Forecasting Chinese Greenhouse Gas Emissions: A Province Level Approach*

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Abstract

Forecasts of Chinese carbon dioxide (CO_2) emissions are critical to any global agreement on mitigating possible global climate change. We provide such forecasts through 2050 using a reduced form model. These estimates are the first based upon provincial-level data (1985-1999). We estimate a reduced form model selected by minimizing the Schwartz Information Criterion in a general to simple search. We consider a Generalized Additive Model with a spline on income as well as popular panel model specifications. The model chosen by the information criterion is a dynamic version of a model popular in the literature on the Environmental Kuznets Curve (EKC). We extend the traditional specification by including aggregate population density, industry composition and technological progress. The EKC type relationship is robust to all specifications considered as well as all of the estimation techniques applied. Our aggregate forecasts of China's CO_2 emissions are based on a specification, which includes province specific lagged emissions. We find that our dynamic model suggests mildly lower estimates of CO_2 emissions given similar GDP and population growth assumptions than those based on aggregate national level data such as the quasi-official Intergovernmental Panel on Climate Change (IPCC) estimates. We again find evidence, which is supportive of an 'inverse U-shape' relationship between per capita CO_2 emissions and per capita income near the current Shanghai income level - without imposing such a relationship a priori. Our results do suggest that province specific per capita emissions follow very different trajectories in sample and out of sample, depending on the inclusion of province specific lagged dependent variables.

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1 Introduction

'The Kyoto Protocol was fatally flawed in fundamental ways. [...] This is a challenge that requires a 100 percent effort; ours, and the rest of the world's. The world's second-largest emitter of greenhouse gases is China. Yet, China was entirely exempted from the requirements of the Kyoto Protocol.

George W. Bush,
Rose Garden Press Conference,
June 11th 2001

The quote above summarizes one of the most potent arguments made by the United States against reducing their greenhouse gas emissions. They argue that a multilateral agreement regulating global greenhouse gas emissions is a pointless undertaking unless China and other large developing countries like India agree to substantial limits on their future emissions.[1] Forecasts of Chinese greenhouse gas emissions play a central role in discussions concerning what policies can or should be adopted concerning global climate change. China is currently the second largest emitter of greenhouse gases. By most current forecasts China will pass the United States by the year 2020 (Intergovernmental Panel on Climate Change, 2000; Siddiqi, Streets, Zongxin & Jiankun, 1994). Developing countries are adamant about negotiating reductions relative to the level of emissions that would be projected to occur normally as they industrialize.[2] Annex I countries (OECD plus the Eastern European countries including Russia), in contrast, agreed to reduce emissions relative to their current base-line emission levels. Determining this baseline level of projected emissions is crucial to any agreement involving the United States and China.

The literature forecasting Chinese CO_2 emissions has taken three distinctly different approaches. The first approach employs univariate as well as multivariate techniques on annually observed aggregate emissions data. The multivariate models mainly focus on the correlation between per capita income/product and emissions. Forecasts are then constructed using aggregate forecasts of China's population growth. This approach puts the same weight on a citizen of a mostly agricultural province as it does on the citizen of Beijing. Almost all available forecasts, including those of the Intergovernmental Panel on Climate Change (IPCC) are based on this data, which is aggregated at the national level. Yang & Schneider (1998) provide modified forecasts, which explicitly take into account rates of technological change and population growth. These forecasts do not utilize additional information contained in data available at a more disaggregate level. The second branch of the literature has addressed this issue by looking at emissions data by industry sector (Sinton & Levine, 1994; Zhang, 1998; Garbaccio, Ho & Jorgenson, 1999*a*; Garbaccio, Ho & Jorgenson, 1999*b*). The third approach, pursued by Zang, May & Heller (2000), uses plant level survey data starting with a few typical as well as extreme cases.

We pursue a fourth approach, which is disaggregating emissions data at the spatial level by looking across China's provinces. China's provinces differ greatly in land area. The largest province by area, Xinjiang, is

[1]This argument is also embedded in a U.S. Senate Resolute (Byrd-Hagel) by which the U.S. Senate went on record as stating that they would not ratify the Kyoto Protocol until there was meaningful participation by the developing countries.

[2]China has justified its policy of "no targets and time-tables" by arguing that Chinese responsibility for historic greenhouse gas emissions on a per capita basis is very low compared to that of other countries, and particularly compared to industrialized countries (Qu, 1990). In 1990, on a per capita basis, China's emissions were one tenth of US per capita emissions and about half the world average.

only 15% smaller than Mexico while the smallest province, Shanghai, is about the size of Rhode Island. The largest province in population terms is Sichuan, with 117 million inhabitants in 1999. Tibet has the fewest inhabitants, namely 2.6 million. China's largest provinces are therefore larger than most European countries along either dimension. Understanding the structural difference in per capita emissions is fundamental to understanding the path of China's future CO_2 emissions. The literature on economic growth, uses data at this level of disaggregation to test for convergence of per capita incomes across political subdivisions of countries (Barro & Sala-i-Martin, 1992; Bernard & Jones, 1996). These studies provide significant insight as to the behavior of national aggregates. The focus of this paper is similar to a growth relationship, namely how China's CO_2 per capita and aggregate emissions will respond to changes in its per capita income. We use a provincial level dataset, which is ideally suited to the task at hand.[3] Our model further addresses the question of how quickly China's provinces adjust current emissions with respect to their historical emissions patters.

The current paper adds to the literature on the environmental Kuznets curve (EKC) hypothesis. The EKC hypothesis suggests that the relationship between per capita emissions and per capita income should look like an inverted U-shaped curve - rising at low levels of income and decreasing after income has reached a certain threshold.[4] Carson, Jeon & McCubbin (1997) found evidence in support of the EKC hypothesis for air pollutants across the 50 United States. For China, there is substantially more variation across provinces both in per capita emissions (a factor of 50) and income levels (a factor of 8) than there is across U.S. states. Since China's per capita income is relatively low compared to that of industrialized countries, we would expect per capita emission levels to be rising with income. The income levels in the richest provinces are sufficiently high that a lower rate of increase in emissions per capita might be observed if an EKC turning point holds for CO_2 emissions. However, previous cross-country estimates for CO_2 emissions suggest that the income turning points for CO_2 emissions are quite high (Schmalensee, Stoker & Judson, 1998) or non-existent (Holtz-Eakin & Selden, 1995).

Our approach differs from traditional EKC type estimations in two ways: First, we add a dynamic aspect to the EKC specification. Our specification differs from the model by Agras & Chapman (1999), who include a first order autoregressive term, in that we add province specific lagged emission terms on the right hand side of the equation. This allows provinces to track their emissions at different rates. The traditional model specification of EKC type relationships, which hypothesizes a purely contemporaneous relationship between per capita income and emissions, implicitly assumes that one can adjust per capita emissions immediately. We argue that it takes time to adjust technology and therefore suggest that a dynamic model is the appropriate specification.[5]

Second, we do not specify emissions as a second (or third) order polynomial in income by default. We allow for a more flexible specification by estimating a generalized additive model (GAM) with a spline

[3]Similar in spirit to our paper in the sense of using provincial level Chinese data to look at a growth related phenomenon is Branstetter & Feenstra (2001) who examine trade and foreign direct investment.

[4]Note that the EKC hypothesis has been the subject of considerable debate in the literature. For discussions and empirical evidence see Grossman & Krueger (1995), Selden & Song (1994), Arrow, Bolin, Costanza, Dasgupta, Folke, Holling, Jansson, Levin, Mäler, Perrings & Pimentel (1995), Cavlovic, Baker, Berrens & Gawande (2000), and recent special issues of *Environment and Development Economics (1997)* and *Ecological Economics (1997)*.

[5]We estimated a contemporaneous specification, by regressing per capita emissions on a second up to a fifth order polynomial of per capita income. All terms were significant at the 1% level, suggesting an EKC type relationship in the reasonable range of income. When conducting our specification search in section 4.2, we reject this specification in favor of a dynamic empirical model.

on income (Hastie & Tibshirani, 1990). The GAM suggests a nonlinear relationship between per capita income and emissions. We test this model by minimizing an information criterion favoring a parsimonious model specification, which is in the best interest of a forecasting model. Further we condition on additional variables available at the provincial level and assumed to be exogenous to per capita income, as well as including province specific lagged dependent variables. This approach allows us to look at how factors like technological change and changes in population density as well as structural differences between coastal and inland provinces affect per capita emissions over time.

The paper is organized as follows. First, we provide a brief overview of China from a provincial perspective. Next, we define key concepts and discuss our data sources. This section also includes a discussion of the issue of converting waste gas emissions (the quantity measured by the Chinese National Environmental Protection Agency, NEPA) into CO_2 emissions. After that we estimate a set of models, which are the basis for predicting greenhouse gas emissions. These models are used to examine the relationship between CO_2 emissions and various factors, paying particular attention to the per capita emission-per capita income relationship. To forecast future Chinese CO_2 emissions it is necessary to make assumptions about a variety of different factors such as population growth, migration, changes in per capita income, and technological change. These assumptions can be used in conjunction with the models estimated to forecast future Chinese CO_2 emissions. We examine the sensitivity of the forecasts to changes in the key assumptions. We conclude by comparing our estimates to those in the existing literature.

2 Background

In order to forecast Chinese greenhouse gas emissions we need to gain an understanding of five fundamental relationships:

- How do emissions respond to changes in population size?
- How do emissions react to shifts in the internal distribution of population?
- How do emissions respond to economic growth?
- What impact does industrial structure have on emissions?
- How do advances in technology affect emissions?

The first question is especially interesting when considering China's past and projected population growth. China's population has increased by 234% since 1950, making it the world's most populous country by a margin of about 285 million people, which is about the current size of the US population. The past two decades have been characterized by increased urbanization and efforts by the Chinese government to locate people in less densely populated areas - essentially trying to offset migration to urban centers. Per capita emissions depend greatly on the scale of industrial activity, which is highly concentrated in the coastal areas and urban centers. Population density varies greatly across the provinces. The simple linear correlation coefficient between provincial population density and per capita waste gas emissions is 0.606 for our sample. This suggests scale effects, which we will formally explore in section 4.

Provincial population density depends on differential birth and mortality rates, as well as existing and changing migration patterns within the PRC. Aggregate forecasts, such as those provided by the Intergovernmental Panel on Climate Change (2000), incorporate overall population growth, but ignore the impact of internal migration and differing rates of population growth across provinces. These aggregate models cannot explicitly model different scenarios of internal migration and population growth. We incorporate four population growth scenarios provided by Chesnais & Minglei (1998) into our forecasts. We use these demographic forecasts as exogenous scenarios and make no policy statements about the possibly optimal distribution of population across China's provinces. We simply show how sensitive aggregate forecasts are to changes in provincial population density.

The third point relates to the pollution income relationship (PIR). If this PIR is an *inverse U-shape*, it is commonly referred to as an Environmental Kuznets Curve (EKC). The typical EKC paper regresses per capita emissions on a polynomial of per capita income. This is a very controversial subject, especially when testing whether such a relationship holds for CO_2. There is some empirical cross country evidence in favor of such a relationship for the flow pollutants SO_2, NO_x, CO, suspended particulates and river pollution. The evidence for stock pollutants such as solid waste and CO_2 is rather contradictory. Lieb (2001) provides an excellent summary of the major EKC studies up to date. He further provides a theoretical model which gives rise to an EKC for flow pollutants due to '[...] ever rising stock pollution'. We use a more general empirical modelling approach, which does not assume a specific functional form a priori. We use a Generalized Additive Model (GAM) after Hastie & Tibshirani (1990), where we estimate the PIR via a spline and a loess data smooth. Section 4 shows in more detail that the smoothers suggest an upward sloping nonlinear relationship. We then test this model versus a parametric panel and OLS model. The Schwartz Information Criterion chooses the OLS model over the GAM, suggesting an EKC type PIR.

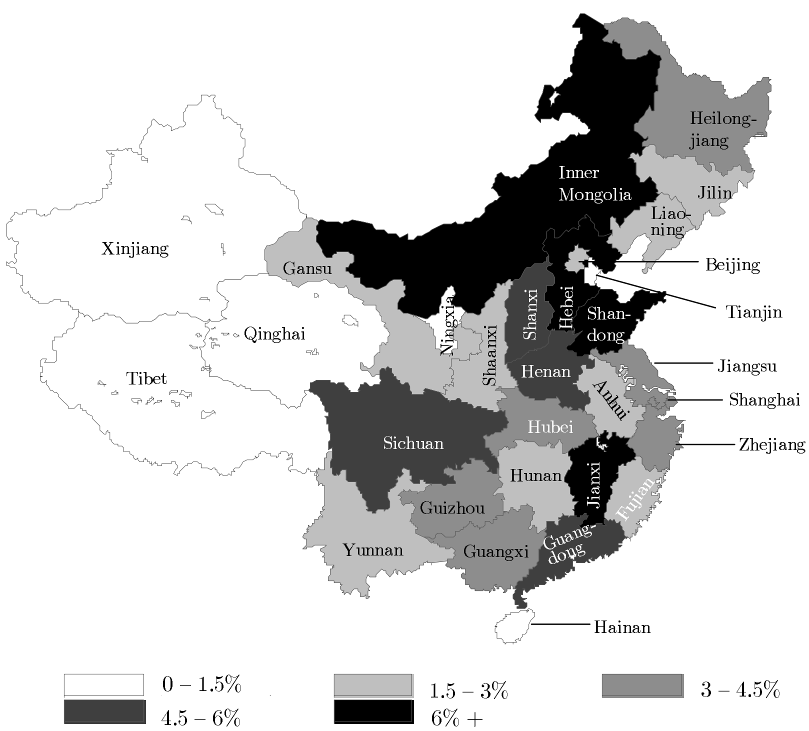
The next issue relates to the widely variable composition of industry across China's provinces. We use the term 'industry composition' to mean the share of *heavy/primary goods* processing industry in total output. This admittedly rather broad definition is specific enough for the purposes of this paper. Primary/heavy industry (*e.g* steel mills) concentrate around deposits of these natural resources, since transportation of unrefined ore is extremely costly. Provinces with high deposits of natural resources such as coal and iron ore tend to have a higher concentration of heavy industry. Provinces producing coal, steel and cement would be expected to produce a disproportionately larger amount of CO_2. We show that provinces with higher initial shares of heavy industry produce a significantly larger amount of per capita CO_2 emissions - after adjusting for income and other factors. As time and the development process continue, one would expect a shift of industry composition towards lighter industries. This is thought to be due to improvements in technology as well as the decreased dependence on the export of processed primary goods.

Lastly - controlling for initial industry composition and the possible inclusion of a time trend variable in the estimation fails to acknowledge the fact that provinces do follow differing paths of technological progress. The time fixed effects commonly included in EKC type studies capture shocks to preferences and technology *common to all provinces*. We argue, however, that provinces follow different paths of technological progress. This path of technological evolution is thought to depend on characteristics of a province's capital stock (*e.g.* age and efficiency) as well as the ability of the province's authorities to effectively enforce existing environmental legislation. Both of these aspects vary widely across provinces and are difficult to model empirically due to data limitations. We overcome this shortcoming by letting a province's elasticity of emissions with respect to past emissions vary across provinces. Since we are estimating this elasticity, the model is specified in logs. These elasticities should be positive and less than one in magnitude. This approach will allow us to implicitly model the variability of technological progress and environmental enforcement across provinces.

The correlation between per capita CO_2 emissions and per capita income as well as the elasticities discussed in the previous paragraph are at the center of this study. In order to estimate a model with valid parameter estimates and meaningful policy conclusions, it is essential that there be a sufficient degree of time-series and cross-sectional variability in the data. Below we discuss our data. We also provide a brief discussion of China's Environmental agencies and legislation. We empirically model the relationship in section 4.

China's modern economic growth has largely been fuelled by the exploitation of its massive coalfields. Coal made up 76% of total energy consumption in the 1990s. The burning of coal for electricity and heating causes more than 90% of air pollution. Most coal deposits are located in the north and northwest regions such as Inner Mongolia and Shanxi. Of these, Shanxi is the largest producer with nearly 30% of the total coal output in China. Coal is shipped south by boat and rail for further processing and consumption. Figure 1 shows the share of total waste gas emissions across China's provinces. The relatively sparsely populated coal producing provinces do contribute a disproportionately large share of waste gas emissions.

Figure 1: Provincial Shares of Total Waste Gas Emissions (in 1999)



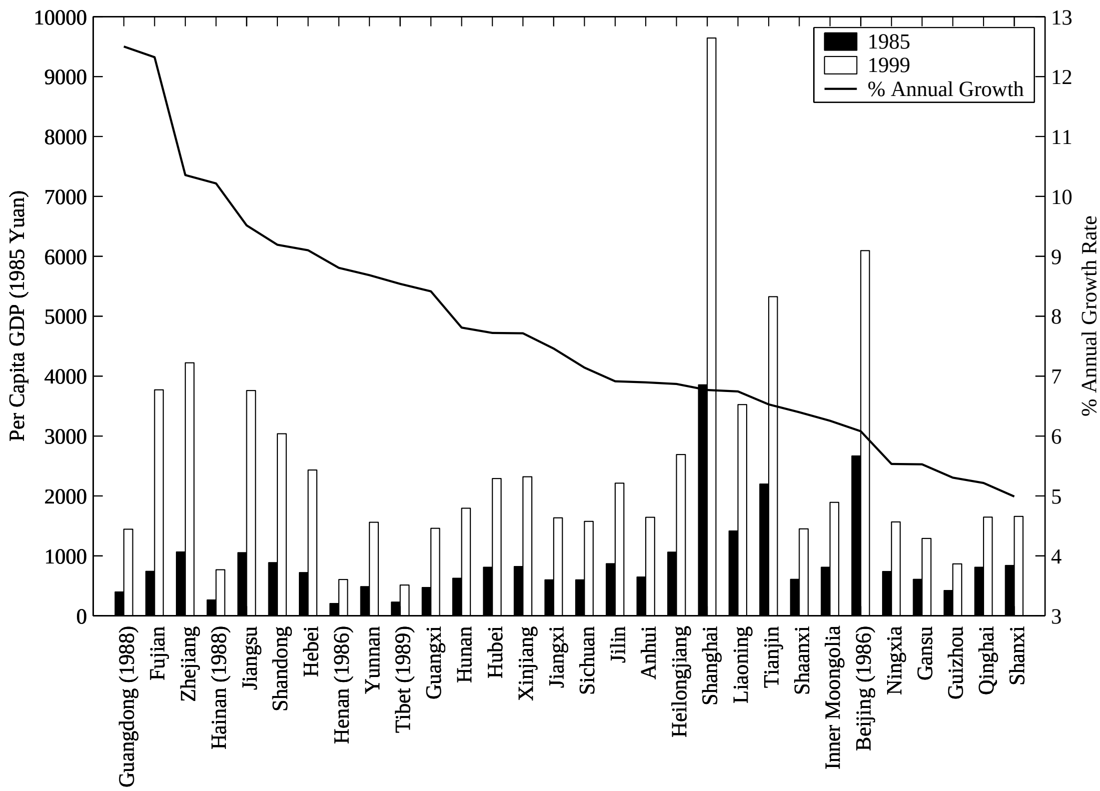
Only 6.43% of the total Chinese population lives in the six Northwest regions[6], which account for 54% of total Chinese territory. 42% of the population live in the relatively small coastal provinces. While the current population distribution remains much the same from the records of the 1930s (Lin & Huang, 1997), current

[6]Inner Mongolia, Ningxia, Xinjiang, Tibet, Gansu and Qinghai

population growth rates vary substantially across provinces. For instance, in 1999, the natural growth rate of the population in Tianjin was 0.21% while Beijing, Anhui, and Guangxi had average annual growth rates of 0.85%. In contrast, Guizhou, Tibet, and Guangdong have growth rates of more than 1.5% per annum. Population migration is increasing and now averages between 50 million to 80 million annually. There is evidence of population net outflow from the Northwest provinces of Tibet, Qinghai, Xinjiang, Sichuan, Guizhou, Yunnan, Shaanxi and Gansu (Lin & Huang, 1997).

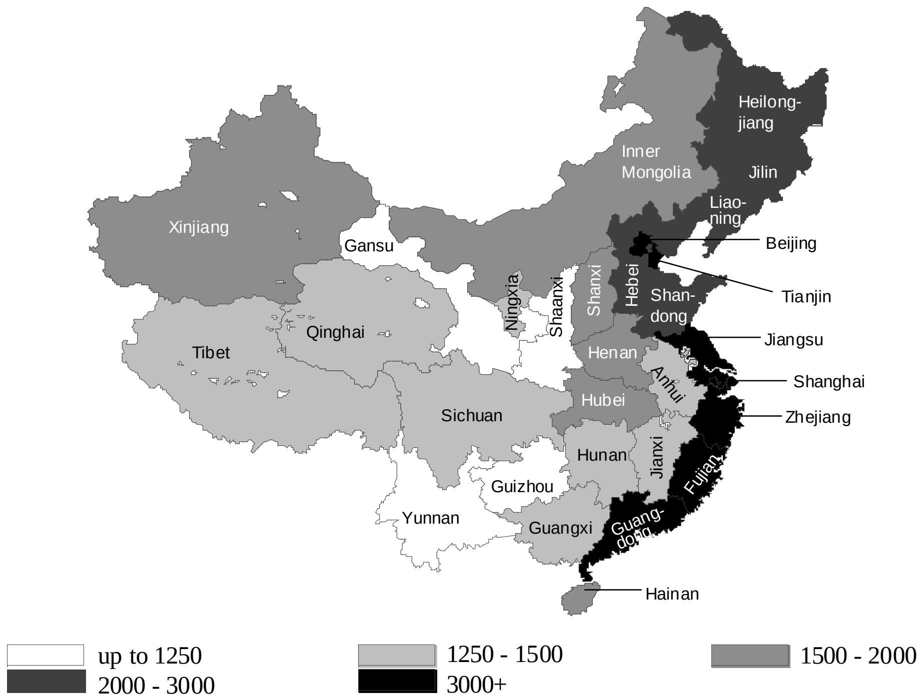
Changes in per capita income are the driving force behind the EKC hypothesis. Figure 2 displays per capita income for 1985 and for 1999 (the first and last year of our sample) in terms of per capita 1985 Yuan. Provinces are ordered by compound annual growth rate of per capita income over the fifteen-year period. Two things to note from the figure are: (a) the very large increases in per capita income over this fifteen-year period, and (b) substantial differences in the growth rates between provinces.

Figure 2: Provinces per capita income (1985 Yuan) and annual growth in 1999



The latter are reflected in the many changes in the provincial income ranking over the fifteen-year period even though the three initially wealthiest provinces, Shanghai, Beijing, and Tianjin have retained their earlier rankings. The large increase in Chinese per capita income appears to be due in large part to the reforms that started in 1979. Over time progressively more reforms with respect to foreign direct investment, joint ventures, and imports were allowed. It is noteworthy that the coastal provinces contain all of the special economic zones (SEZs). Figure 3 underlines the importance of provincial access to trade as well as the implications of trade and FDI liberalization. China's per capita wealth is heavily concentrated in the coastal provinces. We will explore the relationship between per capita emissions and per capita income in detail.

Figure 3: 1999 Provincial per capita income in 1985 Yuan



China's government has been cautious about making any commitment to carbon emissions reduction, China has paid considerable attention to energy efficiency improvements and has achieved notable successes in the past decades (Sinton, 1996). The energy intensity of the Chinese economy (measured by primary energy consumption per unit of national income) has decreased steadily since 1977. According to Chinese energy analysts, the major factors driving down the energy intensity have been the increasing share of light industries and investment in energy conservation (**?**). More recent work (Garbaccio et al., 1999*b*) has tended to assign more of the responsibility for the drop in Chinese energy intensity to technological change. Pollution control, especially in coal fired power plants, is focused more on improving the efficiency of coal furnaces (*e.g* increasing the furnace temperature) than installing end of pipe technologies such as scrubbers. This due to the large fixed investment necessary to install scrubbers as well as the increased output of electricity per unit of coal. Due to the inefficiency of most current coal fired Chinese power plants, this trend is expected to continue in the near future. Although there has been some thought given to switching away from energy production using coal and using more renewable energy sources, a change in the composition of inputs seems unlikely. The overall outcome is likely to be a much larger electric generating capacity with a mix of energy sources similar to the present where coal is used to provide the bulk of the electric power supplied.

In the mid 1970s, China established the National Environmental Protection Agency (NEPA) with a network of environmental protection departments, bureaus and offices at provincial, municipal, and county levels. Under the leadership of NEPA China has developed "by far the largest application of a market based regulatory instrument in the world" (Wang, 2000). In the late 1990s the demand for environmental quality emerged in major cities. Due to differences in public concern and to devolution of responsibilities from Beijing, provincial and city governments have become important from an environmental policy making perspective. The individual leadership of the local governments and the severity of pollution impact affect implementation at these levels (Wang & Wheeler, 1996; Wang, 1999). Some provinces/cities adopted air pollution emission permit policies even before the implementation of any national legislation. Examples are Shanghai, Tianjin, and Xuzhou City of Jiangsu Province (National Environmental Protection Agency, 1996). These cities are high-income cities with high degrees of openness. By 1983 all provinces except for Tibet[7] had established an implementation system. In this sense, environmental policy making in China, once characterized by a top-down model, is now being moved down to the province and city level.

The large degree of cross sectional and time series variation in the income and pollution data is bound to provide some interesting results when forecasting future CO_2 emissions for the PRC. Further, since we are disaggregating our data at the provincial level, we hope to be able to provide some interesting policy conclusions well suited to China's decentralized approach for enforcing environmental regulations.

3 Data

We will estimate a set of models using a province-level panel data set for 30 Chinese provinces during the period 1985-1999. Most of the provincial data used in this study have been collected from the China Statistical Yearbooks of the corresponding years. For 25 of the provinces we have one observation for every year of the sample period (15 years), while for few of the provinces there are only data available for eleven, twelve or thirteen years. The result is an unbalanced panel data set with 438 observations.

3.1 Waste Gas Emissions

The original source of our data on waste gas emissions (WGE) is China's Environmental Yearbook published by China's NEPA. WGE are measured in billions of cubic meters. They are very heterogeneously distributed between provinces. The coastal provinces[8], forming 14% of the area of the country, account for about 41% of waste gas emissions in 1999. This largely reflects the uneven distribution of population and economic activity in China. Per capita waste gas emissions (PWGE) also display high variability between provinces. Figure 4 shows the ranking of provinces according to 1985 per capita waste gas emissions. Provinces with higher PWGE tend also to be the provinces with higher income per capita. The simple correlation between the two variables is 0.82. Note that the coastal provinces also tend to have high PWGE. The average annual rate of increase of WGE during the sample period was 5.64%. However, that rate of change differed between provinces. While WGE in Hainan increased at an annual rate of 12.73%, the corresponding change of WGE in Tianjin was -0.57%.

3.2 Converting waste gas emissions to CO_2 emissions

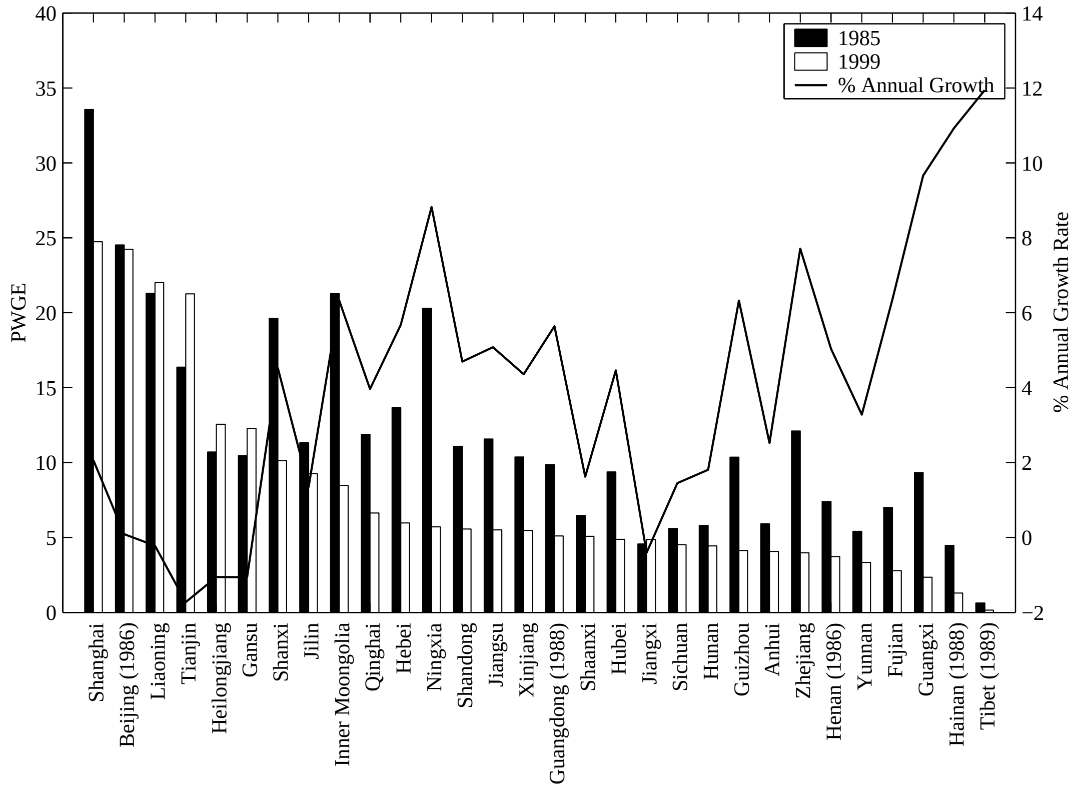
Data on China's carbon dioxide emissions are only available at a national level [9] (Oak Ridge National Laboratory, 1998). Waste gas emissions are obtained by the local NEPA agencies by measuring the composition of fossil fuels used on a provincial level. The authorities then use an estimated engineering relationship,

[7] Tibet began pollution charges in March 1991.

[8] Coastal region provinces (from north to south) are: Liaoning, Hebei, Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Hainan, Guangdong, and Guangxi.

[9] This is true of most countries since CO_2 is not a directly regulated pollutant and its estimate are largely derived from fossil fuel consumption.

Figure 4: 1985 & 1999 per capita Waste Gas Emissions (thousands of m^3)



which allows them to convert inputs into waste gas emissions. This method is also the one applied by Oak Ridge National Laboratory (1998) to obtain aggregate CO_2 emissions for single nations. Since we do not know the exact engineering relationship used by NEPA we convert WGE into CO_2 (carbon equivalent) emissions by aggregating waste gas emissions across provinces by year and using this variable to predict CO_2. We estimate the following equation:

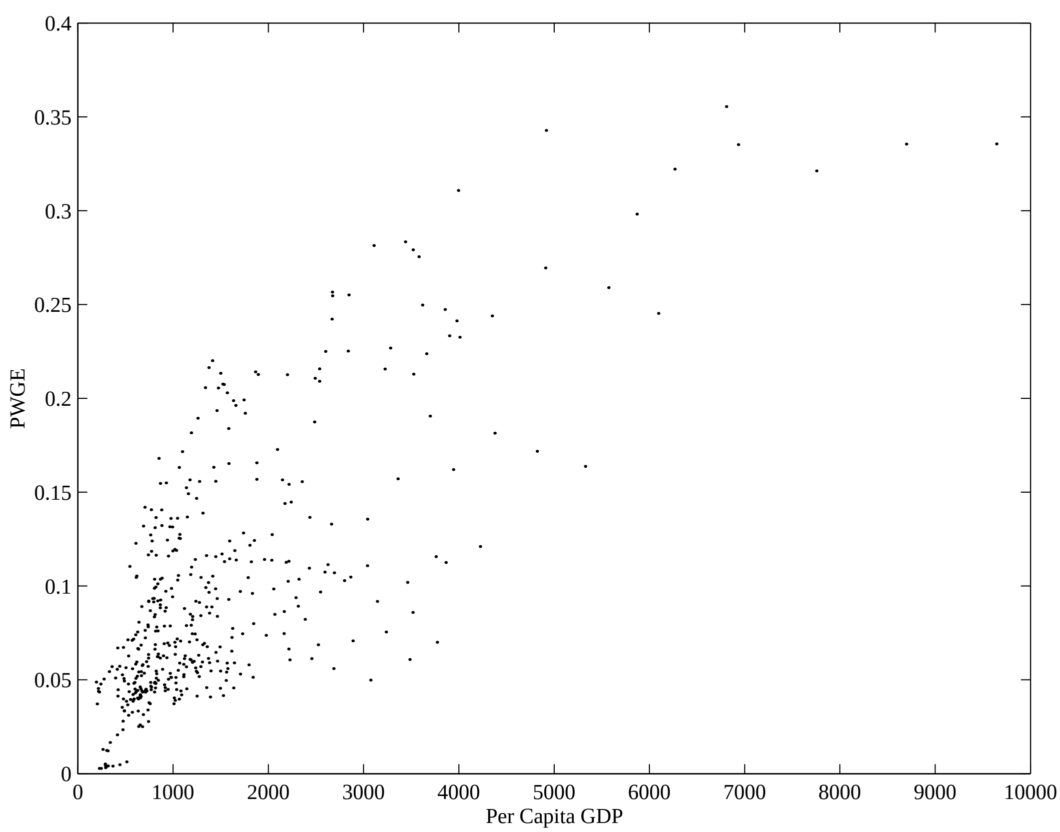
$$CO_{2t} = 8.60\, WGE_t + \eta_t \tag{1}$$

The heteroskedasticity consistent (White) t-statistic is 95.55. This almost perfect linear correlation (.982) suggests that WGE is a good proxy for CO_2. This allows one to predict per capita WGE emissions at the provincial level and then use the conversion factor above (8.60) to derive CO_2 (carbon equivalent) estimates. This relationship will hold if China keeps its focus on combustion efficiency versus end-of-pipe technologies such as scrubbers. By most estimates this shift is not expected to happen in the near future. Further, since transportation plays a large role in greenhouse gas emissions, this relationship may break down if there will be a large increase in the number of automobiles. This is also unlikely to happen in the near future due to China's limited oil resources and resistance to relying on oil imports. We will conduct all of our estimations using waste gas emissions and convert them for comparison purposes in section 5.

3.3 Socioeconomic Data

All of the data on waste gas emissions, per capita GDP, industrial composition, and population characteristics have been collected from the Chinese Statistical yearbooks (1986-2000). Our measure of GDP was calculated by deflating provincial nominal GDP using the national consumer price index for China as a deflator with 1985 as the base year. To get the per capita GDP measure we divide by the total provincial population at year end. Per capita GDP shows a high variability between provinces as discussed in section 2. Figure 5 plots per capita GDP against per capita waste gas emissions for the panel. Population density is calculated as total provincial population divided by total are in square miles. Our variable for industry composition is the ratio of value added by heavy industry over total value added by heavy and light industry per province. We only include industry composition for the first year data is available for all provinces, since we proxy for technological improvement by including a time trend. The Chinese Statistical Office has also changed its definition of heavy industry in the latter part of our sample, which makes it impossible to provide a consistent variable. We include this ratio for 1990, which is the first year for which we have observations for all provinces. We further include a dummy variable for coastal provinces. Coastal provinces contain all of the special economic zones, and due to their favorable location attract most of the foreign direct investment (FDI). This makes these provinces structurally different.

Figure 5: The relationship between per capita waste gas emissions and GDP



4 Empirical Models and Results

Instead of modelling waste gas emissions by using the reduced form approach adopted by Grossman & Krueger (1995), we first explore a Generalized Additive model to provide a more flexible functional form for the PIR. We then use the Schwartz Information Criterion (SIC) to test whether this specification is preferable to a more restrictive fixed effects model.

4.1 Generalized Additive Model

The specification we use is in per capita terms and predicts per capita waste gas emissions in terms of a spline/loess data smooth on income. Initial industry composition, a coast dummy variable, a time trend and province specific lags enter the equation linearly. This approach allows us to estimate the net effect of economic growth on per capita waste gas emissions. Per capita GDP is the dominant variable used in the literature to test for economic growth. It is not a one to one mapping into personal income, which is the driving force behind the EKC hypothesis, but has been adopted as the main proxy for income in the literature on the subject. We estimate the following model as a GAM[10]:

$$\begin{aligned} ln(PWGE_{it}) &= \alpha + f(GDP_{it}) + \beta_1 ln(COMP_{it_o}) + \beta_2 ln(PDENS_{it}) \\ &+\beta_3 COAST_i + \sum_{i=1}^{30} \beta_{3+i} ln(PWGE_{it-1}) + \beta_{34} ln(TIME_t) + \varepsilon_{it} \end{aligned} \tag{2}$$

Since we do not intend on using this model for forecasting purposes, we only explore the form of the function f, which determines the shape of the PIR. We used a spline as well as a loess data smooth to estimate equation 2. The shape of the PIR for both estimation techniques is almost identical and depicted in figure 6. The shape of the PIR clearly shows a functional form which resembles the rising slope of an EKC type relationship.

This finding is not surprising, for two reasons: China is rapidly developing, but its per capita income in PPP terms is still below that of most industrialized countries. We would therefore expect China to be on the rising part of an EKC. Further, the literature suggests that turning points for CO_2 would be rather high compared to flow pollutants like SO_2 or NO_x. In the next section we will go ahead and estimate a regular parametric model and compare it to the GAM.

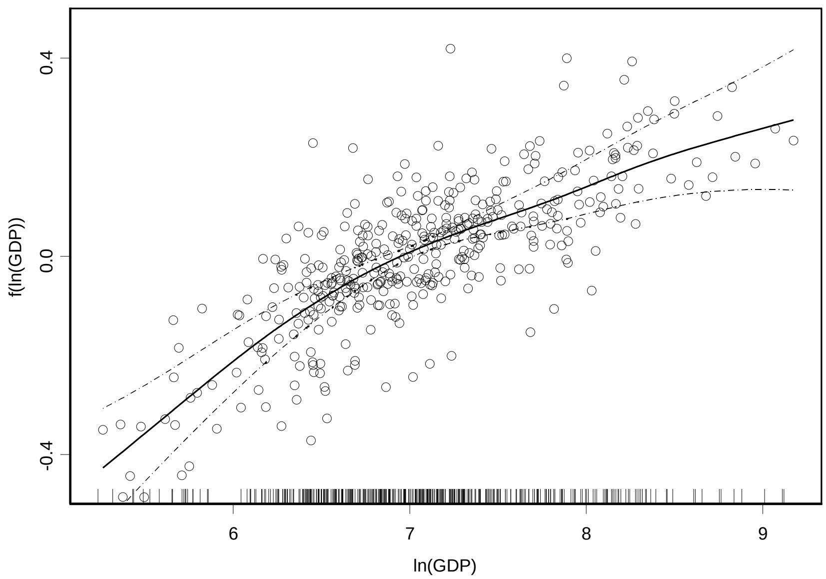
4.2 Specification Search

We conduct general to simple specification using the Schwartz Information Criterion (SIC). The most general initial model is given as equation (3) below:

$$\begin{aligned} ln(PWGE_{it}) &= \beta_1 ln(GDP_{it}) + \beta_2 (ln(GDP_{it}))^2 + \beta_3 ln(COMP_{it_o}) \\ &+\beta_4 ln(PDENS_{it}) + \beta_5 COAST_i + \sum_{i=1}^{30} \beta_{5+i} ln(PWGE_{it-1}) \\ &+ \sum_{i=31}^{60} \beta_{5+i} ln(PWGE_{it-2}) + \alpha_t + \gamma_i + \varepsilon_{it} \end{aligned} \tag{3}$$

[10] This is the model preferred by the SIC - the PIR for the other estimated models is similar

Figure 6: Predicted PWGE from Income using GAM



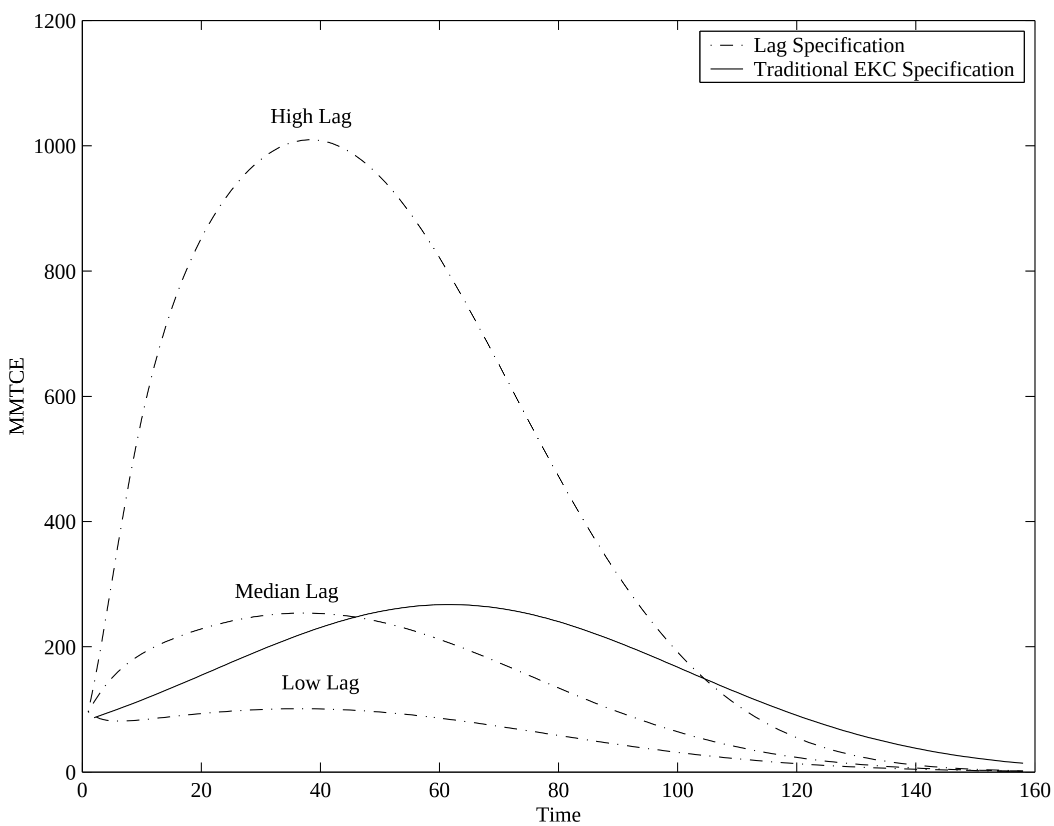
where i is a province index, t is a time index, γ_i is a province specific fixed/random effect, α_t is a year specific fixed/random effect and ε_{it} is the error term. The variables are $PWGE_{it}$, per capita waste gas emissions (100 thousand m^3), GDP_{it}, per capita gross domestic product in real terms (yuan 1985), $COMP_{it_o}$, industry composition in 1990, and $COAST_i$ is a dummy variable for the coastal provinces. The variable $PDENS_{it}$ is the population density for province i at time t. We include one and two-period province specific lagged dependent variables in the initial specification, which allow provinces to track their emissions at different rates. As discussed in the previous section we adjust for differences in initial industry composition. The time fixed effects adjust for shocks to preferences and technology common to all provinces. The province specific fixed effects capture structural differences in the conditional mean of per capita waste gas emissions across provinces. These differences contain structural differences, which we may not be able to capture, given our data restrictions. We adjust for initial industry composition to capture differences in the initial pollution intensity of industry - assuming that heavy industry is more pollution intensive than light industry.

We conduct a general to simple specification search using the SIC instead of more common model selection criteria, since measures such as the R^2 or the adjusted R^2 don't or only slightly punish for non-parsimony. Alternative model selection criteria such as the AIC will choose less parsimonious models compared to the SIC (Diebold, 2001). We will ultimately use this model to forecast China's CO_2 emissions and therefore prefer a parsimonious model. We first estimate model 3, a two-way error component model[11], and compare it to a model with time only fixed effects, province specific fixed effects and a model with no fixed effects. The model

[11]For this model to be identified, we need to restrict the parameters on initial industry composition and the coastal dummy to be zero for this estimation.

with no fixed effects has a slightly lower SIC than the model with time fixed effects only. We include a simple time trend and obtain the lowest SIC. We then estimate the model with a simple time trend and compare the sample selection criterion for this model to a model imposing the restriction that $\forall j \epsilon [35, 64] \beta_j = 0$, which suggests an AR(1) over an AR(2) specification. The SIC suggests an AR(1) specification over an AR(2) and AR(0) specification. This finding confirms our conjecture from section 2, which suggested that technology and therefore per capita emissions *do not adjust contemporaneously.* The information contained in a one period lag suggests that provinces adjust their per capita emissions rather slowly. The fact that the model rejects the AR(2) specification further suggests that the non-immediate past does not contain any information valuable for forecasting purposes. This supports a story, which argues that provinces may not be stuck in a 'bad technology' state stemming from a history of high emissions industries. In terms of predicting per capita emissions, this has quite strong implications. The traditional contemporaneous EKC specification suggests that the turning point or threshold level of per capita income is the same across all provinces. In our model, two provinces with identical time paths of income may follow a quite different path of per capita emissions. Figure 7 shows projected per capita emissions for three provinces with identical starting per capita income, which grows at 5% per period.

Figure 7: Traditional EKC vs. Lag specification



The thick line shows the predicted per capita emissions of the estimated contemporaneous model. Small changes in the lag parameter have tremendous implications for the turning point of per capita emissions. A province with a parameter estimate of 0.8 will have a drastically higher turning point of predicted per capita emissions than a province with a parameter estimate of 0.70 on its lag.

We argue that the lags contain some information as to the age and pollution intensity of a province's capital as well as the ability of local authorities to enforce environmental legislation. The higher a provinces parameter estimate on the lagged dependent variable, the slower it adjusts its next period emissions according to an EKC type relationship. This may be due to an aging capital stock. The average age of a province's capital stock should be highly correlated with these elasticities, yet we cannot test this since we lack the necessary data at this point in time. Although it may be quite easy to adjust single power plants' or production facilities' equipment, it is a long process to decrease the average age of an entire province's capital stock.

We further test whether a more parsimonious dynamic model is preferred by the SIC, which would amount to the restriction that $\vee i, j \epsilon [1, 30] \beta_{5+i} = \beta_{5+j}$. This simple restriction implies that all provinces have the same elasticity of current emissions with respect to past per capita emissions. We argue that this elasticity varies across provinces. We test for whether our specification is preferable to a pooled model and reject pooling at the 1% level. This is quite a strong result, since we would gain 29 degrees of freedom by pooling. In summary we argue that a smaller relative parameter estimate on a province's lagged per capita waste gas emissions indicates faster speed of adjustment and therefore a province with a high rate of technological innovation, whereas a larger (closer to one) parameter estimate would indicate a slow rate of adjustment. We will outline the remainder modelling strategy in the next paragraph.

Our model selection criterion further rejects the inclusion of higher order polynomial terms yet suggests the inclusion of population density and the coastal dummy variable. Model 4 below minimizes the Schwartz Information Criterion. It is preferable to the GAM model since, the spline on income takes up additional degrees of freedom.

$$\begin{aligned} ln(PWGE_{it}) = \alpha + \beta_1 ln(GDP_{it}) + \beta_2 (ln(GDP_{it}))^2 + \beta_3 ln(COMP_{it_o}) + \beta_4 ln(PDENS_{it}) \\ + \beta_5 COAST_i + \sum_{i=1}^{30} \beta_{5+i} ln(PWGE_{it-1}) + \beta_{36} ln(TIME_t) + \varepsilon_{it} \end{aligned} \tag{4}$$

We test for serial correlation in the error terms and fail to reject the null hypothesis of no serial correlation after including the first order province specific lags. [12]

4.3 Estimation Results

Table 1 reports the estimation results. We report estimation results for a traditional EKC type model, estimated via fixed effects. We do not estimate this model via the random effects estimator even though it is the most popular estimator in the EKC literature. In our case we have observations for each province, which is the entire cross section - not a random sample from it. The appropriate panel estimator for a static model of this nature is the fixed effect estimator (Baltagi, 1995). We juxtapose these results with the parameter estimates of our 'lag-specification'. The traditional fixed effects model presented here, allows for

[12] A Shapiro-Wilk test for normality of the studentized residuals of the model rejects the null hypothesis of a normal distribution. Since non-normal error terms may produce biased parameter estimates, we estimate the model using a robust regression algorithm. The parameter estimates on the lagged dependent variables are uniformly higher, which is offset by a larger negative parameter estimate on the time trend. The model produces initially higher forecasts, but the aggregate forecasts converge to values similar in magnitude to the ones reported in the next section. Robust forecasts are available upon request from the authors.

province specific fixed effects - differences in intercept. It does, however, restrict the per capita emissions to follow an imposed similar path across provinces. The 'lag specification' does not impose this restriction. Of particular importance are the signs and magnitudes of β_1 and β_2 in Table 1. In this particular case, emissions and per capita GDP will show an inverted-U shape relationship given that $\beta_1 > 0$ and $\beta_2 < 0$. This relationship may be amplified by effects originating in the juxtaposition of data from more and less developed regions. Vincent (1997) provides a convincing argument in this direction. Since we use data from a single developing country, these effects may not be as strong, yet still present due to the widely differing states of development of China's regions. It is noteworthy that this relationship holds across both models[13]. The estimated turning point is quite variable across the three models. The turning point for the lag specification estimated by Ordinary Least Squares is at 10391 Yuan, which is slightly above Shanghai's current income. One should note, however, that the confidence interval on the estimate of the turning point, $exp(-\beta_1/2\beta_2)$, is rather large. We check our specification by comparing the model predictions in sample versus the predictions from the generalized additive model of equation 2. The in sample predicted values of this GAM estimation are highly correlated (ρ=0.999) with the in sample predictions of the parametric model, providing further evidence in favor of our specification.

The parameter estimate on initial industry composition is positive as expected, yet statistically insignificant in both models. We conducted a likelihood ratio test and failed to reject the omission of industry composition from the estimation. The parameter has the expected sign, indicating that a 1% higher value of the initial heavy to light ratio of industry results in a 0.6-0.9% increase in per capita waste gas emissions. The parameter estimate on population density is positive, significant and rather large in magnitude in both models. Our approach differs from the IPCC forecasts in this aspect. Our estimation suggests that increased population density will result in significantly higher per capita waste gas emissions. Migration and aggregate population growth will separately affect per capita and aggregate emissions. An increase in population of a province, whose land area is fixed, will have scale effects on per capita emissions of its inhabitants. Therefore a province with low immigration and high natural population growth may experience similar emissions as a province with high immigration and very low natural population growth. We will incorporate this effect when producing forecasts and demonstrate that different scenarios will have very strong consequences on the path of China's aggregate emissions. The parameter estimate on the dummy variable $COAST_i$ is negative and marginally statistically significant. The coastal provinces attracted 89% of the total foreign direct investment in 1999. Influx of foreign direct investment is tied to an influx of foreign technology, which replaces older and less efficient capital stock accumulated throughout earlier years. This structural difference as well as the location of China's special economic zones, which provide these provinces with the access to foreign technology, may account for this lower per capita emission level. The parameter estimate on the time trend, $ln(TIME_t)$, indicates that as time progresses and technology common to all provinces improves, per capita emissions decrease slightly each year. This time trend captures a combination of technology improvements as well as shifts in preferences towards better environmental quality. It carries the expected sign and is significant in both models.

The estimates for individual provinces' elasticities with respect to the previous period's emissions, which are the parameters on the province specific AR(1) terms, are quite variable. Figure 8 plots the parameter estimates for the provinces from the lag-model in the top panel. The bottom panel displays the estimated

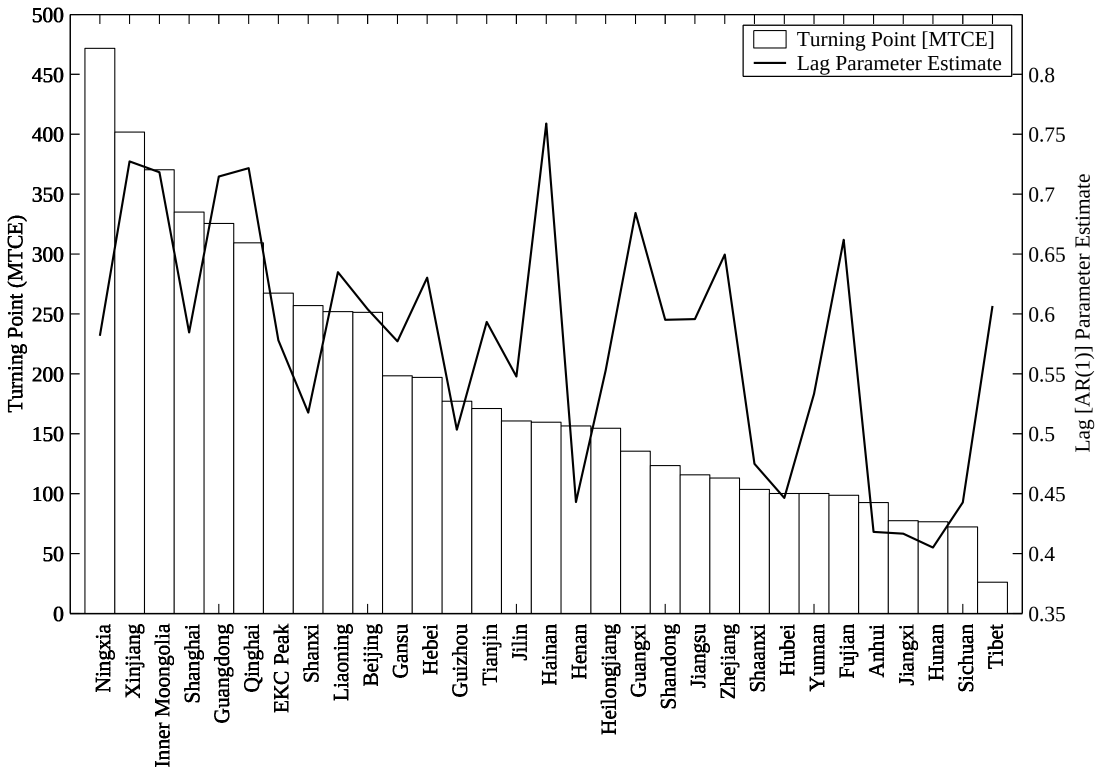
[13]It is very noteworthy that the EKC relationship held for **all** the models considered in the model selection process outline above

Table 1: Parameter Estimates

Parameter	Fixed Effects Estimate	Robust t-Statistic	Lag Model Estimate	Robust t-Statistic
Constant$_i$	2.949	1.500	0.996	1.219
ln(GDP$_{it}$)	1.526	6.358	0.718	3.902
(ln(GDP$_{it}$))^2	-0.086	-5.375	-0.039	-3.250
ln(Comp$_{it_o}$)			0.894	1.547
Coastal$_{it}$			-0.647	-1.955
ln(Pdens$_{it}$)	1.199	3.232	0.335	4.653
ln(Time)	-0.067	-1.914	-0.048	-2.667
Beijing			0.604	11.185
Tianjin			0.593	11.860
Hebei			0.630	11.053
Shanxi			0.518	9.250
Inner Mongolia			0.718	16.698
Liaoning			0.635	9.478
Jilin			0.548	10.960
Heilongjiang			0.553	11.286
Shanghai			0.585	11.700
Jiangsu			0.596	12.957
Zhejiang			0.650	15.476
Anhui			0.418	5.291
Fujian			0.662	16.146
Jiangxi			0.417	6.043
Shandong			0.595	11.900
Henan			0.443	6.239
Hubei			0.446	6.758
Hunan			0.405	5.786
Guangdong			0.715	17.024
Guangxi			0.684	15.200
Hainan			0.759	11.859
Sichuan			0.443	6.815
Guizhou			0.503	8.246
Yunnan			0.533	7.107
Tibet			0.607	2.850
Shaanxi			0.475	7.917
Gansu			0.577	11.096
Qinghai			0.722	13.885
Ningxia			0.582	11.878
Xinjiang			0.727	14.255
R^2	0.5354		0.9854	
Observations	408		408	

turning points implied by these parameter estimates.[14] Figure 8 illustrates two points, which are not imme-

Figure 8: Lag parameter estimates and implied turning points



diately obvious. We previously argued that a higher parameter estimate on the lagged dependent variable indicates worse technology or an older capital stock. In order to test for this, we would require data on the age or state of capital by province. Since this data is not currently available it is difficult to rigorously explore this argument. Since we control for per capita wealth and coastal location, the parameter estimates capture a conditional effect, which one may not be able to directly extract empirically otherwise. The ordering of the OLS lags indicates that the poorer as well as coal producing provinces have the highest lags. Figure 8 demonstrates the difference between our proposed specification and the traditional EKC specification. The traditional EKC estimation explains quite a large share of the variance in per capita emissions, yet if we test for serial correlation in the error terms, we reject the null hypothesis of no serial correlation at the 1% level in all non-dynamic models. We interpret this as evidence in favor of a dynamic specification. The figure shows that we would expect drastically different turning points across provinces, compared to the turning point estimated by a traditional EKC model. The coal producing provinces are expected to have significantly higher turning points compared to coastal provinces and urban centers such as Beijing and Shanghai. The fact that Tibet has the lowest expected turning point may be misleading. This is mainly due to the low population density of Tibet, not its relatively low per capita income. Guizhou, the poorest province in per capita terms, is only one tenth of a standard deviation below the mean turning point.

[14]For the projected turning points, we use the population growth/migration scenario A with the low GDP growth scenario, as well as the Ordinary Least Squares parameter estimates.

5 Forecasting CO_2 Emissions

To forecast CO_2 emissions, we will forecast waste gas emissions using the lag specification presented in the previous section. We then covert those waste gas emissions into CO_2 (carbon equivalent) emissions using the conversion factor estimated in Section 3.2. To make use of the models estimated in section 4.3, we need to make assumptions about the time paths of the predictor variables in each model. The independent variables, whose future values are unknown, are provincial per capita GDP and population density. We provide forecasts combining different scenarios for each of those two variables. We choose a model of no population growth and constant 5% growth of per capita GDP as the baseline forecast. We then examine the sensitivity of the results to differences in assumptions about the paths of predictor variables.

5.1 Alternative Scenarios

The two models only require assumptions about future levels of per capita GDP and population, since the land area of provinces is fixed. Different assumptions about the future trends of the explanatory variables are likely to imply very different per capita and aggregate emissions levels. Rather than be inclusive about all possible sets assumptions, we will attempt to illustrate the impact of the range of assumptions typically made concerning Chinese GDP and population growth rates. There is a literature forecasting GDP and a variety of other provincial level variables for China, yet we employ only two GDP growth scenarios, since we believe that forecasting GDP over a 50 year horizon is more guessing than actually forecasting. The two different scenarios demonstrate the sensitivity of our forecasts to changes in the assumptions regarding GDP growth rates very well. Two alternative sets of assumptions are made concerning the GDP growth rate: 1) a slow growth case, and 2) a high growth case. For the slow growth case, we use the assumption made in Scenario IS92a of the quasi-official IPCC forecasts. This prediction assumes a national annual rate of growth of 5.37% for the period 2000-2025 and 3.54% for the period 2025-2050. For the high growth case, we assume an annual rate of growth of 6.53% until 2025 and then a slowing down beyond that to 3.51 for the period 2025-2050. In both cases, we split the national GDP growth between provinces according to their relative share of national growth during the sample period. The two GDP growth scenarios may seem to be very similar, yet a 1% difference i per capita GDP growth over 50 years is quite drastic.

Population projections are crucial to our forecasts. Official estimates of population are only available at a national level. However, we require provincial level population projections, which are provided by Chesnais & Minglei (1998). We consider their four different scenarios, which incorporate internal migration and natural population growth. The four scenarios can be characterized as follows: Scenario A is characterized by constant natural birth and death rates across provinces. Scenario B is characterized by decreasing natural birth rates and constant death rates. Scenario C is characterized by decreasing mortality and constant birth rates. Scenario D is characterized by decreasing birth and mortality rates. Chesnais & Minglei (1998) provide a very detailed account regarding the assumptions underlying the population model. The model incorporates the current and future age structure of the single provinces, which indirectly incorporate migration patterns within China. Table 2 indicates the average growth rates for per capita GDP and population. Since we only consider two scenarios of GDP growth, we consider a total of eight different population/GDP scenarios for forecasting purposes. Table 2 summarizes the assumptions made for each scenario. The letter refers to the population growth scenario used. Slow (fast) refers to the slow (fast) GDP growth scenario.

Table 2: Assumptions concerning GDP and population growth rates

		Scenario							
	Year	A-slow	B-slow	C-slow	D-slow	A-fast	B-fast	C-fast	D-fast
GDP	2000 - 2025	5.37%	5.37%	5.37%	5.37%	6.53%	6.53%	6.53%	6.53%
(growth p.a.)	2026 - 2050	3.54%	3.54%	3.54%	3.54%	3.51%	3.51%	3.51%	3.51%
Population	2000 - 2020	1.16%	0.61%	1.26%	0.71%	1.16%	0.61%	1.26%	0.71%
(growth p.a.)	2021 - 2050	0.67%	-0.21%	0.89%	-0.01%	0.67%	-0.21%	0.89%	-0.01%

5.2 Sensitivity To Alternative Scenarios

In this section we look at how the different scenarios defined in Table 2 influence forecasts of CO_2 emissions using the same model. Figure 9 displays aggregate forecasts of Chinese CO_2 emissions until the year 2050. The forecast in Figure 9 under the assumption of slow rate of growth of GDP depend critically on the assumption about the rate of growth of population (Scenario A vs. Scenarios B, C, and D). These results suggest that changes in population density patterns will have a large impact on CO_2 emissions. The dashed line indicates the forecast made using the slower rate of GDP. It is noteworthy how close together the forecasts for the same population scenario and differing GDP growth scenario are. Our forecasts suggest that the distribution of population across China's provinces may have a drastic impact on the PRC's aggregate CO_2 emissions. In all eight cases considered, projected CO_2 emissions are higher than the projections under the baseline scenario. This is not surprising, since it assumes zero population growth and per capita emissions are quite sensitive to changes in population density. Forecasts based on national aggregates cannot pick up this effect, which leads to some interesting policy conclusions. Some of the differences found between studies using national aggregate data and studies using provincial data may reflect the fact that for the first kind of works the same rate of growth of population is applied to all the provinces. This is an assumption, which has tremendous implications regarding optimal policy measures relating internal migration and urbanization to future CO_2 emissions. These estimation results do suggest that China may be able to make tremendous progress towards potentially agreed upon emission reductions by considering population migration patterns.

5.3 Intertemporal Distribution of PWGE

In the previous section we addressed internal migration policy as one possible policy measure to efficiently reduce aggregate emissions. A crucial component influencing future per capita emissions is the state of technology in individual provinces. In order to maximize the marginal value of each dollar spent on pollution abatement technology or improved production technologies, it is important to understand which provinces are expected to experience the highest overall per capita emissions over the next 50 years. Figure 10 compares Beijing's projected emissions under the 8 scenarios to Shanxi's projected emissions over the next fifty years for all eight scenarios. Beijing is a wealthy province with high population density, which is expected to experience some outward migration over the next fifty years. Shanxi is a relatively poor province with projected immigration and rather high birth rate. The parameter estimates on their respective lags are higher for Beijing than that of Shanxi.

Figure 9: Aggregate Forecasts of China's CO_2 Emissions

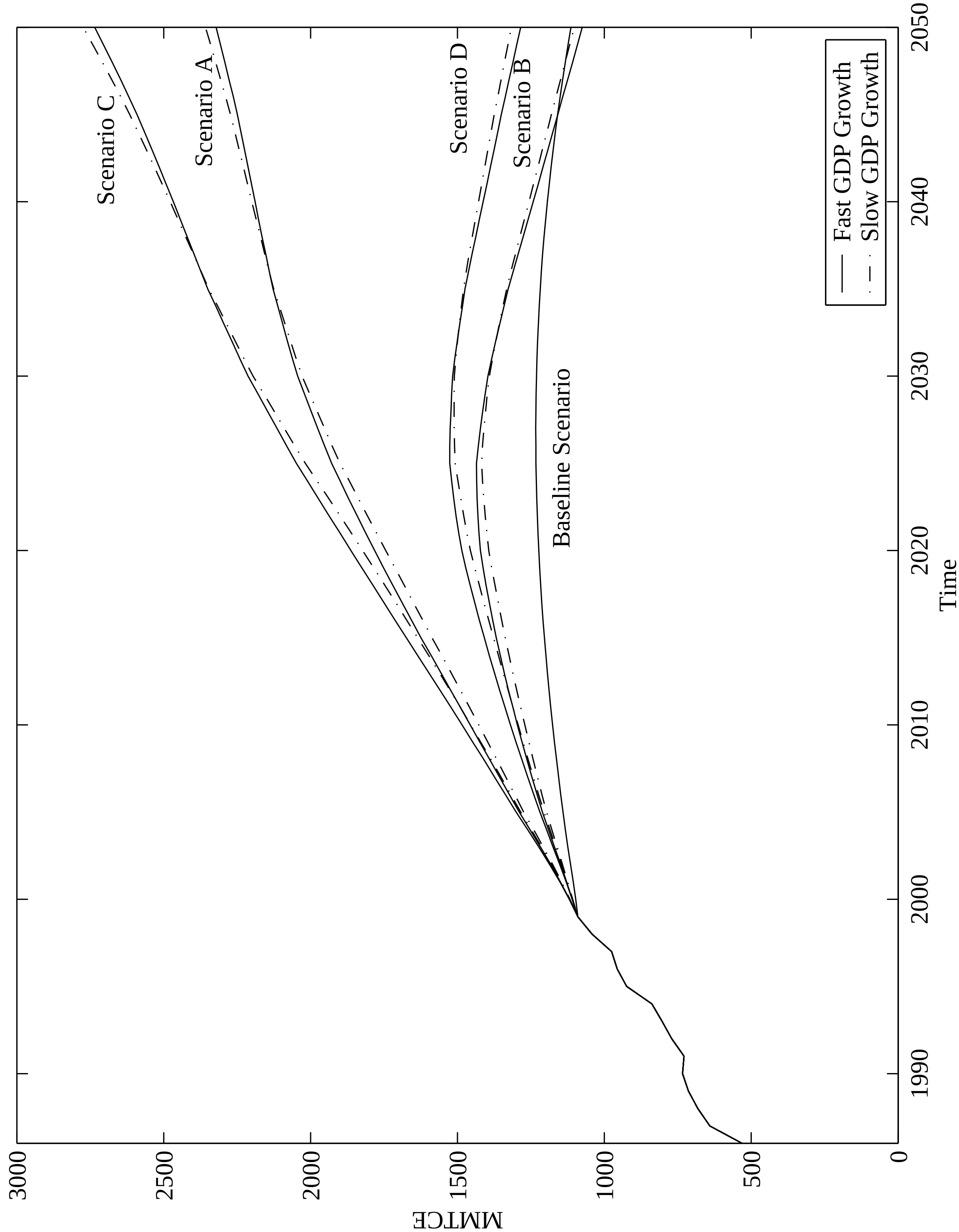
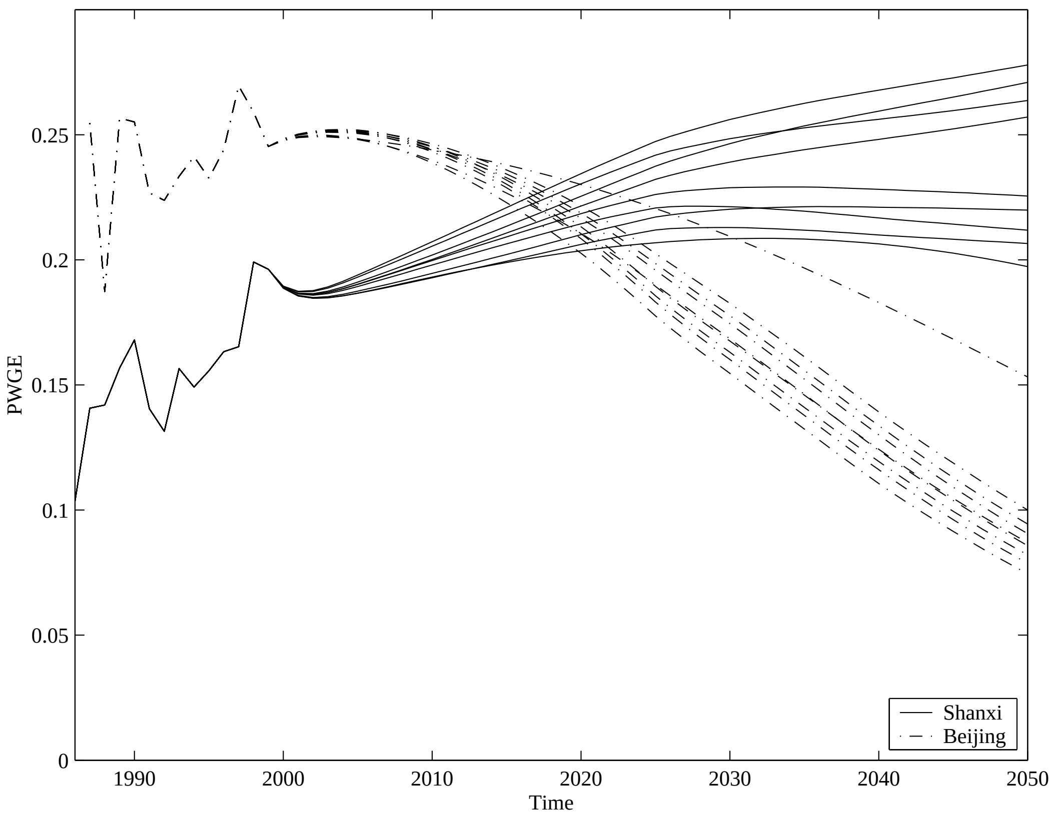


Figure 10: Per Capita Forecasts for Beijing and Shanxi



From the picture above we can see that the income effect ('projected rises in per capita income') in conjunction with the population effect outweighs the smaller elasticity of PWGE with respect to the previous periods $PWGE_{t-1}$. This figure demonstrates that there are three forces at work when considering future provincial CO_2 emissions. The three factors that matter here are the starting point of per capita GDP (γ_i), the starting point of PWGE (ω_i) and finally the province specific parameter estimate of the lag (λ_i). These three "parameters" determine the underlying process of future emissions. Table 3 shows how the per capita emissions are broken up for all thirty provinces considering our scenario A-high. The table classifies each province according to whether γ_i, ω_i and λ_i are closest to the sample minimum (l), mean (m) or maximum (h). We then predict emissions and calculate total per capita emissions per decade in our forecast horizon. We also indicate total per capita emissions over the next fifty years as well as the anticipated peak year.[15] This table points the finger not at one aspect of a province that should be remedied by new and innovative policy conclusions across all provinces. These forecasts suggest that in order to manage aggregate CO_2 emissions, NEPA should target specific provinces. It is apparent from Table 3, that the provinces extracting their massive natural resources are anticipated to produce the highest per capita levels of CO_2 emissions. In order to target these provinces, our research suggests investments in cleaner technologies as well as limitations to immigration into these provinces may have a strong effect on emissions. On the other hand, the high per capita emissions in these provinces are most likely exaggerated, since the processed or

[15] If the peak is 2050, this should be interpreted as a peak outside the forecasting horizon of our model.

Table 3: Predictions of per capita emissions for Scenario A - high

Province	$(\lambda_i,\gamma_i,\omega_i)$	2001-10	2011-20	2021-30	2031-40	2041-50	Total	Peak Year
Ningxia	(m,m,m)	14%	17%	20%	23%	26%	17.73	2050
Inner Mongolia	(h,m,m)	15%	20%	22%	22%	21%	16.38	2031
Xinjiang	(h,m,m)	11%	15%	20%	24%	29%	12.87	2050
Guangdong	(h,l,m)	12%	17%	21%	24%	25%	12.29	2050
Shanxi	(m,m,m)	17%	19%	21%	22%	22%	11.69	2050
Qinghai	(h,m,m)	12%	16%	21%	24%	26%	11.49	2050
Shanghai	(m,h,h)	29%	25%	20%	15%	11%	11.18	2000
Liaoning	(m,m,m)	22%	23%	21%	19%	16%	11.17	2015
Beijing	(m,h,h)	28%	25%	20%	15%	11%	8.98	2004
Hebei	(m,m,m)	18%	21%	22%	21%	18%	8.79	2023
Gansu	(m,l,m)	16%	20%	22%	22%	20%	8.69	2029
Jilin	(m,m,m)	19%	21%	21%	20%	19%	7.61	2022
Heilongjiang	(m,m,m)	19%	21%	21%	20%	19%	7.35	2023
Tianjin	(m,m,m)	24%	24%	21%	17%	14%	7.01	2006
Guizhou	(m,l,m)	14%	17%	20%	23%	26%	6.82	2050
Henan	(l,l,m)	14%	18%	21%	23%	24%	6.37	2050
Guangxi	(h,l,m)	14%	17%	21%	23%	25%	6.19	2050
Hainan	(h,l,l)	10%	14%	20%	25%	30%	6.05	2050
Shandong	(m,m,m)	20%	21%	21%	20%	18%	5.67	2019
Jiangsu	(m,m,m)	22%	22%	21%	19%	16%	5.23	2014
Hubei	(l,m,m)	19%	21%	21%	20%	19%	4.63	2022
Shaanxi	(l,l,m)	16%	19%	21%	22%	22%	4.61	2050
Zhejiang	(m,m,m)	24%	23%	21%	18%	14%	4.41	2000
Fujian	(m,m,m)	20%	22%	22%	20%	16%	4.26	2018
Anhui	(l,m,l)	17%	19%	21%	22%	22%	4.08	2050
Yunnan	(m,m,l)	15%	18%	21%	23%	24%	4.07	2050
Hunan	(l,m,l)	17%	20%	21%	21%	21%	3.56	2035
Jiangxi	(l,m,l)	17%	20%	21%	21%	20%	3.53	2031
Sichuan	(l,m,l)	18%	20%	21%	21%	20%	3.48	2030
Tibet	(m,l,l)	10%	16%	22%	26%	26%	0.94	2041

Table 4: Range Of Projected CO_2 Emissions from Different Studies (billion metric tons of carbon)

Year	**IPCC* (2000)**	**Yang and Schneider (1998)**	**Ho et al. (1998)**	**Garbaccio et al. (1999)**	**Lag-Specification****
2020	1.73 - 2.50	—	—	2.13	1.39 - 1.86
2022	—	—	—	2.30	1.41 - 1.94
2025	—	1.16 - 1.80	—	—	1.42 - 2.05
2050	2.32 3.90	1.54 - 3.14	2.84 - 4.66	—	1.08 - 2.77

Note: * Projected values for China have been obtained by using CO_2 emissions for the year 1999 and the rates of growth calculated for the region "China and centrally planned Asia". ** Due to its unrealistic nature, we exclude the baseline model from the prediction band.

unprocessed primary goods are shipped south and to the coast for further processing, or in the case of coal for electricity production. Demand side measures targeted at electricity conservation and smarter resource management may offset the estimated effects presented in Table 3 quite a bit.

5.4 Comparison With Other Studies

The projections of CO_2 emissions from this study are subject to a great deal of uncertainty, as are any forecasts over such a long time horizon. It was our initial goal to provide a set of forecasts based on a different level of aggregation to those provided by the studies cited in section 1. Below we compare our forecasts to those of previous studies. Table 4 summarizes those comparisons.

First, we compare our estimated CO_2 emissions and the values obtained according to the average annual growth rates of CO_2 estimated by the IPCC (Intergovernmental Panel on Climate Change, 2000) for the period 1990-2050. However, when making the comparison, one needs to keep in mind that the annual growth rates estimated by the IPCC represent an average for the region "China and centrally planned Asia". We have made the projections by applying those rates of growth to the Chinese CO_2 emissions of 1997. Table 4 shows the range of values of the projected CO_2 emissions for the year 2020[16] under the A1B, A2, B1 and B2 marker scenarios of IPCC, and our projections. We note that our range of forecasts is narrower than that provided by the IPCC. The information contained in the data at the spatially disaggregate level should contain more information than the aggregate data. Our prediction band is narrower, even after considering a wide variety of population and GDP growth scenarios. This is also true for the point forecasts made for the final year in our forecasting horizon (2050).

Yang & Schneider (1998) provide a set of estimates for the region "China and centrally planned Asia" by using a different analytical framework[17]. Their projected carbon emissions for the year 2050 range between 1.54 and 3.14 billion metric tons - depending on the considered assumptions about the evolution of the main determinants. This range of values is very similar to the estimated range of values of CO_2 emissions by using our model. Our range of point forecasts is similar, but slightly lower compared to the point forecasts

[16]We compare the values for the year 2020 because the IPCC estimated rates of growth apply until that year

[17]In the framework used by Yang & Schneider (1998), emissions are decomposed into four factors which, when multiplied together, determine the magnitude of emissions in one year. These factors are population size, GDP per capita, energy intensity, and carbon intensity.

provided by Yang & Schneider (1998). This is also true when we compare our forecasts to Garbaccio et al. (1999*a*). The point forecasts provided by their study lie outside the interval spanned by our estimates. We anticipate drastically lower emissions. This is also true when considering the projected CO_2 emissions found by Ho, Jorgenson & Perkins (1998). According to their work, CO_2 emissions for the case of China by the year 2050 will range from 2.84 and 4.66 billion metric tons. Our projections for the same year suggest structurally lower levels.

6 Conclusion

We provide CO_2 emission forecasts for China through the year 2050 under several alternative scenarios and model specifications. Our results suggest that Chinese CO_2 emissions will be slightly lower (given common overall GDP and population growth assumptions) than those projected by models based on national aggregate level data. We predict per capita CO_2 emissions using a model based on the Environmental Kuznets Hypothesis. We expand the traditional specification by adding additional variables available at the regional level and adding a province specific dynamic component to the model. Our specification strongly supports the EKC hypothesis with the turning point being close to the present income of Shanghai. However, most of China's provinces are far from Shanghai's income and will therefore experience rising per capita emissions due to a positive income effect.

We believe that there are several major advantages to using provincial level data. It allows us to take account of a large degree of spatial heterogeneity across provinces. These large differences should not be surprising given that many of China's provinces encompass larger areas and have larger populations that most of the major European countries. Use of provincial level data has also tended to substantially reduce the problem of multicollinearity between variables, a problem that plagues national aggregate level data. Hence we believe that we have improved the precision of parameter estimates. Finally, the use of provincial level data allows one to explicitly examine the implication of large-scale population movements. Such movements have take place in other countries where regional differences of the scale currently present in China have been observed.

Further reforms and increased differentiation in environmental regulation continue to take place on provincial and city level (Wang, 1999). One key question for any Chinese participation in an agreement to reduce its CO_2 emissions is how well China could implement such an agreement at the provincial and local levels. Work by Branstetter & Feenstra (2001) suggests that conflicting objectives at the provincial level will interfere with efforts to implement reforms and regulations required of China by WTO membership. The story with pollution regulations may be more favorable, at least in some of the fast growing provinces, due to local demand for improved air quality. A shift toward a larger pollution tax on waste gas emissions may also in the longer run improve economic efficiency given China's current tax structure.

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