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Forecasting the path of China's CO₂ emissions using province-level information

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Abstract

Our results suggest that the anticipated path of China's carbon dioxide (CO₂) 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 data set 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.

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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 has long been projected to overtake the United States as the leading emitter of carbon dioxide (CO₂). 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 CO₂ reductions. Efforts to reach such an agreement failed in the late 1990s 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 US Senate. This paper presents econometric forecasts that strongly suggest that the short to medium term path of Chinese CO₂ emissions has increased by a factor of two or more since that time. Our best forecast has China's CO₂ emissions correctly surpassing the United States in 2006 [39] rather than 2020 as previously anticipated [30,43,40]. Our focus in this paper is on exploring

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alternative econometric specifications for forecasting China's CO₂ emissions using a rich new panel data set from 1985 to 2004 at the provincial level. The prediction of a dramatic recent increase in the predicted path of China's CO₂ 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 [30] and the recent Stern Review [48] as well as the popular environmental Kuznets curve (EKC) 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 CO₂ 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 CO₂ emissions exploits time series variation across countries [50,30], cross sectional variation on industry sectors [18,46,52,20,21] or adopts a case study approach of the factors influencing the performance of specific plants [51]. Second, we adopt an explicit forecasting approach to model selection. Instead of choosing a specific reduced form model a priori (e.g. [42,28]), 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 [36,4,10]. 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 [49,31].

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 BAU emissions at the strike date. Underprediction of emissions may result in a country withdrawing from an agreement if it finds itself far above the agreed anticipated emissions path. The US has argued that it would not join an agreement such as Kyoto, since it would then be 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 any international climate agreement.

2. Background

The literature on modeling and forecasting CO₂ emissions can be split into three strands. The starting point for the first two is the classic IPAT identity [17,27]:

$$I = P \cdot A \cdot T, \quad (1)$$

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.² Conceptually, this identity has given

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

²In the literature on predicting GHG emissions the IPAT identity is referred to as the Kaya identity.

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 underlie much of the IPCC special report on emission scenarios (SRES) [30]. The common empirical implication underlying all IPAT models is that pollution should be monotonically increasing in P and A and monotonically decreasing for improvements in T . Yang and Schneider [50] provide a decomposition analysis along these dimensions across countries. Zhang [53] has decomposed historical aggregate CO₂ 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.

The second branch of the literature based on the IPAT identity 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 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 [23,42]. 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 is that the reduced form specification does not separate the income effect from other factors driving emissions [13,2]. The empirical evidence on whether a turning point for CO₂ exists is mixed [34]. Since CO₂ emissions stem largely from energy use, any potential downturn in per capita emissions could be due to agents' preferences or policies regarding energy consumption and production rather than CO₂.

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 [8]. This approach to modeling emissions is very useful from a policy perspective, since one can easily simulate the impacts of different policy instruments or shocks on the economy and resulting changes in emissions. Although these models are often used to draw out-of-sample predictions, they are not forecasting models, since they are not calibrated according to their out-of-sample predictive ability. 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. Accordingly, CGE models require very detailed data; typically these data are only available at infrequent intervals. For example, the CGE models for China are largely based on the 1997 input output tables, although the 2002 input output tables were recently released [20,21,26].

In this paper we draw on aspects from these three strands of the literature to construct a reduced form forecasting model of China's aggregate CO₂ emissions for the next decade.

First, we allow for a non-linear emission income relationship with the possibility of income having a non-monotonic effect on CO₂ 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 US [11]. We will extend the restrictive second order polynomial specification first proposed by Grossman and Krueger [23] by allowing for a flexible functional form of the pollution income relationship using the semi-parametric generalized additive model (GAM) framework [24].

Second, we 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 CO₂/\$. 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.³ 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. Such a model would require 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 [29], 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 [35] shows that per capita emissions of criteria pollutants depend on emissions in neighboring countries. Auffhammer and Steinhauser [4] show that allowing for dependence in aggregate CO₂ emissions across the US 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

Our analysis is based on province-level panel data for 30 Chinese provincial entities⁴ 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 [47]. 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 CO₂ over time broken down by sector. Alas, these data do not exist as measuring emissions of CO₂ from a large number of widely dispersed mobile and stationary sources would be prohibitively costly. 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 et al. [37] are the main data source of national level CO₂ 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 (WGEs), which are calculated in a very similar way. As discussed below, we will use this indicator to proxy for CO₂ emissions at the province level.

SEPA uses an estimated engineering relationship, which allows them to convert fuel usage into WGEs. Since we do not know the exact engineering relationship used by SEPA we convert WGE into CO₂ emissions by aggregating WGEs across provinces by year and using this variable to predict aggregate CO₂ emissions. The well-known restructuring of 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 enterprises drastically improved the efficiency of China's energy producing and consuming sector [45]. In order to obtain a conversion factor for WGE to CO₂ that allows for this major structural change in the late 1990s, we estimate the following equation:

$$\text{CO}_{2t} = 8.051\text{WGE}_{1985:1997,t} + 5.673\text{WGE}_{1998:2004,t} + \eta_t, \quad (2)$$

where $\text{WGE}_{1998:2004}$ are aggregate annual WGEs for China if $t > 1997$ and zero otherwise. $\text{WGE}_{1985:1997}$ 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, which suggests that WGE

³Agras and Chapman [1] allow for a dynamic adjustment process for CO₂ using a sample of 34 countries from 1971–1989. The dynamic adjustment process is assumed to be the same for all countries.

⁴Beijing, Shanghai and Tianjin are provincial-level municipalities; Guangxi, Inner Mongolia, Ningxia, Tibet and Xinjiang are autonomous regions. Chongqing 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.

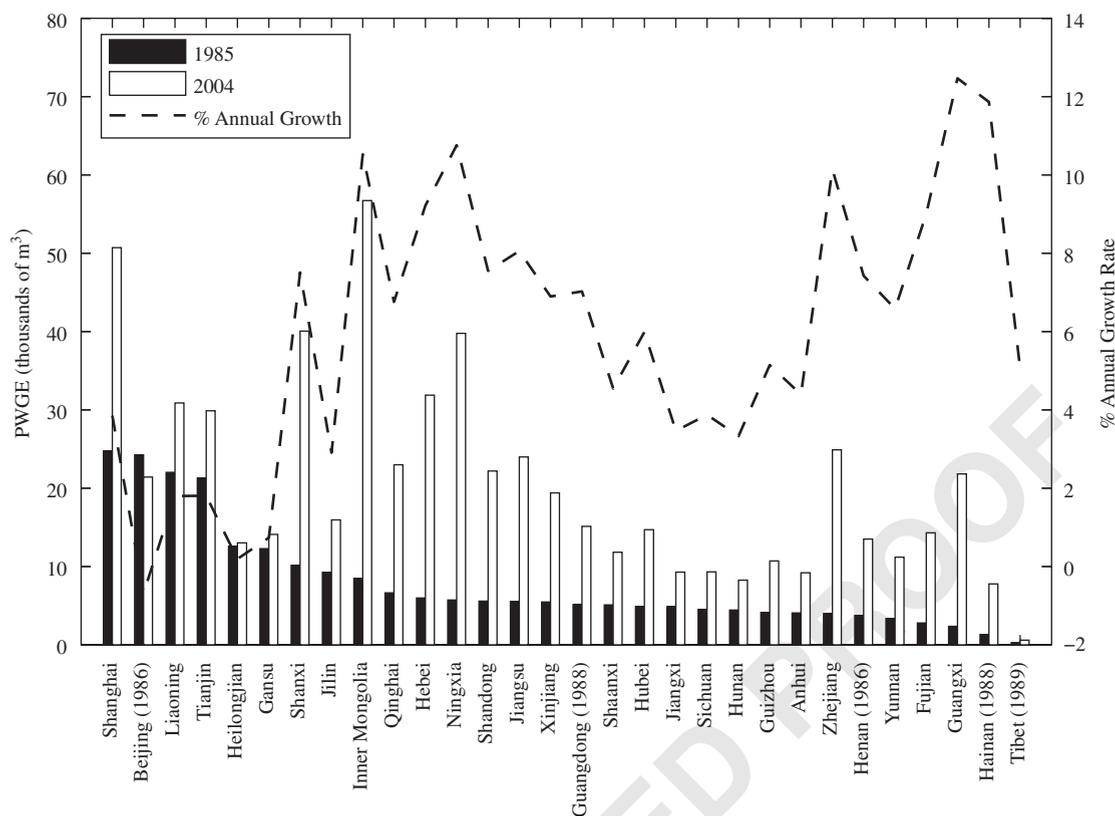


Fig. 1. 1985 and 2004 per capita waste gas emissions (and annual growth over sample period).

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).⁵

One concern regarding official statistics from developing countries is that chronic underfunding of data collection agencies may lead to fabricated data. We check for this using two approaches. First, private communications with SEPA officials indicated that data are generally based on surveys of consumption and emissions. WGEs are calculated for fuel burning and industrial activities covering 85% of emissions in a region. Second, we conduct a test for data fabrication based on Benford's law [6,33]. The distribution of the first digits follows Benford's law quite closely ($\hat{\rho} = 0.92$), which provides some evidence speaking against fabrication.⁶ 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.

Estimation using provincial-level data promises to improve forecast performance if there is sufficient heterogeneity in the time series across provinces [36]. WGEs are heterogeneously distributed across provinces, with 14% of the country accounting for about 54% of WGEs in 2004.⁷ This largely reflects the uneven distribution of population and economic activity in China. Per capita waste gas emissions (PWGEs) also display high variability between provinces. Fig. 1 shows the ranking of provinces sorted by PWGEs in the first

⁵It is important to note that the national WGE series is smooth while there is a clear break in the aggregate CO_2 emission series between 1997 and 1998 [44]. 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, as seems likely, then our approach would underestimate China's carbon emissions.

⁶The EPA's toxic release inventory (TRI), which has been used in hundreds of studies, does not pass this test [15].

⁷These are the coastal region provinces: Liaoning, Hebei, Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Hainan, Guangdong, and Guangxi.

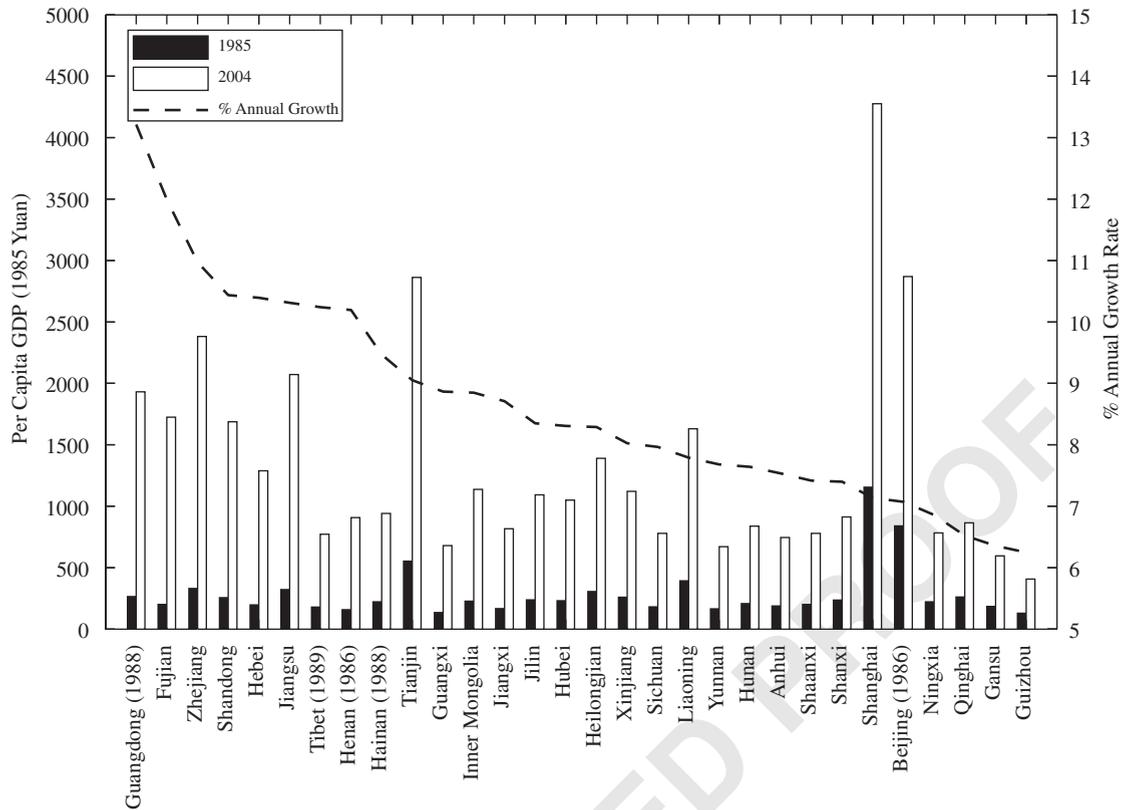


Fig. 2. Provincial per capita income (in 1985 Yuan) and annual growth over sample period.

available year. Provinces with higher PWGE tend also to be the provinces with higher income per capita, which are the coastal provinces. Fig. 1 also depicts 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's end. Fig. 2 displays per capita income for 1985 and 2004, with provinces ordered by annual growth rate of per capita income over the 20-year period. Two things to note from the figure are: (a) the very large increases in per capita income over this 20-year period and (b) the substantial differences in the growth rates between provinces. Further there are many changes in the provincial income ranking over the 20-year period (though Shanghai, Beijing and Tianjin are the three wealthiest provinces in both years). China's per capita wealth is now heavily concentrated in the coastal provinces, which contain all of the special economic zones (SEZs).

Population density is calculated as total provincial population divided by total area in square miles.⁸ 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 state statistical bureau in the middle of our sample

⁸Population density in the year 2000 is highly correlated with provincial age structure. It may therefore proxy not only for density and urbanization, but other demographic variables.

prevents us from constructing consistent time series. Further, the lack of consistent population time 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 province-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.

During our sample period, China experienced significant changes in the number and ownership patterns of motor vehicles. Until the late 1990s automobiles were largely owned by state owned enterprises and government officials. More recently the number of personal cars has grown at roughly 20% per year. In Beijing, for example, ownership is roughly 12% of the US average, with traffic congestion approaching US levels. For Shanghai per capita private car ownership is roughly 3% of the US average. In light of these observations, we collected data on the number of privately owned vehicles by province from 1985 until 2004.

We have also constructed time invariant, province specific variables. 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”.⁹

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

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 [25]. 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 (AIC), adjusted R^2 or R^2 , since it punishes the inclusion of additional parameters more heavily [16]. Our most general model is

$$\ln(\text{PWGE}_{it}) = \eta_i + \gamma_t + f(\text{GDP}_{it}) + f(\text{GDP}_{it-1}) + \pi_i \ln(\text{PWGE}_{it-1}) + \varphi_i \ln(\text{PWGE}_{it-2}) + \rho \sum_{j=1}^k w_{ij} \ln(\text{PWGE}_{j,t-1}) + \mathbf{Z}_{it} \boldsymbol{\delta} + \varepsilon_{it}, \quad (3)$$

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 PWGEs; GDP_{it} is per capita gross domestic product in real terms (based on 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 GAM 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 [14]. In order to capture the potentially heterogeneous speed of adjustment in 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. \mathbf{Z}_{it} is a vector of exogenous variables, some of which vary across time and provinces (population density, per capita car ownership rates, fuel mix) and some of 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

⁹The 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.

observables in a model without fixed effects may be beneficial, if these are not correlated with unobservables left in the disturbance.¹⁰

Finally, we allow for spatial dependence in per capita emissions across provinces to see whether adding information on spatial dependence of CO₂ 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 can yield more efficient forecasts.

There are two main factors which may lead to spill-over effects across provinces, which we allow for by including spatial lags. First, the opening of China's economy happened differentially across provinces. The coastal provinces were opened to foreign direct investment earlier, since all of the SEZs 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 [38]. 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 or 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 spill-over effects proxied for by spatial lags.

We base our notion of spatial dependence on the STAR estimator provided by Giacomini and Granger [22], 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. The approach proposed by Giacomini and Granger [22] assumes a known weight matrix. We construct a rook contiguity weight matrix, which is normalized to unity row sums.¹¹ The w_{ij} are the weights given to the previous year's CO₂ 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 , AIC and BIC 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 per-capita emissions. Auffhammer and Steinhauser [5] show that selecting a model using a selection criterion defined over per capita loss only may lead to a "best" model which is suboptimal in terms of out-of-sample forecast performance for aggregate emissions.

Table 1 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. Models (1)–(3) are static benchmark models. Model (1) is the classic EKC [23] specification, which is a quadratic in income with year and province specific fixed effects.¹² 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

¹⁰If one introduces fixed effects and lagged dependent variables then least squares yields biased yet consistent estimates using large T asymptotics [41]. This is appropriate here, since the number of provinces is assumed to be constant.

¹¹We 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.

¹²The 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.

Table 1
Selected estimation results from specification search

Dep. Var: log(PWGE _{<i>t</i>})	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(GDP)	0.361 (0.069)***	0.399 (0.070)***	0.347 (0.072)***	0.065 (0.041)	0.205 (0.026)***	0.157 (0.026)***	
log(GDP) ²	-0.082 (0.017)***	-0.096 (0.017)***	-0.085 (0.019)***	-0.020 (0.010)**	-0.009 (0.010)		
Population density		0.924 (0.305)***			0.106 (0.044)**		
Cars per capita			0.011 (0.025)				
log(PWGE _{<i>t-1</i>})				0.795 (0.026)***	0.607-0.876 ^a	0.820 (0.025)***	0.817 (0.025)***
log(time)					-0.079 (0.019)***	-0.063 (0.016)***	-0.064 (0.017)***
Initial industry comp.					0.834 (0.390)**		
$\sum_{j=1}^k w_{ij} \ln(\text{PWGE}_{j,t-1})$						0.104 (0.034)***	0.118 (0.034)***
Income spline: low							0.147 (0.040)***
Income spline: medium							0.174 (0.028)***
Income spline: high							0.094 (0.041)**
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	0.262	0.261	0.260	0.995	0.984	0.985	0.985
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

^aRange of province specific lag coefficients.

(4) augments the first model by adding a pooled lag of emissions. Unsurprisingly, the fit improves tremendously; indeed the AIC identifies (4) as the preferred model. It also has the lowest RMSFE out of all models considered and an R^2 close to 1.

Models (1)–(4) in Table 1 use time specific fixed effects in order to capture exogenous technological change common across all provinces [42,23]. Time specific fixed effects capture unobservable *in-sample* shocks common to all provinces. However, 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 in-sample fixed effects on time trends or splines and then using these estimated relationships to predict out-of-sample values. Second, 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.

By restricting our attention to models with a common intercept and time trend, we save 48 degrees of freedom. 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

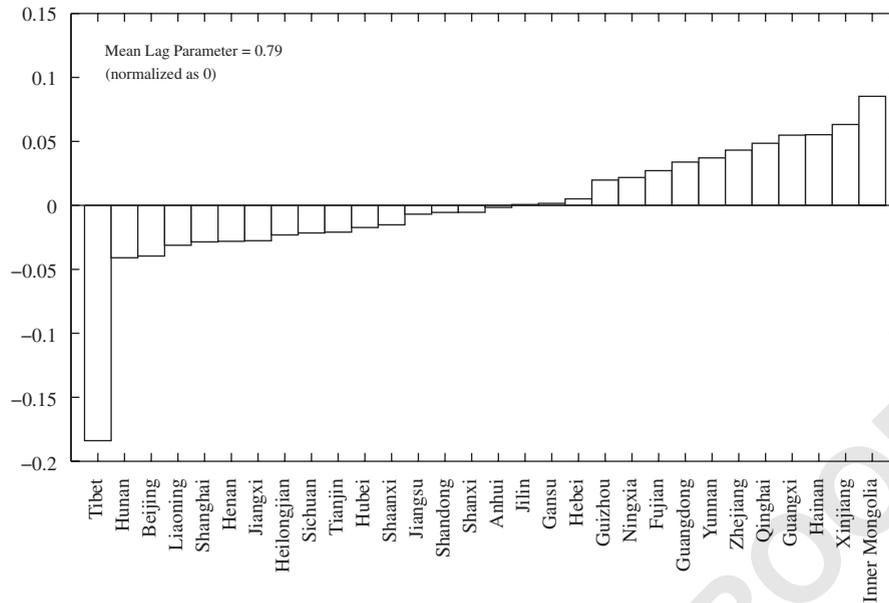


Fig. 3. Lag parameter estimates for model (5) (deviation from mean).

technological changes that reduce carbon intensity. Logarithmic time trends arise naturally from a translog functional form and have frequently been used to proxy for exogenous technological change [7,9]. A logarithmic time trend suggests that the impact of technological change on emissions decreases over time. It is widely believed that technological progress was very rapid in the years following the 1978 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 past 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.

The best model given these restrictions includes province specific lagged emissions, proxying for heterogeneous rates of capital replacement. We denote this as model (5), and display the variation of these lags across provinces in Fig. 3.¹³

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 PWGEs 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.

¹³We 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.

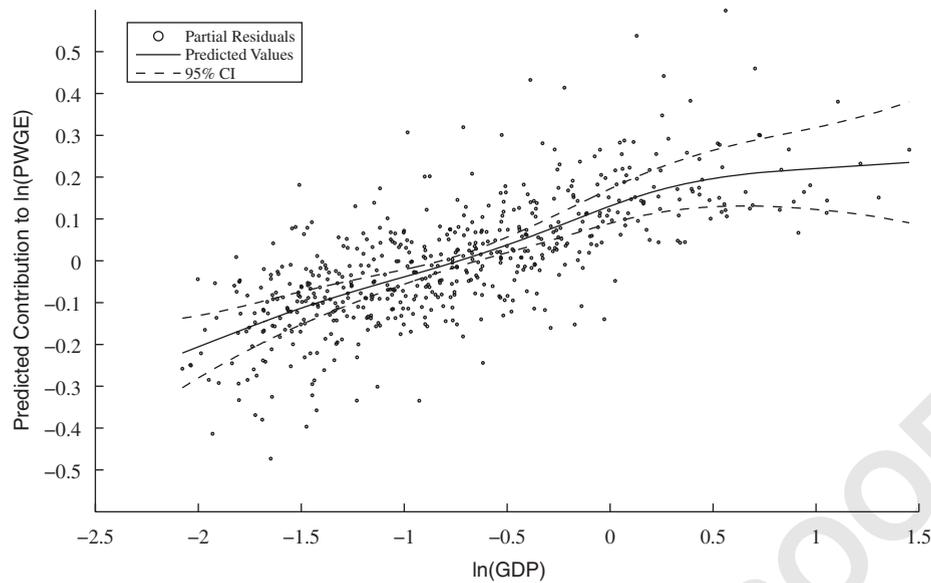


Fig. 4. Waste gas/income functional form—generalized additive model (specification 4).

Model (6) has the lowest BIC. 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 to 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 to 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, we estimate model (4) using the GAM framework [24]. 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 Fig. 4 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 an *ex ante* imposed restrictions. While the depicted shape is not inconsistent with the rising section of an EKC relationship, the highest income provincial entities are far away from a potential turning point level of income. Because the GAM requires a large 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 reject the null of equality at the 1% level. Second, we calculate predicted aggregate WGEs 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 an MSE 43.88% higher than the same model estimated using province-level data, suggesting large gains from disaggregation, which is consistent with the literature (e.g. [36,4,10]).

5. Forecasting CO₂ emissions

In this section we construct forecasts of aggregate Chinese CO₂ emissions. The simulation exercise we conduct in this paper follows the second strand of the literature discussed in Section 2. 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 [42]. While other studies have focused on constructing forecasts to the year 2100 [30] or 2050 [42] we limit our forecasting horizon to 2010. 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 one should predict the fixed effects. We now take each of these issues up in turn.

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 province population growth forecasts through the year 2050 [12]. 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. 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. The aggregate annual growth rates for scenarios A, B, C and D between 2000 and 2010 are 0.91%, 0.40%, 1.03% and 0.51%, respectively. Chesnais and Sun [12] 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.

To illustrate the impact of the range of assumptions typically made concerning Chinese GDP and population growth rates, we consider three GDP and four population growth scenarios to demonstrate the sensitivity of our forecasts to changes in population and GDP growth. The population forecasts are taken from [12]. We assume that the aggregate GDP growth rate (ξ_t) and population growth rate (ϕ_t) are jointly distributed as $f(\xi_t, \phi_t) \sim N_2[\mu_\xi, \mu_\phi, \sigma_\xi^2, \sigma_\phi^2, \rho]$ and that in and out-of-sample population and GDP growth rates can be characterized by this bivariate normal distribution. We calculate ϕ_t for each year from 2005 to 2010 using 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 $\beta = \rho\sigma_\xi\sigma_\phi / \sigma_\phi^2$ 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 use three values for μ_ξ to simulate forecasts for different GDP growth scenarios: 3.02% (low growth), 5.02% (medium growth), and 7.02% (high growth). 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. Given China’s recent explosive growth these scenarios are likely still conservative, yet consistent with the IPCC SRES [30].

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 [28] set the time fixed effect equal to the last in-sample year, while Schmalensee et al. [42] 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

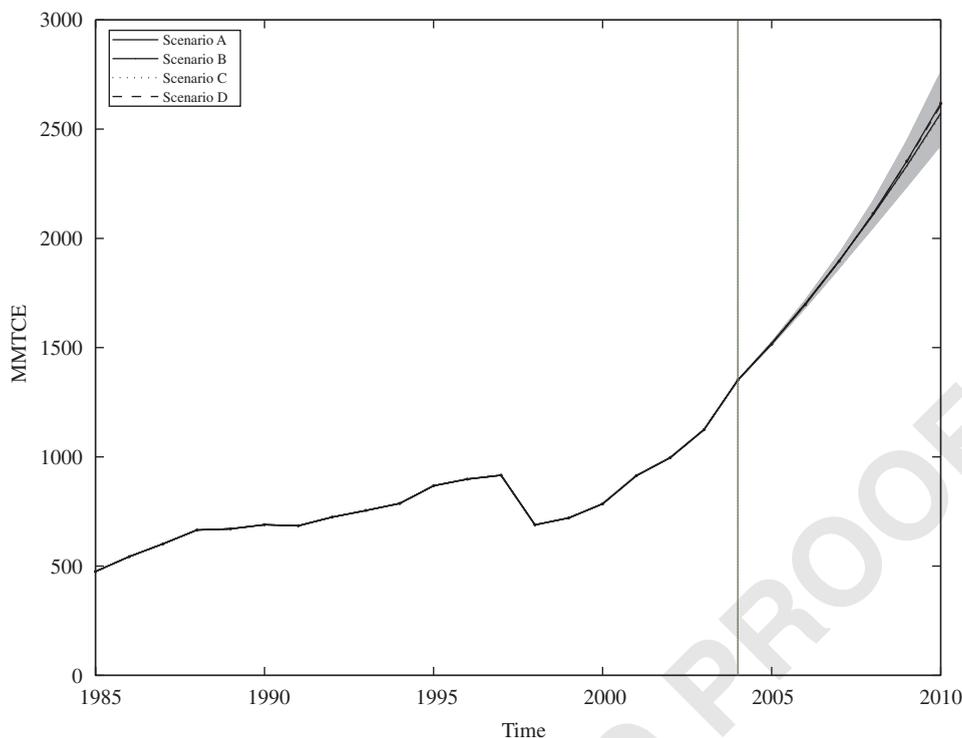


Fig. 5. Aggregate forecasts of China's CO₂ emissions—model (4).

sample. We estimate a model, which allows for a breaking point in the time trend:

$$\gamma_t = \alpha_0^{<B} + \alpha_1^{\geq B} + \alpha_2 \cdot t^{<B} + \alpha_3 \cdot t^{\geq B} \quad (4)$$

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. Allowing the breaking point to be any year between 1992 and 1998, we 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 scenarios. Fig. 5 displays aggregate forecasts of Chinese CO₂ emissions based on model (4), the dynamic EKC specification, and Fig. 6 those for model (7), which is the spatial lag income spline specification.¹⁴ 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.¹⁵ Further, since we assume imperfect correlation between the aggregate population growth rate and aggregate GDP growth rate, we allocate a little bit less GDP to a much smaller number of people for a given GDP growth scenario,

¹⁴The discontinuous drop in the CO₂ emission series is not being driven by reported WGEs, but by the change in the waste gas to CO₂ conversion formula, as shown in Eq. (2).

¹⁵If one considers forecasts over a longer horizon, such as in [3], population is the dominant influence over the emission trajectory.

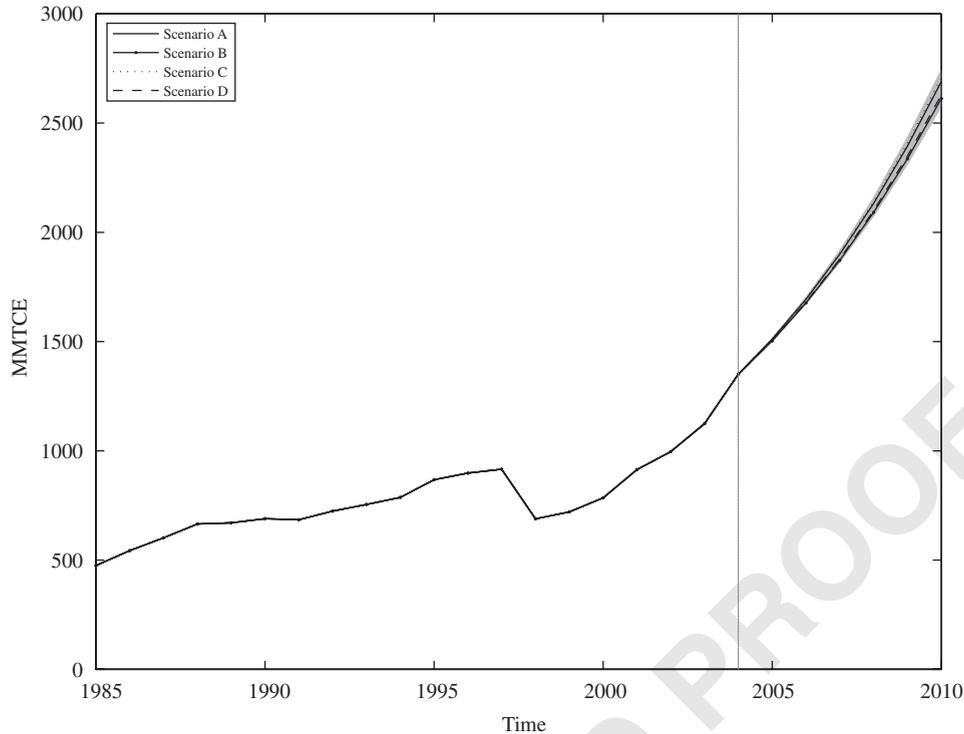


Fig. 6. Aggregate forecasts of China's CO₂ emissions—model (7).

contributing to the similarity of forecasts across population scenarios.¹⁶ 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.¹⁷

Fig. 7 displays the forecasts using model (6), which is linear in income and contains temporal and spatial lags of emissions. Fig. 8 displays the forecasts from the static EKC 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 MMTCE, 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 also have higher initial per capita WGEs. A static EKC model 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 that causes

¹⁶We constructed forecast scenarios assuming a per capita GDP growth rate, which drives the point forecasts slightly apart, but does not change the picture significantly.

¹⁷It should be noted that the turning points have large confidence intervals, since their distribution is fat tailed.

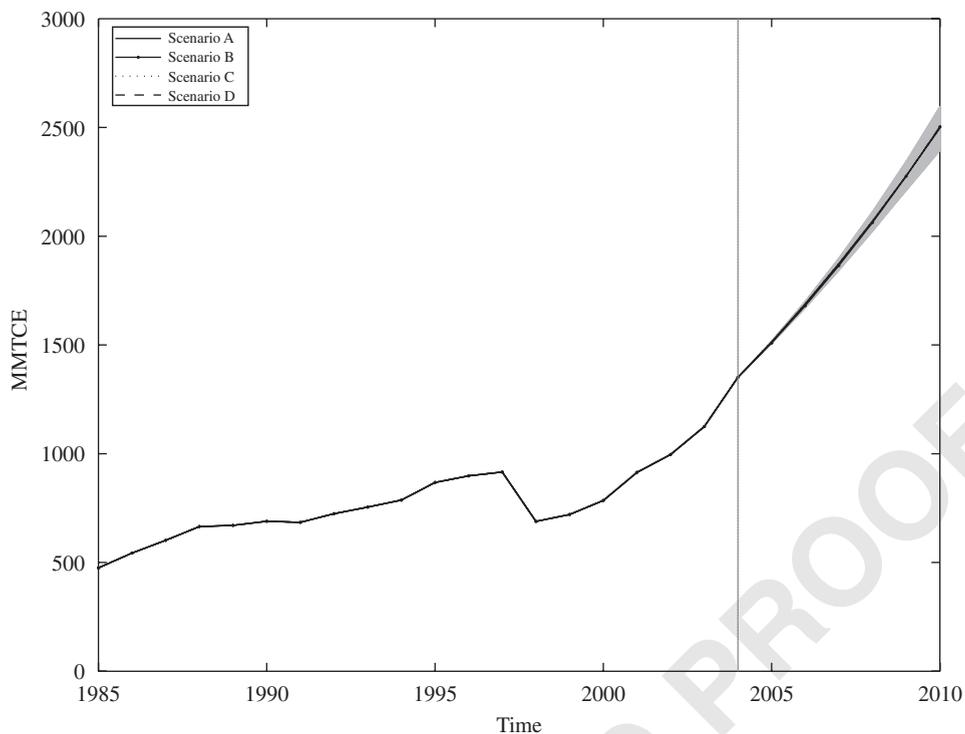


Fig. 7. Aggregate forecasts of China's CO₂ emissions—model (6).

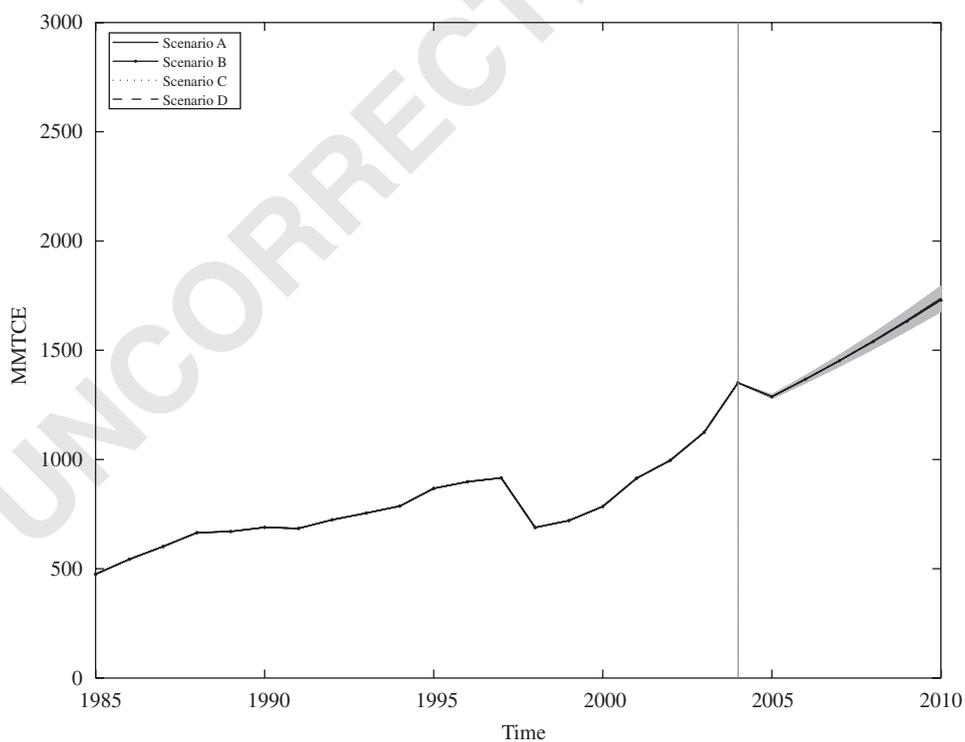


Fig. 8. Aggregate forecasts of China's CO₂ emissions—model (1).

Table 2
Forecasts of aggregate year 2010 CO₂ 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 drop in per capita emissions.¹⁸ This is similar to a [29] partial adjustment model of energy demand, where provinces with a given level of income have a desired level of energy consumption (or, as in our case, WGEs). 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 the 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.

To check the robustness of our results to the sample period, we estimate each forecasting model using the sample ending in 1999, 2000, 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 2 shows the predicted emissions for the year 2010 for all seven considered models and the six different information sets. Two points emerge. First, the rankings of models persist across forecasting horizons. 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). 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 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 geared towards reducing the carbon intensity of China's economy present a unique opportunity to deviate from the high growth emissions path presented here.

The projections of CO₂ emissions from this study are subject to a great deal of uncertainty, as are any economic forecasts over a 10 year horizon. In Table 3 we compare our forecasts to the experienced in-sample growth and forecasts from three most recent studies projecting China's CO₂ emissions into the future.

There are a large number of studies forecasting China's CO₂ emissions, yet most of them are based on data from almost a decade ago [50,31]. Since then, China's economic and technological growth has accelerated beyond anticipation. The 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 forecasts in [50] provide an even lower range of growth. The three most recent studies are [18,19,32]. 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 study in [19], Table 3 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 [32] use the Integrated Policy

¹⁸While 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.

Table 3
Historical and 2010 projected emissions growth rates

	Time begin	Horizon end	Annual growth rate (%)
Marland et al. [37]	2000	2003	14.40
This study ^a	2000	2004	14.53
This study ^a	1995	2004	9.50
This study ^c	2000	2010	11.05–11.88
Yang and Schneider [50]	2000	2025	1.93–3.10
IPCC [30] ^b	2000	2010	2.58–4.82
ERI [18]	2000	2010	4.18
Fridley [19]	2000	2010	5.00–5.02
Jiang and Hu [32]	2000	2010	4.12

^aBased on our WGE measure, which is almost identical to Marland et al. [37].

^bThe figures reported here are taken from the illustrative marker/scenarios from SRES. These include A1B, A2, B1, B2, A1FI and A1T. We report growth rates for the region ASIA.

^cThe range provided here uses models (4), (6) and (7).

Assessment Model for China (IPAC) to arrive at predictions. We cite the baseline scenario, which assumes no explicit policy intervention.

Table 3 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. Assuming an 11% growth rate of GDP, these forecasts imply an aggregate emissions elasticity with respect to income slightly above unity (1.03–1.11). The forecasts from the alternative studies are closest to those from model (1), 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 emission reductions by the year 2010 from current Annex I countries that have ratified the Kyoto protocol, relative to the predicted level in the absence of the agreement, amount to 115.90 million metric tons of carbon [49]. 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.

6. Conclusion

At the end of the last century, it was conceivable that China's CO₂ per capita emissions growth rates were slowing down, suggesting a moderate growth emissions trajectory as income in China increased. Our paper suggests, that over the next 10 years such a downturn is highly unlikely unless there are substantial changes in China's energy policies. In addition, our results clearly reject the static EKC 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 forecast of Chinese CO₂ emissions. To put the size of the increase in emissions in sharp perspective, it is significantly larger than the decrease in emissions embodied in the Kyoto protocol.

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 to 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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