# Forecasting China's Carbon Dioxide Emissions: A Provincial 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 selected using a general to simple search strategy. These estimates are the first based upon provincial-level data (1985-2000). The model chosen by the information criterion is one that melds the standard approach taken in the science and engineering literature with the environmental Kuznets curve approach popular in the economics literature whereby per capita emissions can first rise and then fall with increases in income. Other aspects of the model allow for the possibility that the rate of technological change varies across provinces and the possibility of population density effects. We find statistical support for the presence of an inverted U shaped environmental Kuznets relationship with the projected turning point being not too far above Shanghai's current income level. Our model suggests 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. However, in contrast to conventional wisdom, uncertainty over demographic changes is likely to dominate uncertainty over changes in per capita GDP. It 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.

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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

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 and Jiankun, 1994; Panayotou, Sachs and Zwane, 2002). Developing countries are adamant about negotiating reductions relative to the level of emissions that would be projected to occur normally as they industrialize.[2] Kyoto Protocol Annex I [3] countries, 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 climate agreement involving commitments by both the United States and China to reduce greenhouse gas emissions.

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 model but more typically done using population, income and some measure of technology as predictors. Forecasts following this approach are common in the science and engineering literature (*e.g.,* Yang and Schneider, 1998) and in the policy arena form the basis for the quasi-official estimates of the Intergovernmental Panel on Climate Change (IPCC). Models with an explicit economic orientation usually add policy variables that allow for fuel switching, induced technological change, and emissions trading.[4] 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 and Levine, 1994; Zhang, 1998; Garbaccio, Ho and Jorgenson, 1999a; Garbaccio, Ho and Jorgenson, 1999b). 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 and Heller, 2000).

We pursue a fourth approach, disaggregating emissions and other possible predictor variables at the

[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]The Kyoto Protocol defines Annex I countries as developed countries and other nations which have committed themselves to reductions in carbon emissions. These are essentially the OECD plus the Eastern European countries including Russia.

[4]See for instance the 1999 special issue of the *Energy Journal* edited by John Weyant on the cost of the Kyoto Protocol. The economically oriented models are typically identified by exploiting cross-sectional or panel variation *across countries.*

spatial level by looking across China's provinces. China's provinces differ greatly in land area.[5] The largest province by area, Xinjiang, is only 15% smaller than Mexico while the smallest province, Shanghai, is approximately twice the size of Luxembourg. The largest province in population terms is Sichuan, counting 115 million inhabitants. Tibet, with the fewest inhabitants, has 2.6 million. Thus the Chinese provinces span much of the range of the country level datasets used with respect to area and population. 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 and 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 eliminates $P$, and implicitly assumes that the elasticity of emissions with respect to population equals one. The inclusion of coefficients on one or more of the variables is justified 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 increasing income has been the main factor increasing emissions, while changes in aggregate population size have had a much lesser impact. His estimates show that changes in technology as proxied by energy intensity are between those of the income and population effects in terms of absolute magnitude and work 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. In the case of China, anecdotal evidence suggests that better technology, in the sense of more energy efficient and cleaner capital stock, is found in the wealthier provinces. Separating the two effects in an empirical

[5] 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 and Sala-i-Martin, 1992; Bernard and 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.

study is crucial for designing correct policy solutions. There is some empirical work (*e.g.,* Kalirajan and Zaho, 1997) suggesting that technology development in the wealthy coastal provinces has far outpaced that of many of the poorer 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.[6] 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 for an EKC relationship with the possibility of income having 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. Each of these modifications are taken up in turn.

## 2.1 Generalizing the IPAT Model

The inverted U-shaped environmental Kuznets curve was first identified by economists at the World Bank (Shafik and Bandyopadhyay, 1992) and became an important part of the NAFTA debate (Grossman and 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 al.*, 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 and 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 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

[6] The original Ehrlich and 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 and 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 and 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) with mixed results.

the income turning points for $CO_2$ emissions are quite high (Schmalensee, Stoker and Judson, 1998) or non-existent (Holtz-Eakin and Selden, 1995).

Some of these issues are addressed in this paper, which is the first study estimating the shape of the relationship between an environmental pollutant and income solely within a developing country. First, by using data for a single country which are 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 and McCubbin (1997), who found evidence in support of the EKC hypothesis for air pollutants, including $CO_2$, across the 50 U.S. states by showing that per capita emissions fell with increasing income. China has considerably more variation across provinces both in per capita emissions (a factor of 50) and income levels (a factor of 8) than there is across the 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 using a third order polynomial in income, which is popular in the literature (Sengupta, 1996; Moomaw and Unruh, 1997), effectively allowing emissions to plateau and then increase again at higher levels of income. Furthermore, we allow for an even more flexible functional form in the semi-parametric Generalized Additive Model (GAM) framework (Hastie and 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. Emissions in the industrial and power generating sector largely depend on the quality speed of replacement of the capital stock. In an ideal setting one would like to model and estimate the emission process much like a dynamic production model, popular in the Macroeconomics literature. Such a model would require quality data on capital stock and other inputs to production across time and provinces, which is not available. Since we believe that it does take time to adjust the capital stock/technology we employ a dynamic model. We proxy for differential rates of capital replacement 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.[7]

We further introduce dynamics by allowing for changes in population and population density 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 include 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

[7] To our surprise, the only empirical paper we have found that allows for a dynamic adjustment process is Agras and Chapman (1999), who find clear evidence in support of such a relationship using a sample of 34 countries from 1971-1989. They correctly perceived the issue as one of a capital adjustment process. 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.

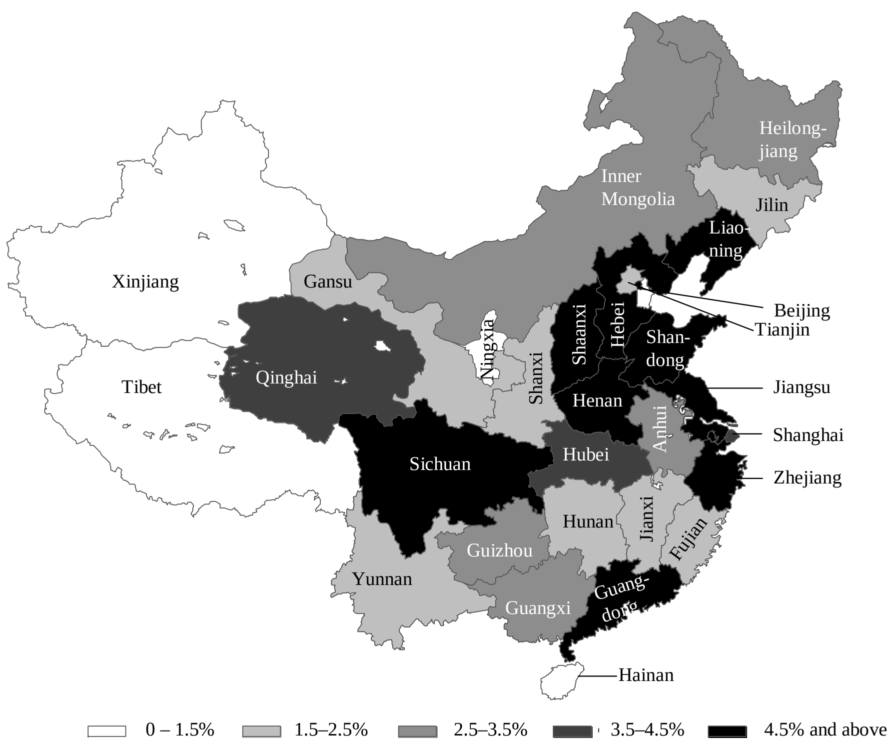
likely to produce a significantly larger amount of per capita $CO_2$ emissions - after adjusting for income and other factors. As time and the development process continue, one would expect a shift of industry composition towards lighter industries. We use a simple time trend to adjust for exogenous 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 test for such effects to some extent 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 coal producing provinces 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 roughly 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 0.46 for our sample. It might be more desirable to include a measure of urbanization, such as share of urban population in a province, yet for political and jurisdictional reasons a good measure does not exist. Population density is a reasonable proxy for urbanization, since for the existing measures, differences in population density are highly correlated with differences in urbanization across provinces. 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[8] accounting 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 and 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 people annually. There is evidence of population net outflow from the Northwest provinces of Tibet, Qinghai, Xinjiang, Sichuan, Guizhou, Yunnan, Shaanxi and Gansu (Lin and 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.

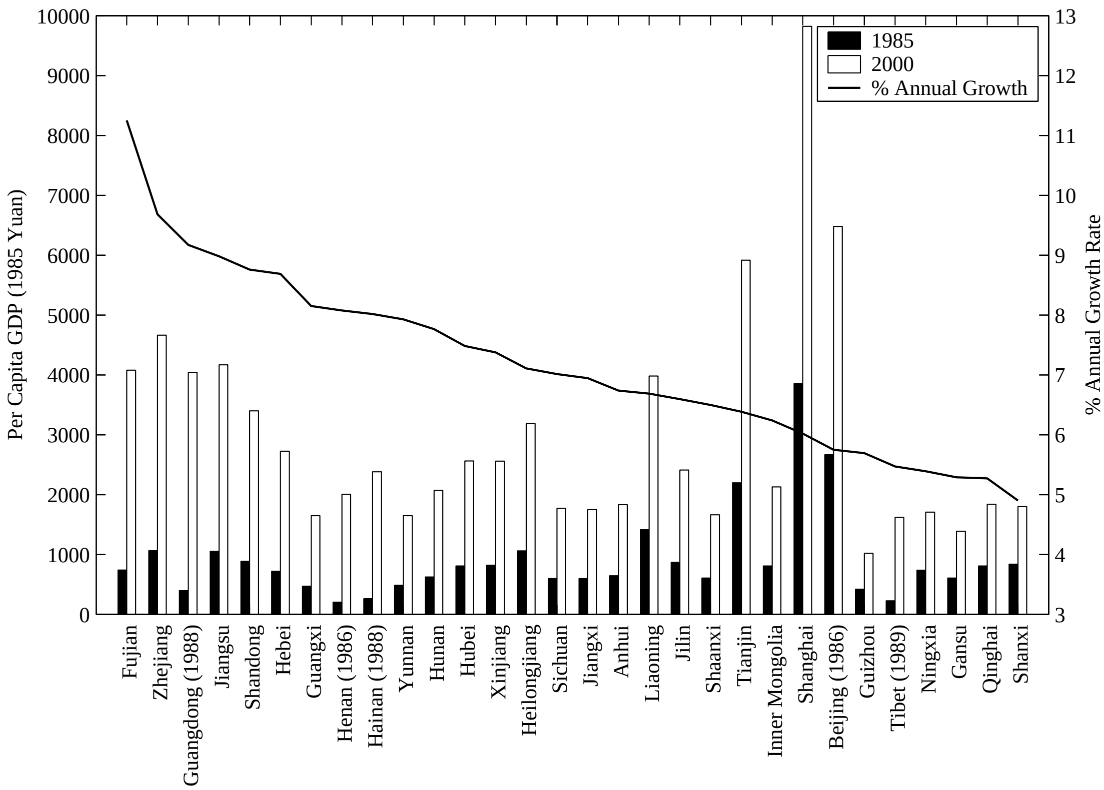
Further note that (b) reflects the many changes in the provincial income ranking over the fifteen-year period even though the three initially wealthiest provinces, Shanghai, Beijing, and Tianjin have retained their earlier rankings. The large increase in Chinese per capita income appears to be due in large part to the reforms that started in 1979. Over time progressively more reforms with respect to foreign direct investment (FDI), joint ventures, and imports were allowed. China's per capita wealth is now heavily concentrated in the coastal provinces, which 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.

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 and Levine, 1994). More recent work (Garbaccio *et al.* 1999b) 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 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 well into the future.

Investments in non-coal energy generation capacity, such as hydro- and nuclear powered plants, have

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

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

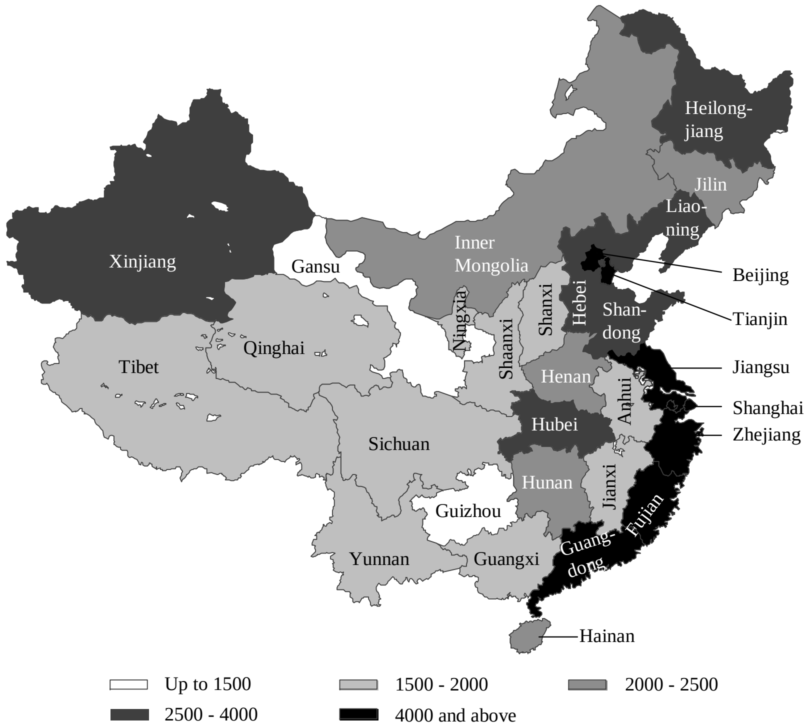



increased in recent years. The biggest and most well known project of this sort is the Three Gorges Dam, which will drastically increase the total amount of electricity generated from hydro sources. Due to the tremendous increase in the overall quantity of energy demanded, however, the shares of energy inputs have remained almost constant over the past 10 years. We find that projections of this trend make a change in the composition of inputs seem unlikely. The overall outcome is apt to be a large scale increase 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 and 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 provinces except for Tibet[9] had established an implementation system. In this sense, environmental policy

[9] Tibet began pollution charges in March 1991.

Figure 3: 2000 Provincial Per Capita Income in 1985 RMB




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.

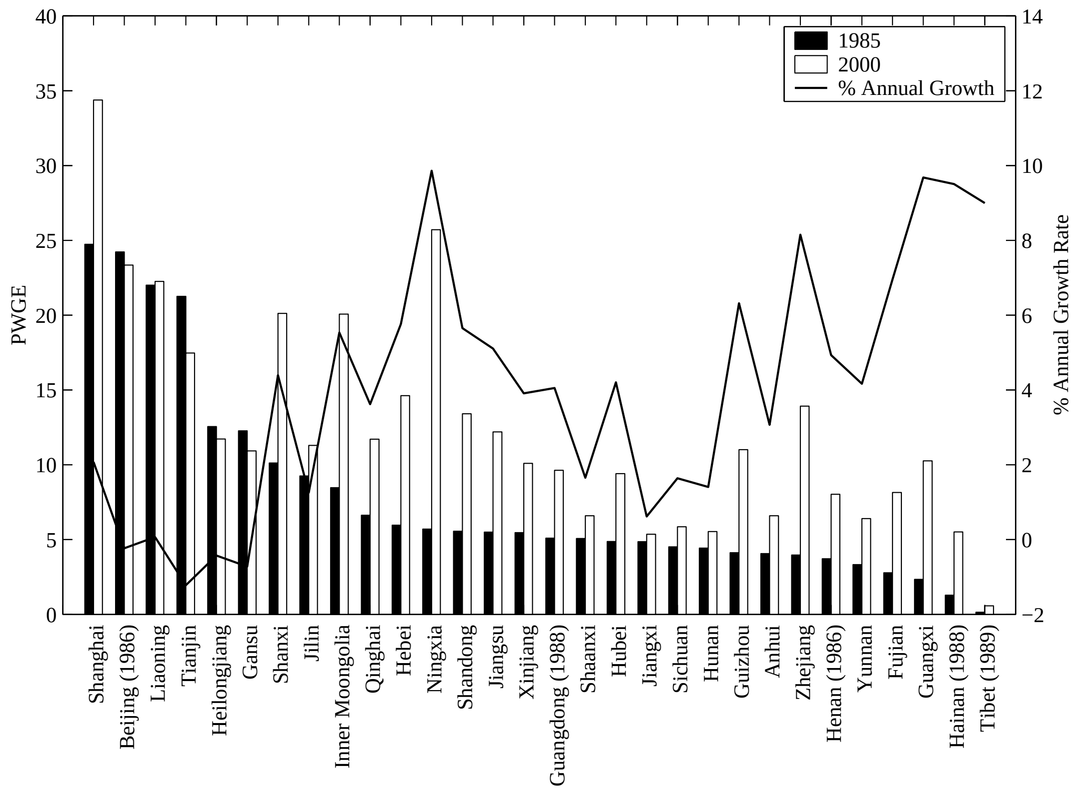
## 3.1 Waste Gas Emissions

The main air pollutant variable used in China is waste gas emissions (WGE), which is reported in China's official Environmental Yearbook. WGE are measured in billions of cubic meters and are very heterogeneously distributed between provinces. The coastal provinces[10], 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 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.

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

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 Proxying for $CO_2$ emissions

Data on China's carbon dioxide emissions are only available at a national level (Oak Ridge National Laboratory, 1998). It would be desirable to have data on provincial $CO_2$ emissions rather than waste gas emissions. Country level $CO_2$ emissions levels are calculated by using annual energy consumption data, which are based on country level fossil fuel consumption. Waste gas emissions on a provincial level are obtained by the local NEPA agencies in a similar way. The authorities use an estimated engineering relationship, which allows them to convert fossil fuel usage into waste gas emissions. 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 $CO_2$. The simple correlation between provincial energy consumption and waste gas emissions is 0.92 for 1989, and 0.94 for 1995 suggesting that provincial waste gas emissions are calculated in much the same way as are national level $CO_2$ emissions. Since province level fossil fuel and energy consumption data are only available for a few years, we use the waste gas emissions data and convert it into $CO_2$ instead of constructing our own measure of province level $CO_2$ emissions. 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. 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 degree of 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 FDI. Our dummy variable allows for the possibility that these provinces are 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. As such we use a specification search based on Hendry (1985). Within this framework we choose the Schwarz Information Criterion (SIC) as our model selection criterion. 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 includes fixed time and province effects as well as a longer (two-period) lag structure. It is given as:

$$ln(PWGE_{it}) = \gamma_t + \eta_i + f(GDP_{it}) + f(GDP_{it-1}) + \beta_1 ln(Pdens_{it}) +$$

$$\sum_{i=1}^{30}\beta_{1+i}ln(PWGE_{it-1})+\sum_{i=1}^{30}\beta_{31+i}ln(PWGE_{it-2})+ \\ \delta Z_{it}+\epsilon_{it} \tag{3}$$

where $i$ is a province index, $t$ is a time index, $\gamma_i$ is a province fixed effect, $\alpha_t$ is a year fixed effect and $\varepsilon_{it}$ is the usual Gaussian error term. $PWGE_{it}$ measures per capita waste gas emissions (100 thousand $m^3$); $GDP_{it}$ is per capita gross domestic product in real terms (RMB 1985). We search over higher order polynomial specifications, which allow for per capita emissions to taper off at some level of income and then later increase at higher levels of income, as has been suggested by some studies. $f(\cdot)$ is a higher order polynomial in income, where in our most general specification we use a fifth order polynomial. The variable $PDENS_{it}$ is the population density for province $i$ at time $t$. $Z_{it}$ is a vector of exogenous variables defined here as $COMP_{it_o}$, industry composition in 1989 and $COAST_i$ is a dummy variable for the coastal provinces. We include one and two-period province specific lagged dependent variables in the initial specification allowing provinces to track their emissions at different rates. As discussed in the previous section we adjust for differences in initial industry composition. We do this to capture differences in the initial pollution intensity of industry - assuming that heavy industry is more pollution intensive than light industry.

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 not captured by the coastal dummy or initial industry composition. The province specific dummy variables in conjunction with the province specific lags create econometric issues that are addressed in the literature on dynamic panels. An estimation problem arises, since the fixed effects are no longer independent of the error terms requiring an estimation technique other than least squares. If one believes that all provinces follow the same autoregressive process, which in this context is equivalent to $\vee i, j\epsilon[1,30]\beta_{1+i}=\beta_{1+j}$, Arellano and Bond (1991) and Arellano and Bover (1995) provide a GMM estimator that allows consistent parameter estimation. If one relaxes this restriction, estimation of such a dynamic heterogenous panels relies on Bayesian techniques or parametric approaches (*e.g.,* Pesaran and Smith, 1995). We limit the space of dynamic panel specifications to equation 3 without lagged income and estimate both the dynamic heterogenous panel as well as the simpler dynamic panel.

The model selection criterion prefers a model with no province specific fixed effects, both for the dynamic heterogenous and the simple dynamic specification. We therefore limit the most general model to:

$$ln(PWGE_{it})=\gamma_t+f(GDP_{it})+f(GDP_{it-1})+\beta_1 ln(Pdens_{it})+ \\ \sum_{i=1}^{30}\beta_{1+i}ln(PWGE_{it-1})+\sum_{i=1}^{30}\beta_{31+i}ln(PWGE_{it-2})+ \\ \delta Z_{it}+\epsilon_{it} \tag{4}$$

We first estimate equation 4, and compare it to a model with a common intercept, no fixed effects and include $COASTAL_i$ as well as $COMP_{it_o}$. This model with no fixed effects has a slightly lower SIC than the model with time fixed effects only. This is a good indicator that the coastal dummy and initial industry composition capture most of the structural differences in "starting point" emissions.[11] This model with a

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

simple logarithmic time trend has the lowest SIC. Section 4.3 addresses the role of time in greater detail. We then adopt this model and test the restriction that $\forall j \epsilon [32, 61] \beta_j = 0$, which suggests an AR(1) over an AR(2) specification. The SIC suggests an AR(1) specification over an AR(2). We then estimate the model without lagged dependent variables where the SIC strongly prefers the AR(1) specification. This finding suggests 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 finding that the AR(2) does not provide a significant improvement over the AR(1) specification further suggests that the non-immediate past does not contain any additional information valuable for forecasting purposes. We discuss the information contained in the province specific lag parameters in more detail in Section 4.5.

We further test for pooling of the province specific lags, which amounts to testing the restriction $\vee i, j \epsilon [1, 30] \beta_{1+i} = \beta_{1+j}$. This restriction implies that all provinces have the same elasticity of current emissions with respect to past per capita emissions. We find 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. The inclusion of the province specific lags is quite different from a traditional fixed effects model from a conceptual as well as econometric perspective. The fixed effects model implies that provinces follow a similar trajectory at a level offset by the province specific fixed effect. The lag parameter model implies that a province follow a different shaped trajectory through time, which may also differ in level or starting point, depending on differences in initial industry composition and coastal location. From an econometric perspective, one would expect that, given a moderate sized sample, the inclusion of province specific lag parameters might absorb most of the variation and make the remaining parameter estimates statistically insignificant. This is not the case here, which we take as further evidence in favor of our final specification given in equation 5.

The SIC further rejects the inclusion of the higher order polynomial term for all models, but does suggest the inclusion of population density and the coastal dummy variable. Model 5 below minimizes the SIC.[12]

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

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]

The estimated model implies that there are no spatial spillover effects across provinces. We estimated equation 5 using the $STAR$ estimator recently proposed by Giacomini and Granger (forthcoming), which allows for first order spatial correlation in a VAR model. Essentially, this estimator allows for spillover effects of first order neighbors, which are provinces sharing a direct border.[14] A likelihood ratio test rejected

[12]The SIC picked a $ln(TIME)$ specification of the time trend over a simple linear time trend as well as a Box-Cox transformation. When replicating these results, it matters what the starting value of the time trend is. In our case, $1985 = 1$. Section 4.3 addresses this issue further.

[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. The robust regression forecasts are available upon request from the authors.

[14]The spatial effect is somewhat stronger, yet still insignificant when omitting the explicitly spatial variable $COAST_i$ from

such effects at the 5% level, providing further evidence in favor of the chosen level of disaggregation.

There has been considerable interest in the literature on whether the shape of the pollution income relationship 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 pollution income relationship, we estimate equation 5 via a Generalized Additive Model.

### 4.2 Generalized Additive Model

The Generalized Additive Model (GAM) given in equation 6 is estimated using a smoothing spline as well as a Loess data smoother (Cleveland and Devlin, 1988). The model below puts no parametric restrictions on the shape of the pollution income relationship. The smoothers will give us an indication of the functional form without any *ex ante* imposed restrictions.

$$\begin{aligned} ln(PWGE_{it}) = \alpha + g(ln(GDP_{it})) + \beta_1 ln(COMP_{it_o}) + \beta_2 ln(PDENS_{it}) \\ + \beta_3 COAST_i + \sum_{i=1}^{30} \beta_{3+i} ln(PWGE_{it-1}) + \beta_{34} ln(TIME_t) + \varepsilon_{it} \end{aligned} \tag{6}$$

The shape of the pollution income relationship is depicted in Figure 5, which suggests a functional form resembling the rising slope of an EKC type relationship. Since China is a developing country, most of the observations are well below the turning point. The shape is consistent with the rising section 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 as is typical of most cross country studies. When using our model selection criterion, we find that the parametric specification in equation 5 is preferred to the GAM model. The in sample predictions are, however, almost identical.

### 4.3 The Role of Time

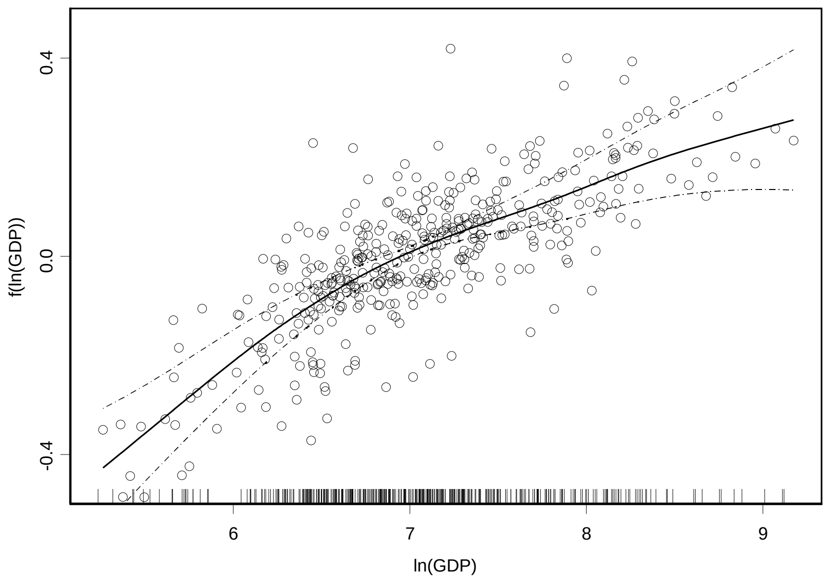
The most general model uses time specific fixed effects in order to capture exogenous technological change common across all provinces. Our preferred model specifies this change as a $ln(TIME_t)$. The literature traditionally includes time linearly. A linear time trend produces very different forecasts from a logarithmic time trend over the long time horizon considered in this study. Including the time trend as a natural log creates an issue, since any scaling of $TIME_t$ now changes the magnitude of technological change, essentially decreasing its impact on aggregate emissions the longer the forecasting horizon. Schmalensee *et al.* (1998) use a linear as well as a log linear forecast of time specific fixed effects. In order to test for the validity of the chosen model, we ran our model with time fixed effects and regressed these fixed effects on several different specifications of time. The logarithmic specification explained 69% of the variation in the fixed effects. A linear time trend explained 13% and a square root explained 32% of the variation in the time fixed effects.[15]

This non-linearity in time is likely due to a slowing of technological change over time. It is widely believed that technological progress was very rapid in the years following the 1979 reforms. This was the case since replacing the least efficient old technology was often cost effective and produced relatively large reductions in emissions. This phenomenon cannot continue linearly into the future, since these increases

the $STAR$ estimation.

[15] A Box-Cox transformation of $Time_t$ resulted in a lambda of -0.38, which lies between a logarithmic and a square root specification of the time trend. When testing the specification of square root time trend versus a logarithmic time trend in the full model, a likelihood ratio test does not reject either specification, but clearly rejects the linear specification.

Figure 5: Predicted PWGE from Income using GAM




in energy efficiency and therefore cleaner technology become more expensive at the margin. One would therefore expect a slowing of this notion of technological change, which is what our results suggest. This slowing down of technological change is amplified by a change in the composition of goods produced towards more energy intensive goods.

## 4.4 Preferred Model Results

Table 1 reports the estimation results from our preferred model.[16] Of particular importance are the signs and magnitudes of $\beta_1$ and $\beta_2$ 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 11,278 RMB, which is not too far above Shanghai's current income. The inclusion of the population and technological change variables has significantly decreased the expected level of income at which the turning point occurs. The confidence interval on the estimate of the turning point, $exp(-\beta_1/2\beta_2)$ is rather large.[17] We check our specification by comparing the model predictions in sample versus the predictions from the generalized additive model of equation 6. The in sample predicted values of this GAM estimation are highly correlated ($\rho$=0.999) with the in sample predictions of the parametric model providing further evidence in support 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

[16]We estimated this model using the traditional specification without lags and population density and obtain $LPWGE_{it} = -2.08 + 1.10 \cdot ln(GDP_{it}) - 0.02 \cdot (ln(GDP_{it}))^2 - 0.24 \cdot ln(Time)$. When we include population density, we obtain $LPWGE_{it} = -3.77 + 1.75 \cdot ln(GDP_{it}) - 0.07 \cdot (ln(GDP_{it}))^2 - 0.20 \cdot ln(Time) + 0.10 \cdot ln(PDENS_{it})$. The $R^2$ is 0.47 and 0.45 respectively.

[17]The 80% confidence interval is RMB 5,906 to RMB 44,250. The 90% confidence interval is from RMB 5,180 to RMB 93,370. We use a simple parametric residual based bootstrap to obtain these values empirically, since the distribution of a ratio of two normals is fat-tailed.

Table 1: Parameter Estimates

| Parameter | Lag Model Estimate | Robust Standard Error |
|---|---|---|
| $\text{Constant}_i$ | 0.815 | 0.863 |
| $\ln(\text{GDP}_{it})$ | 0.745 | 0.199** |
| $(\ln(\text{GDP}_{it}))^2$ | -0.040 | 0.012** |
| $\ln(\text{Comp}_{it_o})$ | 1.707 | 0.707** |
| $\text{Coastal}_{it}$ | -0.371 | 0.286 |
| $\ln(\text{Pdens}_{it})$ | 0.305 | 0.064** |
| ln(Time) | -0.061 | 0.019** |
| Beijing | 0.642 | 0.048** |
| Tianjin | 0.649 | 0.045** |
| Hebei | 0.669 | 0.052** |
| Shanxi | 0.562 | 0.055** |
| Inner Mongolia | 0.794 | 0.035** |
| Liaoning | 0.629 | 0.069** |
| Jilin | 0.620 | 0.044** |
| Heilongjiang | 0.601 | 0.046** |
| Shanghai | 0.642 | 0.045** |
| Jiangsu | 0.663 | 0.042** |
| Zhejiang | 0.785 | 0.047** |
| Anhui | 0.565 | 0.069** |
| Fujian | 0.757 | 0.040** |
| Jiangxi | 0.520 | 0.060** |
| Shandong | 0.662 | 0.046** |
| Henan | 0.496 | 0.065** |
| Hubei | 0.555 | 0.057** |
| Hunan | 0.508 | 0.061** |
| Guangdong | 0.778 | 0.044** |
| Guangxi | 0.760 | 0.039** |
| Hainan | 0.819 | 0.059** |
| Sichuan | 0.544 | 0.056** |
| Guizhou | 0.605 | 0.052** |
| Yunnan | 0.671 | 0.064** |
| Tibet | 0.528 | 0.152** |
| Shaanxi | 0.558 | 0.052** |
| Gansu | 0.617 | 0.050** |
| Qinghai | 0.756 | 0.041** |
| Ningxia | 0.634 | 0.046** |
| Xinjiang | 0.797 | 0.041** |
| $R^2$ | 0.9854 | |
| Observations | 468 | |

** Significant at 1% level.

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 1.7% 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. This finding is consistent with work by Murthy *et al.* (1997) on rural-urban differences in India based on an input-output modelling perspective. Migration and aggregate population growth will separately affect per capita and aggregate emissions. Murthy *et al.* (1997) suggest that the population density effect works through a uniform increase in energy demand across income groups as individuals relocate from agricultural areas to the cities. This is thought to be due to changes in lifestyle, such as the increased use of electricity, public transportation and hot water. Therefore, increases in population of a province, whose land area is fixed, will have scale effects on per capita emissions of its inhabitants. 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 FDI in 1999. Influx of FDI 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.

## 4.5 Exploring the Lag Parameters

In another specification we allowed the AR(1) parameters to change in the middle of the sample (1993) and only three provinces show a statistically significant change using standard testing in levels. The lag parameter estimates on Beijing and Shanghai decrease 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. When adjusting for the fact that multiple comparisons are being made by using a sequential test proposed by Holm (1979), we fail to reject the null of parameter stability. We also allowed for separate break dates for coastal and non-coastal provinces. Again. there is no significant evidence of separate structural breaks for the two groups. This result contradicts a popular argument hypothesizing a 'new China' in the sense of a dramatic structural changes on every level of society resulting in improved environmental quality across all provinces. The distribution of the lag parameters, with the exception of Tibet, which is fundamentally different from the rest of China, suggests a group of provinces which can be classified as the 'new China', namely the coastal provinces. The 'new China' does not have a magical split, nor is there any evidence that the 'old China' has started moving towards it. The structural break tests further suggest that the lag parameter estimates are somewhat stable and warrant further investigation as to what drives differences in the parameters.

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 lagged emissions.[18] Figure 6 plots the parameter estimates for the provinces from the lag-model in deviation form.[19] Generally speaking, these estimates suggest that a smaller relative parameter estimate on a province's lagged per capita waste gas emissions indicates faster speed of adjustment. Correspondingly, a larger (closer to one) parameter estimate would indicate a relatively slower rate of adjustment.

Upon casual inspection, 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 a stylized province assuming a GDP growth rate of 5.02% per period, identical starting conditions (per capita income, industry composition, population density) and allow the lag parameter to vary from the highest to the lowest estimated value.

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*. This argument carries even more weight when considering the fact that the area under the curves in Figure 7 represent the sum of an individual's emissions over the forecasting horizon. The sample high lag parameter implies drastically larger lifetime emissions, compared to even the median lag parameter. For comparison purposes, Figure 7 shows the predicted per capita emissions of the estimated contemporaneous EKC fixed effects model using a solid line. The EKC model implies a drastically different trajectory compared to our preferred model since it restricts each province to follow an identical trajectory offset by differences in the intercepts.

Table 2 shows results from regressing the lag parameters on a set of province specific characteristics and may provide some insight as to what factors drive these lag parameters. The regressions explore variation in three sets of lag parameters that are obtained from estimating equation (5) with and without $Coastal_i$ and $Comp_{it_o}$ as indicated in the first two rows of the Table.

Models (1) and (2) address the issue of whether province differences in coal prices drive the magnitude of lag parameters. Spot market coal price data are available only sporadically for some provincial capitals from *China Price*, a Chinese Trade publication specializing in monitoring resource and other input prices. The Spearman correlation coefficient between prices available for 1994 and 1997 is 0.93. This suggests that relative coal prices across provinces are fairly stable. Inspecting the available data, the differences in coal prices are positively correlated with the distance of the province to the large coal deposits. This suggests that transportation costs may be responsible for a large share in the across province variation in coal prices. Model (1) shows that price is significant in a regression without the inclusion of industry composition in the original estimation. Model (2) shows that the inclusion of industry composition in the original estimation makes the parameter estimate on coal price not significantly different from zero.[20] This suggests that relative coal prices may have influenced initial industry composition, but are not needed once it is controlled for in the forecasting equation.

The question of interest to policymakers is what factors, which can be changed through policy, deter-

[18]All of our provincial lagged emission coefficients except one (Qinghai) are smaller, that is more responsive, than the 0.84 estimate that Agras and Chapman (1999) obtain from their sample of countries. When we pool the lagged dependent variable, we obtain a lag parameter estimate of 0.66.

[19]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.

[20]In addition to an indirect effect on $CO_2$ emissions via industry composition there may also be a direct price effect. It is possible to take the residuals from the waste gas forecasting equation for the years in which coal price data are available and regress the residuals on these prices. We found a significant effect, but it is small relative to the price effect via initial industry composition. Still it is likely to be desirable to explore the direct impacts of a coal tax.

Figure 6: Lag Parameter Estimates (Deviation from Mean)

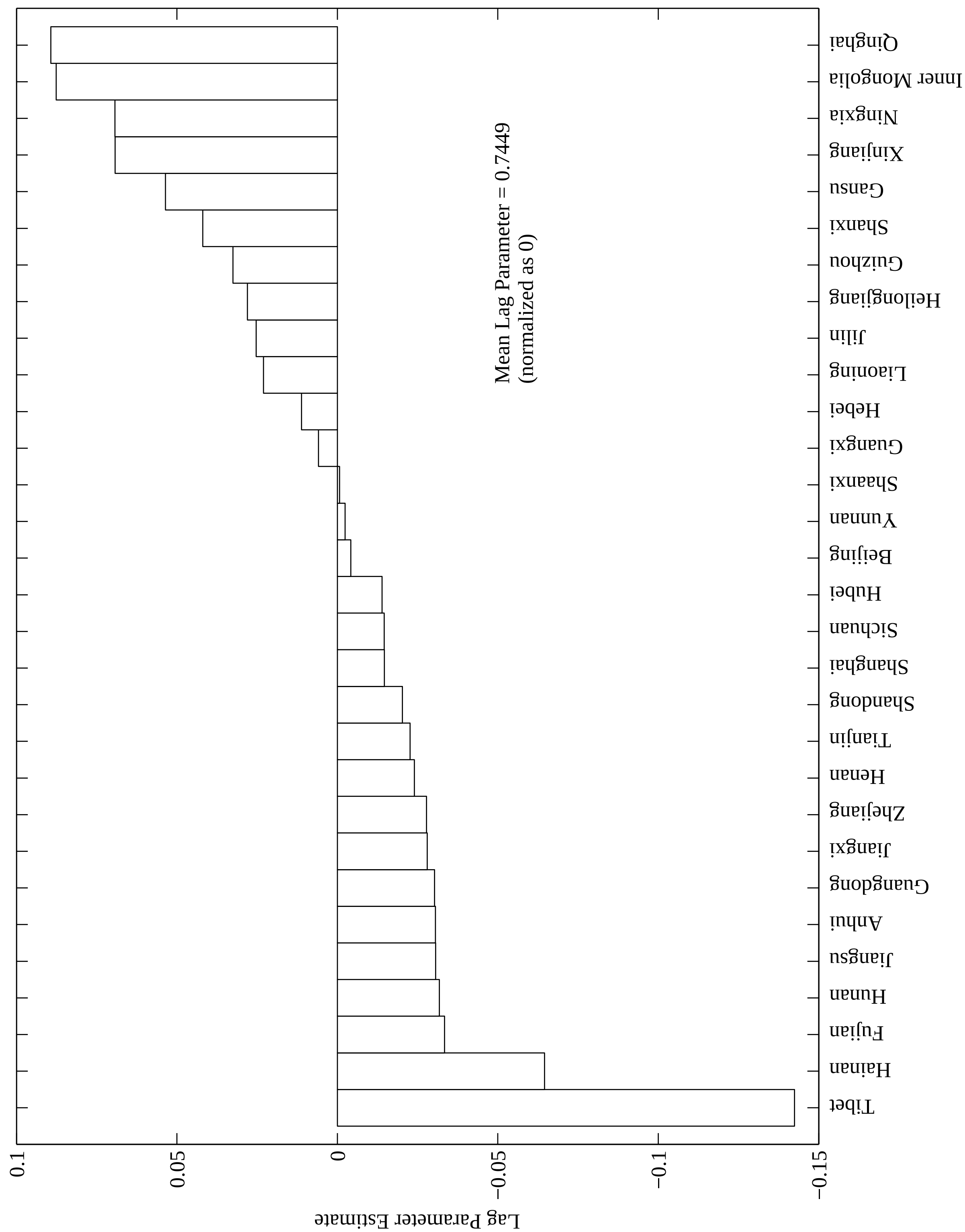


Figure 7: Traditional EKC vs. Lag Specification

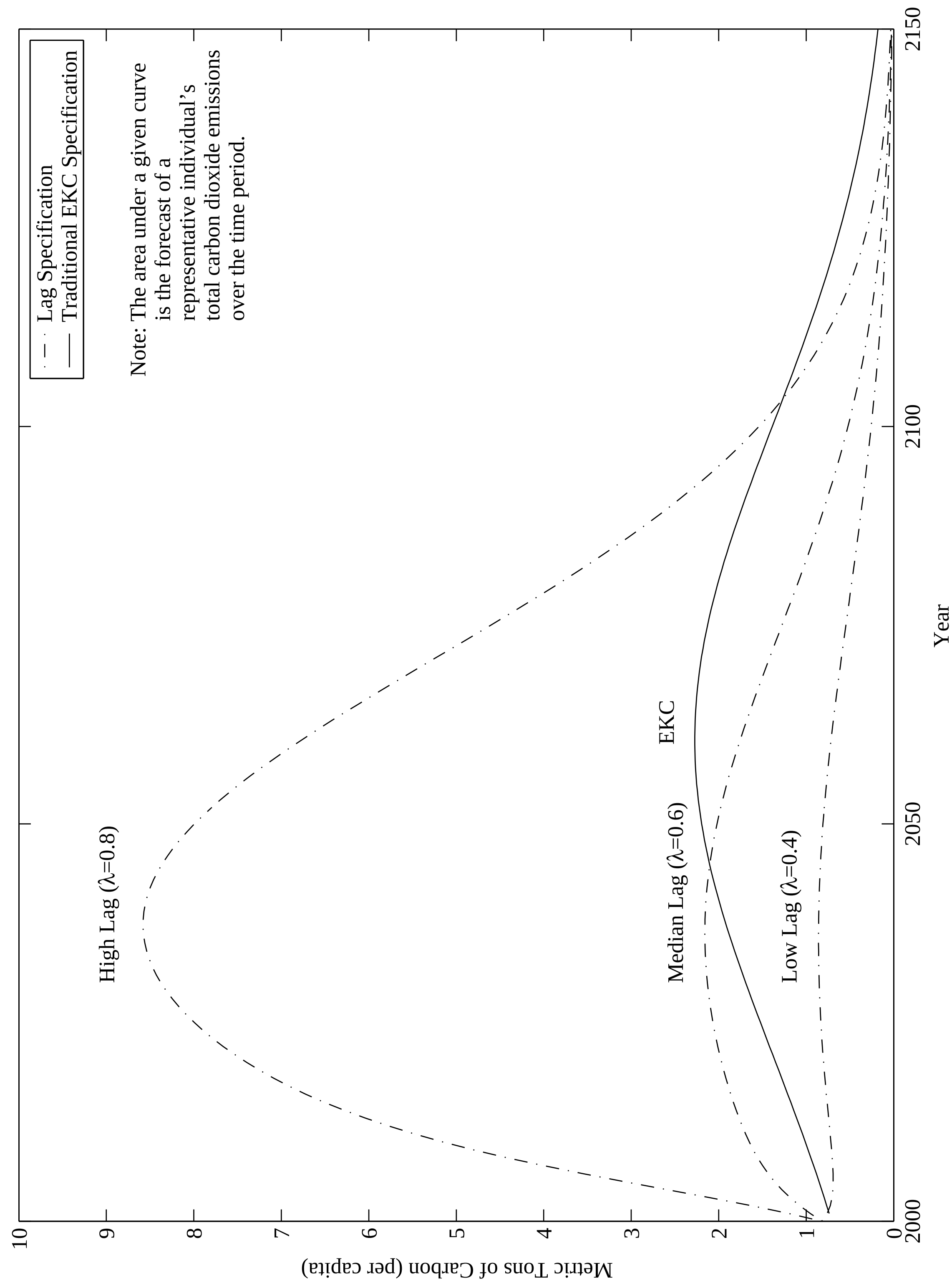


Table 2: Lag Parameter Regressions

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) |
|---|---|---|---|---|---|---|
| $Coastal_i$ | No | Yes | Yes | Yes | Yes | Yes |
| $Comp_{it_o}$ | No | No | Yes | No | Yes | Yes |
| Coal Price | 0.0002 | 0.0003 | | | | |
| | (3.95)** | (0.87) | | | | |
| $\%\Delta_{2000,1985}FDI$ | | | -0.002 | -0.002 | -0.002 | -0.002 |
| | | | (2.14)* | (2.39)* | (2.22)* | (2.47)* |
| Ambient $SO_{2(1995)}$ | | | | | -0.0002 | |
| | | | | | (1.00) | |
| $\%\Delta_{2000,1990}Electricity$ | | | | 0.09 | | |
| | | | | (1.69) | | |
| $\%\Delta_{2000,1985}Pdens$ | | | 0.386 | | | |
| | | | (1.94) | | | |
| Constant | 0.813 | 0.597 | 0.631 | 0.641 | 0.704 | 0.69 |
| | (46.59)** | (11.96)** | (16.57)** | (16.48)** | (25.66)** | (28.86)** |
| Observations | 26 | 26 | 30 | 30 | 30 | 30 |
| $R^2$ | 0.39 | 0.03 | 0.28 | 0.25 | 0.21 | 0.18 |

** Significant at 1% level * Significant at 5% level.

mine the magnitude of the lags. There are two different possible scenarios. The first scenario suggests that as population density increases in some provinces, the increased demand for electricity and goods will spark new construction in generating and production capacity. This would in turn decrease average capital vintage. If the installed new capacity is more energy efficient and therefore cleaner, one would expect a relatively large decrease in the lag parameter.

Model (3) suggests, however that increased population density does not have a negative effect on the lags. The suggested effect is positive and approaching statistical significance at the 5% level. This would suggest that provinces with proportionately larger increases in population density have higher lags, providing some evidence working against a decreasing capital vintage story. Further, model (4) suggests that increases in provincial electricity production have a significant and positive effect on the lags. This again suggests that the added new capacity does not decrease the lags through the decreasing capital vintage.

Models (3) - (6) suggest that FDI has a significant and negative impact on the lag parameters. Different jurisdictions compete over FDI since it provides not only a source of new financial capital, but spillover effects such as new jobs and access to better technology. There two general ways of replacing or adding to the existing power supply. The traditional way is to put in place status quo Chinese technology, which largely is a derivative of older Russian technology. These plants have slightly increased thermal efficiency compared to the oldest plants currently in operation. The second option is to put in place state of the art Japanese technology power generating capacity. Since FDI is explicitly tied to access to advanced technology this source of investment capital could be the source of a second order effect decreasing the magnitude of the lags. Overall our results suggest that the slow and automatic replacement of China's capital stock in response to meeting a growing energy demand will not decrease the lag parameters and consequently per capita emissions trajectories. Our results suggest that there is a large role for province level pollution control policy coupled with an influx of FDI and state of the art technology. As labor costs in the coastal provinces rise, the uneven distribution of FDI across provinces is expected to shift towards the interior in the future (Wei, Lio, Parker and Vaidya, 1999). Further, if provinces do compete over FDI by providing tax breaks (Barros and Cabral, 2000), lower performance requirements for multinationals

(Davies and Ellis, 2001) or by providing better infrastructure such as roads and reliable power generation (Cheng and Kwan, 2000) these provide potentially meaningful policy tools for increasing the inflow of foreign capital and technology.

There are two caveats which may change the magnitude of the lag parameters over time; both are driven by the nature of fundamental structural change currently taking place in China.

The first stems from China's changing transportation sector, namely a dramatically non-linear increase in the number of cars, which may cause some bias in our forecasts. Our sample period captures the large increase in the number of cars over the last five years. If the rates of growth in the number of automobiles per province change at different rates during the forecasting horizon, the lag parameter estimates, while valid in sample, may not provide correct out of sample predictions.

Another source of potential bias of our long term forecasts stems from the fact that China's power generators have focused on increasing thermal efficiency. This has reduced both $CO_2$ and other air pollutants. Model (5) includes ambient $SO_2$ concentrations in the provincial capital for 1995. This variable has the expected sign, in the sense that higher ambient $SO_2$ levels are associated with lower lagged emission parameters although the effect is not large and is insignificant. It is possible that the link between $CO_2$ and other air pollutants could be broken in the future if China moves away from improvements in thermal efficiency as the primary means of reducing all air pollutants and moves towards investments in scrubber technology, which would reduce only local and regional air pollutants. To date, investments in scrubbing technology have been small in magnitude and a shift in pollution control strategy towards scrubbing by most estimates is not expected to happen in the moderate term future. This is not surprising, since the cost of a scrubber for a small capacity coal fired power plant starts at about US$ 150 million (2002 US dollars). The larger power plants require an investment of about US$ 500 million for a scrubber. Since these scrubbers cannot remove $CO_2$ from the emitted waste gas stream, the amount of $CO_2$ emitted per ton of coal is not changed by installing a traditional scrubber. The implication of installing scrubbers on a large scale would likely be an increase in the lagged emission coefficients because local and regional air pollution could still be improved through the use scrubbers.

# 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 4.4, 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 and 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 EKC and the lab model only require assumptions about future levels of per capita GDP and population since the land area of provinces is fixed. [21] 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. The three alternative sets of assumptions are a slow growth case, a medium growth case, and a high growth case. We consider a special case of the third scenario, which assumes that the EKC type pollution income relationship does not hold beyond the turning point. In this model we let provincial per capita GDP grow up to the estimated turning point and hold it fixed at that level for the remaining forecasting time periods, similar to Panayotou *et al.* (2002).

To make use of our model for forecasting purposes we require province level population projections. Official estimates of population are only available at a national level. A recent demographic study by Chesnais and Minglei (1998) provides province level population forecasts through the year 2050. Four scenarios are considered that 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 and 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 ($\xi_t$) and population growth rate ($\phi_t$) are jointly distributed as $f(\xi_t, \phi_t) \sim N_2[\mu_\xi, \mu_\phi, \sigma^2_\xi, \sigma^2_\phi, \rho]$ 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 $\mu_\phi$, $\sigma_\phi$ and $\rho$ respectively. Three different pairs of values for $\mu_\xi$ and $\sigma_\xi$ 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 of provincial aggregate GDP. 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 and Minglei (1998) are used. We calculate $\phi_t \forall$ t $\epsilon$ [2001,2050] from these forecasts and use the conditional marginal distribution $g(\xi_t|\phi_t) = N[\alpha + \beta\phi_t, \sigma^2_\xi(1-\rho)^2]$, where $\alpha = \mu_\xi - \beta\mu_\phi$ and $\beta = \frac{\rho\sigma_\xi\sigma_\phi}{\sigma^2_\phi}$ to obtain realizations of

[21] This is also true for the most simple IPAT specifications, yet a more involved modeling of technology under IPAT usually requires data on energy intensity and carbon intensity of GDP.

Table 3: 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% |

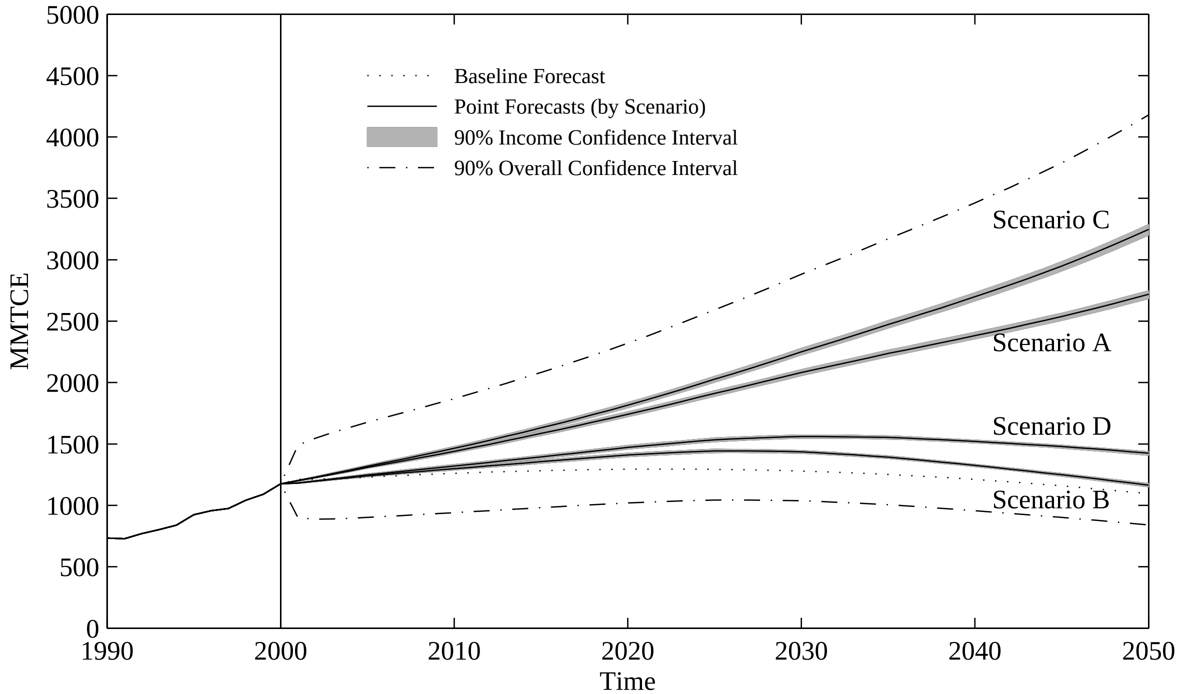
the aggregate GDP growth rate. Table 3 summarizes the scenarios in consideration. Since we only consider three scenarios of GDP growth, a total of twelve different population/GDP scenarios for forecasting purposes are considered.

## 5.2 Sensitivity To Alternative Scenarios

In this section we look at how the different scenarios defined in Table 3 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 solid line indicates the median point forecast for each population growth scenario, while the shaded area around the point forecast indicates the 90% confidence interval with respect to the uncertainty about realizations of the GDP growth rate. The thick dashed lines indicate the upper bound of the 95% overall confidence interval for scenario C, and the lower bound of the overall confidence interval for Scenario B.[22] The baseline scenario is indicated by the dotted line. It is noteworthy how similar the forecasts for the same population scenario and differing GDP growth scenario are. Our forecasts, however, suggest that the distribution of population across China's provinces may have a drastic impact on the PRC's aggregate $CO_2$ emissions.

[22] We have constructed confidence intervals for each scenario, yet plotting these makes the picture uninformative. We therefore report only the upper bound of the highest forecast and the lower bound of the lower forecast.

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



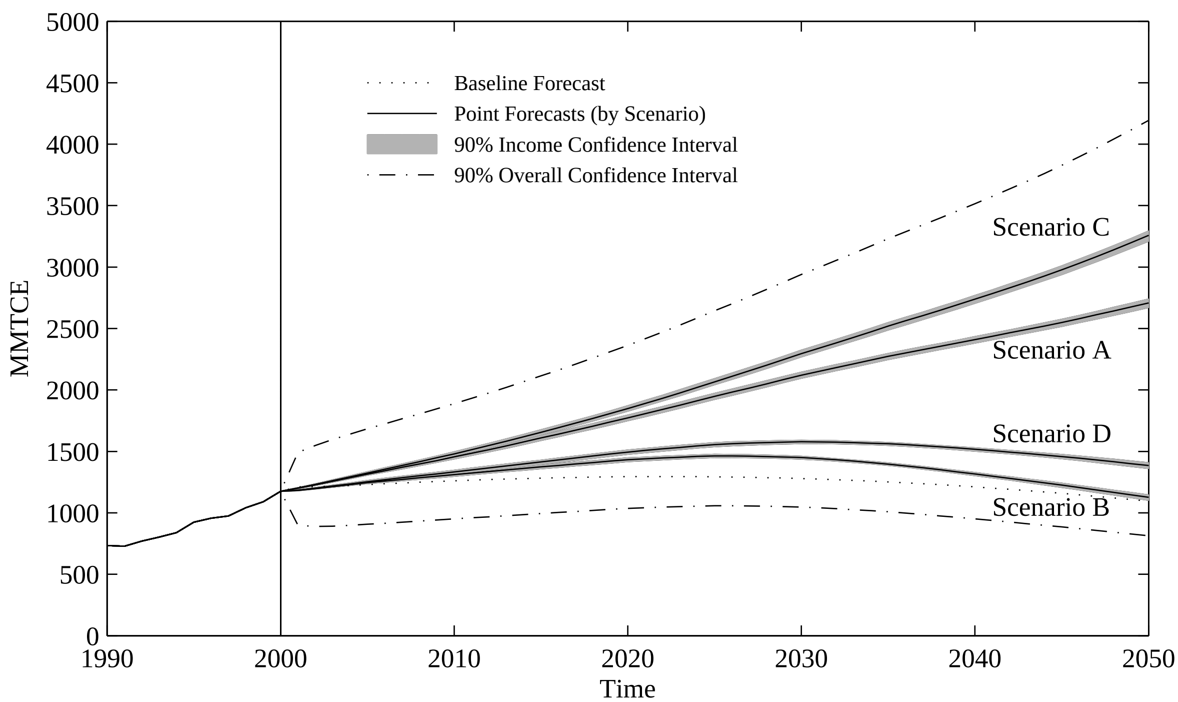
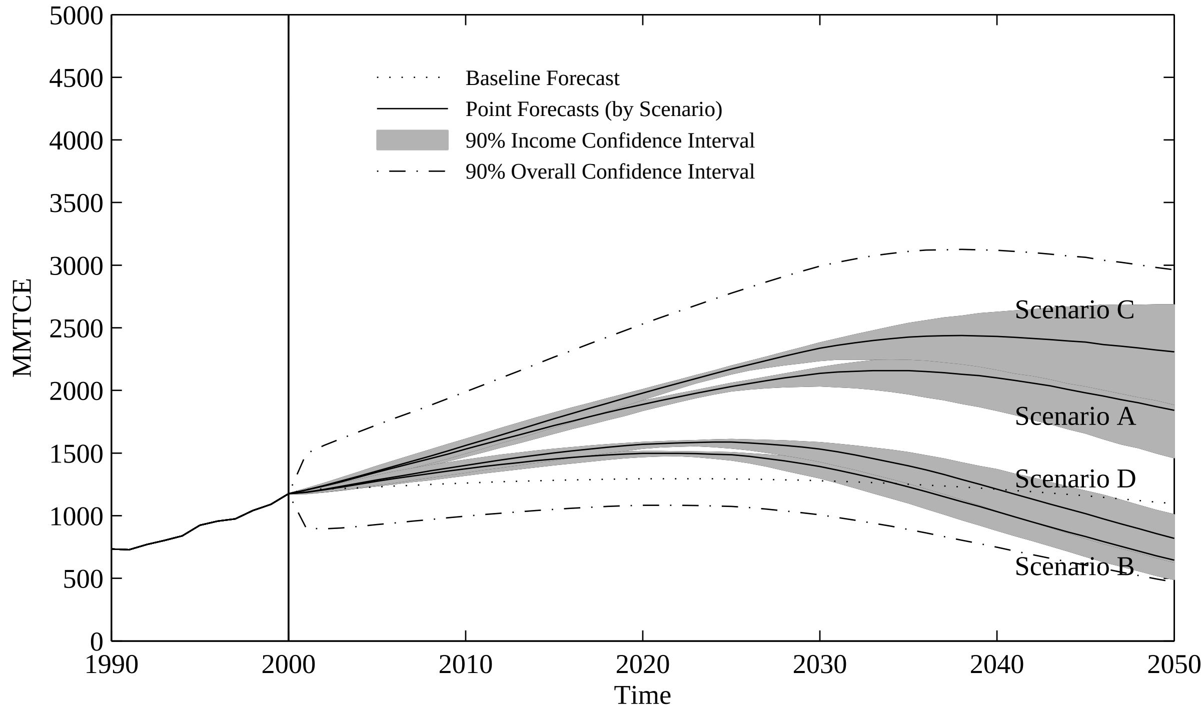
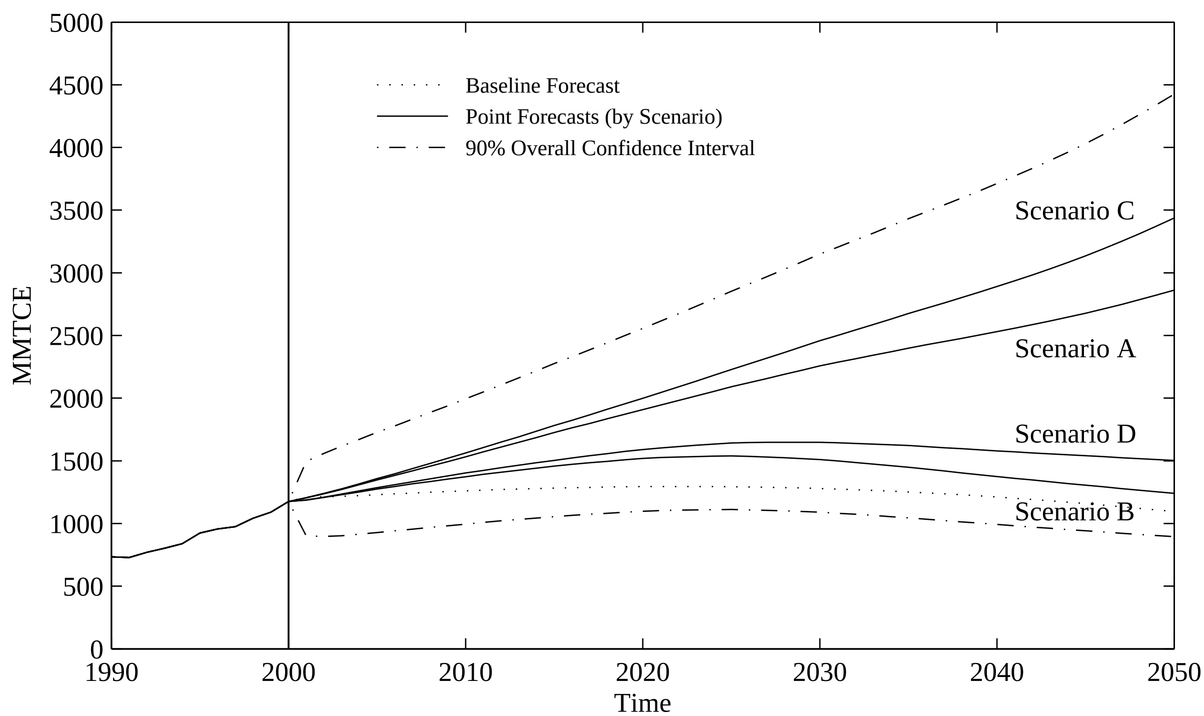



Figure 9: Aggregate Forecasts of China's $CO_2$ Emissions - High GDP Growth



The top panel of Figure 9 depicts forecasts allowing for an EKC type relationship. 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 pollution income relationship. In this high growth scenario, the income effect offsets the population growth effect. The bottom panel of Figure 9 shows our forecasts using the high GDP growth scenario, not allowing GDP to rise above the turning point level. The forecasts are only mildly higher than the ones obtained using the IPCC scenarios.[23] The aggregate emission forecasts by population scenario for China's $CO_2$ emissions are almost identical for all panels until the year 2030. The last panel shows a quite drastic departure of the predictions for the unrestricted EKC model.

IPAT models based on national aggregates are likely to attribute the population density/urbanization effects to income. Even if such a model forecasts well, it is likely to lead to an incorrect understanding of what is driving emission changes hence faulty policy prescriptions.

The obvious alternative to policies designed to reduce the lagged provincial emission parameters are population policies. Such policies could influence aggregate population (through influencing birth rates) or the location of population. China has implemented such policies in the past with varying degrees of success. The issue raised in this paper with respect to $CO_2$ is the tradeoff between technology policies and population policies.

## 5.3 Out of Sample Performance

Since the chosen model selection criterion selects models based on in-sample performance, we compare the out-of sample performance of model 5 to that of two basic EKC and IPAT specifications. Figure Table 4 lists the one step ahead mean square forecasting error (MSFE) using all available information in the year 1999 and forecasting one step ahead. The last row in the table reports the ratio of a models MSFE to that of the lag specification. Since we are constructing long range forecasts, it would be helpful to compare i.e. 10 step ahead forecasts across models, but since we only have 15 years of data for each province, it limits the range of possible comparisons.

Table 4: Out of Sample Forecast Performance of Selected Models

| | IPAT ln(time) | IPAT Linear time | EKC | EKC with Pdens | Lag Specification |
|---|---|---|---|---|---|
| MSFE | 760,448 | 4,237,674 | 691,706 | 251,032 | 250,796 |
| MSFE/ MSFE(Lag Spec) | 3.0321 | 16.8969 | 2.7580 | 1.0009 | 1.0000 |

The first two IPAT models restrict emissions to be linear in income and model technology as a log and linear time trend respectively. The third model estimates a simple EKC model with province fixed effects and a log time trend. All three of these models are clearly outperformed by the lag specification. It is noteworthy, however, that including population density in the basic EKC framework improves out of sample performance drastically. We take this as further evidence in support of the argument that including population scale effects is crucial when constructing emissions forecasts. Even though the chosen model does not outperform the EKC model with population density in a statistically significant way, we argue

[23] We do not show the income confidence interval for this scenario, since we assume that income is equal to the threshold level if the actual realization is greater than it. This provides income confidence intervals that are too small.

that the dynamic nature of the proposed model will most likely provide better long term forecasts than the static EKC model.

## 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 5 summarizes those comparisons.

Table 5: Range Of $CO_2$ Emission Point Forecasts 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.* (2002)**** | **Lag-Specification***** |
|---|---|---|---|---|---|---|
| 2020 | 1.73 - 2.50 | — | — | 2.13 | 2.34 | 1.40 - 1.93 |
| 2022 | — | — | — | 2.30 | | 1.41 - 2.03 |
| 2025 | — | 1.16 - 1.80 | — | — | | 1.43 - 2.17 |
| 2050 | 2.32 3.90 | 1.54 - 3.14 | 2.84 - 4.66 | — | 1.71 | 0.50 - 3.44 |

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". **Projected flow of $CO_2$ emissions from fossil fuels 1996-2050 ***Due to its unrealistic nature, the baseline model was not included in our prediction band.

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 5 shows the range of values of the projected $CO_2$ emissions for the year 2020 under the A1B, A2, B1 and B2 marker scenarios of IPCC, and our projections.[24] 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 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). It is important to note, however, that our forecasts start to diverge drastically from the IPCC forecasts if we adopt higher GDP growth rates, such s the observed in-sample 8.9% p.a. growth rate. Due to the nonlinearity in our model, growing income has a smaller marginal effect as provinces become wealthier, suggesting even lower emissions if one believes in drastic income growth.

Yang and Schneider (1998) provide a set of estimates for the region "China and centrally planned Asia" by using a different analytical IPAT type framework.[25] 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 wider compared to the point forecasts provided by Yang and Schneider (1998). This is mostly due to the income

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

[25] In the framework used by Yang and 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.

effect in the fourth, unrestricted EKC model. Our forecasts are systematically lower when compared to Garbaccio *et al.* (1999a). 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 and 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 lower levels. Overall, our forecasts provide somewhat lower forecasts, than all of these models, when adopting the same assumptions as the individual papers.

# 6 Conclusion

Conventional wisdom holds that China will soon be the largest emitter of $CO_2$ and that increases in China's emissions will largely be driven by increases in China's per capita income. This poses a clear dilemma. No greenhouse gas agreement can effectively work without China's active participation but China is unlikely to agree to cutbacks in projected $CO_2$ if it comes at the expense of substantial reductions in the per capita GDP growth rate.

Our work using provincial level Chinese data suggests that the conventional wisdom as reflected in the IPAT type models used in the quasi-official IPCC reports is wrong. While it is true that increases in per capita income have been the major driving force behind increases in Chinese $CO_2$ emissions in the past, this is unlikely to be true in the future, due to a strong environmental Kuznets curve effect. In the past, most Chinese provinces were on the steeply upward sloping part of that inverted U, whereby per capita emissions first increase rapidly with income, then are flat and eventually decline. Now many provinces appear to be near the flat part of the inverted U, so that increases in income will have little direct impact on per capita $CO_2$ emissions.

Our work instead points to population factors as being the dominant force driving increases in Chinese $CO_2$ emissions in the future. The range of reasonable uncertainty over changes in the size of the overall population as reflected in mortality rates, and more importantly, fertility rates, exceeds current $CO_2$ emissions for the European Union. Rural to urban migration is also an important component to understanding the path of Chinese $CO_2$ emissions.

The other major contribution of our work is to start separating a technology effect from the simple income driven environmental Kuznets curve story. Even after accounting for an environmental Kuznets curve relationship operating across provinces there remains a large province specific technology effect. It is easy to show that the "average" environmental Kuznets curve story fails to account for dynamics and that small differences in the way that provinces track their past emissions can result in very different cumulative emissions paths. Our initial efforts here suggest that the technology effect is to some degree explainable and we see a number of useful directions that such efforts might take.

Clearly, our results point to more optimistic possibilities for China and climate change agreement. Since our estimates are lower than those of the IPCC for the same assumptions, China might be well advised to accept those estimates as their baseline from which to negotiate. A key question for Chinese participation in any agreement to reduce its $CO_2$ emissions is the tradeoff between national and province level environmental and industrial policy. There are national policies that if implemented everywhere could substantially reduce China's $CO_2$ emissions (Garbaccio, Ho and Jorgenson, 1999a). Two issues arise in thinking about such regulation. The first is their efficiency relative to spatially decentralized implementation and the second is their feasibility given the devolution of much of the environmental regulatory apparatus to the provincial level (Wang and Wheeler, 1999). The issue of national versus provincial coordination becomes a particularly interesting one if, as our results suggest, the problems of lagging technological change are concentrated in a small number of provinces that are large coal producers.

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