THE RELATIONSHIP BETWEEN CO_2 EMISSIONS AND LIVING STANDARDS IN CHINA: A TIME SERIES APPROACH

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Abstract

As China has become the largest emitter of greenhouse gases, there are billions of tons of Carbon Dioxide (CO_2) emitted every year. Due to the fact that pollution is a serious issue, China is confronted with substantial environmental challenge, as well as issues of living standards. It is important to study how CO_2 emissions affect living standards, which is measured by GDP per capita. The ARIMA time series model is used to estimate this relationship, which is based on a time series dataset over 20 years (from 1993 to 2013). We expect a positive relationship between CO_2 emissions and GDP per capita, and the results confirm that our hypothesis is accurate. More specifically, living standards in China are positively affected by total CO_2 emissions and the living standards of the previous year.

Key words: China, CO_2 emissions, GDP per capita, ARIMA time series model.

Contents

1. Introduction

During the last few decades, the relationship between human economic activities and environmental quality has been widely studied. Nowadays, the situation is much more severe. Human economic activities are causing greenhouse gases (GHG) emissions that are resulting in global warming and ocean acidification. According to the Intergovernmental Panel on Climate Change (IPCC), Fifth Assessment Report, the temperature of the atmosphere and oceans has increased and the sea level has risen. Due to increasing temperatures, the amount of snow and ice has gradually decreased, while the concentration of GHG has increased (Stocker, 2013). In terms of carbon dioxide (CO_2), the concentration of CO_2 has increased by 40% since pre-industrial times. Thus, CO_2 emissions are one of the most significant pollutants, which need to be investigated and analyzed further.

Stern (2007) 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 IPCC was established to provide scientific and technological advice for problems caused by GHG. Because GHG are global pollutants and the damages are independent of the location of the source, international cooperation is required to reduce emissions, such as the Kyoto Protocol in 2005. At that time, there was no mandate in China about reducing emissions, but China's economic development has been facing serious challenges since then. Since the reform and opening policy was implemented in 1978, China's economic development has achieved remarkable successes. However, this rapid economic growth has inevitably brought some concerns, such as large consumption of natural resources and increases in CO_2 emissions. As a result, by 2007, China overtook the United States as the largest emitter of GHG, demonstrating the magnitude of China's CO_2 emissions (Zhou et al., 2011).

As the largest emitter of GHG and second largest economy, China is facing increasing international pressure to reduce its GHG emissions and is responsible for GHG reduction. Therefore, the Chinese government had set a short-term goal for reducing energy intensity between 2006 and 2010. Moreover, a longer-term goal was set to reduce carbon intensity by 2020 (Zhou et al., 2011). As the policy was introduced, the growth of CO_2 was intended to slow down, yet it remains questionable how living standards in China will be affected by CO_2 reductions. In this paper, the relationship between CO_2 emissions and living standards is studied. A time series ARIMA model is generated to test the hypothesis, which is based on a 21-year dataset. As a result, findings from this paper demonstrate that living standards in China are positively affected by total CO_2 emissions and the living standards of the previous year.

The rest of this paper has the following structure. Section 2 reviews the literature on the Environmental Kuznets Curve (EKC) hypothesis and empirical evidence. In Section 3, characteristics of CO_2 emissions in China are compared with world levels. Section 4 discusses the related policy background. In Section 5, the process of selecting an econometric model is shown. Section 6 presents the empirical analysis. Finally, Section 7 provides conclusions and discussions of future research.

2. Literature Review

In this section, we review some classical theories in the field of environmental economics. Above all, the Environment Kuznets Curve (EKC) hypothesis is the most important one. The EKC hypothesis indicates that GHG emissions are correlated to output under a scale effect, composition effect and abatement effect. Those effects can generate an inverted U-shaped relationship between CO_2 emissions and economic growth, which is also referred to as the EKC. Besides, under the abatement effect, some other indicators, like energy intensity and urbanization, may affect CO_2 emissions when income level is high. Although we study how CO_2 emission affect living standards, we can get some ideas from the EKC in an inverse direction.

2.1 The Environmental Kuznets Curve (EKC)

In 1955, the future Nobel laureate Simon Kuznets proposed the Kuznets curve to study the relationship between income distribution and economic growth. As an economy grows, income inequality may also increase. After per capita income reaches a certain level, income inequality will decrease with economic growth. Therefore, the Kuznets curve has an inverted U-shape (Kuznets, 1955). These years, the relationship between economic growth and environmental pollution has been widely studied by environmental economists. Grossman and Kruger (1991), in the study of potential impacts of the North American Free Trade Agreement (NAFTA) on the environment, found empirical support for an inverted U-shaped curve between per capita GDP and a variety of environmental pollutants. The inverted U-shaped curve can be derived from three effects, which are the scale effect, composition effect and abatement effect. Those three effects were hypothesized to explain the impacts of economic development on environmental quality (Pannayotou, 2003).

2.1.1 Scale Effect

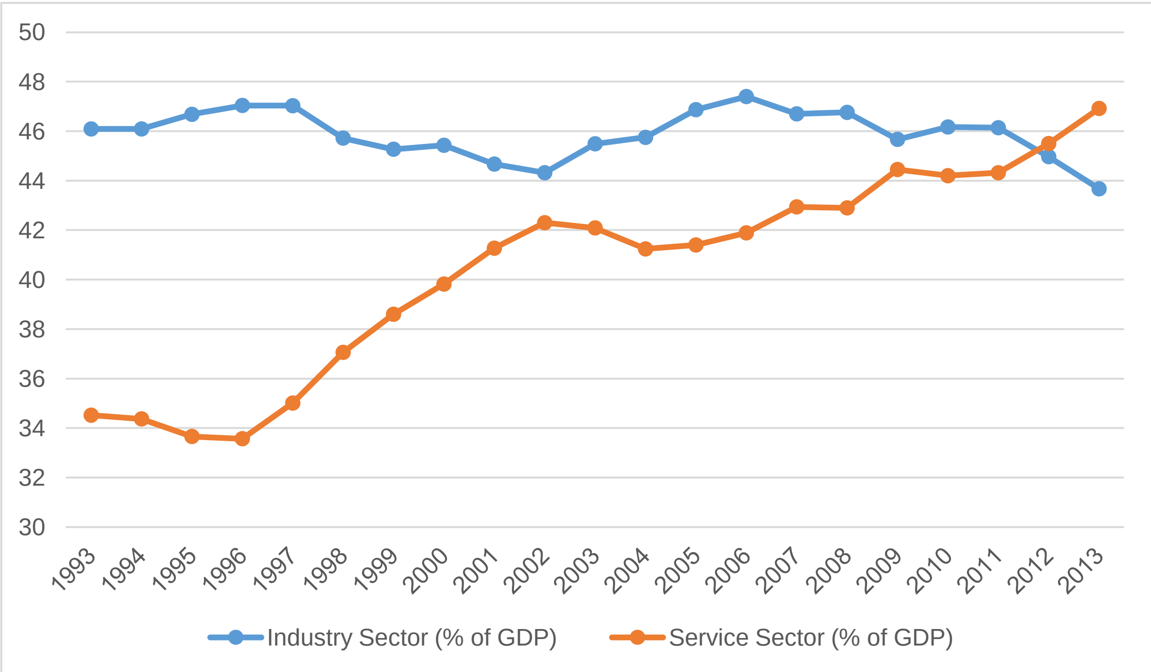
Generally, due to a large scale of economic activities leading to worse environmental quality, income growth increases pollution monotonically. Friedl and Getzner (2003) suggested that the relationship between CO_2 emissions and average income was positive. Therefore, the scale effect on CO_2 emissions is a monotonically increasing function of income while holding the composition and abatement effects constant. The larger scale of economic activities causes energy consumption to increase and CO_2 emissions increase as well (Shi, 2003). Inversely, if CO_2 emissions decrease due to the contraction of economic activities under an environmentally friendly policy, average income will also decrease. As a result, the living standard of domestic households will go down.

2.1.2 Composition Effect

The composition effect refers to an inverted U-shaped relationship between income and environmental pollution. The share of GHG emitted from the industrial sector will rise when income begins to increase from low levels. Initially, this composition effect causes CO_2 emissions to increase. However, as income increases further, the shift from the industrial sector to the service sector will cause a reduction in pollution intensity. At that time, this composition effect can potentially cause a reduction of CO_2 emissions if the composition effect outweighs the scale effect. Therefore, 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).

The dynamic evolution of the industrial structure needs to be emphasized here. Pannayotou (1993) explained that the dynamic evolution of the industrial structure is dependent on the speed of economic growth if the industrial structure switched from labour-intensive, through capital (energy) intensive, and then to technology intensive. As a result, the regions that were industrialized early are becoming more diversified with a larger share of GDP in the service sector, which leads to a reduction of per capita GHG emissions per unit of GDP. In addition, manufactures may be moved to some cheap areas. The above theory holds true for parts of China, which are experiencing what already happened in the United States. More specifically, we can take a look at how the industrial structure in China has changed in recent years.

Figure 1: Changes in Industrial Structure



Source: World Development Indicators Online Database, World Databank.

Due to the reform and open policy back in 1978, China has kept sustained and stable economic growth these years, which contributed to its national economy. As shown in Figure 1, the share of the industrial sector went upward from 1993 to 1996, but fell from 1997 to 2013. It increased from 46.09% in 1991 to 47.04% in 1996 and then decreased from 47. 03% in 1997 to 43.67% in 2013. In the last 10 years, it fluctuated slightly around 46%. The share of the service sector had an upward trend, rising from 34.52% in 1993 to 46.92% in 2013. Even though the share of the service sector is increasing, it is still far below the level of developed countries.

In general, the industrial sector emits more CO_2 than the agricultural and service sectors. The production process generates a large amount of CO_2 because the dependence of the industrial sector on raw materials and energy is relatively high. For example, 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, which 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).

2.1.3 Abatement Effect

The abatement effect is due to the demand for environmental quality depending on levels of per capita income. On the demand side, the abatement effect varies at different levels of per capita income. At low-income levels, even though income increases, that will not cause a large effect on the demand for environmental quality since the increase of income directly raises the demand for food and shelters. In contrast, at higher levels of income, the increase of income may raise the demand for environmental quality. Finally, at high levels of income, people are willing to spend more money on pollution abatement. Besides, supply begins to increase because of stricter environmental regulations. As a result, the abatement effect is expected to be a monotonically decreasing function of income (Pannayotou, 2003).

If the latter two effects dominate the scale effect at some income level, those three effects can work together and result in the EKC relationship between economic growth and environmental quality. Absolutely, as CO_2 emissions vary due to some policy, that will influence per capita GDP, which is a typical measurement of living standards, throughout those effects. Also, there are many other factors affecting CO_2, like energy intensity and urbanization. Those two indicators have more significant effects on CO_2 emissions when the level of income is relatively high.

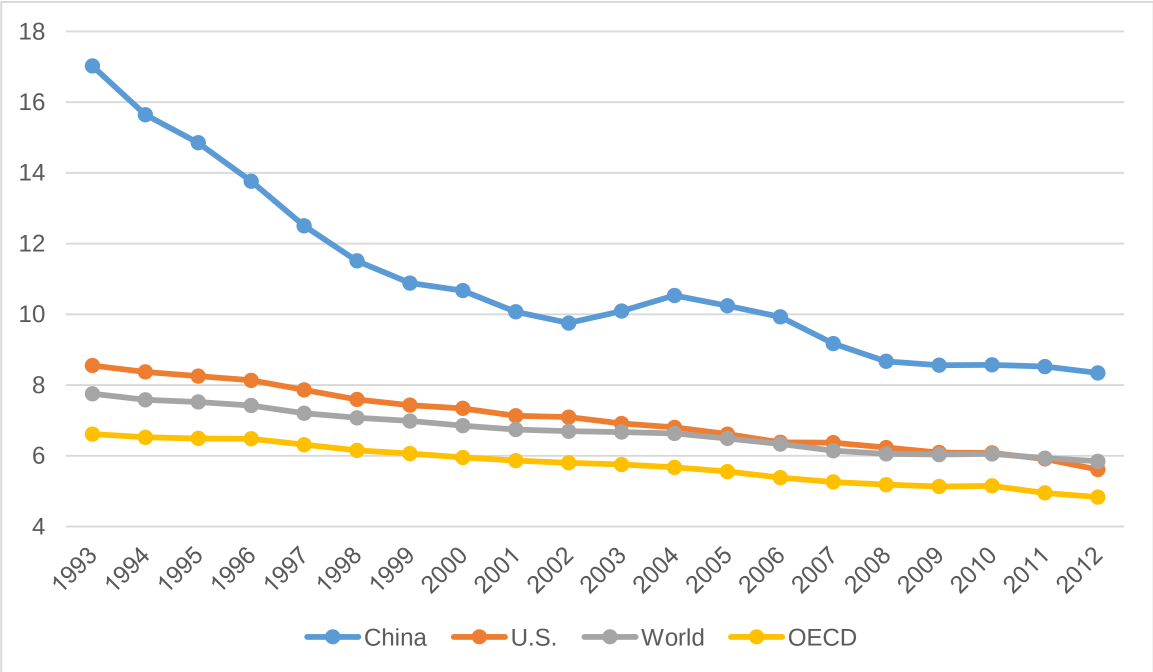
2.2 Energy Intensity

Energy intensity is a component of the abatement effect. Generally, energy intensity is a measurement of the energy efficiency of a nation's economy, which is calculated as units of energy per unit of GDP. High energy intensities indicate a high price or cost of converting energy into GDP.

Energy intensity is related to total GHG emissions. Actually, there are two factors that determine total GHG emissions: energy efficiency and GHG intensity. First, with development of technology, less energy is used to make each unit of output, leading to a decrease of CO_2 emissions. Second, both the substitution of lower GHG technology and less GHG-intensive energy work together to decrease GHG intensity, which decreases total GHG emissions. Although, the scale effect can still raise GHG, the result depends on which effect dominates.

The following figure shows that energy intensity of China was significantly higher than the world average level from 1993 to 2012. In 1993, China's energy intensity was 2.4 times higher than the world level, 2.2 times higher than the U.S., and 2.9 times higher than the OECD countries. However, by 2012, the energy intensity of China decreased to 8.34, which was 1.43 times higher than the world level, 1.49 times higher than the U.S., and 1.73 times higher than the OECD countries. We can find that there is a gap between energy intensity of China and that of the world together with developed countries' levels, but the gap has been greatly reduced. The trend of the gap has been gradually deceasing over the last three decades, but China's energy intensity increased from 2002 to 2004, probably because China has entered a new growth cycle. Besides, there exists a rapid growth of investment in fixed assets. After 2004, the energy intensity of China declined again up to now since Chinese policymakers have attached great importance to energy intensity reduction. Under great pressure from international climate change negotiations, China eventually has pledged to cut its unit GDP carbon emissions by 40–45% by 2020 compared with the 2005 level (Yan, 2015).

Figure 2: International Comparison of Energy Intensity



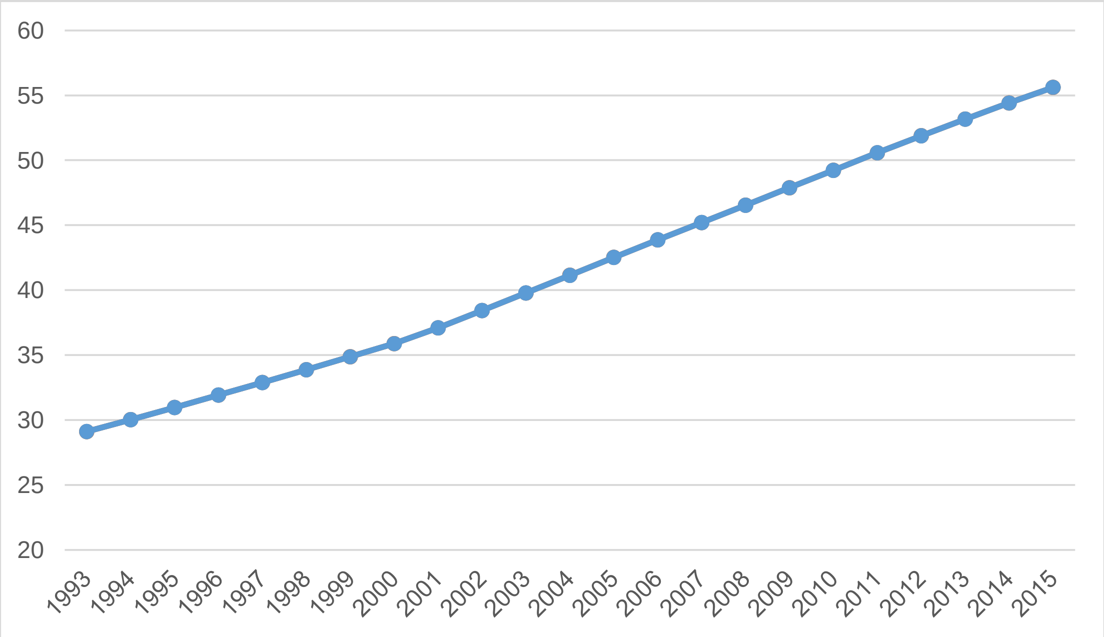
Source: World Development Indicators Online Database, World Databank.

2.3 Urbanization

With the process of industrialization, more and more people move from rural to urban areas. When people move from the countryside, there is no doubt that the living standard will be higher. Meanwhile, more human activities may lead to an increase of GHG emissions. However, the relationship between urbanization and CO_2 emissions is ambiguous. As far as I am concerned, urbanization here plays a greater role in the relationship between CO_2 emissions and living standards.

Figure 3: Changes in the Level of Urbanization

(Proportion of Urban Population %)



Source: World Development Indicators Online Database, World Databank.

As shown in the above figure, the proportion of urban population increased from 29.1% in 1993 to 55.61% in 2015. It increased by 26.51 percentage points and the urbanization rate increased by 1.15 percentage points annually.

Urbanization can lead to economies of scale. As there are more and more people moving to urban areas, it may be more cost effective to build roads, sidewalks and schools. Furthermore, economies of scale may lead to a shift in the process of production and in lifestyle. For example, households will consume more electric appliances and automobiles may become more affordable for households (Wei et al., 2011). When urban centers grow, the scale will be larger so that more development of service and transport sectors will be needed. As a result, urbanization has an impact on energy demand, thereby affecting CO_2 emissions.

On the other hand, urbanization tends to decrease birth rates by delayed childbearing.

When people live in urban environments, they may give birth at older ages and tend to be more receptive to the governmental effort to further childbearing (Yi and Vaupel, 1989). Consequently, urbanization may lead to a decrease of population growth, which causes CO_2 emissions to decrease.

The above effects suggest that energy consumption increases during the initial period of urbanization. However, with the advanced technology promoting energy efficiency, net energy consumption declines later on. The relationship between urbanization and CO_2 emissions varies in the following way: With the development in the levels of urbanization, CO_2 emissions are expected to increase through changing lifestyle and consumption patterns. If further economic growth occurs, the high demand for environmental quality may then push the government to adopt some related policies to reduce CO_2 emissions, which is already happening. Under the environmental-friendly policies, the relationship between CO_2 emissions and living standards needs to be studied further.

2.4 Empirical Evidence

There are many classical models that we can learn from. First of all, two identities of York et al. (2003), the IPAT identity and ImPACT identity, are very important. Those two identities are used to study the impacts of activities on climate change. Basically, the IPAT identity is widely used to analyze the impacts of human activities on the environment. This identity is actually explained as I=PAT. On the 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 formula, environmental impacts are a multiplicative output of the three factors (population, affluence and technology).

Furthermore, Waggoner and Ausubel (2002) generated the ImPACT identity. They developed the IPAT by decomposing T (technology) into C (consumption per unit of GDP) and T (impact per unit consumption). This formula, I=PACT, is a model focusing on estimating the factors that can decrease the impacts. Compared with IPAT, the ImPACT identity stresses that the overall emissions equal the product of population (P), per capita GDP (A), energy consumption per unit of GDP (C) and emissions per unit of energy consumption (T).

Based on the above two identities, Dietz and Rosa (1994) developed a STIRPAT model. This model is more practical because IPAT and ImPACT are limited for testing the hypothesis when two accounting equations assume a proportional relationship in a function among factors. Besides, Grossman and Krueger (1995) explained that IPAT and ImPACT were not useful for testing the EKC hypothesis as a result of affluence (A). The affluence here was measured by per capita GDP but it might have both non-monotonic and non-proportional environmental impacts under the EKC hypothesis.

Alternatively, we can put the affluence in another perspective. The objective of this paper is to study the relationship between CO_2 emissions in China and living standards. There are many kinds of measurements of living standards and the most popular one is per capita GDP. Whether IPAT, ImPACT or STIRPAT, they all have in common that there exists some correlation between environmental emissions and per capita GDP.

Apart for the environmental models, there are also some empirical analyses of China. Du et al. (2012) investigated the driving forces, emission trends and reduction potential of China's CO_2 emissions based on a provincial panel dataset covering the years 1995 to 2009. A series of static and dynamic panel data models are estimated. Then, an optimal forecasting model is used to forecast the emissions trend and reduction potential up to 2020. The estimation results show that economic development, technological progress and industry structure are the most important factors affecting CO_2 emissions. On the other hand, the impacts of energy consumption structure, trade openness and urbanization level are negligible. In addition, the inverted U-shaped relationship between per capita CO_2 emissions and economic development is not strongly supported by the estimation results. However, the impact of capital adjustment speed is significant. Scenario simulations further show that both per capita and aggregate CO_2

emissions of China will increase continuously up to 2020 while the reduction potential is very large.

Furthermore, the environmental Kuznets curve hypothesis was also used to study the case of Canada. He and Richard (2010) found a positive relationship between GDP per capita and CO_2 per capita. More specifically, the relationship between the two is monotonically increasing but the slope of this function changes often over time. Their study suggests that the EKC model does not generally fit all countries because the chosen function matters a lot. In their view, country-specific characteristics such as technological progress, structural evolution and external shocks should be considered. Therefore, they applied more flexible estimation methods, the semiparametric and nonlinear parametric modeling methods, to provide more robust inferences. Besides, they used time series data on Canada from 1948 to 2004 and they deemed that an investigation of time series data of a single country seems to be a promising approach.

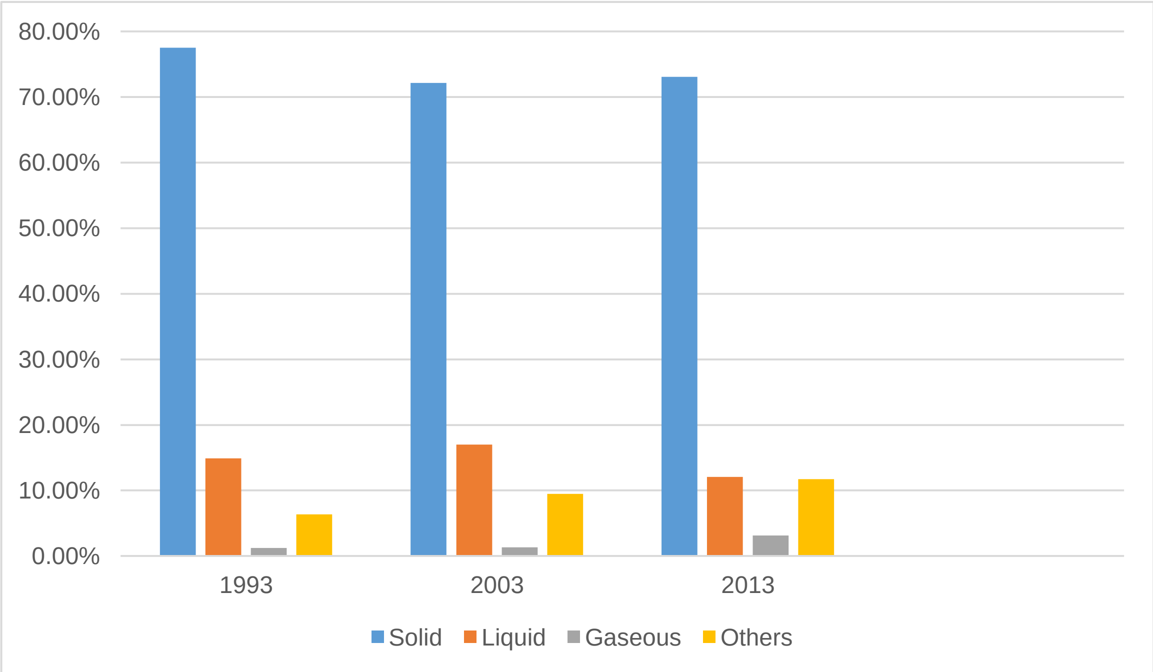
Based on the above reviews, we can see that many factors have an impact on CO_2 emissions and the estimation results from some studies provide statistical evidence that does not support the EKC hypothesis. Different countries, different methodologies and different kinds of data may lead to different relationships between CO_2 emissions and economic growth. This paper intends to analyze the relationship between CO_2 emissions and living standards according to the policy background and the characteristics of CO_2 emissions in China. Thus, it is necessary to select an appropriate model to obtain consistent and valid estimates.

3. Characteristics of CO_2 Emissions in China

3.1 The Impact of Economic Development on CO_2 Emissions

As urbanization spreads throughout China, all kinds of industries developed rapidly in both private and public sectors during the last few decades. With economic development, people began to live in apartments which are in good conditions and easily got access to food and clean water. In this way, the living standards of the Chinese people kept increasing. However, lots of fuels (solid fuels, liquid fuels and gaseous fuels) were burned and a great amount of cement was produced. As a result, CO_2 emissions in China 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 4 shows, the share of CO_2 emissions from solid fuel combustion was dominant in 1993, 2003 and 2013. By contrast, the share of CO_2 emissions from gaseous fuel combustion was lowest in 1993, 2003 and 2013. Furthermore, the share of CO_2 emissions from gaseous fuel combustion kept deceasing from 1993 to 2013. Similarly, the share of CO_2 emissions from solid fuel combustion also decreased from 1993 to 2013. Figure 2 also shows that CO_2 emissions from "other sources" increased sustainably from 6.37%% in 1993 to 11.57% in 2013. More specifically, cement production is an important component of the other categories (World Databank).

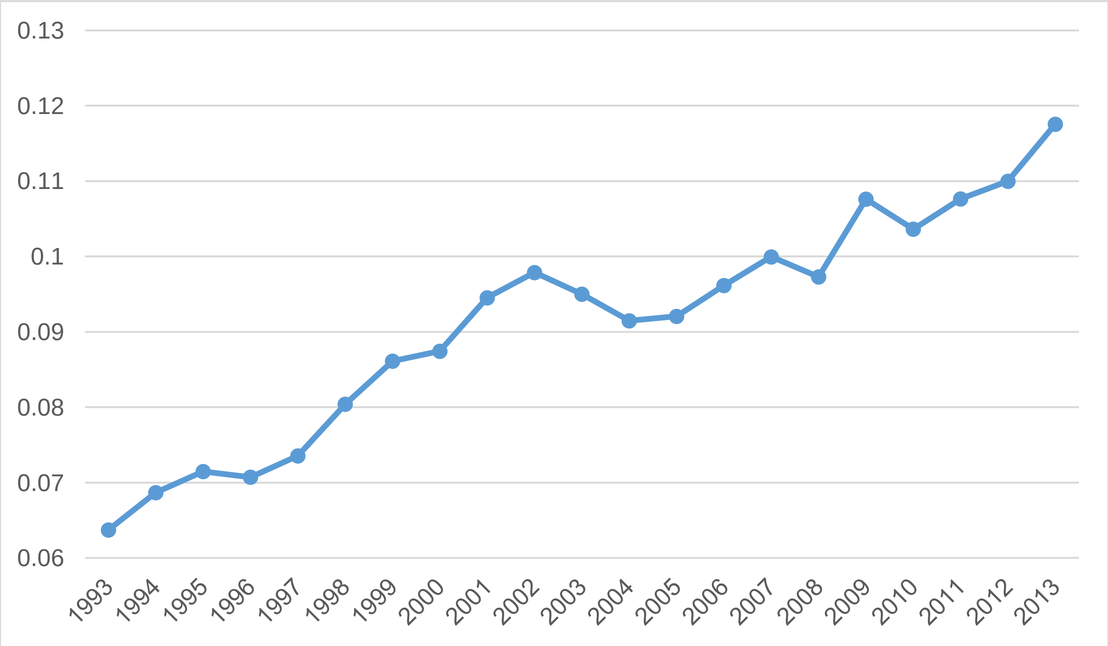
Figure 4: Share of CO_2 Emissions from Solid, Gaseous and Liquid Fuels in China



Source: World Development Indicators Online Database, World Databank.

As shown in Figure 5, cement production played an important role in increasing CO_2 emissions in China. Even though the total amount of China's CO_2 emissions increased rapidly during these 20 years, the share of China's CO_2 emissions from cement production also increased from 6.37% to 11.76%. Meanwhile, the proportion of China's CO_2 emissions from cement production out of global CO_2 emissions from cement production has been among the top group in the world since 1990. In addition, China's CO_2 emissions per unit of cement production were significantly higher than the major developed countries. As a result, CO_2 emissions from cement production may be an essential factor pushing up total CO_2 emissions of China (Carbon Dioxide Information Analysis Center).

Figure 5: Share of CO_2 Emissions from Cement Production

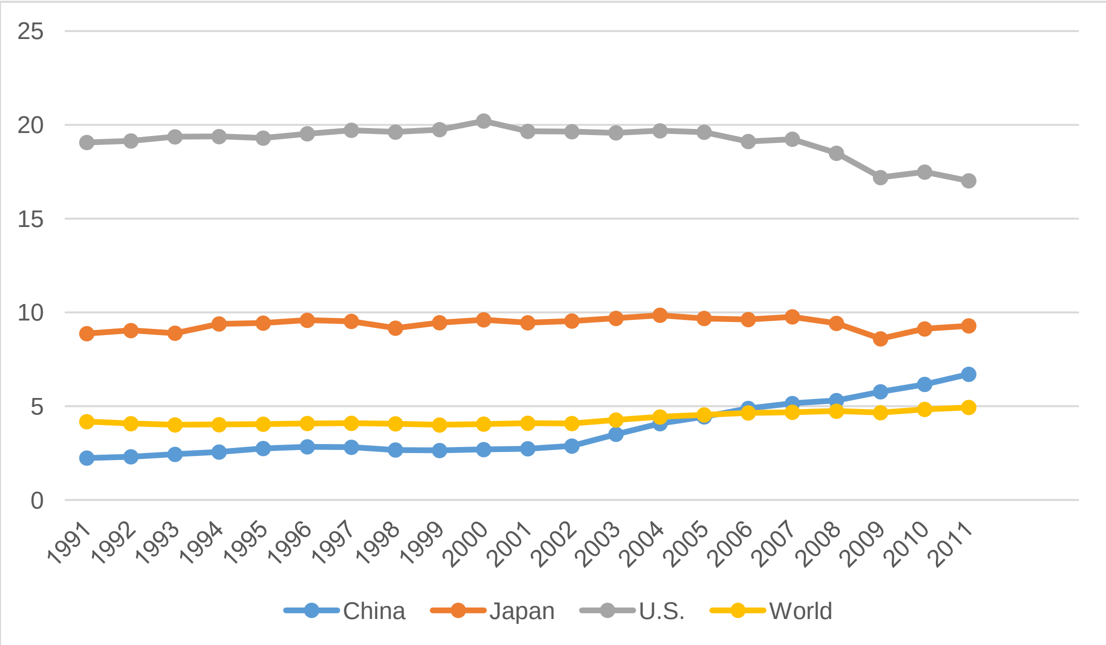


Source: World Development Indicators Online Database, World Databank.

3.2 Low Per Capita Emissions

Industrialization and energy consumption in China are growing rapidly. Overall, total CO_2 emissions of China have increased from 2.58 to 9.72 billion tonnes between 1991 and 2011, an increase of 277%. However, per capita CO_2 emissions in China are significantly lower than those in the major developed countries and the world average. As shown in Figure 6, in 1991, per capita CO_2 emissions of China were 2.25 metric tonnes and were equivalent to 53.75% of the world average, which was 4.18 metric tonnes per capita. Moreover, it was equal to 11.80% of the United Sates' 19.06 metric tonnes CO_2 per capita, and to 25.35% of Japan's 8.87 metric tonnes CO_2 per capita. In 2006, CO_2 emissions of China passed the world average level for the first time. Per capita CO_2 emissions of China were 4.9 metric tonnes, which was 104% of the world average (4.7 metric tonnes CO_2 per capita). By 2011, per capita CO_2 emissions of China had increased to 6.71 metric tonnes and 135.8% of the world average, which was 4.94 metric tonnes CO_2 per capita. In addition, it was equivalent to 39.4% of the United States' 17 metric tonnes CO_2 per capita, and 72% of Japan's 9.3 metric tonnes CO_2 per capita. Consequently, China produced large amounts of CO_2 emissions year after year, but the per capita CO_2 emissions of China are relatively low (World Databank).

Figure 6: Per Capita CO_2 Emissions of China, Japan, the U.S. and the World Average Level



Source: World Development Indicators Online Database, World Databank.

3.3 Large Regional Disparities in CO_2 Emissions of China

Currently, China is the largest emitter of carbon dioxide in the world. Furthermore, the manufacturing industry is the largest contributor to China's CO_2 emissions. Therefore, the manufacturing industry has great practical impacts on regional disparities in China's CO_2 emissions (Xu and Lin, 2016). Using panel data from 2000 to 2014, they examine the driving forces of the industry's CO_2 emissions at the regional level. The results show that economic growth dominates the industry's CO_2 emissions, and its impact varies across regions. Due to differences in industrial structure and the building industry, the influence of industrialization on CO_2 emission in the central region is stronger than that in both eastern and western regions.

Besides, the impact of urbanization declines continuously from the western regions to the central and eastern regions because of differences in human capital accumulation and private car ownership. Energy structure also produces a different effect in the three regions on account of differences in coal consumption.

4. Policy Background

As the Chinese leader, Xiaoping Deng introduced the open-door policy to reform the domestic economy, it was a turning point in China's economic fortune that truly put China on the path to becoming "The World's Factory". Chinese economic policy then shifted to encouraging and supporting foreign trade and investment. From the 1990s, China was on the fast track of labor intensive industries and took the share of that market from the "Four Small Tigers" in Asia with the advantage of low labor costs. China has mastered the labor intensive sector and performed far ahead of other countries. However, under the benefits of rapid economic growth, China's government has not realized the potential risks for the environment and climate until the turn of the century. With the environment becoming worse and worse, especially in the central and eastern areas, Chinese policy makers began to deal with this serious situation by introducing corrective policies.

China's 11th Five-Year Plan (11th FYP), from 2006 to 2010, was historic for its action on climate change, effectively reversing a rapidly increasing trend of energy intensity, as measured by energy use per unit of GDP (Ye, 2011). Within five years, this energy intensity was cut by more than 19 per cent, leading to avoid 1.55 billion tons of carbon dioxide emissions, which was five times the emission reduction committed by the EU under the Kyoto Protocol. However, at the same time, China surpassed the United States as the world's largest carbon emitter. Soon afterward, China became the largest energy consumer as well. Intensive regulations were implemented to achieve a cumulative 12.5 per cent reduction in energy intensity between 2007 and 2009. Although, action to save energy slowed down in the first half of 2010 and energy intensity began to grow again, it was significant that the Five-Year Plan played a great role in reducing CO_2 emissions in China.

After the Paris Agreement of 2015, more and more people around the world were looking forward to what action China would take to deal with environmental problems. It turned out that China continued to make a global effort to address climate change and the 12^{th} Five-Year

Period (FYP) (2011-2015) did mark a new era in China's climate action (Song and Ye, 2015). Climate policies shifted from setting broad goals or statements of priority to an emerging climate policy framework comprised of specific instruments to drive emissions reductions. More specifically, China took three actions from different aspects: limiting energy and coal consumption, gapping GHG growth and implementing a national carbon scheme. All the actions reduced CO_2 emissions efficiently.

5. Methodology

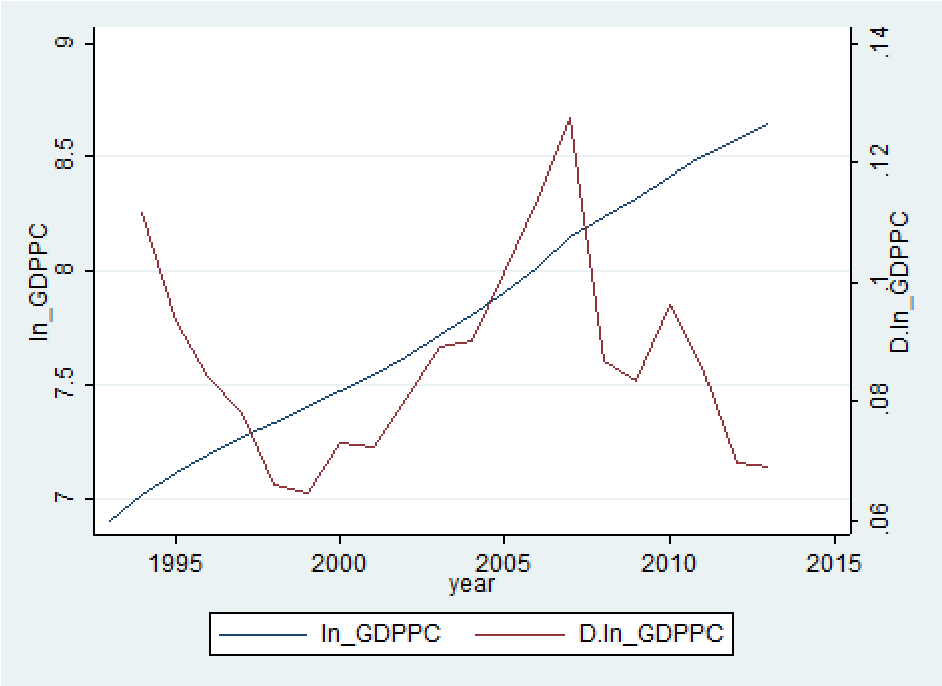
In this section, the econometric equation is constructed. Then, tests for the selection of the time series model will be explained.

This paper generates a time series ARIMA model to test the hypothesis that CO_2 emissions have a significant positive effect on living standards in China. Living standards are calculated by per capita GDP. We use a time series dataset from 1993 to 2013. The benchmark model is shown below. The dependent variable is ln_GDPPC, the log of per capita GDP. The independent variable is ln_CO2e, which refers to the log of total CO_2 emissions in China.

$$\ln\_GDPPC_t = \beta_1 + \beta_2 \ln\_CO2e_t + \varepsilon_t \quad (1)$$

Once we intend to use the ARIMA model, we need to choose the values of three instruments: autogressive order (p), integrated or difference order (d) and moving-average order (q). Initially, we can generate some graphs to make a general decision. Then, we will do some specific tests about the ambiguous parts.

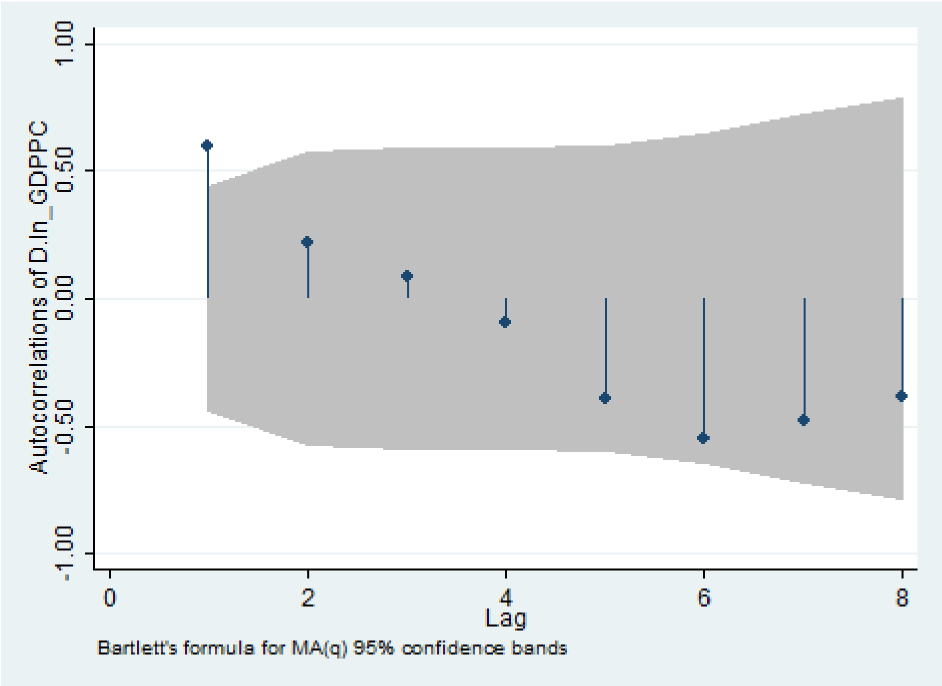
Figure 7: Line Plot of Stationarity



Source: Stata

As shown in Figure 7, ln_GDPPC has an increasing trend, which is not stationary. After using the difference of ln_GDPPC (D.ln_GDPPC), we get the red line. Obviously, D.ln_GDPPC fluctuates slightly around 7.5, which is relatively stationary. Thus, we can choose the value of integrated or difference order (d) equal to 1. However, we will use the Dickey-Fuller test later to confirm stationarity.

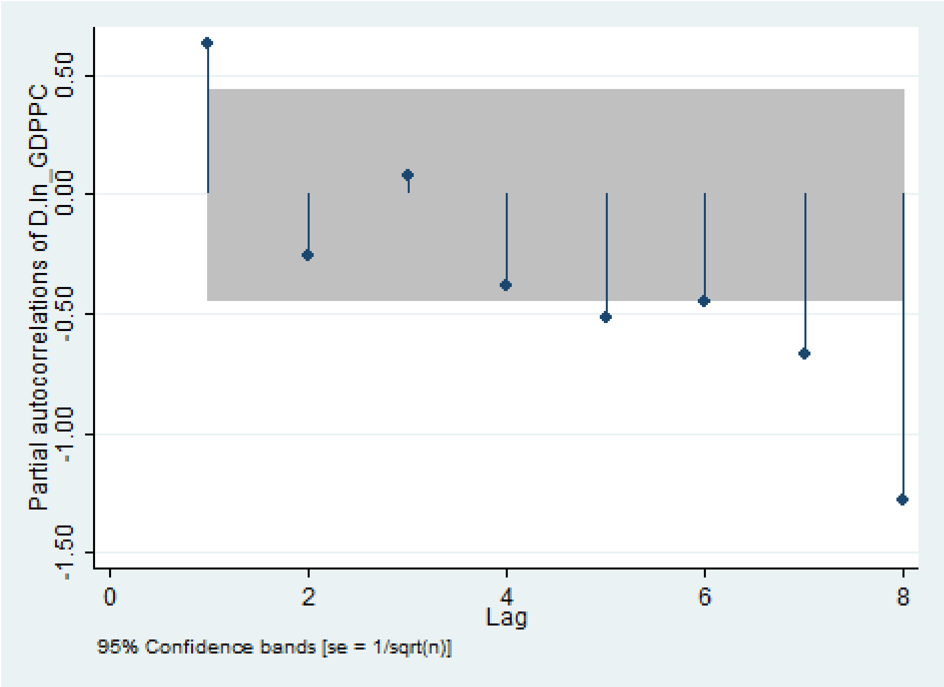
Figure 8: Correlogram



Source: Stata

In Figure 8, we see that the confidence interval (grey area) covers almost all the dots, except for the first one. However, the first dot is just near the edge of the confidence interval and the difference of magnitude is not very large. As a result, we can choose the value of the moving-average order (q) equal to 0.

Figure 9: Partial Correlogram



Source: Stata

For the last value of autogressive order (p), we can generate the partial correlogram. As shown in Figure 9, the confidence interval covers almost all the dots, except for the first one (lag=1) and the 8th one (lag=8). We can just omit the situation that the value of the lag is 8 because it is relatively high. Consequently, we can choose the value of autogressive order (p) equal to 1. Similarly, we will also use the Durbin-Watson and Breusch-Godfrey tests to see whether this is a good choice.

The Dickey-Fuller test is widely used for testing the existence of unit roots. Here, we use it to measure the value of integrated or difference order (d). The null hypothesis is that there is a unit root and the alternative hypothesis is that there is no unit root. As we can see in Table 1, the p-value for the test is 0.2649, which is greater than 0.10. This means that we cannot reject the null hypothesis at the 10% level of significance. Thus, the value of integrated or difference order (d) should be 0.

Table 1: The Dickey-Fuller Test for Unit Root

Number of obs = 19				
		Interpolated Dickey-Fuller		
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.051	-3.750	-3.000	-2.630
MacKinnon approximate p-value for Z(t) = 0.2649				

Source: Stata

Then, we use the Durbin-Watson and Breusch-Godfrey tests to measure the value of autogressive order (p). It is known that autocorrelation can be eliminated by correcting the dynamic specification of the model. We can estimate the following alternative specifications (mod2, mod3 and mod4) of the benchmark model, and store the results for each equation after the test. Therefore, we can figure out which one is the best.

$$\ln\_GDPPC_t = \beta_1 + \beta_2 \ln\_CO2e_t + \beta_3 \ln\_GDPPC_{t-1} + \varepsilon_t \quad (2)$$

$$\ln\_GDPPC_t = \beta_1 + \beta_2 \ln\_CO2e_t + \beta_3 \ln\_GDPPC_{t-1} + \beta_4 \ln\_GDPPC_{t-2} + \varepsilon_t \quad (3)$$

$$\ln\_GDPPC_t = \beta_1 + \beta_2 \ln\_CO2e_t + \beta_{.} \ln\_GDPPC_{t-1} + \beta_4 \ln\_GDPPC_{t-2} + \beta_5 \ln\_GDPPC_{t-3} + \varepsilon_t \quad (4)$$

When we use the benchmark model (mod1) to perform the Durbin-Watson test, we get the Durbin-Watson d-statistic (2,21) equal to 0.2786857. The Durbin-Watson test is a test for first-order autocorrelation of the AR(1) type. The null hypothesis is that there is no autocorrelation and the alternative hypothesis is that there is positive autocorrelation. Note that I have specified a positive value of p under the alternative hypothesis because the observed value of the DW statistic is consistent with positive autocorrelation. Given a sample of T = 21 observations and k = K - 1 = 1, the appropriate 5% critical values for the test are dL = 1.22 and dU = 1.42. Since the observed value of the statistic, 0.2786857, is well below dL, at the 5%

level of significance we must reject the null hypothesis in favor of the alternative hypothesis that there is positive autocorrelation.

Then, we use the Breusch-Godfrey test. For this test, the null hypothesis is that there is no autocorrelation for order p and the alternative hypothesis is that there is autocorrelation for order p. For each of the four dynamic models, the same three Breusch-Godfrey tests are carried out and we can get four different tables, including 12 test statistics.

Table 2: The Breusch-Godfrey test for autocorrelation in mod1

lags(p)	chi2	df	Prob>chi2
1	12.974	1	0.0003
2	14.481	2	0.0007
3	14.978	3	0.0018

Source: Stata

Table 3: The Breusch-Godfrey test for autocorrelation in mod2

lags(p)	chi2	df	Prob>chi2
1	7.468	1	0.0063
2	7.567	2	0.0227
3	7.886	3	0.0484

Source: Stata

Table 4: The Breusch-Godfrey test for autocorrelation in mod3

lags(p)	chi2	df	Prob>chi2
1	3.532	1	0.0602
2	4.090	2	0.1294
3	7.582	3	0.0555

Source: Stata

Table 5: The Breusch-Godfrey test for autocorrelation in mod4

lags(p)	chi2	df	Prob>chi2
1	0.345	1	0.5567
2	0.363	2	0.8342
3	1.087	3	0.7803

Source: Stata

Looking at the p-values for the nine test statistics, we can see that for the model with one lag of ln_GDPPC the p-value for the test for autocorrelation of order 1 is 0.0063, which is less than 0.10. This means that we can reject the null hypothesis at the 10% level of significance. However, the p-values for the tests for autocorrelation of order 2 and 3 are smaller than 0.1, so we can also reject the null hypothesis in these two cases. If there is still autocorrelation in the model, it appears to be at most of order 3. For the model with two lags of ln_GDPPC, the p-values for the test for autocorrelation of order 2 are greater than 0.1, so we cannot reject the null hypothesis of no autocorrelation for this model. Similarly, for the model with three lags of ln_GDPPC, the p-values are all greater than 0.1, so again we cannot reject the null hypothesis at the 10% level of significance. As a result, we find that the value of autogressive order (p) is 1.

Furthermore, a common method of choosing the appropriate dynamic specification for a regression model is to rely on information criteria such as Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). The specification that minimizes the value of the information criterion is deemed the best. We present the AIC and BIC values for the four models in a summary table. According to these criteria, mod2 is the best (p=1). The conclusion is the same as what we get from the above tests.

Table 6: Akaike's Information Criterion and Bayesian Information Criterion

Model	obs	11(null)	11(model)	df	AIC	BIC
mod1	21	-16.5130	15.6565	2	-27.3131	-25.2240
mod2	20	-14.7875	57.5792	3	-109.158	-106.171
mod3	19	-13.2071	57.3864	4	-106.773	-102.995
mod4	18	-11.7274	55.3038	5	-100.608	-96.1558

Source: Stata

Consequently, the autogressive order is 1, integrated or difference order is 0 and moving-average order is also 0 (p=1, d=0 and q=0). The final time series model we will use is ARIMA(1,0,0), also known as AR(1), which is strictly unbiased. The final model is shown below:

$$\mathrm{ln\_}GDPPC_t = \beta_1 + \beta_2 \,\mathrm{ln\_}CO2e_t + \beta_3 \,\mathrm{ln\_}GDPPC_{t-1} + \varepsilon_t$$

6. Empirical Analysis

Since we have eliminated non-stationarity and autocorrelation, we can get the final model we want. In this section, both the specification and results will be analyzed step by step in order to obtain valid conclusions.

First of all, we look into the benchmark model (mod1) and analyze the results. After we carry out a simple linear regression between ln_GDPPC (log of GDP per capita) and ln_CO2e (log of total CO_2 emissions), we get the following table.

Table 7: Results of Benchmark Model (mod1)

Source	SS	df	MS	Number of obs		=	21
Model	5.64899679	1	5.64899679	F(1,19)		=	387.75
Residual	0.276802017	19	0.014568527	Prob>F		=	0.0000
Total	5.92579881	20	0.296289941	R-squared		=	0.9533
				Adj R-squared		=	0.9508
				Root MSE		=	0.1207
ln_GDPPC	Coef.	Std. Err.	t	P>$\|t\|$	[95% Conf. Interval]		
ln_CO2e	1.197236	0.0607998	19.69	0.000	1.069981	1.324492	
_cons	-10.69995	0.9382889	-11.40	0.000	-12.66382	-8.736093	

Source: Stata

Due to a small sample size, the estimates are not consistent. However, they can still bring us a general idea on the relationship between living standards (GDP per capita) and total CO_2 emissions in China. Both R-squared and Adjusted R-squared are very high, greater than 0.95. This means that the regression model is well-fitted. Then, we focus on the p-value of ln_CO2e and it is 0.000, which is smaller than 0.01. This means that the coefficient is statistically significant at the 1% level. Moreover, CO_2 emissions have a positive effect on GDP per capita in China.

Then, we go to the next model (mod2) that is more unbiased. After we carry out mod2 by just using OLS, we get Table 8. We see that both R-squared and Adjusted R-squared are even higher than those of the benchmark model (mod1), which are greater than 0.99. This means that mod2 with the specification of one lag is much more well-fitted. Then, we look into the p-values of ln_CO2e and one lag of ln_GDPPC. Once we add a new variable or specification in the model, the p-value of ln_CO2e rises to 0.012, which is greater than 0.01 but still smaller than 0.1. So, the coefficient is statistically significant at the 10% level of significance, but not 1% anymore. On the other hand, the p-value of one lag of ln_GDPPC is 0.000, which is smaller than 0.01. This means that the coefficient is statistically significant at the 1% level of significance. Above all, CO_2 emissions still have a positive effect on GDP per capita. Furthermore, the one lag of GDP per capita also has a positive impact on GDP per capita in China. Thus, we can make sure that the time series model will be well-fitted in this dataset.

Table 8: Results of the Final Model by OLS (mod2)

<table>
<tr><td>Source</td><td>SS</td><td>df</td><td>MS</td><td colspan="2">Number of obs</td><td>=</td><td>20</td></tr>
<tr><td>Model</td><td>5.13400626</td><td>2</td><td>2.56700313</td><td colspan="2">F(2,17)</td><td>=</td><td>11801.93</td></tr>
<tr><td>Residual</td><td>0.003697619</td><td>17</td><td>0.000217507</td><td colspan="2">Prob>F</td><td>=</td><td>0.0000</td></tr>
<tr><td>Total</td><td>5.13770388</td><td>19</td><td>0.270405468</td><td colspan="2">R-squared</td><td>=</td><td>0.9993</td></tr>
<tr><td colspan="4" rowspan="2"></td><td colspan="2">Adj R-squared</td><td>=</td><td>0.9992</td></tr>
<tr><td colspan="2">Root MSE</td><td>=</td><td>0.01475</td></tr>
<tr><td>ln_GDPPC</td><td>Coef.</td><td>Std. Err.</td><td>t</td><td>$P>\lvert t\rvert$</td><td colspan="3">[95% Conf. Interval]</td></tr>
<tr><td>ln_CO2e</td><td>0.961464</td><td>0.0340619</td><td>2.82</td><td>0.012</td><td>0.024282</td><td colspan="2">0.1680108</td></tr>
<tr><td>ln_GDPPC
L1.</td><td>0.9216178</td><td>0.0286117</td><td>32.21</td><td>0.000</td><td>0.8612525</td><td colspan="2">0.9819832</td></tr>
<tr><td>_cons</td><td>-0.7934509</td><td>0.3152132</td><td>-2.52</td><td>0.022</td><td>-1.458493</td><td colspan="2">-0.1284091</td></tr>
</table>

Source: Stata

Finally, we carry out mod2 by using ARIMA. As we discussed in the last section, the final model we will use is ARIMA(1,0,0), also known as AR(1). Because we have solved the problems of stationarity and autocorrelation, we can focus on the final table with consistent and valid estimates, then analyze the results.

Table 9: Results of the Final Model by ARIMA (mod2)

Sample	1993-2013			Number of obs	=	21
Log likelihood	=	29.97721		Wald chi2(2)	=	304.09
				Prob>chi2	=	0.0000
ln_GDPPC	Coef.	OPG Std. Err.	z	P> $\lvert z \rvert$	[95% Conf. Interval]	
ln_GDPPC						
ln_CO2e	0.880459	0.176218	5.00	0.000	0.5350781	1.22584
_cons	-5.871264	2.784306	-2.11	0.035	-11.3284	-0.4141243
ARMA						
ar L1.	0.9815346	0.0905042	10.85	0.000	0.8041497	1.158919
/sigma	0.0536545	0.014577	3.68	0.000	0.0250841	0.0822249

Source: Stata

Prob > chi2 is the probability of getting a Wald test statistic as extreme as, or more than that observed under the null hypothesis. The null hypothesis is that all the coefficients are equal to zero. In other words, this is the probability of obtaining this chi-square statistic (304.09) if there is in fact no effect of the predictor variables. This p-value is compared to a specified alpha level, our willingness to accept a type I error, which is typically set at 0.05 or 0.01. The p-value from the Wald test that is smaller than 0.01 would lead us to conclude that at least one of the regression coefficients in the model is not equal to zero. The parameter of the Chi-Square distribution used to test the null hypothesis is defined by the degrees of freedom in the prior line, chi2(2). Then, we can find that both p-values of ln_CO2e and one lag of ln_GDPPC are smaller than 0.01. This means that coefficients are statistically significant at the 1% level of significance. Consequently, ln_GDPPC can be positively affected by ln_CO2e and one lag of ln_GDPPC. In other words, more realistically, the living standards in China are positively affected by CO_2 emissions and living standards of the previous year.

7. Conclusions

This paper studies the relationship between CO_2 emissions and living standards in China from 1993 to 2013. We used an ARIMA model derived from the time series model to analyze a 21-year dataset. During the process of selecting the best fitted model, some statistical tests were applied. The Dickey-Fuller test was used to test whether the model was stationary or not. In addition, the Durbin-Watson and Breusch-Godfrey tests were also used to test whether the model had autocorrelations or not. As a result, the final model we used is ARIMA(1,0,0), also known as AR(1). We hypothesized that CO_2 emissions would have a significant positive effect on living standards in China. The results show that our hypothesis is true: living standards in China are positively affected by CO_2 emissions and the living standards of the previous year.

A contribution of this paper is that we use a time series model to study the relationship between CO_2 emissions and living standards instead of a panel data model. Moreover, what we focused on is the impact of CO_2 emissions on living standards. This in itself brings us a brand new perspective in an inverse direction. It is widely acknowledged that a large consumption of natural resources and an increase in CO_2 emissions is inevitable in the process of China's economic development. However, how to effectively reduce CO_2 emissions has become one of the main focuses of international politics and economic concerns, as well as academic research. With the appropriate policies introduced, the growth of CO_2 emissions will continue to decrease. Under this situation, how living standards will be affected by reducing the growth of CO_2 emissions will potentially become a hot issue.

Nevertheless, there are still some limitations to this study. The living standards we use in this paper, as a regressor, is GDP per capita, which is a widely used measurement. However, this measurement does not reflect citizens' personal feelings, such as whether or not they are satisfied with the air quality. In other words, with CO_2 emissions increasing, living standards should be lower according to the air quality. Unfortunately, we do not have such factors that indicate the satisfactions of living standards, except for GDP per capita.

Appendix

All the data are collected from World Development Indicators Online Database, World Databank if not annotated.

All the data range from 1993 to 2013 if not annotated.

Per capita GDP is used as a proxy measure for living standards. In order to eliminate the impact of price factors, per capita GDP is adjusted by the GDP deflator. Thus, I choose the per capita GDP which is based on the constant US dollars in 2010.

The CO_2 emissions in China are calculated by kiloton.

In the section of Energy Intensity, the energy intensity level of primary energy is the ratio between energy supply and gross domestic product (GDP) measured at purchasing power parity (PPP) in 2011.

In the section on Urbanization, the urban development is the number of urban population.

In the section of Characteristics of CO_2 Emissions in China, the share of CO_2 emissions from cement production is collected from Carbon Dioxide Information Analysis Center (CDIAC). Per capita CO_2 emissions of China, Japan, the United States and the world average are calculated by metric tons per capita, which range from 1991 to 2011.

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