ANALYZE CHINA'S CO_2 EMISSION PATTERN AND FORECAST ITS FUTURE EMISSION

by

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Abstract

Greenhouse gas emission from China is projected to exceed that from the U.S. according to the widely cited paper Forecasting the Path of China's CO2 Emissions Using Province Level Information, published by Professor Auffhammer and Carson from UC Berkeley. This conclusion has important implications on international relations and strategies in combating global climate change. The current work examines the statistical basis of this projection. The results suggest that the conclusion is potentially flawed for the following two reasons. First, the model proposed by Auffhammer and Carson assumes a common relationship between CO2 emission and GDP growth for all 30 provinces over the study period. Second, the preferred models in Auffhammer and Carson's work failed to properly address time dependence in data. The two structural errors in the models will potentially lead to biased predictions because the models' incorrectly handled data and model error. The current study developed models that corrected the two model error structure issues in UC Berkeley's paper. These models result in different CO2 emission trajectory from the ones predicted by Auffhammer and Carson.

Table of Contents

I. Introduction

Global climate change is among the most pressing issues facing by the humanity, as anthropogenic greenhouse gas, especially carbon dioxide (CO_2), emission from fossil fuel combustion being the primary suspect of the culprit. Being the largest developing economy, China has experienced a rapid economic growth in the past 30 years resulting in rapid increase of carbon dioxide emission. It is of great significance to understand China's past CO_2 emission path and make a reasonable prediction of its future emission so that the international society can better engage China in important international treaties regulating greenhouse gases emission and at the same time provide a case study for other developing countries to draw useful lessons.

A lot of work has been done in studying the trajectory of environmental pollutants including CO_2. Some of them apply Environmental Kuznets Curve (EKC) hypothesis and demonstrate that there is an "inverted U-shaped" relationship between the CO_2 emission and the economic growth, measured by per capita gross domestic product (GDP). Different turning points are given by various studies. Holtz-Eakin and Selden (1995) estimate a turning point of $35,428 (1986 US$), suggesting that the emission of CO_2 will not begin to decrease until the economic growth reach a very high level. However, some other studies show the emission path can be monotonically increase or even have an "N Shape" which presents more than one turning points. The World Bank and Shafik (1994) find evidence to support the claim that CO_2 emission increase monotonically with GDP. In a recently paper, Auffhammer and Carson (2007) reach the same conclusion in examining China's CO_2 emission. Sengupta (1996) models the CO_2/GDP relationship and finds a much lower turning point of $8,740 (1985 US$) but also find the tendency of increasing emissions beyond $15,300, indicating that emissions decline in the mid-level income and start to take off again with GDP growth.

Specifically, many literatures focus on studying China's CO_2 emission given the importance of China's emission at both regional and global scale. The undergone transformation from a centrally planned to a market-orientated economy is proved to be an economic success leading to dramatically improved quality of living of Chinese people. However, China's 9.7% average annual GDP growth (Hubacek and Guan and Barua, 2007) is fueled by a significant input of natural resource and the most notable source is the primary energy which is majorly fossil fuels. During the period of 1990 to 2004, the total energy consumption of China grew from 18EJ (10^{18}J) to 58EJ at an annual rate of 5.0% (Sinton, 2004), and the annual CO_2 emission grew by 4.8%. (US EPA, 2006) In a global scale, China's emission in 2006 contributes to 20.6% (EIA, 2007) of the world total CO_2 emission, growing from 8% in 1980. Many works have been done to forecast China's future CO_2 emission path. Jiang and Hu (2006) forecasted China's CO_2 emission from energy consumption perspective using different policy scenarios. Garbaccio, Ho and Jorgenson (1999) and Energy Research Institute (2004) exploited the cross sectional variation on industry sectors. Intergovernmental Panel on Climate Change (2000) examined the time series variation cross countries. The prediction results given by different research cover a wide range despite the consensus that China's CO_2 emission will continue to grow in the short term or even medium term.

In a most recent paper, Auffhammer and Carson (2007) used Chinese province level information to forecast the nation's future CO_2 emission path by employing multiple linear regression They concluded that by the end of 2010, China's annual CO_2 emission growth rate will reach to the range of 11.05% - 11.88% (much higher than the same indicator given by similar studies) and this single country's CO_2 emission can offset all the CO_2 reduction achieved by Annex I countries under Kyoto Protocol in absence of the agreement.

While Auffhammer and Carson's work received wide publicity, the technical basis of their work has not been carefully scrutinized. Uncertainty structure of a statistical model is of crucial importance in ensuring the resulting model is useful for projecting outcomes beyond the range of data used to develop the model. However, with further inspection we find that Auffhammer and Carson's prediction model is not strictly convincing for the following reasons. First, the way they construct their time series model is statistically unsubstantiated. Second, by using a single common model to predict the nation's emission they didn't fully account the heterogeneities in both GDP and waste gas emission among different provinces in their model. Failing to properly consider the time sequence and heterogeneities will jeopardize the accuracy of the prediction and lead to misjudge of the future situation.

In this paper, we will use the same data as Auffhammer and Carson but build up Autoregressive Integrated Moving Average, a.k.a. ARIMA model to properly handle the dynamic link of the waste gas emission throughout study horizon and use multilevel model to account for the difference among provinces. The remaining part of the paper will be structured as follow. Section II will talk about the data we use. We will talk about the unsubstantiated points that Auffhammer and Carson's paper are subject to in more details in critic section. Our analysis models and prediction model their results will be given in Section IV and finally in Section V we will discuss our results and compare them to Auffhammer and Carson's results.

II. Materials and Methods

1. Data

We are using the same data Auffhammer and Carson used. It is a province level panel data set collected from China Statistic Yearbook and it contains information on per capita GDP, waste gas emission and other socioeconomic data for 30 Chinese provinces over a 20-year period (with a few exceptions for several provinces which only possess observations of 16, 17 or 18 years).

Direct measurement of CO_2 emission is extremely hard because the mobile emitting sources are widely spread and the cost to capture all of them is prohibitively high. Therefore, CO_2 emission of a country is largely estimated based on other indicators. One widely used indicator is the fossil fuel consumption modified by some multipliers according to the carbon content to derive the CO_2 emission. Andres, Marland and Boden (1999, 2001) have done a lot of work using this method. Unfortunately, the critical information for that method, the province level data on fossil fuel consumption is not available for China. In Auffhammer and Carson's work, they adopted the method employed by China Ministry of Environmental Protection, using waste gas emission (WGE) to calculate the CO_2 emission as it is showed in the following equation,

$$CO_{2t} = 8.051WGE_{1985:1997,t} + 5.673WGE_{1998:2004,t} + \eta_t$$

Where, WGE1998:2004 are aggregate annual WGEs for China if t> 1997 and zero otherwise.

WGE 1985:1997 equals aggregate annual WGEs for China if t<1998 and zero otherwise.

(Auffhammer and Carson, 2007) A dramatic change in fuel consumption structure happened in

1997 when many small coal mines were closed to ensure a better quality of coal and to improve the energy efficiency had also became an important energy policy since them. Hence, the calculation of CO_2 using WGE is divided into two period, more weight has been put on to the phase before 1997 due to the worse coal quality and inefficient energy use, and vice versa after 1997.

2. *Critic*

In Auffhammer and Carson's work, they use a single common model and aggregated GDP growth rate and population growth rate across the country to predict China's Future CO_2 emission. Though they allow the spatial dependence to account for spill-over effect across provinces, it is suspicious that to pool all provinces together to forecast future CO_2 emission will only yield biased prediction, because the heterogeneities in both GDP and waste gas emission among different provinces are not fully accounted in their model. We need to recognize the fact that China is a large developing country with a high level of social and economic diversity. The uneven degree of development of its east coast and west inner land and the different industries emphasis of southern provinces and northern provinces make each province a unique unit with its particular growth pattern of GDP, WGE and also population. It is believed that one can understand China's CO_2 emission patter better only through properly accounting for the idiosyncratic characteristic of its provinces.

Another serious weakness in Auffhammer and Carson is the misuse of the lagged waste gas emission in their waste gas emission regression model. In their best fit model, Model 4, they have the model specification as following:

$$WGE_t=\beta_0+ \beta_1 GDP_t+ \beta_2 GDP_t^2+ \beta_3 WGE_{t-1}+\varepsilon$$

where GDP is the logarithm term of annual per capita GDP. They believe WGE in year t is correlated with the emission in the previous year which is legitimate and GDP and GDP square in the same year, but the way they construct the correlation is troublesome for the following reason. The underlying assumption of Auffhammer and Carson's model is the residuals of each year's WGE are not correlated. Statistically speaking, the WGE for each province in a specific year is a population and it has its mean and variation associate with it. When constructing a model using WGE we are drawing sample from the population and the sample has its own mean and observed error which are different from the true mean and error of that population. If we believe WGE is time dependent, a legitimate way to set up the dynamic link between the WGE in consecutive years is to use the population in year t-1 to infer the population in year t rather than correlating the sample of WGE in year t-1 with the population in year t because it will cause the residual of WGE_t and WGEt-1 to be correlated.

Therefore, in order to obtain an accurate prediction of China's future CO_2 emission we need to fully capture the characteristic of each province and properly construct the dynamic link of annual WGE. In our study, we use multilevel model to conduct provincial level analysis and prediction of waste gas emission then derive national CO_2 emission from that to address the first issue. AutoRegressive Integrated Moving Average (ARIMA) model is applied to address the time dependence of WGE. We believe only in this fashion we can properly account for the idiosyncratic characteristic of different Chinese provinces.

III. Models and Results

1. Potential Errors of Auffhammer and Carson's model

In Auffhammer and Carson's paper, they assume the difference between provinces only exits at the initial level of their emissions and all the provinces share the same WGE growth rate. In preliminary step, we conduct tests on GDP and WGE for all the 30 Chinese provinces over 20 year. Figure 1 and Figure 2 show the overtime changes of WGE (per capita waste gas emission expressed in logarithm term, the same hereafter)and GDP (per capita gross domestic production expressed in logarithm term, the same hereafter) of each province, respectively. It is clear that there is no two provinces share the same GDP pattern and WGE growth and the differences among provinces in WGE and GDP are not only in the initial level but also in the rate of growth which is reflected by the slope. Figure 3 shows as per capita GDP increases in different provinces, the growth pattern of per capita waste gas emission are not identical for all provinces. Two extreme examples are Beijing (the top second from right) and Hai Nan (right below Beijing). Thought a little vague, the former shows a similar trend of inverted U shape curve which suggests that the emission has started to decrease after peaking in the middle as the GDP continuous to increases. Hai Nan presents a completely different path, starting at a relatively low emission level it grows at a very high rate and shows no evidence to level off in the near future. Except for Beijing, all the other provinces have an increasing trend of waste gas emission as the GDP grows; however, both the initial level of emission and the growth rate differentiate provinces from each other.

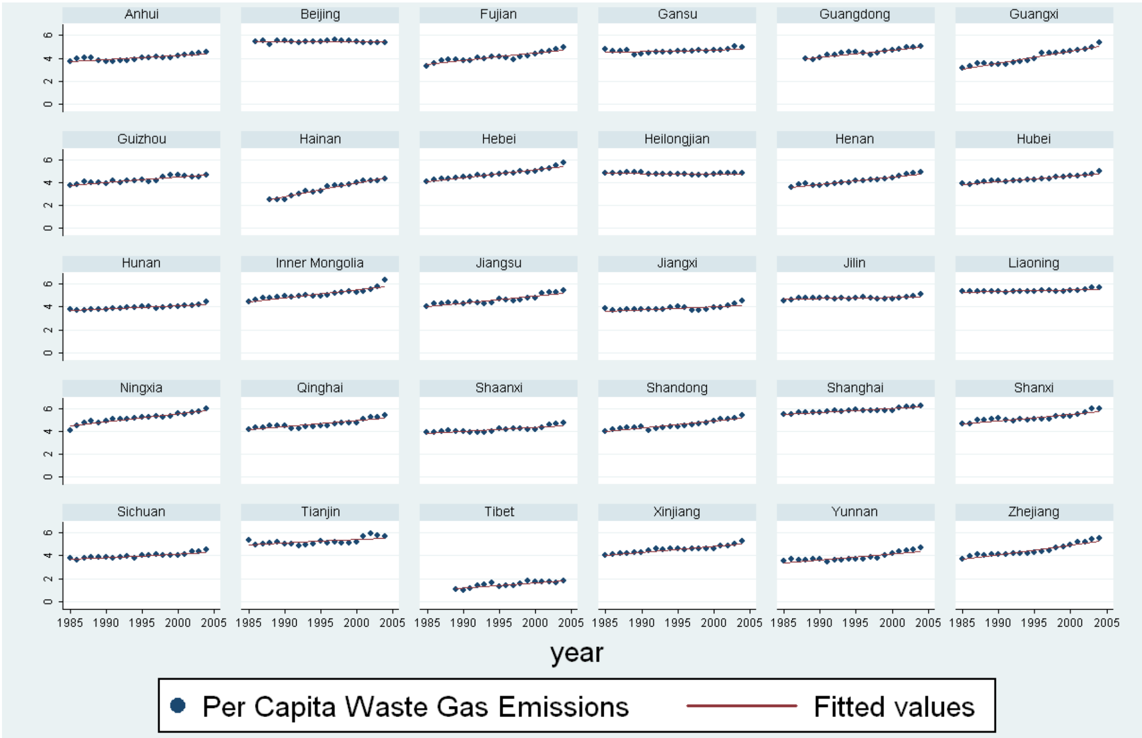


Figure 1 Chinese Provinces per Capita Waste Gas Emissions over 20 Years

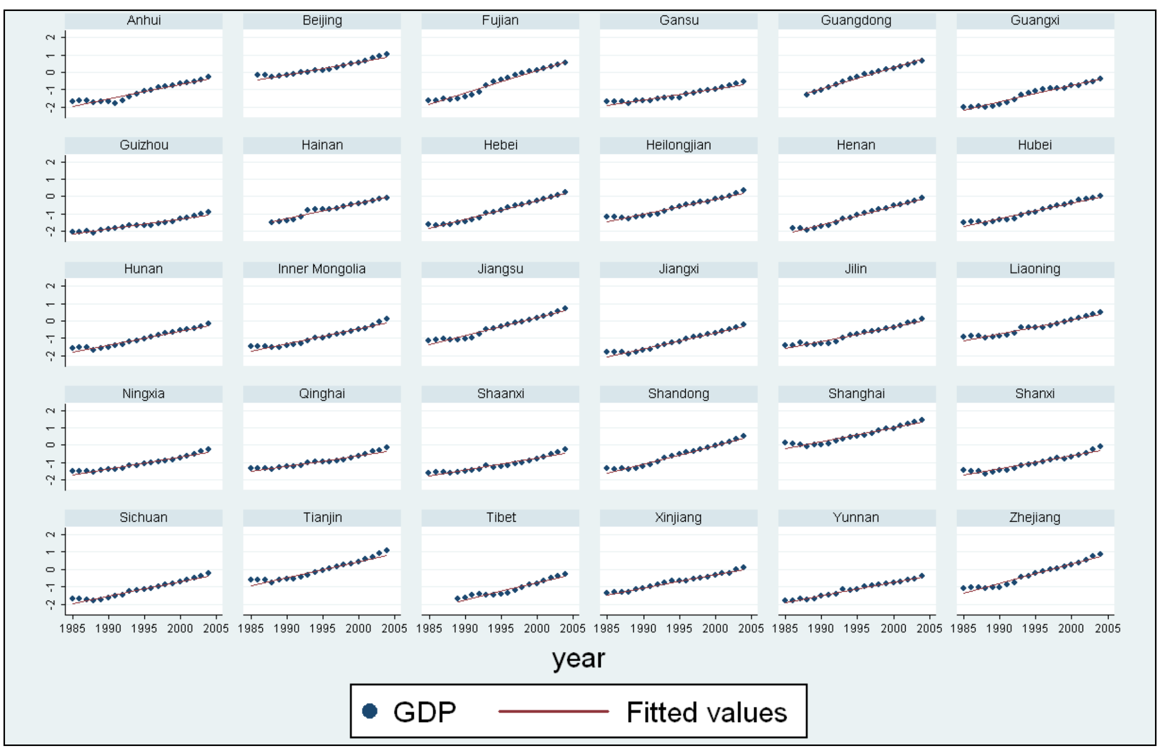


Figure 2 Chinese Provinces Per Capita GDP over 20 Years

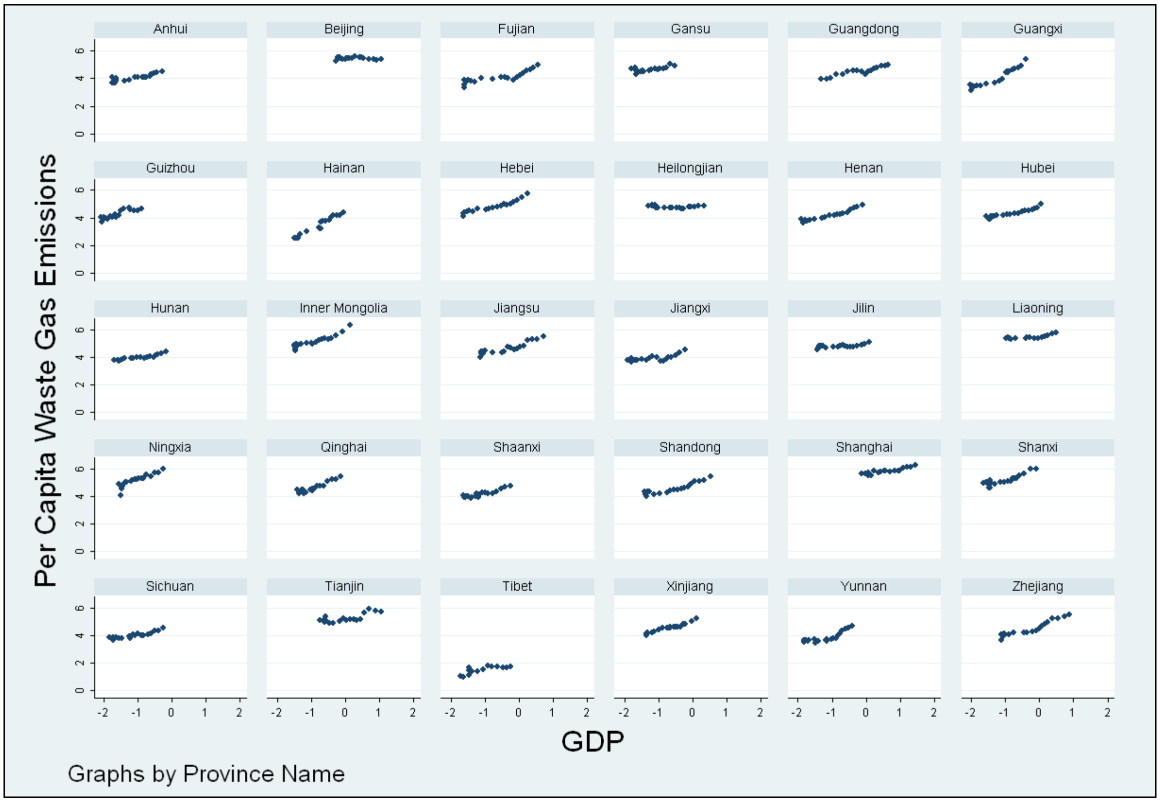


Figure 3 Chinese Provinces per Capita WGE VS. Per Capita DGP

2. Proposed models

To correct the above mentioned imperfections in Auffhammer and Carson's work, we employ ARIMA to conduct time series analysis with a proper error structure and use multilevel regression model to account for each province's unique emission fashion. In prediction, instead of conducting national level prediction we still take the advantage of the provincial data and extend our ARIMA model by updating predict variable per capita GDP with more recent data and forecast the WGE to 2010.

a. Multilevel Model

As graphs in critic section showed different WGE and GDP pattern for different provinces, we further run multiple regression model that is similar to the Model 4 in Auffhammer and Carson's paper by regressing WGE of each province in year t on GDP and GDP square in the same year and WGE from last year. We have our province level Multiple Regression Model (MRM) model specification as following

$$WGE_t = \alpha_1 GDP + \alpha_2 GDP^2 + \alpha_3 WGE_{t-1} + C$$

See Appendix I for codes in R

The only difference between MRM and Model 4 from Auffhammer and Carson's paper is that MRM controls on province level and allows the regression intercepts and slopes of GDP and GDP square to various between provinces. In contrast, Model 4 from Auffhammer and Carson used fixed-effect that only accounted for different initial emission levels which are the constant terms of the regression but assumed every province have the same slope, Our results from MRM suggests that their assumption is not true. Figure 4 shows the MRM intercepts and slope for GDP for 30 provinces (provinces are coded by number from 1 to 30. See appendix II for reference).

Intercept and GDP slope values for each province are represented by the circles and the dark lines show the standard error and the longest gray lines indicate the 95% confidence intervals. The variation in both the average level of WGE (intercept) and the change rate of WGE in response to GDP growth (slope of GDP) suggest that it is inappropriate to integrate all provinces into one model which can still yields accurate estimation.

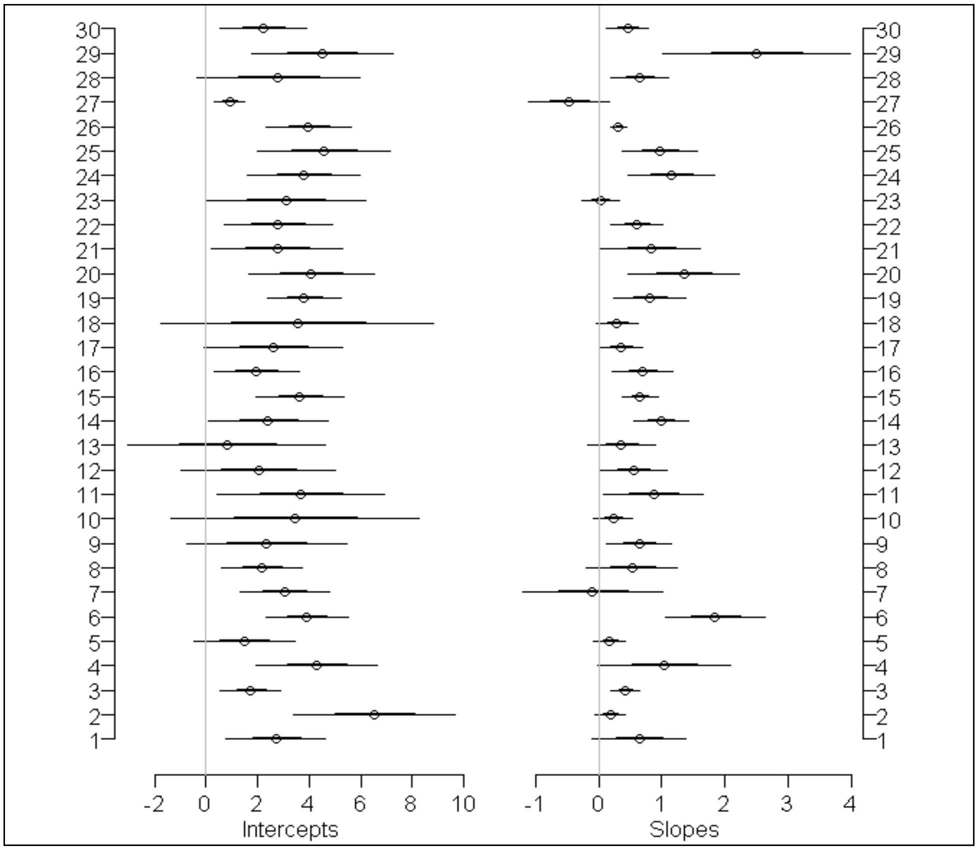


Figure 4 Multiple Regression Model Intercepts and Slopes Separately fitted for All Provinces

A fix can be made by applying multilevel model which allows the variables to vary on more than one level. In our study, we use panel data that contains information for 30 provinces over 20 years. It is legitimate to assume that in addition to fixed-effects, there are random effects on both province level and year level. We start our multilevel analysis with the simplest multilevel model, MLM1: WGE changes in response to GDP and GDP^2 growth and difference among provinces are considered. Though the WGE overtime is auto-correlated, we don't include the lagged WGE due to the concern of error structure.

Table-1 MLM1Random Effects and Fixed Effects

Random Effects					
Groups	Name	Variance	Std.Dev.	Correlation	
province	Intercept	0.705	0.839		
	gdp	0.458	0.677	0.53	
	gdp2	0.062	0.249	0.538	0.824
Residual		0.013	0.116		

Fixed Effects			
	Estimate	Std. Error	t value
Intercept	5.040	0.1545	32.53
gdp	0.927	0.131	7.06
gdp2	0.235	0.051	4.61

MLM1 has the same model specification with Model 1 of Auffhammer and Carson's except that we are using multilevel analysis while they are using ordinary least square (OLS) model. The model coefficient estimates given in the Fixed Effects table are the national overall average values and there is a large discrepancy between our national average coefficient estimates and the estimation given by Auffhammer and Carson's Model 1. It indicates that if the random effect is not considered, the regression result can be greatly biased.

Table-2 Coefficient Estimates of Model 1-4 in Auffhammer and Carson

Dep. Var: WGE	Model 1	Model 2	Model 3	Model 4
GDP	0.361***	0.399***	0.347***	0.065
GDP^2	-0.082***	-0.096***	-0.085***	-0.020**
Population Density		0.924***		
Per Capita Cars			0.011	
WGE in Year t-1				0.795***

The Random Effects table reports the variance estimated of each prediction variable across 30 provinces. We extract them from the model and they indicate the difference between the intercept and coefficient estimates for each province and the national overall average. As it is shown in Table-3, there is a big variance between a specific province's intercept and coefficient values and the national overall mean and also among provinces. The same information is reinforced by Figure-5.

Table-3.Random Effects of MLM1

Province	Intercept	GDP	GDP2
Anhui	-0.204	0.177	0.071
Beijing	0.433	-0.901	-0.351
Fujian	-0.703	-0.159	0.002
Gansu	0.506	0.357	0.185
Guangdong	-0.444	-0.398	-0.192
Guangxi	1.145	1.536	0.297
Guizhou	0.068	-0.620	-0.376
Hainan	-0.511	0.643	-0.078
Hebei	0.311	0.104	0.020
Heilongjian	-0.261	-0.720	-0.021
Henan	-0.015	0.183	0.003
Hubei	-0.205	-0.028	0.004
Hunan	-0.621	-0.286	-0.085
Inner Mongolia	0.951	0.473	0.152
Jiangsu	-0.262	-0.122	0.071
Jiangxi	-0.444	0.125	0.098
Jilin	-0.088	-0.548	-0.084
Liaoning	0.421	-0.579	0.000
Ningxia	1.109	-0.002	-0.252
Qinghai	0.650	0.685	0.209
Shaanxi	0.010	0.288	0.099
Shandong	-0.174	0.006	0.094
Shanghai	0.576	-0.673	-0.139
Shanxi	1.200	0.737	0.276
Sichuan	-0.326	0.036	0.014
Tianjin	0.117	-0.561	0.062
Tibet	-3.356	-1.271	-0.633

Xinjiang	0.021	-0.047	-0.078
Yunnan	0.547	1.591	0.553
Zhejiang	-0.445	-0.023	0.081

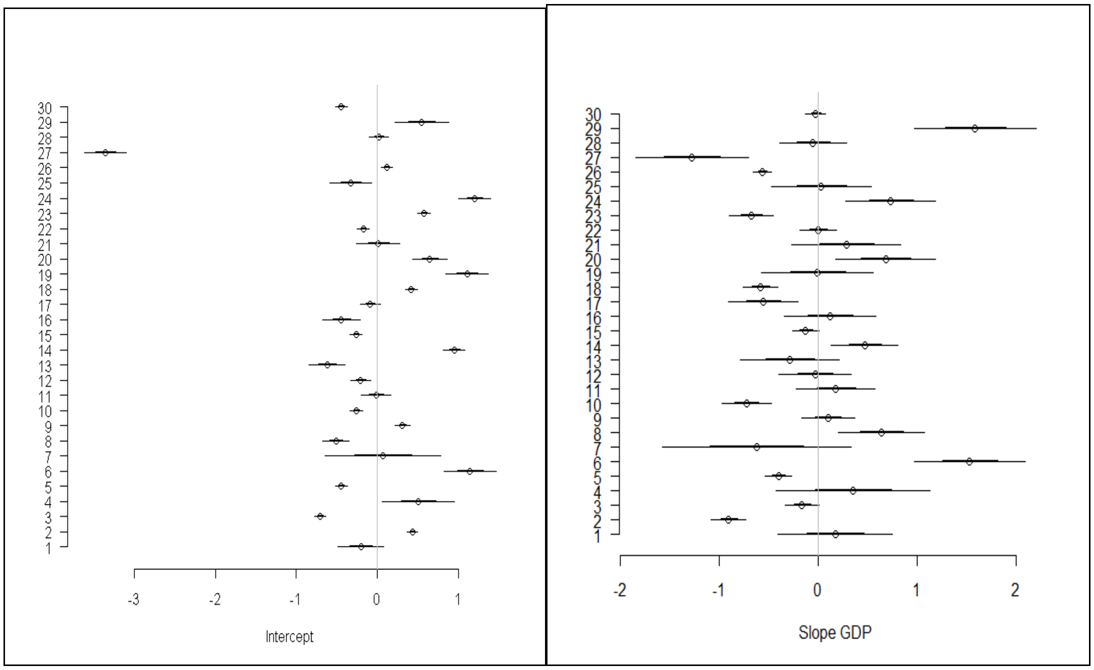


Figure-5.Intercept and Slope of GDP of MLM1

Further, we suspect that the rapid economics growth rate in the 20 years study period could make each year's emission distinct from the previous and following years. Therefore, we introduce the variable YEAR as another level to control for. We run the similar multilevel model with two control levels and it turns out the variance for the intercept and coefficient estimates for GDP and GDP^2 at different year is smaller than the variance among different provinces by two magnitudes (Table-4), which suggests YEAR may not be a proper variable to group the emissions. In fact, the emissions for a particular province are yearly auto-correlated, which is the time dependence issue that we will address in our next session. As a result, we decide to conduct multilevel regression analysis only on province level and account for the time dependence issue in autoregressive model. This becomes our model 2, MLM2.

Table-4 Random Effects and Fixed Effects for MLM2

Random effects					
Groups	Name	Variance	Std.Dev.	Corr.	
province	Intercept	0.712	0.844		
	gdp	0.449	0.670	0.549	
	gdp2	0.070	0.265	0.524	0.854
year	Intercept	0.003	0.050		
	gdp	0.001	0.033	0.823	
	gdp2	0.001	0.024	-0.930	-0.974
Residual		0.011	0.106		
Fixed effects					
	Estimate	Std. Error	t value		
Intercept	5.000	0.158	31.67		
gdp	0.825	0.143	5.79		
gdp2	0.168	0.064	2.64		

After deciding to control only on province level, we look at what variables are appropriate to be considered as predict variables. As most literatures suggested, the pollution level is highly related to the economic status, which means the GDP will be an indispensable predictor in deciding WGE. Besides GDP, there are other variables that may affect the WGE as well. For example, population density, per capita car ownership and last year's waste gas emission may all have significant impact on WGE. We define these three variables in the same way they are defined in Auffhammer and Carson's paper. Population density is calculated as total provincial population divide by total area in square miles. The per capita car ownership is defined as the total number of private car divide by the population of the province, and last year's waste gas emission is calculated in logarithm to be consistent with WGE. We build up different multilevel models to incorporate these three variables and try to compare our results with those from Auffhammer and Carson.

In multilevel model with population density, we have three predict variables GDP, GDP^2 and POP (for population density) and this becomes our model 3, MLM3. Table-5 reports the variances and coefficient estimates for this model.

Table-5 Random Effects and Fixed Effects for MLM3

Random effects						
Groups	Name	Variance	Std.Dev.	Corr		
province	Intercept	0.926	0.962			
	gdp	0.446	0.668	0.022		
	gdp2	0.056	0.236	-0.482	0.865	
	pop	0.080	0.282	0.798	-0.227	-0.599
Residual		0.013	0.114			

Fixed effects			
	Estimate	Std.Error	t value
Intercept	6.122	0.392	15.617
gdp	0.921	0.129	7.124
gdp2	0.248	0.049	5.050
pop	0.273	0.108	2.528

In terms of variance components, there is still a large between-province variance in the initial level of emission which is represented by the intercept, and the GDP. The variance explained by GDP^2 becomes smaller compare to MLM2 and it is even smaller than the variance of population density. The reason for variance of GDP^2 becomes smaller may because GDP^2 and POP are negatively correlated. When POP is omitted from the regression, GDP^2 picked up some of the effects that should be explained by POP. The coefficient estimates of GDP and intercept increase while GDP^2 decreases due to the same reason we discussed above. Our coefficient estimates suggest that even though the exact effect of the predict variables are different for each province, in general GDP has the largest impact and GDP^2 and POP have similar impact on WGE. In contrary to Auffhammer and Carson's results that shows that population density is very influential and GDP^2's impact is negative, our results suggests that GDP is the most significant waste gas emission predictor and GDP^2 still has the positive impact on WGE while population's impact in our model is far from significant. We suspect the validity of Auffhammer and Carson's result, especially the fact that they had a negative coefficient estimate for GDP^2 which suggests the EKC is true in current China's situation. However, as we can see from our preliminary steps, the general trends of CO_2 WGE for all provinces but Beijing are still going up and there is no sign for level-off and downturn in the near future.

Our next step is to extract the random effects from MLM3. Random effect refers to the hierarchy of different population whose difference relate to the hierarchy. In our case, the impact of GDP and population on WGE are different on province level as it is shown in Figure-6.

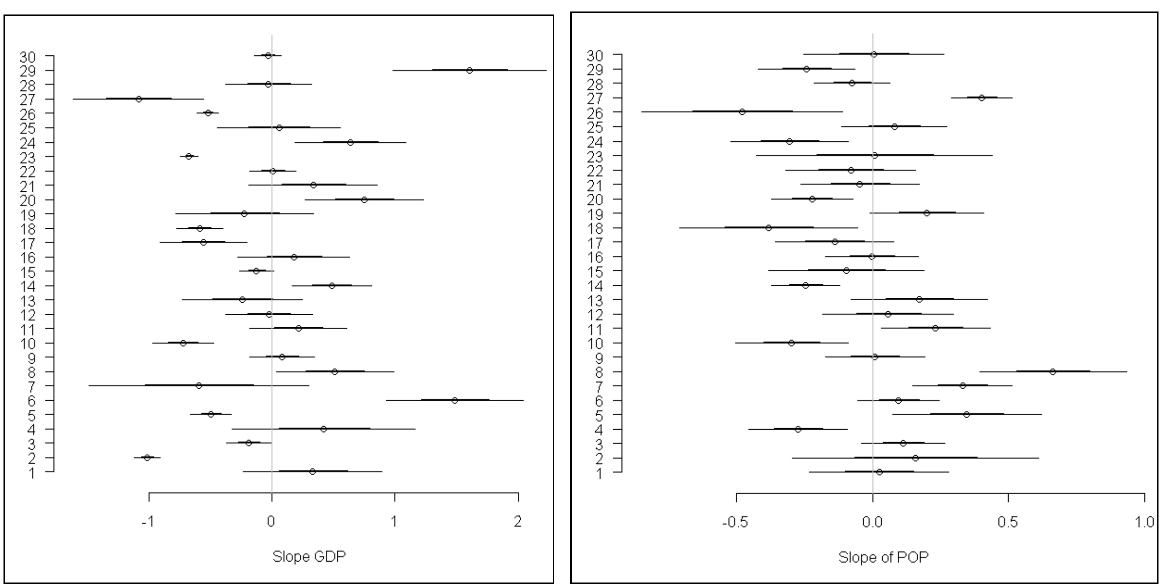


Figure-6 Slope of GDP and POP of MLM3

We also fit multilevel model with per capita car ownership and GDP and GDP^2. MLM4 model is the same as Model 3 in Auffhammer and Carson's paper expect for the multilevel method we are using. Table-6 summaries the random and fixed effects and Figure-7 shows the slopes of GDP and CAR. Like MLM 3, in fixed effects, the impacts of the three predictors on WGE are all positive with GDP having the most significant effects while the impact of GDP^2 and CAR's are much smaller than GDP. In terms of random effect, there is also a great variance in GDP at province level, but the GDP^2 and CAR's diversities are not as large as GDP. Our results of MLM4 are different from the results of Auffhammer and Carson's Model 3 in the same fashion that our MLM3 results differ from their Model 2.

Table-6 Random Effects and Fixed Effects for MLM4

Random effects						
Groups	Name	Variance	Std.Dev.	Corr		
province	Intercept	0.942	0.971			
	gdp	0.482	0.694	0.494		
	gdp2	0.073	0.270	0.231	0.744	
	car	0.031	0.175	-0.581	-0.121	0.407
Residual		0.011	0.102			

Fixed effects			
	Estimate	Std. Error	t value
Intercept	4.527	0.197	23.034
gdp	0.779	0.136	5.707
gdp2	0.274	0.055	4.993
car	0.119	0.037	3.233

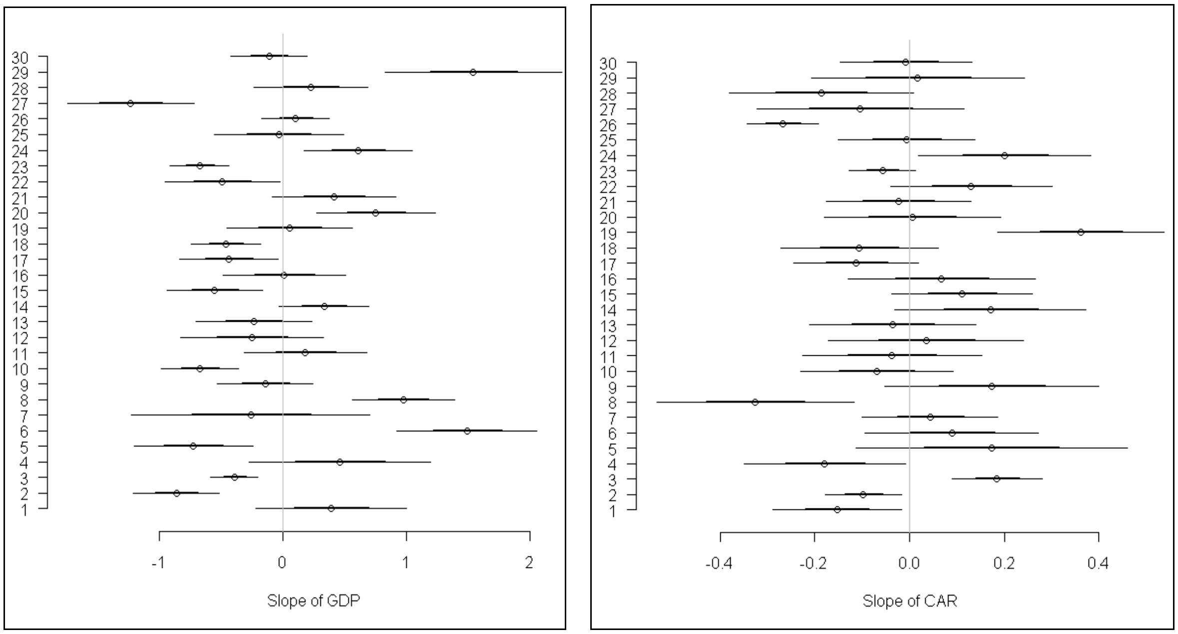


Figure-7 Intercept and Slope of GDP and CAR of MLM4

In Auffhammer and Carson's paper, their best fitted Model 4 used GDP, GDP^2 as well as lagged WGE as predict variables. In order to compare results, we also fit multilevel regression model (MLM5) with these three variables, ignoring the error structure issue.

Table-7 Random Effects and Fixed Effects for MLM5

Random Effects			
Groups	Name	Variance	Std.Dev.
province	Intercept	0.023	0.151
	gdp	0.002	0.046
	gdp2	0.001	0.032
	lwge	0.002	0.040
Residual		0.012	0.109
Fixed Effects			
	Estimate	Std. Error	t value
Intercept	0.349	0.063	5.53
gdp	0.112	0.022	5.1
gdp2	0.027	0.012	2.25
lwge	0.949	0.014	69.74
Correlation of Fixed Effects			
	Intercept	gdp	gdp2
gdp	0.194		

gdp2	-0.145	0.863	
lwge	-0.982	-0.058	0.231

The impact of LWGE (lagged WGE) is different from that of POP and CAR in the earlier models, because in MLM5 LWGE becomes the most significant variable once it is added into the regression. In the fixed effects table, the overall average coefficient estimate for LWGE is 0.94868 and it is nearly one magnitude larger than the effect of GDP. The impact of GDP^2 is still positive thought it is the smallest. In random effects, the variance for all predictors become much smaller compare to previous models. This evidence suggests that LWGE is an important factor in analyzing WGE and this result is not surprising given the possibility of temporal autocorrelation of waste gas emission. However, simply use LWGE as another predict variable is not appropriate. We will address this issue in autoregressive model in next section. Figure-8 and Figure-9 compare the estimated intercept and slope of GDP from multiple linear model and multilevel model. It is obvious that the results from these two models are quite different. The black lines represent the MLM 5 and the gray lines show the multiple linear result. By using SLM, the initial level of emission is larger than MLM 5 and GDP's impact on WGE is greater too. As a result, the estimated WGE will very likely be biased upward and the total CO_2 emission prediction can be larger than it actually is.

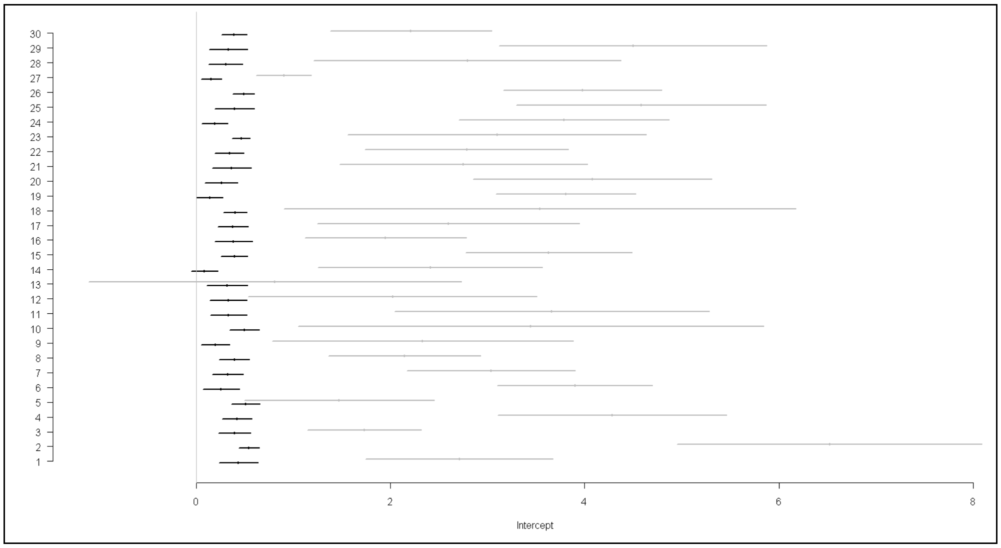


Figure-8 Comparison of Intercept from SLM and MLM 5

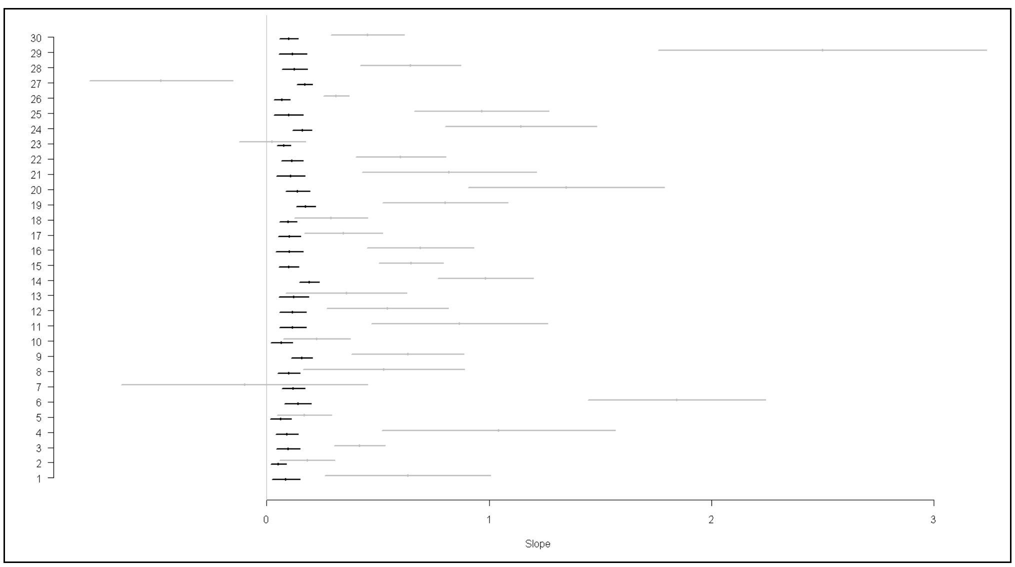


Figure-9 Comparison between Slope of GDP from SLM and MLM 5

To summarize, we use multilevel model to construct four models that are similar to Auffhammer and Carson's Model 1-4. Our models suggest that differences between provinces are both in model intercept and slope, while Auffhammer and Carson assumes only model intercepts vary by province.

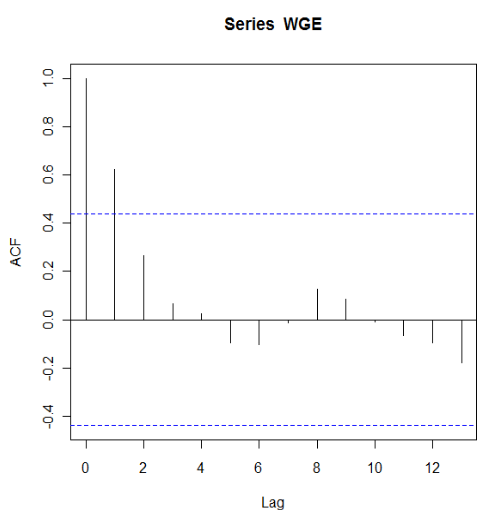
b. Autoregressive Model ARIMA

We believe there is time dependence within each province's waste gas emission and MLM5 in last section supports this perspective, while the exact relationship various. In order to set up a proper dynamic link that properly accounts for the autocorrelation while can still avoid wrong error structure, we chose Autoregressive Integrated Moving Average (ARIMA) model to conduct time series analysis.

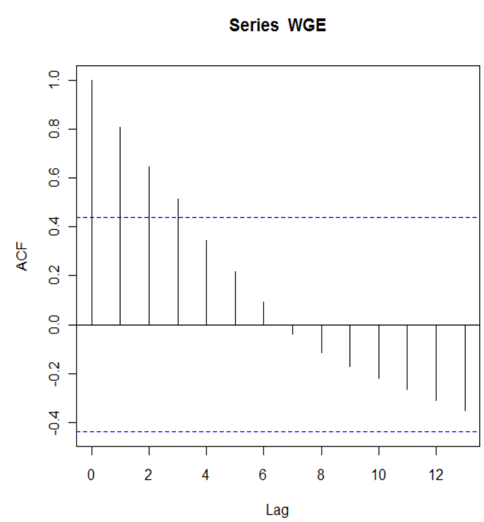
ARIMA model a univariate time series model. It is composed of three parts, the order of autoregressive, degree of differencing, and moving average, represented by parameters ARIMA (p, d, q) respectively. We prefer ARIMA over other autoregressive models, for instance Autoregressive Moving Average (ARMA) Model and Autoregressive (AR) model, for the following reasons. First, by applying degree of differencing, ARIMA allows data to be non-stationary, which means in our case the mean and variance of the WGE could change over time. Second, ARIMA is flexible in adding external predict variables. Since we expect waste gas emission is not only affected by its autocorrelation but also by some other external factors like GDP. Neither ARMA nor AR allow external predict variables but ARIMA.

Recognizing the uniqueness of each province's emission pattern, we fit specific model for each province. For order of differencing and moving average, we fix both of them to be one for all provinces because we believe the main reason for various emission patterns is the degree of autocorrelation of emission in consecutive years and our focus is to find proper number of lag terms.

In determining order of auto regression, Autocorrelation Coefficient (ACF) plot is a good guide to detect the autocorrelation in WGE. A lag term is considered significant correlated with its previous term when its ACF value is greater than the significance level (dependents on specific case). Figure-10 shows ACF plots for Jiangxi Province and Zhejiang Province. The difference between these two provinces are clear as there is only one significant lag term of WGE for Jiangxi province while the significance of autocorrelation of WGEs in Zhejiang province phases out until the forth lagged term. The justification of number of lag terms can be complemented by plotting different number of lag terms against the rest of WGE data, as it is shown in Figure-11 for the same two provinces. Our decision of order of auto regression is further reinstated by the plots. Both ACF plot and lagged term panel plot are conducted for each province to determine the appropriate number of lagged term. Across 30 provinces the numbers of lagged term various, ranging from 1 to 3.

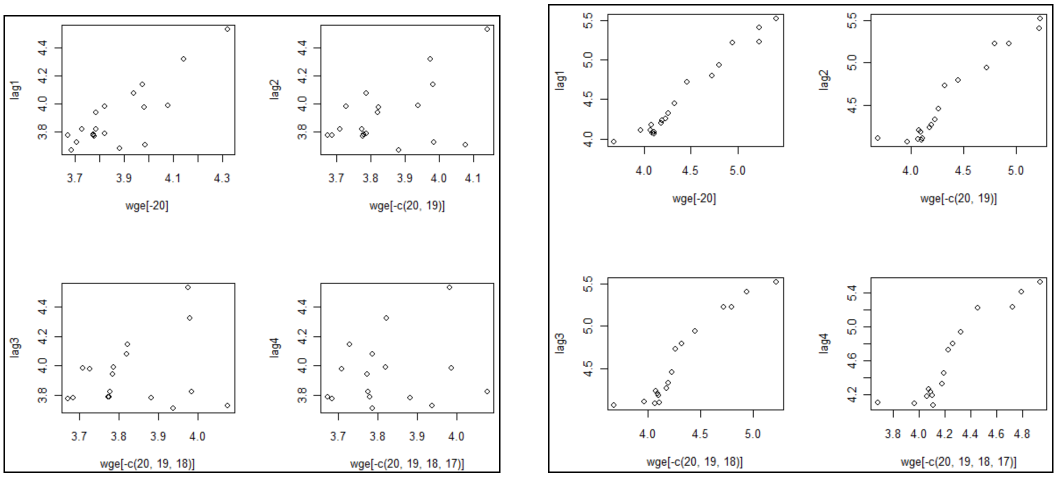


ACF Plot of Jiangxi Province



ACF Plot of Zhejiang Province

Figure-10 Autocorrelation Coefficient Plot



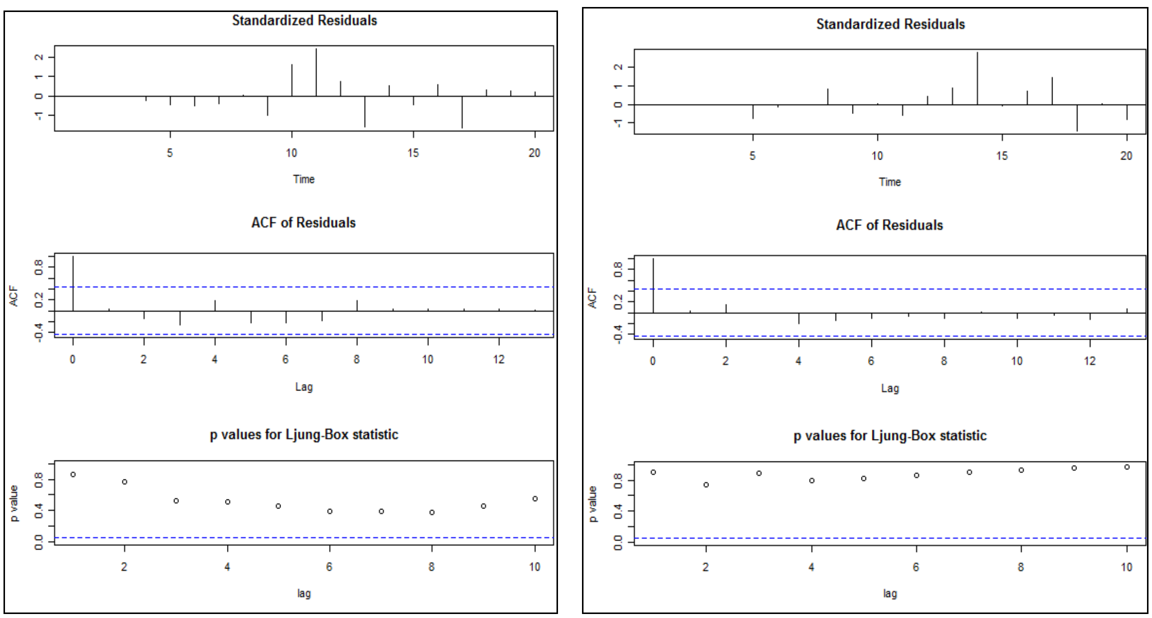
Jiangxi Province Zhejiang Province

Figure-11 Lagged Term Panel Plot

After determining the parameters of ARIMA model, we also include two external predict variables GDP and GDP^2 in ARIMA to carry out the prediction. Environmental economics theory suggests that as GDP per capita increases, the associated pollution will first increase and then decrease after reaching a peak level. An inverted-U shaped relationship between pollution and GDP per capita is proposed by Environmental Kruznets Curve (EKC) Theory. Hence, GDP is very important in exploring WGE path and if EKC is true, a quadratic term of GDP should also be employed. Finally, we have our ARIMA model specification as following

$$\mathrm{WGE_t} = \sum_{\mathrm{n=1}}^{j} \alpha_{\mathrm{n}} * \mathrm{WGE_{t\text{-}n}} + \mathrm{e_t} + \mathrm{e_{t\text{-}1}} + \beta_1 * GDP + \beta_2 * GDP^2$$

In the equation, n is the order of auto regression and j is the upper level value of n which is determined by the significance of the autocorrelation coefficient we described above. A well fitted model will result in independent residuals and this can be tested by ACF of residual and Ljung-Box Test which examines the independency of residuals in time series model. Figure-12 shows standardized residuals, ACF of residuals and the Ljung-Box Test for Shangxi and Zhejiang Province. In ACF of residual plot, no lagged term exceeds the significance level. It indicates that there is no significant correlation among WGE residuals. We can also see from Ljung-Box plot that all of the p-values for Ljung-Box statistic for given numbers of lags are a lot larger than 0.05 significant level; therefore we cannot reject the null hypothesis that the residuals are independent. Hence, we are convinced about the fitness of our model. Again, the same test is done for every province and the results support our model and parameters chosen.



Jiangxi Province

Zhejiang Province

Figure-12 Model Residuals

Table-8 summarizes ARIMA model results for each province. There are nine provinces having a order of auto regression of 3 and they are Hebei, Jiangsu, Zhejiang, Anhui, Shandong, Henan, Guangxi and Sichuan. There are seven provinces only have one lag year significant and they are Beijing, Tianjin, Inner Mongolia, Liaoning, Jilin, Tibet and Jiangsu, and the rest provinces have an auto regression order of two. The coefficient estimates of GDP are all positive except Tibet. Tibet is culturally and economically different from the rest part of China and it is considered the most pristine area in China without many existing industries. Our negative coefficient estimate of

Tibet suggests that the growth of per capita GDP does not trigger an obvious growth of waste gas emission and we believe it is very likely the case given Tibet's social and economic background. Only three provinces have negative coefficients for GDP^2 term, Beijing, Guizhou and Tibet. The negative sign of GDP^2 implies that a typical EKC may exist. Beijing is undergoing a significant industrial restructure through which almost all the polluting industries are moved outside the city and it explains why the inverted-U curve merges. Guizhou and Tibet have different stories. Unlike Being, Guizhou and Tibet are the least two developed areas in China and they attract little industries. They are struggling to develop their economy on sectors other than heavy industries and manufactory which give out pollutants. As a result, their pollution doesn't present a proportional increase with their GDP growth.

Table-8 ARIMA Results for 30 Chinese Provinces

Province	AR1	AR2	AR3	MA1	Intercept	GDP	GDP^2
Beijing	-0.1148			-0.7794	5.4874	0.1184	-0.2765
Tianjin	-0.1307			0.3800	5.2301	0.3327	0.0542
Hebei	-0.1197	0.2553	0.4364	-0.2133	5.2763	1.3937	0.6037
Shanxi	0.1874	-0.1017		-1.4506	6.1777	1.5365	0.4579
Inner Mongolia	0.7650			-1.4129	6.1186	2.0301	0.7953
Liaoning	0.2369			-0.9145	5.460	0.4022	0.2950
Jilin	0.6433			-1.3976	4.9621	0.4806	0.2317
Heilongjiang	0.5909	-0.1791		-1.475	4.809	0.2134	0.1718
Shanghai	-0.5324	-0.3729		1.4417	5.7125	-0.1298	0.3091
Jiangsu	0.2118	-0.6368	-0.0021	-1.5351	4.7405	0.8578	0.4183
Zhejiang	-0.3516	0.0414	0.2921	0.4072	4.506	0.5410	0.2684
Anhui	-0.4616	-0.4395	-0.4168	0.7929	4.7719	0.7670	0.1006
Fujian	0.5386	-0.1856		-1.5129	4.2678	0.8623	0.3681
Jiangxi	0.8039	-0.4282		-1.5625	4.7445	1.3833	0.477
Shandong	0.2677	-0.0553	-0.2934	-1.5316	4.8559	0.952	0.3566
Henan	-0.7233	-0.3573	-0.5354	0.5996	5.0448	1.1879	0.2799
Hubei	-0.0535	0.2007	-0.2276	-1.6144	4.8281	1.0040	0.3348
Hunan	-0.5456	-0.4741		1.6443	4.4849	0.8146	0.2367
Guangdong	0.9662	-0.3882		-1.6483	4.6033	0.5717	0.0486
Guangxi	-0.9155	-0.3186	-0.1345	1.5949	6.3425	2.9760	0.7907
Hainan	0.5238	-0.7439		-1.6343	4.5055	1.3526	0.0281
Sichuan	-0.1969	-0.1593	-0.3442	-1.4976	4.7036	1.0123	0.2909

Guizhou	0.3959	-0.7481		-1.5299	5.1915	0.561	-0.0232
Yunnan	0.2020	0.2779		-1.5089	5.6566	2.7384	0.9075
Tibet	0.1612			-1.668	1.577	-1.1469	-0.9436
Shaanxi	0.4413	-0.1648		-1.6278	5.099	1.4655	0.4939
Gansu	0.4601			-1.5056	5.7161	1.8899	0.7568
Ningxia	-0.1006	0.2215		-1.422	6.133	1.2192	0.24
Qinghai	0.3446	0.2800		-1.5032	5.6937	1.4109	0.2536
Xinjiang	-0.3792	-0.3510		0.1368	5.1541	1.1653	0.3145

c. Predictive Models

Auffhammer and Carson's paper is built based on a 20-year panel data (1985-2004). For now, we have another three years data available so that we can extend the dataset to a 23-year panel data (1985-2007) and use it to carry out our prediction of China's CO_2 emission to 2010.

We transform 2005-2007 provincial per capita GDP into 1985-based data using province specific GDP deflators so that they are consistent with the original data used by Auffhammer and Carson. The details of calculating the deflators are described as below. First, the deflator of 2004 is calculated by dividing the nominal per capita GDP in 2004 by the real 2004 GDP in 1985 currency. Then, we draw Retail Price Index (RPI) from each province's statistical yearbook and use it as an index of inflation. Last, province specific deflator of 2005-2007 is calculated by multiply 2004 deflator by province specific RPI. Once the deflator is obtained for each province each year, we are able to translate the new GDP information into comparable format with Auffhammer and Carson.

In terms of prediction, instead of constructing one national level model, we fit ARIMA prediction model for each province respectively and this allows us to choose the best order of lag for each province. The new GDP data enters the prediction as part of the predict variables GDP and GDP^2. Take Beijing for example. The logarithm term of per capita GDP in 1985 currency for 2005-2007 are 2.97, 3.07, 3.21 and the corresponding square terms are 8.84, 9.45, and 10.30. When fitting ARIMA prediction model for Beijing, our previous model tells us that the optimal parameters for the auto regression order, degree of differencing and the order of moving average are all 1. We adapted those parameters in our prediction model and add the new GDP and GDP^2 data into predict variable vectors. We want to predict 6 years ahead from 2004 in order to compare our result to Auffhammer and 's. The specific model for Beijing and its result are included in Appendix I as a case study.

The same procedures are taken for the other 29 provinces and the specific GDP information of each province are incorporate into their models. Table-9 gives the waste gas emissions for 30 Chinese provinces in our prediction period.

Table-9 ARIMA Prediction Model Result for 30 Provinces

Province	Year	LPWGE	Province	Year	LPWGE	Province	Year	LPWGE
Beijing	2005	3.392171	Zhejiang	2005	7.816653	Hainan	2005	5.90617
Beijing	2006	3.241895	Zhejiang	2006	8.094967	Hainan	2006	6.110794
Beijing	2007	3.021084	Zhejiang	2007	8.315766	Hainan	2007	6.162561
Beijing	2008	3.39901	Zhejiang	2008	7.815504	Hainan	2008	5.805519
Beijing	2009	3.24111	Zhejiang	2009	8.077241	Hainan	2009	5.990779
Beijing	2010	3.021174	Zhejiang	2010	8.308529	Hainan	2010	6.174571
Tianjin	2005	6.764247	Anhui	2005	5.470138	Sichuan	2005	5.80841
Tianjin	2006	6.856086	Anhui	2006	5.607248	Sichuan	2006	6.189714
Tianjin	2007	6.913865	Anhui	2007	5.734326	Sichuan	2007	6.417894
Tianjin	2008	6.767168	Anhui	2008	5.477938	Sichuan	2008	5.860653
Tianjin	2009	6.855704	Anhui	2009	5.595548	Sichuan	2009	6.173684
Tianjin	2010	6.913915	Anhui	2010	5.728591	Sichuan	2010	6.434328
Hebei	2005	8.63131	Fujian	2005	7.166458	Guizhou	2005	5.632103
Hebei	2006	9.043127	Fujian	2006	7.419064	Guizhou	2006	5.688867
Hebei	2007	9.465371	Fujian	2007	7.748133	Guizhou	2007	5.629839
Hebei	2008	8.653664	Fujian	2008	7.144778	Guizhou	2008	5.46084
Hebei	2009	9.058366	Fujian	2009	7.414651	Guizhou	2009	5.611148
Hebei	2010	9.473134	Fujian	2010	7.749781	Guizhou	2010	5.727192
Shanxi	2005	8.291603	Jiangxi	2005	6.515785	Yunan	2005	8.54936
Shanxi	2006	8.637012	Jiangxi	2006	6.750022	Yunan	2006	9.082228
Shanxi	2007	9.000607	Jiangxi	2007	7.022536	Yunan	2007	9.517702

Shanxi	2008	8.319791	Jiangxi	2008	6.480548	Yunan	2008	8.537646
Shanxi	2009	8.634395	Jiangxi	2009	6.749045	Yunan	2009	9.088563
Shanxi	2010	8.997249	Jiangxi	2010	7.03684	Yunan	2010	9.515725
Inner Mongolia	2005	10.77475	Shandong	2005	7.90464	Tibet	2005	-0.27189
Inner Mongolia	2006	11.72687	Shandong	2006	8.299733	Tibet	2006	-0.66718
Inner Mongolia	2007	12.61082	Shandong	2007	8.59972	Tibet	2007	-1.1007
Inner Mongolia	2008	10.77316	Shandong	2008	7.930685	Tibet	2008	-0.28401
Inner Mongolia	2009	11.72565	Shandong	2009	8.281942	Tibet	2009	-0.66913
Inner Mongolia	2010	12.60989	Shandong	2010	8.568712	Tibet	2010	-1.10101
Liaoning	2005	7.15288	Henan	2005	6.711656	Shaanxi	2005	6.86087
Liaoning	2006	7.339452	Henan	2006	7.017141	Shaanxi	2006	7.26288
Liaoning	2007	7.507447	Henan	2007	7.332494	Shaanxi	2007	7.65736
Liaoning	2008	7.150763	Henan	2008	6.711303	Shaanxi	2008	6.875238
Liaoning	2009	7.338951	Henan	2009	7.017982	Shaanxi	2009	7.266632
Liaoning	2010	7.507329	Henan	2010	7.292524	Shaanxi	2010	7.656645
Jilin	2005	5.874211	Hubei	2005	6.733266	Gansu	2005	7.46501
Jilin	2006	6.023379	Hubei	2006	7.04706	Gansu	2006	7.980291
Jilin	2007	6.218587	Hubei	2007	7.276518	Gansu	2007	8.393202
Jilin	2008	5.866363	Hubei	2008	6.759398	Gansu	2008	7.483004
Jilin	2009	6.018331	Hubei	2009	6.998506	Gansu	2009	7.988569
Jilin	2010	6.215339	Hubei	2010	7.308901	Gansu	2010	8.397011
Heilongjiang	2005	5.508643	Hunan	2005	5.506042	Ningxia	2005	7.45892
Heilongjiang	2006	5.59058	Hunan	2006	5.63134	Ningxia	2006	7.705947
Heilongjiang	2007	5.651223	Hunan	2007	5.845812	Ningxia	2007	7.869501
Heilongjiang	2008	5.513372	Hunan	2008	5.502115	Ningxia	2008	7.487427
Heilongjiang	2009	5.593028	Hunan	2009	5.643337	Ningxia	2009	7.687749
Heilongjiang	2010	5.651822	Hunan	2010	5.841129	Ningxia	2010	7.877647
Shanghai	2005	7.970954	Guangdong	2005	6.054312	Qinghai	2005	7.18769
Shanghai	2006	8.149969	Guangdong	2006	6.177473	Qinghai	2006	7.451705
Shanghai	2007	8.352742	Guangdong	2007	6.268331	Qinghai	2007	7.618219
Shanghai	2008	7.966385	Guangdong	2008	6.044643	Qinghai	2008	7.186107
Shanghai	2009	8.1506	Guangdong	2009	6.167279	Qinghai	2009	7.447936
Shanghai	2010	8.35411	Guangdong	2010	6.262236	Qinghai	2010	7.616476
Jiangsu	2005	8.852135	Guangxi	2005	9.403791	Xinjiang	2005	7.109223
Jiangsu	2006	9.343478	Guangxi	2006	10.062821	Xinjiang	2006	7.319222
Jiangsu	2007	9.657356	Guangxi	2007	10.740152	Xinjiang	2007	7.482092
Jiangsu	2008	8.788861	Guangxi	2008	9.397175	Xinjiang	2008	7.101848
Jiangsu	2009	9.241898	Guangxi	2009	10.067495	Xinjiang	2009	7.330062
Jiangsu	2010	9.67585	Guangxi	2010	10.742723	Xinjiang	2010	7.48057

The next step is to integrate the province level predictions into national level by adding up the predicted WGE of each province in each year. So far, our waste gas emissions are expressed in per capita unit and in logarithm term and they are still only a proxy for Carbon Dioxide emission.

Therefore, we need to do a series of transform and conversion to get the total national CO_2 emission. Taking the exponential of the log national per capita waste gas emission is the first step and then we use engineering relationship to convert WGE into CO_2. In order to be consistent, we use the same equation Auffhammer and Carson used in constructing their WGE and CO_2 relationship, and it is shown as following.

$$CO_{2t}=5.673WGE_t+\eta_t.$$

According to the equation the national per capita CO_2 emission equals to 5.673 times national per capita waste gas emission. The national total CO_2 emission for a specific year is the product of national per capita CO_2 and national population.

For population, we have new population data of 2005-2007 available from China National Bureau of Statistics. For the remaining three years, we use the same population growth rate assumptions Auffhammer and Carson used in their paper to conduct scenario analysis. There are four population growth scenarios. In Table-10 we summarized them.

Table-10 Population Growth Rates Assumptions

Population Scenarios	A	B	C	D
Mortality Rate	Constant	Constant	Decrease	Decrease
Birth Rate	Constant	Decrease	Constant	Decrease
Aggregated Growth Rate	0.91%	0.40%	1.03%	0.51%

China National Bureau of Statistics publishes the annual population growth rate till 2007. It shows that the natural growth rate keep falling in the past twenty years and in the twenty-first century the natural growth rate has drop from around 0.7% to 0.5%. In comparison with the actually growth rate, we find our Scenario D gives the closeted estimation of China's population growth. Therefore, we use the population growth rate of 0.51% as our best estimation of population growth pattern. Then the national CO_2 emission can be obtained by multiply the national per capita CO_2 emission by the total population. The national CO_2 is reported in Table-11 with a comparison to Auffhammer and Carson's best fitted model result.

Table-11 National CO_2 Emission (MMT)

Year	National CO_2	AFFUHAMMER AND CARSON 's Model $
2005	1,440	
2006	1,660	
2007	1,860	
2008	1,440	
2009	1,710	
2010	1,990	2.65E+09

V. Discussion and Conclusion

Our work is based on Auffhammer and Carson's work of forecasting China's CO_2 emission using provincial level information. We pointed out that Auffhammer and Carson work is subject to certain statistically unsubstantiated points. For example they impropriate incorporated lagged WGE in time series analysis and they didn't fully account for the heterogeneity of different provinces. As we recognize the time dependence of WGE, we apply ARIMA model to conducting time series analysis without trigger the mis-constructed error structure. Besides, we use multilevel model to illustrate how emission patters can be different among provinces.

Though we are able to use the most recent provincial level data, our prediction results are still subject to some limitations. First, there is only one observation in each year for every province. The small sample size leads to larger standard error and a low statistical power, and as a result the uncertainty of our model could also be large. However, the fact that China's emission data report system only release annual WGE information makes the small sample issue inevitable. As China is putting effort to improve the pollution monitor system, we are expecting more valid data being report on a timely manner.

Our model reveals that the important factors in predicting CO_2 emission to 2010 are GDP and its square term and the emission from previous year, while the car ownership and population density don't play a significant role in our analysis. In fact, besides the above mentioned predictors there are also some other factors may have impact on China's CO_2 emission. For an instance, the coal-rich provinces like Shanxi are expected to have a greatly different fuel structure from other provinces with little coal reserve. Another example is to exam the industrial structure across the country. A large amount of "Made in China" products are originated from southeast China, and it results the economy of southeast provinces heavily relies on manufacture which is energy intensive. At the same time, southwest China is the last frontier of China. Few heavy industries locate in that region while the carbon-free tourism makes profits to those provinces. The stories indicate that there are more factors on the macro-economy level such as industrial structure and fuel consumption that may have significant impact on predicting CO_2 emission while they are currently missing from our model. In future work, our multilevel model can be further developed to include province level predictors to take industrial structure and fuel consumption along with other macro factor into consideration. The benefits of including provincial level predictor are not only making the forecast more accurate, it can also shed some light on China' climate change policy-making perspective. With province level predictor, province policy-maker can have a better understanding about what makes the most significant contribution to their CO_2 emission and therefore be able to tackle the major issue.

In conclusion, our study provides critics for Auffhammer and Carson's work on forecasting China's CO_2 emission. We point out that from a strict statistical point of view, their work is subject to a mis-constructed dynamic link and at the same time they failed to consider heterogeneities of different Chinese provinces. As a result of these drawbacks, they are likely to overestimate China's future CO_2 emission. With the most updated provincial emission data, we use ARIMA and multilevel model to analysis China's CO_2 emission. Our forecast of China's CO_2 emission in 2010 is 1,990 MMT and it supports our speculation that Auffhammer and Carson's prediction results are biased.

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The author wants to appreciate Dr. Song S. Qian for his over one year advising on this project. This work won't be accomplished without his profound knowledge of statistical analysis and his experience with pollution management in China.

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Last, the author wants to thanks her parents and other family member who are thousands of miles away from the U.S for their unconditional supports throughout her master's study. She won't make it without them.

Appendix I

R Codes:

Multiple Regression Model

*LinearModel.1<-lm(wge~gdp*province+gdp2*province+lwge*province-1-gdp)*

Multilevel Model 1

MLM1<- lmer(wge~gdp+gdp2+(1+gdp+gdp2|province))

Multilevel Model 2

MLM2<-lmer(wge~gdp+gdp2+(1+gdp+gdp2|province)+(1+gdp+gdp2|year))

Multilevel Model 3

MLM3<-lmer(wge~gdp+gdp2+pop+(1+gdp+gdp2+pop|province))

Multilevel Model 4

MLM4<-lmer(wge~gdp+gdp2+car+(1+gdp+gdp2+car|province))

Multilevel Model 5

MLM5<-lmer(wge~gdp+gdp2+lwge+(1+gdp+gdp2+lwge|province))

Prediction Model for Beijing

Beijing<-arima(WGE, order=c(1,1,1),xreg=cbind(1,gdp,gdps),method=c("CSS"))

predict(Beijing, newxreg=cbind(1, c(2.97,3.07,3.21), c(8.84,9.45,10.30)),n.ahead=6)

Beijing Model Results

2005	2006	2007	2008	2009	2010
3.392171	3.241895	3.021084	3.399010	3.241110	3.021174

Appendix II

Index Number	Province Name
1	Anhui
2	Beijing
3	Fujian
4	Gansu
5	Guangdong
6	Guangxi
7	Guizhou
8	Hainan
9	Hebei
10	Heilongjian
11	Henan
12	Hubei
13	Hunan
14	Inner Mongolia
15	Jiangsu
16	Jiangxi
17	Jilin
18	Liaoning
19	Ningxia
20	Qinghai
21	Shaanxi
22	Shandong
23	Shanghai
24	Shanxi
25	Sichuan
26	Tianjin
27	Tibet
28	Xinjiang
29	Yunnan
30	Zhejiang

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