Forecasting Chinese Carbon Dioxide Emissions: A Provincial Approach[1]

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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 (1985-2000). We estimate a reduced form model selected by minimizing the Schwartz Information Criterion in a general to simple search. The model chosen by the information criterion is a dynamic version of a model popular in the literature on the Environmental Kuznets Curve (EKC), wherby per capita emissions first rise and then fall with increasing income. We extend the traditional specification by including aggregate population density, industry composition and technological progress that varies across provinces. In our preferred model we find that the turning point of the inverse U shaped EKC relationship is near the current Shanghai income level. 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. Our model also predicts that province specific per capita emissions are likely to follow very different income/pollution trajectories. This in turn suggests that province specific policies to reduce CO_2 emission levels may be desirable.

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

This remark by President Bush summarizes one of the most potent arguments made by the United States against reducing their greenhouse gas emissions: 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; Panayotou, Sachs & Zwane, forthcoming). 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 1990 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 explains annually observed aggregate emissions data. This is sometimes done in a univariate time series modelling but more typically done using population, income and some measure of technological as predictors. Forecasts following this approach include those of the Intergovernmental Panel on Climate Change (IPCC) as well as those by Yang & Schneider (1998). Models with an explicit economic orientation usually add policy variables that allow for fuel switching, induced technological change, and emissions trading.[3] Such models typically cover multiple countries or regions. National aggregate level models do not utilize additional information contained in data available at a more disaggregate level. The second approach taken in the literature addresses this obvious limitation of using aggregate country level data by looking at emissions data by industry sector (Sinton & Levine, 1994; Zhang, 1998; Garbaccio, Ho & Jorgenson, 1999*a*; Garbaccio, Ho & Jorgenson, 1999*b*). This has been done with both aggregate sectoral level data and with random samples of firms stratified by sector. The third approach gives up the nationally representative nature of the second approach but gains considerable detail by doing case studies of the factors influencing the performance of specific plants (*e.g.*, Zang, May & Heller (2000)) .

[1]This argument is also embedded in a 1997 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 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.

[3]See for instance the 1999 special issue of the Energy Journal edited by John Weyant on the cost of the Kyoto Protocol.

We pursue a fourth approach - disaggregating emissions and other possible predictor variables at the spatial level by looking across China's provinces. China's provinces differ greatly in land area.[4] The largest province by area, Xinjiang, is 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, counting 115 million inhabitants. Tibet, with the fewest inhabitants, has 2.6 million. China's largest provinces are therefore larger than most European countries along either dimension. Exploring variation in CO_2 emissions across provinces will allow us to explore the sensitivity of these emissions to the spatial distribution of population, income and technological changes.

2 Background

Our starting point is the classic IPAT model (Ehrlich & Holdren, 1971; Holdren, 2000):

$$I = P \cdot A \cdot T \tag{1}$$

where I stands for impact, typically measured in terms of the emission level of a pollutant, P is population size, A represents a society's affluence and T represents a technology index. Conceptually, this model has long dominated science and engineering oriented discussions of the pollution generation problem at the country and regional level including those underlying most of the IPCC's emission scenarios. There are many empirical variants of the model. They often involve specification in per capita terms, which effectively eliminates P, and inclusion of coefficients on one or more of the variables under the guise that the researcher at best has an income proxy for A and that the use of time or energy intensity as a proxy for technology will require an estimated scale parameter to convert it into the technology index needed for IPAT. Transformations of the basic IPAT model such as taking logs or working in terms of percent change are also frequently seen. The common empirical implication underlying all of the IPAT family of models is that pollution should be monotonically increasing in P and A and monotonically decreasing for improvements in T.

With respect to China, Zhang (2000) has decomposed past CO_2 emissions along the IPAT lines and found that income has been the main factor increasing emissions, while changes in aggregate population size have a much lesser impact. His estimates show that changes in energy intensity are between those of the income and population effects in terms of absolute magnitude and working in the opposite direction. Economists working on the relationship between pollution levels and income have frequently found an empirical relationship known as the environmental Kuznets curve (EKC) that suggests that pollution first rises with income up to some point and then falls after some threshold level, forming an inverted U-shape relationship (Barbier, 1997). This possibility of an inverted U-shaped relationship with a downward side where increases in income lead to decreases in pollution clearly contradict one of the key assumptions underlying the IPAT model. One obvious way around this difficulty is to allow for the possibility that the level of technology is dependent upon the affluence level. This greatly complicates the interpretation of the IPAT relationship but makes it much more interesting from an economic and policy perspective.

[4]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). Such studies provide significant insight as to the behavior of national aggregates by allowing the researcher to holding constant factors that are hard to control for across countries.

In the case of China, there is substantial anecdotal evidence that technology development in the coastal provinces has far outpaced that of many of the inland provinces.

There is also a difficulty in the IPAT formulation with respect to population. Most empirical formulations assume that each person makes the same contribution. This restriction can easily be relaxed by including some measure of population as a predictor variable so that increasing or decreasing scale effects with respect to total population size are possible. Perhaps more fundamental though is that the IPAT formulation does not distinguish between people living in different locations.[5] After accounting for the large increase in overall population this century, the major demographic change that has occurred worldwide is large scale rural to urban migration that now seems to be occurring at an accelerating rate in developing countries (United Nations, 1996). To the extent that a Chinese farmer living in a rural area uses less fossil fuel based energy than a Chinese factory worker with similar income the degree of urbanization or population density may be an important determinant of emission levels.

Our modelling framework will modify the IPAT framework in three basic ways. First, we will allow income to have a non-monotonic effect on CO_2 emissions. Second, we allow for the possibility of province specific technology effects both with respect to the usual time trend but also with respect to initial conditions at the beginning of our sample period. Third, we will allow for the possibility of both overall population scale effects and population density scale effects. We take up some specific specification issues in next section, which looks more closely at the EKC literature.

2.1 Environmental Kuznets Curve Relationship

The inverted U-shaped environmental Kuznets curve was first identified by economists at the World Bank (Shafik & Bandyopadhyay, 1992) and became an important part of the NAFTA debate (Grossman & Krueger, 1995). The nature of the relationship has been controversial ever since (Barbier, 1997; Lieb, 2001). There are a number of reasons for the controversy. First, the existence of such an empirical relationship tends to fuel the belief that all one needs in order to solve the pollution problem in developing countries is to increase income rather than focusing attention on the need for good environmental policies (Arrow et el., 1995). Second, while theoretical justifications for the existence of an EKC relationship have been put forth, there is not yet agreement on the nature of the underlying mechanism and, in particular, whether it is mainly preference or technology driven. Third, the empirical relationship is somewhat suspect and to some extent may be an artifact of the juxtaposition of data from more and less developed regions (Vincent, 1997). Much of the issue here stems from data quality being correlated with development level and the fact that there is data from substantially fewer developing countries than one would like to see. Fourth, some researchers (Moomaw & Unruh, 1997) have argued in favor of more general pollution-income relationships than an inverted U-shape. Fifth, it is sometimes argued that the empirical evidence in favor

[5] The original Ehrlich & Holdren (1971) contains a short discussion of population density but invokes an early notion of the "environmental footprint" and suggests focusing more on better modelling of the affluence factor is more important. While population projection play a large role in the IPCC emissions scenarios there has been surprisingly little work on the secondary effects of population such as population density and urbanization on greenhouse gas emissions (Gaffin, 1998). Murthy, Panda & Parikh (1997) provide one of the few analyses in the economics literature. Looking at rural-urban differences in India, they find on a per rupee basis that urban dwellers are responsible for about 25% higher CO_2 emissions than rural dwellers. The inclusion of population density has long been common in studies dealing with deforestation (Cropper & Griffiths, 1994), since more densely populated areas require more farming land to support consumption in the absence of technological change and has been looked at in at least one EKC study (Panayotou, 1997*a*) with mixed results.

of an EKC for stock pollutants like solid waste and CO_2 is substantially weaker than for flow air pollutants like SO_2, NO_x, CO, TSP and many flow water pollutants. In particular, some 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).

Some of these issues are addressed in this paper. First, by using data for a single country, which is collected using consistent definitions and procedures we avoid the data comparability issue. In this sense our study represents the developing country counterpart of Carson, Jeon & McCubbin (1997), who found evidence in support of the EKC hypothesis for air pollutants, including CO_2, across the 50 United States. They found that per capita emissions fell with increasing income. China has 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 China to be on the upside of the EKC inverted U, that is per capita emission levels should 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 at a level that is meaningful for the purpose of a climate agreement. Second, we will test for more general functional forms of the pollution income relationship (PIR) using a third order polynomial in income, which is popular in the literature (Sengupta, 1996; Moomaw & Unruh, 1997) as well as an even more flexible form allowed for in the semi-parametric Generalized Additive Model framework (Hastie & Tibshirani, 1990). Third, we move away from the simple income-pollution EKC models by starting to explicitly model technology impacts in a more realistic manner. The traditional model specification of EKC type relationships hypothesizes a purely contemporaneous relationship between per capita income and emissions, implicitly assuming 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. This is done by allowing for lagged emissions to influence current emissions, which one would expect, unless the capital stock could instantaneously adjust, and by allowing the nature of this adjustment process to differ across provinces.[6]

We further introduce dynamics by allowing for changes in population density over time. We also allow for provincial population to change over time. This will later allow us to examine the possibility of differential population growth and migration scenarios that cannot be looked at in models based on aggregate national data. Finally, in order to help capture exogenous technological and resource endowment effects, we utilize a commonly used variable on composition of industry across China's provinces. This industry composition variable is defined as the share of heavy/primary goods processing industry in total output. Though admittedly a rather broad definition, it is likely to be useful 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 with higher initial shares of heavy industry are likely to produce a significantly larger amount of per capita CO_2

[6] To our surprise, the only empirical paper we have found that allows for a dynamic adjustment process is Agras & Chapman (1999), who find clear evidence in support of such a relationship using a sample of 34 countries from 1971-1989. Agras & Chapman (1999) correctly perceived the issue as one of a capital adjustment process and as such saw the flaw. In their model, the dynamic adjustment process is assumed to be the same for all countries in the sample and they allow for the possibility of a price response to the two large oil shocks in the time period they model and for trade related effects.

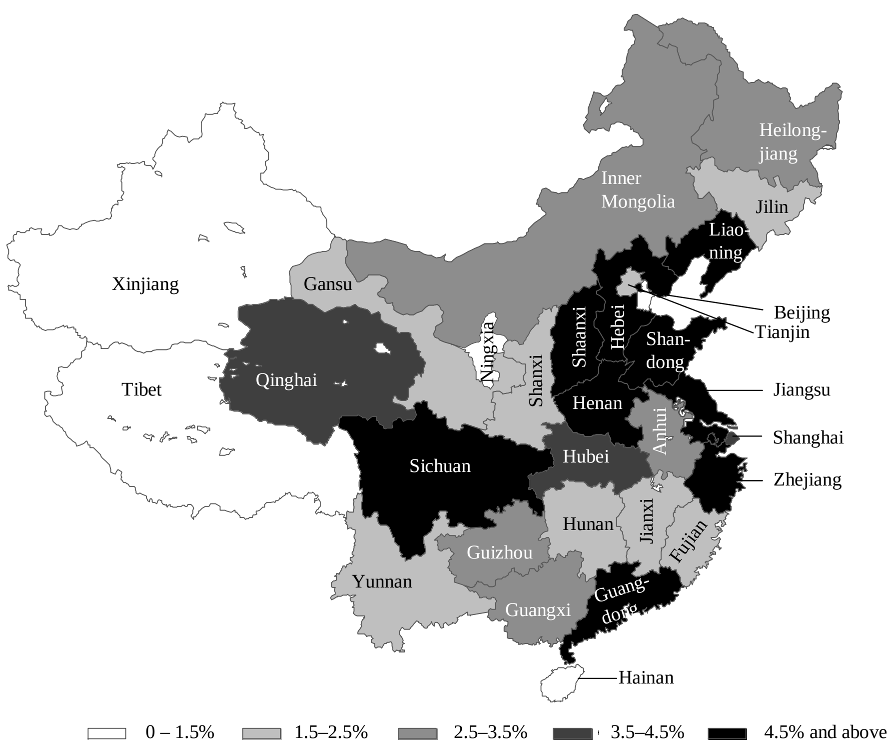
emissions - after adjusting for income and other factors. As time and the development process continue, one would expect a shift of industry composition towards lighter industries. We use a simple time trend to adjust for continued and exogenous technological change through time. There may still be other forces driving emission differences across provinces such as province specific pollution control regulations that do not work through the technology adjustment process. We can weakly test for such effects by allowing for provincial level fixed effects.

The next section describes China from a provincial perspective. 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. A discussion of our data set, empirical specification and estimation of the model appear in subsequent sections.

2.2 China's Provinces

China's modern economic growth has largely been fuelled by the exploitation of its massive coalfields. Coal made up 76% of China's 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 sparsely populated coal producing provinces do contribute a disproportionate share of waste gas emissions.

Figure 1: Provincial Shares of Total Waste Gas Emissions (in 2000)



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. The simple linear correlation coefficient between provincial population density and per capita waste gas emissions is 0.464 for our sample. This suggests density scale effects, which we will formally explore in section 4. Only 6.50% of the total Chinese population live in the six Northwest regions[7], which account for 54% of total Chinese territory. Fourty-two percent 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 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).

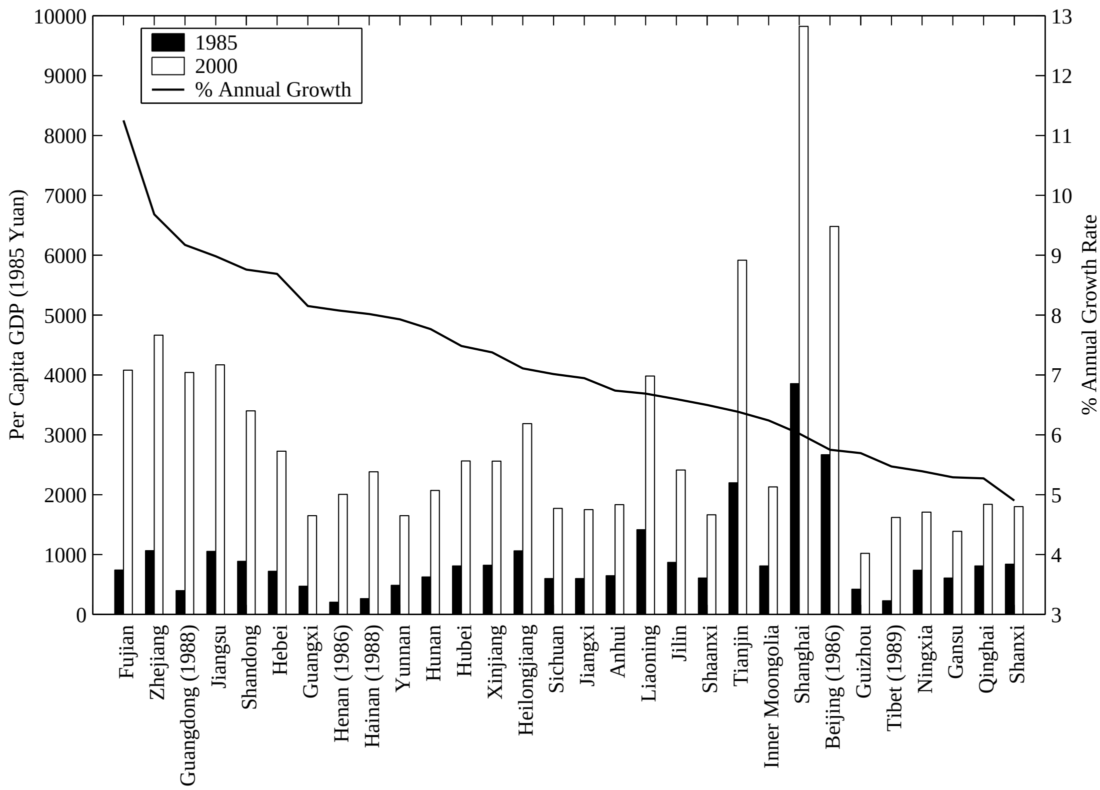
Changes in per capita income are the driving force behind the EKC hypothesis. Figure 2 displays per capita income for 1985 and for 2000 (the first and last year of our sample) in terms of per capita 1985 RMB. Provinces are ordered by compound annual growth rate of per capita income over the fifteen-year 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.

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 Foreign Direct Investment 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.

While 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 (Sinton & Levine, 1994). 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 is due to the large fixed investment necessary to install

[7]Inner Mongolia, Ningxia, Xinjiang, Tibet, Gansu and Qinghai.

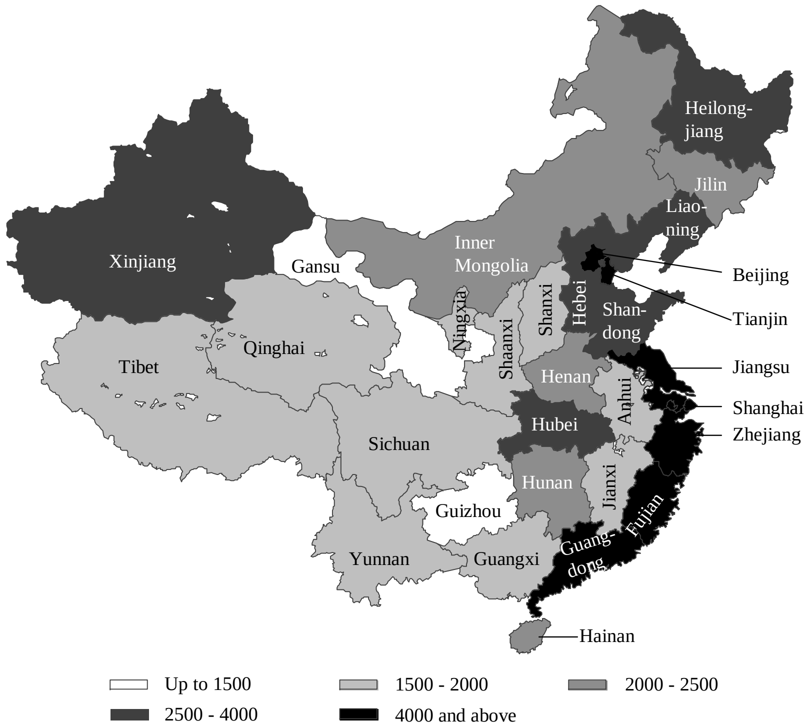
Figure 2: Provincial Per Capita Income (1985 RMB) and Annual Growth in 2000



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 or nuclear power sources, a change in the composition of inputs seems unlikely. The overall outcome is apt to be a large scale change in 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 trade openness. By 1983 all

Figure 3: 2000 Provincial Per Capita Income in 1985 RMB



provinces except for Tibet[8] 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.

3 Data

We will estimate a set of models using a province-level panel data set for 30 Chinese provinces during the period 1985-2000. 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 (16 years), while for a few of the provinces there are only data available for twelve, thirteen or fourteen years. The result is an unbalanced panel data set with 468 observations.

3.1 Waste Gas Emissions

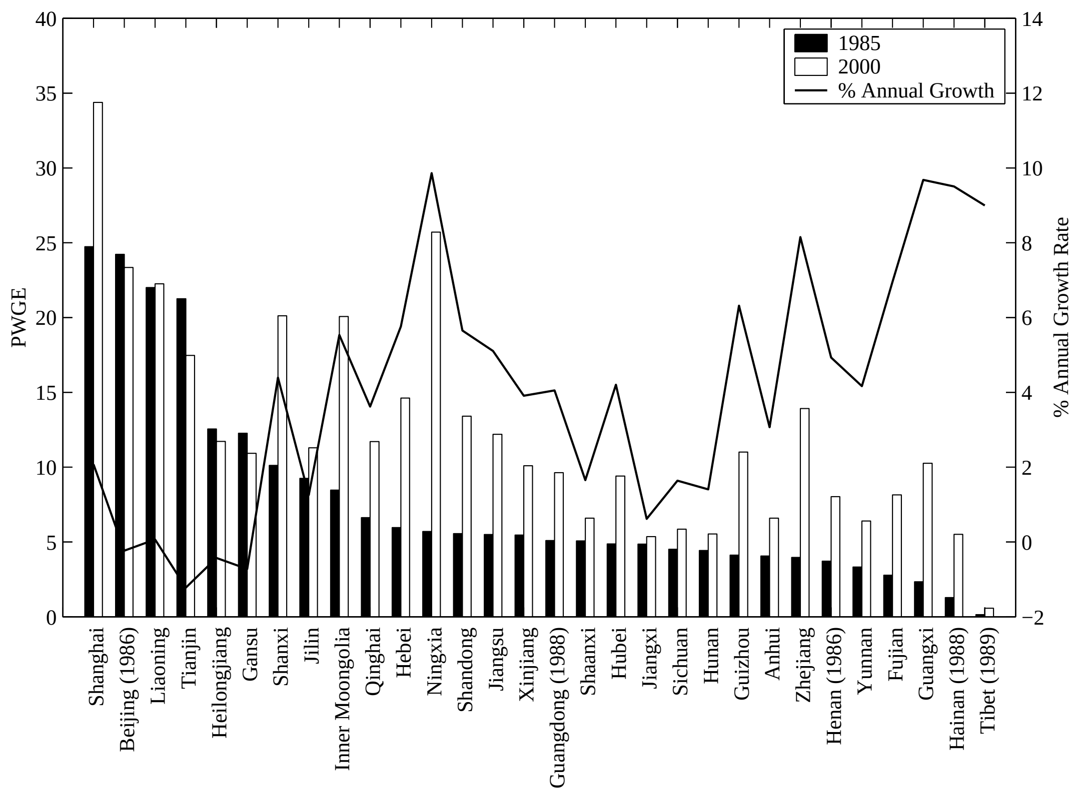
The original source of our data on waste gas emissions (WGE) is China's Environmental Yearbook published by China's NEPA. WGE are measured in billions of cubic meters and are very heterogeneously distributed between provinces. The coastal provinces[9], forming 14% of the area of the country, account for about 54% of waste gas emissions in 2000. This largely reflects the uneven distribution of population and

[8]Tibet began pollution charges in March 1991.

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

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 0.56. 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%.

Figure 4: 1985 & 2000 Per Capita Waste Gas Emissions (thousands of m^3)



3.2 Converting waste gas emissions to CO_2 emissions

Data on China's carbon dioxide emissions are only available at a national level (Oak Ridge National Laboratory, 1998).[10] 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, 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

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

to predict CO_2. We estimate the following equation:

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

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 moderate term future, although it may impact our long term forecasts. Further, since transportation plays a large role in greenhouse gas emissions, this relationship may break down if there are large increases 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 (1986-2001). 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. Population density is calculated as total provincial population divided by total area 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 with available data 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 1989, 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.

4 Empirical Models and Results

The adopted modelling philosophy has to accommodate the two main purposes of this paper, which are to forecast China's CO_2 emissions and to understand how population, income and technological change affect individual provinces' emissions. We use a general to simple specification search based on Hendry (1985). Within this framework we choose the Schwarz Information Criterion (SIC) in order to select our model. We choose this criterion since the R^2 will always prefer a less parsimonious model and it can be shown that the adjusted R^2 does not sufficiently penalize models for the inclusion of too many parameters. We choose the SIC over the Akaike Information Criterion, since it punishes the inclusion of additional parameters more heavily (Diebold, 2001). Thus we prefer and will ultimately use a parsimonious model to forecast China's CO_2 emissions.

4.1 Specification Search

Equation 3 below is our most general model. It models the pollution income relationship (PIR) as a third order polynomial, allowing for an N-type relationship suggested by some studies. This most general model includes fixed time and province effects as well as a longer (two-period) lag structure. The most general initial model is given as:

$$
\begin{aligned}
ln(PWGE_{it}) = \beta_1 ln(GDP_{it}) + \beta_2 (ln(GDP_{it}))^2 + \beta_3 (ln(GDP_{it}))^3 + \beta_4 ln(COMP_{it_o}) \\
+\beta_5 ln(PDENS_{it}) + \beta_6 COAST_i + \beta_7 FDI_{it} + \sum_{i=1}^{30} \beta_{7+i} ln(PWGE_{it-1}) \\
+\sum_{i=1}^{30} \beta_{37+i} ln(PWGE_{it-2}) + \alpha_t + \gamma_i + \varepsilon_{it}
\end{aligned}
\tag{3}
$$

where i is a province index, t is a time index, γ_i is a province fixed effect, α_t is a year fixed effect and ε_{it} is the usual Gaussian 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 (RMB 1985), $COMP_{it_o}$, industry composition in 1989, $COAST_i$ is a dummy variable for the coastal provinces and FDI_{it} is Foreign Direct Investment (RMB 1985). 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 allows 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, if significant will capture differences in "starting point" emissions, which are not captured by the coastal dummy or initial industry composition. 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 first estimate equation 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 with no fixed effects has a slightly lower SIC than the model with time fixed effects only. The SIC prefers the model without province specific fixed effects. This is a good indicator that the coastal dummy and initial industry composition capture the structural differences in "starting point" emissions. We include a simple time trend and obtain the lowest SIC.[12] 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 $\forall j \epsilon [38, 67] \beta_j = 0$, 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

[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.

[12] We also estimated a model with province specific time trends. The SIC was higher and the results added no additional insight when compared to a model with a time trend common across provinces.

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.

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 - a province with a high rate of technological innovation. Correspondingly a larger (closer to one) parameter estimate would indicate a slow rate of adjustment.

Our model selection criterion further rejects the inclusion of the third order polynomial term as well as FDI_{it} for all models, yet suggests the inclusion of population density and the coastal dummy variable. Model 4 below minimizes the Schwartz Information Criterion.

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

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[13].

There has been considerable interest in the literature on whether the shape of the PIR is more general than an inverse U. We turn to this topic in the next section. Since we assumed a rather restrictive parametric form of the PIR, we estimate equation 4 via a Generalized Additive Model.

4.2 Generalized Additive Model

The Generalized Additive Model given in equation 5 is estimated using a smoothing spine as well as a Loess data smoother (Cleveland & Devlin, 1988). The model below puts no parametric restrictions on the shape of the PIR. The smoothers will give us an indication of the functional form without any ex ante imposed restrictions.

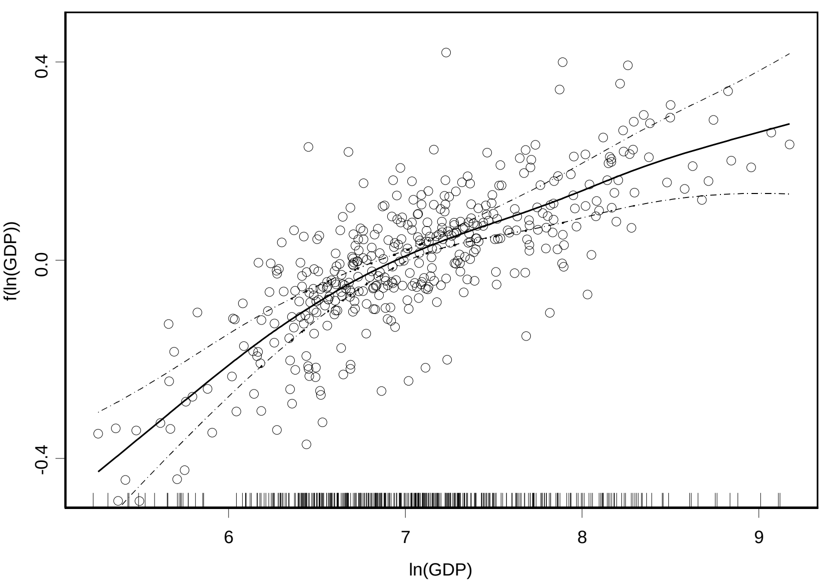
$$\begin{aligned} ln(PWGE_{it}) = \alpha + f(ln(GDP_{it})) + \beta_1 ln(COMP_{it_o}) + \beta_2 ln(PDENS_{it}) \\ + \beta_3 COAST_i + \sum_{i=1}^{30} \beta_{3+i} ln(PWGE_{it-1}) + \beta_{34} ln(TIME_t) + \varepsilon_{it} \end{aligned} \tag{5}$$

The shape of the PIR is depicted in Figure 5. The shape of the PIR clearly shows a functional form which resembles the rising slope of an EKC type relationship. Since China is a developing country, most

[13] 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.

of the observations are well below the turning point. The shape is consistent with the upward rising, but decreasing slope part of an EKC relationship. We note that the power of this method, given our sample, relies on observations from the left rather than the right tail of the income distribution. When using our model selection criterion, we find that the parametric specification in equation 4 is preferred to the GAM model. The in sample predictions are, however, almost identical.

Figure 5: Predicted PWGE from Income using GAM



4.3 Preferred Model Results

Table 1 reports the estimation results from our preferred model.[14] 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 $\beta_2 < 0$. The turning point for the model reported in Table 1 is at 13143 RMB, which is slightly above Shanghai's current income, although 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 5. 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

[14]We estimated this model using the traditional specification without lags and population density and obtain $LPWGE_{it} = -2.11 + 1.42 \cdot ln(GDP_{it}) - 0.07 \cdot (ln(GDP_{it}))^2 - 0.04 \cdot ln(Time)$. When we include population density, we obtain $LPWGE_{it} = 3.07 + 1.43 \cdot ln(GDP_{it}) - 0.08 \cdot (ln(GDP_{it}))^2 - 0.02 \cdot ln(Time) + 1.19 \cdot ln(PDENS_{it})$. The R^2 is 0.47 and 0.45 respectively.

Table 1: Parameter Estimates

Parameter	Lag Model Estimate	Robust t-Statistic
Constant_i	0.932	1.070
$\ln(\text{GDP}_{it})$	0.756	3.750
$(\ln(\text{GDP}_{it}))^2$	-0.040	-3.060
$\ln(\text{Comp}_{it_o})$	1.435	1.880
Coastal_{it}	-0.458	-1.540
$\ln(\text{Pdens}_{it})$	0.375	4.080
ln(Time)	-0.062	-3.190
Beijing	0.625	11.970
Tianjin	0.624	12.060
Hebei	0.663	12.340
Shanxi	0.563	9.790
Inner Mongolia	0.813	20.210
Liaoning	0.638	8.920
Jilin	0.614	13.540
Heilongjiang	0.610	12.680
Shanghai	0.605	10.490
Jiangsu	0.634	12.370
Zhejiang	0.746	12.430
Anhui	0.522	6.480
Fujian	0.733	15.880
Jiangxi	0.504	7.890
Shandong	0.639	12.500
Henan	0.462	6.250
Hubei	0.529	8.460
Hunan	0.485	7.350
Guangdong	0.742	13.280
Guangxi	0.751	18.600
Hainan	0.783	11.320
Sichuan	0.529	9.010
Guizhou	0.591	10.910
Yunnan	0.654	9.750
Tibet	0.746	2.860
Shaanxi	0.548	10.070
Gansu	0.638	11.680
Qinghai	0.844	9.130
Ningxia	0.642	13.240
Xinjiang	0.828	16.260
R^2	0.9677	
Observations	468	

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 1.4% increase in per capita waste gas emissions. The parameter estimate on population density is positive and significant. 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.

There is considerable variation in individual provinces' elasticities with respect to the previous period's emissions, as indicated by the parameters on the province specific AR(1) terms.[15] Figure 6 plots the parameter estimates for the provinces from the lag-model in deviation form.[16] The provinces with lagged parameter values that are substantially below the average tend to be the coastal provinces that have received substantial FDI, whereas the provinces with substantially higher lagged parameter values tend to be provinces which are large coal producers with substantial concentrations of heavy industry. Figure 7 demonstrates the impact of differing lag parameter estimates on projected per capita emissions. We simulate three provinces with identical starting per capita income, which grows at 5.02% per period.

Figure 6 illustrates two points, which are not immediately 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. In another specification we allowed the AR(1) parameter to change in the middle of the sample and only three provinces show a statistically significant change. The lag parameter estimate on Beijing and Shanghai decreases mildly, whereas the parameter estimate on Guizhou increases slightly. Even though these changes are significantly different from zero, they are rather small in absolute magnitude. This result contradicts a popular argument

[15] All of our provincial lagged emission coefficients except one (Qinghai) are smaller, that is more responsive, than the 0.84 estimate that Agras & Chapman (1999) obtain from their sample of countries.

[16] The parameter estimates given in Figure 6 are obtained from an estimation omitting the coastal dummy as well as initial industry composition to extract the overall differences in technological progress. This estimation suggests that a fruitful approach for future work would be to develop a model to predict the magnitude of the lag parameters using variables such as industrial composition, coal deposits, FDI and provincial environmental regulations

Figure 6: Lag Parameter Estimates (Deviation from Mean)

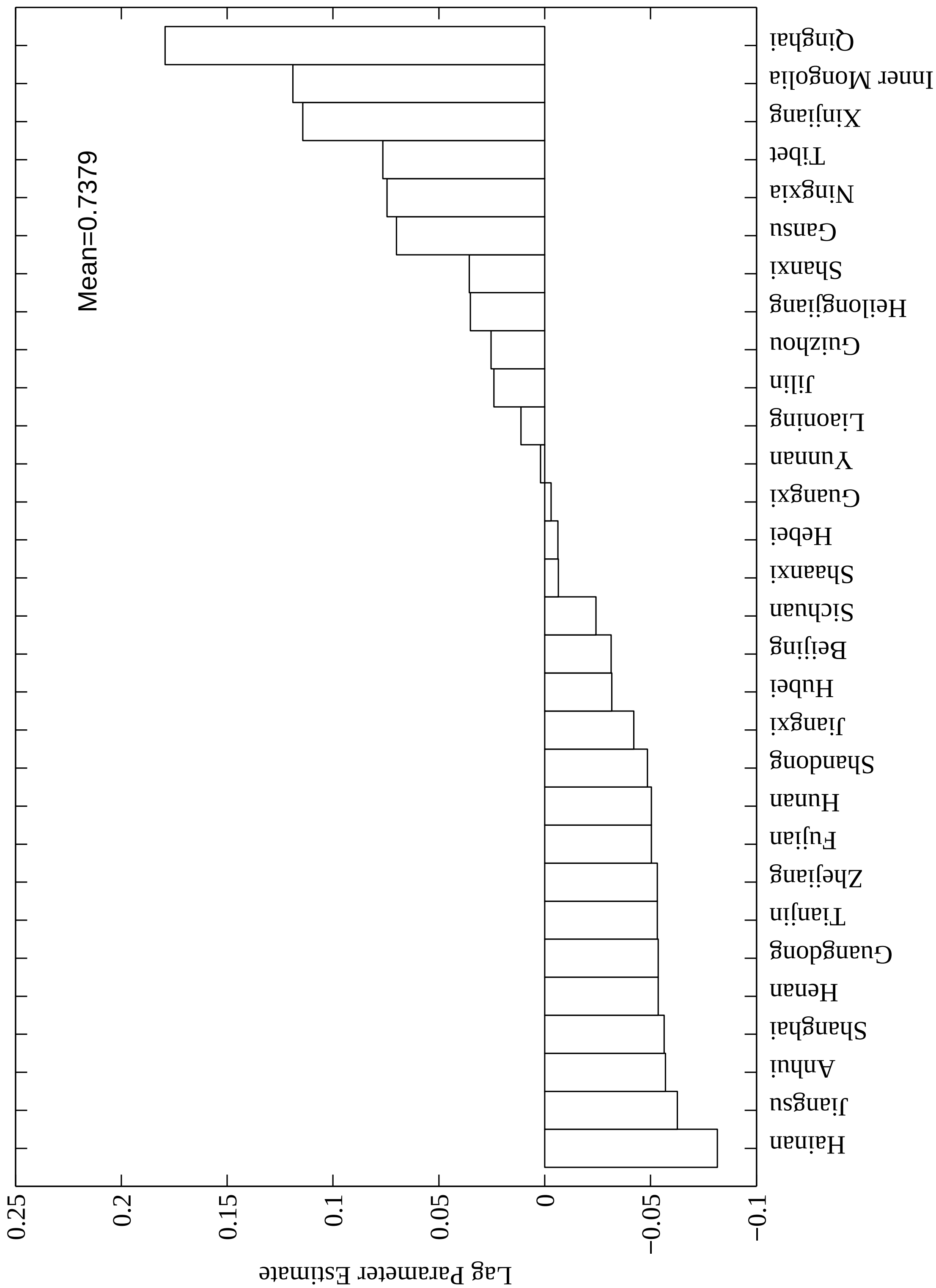
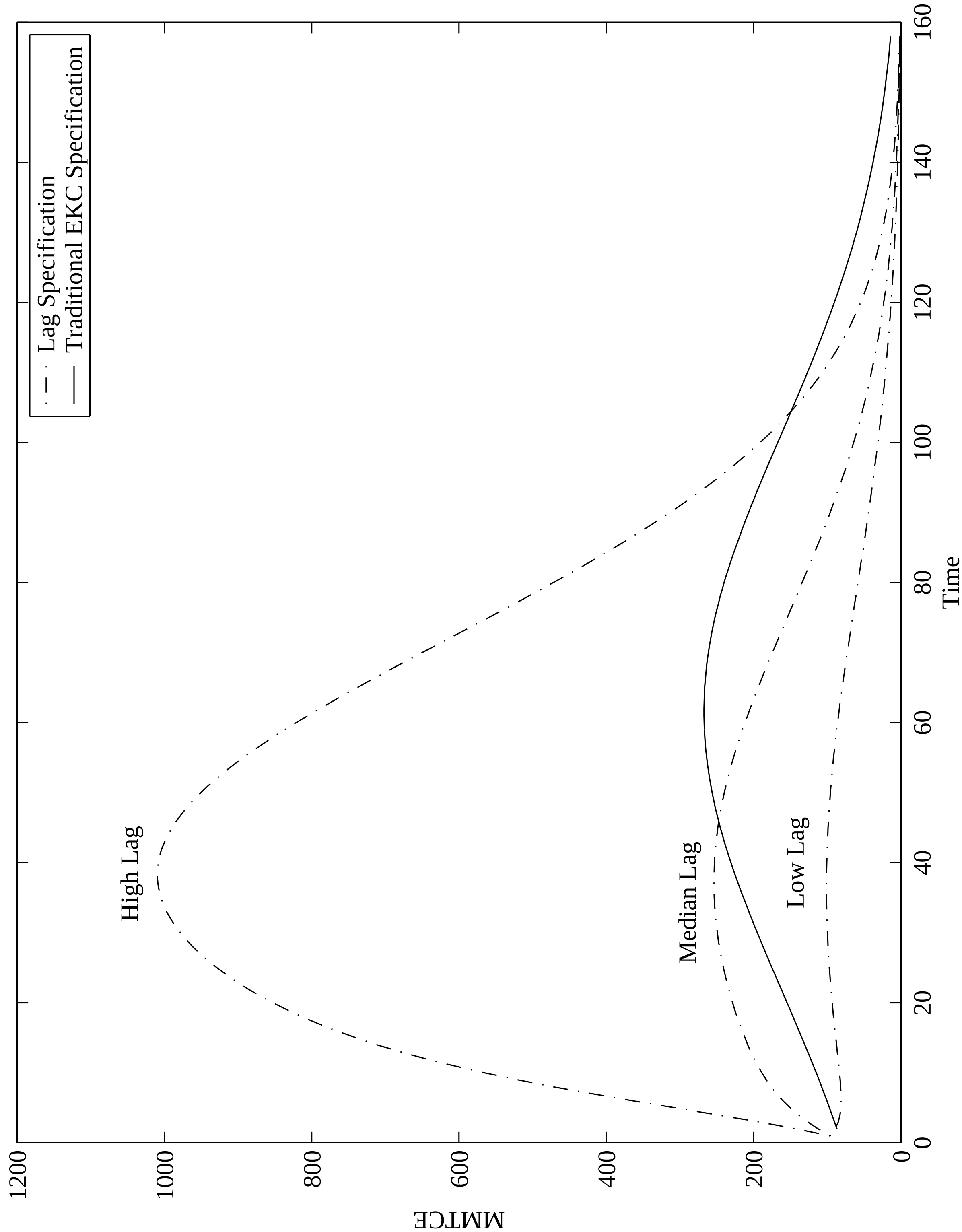


Figure 7: Traditional EKC vs. Lag Specification



hypothesizing a 'new China', which conjectures dramatic structural changes on every level of society resulting in improved environmental quality.

The thick line in Figure 7 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 0.80 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, ceteris paribus.

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 province's 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.

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. Those waste gas emissions are then converted 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. The provincial population forecasts are based on the projections by Chesnais & Minglei (1998). The GDP growth scenarios are based on IPCC projections as well as one scenario using in-sample historical GDP growth. We choose a model of no population growth and constant 5.02% growth of per capita GDP, which corresponds to the assumption for our medium GDP growth scenario, 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 of assumptions, we will attempt to illustrate the impact of the range of assumptions typically made concerning Chinese GDP and population growth rates. We limit our analysis to only three GDP growth scenarios. The three different scenarios demonstrate the sensitivity of our forecasts to changes in the assumptions regarding GDP growth rates very well. The three alternative sets of assumptions are a slow growth case, a medium growth case, and a high growth case.

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). Four scenarios are considered, 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 mortality rates across provinces. Scenario B is characterized by decreasing natural birth rates and constant mortality 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.

We assume that the GDP growth rate (ξ_t) and population growth rate (ϕ_t) are jointly distributed as $f(\xi_t, \phi_t) \sim N_2[\mu_\xi, \mu_\phi, \sigma_\xi^2, \sigma_\phi^2, \rho]$ and in and out of sample population and GDP growth rates can be characterized by this bivariate normal distribution. The distribution is parameterized by using the in sample mean and standard deviation of the population growth rate as well as its correlation coefficient with aggregate GDP growth for μ_ϕ, σ_ϕ and ρ respectively. Three different pairs of values for μ_ξ and σ_ξ for our out of sample predictions are used as we consider a slow, medium and high GDP growth scenario. The parameters for the slow growth scenario are derived from a distribution based on Scenario IS92a of the quasi official IPCC forecasts. The IPCC provides two possible values for this scenario, which we take to be the upper and lower 5th percentile of the marginal growth rate distribution. The mean of the GDP growth rate for the medium growth scenario is only 0.5% larger than the mean of the low growth scenario. Although this seems to be a small difference, a 0.5% higher GDP growth rate over a 50 year horizon has a drastic impact on per capita income. The high growth scenario uses China's in sample aggregate GDP growth rate and variance. These values are admittedly very high, and by most forecasts China's economy is not expected to follow the high growth path it has in the years covered by our sample. The results using these parameters do show the drastic impact of the income effect in the upper regions of the future provincial income distribution on CO_2 emissions.

We do not forecast the population growth rate, as the four scenarios provided by Chesnais & Minglei (1998) are used. We calculate $\phi_t \forall$ t ϵ [2001,2050] from these forecasts and use the conditional marginal distribution $g(\xi_t|\phi_t) = N[\alpha + \beta\phi_t, \sigma_\xi^2(1-\rho)^2]$, where $\alpha = \mu_\xi - \beta\mu_\phi$ and $\beta = \frac{\rho\sigma_\xi\sigma_\phi}{\sigma_\phi^2}$ to obtain realizations of the aggregate GDP growth rate. Table 2 summarizes the scenarios in consideration. Since we only consider three scenarios of GDP growth, a total of twelve different population/GDP scenarios for forecasting purposes are considered.

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 8 displays aggregate forecasts of Chinese CO_2 emissions based on the conservative slow and medium GDP growth assumptions for all four population scenarios until the year 2050. The forecast in Figure 8 under the assumption of slow *and* medium 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 thick line indicates the median point forecast for each population growth scenario, while the dashed lines indicate the 90% confidence interval. It is noteworthy how similar the forecasts for the same population scenario and differing GDP growth scenario are. Our forecasts suggest that the

Table 2: Assumptions Concerning GDP and Population Growth Rates

	A-Slow	B-Slow	C-Slow	D-Slow
Mortality Rate	Constant	Constant	Decreasing	Decreasing
Birth Rate	Constant	Decreasing	Constant	Decreasing
GDP Growth Mean	4.46%	4.46%	4.46%	4.46%
GDP Growth StDev.	0.47%	0.47%	0.47%	0.47%

	A-Medium	B-Medium	C-Medium	D-Medium
Mortality Rate	Constant	Constant	Decreasing	Decreasing
Birth Rate	Constant	Decreasing	Constant	Decreasing
GDP Growth Mean	5.02%	5.02%	5.02%	5.02%
GDP Growth StDev.	0.77%	0.77%	0.77%	0.77%

	A-Fast	B-Fast	C-Fast	D-Fast
Mortality Rate	Constant	Constant	Decreasing	Decreasing
Birth Rate	Constant	Decreasing	Constant	Decreasing
GDP Growth Mean	8.90%	8.90%	8.90%	8.90%
GDP Growth StDev.	4.66%	4.66%	4.66%	4.66%

distribution of population across China's provinces may have a drastic impact on the PRC's aggregate CO_2 emissions.

Figure 8: Aggregate Forecasts of China's CO_2 Emissions - Slow and Medium GDP Growth

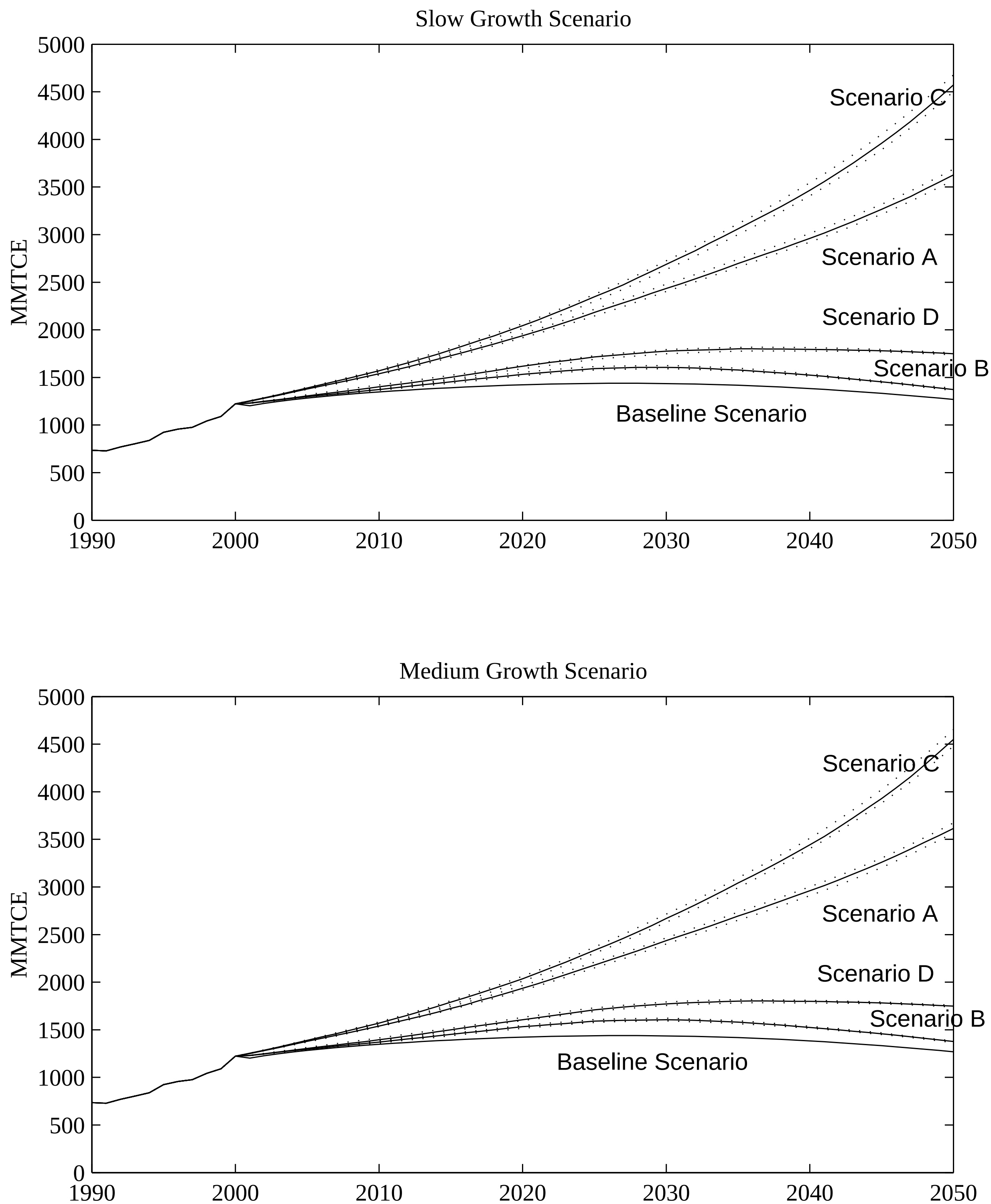


Figure 9: Aggregate Forecasts of China's CO_2 Emissions - High GDP Growth

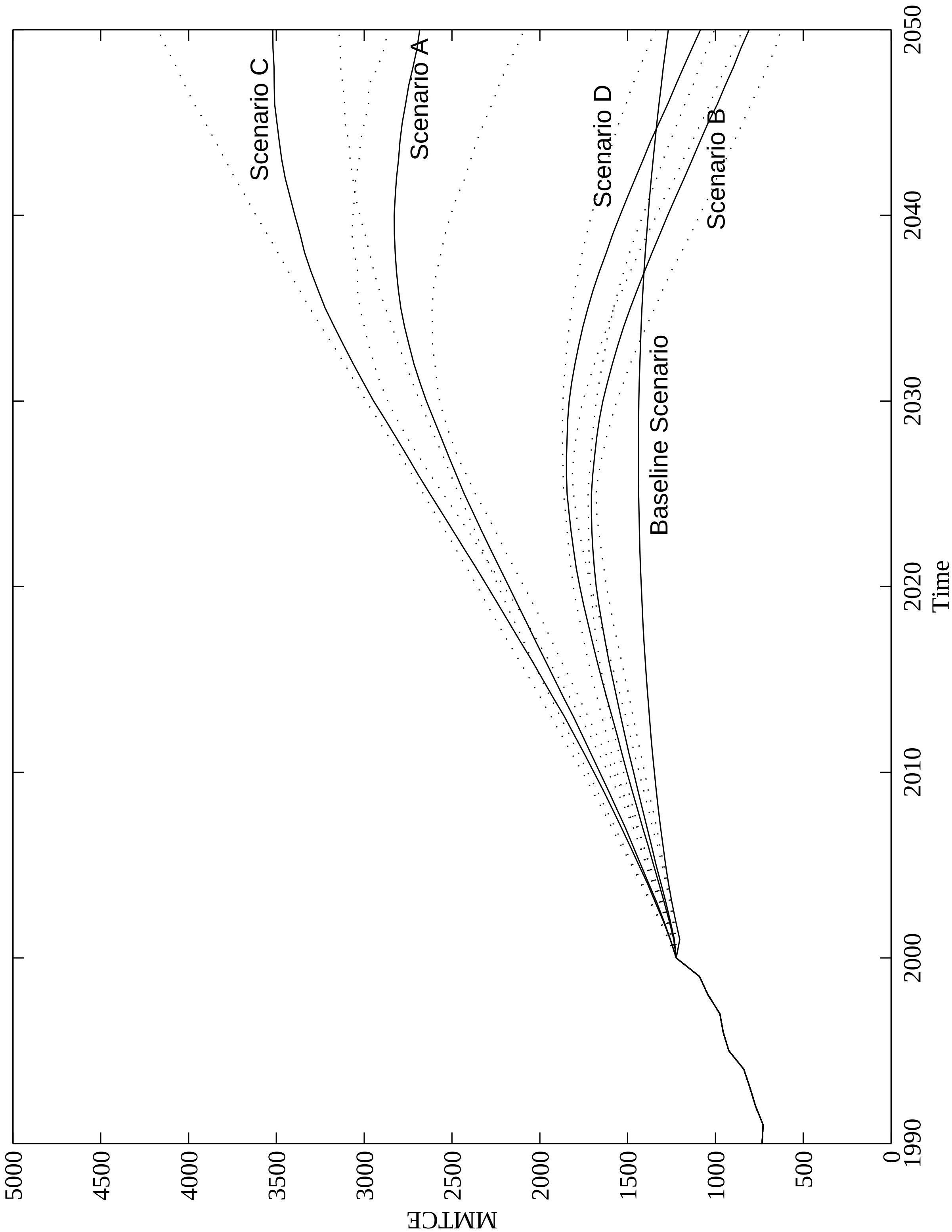


Table 3: Range Of Projected CO_2 Emissions from Different Studies (billion metric tons of carbon)

Year	**IPCC*** **(2000)**	**Yang and Schneider (1998)**	**Ho *et al.* (1998)**	**Garbaccio *et al.* (1999)**	**Panayotou *et al.* (1999)*****	**Lag-Specification****
2020	1.73 - 2.50	—	—	2.13	2.34	1.54 - 2.30
2022	—	—	—	2.30		1.56 - 2.42
2025	—	1.16 - 1.80	—	—		1.60 - 2.62
2050	2.32 3.90	1.54 - 3.14	2.84 - 4.66	—	1.71	0.81 - 4.56

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, the baseline model was not included in our prediction band. ***Projected flow of CO_2 emissions from fossil fuels 1996-2050

Figure 9 shows our forecasts using the high GDP growth scenario. This scenario reflects historical GDP growth for the PRC for the past 15 years. These years have been a period of high growth and it is expected that GDP growth will slow down in the near future. As one can see from Figure 9, the higher levels of GDP growth push per capita income past the estimated turning points; and depending on the population growth scenario, suggests an aggregate 'Kuznets' type PIR. In this high growth scenario, the income effect offsets the population growth effect.

Forecasts based on national aggregates cannot pick up the population density 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 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 3 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 3 shows the range of values of the projected CO_2 emissions for the year 2020[17] under the A1B, A2, B1 and B2 marker scenarios of IPCC, and our projections. We note that, in the medium term, our range of forecasts is lower than that provided by the IPCC. The information contained in the spatially disaggregated data should contain more information than the national aggregate data. Our point

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

forecasting prediction band is slightly 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[18]. 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 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 and are considerably higher. This is also true when considering the projected CO_2 emissions found by Ho, Jorgenson & Perkins (1998). According to their work, Chinese CO_2 emissions by the year 2050 will range from 2.84 and 4.66 billion metric tons. Our projections for the same year suggest somewhat levels.

6 Conclusion

We provide CO_2 emission forecasts for China through the year 2050 under several alternative scenarios. Our results suggest that Chinese CO_2 emissions will be somewhat lower (given a common overall GDP and population growth assumptions) than those projected by models based on national aggregate level data with somewhat tighter confidence intervals.

In developing our estimates, we clearly reject the standard IPAT type models that underlie most estimates being used by the IPCC (2000). First, we find that while a coefficient of 1.0 on population typically assumed by these models cannot be rejected, differences in population density do play a sizeable role in helping to predict CO_2 emissions. This finding is consistent with work by Murthy et al. (1997) on rural-urban differences in India based on an input-output modelling perspective. Our result has important implications if large-scale migration from rural provinces to urban areas take places as many demographers believe is likely.

Second, our estimation results are consistent with the inverted U-shaped pollution income relationship posited by the Environmental Kuznets curve hypothesis. This result either rejects the IPAT family of models' common assumption that pollution emissions are monotonically increasing in terms of income, or, it requires one to adopt a considerably more complex specification of technology, which effectively breaks the independence assumption between the IPAT affluence and technology factors. Our estimated EKC relationship plays a key role in helping to offset the increase in CO_2 emissions projected to occur with increases in population density.

During the time period considered, China's most populous provinces are projected to be on the flat part of the EKC inverted-U and in many instances on the declining side of that inverted-U. Because of this our results show that uncertainty about future Chinese CO_2 emissions shift from being driven primarily by uncertainty about growth in income to one where the uncertainty is strongly dominated by variation

[18] 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.

in population projections. Indeed, using four different but plausible provincial population scenarios, the difference between our highest and lowest forecasted aggregate emissions is roughly equal in magnitude to the European Union's total current emissions.

Third, our technology specification is much richer than those in most IPAT type models. We reject both static specifications and simple dynamic specifications where the units of observation have similar technological responses. The model our specification tests prefers is a simple first order autoregressive process defined in terms of past emissions, which can vary across provinces. This suggests quite different speeds of technological progress, likely in the form of average capital vintage and energy efficiency across China's provinces. Spatial heterogeneity across provinces appears to be well captured by this specification when coupled with two initial conditions, the ratio of heavy to light industry and proximity to the coast. Once these are taken into account, statistical tests suggest the unit fixed effects specification that is common to much of the EKC literature is no longer needed. Statistical tests also suggest that a single exogenous technological trend is sufficient rather than province specific trends.

Moving beyond the standard IPAT family of models, we believe that there are several major advantages to using provincial level data. It allows the researcher to exploit a large degree of spatial heterogeneity across provinces that is otherwise ignored by models using national aggregate level data. China is especially well suited to this approach. Many of China's provinces encompass large areas and have larger populations than most of the major European countries, in addition to a substantial amount of variation in income and emissions data. This variation substantially reduces the problem of multicollinearity; a problem that plagues national aggregate level data and helps to improve the precision of our parameter estimates. The key to being able to use subnational level data is the consistency with which variables are collected across provinces as well as having an adequate number of time periods. In this regard, China looks ideal and provides some of the first evidence on the nature of the pollution income relationship developed solely in the context of a single major developing country.

Much of the message in our results is contained in the coefficients on lagged emissions for each province. In this sense, our work starts to unravel the EKC black box that bothers many commentators (Arrow et al., 1995). Differences in the estimated coefficients can result in radically different CO_2 trajectories even though all incorporate a common underlying EKC component. Policy measures should be designed to bring down the estimated lagged emissions coefficient.

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. Clearly there has been work at the national level, which would likely have the effect of reducing the lag division parameters (Garbaccio, Ho and Jorgenson, 1999a). As China's environmental decision making continues to devolve to provincial and city levels (Wang & Wheeler, 1999), the national-provincial coordination issue becomes a particularly interesting one if as our results suggest problems are concentrated in a small number of provinces which are large coal producers.

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