Forecasting The Path of China's CO_2 Emissions Using Province Level Information

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Abstract

Our results suggest that the anticipated path of China's Carbon Dioxide (CO_2) emissions has dramatically increased over the last five years. The magnitude of the projected increase in Chinese emissions out to 2010 is several times larger than reductions embodied in the Kyoto Protocol. Our estimates are based on a unique provincial level panel data set from the Chinese Environmental Protection Agency. This dataset contains considerably more information relevant to the path of likely Chinese greenhouse gas emissions than national level time series models currently in use. Model selection criteria clearly reject the popular static environmental Kuznets curve specification in favor of a class of dynamic models with spatial dependence.

Keywords: Forecasting, Climate Change, China, Model Selection

JEL Codes: Q43, C53

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1. Introduction

The People's Republic of China (PRC) has long been seen as the key future participant to an effective agreement limiting the adverse impacts of climate change. It is currently the number two emitter of carbon dioxide (CO_2) and is about to overtake the United States, who has held this position since 1890, as the leading emitter. Further, the United States has long preconditioned its adherence to any international agreement such as the Kyoto Protocol on China's formal concurrence that it would also undertake substantial CO_2 reductions. Efforts to reach such an agreement failed in the late 1990's during the Clinton administration and the Bush administration decided not to pursue policies that would allow it to sign the treaty and have it ratified by the U.S. Senate. This paper presents econometric forecasts that strongly suggest that the short to medium term path of Chinese CO_2 emissions has increased by a factor of two or more since that time. Our best forecast has China's CO_2 emissions surpassing the United States before the year 2010 rather than 2020 as previously anticipated (Intergovernmental Panel on Climate Change, 2000; Siddiqi, Streets, Wu and He, 1994; Panayotou, Sachs and Zwane, 2002). Our focus in this paper is on exploring alternative econometric specifications for forecasting China's CO_2 emissions using a rich new panel dataset from 1985 to 2004 at the provincial level. The prediction of a dramatic recent increase in the predicted path of China's CO_2 emissions over the short to medium term horizon is shown to be robust to a wide range of alternative specifications. We show, however, that it is possible to strongly reject both the standard engineering specifications that appear in the Intergovernmental Panel on Climate Change (2000), and the recent Stern Report (2006) as well as the popular environmental Kuznets curve specification. All of the "best" models are dynamic in nature employing some type of lag structure, which is consistent with the nature of an installed durable capital stock.

This paper makes four main contributions to the technical literature on forecasting CO_2 emissions. This is the first paper exploring spatial and time series variation in order to provide out of sample forecasts of China's aggregate emissions. The literature on forecasting Chinese CO_2 emissions exploits time series variation across countries (*e.g.* Yang and Schneider, 1998; Intergovernmental Panel on Climate Change, 2000), cross sectional variation on industry sectors (Energy Research Institute, 2004; Sinton and Levine, 1994; Zhang, 1998; Garbaccio, Ho and Jorgenson, 1999a; Garbaccio, Ho and Jorgenson, 1999b) or adopts a case study approach of the factors influencing the performance of specific plants (*e.g.* Zhang, May and Heller, 2001). Second, we adopt an explicit forecasting approach to model selection. Instead of choosing a specific reduced form model a priori (e.g. Schmalensee, Stoker and Judson, 1998; Holtz-Eakin and Selden, 1995), we conduct a specification search across a large class of static and dynamic reduced form models. The "best" model is chosen based on out of sample forecast performance and a set of information theoretic model selection criteria. Third, we allow for spatial dependence in emissions across provinces, which has been shown to improve forecasts of aggregate variables if there is sufficient heterogeneity at lower levels of aggregation (Marcellino, Stock and Watson, 2003; Auffhammer and Steinhauser, 2007; Carson, Cenesizoglu and Parker, 2005), which we will show is the case here. Finally, our modeling approach uses an annually updated and publicly available source of data, which allows for frequently updateable forecasts and model improvement. This feature is a main advantage over forecasts using infrequently updated sources of data (Department of Energy, 2006; Intergovernmental Panel on Climate Change, 2001).

Business as usual (BAU) forecasts of Chinese greenhouse gas emissions are of central importance to discussions of climate change for three main reasons. First, the predicted physical impacts from climate change are calculated using global circulation models, which take emissions as inputs. Since China is responsible for a large (15%) and growing share of global emissions, using optimal forecasts of its emissions is an important factor in determining future impacts and addressing critical issues involving the role of prevention versus mitigation. Second, China and many other developing countries are adamant about negotiating reductions relative to the level of emissions that would be projected to occur normally as they industrialize - a baseline emissions level in the future instead of in the past as under Kyoto.[1] Constructing optimal predictions of the BAU emissions path decreases the probability of overly stringent reductions or the creation of "hot-air" under such a potential agreement. The costs of additional cutbacks for an agreement with a baseline in the past (such as Kyoto) depend crucially on what the BAU emissions at the strike date are (e.g. the first commitment period). Underprediction of emissions may result in a country not ascending to or withdrawing from an agreement, since it finds itself far above the agreed antici-

[1]China has justified its policy of "no targets and time-tables" along the same lines of reasoning as Indian Prime Minister Manmohan Singh (2005) citing *a common but differentiated responsibility.* They argue that the major responsibility of curbing emissions rests with the developed countries, which have accumulated emissions over a long period of time.

pated emissions path.[2] The US has argued that it would not join an agreement, which would put it at an economic disadvantage. The signing of a possible successor agreement, entailing cutbacks by the US and China would depend on the expected costs of intentionally reducing emissions relative to the BAU emissions path. Chinese and US BAU emissions therefore will play a central role in each country's decision to participate in a bilateral or multilateral climate agreement.

The remainder of the paper is structured as follows. The next section provides an overview of the empirical modeling literature and motivates our extensions. Section 3 discusses the data. Section 4 provides the empirical model and estimation results. Section 5 contains the forecasts and compares them to historical and current forecasts shown in the literature. Section 6 concludes.

2. Background

The literature on modeling and forecasting CO_2 emissions can be split into three strands. The starting point for the first two is the classic IPAT identity (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.[3] Conceptually, this identity has given rise to a large literature in science and engineering on the pollution generation problem at the country and regional level. The most relevant of these studies are those underlying most of the Intergovernmental Panel on Climate Change (2000) special report on emission scenarios (SRES), which are the quasi-official forecasts. 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. Yang and Schneider (1998) provide a decomposition analysis along these dimensions across countries. Zhang (2000) has decomposed historical aggregate CO_2 emissions along the IPAT dimensions. He finds that increasing income has been the main factor increasing emissions, while the estimated impact of changes in technology lies between the income and population effects in absolute magnitude.

[2] In 2002 US CO_2 emissions were 13% above 1990 levels.

[3] In the literature on predicting GHG emissions the IPAT identity is referred to as the Kaya identity.

The second branch of the literature using the IPAT identity as an organizing framework uses econometric tools to estimate reduced form models. 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 (Grossman and Krueger, 1995; Schmalensee et al., 1998). This possibility of an inverted U-shaped relationship with negative income elasticity at high levels of income, contradicts the monotonicity in income assumption underlying the IPAT model. The drawback of this model as Copeland and Taylor (2004) and Arrow *et al.* (1995) point out, is that the reduced form specification does not separate the income effect from other factors driving emissions. The empirical evidence on whether a turning point for the odorless and invisible gas CO_2 exists is mixed. For an excellent review of this sizeable literature, consult Lieb (2004).

The third relevant branch of the literature explores variation in emissions at the sector level, making use of nationally aggregated input output matrices. These input output tables are used as a basis for constructing computable general equilibrium (CGE) models of the national economy, which are then used for policy simulation exercises. There is a large literature using CGE models to model carbon emissions for developed and developing countries (Böhringer, Conrad and Löschel, 2003). This approach to modeling emissions is very useful from a policy perspective, since one can easily simulate the impacts of different policy instruments and/or shocks on the economy and resulting changes in emissions. These models, while often used to draw out of sample predictions, are not forecasting models, since they are not calibrated according to their out of sample predictive ability. Further, these models require a tremendous amount of data, which in many countries are provided very infrequently. The CGE models for China are largely based on the 1997 input output tables, although the 2002 input output tables were recently released. The advantages of these models overall are that they provide a tremendous degree of sectoral detail at the cost of having to make a large number of parametric and functional form assumptions to construct the model. Due to infrequent data updates, one further has to make assumptions as to how the composition of the economy is changing over time. The classic references for CGE modeling in the Chinese context are Garbaccio et al. (1999a), Garbaccio et al. (1999b) and Ho, Jorgenson and Perkins (1998).

In this paper we will draw on aspects from these three strands of the literature to construct a reduced form forecasting model of China's aggregate CO_2 emissions for the next decade. We will conduct a search over a large space of models with the following features:

First, we will allow for - but not require - a non-linear emission income relationship with the possibility of income having a non-monotonic effect on CO_2 emissions. By using data for a single country which are collected using consistent definitions and procedures, we avoid the argument that the potential finding of an EKC may be due to a cross country correlation between data quality and income. Income and emissions data for China display 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 (Carson, Jeon and McCubbin, 1997). We will extend the restrictive second order polynomial specification first proposed by Grossman and Krueger (1995) by allowing for a flexible functional form of the pollution income relationship using the semi-parametric Generalized Additive Model (GAM) framework (Hastie and Tibshirani, 1990).

Second, we will test the frequently made assumption of unitary elasticity of emissions with respect to population. We allow for the possibility of both overall population scale effects and population density scale effects, which are measures showing large temporal and spatial variability in China. If the population elasticity is greater than one, these population effects will have an amplified impact on aggregate emissions. From a forecasting perspective, this is crucial since examining differential population growth and migration scenarios is a feature of key interest to Chinese policy makers and cannot be easily addressed by models based on aggregate national data.

Third, technology in the IPAT models is generally included as an index or in more simple models as emission intensity in CO_2/\$. The EKC literature models technological progress in the form of a time trend or year fixed effects. Further, it hypothesizes a purely contemporaneous relationship between per capita income and emissions, implicitly assuming that one can adjust per capita emissions immediately.[4] We move away from the simple income-pollution EKC models by starting to model technology impacts in a more realistic manner. Emissions in the industrial and power generating sector largely depend on the quality and speed of replacement of the durable 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

[4] Agras and Chapman (1999) allow for a dynamic adjustment process for CO_2 using a sample of 34 countries from 1971-1989.The dynamic adjustment process is assumed to be the same for all countries.

require quality data on capital stock and other inputs to production across time and provinces, which are not available. We proxy for such a data generating process by using a dynamic model made popular in the energy demand literature (Houthakker and Taylor, 1970), which models partial adjustment of capital and allows for lagged emissions to influence current emissions. In the most general version of the model we allow the nature of this adjustment process to differ across provinces.

Finally we allow for spatial dependence in per capita emissions across provinces. Maddison (2006) shows that per capita emissions of criteria pollutants depend on emissions in neighboring countries. Auffhammer and Steinhauser (2007) show that allowing for dependence in aggregate CO_2 emissions across US states uniformly improves model forecast performance for all specifications considered. Without deciding on a specific structure a priori, we let the model selection criterion decide, which model fits the data best.

3. Data Set

We will estimate a set of models using a province-level panel data set for 30 Chinese provincial entities[5] during the period 1985-2004. Unless otherwise noted, the provincial level 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 (20 years), while for a few of the provinces there are only data available for 16, 17 or 18 years. The result is an unbalanced panel data set with 588 observations.

3.1 Waste Gas Emissions

In a perfect world, one would have access to province level emissions of CO_2 over time broken down by sector. These data do not exist for most developed countries, and even less so for any developing countries. The reason for this is that measuring emissions of CO_2 from a large number of widely dispersed mobile and stationary sources is prohibitively costly and ultimately inaccurate. Emissions are therefore calculated using fossil fuel consumption by countries or states. One then uses multipliers based on the carbon content of fuels to calculate carbon emissions. Marland,

[5]Beijing, Shanghai and Tianjin are provincial level municipalities; Guangxi, Inner Mongolia, Ningxia, Tibet and Xinjiang are autonomous regions. Chonqing was elevated to the level of a provincial-level municipality in 1997, but we still count it as part of Sichuan. We refer to provinces and the entities mentioned in this footnote as provinces.

Boden and Andres (2005) are the main source of national level CO_2 emissions up until the year 2003. Comparable data at the province level are not available. However, the state environmental protection administration (SEPA) reports emissions of a composite air pollutant called waste gas emissions (WGE), which are calculated in a very similar way. As discussed below, we will use this indicator to proxy for CO_2 emissions at the province level.

SEPA uses an estimated engineering relationship, which allows them to convert fuel usage into waste gas emissions. Since we do not know the exact engineering relationship used by SEPA we convert WGE into CO_2 emissions by aggregating waste gas emissions across provinces by year and using this variable to predict aggregate CO_2 emissions. The well known restructuring of the China's coal sector in the late 1990s resulted in the closure of thousands of small mines reducing the share of worst quality coal. This and the concurrent shutdown of thousands of inefficient state and privately owned enterprizes drastically improved the efficiency of China's energy producing and consuming sector (Sinton and Fridley, 2000). In order to obtain a conversion factor for WGE to CO_2, which allows for this major structural change in the late 1990s, we estimate the following equation:

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

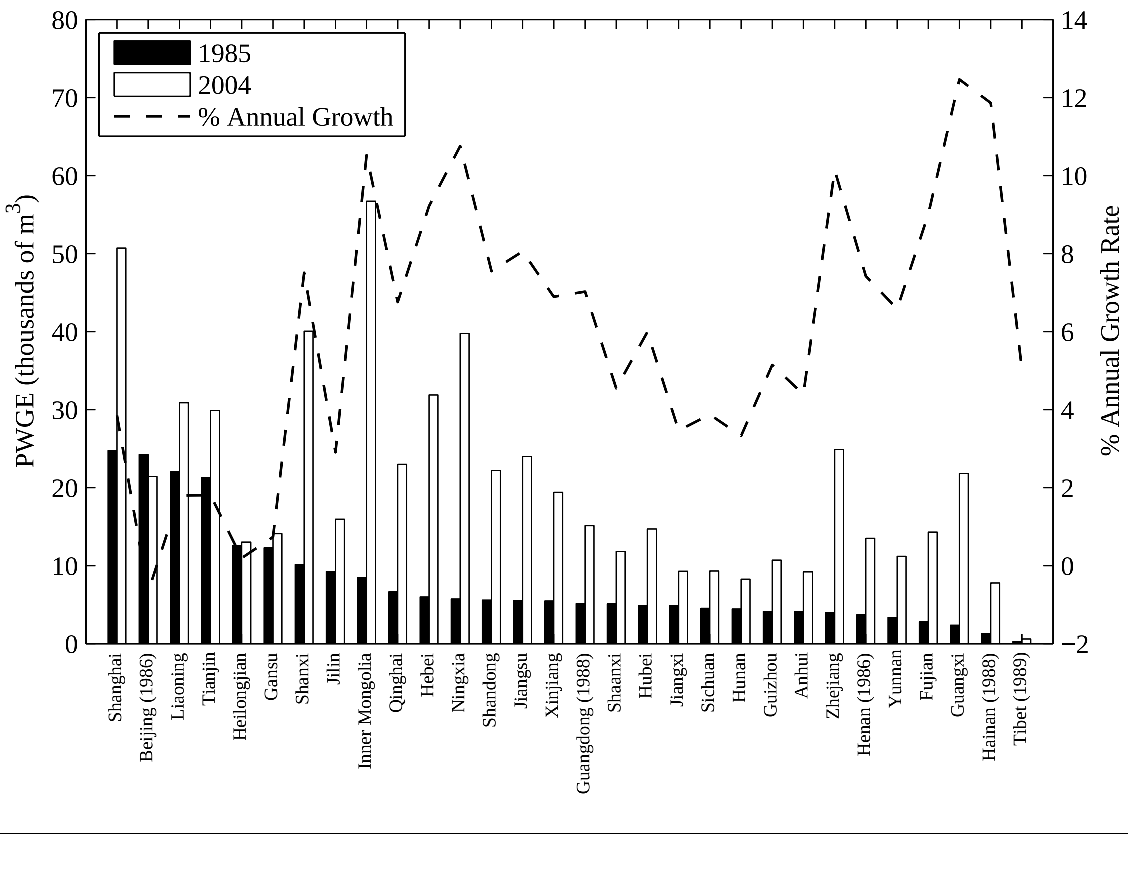
where $WGE_{1998:2004}$ are aggregate annual WGEs for China if $t > 1997$ and zero otherwise. $WGE_{1985:1997}$ equals aggregate annual WGEs for China if $t < 1998$ and zero otherwise. The heteroskedasticity consistent t-statistics are 132.51 and 21.28 respectively. The uncentered R^2 from this regression is 0.995. This almost perfect linear correlation suggests that WGE is a good proxy for CO_2. For the remainder of this paper, we will conduct our estimations using WGE and then use the estimated conversion factors above to convert WGE into million metric tons of carbon equivalent (MMTCE).[6]

One concern raised regarding official statistics from developing countries with often underfunded data collection agencies is that these indicators may be fabricated. We check for this using

[6] It is important to note that the national waste gas emission series is smooth while there is a clear break in the aggregate CO_2 emissions series in 1997/8 as discussed in Sinton (2001). The change in the conversion factor is partially due to structural changes in the energy sector as well as changes in the calculation of the CO_2 series, which assumed away the existence of small mines after 1997. If the national data are under reported, which is likely, this paper and every other paper using these data is underestimating China's carbon emissions, which would paint an even more worrisome picture of future emissions than we are already drawing in this paper.

two approaches. First, private communications with SEPA officials lead us to believe that this is not the case. These indicators are based on surveys of consumption and emissions from the vast majority of sources. Waste gas emissions are calculated for fuel burning and industrial activities covering 85% of emissions in a region (SSB, 2005). Second, we conduct a test for data fabrication based on Benford's law (Benford, 1938; Judge and Schechter, 2006). The distribution of the first digits follows Benford's law quite closely ($\hat{\rho} = 0.92$), which provides some evidence speaking against fabrication.[7] Finally, there is some concern that the data for the year 1998 suffer from bad reporting. We estimate all models putting zero weight on 1998, as well as 1998 and 1999 for the specifications containing lagged dependent variables, and obtain almost identical results.

Figure 1: 1985 & 2004 Per Capita Waste Gas Emissions (and Annual Growth Over Sample Period)



Estimation using provincial level data promises to improve forecast performance if there is sufficient heterogeneity in the time series across provinces (Marcellino et al., 2003). WGEs are

[7]The EPA's Toxic Release Inventory (TRI), which has been used in hundreds of studies, does not pass this test (de Marchi and Hamilton, 2006).

heterogeneously distributed across provinces. The coastal provinces[8], forming 14% of the area of the country, account for about 54% of waste gas emissions in 2004. 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 1 shows the ranking of provinces sorted by per capita waste gas emissions in the first available year. Provinces with higher PWGE tend also to be the provinces with higher income per capita, which are the coastal provinces. The simple correlation between the two variables is 0.47. Figure 1 demonstrates the significant heterogeneity in growth rates of per capita emissions across provinces. On average, the provinces with lower initial emissions are experiencing the most rapid growth of per capita emissions.

3.2 Socioeconomic Data

Our measure of income, per capita GDP, is calculated by deflating provincial nominal GDP using the province specific deflators with 1985 as the base year. To get the per capita GDP measure we divide by the total provincial population at year end. Figure 2 displays per capita income for 1985 and for 2004 in terms of per capita 1985 Yuan. Provinces are ordered by annual growth rate of per capita income over the twenty-year period. Two things to note from the figure are: (a) the very large increases in per capita income over this twenty-year period, and (b) substantial differences in the growth rates between provinces. Further note that the many changes in the provincial income ranking over the twenty-year period even though the three initially wealthiest provinces, Shanghai, Beijing, and Tianjin have retained their earlier rankings. 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.

As additional controls in our most general model, we have collected the following variables across time and provinces. Population density is calculated as total provincial population divided by total area in square miles.[9] It might be more desirable to include a measure of urbanization, such as share of urban population in a province, yet the redefinition of rural versus urban by the

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

[9]Population density for the year 2000 is highly correlated with provincial age structure. It may therefore proxy not only for density and urbanization, but other demographic variables.

state statistical bureau in the middle of our sample prevents us from constructing consistent time series. Further, the lack of consistent population times series for a large number of cities across provinces prevents us from constructing such a measure ourselves.

In order to control for potential province varying trends in fuel mix, we collected provincial level data on the share of coal used in total energy production. These measures are only available for 1990 and then annually from 1995 on. We construct data for the years 1991-1994, by using a piecewise cubic hermite interpolating polynomial.

Finally China has seen tremendous growth rates in the number of vehicles. Until the late 1990s automobiles were largely owned by state owned enterprizes and government officials. We have collected the number of privately owned vehicles by province from 1985 until 2004. While the number of personal cars has grown at roughly 20% per year, the province with the highest number of cars per person is Beijing. This number is roughly 12% of the US average, with traffic congestion

Figure 2: Provincial Per Capita Income (1985 Yuan) and Annual Growth Over Sample Period

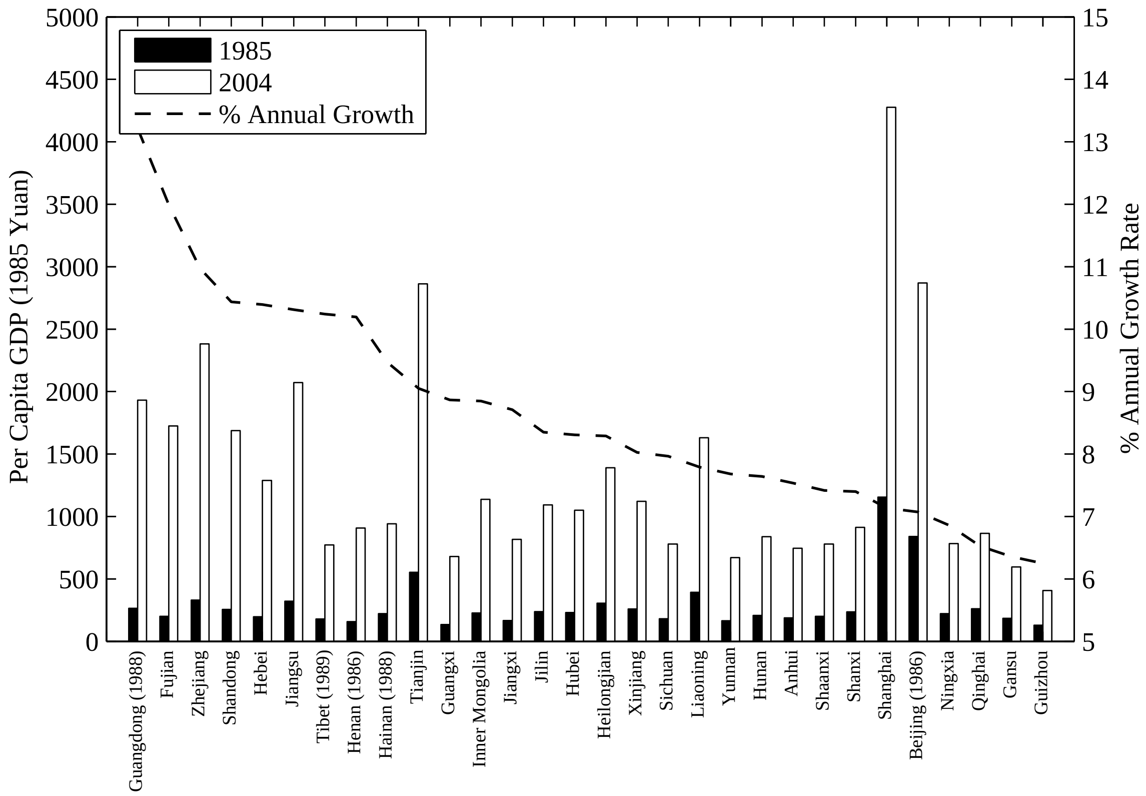
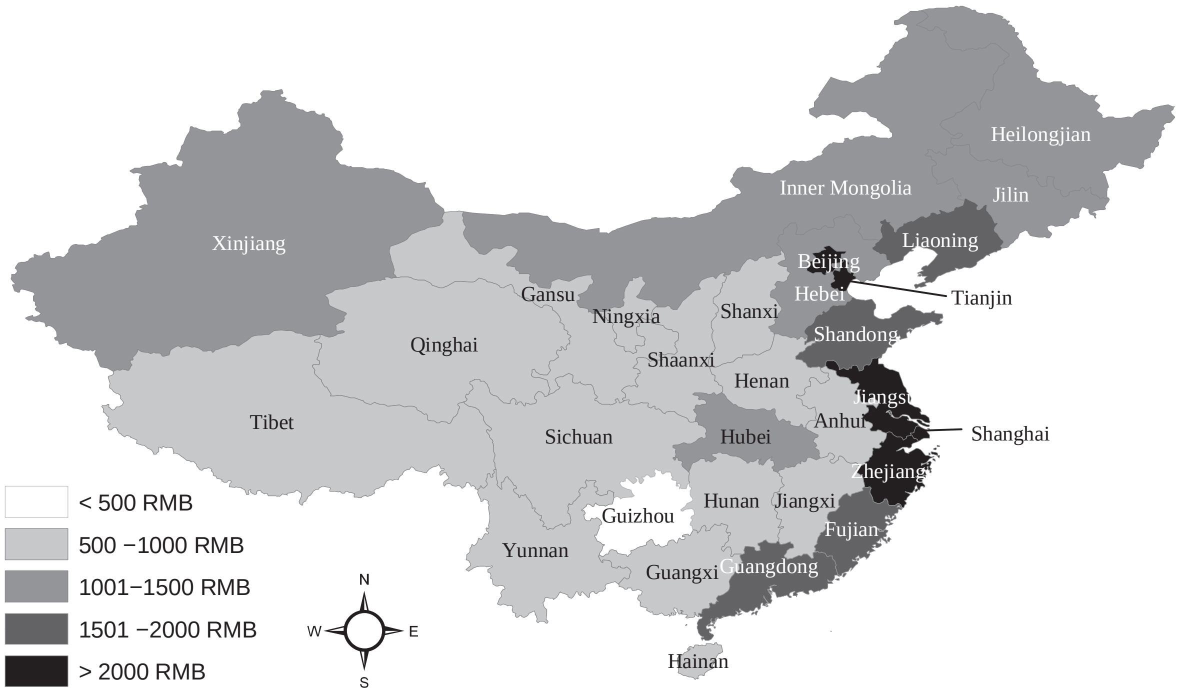


Figure 3: 2004 Provincial Per Capita Income in 1985 RMB



approaching US levels. For Shanghai per capita private car ownership is roughly 3% of the US average. While currently private car ownership is growing faster than income, much of this trend is likely due to a collapse in car prices and the recent establishment of a car credit system.

Further we have collected province specific indicators with no time variation. We calculate a measure of industry composition by taking the ratio of value added by heavy industry over total value added by heavy and light industry per province. We construct this ratio for 1989, which is the first year for which we have observations for all provinces and can be regarded as a “starting point”.[10]

Finally we have created a set of qualitative variables which include whether a province is located at the coast, has a special economic zone, and whether it is a net exporter of coal.

[10]The Chinese Statistical Office has changed its definition of heavy industry in the latter part of our sample, which makes it impossible to provide a consistent variable.

4. Empirical Models and Results

In order to select a forecasting model we use a specification search over a large space of models, similar to Hendry (1985). Within this framework we favor the Bayes/Schwarz Information Criterion (BIC) as our model selection criterion to select between non-nested models and break path dependence. This selection criterion favors a more parsimonious model specification compared to the Akaike Information Criterion, adjusted R^2 or R^2, since it punishes the inclusion of additional parameters more heavily (Diebold, 2001). Equation 3 below is the most general model.

$$\begin{aligned} \ln(\mathrm{PWGE}_{it}) = \quad & \eta_i + \gamma_t + f(\mathrm{GDP}_{it}) + f(\mathrm{GDP}_{it-1}) + \pi_i \ln(\mathrm{PWGE}_{it-1}) + \\ & + \varphi_i \ln(\mathrm{PWGE}_{it-2}) + \rho \textstyle\sum_{j=1}^{k} w_{ij} \ln(\mathrm{PWGE}_{j,t-1}) + \mathbf{Z_{it}} \boldsymbol{\delta} + \varepsilon_{\mathbf{it}} \end{aligned} \tag{3}$$

where η_i is a province fixed effect, γ_t is a year fixed effect and ε_{it} is a stationary ergodic error term. π_i, φ_i and ρ are scalars and $\boldsymbol{\delta}$ is a vector of parameters. PWGE_{it} measures per capita waste gas emissions; GDP_{it} is per capita gross domestic product in real terms (1985 Yuan). $f(\cdot)$ is a generic flexible functional form allowing for a potentially non-linear non-monotonic emissions income relationship. We start with a semi parametric Generalized Additive Model and then search over a variety of parametric specification starting with a fifth order polynomial. We further allow the parameters on income to vary across provinces and types of provinces to allow for differential income turning points as suggested by Dasgupta, Laplante, Wang and Wheeler (2002). In order to capture the potentially heterogeneous speed of adjustment (capital replacement) we include one and two-period province specific lagged dependent variables in the initial specification. The lags proxy for differential rates of capital replacement by allowing for lagged emissions to influence current emissions and by allowing the nature of this adjustment process to differ across provinces. $\boldsymbol{Z_{it}}$ is a vector of exogenous variables discussed in the previous section, some of which vary across time and provinces (population density, per capita car ownership rates, fuel mix) and others which only vary across provinces (initial industry composition, coastal location, coal exporting, SEZs).

The time fixed effects adjust for shocks to preferences and technology common to all provinces. The province specific fixed effects capture differences in unobservable factors across provinces. The model is only identified if we include the time invariant characteristics *or* the province fixed effects. The fixed effects control for differences in all unobservables, yet take up 30 degrees of freedom. Controlling for time invariant observables in a model without fixed effects may be beneficial, if these are not correlated with unobservables left in the disturbance.[11]

Finally we allow for spatial dependence in per capita emissions across provinces to see whether adding information on spatial dependence of CO_2 emissions improves out-of-sample forecasting performance. Finding evidence in support of this hypothesis, would suggest that incorporating a more complete characterization of the spatial structure driving the factors causing emissions may lead to even more efficient forecasts.

There are two main factors, which may lead to spill-over effects across provinces, which we will allow for by including spatial lags. First, the opening of China's economy happened differentially across provinces. The coastal provinces opened to foreign direct investment earlier, since all of the special economic zones were located near the coast. FDI is a well documented source of new know-how and access to new capital. This know-how is likely to spill over to neighboring provinces, yet with a temporal lag. The spatial lags proxy for provinces copying their more efficient neighbors. The second factor giving rise to spatial lags is a political economy one. The central administration has differentially devolved political control. Over the past two decades, China's environmental policy has become increasingly decentralized. This is partially by design and partially by default. There is evidence that a large share of newly installed power generating capital has not been permitted by the central authorities. An interplay of lack of enforcement of environmental policy and technological diffusion would amplify the influence of spatial lags. If provinces see that their neighbors are implementing large amounts of either non-permitted and new power generating capital, they could respond to this by installing more of such capital themselves. This would suggest that ineffective enforcement would lead to regional spillover effects proxied for by spatial lags.

We base our notion of spatial dependence on the STAR estimator provided by Giacomini and Granger (2004), who show that if there is spatial dependence in the series being forecast, failure to account for this correlation across space will result in suboptimal forecasts. CO_2 emissions are strongly correlated with industrial activity, transportation etc. The well documented non-uniform distribution of each of these factors across China's provinces is a likely source of information for

[11]If one introduces fixed effects *and* lagged dependent variables least squares is no longer unbiased. It is only consistent if one relies on large T asymptotics, which we can safely do here since the number of provinces can assumed to be fixed. For a good review of this literature see (*e.g.* Pesaran and Smith, 1995).

potentially improving state level and aggregate forecasts, if we cannot adequately control for these factors. The approach proposed by Giacomini and Granger (2004) assumes a known weight matrix. We construct a rook contiguity weight matrix, which is normalized to unity row sums.[12] The w_{ij} are the weights given to the previous year's CO_2 emissions by its k neighboring states.

4.1 Specification Search and Estimation Results

The specification search was conducted by estimating all identified models nested by the most general model from the previous section. The algorithm estimates each model using all available data and calculates the R^2, Akaike and Bayes Information Criterion for each run. We avoid path dependence of model search by calculating these information criteria for all models. While the AIC and BIC are generally thought to be more appropriate model selection criteria when the goal is to forecast out of sample, they are calculated purely based on in sample fit of each model. In order to overcome this shortcoming, we conduct an out of sample forecast experiment for the best models and a few benchmark specifications. We sequentially construct five one step ahead forecasts of aggregate emissions for the last 5 years in the sample and calculate the root mean square forecast error to get a limited indication of out of sample forecast ability. This measure has the advantage that it defines the loss from forecast error over aggregate emissions instead of over per-capita emissions, as is the case in all of the papers in the economics literature.

Table 1 below lists estimation results from a set of benchmark models as well as the "best models" according to out three model selection criteria - AIC/BIC and MSFE. This table represents a very small subset of the estimated models, but for space constraints listing more estimation results is not feasible. Models (1), (2) and (3) are static benchmark models. Model (1) is the classic Grossman and Krueger (1995) specification, which is a quadratic in income with year and province specific fixed effects.[13] Model (2) augments this specification by including population density. Model (3) adds per capita car ownership to model (1). The model performance measures are listed at the bottom of the table. Including population density slightly improves fit, while the car ownership measure adds no explanatory power. Model (4) augments the first model by adding

[12] We checked the results against a nearest neighbor weight matrix (three, four and five nearest neighbors). The rook contiguity matrix provided the best out-of-sample forecasts.

[13] The IPAT model is a restricted version of model (1), without the quadratic term. A LR test for the quadratic term rejects the IPAT model at the 1% level.

a pooled lag of emissions. Unsurprisingly, the fit improves tremendously. If we used the AIC as our model selection criterion, this model is the preferred model in the entire model selection space. It also has the lowest RMSFE out of all models considered and an R^2 close to 1.

Table 1: Selected Estimation Results from Specification Search

Dep. Var: $\log(\text{PWGE}_t)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(GDP)	.361	.399	.347	.065	.205	.157	
	(.069)***	(.070)***	(.072)***	(.041)	(.026)***	(.026)***	
$\log(\text{GDP})^2$	-.082	-.096	-.085	-.020	-.009		
	(.017)***	(.017)***	(.019)***	(.010)**	(.010)		
Population Density		.924			.106		
		(.305)***			(.044)**		
Cars Per Capita			.011				
			(.025)				
$\log(\text{PWGE}_{t-1})$				.795	.607 - .876†	.820	.817
				(.026)***		(.025)***	(.025)***
log(time)					-.079	-.063	-.064
					(.019)***	(.016)***	(.017)***
Initial Industry Comp.					.834		
					(.390)**		
$\sum_{j=1}^{k} w_{ij} \ln(\text{PWGE}_{j,t-1})$						.104	.118
						(.034)***	(.034)***
Income Spline: Low							.147
							(.040)***
Income Spline: Medium							.174
							(.028)***
Income Spline: High							.094
							(.041)**
Time Fixed Effects	Yes	Yes	Yes	Yes	No	No	No
Province Fixed Effects	Yes	Yes	Yes	Yes	No	Yes	Yes
Province Specific Lags	No	No	No	No	Yes	No	No
Obs.	588	588	588	558	558	558	558
Provinces	30	30	30	30	30	30	30
R^2	.262	.261	.260	.995	.984	.985	.985
AIC	-330.49	-338.49	-328.96	-970.20	-899.26	-953.64	-953.93
BIC	-234.05	-237.82	-228.34	-875.07	-743.58	-932.02	-923.67
RMSFE 1-Step	108.56	122.70	107.29	59.07	71.00	62.94	68.47
Mean SR Income Elasticity (2004)	0.34	0.37	0.32	0.06	0.20	0.16	0.13
Mean LR Income Elasticity (2004)	0.34	0.37	0.32	0.29	1.02	0.87	0.73

† Range of province specific lag coefficients.

Models (1) - (4) in table 1, use time specific fixed effects in order to capture exogenous technological change common across all provinces (Schmalensee et al., 1998; Grossman and Krueger, 1995). Time specific fixed effects capture unobservable *in sample* shocks common to all provinces. Using time fixed effects in a forecasting model raises two issues. First, when constructing out of sample predictions, one needs to predict the fixed effects. This is done by regressing them on time trends or splines and using these estimated relationships to predict what they will be out of sample. Second, of particular relevance in small samples, each fixed effect is an additional estimated parameter, which forecasting model selection criteria punish quite heavily. An alternate modeling strategy is to include a linear or non-linear deterministic time trend.

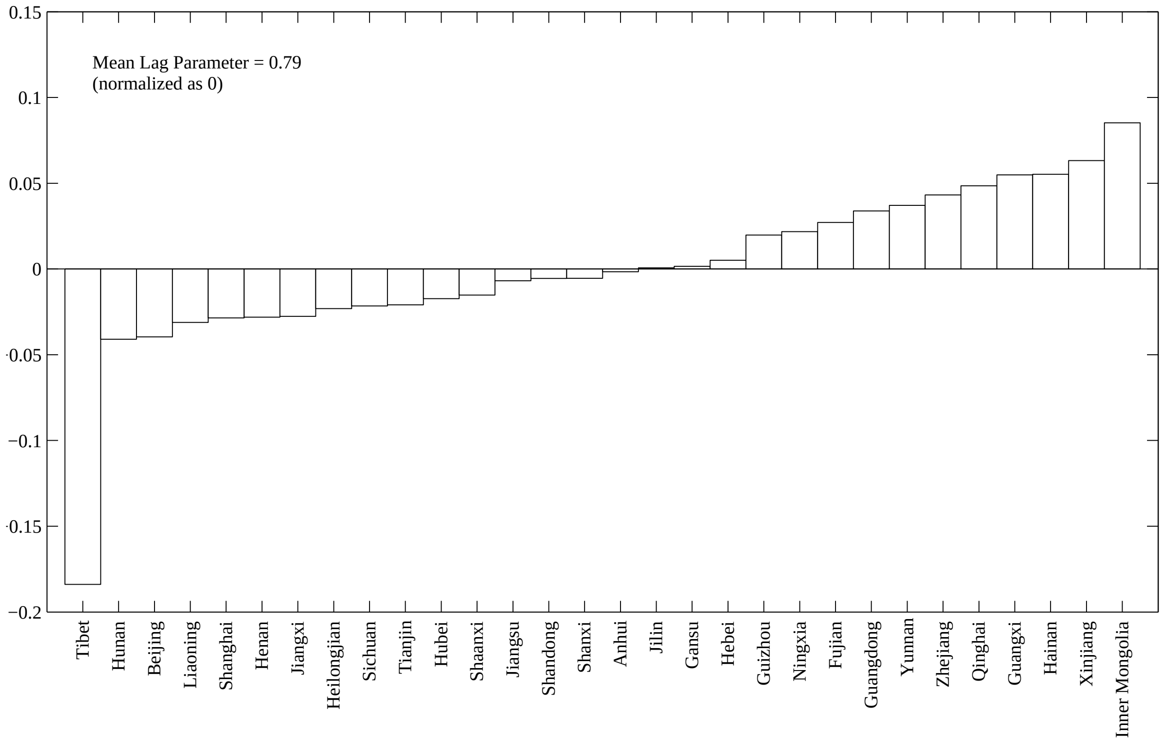
In order to "save" 48 degrees of freedom, we restrict the class of models to the ones with a common intercept and time trend. Model (5) minimizes the BIC given these restrictions on the model universe and our current sample. This specification essentially fixes starting point emissions by the industry composition variable, indicating that provinces with higher initial heavy industry concentrations have higher per capita emissions. It also has a negative logarithmic time trend, which one might interpret as changes in per capita emissions due to carbon intensity decreasing technological change. Logarithmic time trends arise naturally from a translog functional form and have frequently been used to proxy for exogenous technological change (*e.g.* Binswanger, 1974; Calmfors and Forslund, 1991). A logarithmic time trend suggests that the magnitude of technological change has decreasing impact on emissions the longer the forecasting horizon. It is widely believed that technological progress was very rapid in the years following the 1979 economic reforms. Replacing the least efficient old capital was often cost effective and produced relatively large reductions in emissions initially. Improvements in more energy efficient and cleaner technology will become more costly at the margin over time.

The fixed effects in model (4) show an upward trend over the last 3-4 years of the sample. This suggests that the abandonment of energy efficiency programs in the later years of our sample in favor of economic growth has reversed the noted trends in favorable technological change. The very recent refocusing on energy savings and energy efficiency programs, if successful, would lead us to believe a return to efficiency trends of the past. From a forecasting perspective, the log time trend preferred by the BIC will lead to out of sample predictions of favorable technological change which will result in a downward bias of forecasts if there is no return to past efficiency improvements.

This "best" model given these restrictions includes province specific lagged emissions, proxying for heterogeneous rates of capital replacement. Figure 4 below displays the variability in the lags.[14]

[14]We have tested whether the province specific lag coefficients are different from their mean and can only reject the null of equality for four provinces. We further estimated the model allowing for province specific coefficients on the two income terms. The mean short run income elasticity is 0.61 and the long run mean income elasticity is 1.18.

Figure 4: Lag Parameter Estimates for Model 5 (Deviation from Mean)



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. A smaller 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. The estimates are consistent with current efforts to decrease emissions of air pollutants in provinces hosting Olympic events as well as provinces which are attracting the majority of foreign tourists, which are largely the coastal provinces with lower estimated lag parameters.

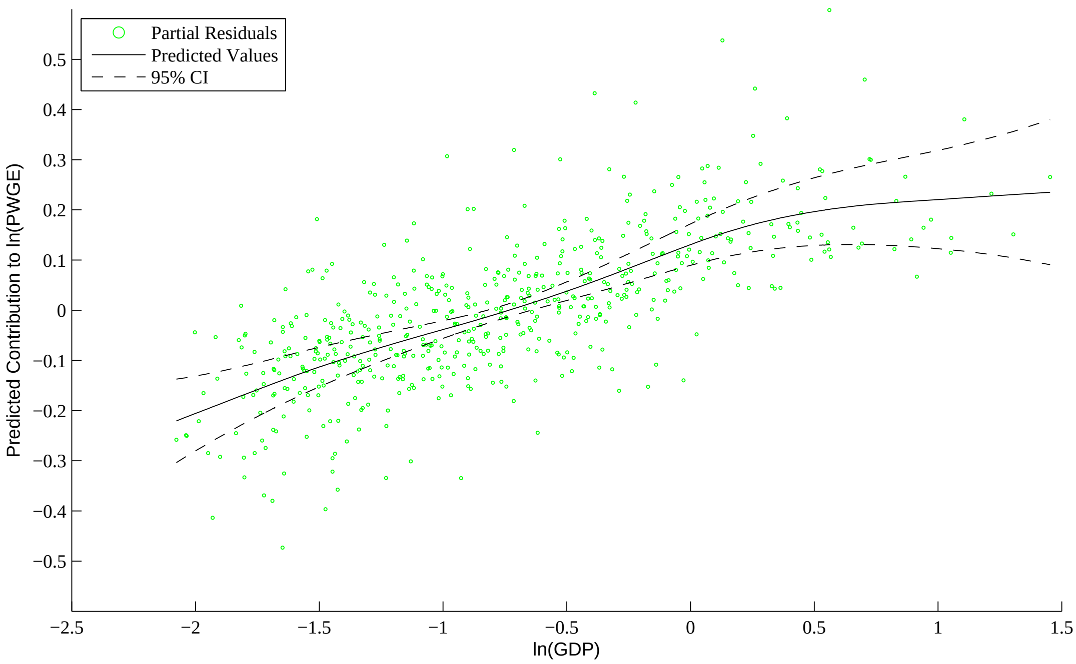
Model (6) has the lowest BIC in the considered model universe. This model has a linear positive income elasticity of 0.157, which is significant at the 1% level. It further includes the lagged pooled emissions as well as lagged weighted emissions of its first order neighboring provinces.

While it includes province fixed effects to control for differences in time invariant unobservable characteristics, it favors a logarithmic time trend over time fixed effects. Out of the eight presented models, it has the second best out of sample predictive ability as measured by one step ahead MSFE. The monotonic linear income effect is opposite to the non-linear EKC type emissions income relationship found in model (4). To test for potential non-linearities in income we follow two strategies. First, we include a spline in income. We consider 3, 5 and 7-knot splines and the one in model (7) minimizes the BIC. We see a slightly decreasing marginal income elasticity, yet no evidence of a negative propensity to emit at high levels of income. This model has very low AIC, and BIC as well as the third best MSFE.

Models (1) - (4) all have time fixed effects and imply short run income elasticities ranging from 0.12 - 0.49. The average income elasticity for model (4) is 0.06 in the short run and 0.29 in the long run. Models (5) - (7) have larger income elasticities. In the short run, these range from 0.16 - 0.22 and in the long run from 0.51 to 1.63, with an average near unity. It is curious that the removal of year fixed effects raises the estimated income elasticities significantly. While we cannot provide a conclusive explanation, it is likely that the less flexible time trend leads the models to attribute residual variation to income instead of noise. This is an issue that deserves further exploration, yet is beyond the scope of this paper.

Second, to step away from this parametric rigidity, we estimate model (4) using the GAM framework (Hastie and Tibshirani, 1990). The advantage of the GAM is its flexibility in determining the functional form between the dependent and independent variables. A cubic spline smoothing is done iteratively in order to minimize the partial residuals, which are the residuals after removing the influence of the other variables in the model. The estimation loop stops when the model fit cannot be improved. The resulting scatter plot in figure 5 shows the "predicted contributions" to the dependent variable from the income term against income itself. The scatter plot between the predicted values and income will give us an indication of the functional form without any *ex ante* imposed restrictions. The shape of the pollution income relationship is depicted in Figure 5, which suggests a linear functional form - not one resembling the rising slope of an EKC type relationship near a turning point. The shape below is not inconsistent with the rising section of an EKC relationship, but even if one believes in a non-linear pollution income relationship, even the highest income provincial entities are very far away from a potential turning point level of income.

Figure 5: Waste Gas / Income Functional Form - Generalized Additive Model



Because the GAM requires a larger number of parameters to be estimated, the BIC prefers the parsimonious model (4). We further conducted a set of in-sample encompassing tests and model (4) encompasses the other two "best" models (6) and (7).

Finally, we would like to know whether there are any estimation gains from using province level data. We use model 4, which is one of the three best models and does not contain any spatial lags to investigate this. First we estimate model 4 and test the restriction of equality of the fixed effects across provinces using an F-test. We strongly reject the null of equality at the 1% level. Second we calculate predicted aggregate waste gas emissions from estimating model 4 using data aggregated to the national level. We then calculate the in-sample mean squared error of aggregate emissions for this aggregated model and those from the "province-level" version reported in table 1. The model using aggregate data has a MSE 43.38% higher than the same model estimated using province level data, suggesting large gains from disaggregation, which is consistent with the literature (*e.g.* Marcellino et al., 2003; Auffhammer and Steinhauser, 2007; Carson et al., 2005).

5. Forecasting CO_2 Emissions

In this section we construct forecasts of aggregate CO_2 emissions for the PRC. The simulation exercise we conduct in this paper follows the second strand of the literature discussed in section 2. Following Schmalensee et al. (1998), we use the estimated coefficients from table 1 to construct out of sample predictions of national emissions by aggregating up province level emission trajectories under different income and population scenarios. While other studies have focused on constructing forecasts to the year 2100 (IPCC, 2001) or 2050 (Schmalensee et al., 1998) we limit our forecasting horizon to 2010 and we even consider that horizon to be quite ambitious. In order to construct aggregate forecasts given our province level model, two issues arise given the "best" models in table 1. First, 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. Second, since one of our "best" models contains time fixed effects, the issue arises as to how on should predict the fixed effects. We now take each of these issues up in turn.

The IPCC SRES provides a large set of scenarios containing assumptions regarding aggregate GDP and population growth. As Schmalensee et al. (1998) correctly note, the assumptions regarding GDP growth tend to be conservative given the recent record of explosive economic growth in the PRC. The assumed GDP growth scenarios are centered around IPCC scenario IS92a assumptions and stated below.

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, so we rely on Chesnais and Sun (1998) who provide province population growth forecasts through the year 2050. We use the provincial population growth rates from 2000 on and calculate predicted population for each province using the 2000 Census population data as a starting point. 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 Sun (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. Big differences in aggregate population only start to be detectable after 2020, which leads to small differences in the aggregate population forecasts over our forecasting horizon.

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 and four population growth scenarios to demonstrate the sensitivity of our forecasts to changes in population and GDP growth.

We assume that the aggregate GDP growth rate (ξ_t) and population growth rate (ϕ_t) are jointly distributed as $f(\xi_t, \phi_t) \sim N[\mu_\xi, \mu_\phi, \sigma_\xi^2, \sigma_\phi^2, \rho]$ and that in and out of sample population and GDP growth rates can be characterized by this bivariate normal distribution. We do not forecast the population growth rate (ϕ_t) directly, as the four scenarios provided by Chesnais and Sun (1998) are used. We calculate ϕ_t $\forall$ [2005, 2010] from these forecasts and use the expected value of the conditional 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. ρ, σ_ξ and σ_ϕ are estimated using the in sample aggregate growth rates. We choose values for μ_ξ to simulate forecasts for different GDP growth scenarios. After obtaining the conditional mean of the growth rate ξ_t, we then allocate the implied GDP growth to provinces according to their share in aggregate growth over the last decade of our sample.

Table 2: Assumptions Concerning Population Growth Rates

Population Scenarios	A	B	C	D
Mortality Rate	Constant	Constant	Decreasing	Decreasing
Birth Rate	Constant	Decreasing	Constant	Decreasing
Aggregate Growth Rate (2000-2010)	0.91%	0.40%	1.03%	0.51%

Table 2 summarizes the four different population scenarios for considered in the forecasting exercise. For each of these population scenarios, we let μ_ξ take on three values: A low growth scenario of 3.02%, a medium growth scenario of 5.02% and a high growth scenario of 7.02%. Given China's recent explosive growth these scenarios are likely still conservative.

As mentioned in the previous section, while time fixed effects are appealing from an in sample perspective, they pose challenges when attempting to forecast out of sample. Holtz-Eakin and Selden (1995) set the time fixed effect equal to the last in sample fixed effect, while Schmalensee et al. (1998) attempt to forecast them out of sample. Following the latter approach, we examined a variety of specifications to forecast the time fixed effects out of sample. We estimate a model, which allows for a breaking point in the time trend:

$$\gamma_t = \alpha_0^{<B} + \alpha_1^{>=B} + \alpha_2 \cdot t^{<B} + \alpha_3 \cdot t^{>=B} \tag{4}$$

which is a regression of the in sample time fixed effects on an intercept and linear time trend, both of which are allowed to break at year B. We estimated the models and produced forecasts using our five 1-step ahead out of sample prediction experiment and calculate the MSFE. We let the breaking point vary between 1992 and 1998, and find that a break in 1996, minimizes the MSFE. We further experiment with specifying t as a log of time and find that a linear trend produces a smaller MSFE. We therefore predict the fixed effects out of sample using the equation above with a breaking point in year 1996.

5.1 Sensitivity To Alternative Scenarios

In this section we produce forecasts for the three best models (Models 4, 6 and 7) as well as the traditional Kuznets curve specification (Model 1). For each model we produce point forecasts for the 12 different population/GDP scenarios. Figure 6 displays aggregate forecasts of Chinese CO_2 emissions based model (4), the dynamic EKC specification, and figure 7 those for model (7), which is the spatial lag income spline specification.[15] In each figure, the solid and dashed lines show the point forecasts for the four population scenarios assuming the medium income growth scenario. The gray shaded area represents the upper and lower bound of the high and low GDP growth forecast scenario across the four population models. As expected, the population scenarios do not have a great impact on aggregate emissions over the 10 year forecasting horizon, since the degree of variability in population levels across the four scenarios is small.[16] Further, since we assume the imperfect correlation between the *aggregate* population growth rate and *aggregate* GDP growth rate to continue, we in a sense allocate “a little bit less” GDP to a much smaller number of people

[15]The discontinuous drop in the CO_2 emissions series is not being driven by reported waste gas emissions, but by the change in the waste gas to CO_2 conversion formula, as shown in equation (2).

[16]If one considers forecasts over a longer horizon, such as in Auffhammer, Carson and Garin-Muñoz (2002), population is the dominant influence over the emission trajectory.

for a given GDP growth scenario, contributing to the similarity of forecasts across population scenarios.[17] Compared to the forecasts from model (7), the model (4) forecasts are more income sensitive, due to the non-linearity in income. The estimated turning point income level is roughly three times Shanghai's current per capita income.[18]

Figure 8 displays the forecasts using model (6), which is linear and income and contains temporal and spatial lags of emissions. Figure 9 displays the forecasts from the static Environmental Kuznets Curve model (1). The predictions from the dynamic model again display little variability due to the income and population assumptions. The level predictions are very similar to the predictions to the previous figure. The predictions from the EKC model, which one may consider as a benchmark specification, are drastically lower and display little variation. The predicted mean emissions across all scenarios for 2010 from the EKC model are 1,713 million metric tons of carbon equivalent, whereas the same figure for model (7) is 2,462 MMTCE. The small degree of variability in the EKC model is due to its static nature. The temporally lagged emissions in model (4) introduce greater variability across scenarios due to their inherent sensitivity to shocks in the past.

The picture emerging from these four panels is that the dynamic "best" models result in significantly higher forecasts than the benchmark EKC model, which has been the main forecasting tool in the economics literature. The forecasts from the three best models provide out of sample predictions, which differ by less than 200 MMTCE, whereas the EKC model predicts emissions 700 MMTCE lower than the lowest predicting "best" model 7. It is important to note that the models with lagged dependent variables produce significantly higher forecasts of emissions. Provinces with high increases in per capita incomes were also the provinces with higher initial per capita waste gas emissions. A static EKC model, such as model (1), attributes the cleaning up of the provincial economies solely to changes in income. If one adopts a more structural perspective, income does not directly cause a cleaning up. It is the scrapping of dirty capital and its replacement with newer equipment with higher thermal efficiency, which causes the drop in per capita emissions.[19] This

[17]We constructed forecast scenarios assuming a per capita GDP growth rate, which drives the point forecasts slightly apart, but does not change the picture significantly.

[18]It should be noted that the turning points have large confidence intervals, since their distribution is fat tailed.

[19]While the lag structure has traditionally been thought of in terms of scrappage rates, it is not actually necessary to actually scrap any existing capital as long as population or per capita consumption is growing. In this case, the new capacity being installed may be cleaner than the existing capacity but the existing capacity limits how fast per capita emissions can decline.

Figure 6: Aggregate Forecasts of China's CO_2 Emissions - Model 4

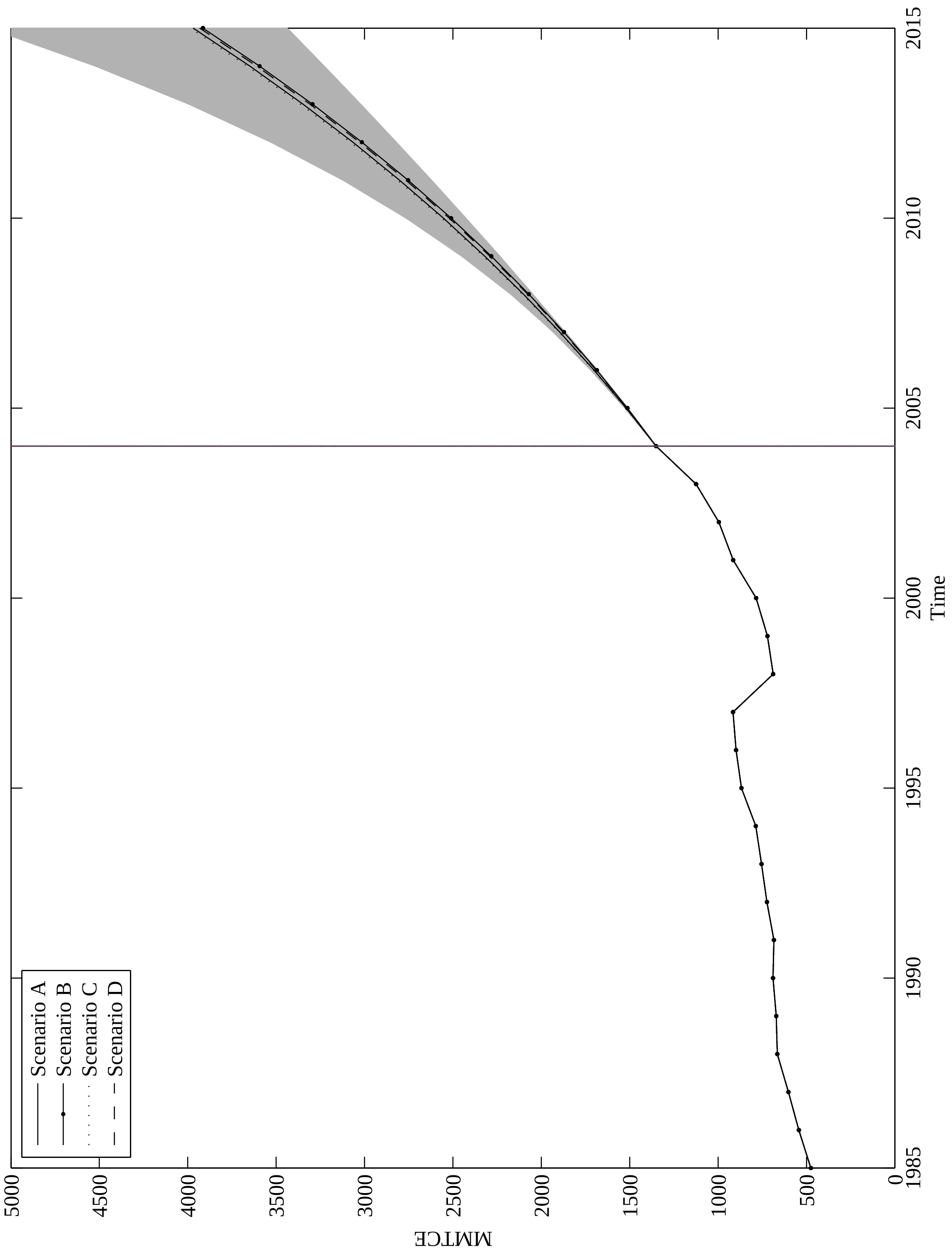


Figure 7: Aggregate Forecasts of China's CO_2 Emissions - Model 7

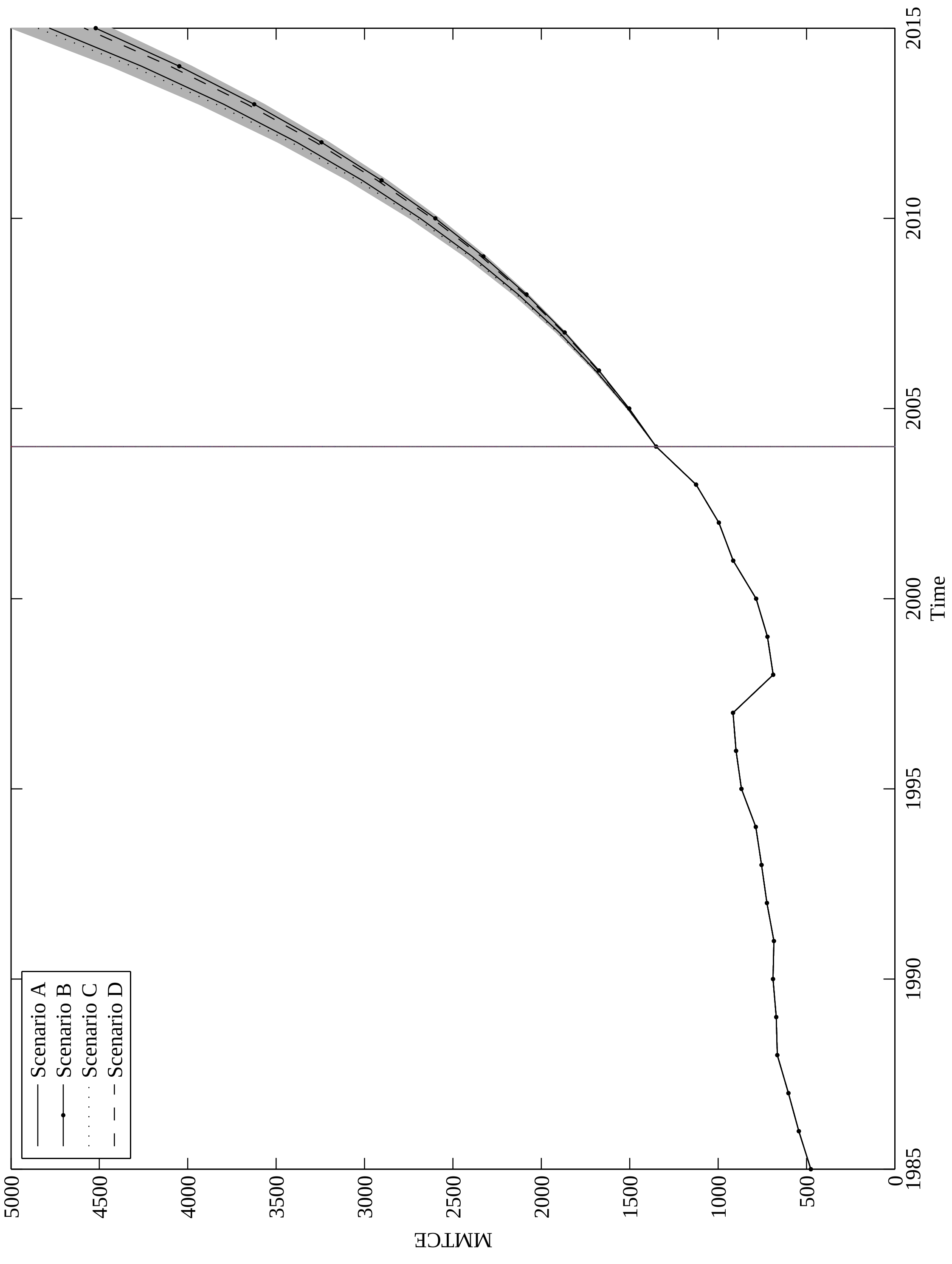


Figure 8: Aggregate Forecasts of China's CO_2 Emissions - Model 6

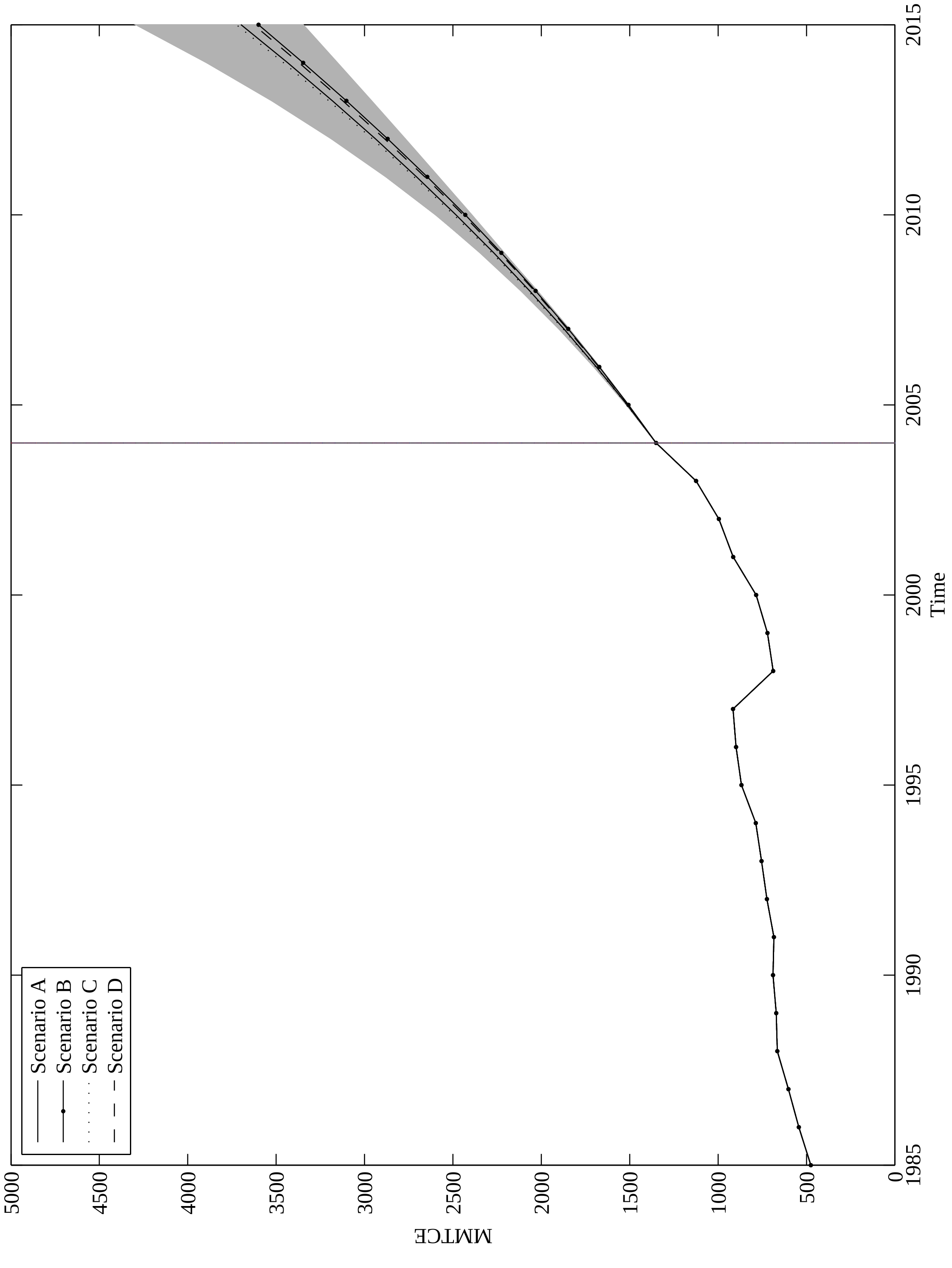
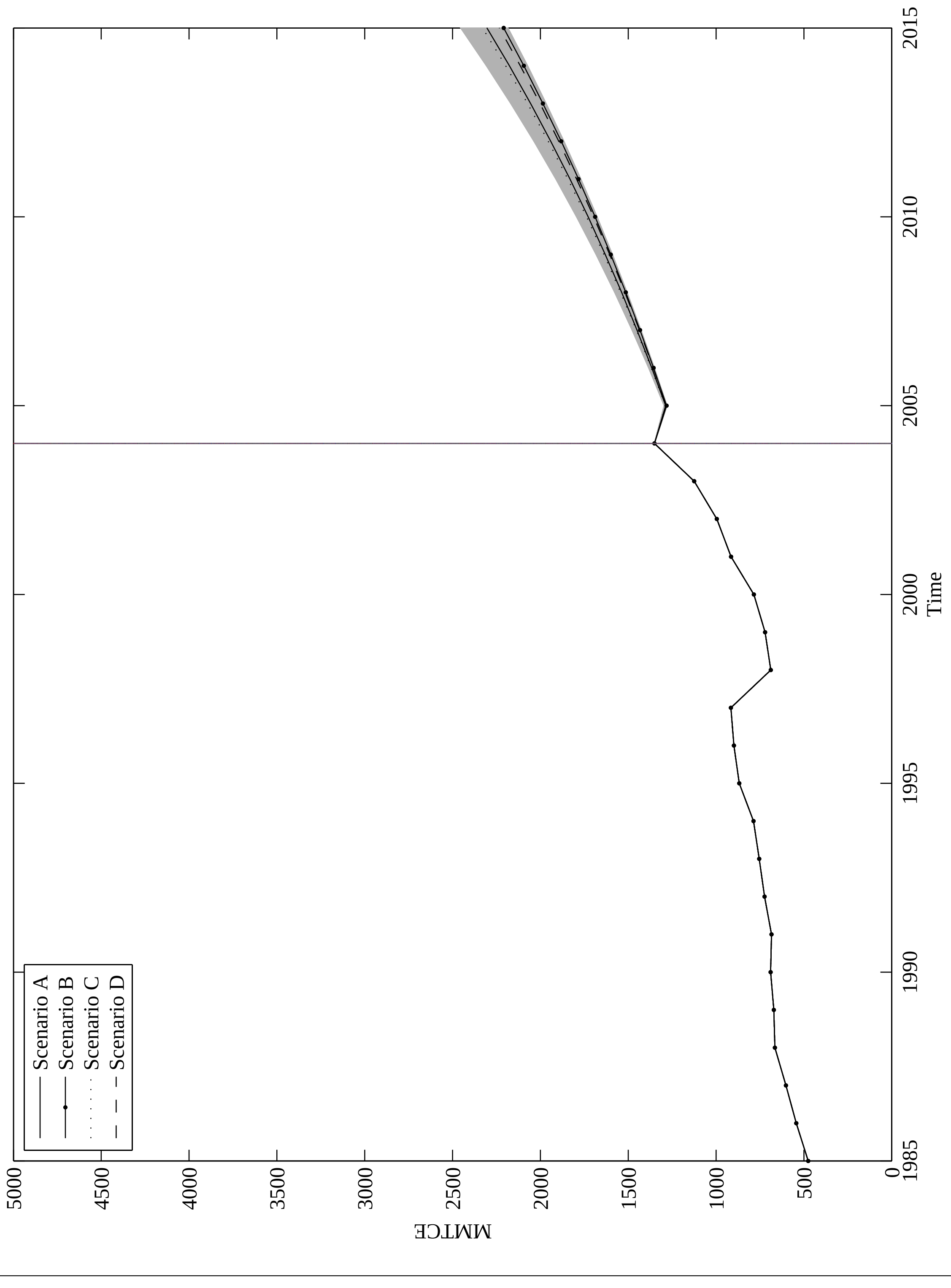


Figure 9: Aggregate Forecasts of China's CO_2 Emissions - Model 1



is similar to a Houthakker and Taylor (1970) partial adjustment model of energy demand, where provinces with a given level of income have a desired level of energy consumption (or in our case waste gas emissions). In any given period, they cannot achieve this desired level, due to their ability to only partially adjust the capital stock. The static model omits this rigidity and implicitly assumes a more speedy capital adjustment process, while the dynamic models properly capture the scrapping of dirty capital, therefore predicting a higher emissions trajectory.

The forecasting model makes use of all data up to and including the year 2004. We conducted a simulation exercise to see whether using different information sets would lead to greatly different forecasts. We estimate the seven forecasting models based on samples ending in 1999, 2001, 2002, 2003 and 2004. We then calculate the forecasts of year 2010 using the 5.02% income scenario described in the beginning of this section. Table 3 below shows the predicted emissions for the year 2010 for all seven considered models and the five different information sets. Two points emerge. First, the rankings of models persist across forecasting horizons, which is reassuring. The second point, which is disconcerting from a global climate change perspective, is that the forecasts have increased monotonically for each model since 1999. The dynamic models show more dramatic increases in predicted emissions than the static model(s), which is not surprising due to their previously mentioned sensitivity to past shocks. The large increase in predicted emissions over time comes from two factors. First, the extraordinarily large increases in China's GDP exceed the 5% scenario greatly. For each added year, we therefore start from a higher benchmark level of income. This acceleration in income growth is accompanied by an acceleration in observed emissions. Further, China's abandonment of energy efficiency programs in favor of economic growth has resulted in an unprecedented increase in emissions of local air pollutants and correspondingly GHG emissions. The performance of any model discussed in section 2 will be sensitive to realized differences in input variables. The advantage of the econometric approach, is its ability to easily update model parameters based on changes in observed data.

The forecasts presented in this section assume that China's provincial economy develops as it has over the in-sample period with respect to factors driving carbon emissions relative to income and population growth. Additional or renewed policy measures driving down the carbon intensity of China's economy present a unique opportunity to deviate from the high growth emissions path presented here.

Table 3: Forecasts of Aggregate Year 2010 CO_2 Emissions by Information Set

Cutoff Year	1999	2000	2001	2002	2003	2004
Model 1	1,095.21	1,165.73	1,388.50	1,531.32	1,601.10	1,712.85
Model 2	1,047.22	1,065.87	1,264.75	1,445.79	1,516.57	1,632.64
Model 4	1,361.30	1,495.84	2,240.22	2,316.80	2,226.59	2,651.02
Model 5	1,666.37	1,889.89	2,856.08	2,658.01	2,457.09	2,933.81
Model 6	1,234.38	1,382.59	1,816.64	1,936.46	1,979.62	2,536.83
Model 7	1,031.91	1,161.87	1,844.29	1,935.15	1,914.54	2,462.37

The projections of CO_2 emissions from this study are subject to a great deal of uncertainty, as are any economic forecasts over a ten year horizon. In table 4 below we compare our forecasts to the experienced in-sample growth and forecasts from three most recent studies projecting China's CO_2 emissions into the future.

Table 4: Historical and 2010 Projected Emissions Growth Rates

	Time Begin	Horizon End	Annual Growth Rate
Marland et al. (2005)	2000	2003	14.40%
This Study*	2000	2004	14.53%
This Study*	1995	2004	9.50%
This Study***	2000	2010	11.05 - 11.88%
Yang & Schneider (1998)	2000	2025	1.93 - 3.10%
IPCC (2000)**	2000	2010	2.58 - 4.82%
ERI (2004)	2000	2010	4.18%
Fridley (2006)	2000	2010	5.00-5.02%
Jiang & Hu (2006)	2000	2010	4.12%

Note: * Based on our WGE measure, which is almost identical to Marland et al. (2005). ** The figures reported here are taken from the Illustrative Marker/Scenarios from SRES. These include A1B, A2, B1, B2, A1F1 and A1T. We report growth rates for the region ASIA. *** The range provided here uses models 4, 6 and 7.

There are a large number of studies forecasting China's CO_2 emissions, yet most of them are based on data from almost a decade ago (Yang and Schneider, 1998; Intergovernmental Panel on Climate Change, 2001) during which China's economic and technological growth has accelerated beyond anticipation. The quasi-official IPCC forecasts are not broken down by country, but for the region ASIA, provide a range of emission growth with an upper bound of 4.82%. The Yang and Schneider (1998) forecasts provide an even lower range of growth. The three most recent studies are Energy Research Institute (2004), Fridley (2006) and Jiang and Hu (2006). The first two studies use a detailed sectoral partial equilibrium model of China's economy using data up to 2002 and

2004 respectively. For the first model we cite the anticipated growth to 2010 using the baseline scenario. For the Fridley (2006) study, table 4 shows the range for the seven scenarios presented in the study. Our forecasts differ from these two studies in the sense that we do not make any assumptions regarding departures from in-sample trends. Both of the engineering studies assume a slowdown of growth due to policy intervention. Jiang and Hu (2006) use the Integrated Policy Assessment Model for China (IPAC) to arrive at predictions. We cite the baseline scenario, which assumes no explicit policy intervention.

Table 4 shows clearly that the best performing econometric models from this study, which assume no policy intervention, predict drastically higher aggregate growth of emissions compared to the other studies cited here. The average annual growth rate for each model across scenarios, ranges from 11.05% to 11.88% over the 2000-2010 period. If we allowed for a higher range of income projections (5%, 8% and 11%), this range would be 12.56% to 13.19%. Assuming an 11% growth rate of GDP, these forecasts imply an aggregate emissions elasticity with respect to income ranging from 1.03 to 1.11, which is slightly above unity. The forecasts from these alternate studies are closest to those from the model 1, the EKC specification, which we have shown above is outperformed on all dimensions by the dynamic models. This leads us to believe that existing models are most likely underpredicting the status quo emissions path of the PRC.

The EIA predicts that all emissions reductions from current Annex I countries, who have ratified the Kyoto protocol, in the year 2010 relative to the predicted level in the absence of the agreement amount 115.90 million metric tons of carbon (Department of Energy, 2006). Even our most conservative forecasts predict an increase of over 600 million metric tons of carbon over year 2000 emissions by 2010 by the PRC alone. The best model forecasts cited here predict gains more than twice that number. This is particularly important, since current forecasting models employed in the literature and by the IPCC are very likely drastically underpredicting short run emission increases by the PRC.

6. Conclusion

At the end of the last century, it was conceivable that China's CO_2 per capita emissions growth rates were slowing down, suggesting a moderate growth emissions trajectory as income in China increased. In this paper we suggest, that over the next ten year time horizon such a downturn is now highly unlikely unless there are substantial changes in China's energy policies. Our conclusion is based upon an extensive econometric exercise that examined a large suite of models. This exercise clearly rejects the static environmental Kuznets curve specification. Each new year of data over the last five years further increases the anticipated emissions path. While there are some substantial differences between estimates from the set of models that appear to have the best forecasting ability, they agree that the magnitude of the increase is quite large relative to existing forecasts of Chinese CO_2 emissions. To put the size of the increase in emissions in sharp perspective, it is several times larger than the decrease in emissions that is embodied in the Kyoto protocol. That is, the disagreement between the models is over how many times larger the increase is likely to be.

Our data source and modeling approach have two strong advantages. First, we are able to exploit much shorter time series dynamics than are possible in a single national time series. Second, we are able exploit the considerable heterogeneity that exists across China's provinces, each of which is generally large compared to most countries. A key feature of all of the better models is the strong influence of the lag structure, which is consistent with the nature of persistent capital investments in energy technology. The open question is whether there are now policy options available that can influence the current trajectory of capital investments in a meaningful way.

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