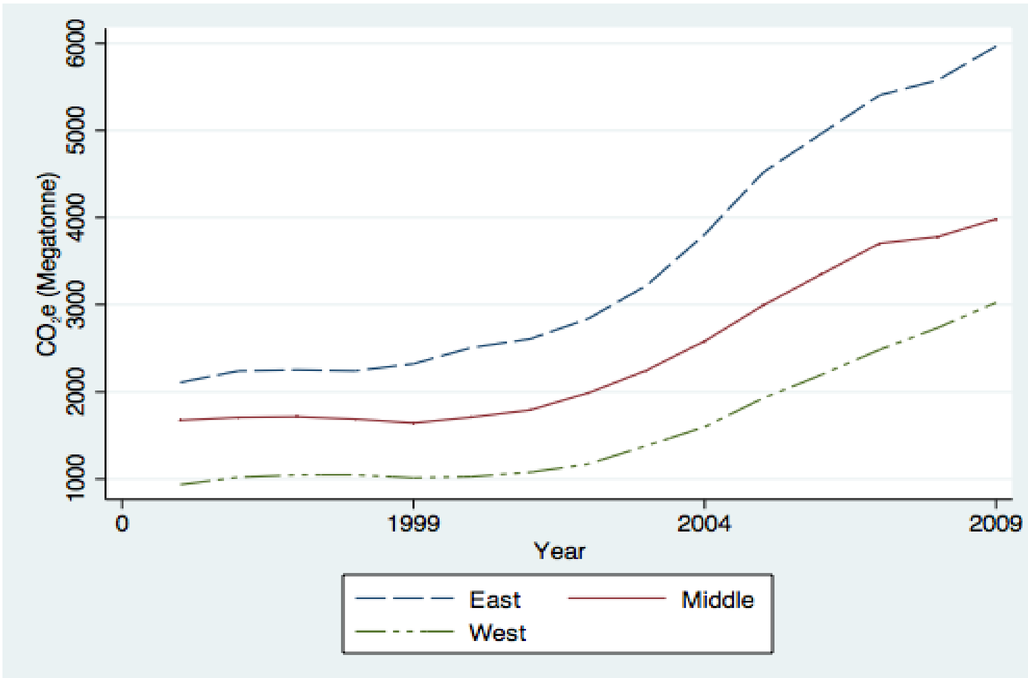

Figure 3.4: Comparison of CO_2 Emissions for the Three Regions in China

Therefore, this paper estimates whether there exits the EKC relationship between per capita CO_2 emissions from cement production and fossil fuel combustion and per capita real GDP in China. Other factors, such as urbanization represented by proportion of urban population, shares of GDP from the industrial and service sectors, and energy intensity of GDP also need to be considered in order to avoid an omitted-variable problem. Due to the required variables, the raw data required to calculate these variables are CO_2 emissions from cement production and fossil fuel combustion, real GDP, urban population, total population, GDP from the industrial sector, GDP from the service sector. The data description is shown in the next part.

Chapter 4

Data

Per capita real GDP is used as a proxy measure for economic development of various provinces. In order to eliminate the impact of price factors, researchers should calculate the per capita GDP of each province adjusted by GDP deflators of different provinces. We use the GDP deflator to convert the nominal GDP into constant prices in 1995 currency.

Data for GDP, total population and urban population in 27 provinces are from the China Population Statistics Yearbook[23] from 1996 to 2008 and the China Population and Employment Statistics Yearbook during 2009 and 2010[22].

Industrial structure is represented with the share of total GDP in the industrial sector and the share of total GDP in the service sector. The share of GDP in the industrial sector is GDP from the industrial sector over the total GDP times 100. The share of GDP in the service sector is GDP from the service sector over the total GDP times 100. Data for GDP from the industrial and service sectors are derived from the online database of National Bureau of Statistics of China and the New China Six Decades Statistical Information Yearbook[27].

Data about the total energy consumption and energy intensity of GDP (metric tonnes of coal equivalent/10000 RMB) are from the China Energy Statistical Yearbook[26]. Data for cement production are from China Cement Almanac[25].

Using this Data from 27 provinces over 1995 to 2009, we can calculate per capita CO_2 emissions from cement production and fossil fuel combustion (metric tonnes) by dividing total provincial CO_2 emissions from cement production and fossil fuel combustion (10000 metric tonnes) by the population. Similarly, per capita real GDP

(RMB per person) is found by dividing real GDP (10000 RMB) in each province by total population (10000 heads). We calculate the proportion of urban population (%) by urban population (10000 heads) over total population (10000 heads) times 100. And energy intensity of GDP (metric tonnes of coal equivalent/10000 RMB) is found by dividing energy consumption (metric tonnes of coal equivalent) by the total GDP (10000 RMB) in each province.

Details of the calculation of CO_2 emissions from cement production and fossil fuel combustion are explained in the first section of chapter on methodology. Also, the model description and specification tests for deciding panel data models are in the second section.

Chapter 5

Methodology

As the amount of CO_2 emissions in each of the provinces is not reported directly by the Chinese government, methods for computing CO_2 emissions from cement production and fossil fuel combustion are required. This paper estimates CO_2 emissions primarily based on 2006 IPCC Guidelines for National Greenhouse Gas Inventory[3]. These guidelines provide a standardized methodology for estimating GHG emissions.

5.1 CO_2 Emissions from Cement Production and Fossil Fuel Combustion Estimates

The 2006 IPCC Guidelines[3] provide three tiers for estimating emissions from cement production and fossil fuel combustion. Methodological complexity is ranked by a tier. Tier 1 is a basic method, Tier 2 is intermediate, and Tier 3 is the most demanding in terms of complexity with the highest data requirements. Tier 1 methods should be feasible for all countries as they are designed for all categories to use readily available national or international statistics combined with provided default emission factors and additional parameters.

A reference approach in the 2006 IPCC Guidelines[3] can be used as an independent check of the sectoral approach in order to compute a "first order" estimate of national GHG emissions when the inventory compiler has limited availability on sources and data structures. During the combustion process, most of carbon is emitted immediately as CO_2. Even though some of carbon is emitted as "non-CO_2" gases, such as carbon monoxide (CO), methane (CH_4) and so on, these eventually oxidize to CO_2 in the atmosphere. The amount of carbon in "non-CO_2-gas" emissions is much smaller than that of carbon in CO_2 emissions. Therefore, Tier 1 is sufficiently accurate to estimate CO_2 emissions from the carbon in a combusted fossil fuel.

The Tier 1 method explains that the carbon content of a fuel is a key determinant of a factor of CO_2 emissions. CO_2 emissions can be estimated based on the total amount of fuels combusted and the carbon content of fuels on average because combustion conditions (combustion efficiency, carbon retained in ashes and slashes etc.) are relatively insignificant. In addition, factors of CO_2 emissions only depend on carbon content of a fuel because efficient fuel combustion leads to maximum oxidation rate of carbon in the fuel, which means that the factors are relatively insensitive to the combustion process. As a result, the Tier 1 method based on fuel carbon content and fuel amount is sufficient to estimate CO_2 emissions from fossil fuel combustion.

The 2006 IPCC Guidelines point out that conversion of energy units is required because energy statistics and other data compilations report production and consumption of solid, liquid and gaseous fuels in physical units such as metric tonnes or cubic meters. Therefore, net calorific values (NCVs) are necessary to convert these data to common energy units. The NCV, alternatively, is called the "lower heating value", which is a useful calorific value in a boiler plant.

The CO_2 produced by burning fossil fuel is calculated by the following formula:

- CO_2 emissions = fossil fuel consumption × NCV× CO_2 emissions factor
- CO_2 emission factor=default carbon content × carbon oxidation factor × (44/12)

The formula is

$$CO_2ff = \sum_{i=1}^{n} ff_i^{PV} \times NCV_i \times CC_i \times O_i \times (44/12) \tag{5.1}$$

CO_2ff represents CO_2 emissions from fossil fuel in units of metric tonnes; i refers to different fuel types; ff^{PV} refers a mass or physical volume of fossil fuel consumption (metric tonnes or cubic meters); NCV refers to the net calorific value of each fuel measured as terajoule/metric tonne (TJ/t) or TJ/m^3; CC refers to the carbon content of fuels (metric tonnes C/TJ or kg/GJ); O refers to a oxidation rate predicted as 100% oxidation, which is a IPCC default value; 44/12 is a molecular weight ratio of carbon

Table 5.1: Net Calorific Value and Carbon Defaults of Different Fuels

Fuel type	NCV(TJ/Gg)	Carbon content(metric tonne/TJ)
Anthracite	20.9	26.8
Coking Coal	26.3	25.8
Coke	28.4	29.2
Coke Oven Gas	18	12.1
Gas Work Gas	15.9	12.1
Petroleum Coke	32.7	26.6
Crude Oil	41.8	20
Gasoline	43.1	19.5
Kerosene	43.1	19.5
Diesel Oil	42.7	20.2
Residual Fuel Oil	41.8	21.1
Liquefied Petroleum Oil	50.2	17.2

Net calorific value taken from China Energy Statistical Yearbook 2010; carbon content, oxidation rate of reference values using the IPCC 2006

to CO_2. Table 5.1 shows the $NCVs$ and default values of carbon content of different fuels. Based on the above information and equations, we are able to compute total CO_2 emissions from fossil fuel combustion.

Basically, there is no CO_2 emissions from cement production. The 1996 IPCC Guidelines recommend clinker data to estimate CO_2 emissions because clinker production emits CO_2 as a by-product. In the production of clinker, a component of cement, calcium carbonate ($CaCO_3$) is calcined and converted to lime (CaO). CaO is also a primary component of cement. As a result, CO_2 is an intermediate product in a cement production. This process can be described as a chemical equation.

$$CaCO_3 + heat \longrightarrow CaO + CO_2 \tag{5.2}$$

In addition, since fossil fuel combustion is the primary energy source during cement production and this causes CO_2 emissions, these should be added to the CO_2 emissions from clinker production, and is included in the above calculation of CO_2 emissions from fossil fuel combustion. Therefore, we are not required to recalculate it.

Even though clinker data is recommended by 1996 IPCC Guidelines, clinker statistics are not readily available in China. Fortunately, the Tier 1 method provides another way to estimate CO_2 emissions from cement production. This paper uses cement production data from China Cement Almanac to estimate clinker production. Gibbs et al (1997)[11] stated that Portland and masonry cement are the two most common types of cement. Moreover, as lime (CaO) is required more by masonry cement than by Portland cement, masonry cement creates additional CO_2 emissions. Unfortunately, data about cement production from China Cement Almanac does not separate cement production by types. In absence of this information, it is reasonable to assume that both masonry cement and Portland cement are produced. According to the 1996 IPCC Guidlines, assuming a clinker fraction of 75% is a good practice.

To estimate CO_2 emissions from cement production, an emission factor for clinker is required. To find this, we multiply CaO by 0.785 and by 0.646. 0.785 refers to the molecular weight ratio of CO_2 to CaO in the raw material mineral calcite ($CaCO_3$), from which most or all of the CaO in clinker is derived. The Tier 1 method uses 64.6% that is the IPCC default value for the fraction CaO in clinker. Therefore, the clinker emission factor is 0.507 metric tonnes CO_2 per tonne of clinker.

Now, we are ready to estimate CO_2 emissions from cement production. Firstly, multiply the mass of cement production by the clinker fraction (0.75), in order to get the mass of clinker production. Then multiply the mass of clinker production times clinker emissions, in order to obtain the mass of CO_2 emissions from clinker production. Finally, add the CO_2 emissions from clinker production to the CO_2 emissions from fossil fuel combustion to obtain the total emissions from cement production and fossil fuel combustion.

CO_2 emissions from the clinker production is calculated according to the following formula:

$$CO_2clc = Mc \times K \times EFclc = Mc \times 0.75 \times 0.507 \tag{5.3}$$

$$CO_2e = CO_2ff + CO_2clc \tag{5.4}$$

where CO_2e is the mass CO_2 emissions from cement production and fossil fuel combustion. CO_2clc represents mass CO_2 emissions from cement production. K is the default clinker content of 75%. $EFclc$ represents the value of the clinker emissions factor of 0.507, and Mc represents the mass of produced cement. Then CO_2e divided by total population of each province is per capita CO_2 emissions from cement production and fossil fuel combustion. Hereafter, we will say per capita CO_2 emissions in short instead of per capita CO_2 emissions from cement production and fossil fuel combustion.

5.2 Model

In this section, the econometric equation is constructed. Then, tests for selection of panel data model will be explained.

This paper generates a panel regression model to test the EKC hypothesis. We use a panel data set for 27 provinces of China from 1995 to 2009. A quadratic term of log of per capita real GDP is added to test the inverted U-shape relationship between per capita real GDP and per capita CO_2 emissions (Andreoni and Levinson, 2001)[1], and cubic term of log of per capita real GDP is used for empirically testing a cubic relationship due to findings of a cubic relationship between per capita real GDP and per capita CO_2 emissions by Friedl and Getzner (2003)[10]. This model, moreover, estimates effects of urbanization and industrial structure on per capita CO_2 emissions. Therefore, the model includes log of per capita CO_2 emissions ($lnCO_2e/p_{it}$) on the left-hand side, and log of per capita real GDP (lny_{it}), quadratic term of log of per capita real GDP ($(lny_{it})^2$), cubic term of log of per capita real GDP ($(lny_{it})^3$), proportion of urban population ($PURB_{it}$), share of GDP from industrial sector (IND_{it}), the share of GDP from service sector (SC_{it}), and log of energy intensity ($lnEI_{it}$).

Due to the panel data set with 27 provinces of China over 15 years, we need to determine whether a fixed-effects or a random-effects model is appropriate. First of all, we take a look at within and between variation of the panel summary statistics. Time-invariant regressors have zero within variation and individual-invariant regressors have zero between variation. Therefore, in Table 5.2, the province has zero within variation and the between variation of the year is zero.

For all other variables, even though the variation across individual provinces (between variation) is more than over time (within variation), there is sufficient variation in both dimensions. As a result, the Hausman test is required to decide whether a random-effects model is appropriate or not.

Table 5.2: Panel Summary Statistics

Variables		**Mean**	**Std.Dev.**	**Min**	**Max**	**Obsrvations**
Province	Overall	14.00	7.80	1.00	27.00	N=405.00
	Between		7.90	1.00	27.00	n=27.00
	Within		0	14.00	14.00	T=15.00
Year	Overall	8.00	4.33	1.00	15.00	N=405.00
	Between		0	8.00	8.00	n=27.00
	Within		4.33	1.00	15.00	T=15.00
Log of per capita CO_2 emissions (metric tonnes)	Overall	1.73	0.67	-0.92	3.49	N=405.00
	Between		0.57	0.72	3.03	n=27.00
	Within		0.36	-0.61	2.73	T=15.00
Log of per capita GDP (RMB)	Overall	9.04	0.71	7.50	10.99	N=405.00
	Between		0.58	0.72	3.03	n=27.00
	Within		0.43	8.19	10.30	T=15.00
Quadratic term of log of per capita GDP (RMB)	Overall	82.25	13.07	56.30	120.84	N=405.00
	Between		10.65	65.32	108.30	n=27.00
	Within		7.83	67.21	102.29	T=15.00
Cubic term of log of per capita of GDP (RMB)	Overall	752.92	181.27	422.39	1,328.41	N=405.00
	Between		148.15	529.88	1129.14	n=27.00
	Within		108.04	542.23	1037.36	T=15.00
Percentage of urban population (%)	Overall	46.72	17.95	1.83	95.32	N=405.00
	Between		17.51	24.69	86.07	n=27.00
	Within		5.14	23.86	64.04	T=15.00
Share of GDP from Industrial sector (%)	Overall	45.34	6.97	23.50	61.50	N=405.00
	Between		5.83	32.15	53.55	n=27.00
	Within		3.97	36.70	57.70	T=15.00
Share of GDP from Service sector (%)	Overall	38.91	7.08	27.67	75.53	N=405.00
	Between		6.42	30.34	65.51	n=27.00
	Within		3.21	25.78	50.48	T=15.00
Log of Energy Intensity (metric tonnes of coal equivalent/10000 RMB)	Overall	0.62	0.46	-0.21	2.06	N=405.00
	Between		0.43	-0.76	1.47	n=27.00
	Within		0.18	0.18	1.21	T=15

A null hypothesis of Hausman test is that a random-effects model is appropriate and an alternative hypothesis is that a fixed-effects model is appropriate. As the p-value is zero, the null hypothesis should be rejected. Therefore, the fixed-effects model is appropriate for the panel data. Furthermore, we are going to test cross sectional dependence, which is also called spatial dependence, in the fixed-effects model. A null hypothesis of Pesaran's test of cross sectional independence is that there is no cross sectional dependence, and an alternative hypothesis is that there is cross sectional dependence. Due to a zero p-value, we reject the null hypothesis so the cross sectional dependence exists in the fixed-effects model.

Next, we test for heteroskedasticity and serial autocorrelation in the fixed-effects model. A modified Wald test for groupwise heteroskedasticity in the fixed-effects regression model rejects the null hypothesis that there is no heteroskedasticity; as a result, heteroskedasticity exists in the fixed-effects model. In addition, a Wooldridge test for autocorrelation in panel data does not reject the null hypothesis that there is no first order autocorrelation. Therefore, this result suggests that there does not exist serial autocorrelation in the fixed-effects model.

A general form of a fixed-effects model is

$$y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \tag{5.5}$$

$$u_{it} = \alpha_i + \varepsilon_{it} \tag{5.6}$$

The error term including time-invariant component of error (α_i) and idiosyncratic error (ε_{it}) in the fixed-effects model is shown in (5.6). α_i in the fixed-effects model represents individual-level effects. The fixed-effects model permits endogeneity that regressors can be correlated with α_i. However, the regressors have to be uncorrelated with ε_{it}.

The estimators of the parameters β in the fixed-effects model must remove the individual effects α_i in order to obtain consistent estimators. The individual effects α_i

can be eliminated as follows:

$$(y_{it} - \bar{y}_i) = (x_{it} - \bar{x}_i)'\beta + (\varepsilon_{it} - \bar{\varepsilon}_i) \tag{5.7}$$

where, for example, $\bar{x}_i = T_i^{-1} \sum_{t=1}^{T_i} x_{it}$. This leads to the within model and the within estimators perform OLS on the mean-differenced data. In the within model, OLS leads to consistent estimates of β as a result of eliminating α_i, even though α_i is correlated with x_{it}.

Thereby, we know how a fixed-effects model generates consistent parameter estimates, and we are able to construct the fixed-effects model with heteroskedasticity and cross sectional dependence.

$$\begin{aligned} lnCO_2e/p_{it} = \alpha_i + \beta_1 lny_{it} + \beta_2(lny_{it})^2 + \beta_3(lny_{it})^3 + \beta_4 PURB_{it} + \beta_5 IND_{it} \\ + \beta_6 SV_{it} + \beta_7 lnEI_{it} + \varepsilon_{it} \end{aligned} \tag{5.8}$$

Because the Modified Wald test shows that heteroskedastic disturbances exist in the fixed-effects model, which means that the error term is not identically distributed, we need heteroskedasticity-robust estimates of standard errors that are consistent. White (1980)[41] demonstrated that heteroskedastic covariance matrix estimator, which is consistent even when the disturbances are heteroskedastic, allowed correct inferences and confidence intervals to be obtained even though the heteroskedasticity was not completely eliminated. However, the covariance matrix estimator only can solve heteroskedasticity of the error term instead of the cross sectional dependence.

This paper introduces another robust standard error for panel regressions with cross sectional dependence; these are the Driscoll-Kraay standard errors (Hoechle, 2007)[14]. The Driscoll-Kraay standard errors are used because the cross sectional dependence of regression residuals can lead to biased statistical inference. Therefore, an assumption of spatially independent disturbances is inappropriate. Also, robust standard errors from covariance matrix estimation, such as White, OLS, or clustered standard errors, are biased and statistical inferences on such standard errors are invalid. The

Driscoll-Kraay standard errors are much better than those covariance matrix estimator when cross sectional dependence exists because the Driscoll-Kraay standard errors allow cross sectional dimensions greater than temporal dimensions. Therefore, statistical inferences with cross sectional dependence in disturbances should be based on the Driscoll-Kraay covariance matrix estimator (Hoechle, 2007)[14].

This paper divides a global sample of China into three regional subsamples, East, Middle and West as levels of economic development in the three regions are highly different. We run the same set of tests on each of the three respective regions data as has been done for the global sample of China. The results show that data from three regions have heteroskedasticity, but exhibit serial autocorrelation (temporal dependency) instead of cross sectional dependence. Based on this situation, Roger (1994)[29] suggested clustered standard errors, which are consistent with heteroskedasticity and serial autocorrelation.

As a result, our fixed-effects model in China has heteroskedasticity and cross sectional dependence, which lead to inconsistent estimates and statistical inferences. When we study a relationship between per capita CO_2 emissions and per capita real GDP, the fixed-effects models of the three regions have heteroskedasticity and serial autocorrelation. In next chapter, we will compare different regression results from both heteroskedasticity-covariance estimation and Driscoll-Kraay covariance estimation. In addition, regression results of three regions of China will be demonstrated. The next chapter explains how these special estimations solve these problems for fixed-effects panel model in detail.

Chapter 6

Empirical Analysis

Due to the possibility of heteroskedasticity, cross sectional dependence and serial autocorrelation among the fixed-effects model, this chapter demonstrates specification analysis in order to obtain consistent estimators and valid statistical inferences.

In fact, the usual covariance matrix estimators equal the heteroskedasticity-robust covariance matrix estimators in the absence of heteroskedasticity. If there exists heteroskedasticty in disturbances in a model, the usual covariance matrix estimates are inconsistent and statistical inferences are invalid. Parameter estimates are consistent but inefficient. White (1980)[41] introduced a heteroskedasticity covariance matrix estimator that is consistent in the presence of heteroskedasticity. The heteroskedasticity-consistent covariance estimator allows us to make valid inferences and construct appropriate confidence intervals.

Model 1 shown in Table 6.1 is a fixed-effects model with robust standard errors. A heteroskedasticity-consistent covariance matrix estimator allows parameter estimates to be consistent and efficient if and only if the heteroskedasticity in disturbances is a single problem in this model. However, the fixed-effects model also displays cross sectional dependence in residuals. The presence of the cross sectional dependence in the fixed-effects model will cause the estimated standard errors of parameters to be inconsistent (Driscoll and Kraay, 1998)[9]. As a result, incorrectly ignoring the spatial (cross sectional) and temporal dependence in residuals can lead to biased statistical results and assumptions of cross sectional independence are inappropriate.

Table 6.1: Comparison of Fixed-Effects Models with Heteroskedasticity-Robust Standard Errors and with Driscoll-Kraay Standard Errors

	(1) Robust SE	(2) D-K SE
Log of GDP per capita (RMB)	-16.40**	-16.40***
	(6.826)	(3.158)
Quadratic term of log of GDP per capita (RMB)	1.929**	1.929***
	(0.732)	(0.348)
Cubic term of log of GDP per capita (RMB)	-0.0717**	-0.0717***
	(0.0261)	(0.0127)
Proportion of urban population (%)	0.00544	0.00544
	(0.00405)	(0.00500)
Share of GDP from industrial sector (%)	0.0104	0.0104***
	(0.00744)	(0.00196)
Share of GDP from service sector (%)	-0.00109	-0.00109
	(0.00473)	(0.00280)
Log of energy intensity of GDP (metric tonnes of coal equivalent/10000 RMB)	0.613***	0.613***
	(0.161)	(0.0959)
Constants	44.25**	44.25***
	(21.23)	(9.517)
N	405	405

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Currently, in panel data models, a Driscoll-Kraay consistent covariance matrix estimation is the method which accounts for both heteroskedasticity and cross sectional dependence in disturbances at the same time. Driscoll and Kraay (1998)[9] demonstrated that the Driscoll-Kraay consistent covariance matrix estimator is a modification of the standard nonparametric time series covariance matrix estimator.

“In this paper we propose a simple modification of the standard nonparametric time series covariance matrix estimator which remedies the deficiencies of techniques which rely on large T asymptotics. In particular, we show that a simple transformation of the orthogonality conditions which identify the parameters of the model permits us to construct a covariance matrix estimator which is robust to very general forms of spatial and temporal dependence as the time dimension becomes large. The consistency result holds for any value of N including the limiting case in which $N \to \infty$ at any rate relative to T. By relying on nonparametric techniques, we avoid the difficulties associated with misspecified parametric estimators. Moreover, since we do not place any restrictions on the limiting behaviour of N, the size of the cross-sectional dimension in finite samples is no longer a constraint on feasibility, and we can be confident of the quality of the asymptotic approximation in finite samples in which N and T are of comparable size, or even if N is much larger than T, provided that T is sufficiently large." (Driscoll and Kraay, 1998)[9].

As shown in Table 6.1, Model 2 is a fixed-effects model with Driscall-Kraay standard errors. Parameter estimates of both two models give same results but the values of Driscoll-Kraay standard errors are much smaller than that of heteroskedasticity-robust standard errors, with the exception of the proportion of urban population. Because the Driscoll-Kraay consistent covariance matrix estimator allows the fixed-effects panel model to make valid statistical inferences in the presence of heteroskedasticity and cross sectional dependence in disturbances, regression results in Model 2 using Driscoll-Kraay consistent matrix estimation technique will be used to analyze the relationship between per capita CO_2 emissions and per capita GDP in the global sample of China.

As can be seen from the results of model 2 with Driscoll-Kraay standard errors, all coefficients of log of per capita real GDP, quadratic term of log of per capita real GDP and cubic term of log of per capita real GDP are statistically significant at 1% level. The signs of the linear term and cubic term are negative, and the sign on the quadratic term is positive. These results provide statistical support that is in line with the hypothesis of an inverted N-shaped curve for China. This supports the hypothesis that when economic development was in the first stage in China, per capita CO_2 emissions fell as the economic growth was based on agriculture and labour intensive industries. In the next stage, when the income levels increase to a certain level, per capita CO_2 emissions increase because a large part of the national GDP is contributed by energy based industries that consume large amount of fossil fuels. However, when the income levels become really high, per capita CO_2 emissions decrease. The results suggest that it may be possible for China to achieve a decoupling of per capita real GDP from per capita CO_2 emissions.

The coefficient of proportion of urban population is positive but statistically insignificant. This suggests that urbanization does not impact per capita CO_2 emissions in China.

The results of Model 2 show that the parameter estimate (β_5) on share of GDP from industrial sector is statistically significant at a 1% level. This suggests that industrialization plays a key role in increasing per capita CO_2 emissions because most of industries in China are still fossil fuel based including electricity, coal, steel, textiles industries. Thereby, energy saving, emission abatement and governmental policies to restrict increasing number of energy-intensive industries are significant ways to reduce per capita CO_2 emissions.

The energy intensity of GDP exhibits positive effects on per capita CO_2 emissions. As energy intensity reflects both energy efficiency and technological levels, a smaller coefficient suggests a higher level of energy efficiency and technology, and a lower level of energy consumption per unit output, thereby reducing per capita CO_2 emissions. There is a big gap between energy intensity of China and that of developed countries such that there is much room for energy saving. However, China is not able to completely change the coal-dominated energy structure in the short term, so we should focus on application of "low-carbon", "energy-saving", and "emission-reduction" technologies to reduce excessive dependence on fossil fuels, and improve the overall efficiency of energy use.

Figure 6.1 is a scatter plot of per capita CO_2 emissions against per capita real GDP. In Figure 6.1, Shanghai has the highest per capita real GDP, 59448.85 (1995 currency) in 2009, but per capita CO_2 emissions is 14.04 metric tonnes. In Shanxi province, which is the biggest "coal-mining" province, it achieves the highest per capita CO_2 emissions in 2007, which is 32.94 metric tonnes, but per capita real GDP, 11947.1 RMB (in 1995 currency) which is much lower than per capita real GDP in Shanghai.

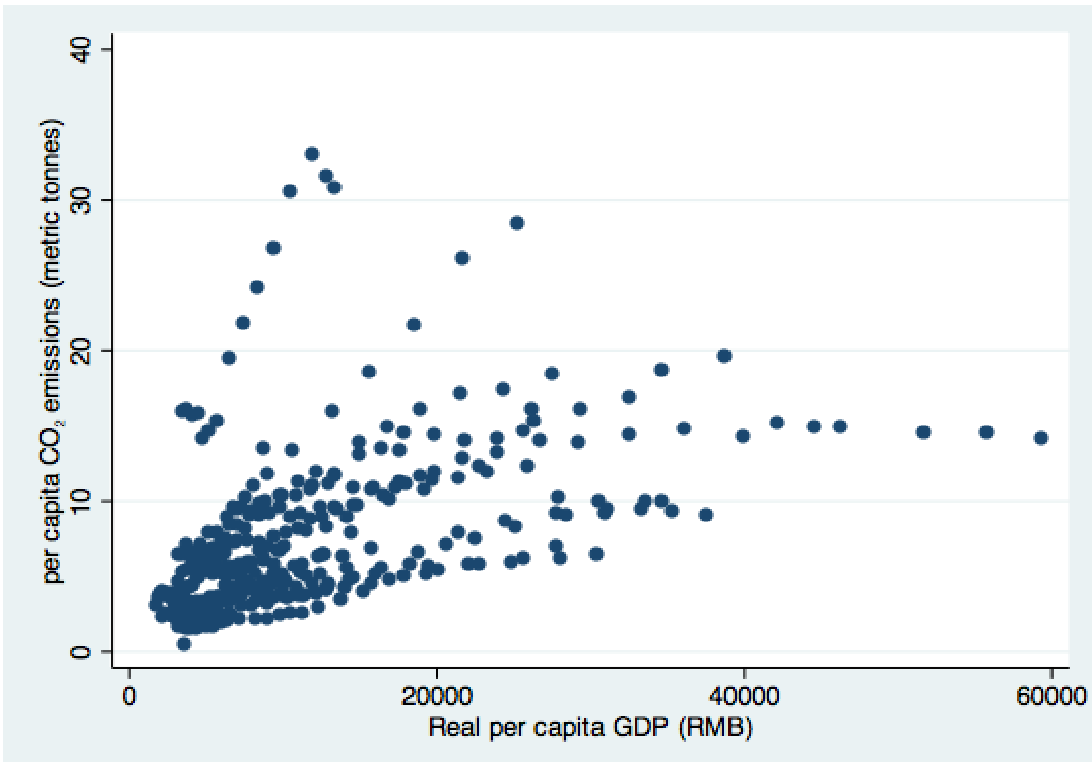

Figure 6.1: Per capita CO_2 emissions vs. Per capita real GDP

In addition, they have totally different industrial structures. In Shanghai, the share of GDP in the industrial sector is 39.89% and the share of GDP in the service sector is 59.36%. In Shanxi province, the share of GDP in the industrial sector is 60% and the share of GDP in the service sector is 35.32%. As a result, when GDP is dominated by the service sector, per capita real GDP is higher but per capita CO_2 emissions are lower than somewhere when GDP is dominated by the industrial sector. When we take a look at Beijing, the share of GDP in the industrial sector is 23.5% but the share of GDP in the service sector is 75%. Beijing has 9 metric tonnes CO_2e per capita and per capita real GDP is 37612.9 RMB (1995 currency). Province-level scatter plot can be found as Figure B.2 in the appendix B.

Figure 6.1 shows a trend of an inverted U shape. At some levels of per capita province-level real GDP, per capita province-level CO_2 emissions peak. But when per capita province-level real GDP exceeds these levels, per capita CO_2 emissions may decrease. This may be because the share of GDP from the service sector is higher than that from the industrial sector.

Based on the above regression results, we can predict values of log of per capita CO_2 emissions holding other variables constant at average levels except of linear term, quadratic term and cubic term of log of per capita real GDP.

$$ln\widehat{CO_2e/}p_{it} = \hat{\beta}_1 lny_{it} + \hat{\beta}_2(lny)^2_{it} + \hat{\beta}_3(lny)^3_{it} + constants + \overline{X}_{it}\hat{\beta} \tag{6.1}$$

in which, $\overline{X}_{it}$ represents a variable vector including average levels of proportion of urban population, share of GDP from industrial sector, share of GDP from service sector and log of energy intensity. As a result, the real function with estimated parameters are shown as following:

$$ln\widehat{CO_2e/}p_{it} = -16.40lny_{it} + 1.929(lny_{it})^2 - 0.072(lny_{it})^3 + 45.317 \tag{6.2}$$

An inverted N-shape curve can be constructed demonstrating a cubic relationship between log of per capita real GDP and log of per capita CO_2 emissions.

A lower and a higher turning point on the log of per capita real GDP can be found in Figure 6.2 up to Equation 6.2 by taking first order condition. The lower point is 6.92 and the higher point is 11.01. As a result, we can predict the per capita province-level real GDP because the exponential of the log of per capita real GDP is per capita province-level real GDP. The exponential of the lower point is 1013.45 RMB (1995 currency) and that of higher point is 60972.06 RMB (1995 currency). The two turning points mean that the model predicts that when the per capita real GDP reaches 1013.45 RMB (1995 currency), the increase in per capita real GDP may increase per capita CO_2 emissions. And when the real income level increases to 60972.06 RMB (1995 currency), the increase of the real income will lead to reduction

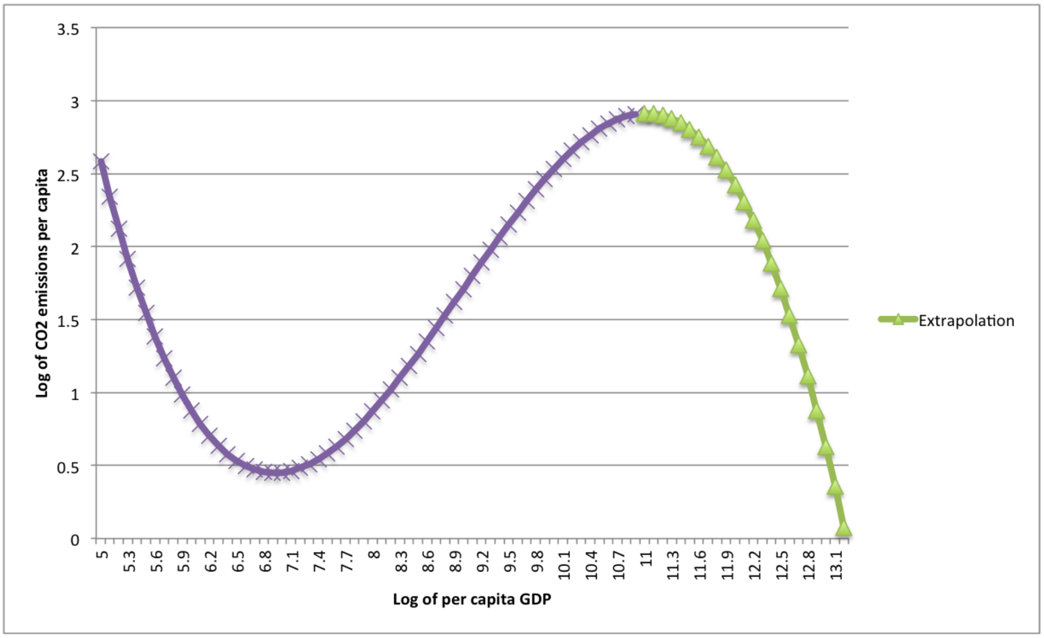

Figure 6.2: Log of per capita CO_2 emissions vs.log of per cpaita real GDP

of CO_2 emissions per capita.

When we take a look at the statistic summary of the panel data, the minimum log of GDP per capita is 7.5 and the maximum level is 10.99. As we can see in Figure 6.2, the range of log of per capita real GDP is on the upward sloping part. Therefore, we can say that per capita CO_2 emissions increases with the economic growth in China during 1995 and 2009. The model predicts that there will be an inverted U-shape curve that will lead per capita CO_2 emissions of China to decrease in the future at an income level of 60972.06 RMB (1995 currency). However, there exists an inverted N curve in China as a whole. It is necessary to note that the actual levels of per capita real GDP in logarithm from the panel data set correspond to the upward sloping part in Figure 6.2. The two turning points are predicted up to a cubic specification.

The exponential of log of per capita real GDP and log of per capita CO_2 emissions allows us to plot the relationship between CO_2 emissions per capita and GDP per capita. The graph is shown below:

In Figure 6.3, the lower point is 1013.45 RMB (1995 currency) and the higher point

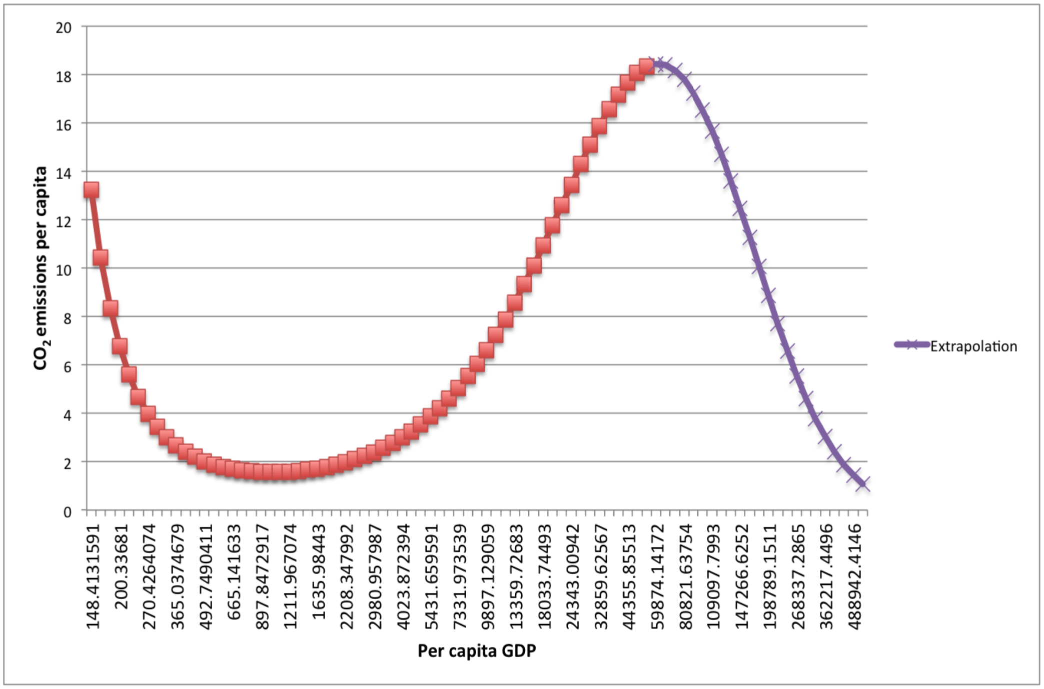

Figure 6.3: Per capita CO_2 emissions vs. Per capita real GDP

is 60972.06 RMB (1995 currency), which is same results obtained by Figure 6.2. The minimum GDP per capita is 1813.6 RMB (1995 currency) and the maximum is 59448.85 RMB (1995 currency) in the panel data of China as a whole. The range of per capita province-level real GDP is upward sloping part and suggesting that there may exist an inverted U-shape curve in the future of China. Therefore, if the model is specified correctly, the statistical results predict that the province-level per capita CO_2 emissions will reduce when province-level per capita real GDP obtains 60972.06 RMB (1995 currency) in the future.

In terms of the downward part at lower income levels in Figure 6.3, increases in the province-level per capita GDP reduce the province-level per capita CO_2 emissions when the province-level per capita real GDP is lower than 1013.45 (1995 currency). Data about energy consumption from World Bank databank show that the share of consumption on solid fuels decreases and the share of consumption on gaseous fuels increases overtime in China. As a result, a shift from solid fuels to gaseous fuels reduces per capita CO_2 emissions with growth of per capita real GDP. This is because technology has been improved with economic growth and gaseous fuels are cleaner than solid fuels. This provides a possible hypothesis for the reason behind early decrease in emissions per capita as incomes rise from low to high levels.

Table 6.2 shows three fixed-effects models with clustered standard errors in the Eastern, Middle and Western regions. Clustered standard errors were used because each regional panel model demonstrates heteroskedasticity and serial autocorrelation in disturbances.

Table 6.2: Regression Results in Fixed-Effects Models with Clustered Robust Standard Errors in Three Regions

	(1) Eastern Region	(2) Middle Region	(3) Western Region
Log of GDP per capita (RMB)	-38.79***	-27.73**	-14.87
	(7.185)	(11.14)	(17.62)
Quadratic term of log of GDP per capita (RMB)	4.289***	3.152**	1.746
	(0.731)	(1.235)	(1.992)
Cubic term of log of GDP per capita (RMB)	-0.154***	-0.115**	-0.0659
	(0.0247)	(0.0456)	(0.0747)
Proportion of urban population (%)	0.00128	0.000990	0.0320**
	(0.00245)	(0.00256)	(0.0114)
Share of GDP from industrial sector (%)	-0.00314	-0.000297	0.00851
	(0.00974)	(0.00231)	(0.0146)
Share of GDP from service sector (%)	-0.0116*	-0.00568	-0.000950
	(0.00600)	(0.00298)	(0.0109)
Log of energy intensity of GDP (metric tonnes of coal equivalent/10000 RMB)	0.813***	0.716***	-0.00215
	(0.0621)	(0.0662)	(0.519)
N	150	120	135
adj. R^2	0.955	0.976	0.814

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Using clustered standard errors relaxes assumptions of independently distributed error terms and independent observations. The clustered standard errors are consistent even though the error terms are correlated within but uncorrelated between clusters.

As a result, parameter estimates and statistical inferences from the fixed-effects models with clustered standard errors in the three regions are consistent and valid (Rogers, 1994)[29].

A cubic relationship between per capita CO_2 emissions and per capita real GDP is statistically significant at 1% level in the Eastern region and at 5% level in the Middle region. However, the cubic relationship is not statistically significant in the Western region. In addition, for the Western region, we found no statistical support for the EKC or the monotonic relationship. The model suggests that economic growth, as measured by the GDP proxy, does not significantly affect per capita CO_2 emissions in the Western region.

Urbanization in the Eastern and Middle regions does not have significant impact on per capita CO_2 emissions. In the Eastern region, urbanization in most areas has developed to a very high level and then slowed between 1995 and 2009. As a result, there are other factors affecting per capita CO_2 emissions. In the Middle region, because large amounts of rural labour forces migrated to the Eastern region, the inadequate urban population has resulted in slow urbanization (Hu, 2008)[15].

However, the estimated parameter of the proportion of the urban population in the Western region is statistically significant at 5% level. This may be because urbanization affects per capita CO_2 emissions in the following ways. Urbanization, industrialization and production require a huge amount of energy, while urbanization accompanied by rising personal income levels and more urban residents boosts energy consumption and increases number of private cars that produce more CO_2.

The share of GDP from the industrial sector was not found to affect per capita CO_2

emissions in the Eastern region. A hypothesis as to why is because some of "energy-based" and "high-GHG-emission" industries have been moved out of developed areas in the Eastern region, such as Beijing and Shanghai, and the share of GDP from the industrial sector has been decreasing. However, the model for the Middle region does not provide reasons that estimated parameter of industrial sector is not statistically significant, even though the main source of GDP in the Middle region is from the industrial sector.

The estimated parameter of the share of GDP from the service sector is statistically significant at 10% level only in the Eastern region. This increase in the share of GDP from the service sector could potentially reduce per capita CO_2 emissions in the Eastern region according to the composition effect because the service sector, such as telecommunication services, finance and insurance services, and education, is less energy intensive. Insignificant coefficients for the service sector in the Middle and the Western regions suggest that the service sector has not developed enough to affect per capita CO_2 emissions. Hence, our results suggest that in order to stop increasing per capita CO_2 emissions, it is important to develop the service sector in the Middle and Western region. When the main contribution of GDP is from the service sector, economic growth by the service sector may decrease per capita CO_2 emissions in the Middle and Western regions in the future.

The coefficients of energy intensity in the Eastern and Middle region are statistically significant at 1% level, but they are not statistically significant in the Western region. Energy intensity reflects the energy utilization efficiency in regional economies, and its changes are summarized as technical and structural factors. As a result, energy intensity does not significantly affect per capita CO_2 emissions in the Western region.

This chapter explains how the fixed-effects model of China with heteroskedasticity and cross sectional dependence obtains consistent coefficients and valid statistical inferences by using the Driscoll-Kraay consistent covariance estimator. The cubic relationship in China suggests that economic development has impacts on per capita

CO_2 emissions. Using clustered standard errors in the three regional models with heteroskedasticity and serial autocorrelation allows for consistent parameter estimators. The results suggest a cubic relationship in the Eastern and Middle regions rather than in the Western region, which suggests that economic development in the Western region cannot significantly affect per capita CO_2 emissions. Given our estimation from the Chinese sample, we predict that there exists an inverted U-shaped curve in the future of China. When per capita real GDP obtains 60972.06 RMB (1995 currency), per capita CO_2 emissions are predicted to decrease with economic growth.

Chapter 7

Conclusion

This paper describes characteristics and drivers of per capita CO_2 emissions from cement production and fossil fuel combustion in China from 1995 to 2009. We use a fixed-effects panel data model derived from $STIRPAT$ model and Kaya identity, and implement Driscoll-Kraay consistent covariance matrix estimation in the global sample of China. Clustered standard errors are used in the three regional panel models with heteroskedasticity and serial autocorrelation to obtain consistent parameter estimates and valid statistical inferences. We predict an inverted N curve as a global curve for China as a whole with an inverted U curve in the future of China. Our results suggest that China's provincial per capita CO_2 emissions decreases with economic growth when China's provincial per capita real GDP obtains 60972.06 RMB (1995 currency).

A summary of our key results is as follows:

First of all, the data suggests that China has a cubic relationship between per capita CO_2 emissions and per capita real GDP at the provincial level. Due to the cubic relationship, we reject the EKC hypothesis for China's economic development over all, but the analysis suggests that there exists an expected EKC in China in a future period at the level of provinces. The Eastern and Middle region demonstrate a cubic relationship, but there does not exist effects of per capita real GDP on per capita CO_2 emissions in the Western region.

Secondly, the share of GDP from service sector affects per capita CO_2 emissions significantly only in the Eastern region. This suggests that increases in the "service-sector" share of GDP can reduce province-level per capita CO_2 emissions in the Eastern region.

Third, the higher "energy-use" efficiency is an important task for the Chinese government because there exists a big gap between energy intensity of China and the energy intensity of developed countries. Also, China is not able to completely change the "coal-dominated" energy structure in the short term, so we should focus on low-carbon, energy-saving, and "emission-reduction" technologies to reduce excessive dependence on fossil fuels, and improve the overall efficiency of energy use.

Based on the above research of China's drivers of per capita CO_2 emissions in the three regions, it is possible that "pollution-intensive" industries may be moving to the Western region for reasons such as lower wages and/or lower pollution regulation. This also provides a possible explanation as to why urbanization significantly increases provincial per capita CO_2 emissions in the Western region.

A contribution of this paper is that we use chemical conversion theory to estimate provincial CO_2 emissions from cement production and fossil fuel combustion in China. It is an important data support for researchers who are going to provincially research CO_2 emissions in China. In addition, the Eastern and Middle region exhibit an inverted N curve separately, but the Western region did not. This paper uses a Driscoll-Kraay consistent covariance matrix estimator which accounts for heteroskedasticity and cross sectional dependence in a fixed-effects model, and uses clustered standard errors to accommodate heteroskedasticity and serial autocorrelation.

Empirical analysis of this paper finds a cubic relationship between province-level per capita CO_2 emissions and province-level per capita real GDP in China. Some of recent researches have criticized empirical work which found support for the EKC hypothesis. Stern (2003)[32] pointed out that there was weak statistical evidence that countries followed an inverted U-shaped pathway as people became richer and richer. Therefore, Stern (2003) considered that the EKC model was unlikely a complete model. Wang (2013)[39] also criticized the EKC estimates as being due to a spurious relationship between pollutants and income levels because of the inadequacy of the quadratic EKC regression. This spurious relationship is the reason of failure of the conventional EKC regression. The quadratic form included in the dynamic panel data model needs to be reconsidered in the future.

We consider these critiques of the EKC as being too extreme because we cannot reject the EKC hypothesis based on our research on the Chinese sample. There exists an expected EKC at the level of provinces in the future of China up to the panel data from 1995 to 2009, even though there is an inverted N curve overall China. In other words, the EKC is a part of the inverted N curve in overall China. Therefore, our research suggests that given current trends, China's province-level per capita CO_2 emissions will reduce in the future of China along with economic growth if China's per capita real GDP achieves 60972.06 RMB (1995 currency).

This paper explains the factors affecting per capita CO_2 emissions. However, findings of this paper are not able to predict how these factors can stabilize the total CO_2 emissions because the fast growth of population may increase the total CO_2 emissions even though per capita CO_2 emissions may decrease. Therefore, in order to stabilize the total CO_2 emissions, a further research on the Kaya identity is required because this identity explains relationships between the total CO_2 emissions, population, GDP per capita, energy intensity and carbon intensity. Figure B.1 in Appendix B shows scatter plots in 27 provinces of China in which total province-level real GDP in 1995 currency against total provincial CO_2 emissions, which may be helpful for the future research.

Appendix A

Glossary

2006 IPCC Guidelines for National Greenhouse Gas Inventory

The 2006 IPCC Guidelines were prepared in response to an invitation by the Parties to the UNFCCC. 2006 IPCC Guidelines provide methodologies for estimating GHGs emissions from cement production and fossil fuel combustion.

CO_2 Emission Factors

CO_2 emission factors are default carbon content, default carbon oxidation factor and 44/12 (molecular weight ratio of CO_2 to C).

Default Carbon Content

Default Carbon Content refers to carbon content of fuels from which emission factors on a full molecular weight basis can be calculated. The 2006 IPCC Guidlines provide default values of the carbon content.

Default Carbon Oxidation Factor

Oxidation factor is the fraction of carbon in fossil fuel, which is oxidized to become CO_2. The default carbon oxidation factor is assumed to be 100% oxidation because a small part of the fuel carbon entering the combustion process escapes oxidation.

Net Calorific Values (NCVs, TJ/Gg)

Net Calorific Values (NCVs) or 'lower heating value' (LHV) is the useful calorific value in boiler plant. The difference is essentially the latent heat of the water vapour produced.

Good Practice

Good Practice is a set of procedures intended to ensure that greenhouse gas inventories are accurate in the sense that they are systematically neither over- nor under-estimate emissions so far as can be judged. Also, uncertainties are reduced so far as possible. Good Practice covers choices of estimation methods appropriate to national circumstances, quality assurance and quality control at national levels, quantification of uncertainties and data archiving and reporting to promote transparency.

Tier 1

The Tier 1 method of estimating GHG emissions is fuel-based, since emissions from all sources of combustion can be estimated on the basis of the quantities of fuel combusted (usually from national energy statistics) and average emission factors. Tier 1 emission factors are available for all relevant direct GHGs.

Tier 2

In the Tier 2 method of estimating energy, emissions from combustion uses similar fuel statistics, as used in the Tier 1 method, but country-specific emission factors are used in place of the Tier 1 defaults. Since available country-specific emission factors might differ for different specific fuels, combustion technologies or even individual plants, activity data could be further disaggregated to properly reflect such disaggregated sources.

Tier 3

In the Tier 3 method for energy emissions estimation, either detailed emission models or measurements and data at individual plant levels are used where appropriate. Properly applied, these models and measurements should provide better estimates primarily for non-CO_2 greenhouse gases, though at the cost of more detailed information and effort.

Reference Approach

The reference approach is designed to calculate CO_2 emissions from fuel combustion, from 2006 IPCC Guidelines.

Appendix B

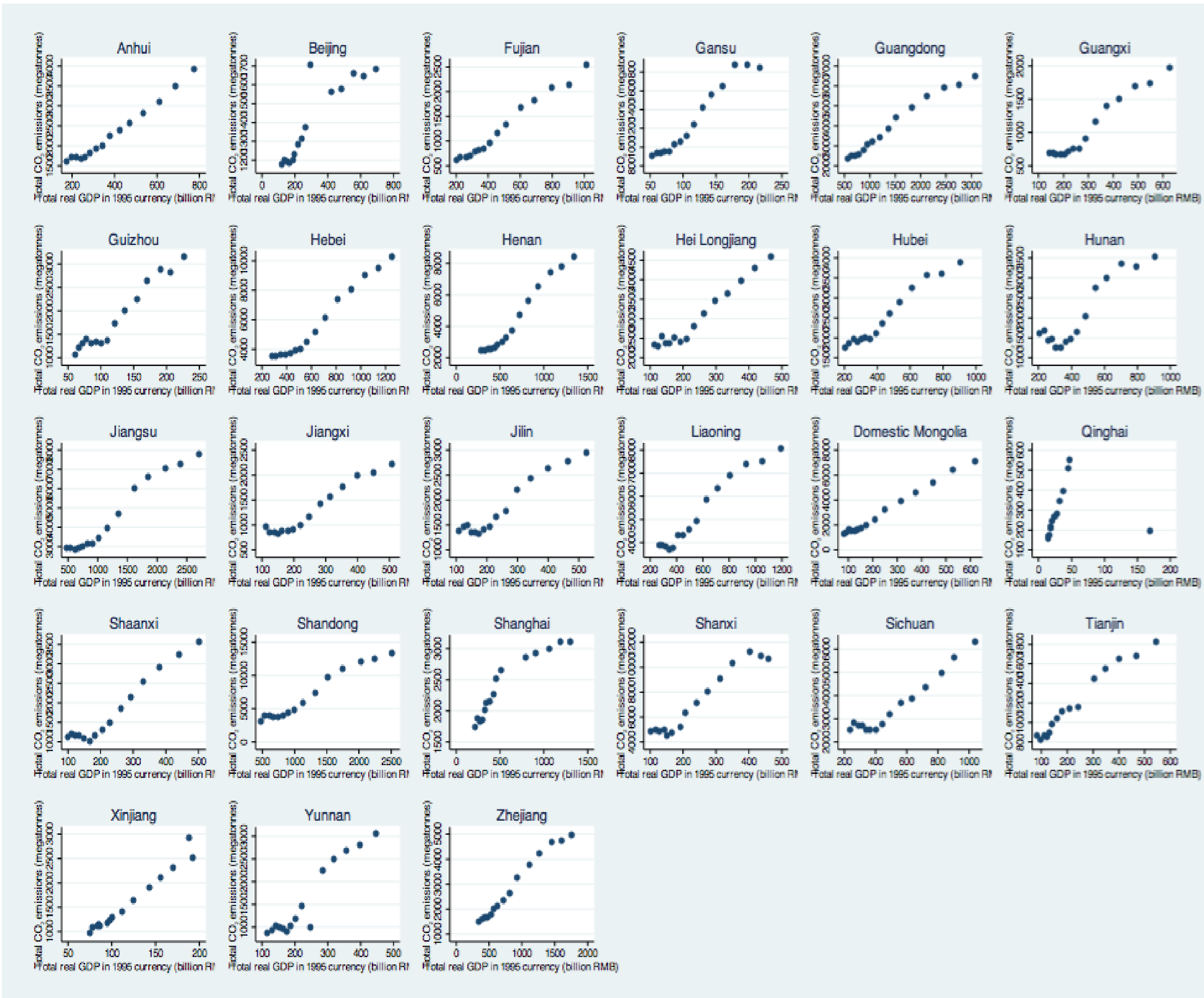

Figure B.1: Total real GDP in 1995 currency vs. Total CO_2 emissions in each of 27 provinces of China

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