Is China on Track to Comply with Its 2020 Copenhagen Carbon Intensity Commitment?*

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April 22, 2014

Abstract

In the 2009 Copenhagen Accord, China agreed to slash its carbon intensity (carbon dioxide emissions/GDP) by 40% to 45% from the 2005 level by 2020. We assess whether China can achieve the target under the business-as-usual scenario by forecasting its emissions from energy consumption. Our preferred model shows that China's carbon intensity is projected to decline by only 33%. The results imply that China needs additional mitigation effort to comply with the Copenhagen commitment. In addition, China's baseline emissions are projected to increase by 56% in the next decade (2011-2020). The emission growth is more than triple the emission reductions that the European Union and the United States have committed to in the same period.

Keywords: climate change, carbon dioxide emissions, China, spatial econometrics.

JEL Classification Numbers: Q43, Q54, C53.

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*This study is supported by the China Natural Science Foundation (No. 71273153) and China National Key Technology R&D Program (No. 2012BAC20B04). We thank Richard Carson, Patrick Chester, Tamara Lynn Sheldon, Stephen Morris and Marty Smith for helpful suggestions. We also benefited from the comments and suggestions from the seminar discussants and participants at Tsinghua University, UC San Diego, PACE Conference, and International Conference on Energy. Of course, all remaining errors are ours.

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1 Introduction

China faces two crucial challenges in tackling climate change. On the one hand, China is one of the most vulnerable countries to the risks of climate change (IPCC, 2007). On the other hand, China is the world's largest emitter of carbon dioxide (CO_2) and it will continue to be the major driving force of global emissions in the future (IEA, 2012; EIA, 2013). In response to the domestic and international pressures on climate change, China has committed to a 40% to 45% reduction target in carbon intensity, defined as CO_2 emissions per unit of GDP, by 2020 relative to its 2005 level. The pledge has been incorporated into the 2009 Copenhagen Accord.[1] Although the Copenhagen commitment is not legally binding like the Kyoto Protocol, China has started a series of measures to limit its carbon dioxide emissions. In particular, the Chinese government set targets to reduce both carbon intensity and energy intensity in its 12th Five-Year Plan (FYP 2011-2015).

Intensity-based targets index emissions with economic activities (Newell and Pizer, 2008). An appropriately designed intensity target can decelerate, stop, or even reverse total emission growth. Compared with absolute emission limits, intensity targets can better accommodate growth needs without placing caps on economic activities (Pizer, 2005). China's carbon intensity has been declining rapidly over decades, which explains why it favors an intensity target. The central policy question is whether China's Copenhagen commitment can accelerate this natural decline (Qiu, 2009). If the intensity target is too loose, China can achieve its target under the business-as-usual (BAU) scenario. Otherwise, compliance requires additional mitigation effort.

In order to determine whether China's Copenhagen commitment is additional,[2] we need to forecast its emission trajectory under the baseline scenario. The knowledge of an emission baseline is essential to assess the additional mitigation effort required for compliance. Furthermore, emission forecasting also provides information necessary to the formation and implementation of a meaningful international climate treaty. China's engagement in climate mitigation hinges on its expected emission trajectory. Over-estimated BAU emissions will exaggerate the abatement target and discourage China from joining in a climate treaty. On the contrary, if BAU emissions are

[1]Source: https://unfccc.int/meetings/copenhagen_dec_2009/items/5262.php.

[2]In the context of climate change, additionality is referred to as the mitigation effort that would not have occurred in the absence of an climate program. Additionality is a major concern in the design of the baseline-and-credit program such as the Clean Development Mechanism, a project-based carbon market created by the Kyoto Protocol (Zhang and Wang, 2011).

under-estimated, China might commit to an overly ambitious target and its compliance will be in question.

China's compliance with the Copenhagen commitment hinges on its provinces' performance on carbon intensity. To the best of our knowledge, there has not been an assessment whether Chinese provinces can achieve their carbon intensity targets. To close the gap in the literature, we use reduced-form econometric models to forecast emission intensities at the provincial level. The advantages of the reduced-form approach includes a smaller data requirement, fewer structural assumptions, transparent comparisons between models, and measurable uncertainties.

Our paper is motivated not only by the emerging policy question whether China's carbon intensity target is binding, but also by the growing economics literature on carbon dioxide emission forecasting (Holtz-Eakin and Selden, 1995; Schmalensee, Stoker, and Judson, 1998; Auffhammer and Carson, 2008; Auffhammer and Steinhauser, 2012). In particular, our paper extends the influential forecasting analysis of China's CO_2 emissions by Auffhammer and Carson (2008). We contribute to the existing literature by a novel synthesis of the recent development in spatial econometrics, data generation by the engineering approach, and setting policy scenarios from government documents. First, we forecast provincial emissions by exploiting a large set of spatial econometric models to explicitly account for spatial-temporal dynamics of CO_2 emissions. Including spatial spillover effects significantly improves forecasting performance especially for a long horizon.

Second, due to the lack of official CO_2 emissions data at the provincial level, we calculate the emissions from the detailed energy consumption data that include 17 types of fossil fuels. Following the guidelines by the Intergovernmental Panel on Climate Change (IPCC, 2006), we have constructed a balanced panel data set of provincial CO_2 emissions from 1985 to 2011. A forecast for a large area such as a currency union or country may be constructed by first obtaining estimates for units at a spatially disaggregated level and then aggregating them to obtain an estimate of the desired total quantity often results in a higher quality forecast than direct estimation of the desired total (Marcellino, Stock, and Watson, 2003; Carson, Cenesizoglu, and Parker, 2011). This is particular true when the units at the disaggregated level exhibit some parameter heterogeneity. The use of provincial information also allows for emission forecasting for each individual province. Furthermore, the data allow us to forecast energy consumption directly, which is used as a robustness check.

Third, we utilize a rich set of policy information in the national and provincial 12th Five-Year Plans (FYPs) for emission forecasting. Provincial socioeconomic planning is closely linked to regional economic and energy consumption trajectories (Huang and He, 2011; Liu et al., 2013). Understanding the governmental development plans enables us to construct realistic BAU scenarios instead of using arbitrary assumptions.

Using the above empirical strategy, we forecast China's carbon intensity in 2020 to be 32.8% below the 2005 level. It implies that China would be short of the 40%-45% Copenhagen target under the BAU scenario. Most provinces are unlikely to achieve the intensity targets without additional mitigation efforts. Only five provinces are likely to meet their targets in the 12th FYPs and only nine provinces are likely to accomplish the Copenhagen commitment. In particular, the less developed central and western provinces will miss the targets significantly, partly reflecting their fast paced industrialization. Nonetheless, caution is needed to interpret the provincial-level results because the point forecasts of some provinces are associated with relatively large uncertainties.

Furthermore, we forecast China's baseline CO_2 emissions to increase by 56.2% from 2011 to 2020. The emission increase is about 3 to 3.7 times of the total committed emission reductions from the European Union and the United States in the same period. In comparison, both the International Energy Agency (IEA) and the U.S. Energy Information Administration (EIA) reported much lower emission forecasts. The emission growth rate predicted by IEA (2012) is only about half of what we predict, despite its relatively optimistic assumption of GDP growth. IEA assumes that China can reduce carbon intensity by 17% during the 12th FYP period while our forecast 8.8% is only about half of that estimate. Although EIA (2013)'s forecast is the highest among the existing studies, it is still 2.1 billion metric tons lower than our forecast for 2020. This gap is about twice of Japan's energy-related CO_2 emissions in 2011. EIA forecasts the annual emission growth rate between 2010 and 2020 to be only 3.9%. However, the actual annual growth rate in 2011 was 9.0%. Therefore, both IEA and EIA appear to be too optimistic about China's future emission growth.

The remainder of the paper is arranged as follows. Section 2 illustrates the background. Section 3 describes the data, variables, and scenario. Section 4 explains the model specification, estimation, forecasting, and selection. Section 5 presents the estimation results and section 6 the forecast results. Section 7 gives further discussion, and section 8 concludes.

2 Background

China's soaring greenhouse gas (GHG) emissions over the last decade have contributed to 65% of the world's emission growth. As early as 2007, China overtook the United States to become the world's largest emitter. In 2010, its carbon dioxide (CO_2) emissions from burning fossil fuels accounted for about a quarter of global emissions. China's once low per-capita emissions have exceeded the average European levels recently.[3] With further economic development that heavily relies on energy use, China's CO_2 emissions will keep rising at a fast pace. The International Energy Agency (IEA) and the U.S. Energy Information Administration (EIA) predict that China will continue to be the fastest-growing major emitter from 2010 to 2020, contributing to between 49% and 69% of the global CO_2 emissions increase (IEA, 2012; EIA, 2013). Even worse, the emission increase is associated with the expansion of coal-fired power plants, which tend to be long lived. Without significant shifts in the current energy consumption pattern, China can be locked in to carbon-intensive infrastructure for decades.

To address the dual challenges of climate change risks and international pressures on mitigation, China has made energy conservation and low-carbon development key national strategies. Most notably, its 11th Five Year Plan (2006-2010) set a binding target of 20% reduction in energy intensity. Since then, energy intensity has been steadily declining, reversing the rising trend in the early 2000s. In the 12th Five Year Plan (2011-2015), China sets a 17% carbon intensity reduction target in addition to a 16% energy intensity reduction target to ensure China's compliance with the Copenhagen commitment to reduce carbon intensity by 40%-45% below the 2005 level by 2020.

Provinces are required to achieve differentiated targets in both energy and carbon intensities. In the 12th Five Year Plan, the carbon intensity reduction target varies from 10% to 19% based on the stage of economic development for each province and the negotiations between the central and provincial governments.[4] Because the regional allocation of reduction targets is not tied to the baseline emission scenarios, the mitigation burden may be neither efficiently nor equitably distributed across provinces. Some provinces are likely to achieve the targets in the BAU scenario while other provinces will need significant mitigation efforts.

Nearly half of China's CO_2 emissions are from the "six most energy-intensive industries" in the

[3] All numbers are based on the statistics from the U.S. Energy Information Administration.

[4] Issued by the State Council of China, available at: www.gov.cn/zwgk/2012-01/13/content_2043645.htm.

secondary industry.[5] These industries were extensively regulated in order to achieve the energy intensity target in the 11th FYP. The regulatory policies include shutdown of inefficient small plants and even blackouts to limit electricity usage . With the ending of the 11th FYP, however, the output value share of the "six most energy-intensive industries" in the secondary industry rebounded by 1% from 2010 to 2011, almost offsetting the decline in the 11th FYP. As a result, the annual rate of decline in national carbon intensity slowed down from -4.1% in 2010 to -0.4% in 2011.[6] Similarly, for provinces, the declining trend of carbon intensities before 2010 slowed down or even reversed in 2011 (Figure 1). In particular, the output value share of the six most energy intensive industries in the secondary industry increased the most in Qinghai, Hainan, and Ningxia provinces (4.1%, 3.2%, and 2.3%) from 2010 to 2011. Correspondingly, their carbon intensities increased by 24.1%, 9.2%, and 6.3% respectively. Therefore, strong and continuous growth of energy intensive sectors will serve as a serious impediment to curbing China's CO_2 emissions.

Although China's central government is promoting the so-called low-carbon development policy, it is facing great challenges from the sub-national level. Many provincial governments still put the highest priority on GDP growth and lack incentives to control the fast expansion of energy intensive sectors. To boost economic growth, some less developed inland provinces even provide preferential policies to attract pollution- and energy-intensive industries transferred from developed coastal provinces. Under the national strategy to stimulate economic growth in central and western China, these provinces may become the carbon hotspots of the future.[7]

3 Data and Variables

3.1 Data

We use provincial data to forecast China's CO_2 emissions, not only because using disaggregated data can increase forecasting efficiency (Marcellino, Stock, and Watson, 2003), but also because

[5] The six most energy-intensive industries are: (1) processing of petroleum, coking, processing of nuclear fuel, (2) manufacture of raw chemical materials and chemical products, (3) manufacture of non-metallic mineral products, (4) smelting and pressing of ferrous metals, (5) smelting and pressing of non-ferrous metals, and (6) production and supply of electric power and heat power. This definition adapts from China's statistic bulletin of 2013, available at: www.stats.gov.cn/tjgb/ndtjgb/qgndtjgb/t20130221_402874525.htm.

[6] This is calculated from provincial statistics, which means the national GDP and emissions are computed as the sum of provincial figures. If using national statistics, the two numbers are -5.5% and -0.2%.

[7] China launched the "Western Development Strategy" and "Rise of Central China Plan" to accelerate the development of central and western China.

sub-national emission forecasting is relatively less studied. Since China's CO_2 emission inventory for provinces is not available, we calculate carbon emissions from energy consumption and carbon emission factors following the IPCC guidelines (IPCC, 2006). In calculating emissions at the sub-national level, inter-regional power transmission leads to the question whether the emissions associated with the transmitted power should be ascribed to production or consumption side. No official guidelines are available on this issue. To avoid inconsistency between consumption level and emissions, we ascribe the CO_2 emitted from the transmitted power across provinces to the consumption side (Huang and He, 2011; Liu et al., 2013).

The provincial CO_2 emissions data used in this paper cover the years from 1985 to 2011. The data are computed from two sources. The first source is the *China Energy Statistical Yearbooks* that provide energy balance sheets for provinces in 1985 and from 1995 to 2011. The energy balance sheets contain detailed consumption data on 17 types of fossil fuels, heat, and electricity, as well as the energy mix for generating heat and electricity in each province. These statistics enable us to compute the consumption side CO_2 emissions for provinces (see Appendix A for more details). However, the *China Energy Statistical Yearbooks* do not publish energy balance sheets for provinces from 1986 to 1994. In addition, the energy balance sheets for Ningxia from 2000 to 2002 and for Hainan in 1985 and 2002 are missing. The energy balance sheets for Sichuan province in 1985, 1995, and 1996 cannot be used, because Chongqing was still a part of Sichuan then and became a municipal city since 1997.

We use provincial statistical yearbooks as a supplemental data source. The provincial statistical yearbooks provide annual energy consumption data by types: coal, coke, crude oil, gasoline, kerosene, diesel oil, natural gas, heat, electricity, etc. To compute CO_2 emissions from energy consumption, we need to compute CO_2 emission factors per unit heat and electricity for provinces in 1985 and from 1995 to 2011, whenever the provincial energy balance sheets are available. To deal with the challenge of missing data, we interpolate the missing emission factors using the average emission factors in the year just before and after the missing period (see Appendix A for more details). By this means, we can impute most of the missing data in the first data source. However, ten data points are still missing because the corresponding final energy consumption data by fuel type are not provided in the provincial statistical yearbooks.[8] The ten missing data points are

[8]The ten data points are Shanghai from 1986 to 1988, Anhui from 1986 to 1989, Hunan in 1986, and Guizhou from

imputed using cubic spline interpolation. Finally, we have a balanced panel data set of provincial CO_2 emissions from 1985 to 2011.

Since we have to make assumptions in calculating provincial emissions whenever the energy balance sheets are not available, we conduct a robustness check by using the provincial energy consumption data from 1985 to 2011 to forecast energy consumption directly. The *China Energy Statistical Yearbooks* provide aggregate energy consumption data at the provincial level from 1985 to 1990 and 1995 to 2011. For the year from 1991 to 1994, the aggregate energy consumption data of provinces are obtained from the provincial statistical yearbooks. Therefore we have a balanced panel data set of provincial energy consumption from 1985 to 2011.

3.2 Key Variables

Most literature uses per-capita emissions (emissions/population) as the dependent variable (see Holtz-Eakin and Selden (1995) and Schmalensee, Stoker, and Judson (1998)). The intensity form dependent variable (emissions/GDP) is also widely used in the literature on economy-emission-energy nexus (Cole, Elliott, and Shimamoto, 2005; Fisher-Vanden et al., 2004). Considering that China's national and provincial emission targets are intensity based, we use carbon intensity as the dependent variable in forecasting.

Many variables can be used to explain the relationship between economy and emissions. We use per-capita GDP (*Inc*) as a general indicator of economic development status. GDP is in 2005 constant values. We also include additional variables to increase explanatory power for the emission dynamics. The ratio of the secondary industry in GDP (*Ind*) is used to account for the structural effect. Rapid urbanization in China also greatly changes the energy use in production and consumption (Dhakal, 2009). Because the data on urban population are not available for the whole period from 1985 to 2011, we use population density (*Popden*) as a proxy. The rapid increase of car ownership in China since 2000 has contributed to the fast growing transport energy demand (He et al., 2005). We use passenger cars per capita (*Car*) to capture the effect of car ownership on China's energy consumption and emissions. The data on these variables are compiled from various editions of the *China Statistical Yearbooks* from 1986 to 2012 and the *China Compendium of Statistics 1949-2008*. Due to data availability, 30 provinces and municipalities except Tibet are included

1986 to 1987.

in our study. Because Tibet only accounts for 0.05% of total national electricity consumption and 0.1% of national GDP, we expect the exclusion of Tibet will not cause a major problem.

4 Model

Two strains of literature exist for emission modeling and forecasting. The first category employs calibrated structural models to simulate future emissions. Examples include bottom-up models in the engineering literature (IPCC, 2000; EIA, 2013) and computable general equilibrium (CGE) models in the economics literature (Jorgenson and Wilcoxen, 1993; Garbaccio, Ho, and Jorgenson, 1999).[9] However, the performance of a structural model depends on the credibility of the structural assumptions and the availability of a large set of parameters estimated in model or taken from elsewhere. It has been argued by some researchers that the IPCC might have underestimated anthropogenic emissions by using overly optimistic assumptions in technology (Pielke, Wigley, and Green, 2008).[10]

The second category is the reduced-form econometric modeling, which requires less data and makes fewer structural assumptions. Formal model comparison in a statistical sense is possible for the reduced-form approach because longer time-series data can be used. In addition, the uncertainties for the point estimates of parameters can be measured through the regression on historical data. In contrast, parameter uncertainty is difficult to assess in the structural modeling approach, in which parameters are fixed by calibration or subjective judgment (Manne and Richels, 1994). For these reasons, we adopt reduced-form models to examine the regional heterogeneity in forecasting China's emissions.

4.1 Specifications

Provincial carbon dioxide emissions exhibit spatial dependence, which arises as a result of technology diffusion and environmental policy spillovers. On the one hand, technology can diffuse across regions through inter-regional connections such as trade (Keller, 2004). Then the related techno-

[9] Most notably, the IPCC has developed large-scale structural models to produce global emission scenarios over a long horizon. These emission scenarios are then used as inputs for the global climate model.

[10] Evidently, the global CO_2 emissions since 2000 followed the upper bounds of the IPCC baseline scenarios even after the 2008 financial crisis (Raupach et al., 2007; Peters et al., 2012, 2013).

logical progress is possible to facilitate improvement in local emissions. On the other hand, local governments may imitate neighbour's environmental policies, which leads to similar emission levels (Fredriksson and Millimet, 2002). As is shown by Giacomini and Granger (2004), ignoring spatial correlation, even when it is weak, leads to highly inaccurate forecasts. In the forecasting literature, several studies have illustrated that spatial panel data models can improve forecasting performance (Girardin and Kholodilin, 2011; Baltagi and Li, 2006; Longhi and Nijkamp, 2007).

However, the application of explicit spatial models in emission forecasting is still limited with the most noted exception by Auffhammer and Carson (2008). Nonetheless, the spillover effects in their study were constrained to be with a temporal lag, rather than the contemporaneous spatial spillover effects that are usually modeled in spatial econometrics (Anselin, Gallo, and Jayet, 2008). Therefore, we account for the two types of spatial dependence in emissions by including a one-period lag spatial spillover term or a contemporaneous spatial spillover term. In addition, we allow for differences in spillover effects between different groups of provinces.

The baseline specification is a dynamic panel data model such that:

$$\ln c_{i,t} = \rho \ln c_{i,t-1} + \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \lambda t + \alpha_i + \epsilon_{i,t}. \tag{1}$$

In this form, $c_{i,t}$ is carbon intensity, $\boldsymbol{x}_{i,t}$ is a vector of additional explanatory variables (including *Inc*, *Ind*, *Popden*, *Car*), t is a trend variable represented by the linear time trend (T) or the logarithm time trend ($\ln T$), α_i is a provincial fixed effect, and $\epsilon_{i,t}$ is an error term. Early reduced-form models use environmental Kuznets curve to forecast CO_2 emissions (Holtz-Eakin and Selden, 1995; Schmalensee, Stoker, and Judson, 1998). Recent studies find that the dynamic models are superior in terms of forecasting performance (Auffhammer and Carson, 2008; Auffhammer and Steinhauser, 2012). Therefore, we also adopt the dynamic model specification.

In spatial econometrics, the spillover effects can be modeled by a spatial lag term, i.e., a weighted average of neighbors' dependent variables, or a spatial error term, i.e., errors with spatially correlated covariance structure. The spatial error term does not explicitly capture the spatial interaction, but, instead, is a special case of a non-spherical error covariance matrix (Anselin, Gallo, and Jayet, 2008). For this reason, we only include the spatial lag.

The spatial dependence is modeled by an $N \times N$ spatial matrix W, where N is the number of provinces. The i,j-th element of W, $w_{i,j}$, is the weight given to region i's neighbor j. We employ two spatial matrices: the rook contiguity weight matrix and the inverse distance matrix (Getis, 2010). In rook contiguity weight matrix, $w_{i,j}$ equals one if provinces i and j are neighbors and zero otherwise. In inverse distance matrix, $w_{i,j}$ is the inverse of distance between the two provinces. In both matrices, $w_{i,j}$, which is the weight of province i on itself, is set to zero. The spatial weight matrices are row standardized such that each row sum up to 1.

Starting from the baseline model, we first include the one-period lagged spatial spillover effects, which is the same spatial model used by Auffhammer and Carson (2008). This model is labeled as S_{lag}:

$$\ln c_{i,t} = \rho \ln c_{i,t-1} + \gamma \sum_{j \neq i} w_{i,j} \ln c_{j,t-1} + \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \lambda t + \alpha_i + \epsilon_{i,t}. \tag{2}$$

In addition, we allow for group-specific spillover effects between eastern provinces and inland provinces, because eastern provinces are more developed and technologically advanced.[11] The trend variable t is also allowed to be different between the two groups of provinces. This model is labeled as S_{lag-g}:

$$\ln c_{i,t} = \rho \ln c_{i,t-1} + \sum_{g=1}^{2} \sum_{j \neq i} \gamma^g w^g_{i,j} \ln c_{j,t-1} + \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \sum_{g=1}^{2} \lambda^g t^g + \alpha_i + \epsilon_{i,t}. \tag{3}$$

In this form, g indexes province (1 for eastern provinces and 2 for inland provinces); $w^g_{i,j}$ is an element of the group-specific spatial weight matrix W^g, which is the product of the spatial weight matrix W and a dummy variable indicating whether province i belongs to group g; t^g is a group-specific trend, which equals T or $\ln T$ if province i belongs to group g and zero otherwise.

We also consider a specification with contemporaneous spatial spillover effects, which is labeled as S_{con}:

$$\ln c_{i,t} = \rho \ln c_{i,t-1} + \varphi \sum_{j \neq i} w_{i,j} \ln c_{j,t} + \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \lambda t + \alpha_i + \epsilon_{i,t}. \tag{4}$$

Moreover, we introduce the group-specific spillover effects in model S_{con}, and derive the model

[11] Eastern provinces include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Inland provinces include the rest 19 provinces.

that is labeled as S_{con-g}:

$$\ln c_{i,t} = \rho \ln c_{i,t-1} + \sum_{g=1}^{2} \sum_{j \neq i} \varphi^g w_{i,j}^g \ln c_{j,t} + \boldsymbol{x}'_{i,t} \boldsymbol{\beta} + \sum_{g=1}^{2} \lambda^g t^g + \alpha_i + \epsilon_{i,t}. \tag{5}$$

For the dynamic panel model in Equation (1) to be stable, the requirement is that $|\rho| < 1$. Similarly, according to Yu, de Jong, and Lee (2008), for spatial dynamic panel models in Equations (2) and (4) to be stable, the requirements are that $|\rho|+|\gamma| < 1$ and $|\rho|+|\varphi| < 1$, respectively.

4.2 Estimation and Forecasting

In dynamic panel data models, the lagged dependent variable is an endogenous variable. The contemporaneous spatial spillover term further introduces simultaneity bias. Because our panel data are short, the OLS estimator can be severely biased. Instead, we use the GMM estimator proposed by Arellano and Bond (1991). Taking model S_{con} as an example, the model is estimated in the first-difference form to eliminate provincial fixed effects:

$$\Delta \ln c_{i,t} = \rho \Delta \ln c_{i,t-1} + \varphi \sum_{j \neq i} w_{i,j} \Delta \ln c_{j,t} + \Delta \boldsymbol{x}'_{i,t} \boldsymbol{\beta} + \lambda \Delta t + \Delta \epsilon_{i,t}. \tag{6}$$

Then lagged dependent variables in levels can be used as instruments. In this case, the GMM estimator is based on the following moment conditions:

$$E(\ln c_{i,t-s} \Delta \epsilon_{i,t}) = 0, \; s \geq 2, \tag{7a}$$

$$E(\sum_{j \neq i} w_{i,j} \ln c_{j,t-s} \Delta \epsilon_{i,t}) = 0, \; s \geq 2, \tag{7b}$$

$$E(\Delta \boldsymbol{x}'_{i,t} \Delta \epsilon_{i,t}) = 0, \text{ and} \tag{7c}$$

$$E(\Delta t \Delta \epsilon_{i,t}) = 0. \tag{7d}$$

We use the one-step GMM estimator with robust standard errors. The maximum lag of instruments is set as six to avoid using too many instruments.

Because the model is estimated in the first-difference form, the forecasting is also carried out in the same manner. With a sample of data up to period T, we first estimate the model with this sample and then make one-step ahead forecasting iteratively to get forecast of $\Delta \ln c_{i,T+1}$, $\Delta \ln c_{i,T+2}, \ldots,$

$\Delta\text{ln}c_{i,T+n}$. Then by adding $\text{ln}c_{i,T}$ with the predicted first differences of this variable, we can get the forecast in levels, i.e., $\text{ln}c_{i,T+1}$, $\text{ln}c_{i,T+2}$, $\ldots$, $\text{ln}c_{i,T+n}$.

It is straightforward to forecast with the baseline model and the spatial model with one-period lagged spatial spillover effects (i.e. S_{lag} and S_{lag-g}). For the spatial model with contemporaneous spatial spillover effects (i.e. S_{con} and S_{con-g}), the forecasting is implemented by the corresponding reduced-form model. Taking S_{con} as an example, the model is estimated in the first-difference form in Equation (6). We rewrite the model for period *T+1* in the following form:

$$\Delta\text{ln}c_{\cdot,T+1} = \rho\Delta\text{ln}c_{\cdot,T} + \varphi W\Delta\text{ln}c_{\cdot,T+1} + \Delta\boldsymbol{x}'_{\cdot,T+1}\boldsymbol{\beta} + \lambda\Delta t + \Delta\epsilon_{\cdot,T+1}. \tag{8}$$

In this form, $\Delta\text{ln}c_{\cdot,T+1}$ is the $N\times 1$ vector representing the dependent variables at period T+1 for N provinces. The reduced form is as follows:

$$\Delta\text{ln}c_{\cdot,T+1} = (I - \varphi W)^{-1}(\rho\Delta\text{ln}c_{\cdot,T} + \Delta\boldsymbol{x}'_{\cdot,T+1}\boldsymbol{\beta} + \lambda\Delta t + \Delta\epsilon_{\cdot,T+1}). \tag{9}$$

Similarly, for the group-specific spillover effects model S_{con-g}, it has the following form for period T+1:

$$\Delta\text{ln}c_{\cdot,T+1} = \rho\Delta\text{ln}c_{\cdot,T} + \varphi^1 W^1\Delta\text{ln}c_{\cdot,T+1} + \varphi^2 W^2\Delta\text{ln}c_{\cdot,T+1} + \Delta\boldsymbol{x}'_{\cdot,T+1}\boldsymbol{\beta} + \sum_{g=1}^{2}\lambda^g\Delta t^g + \Delta\epsilon_{\cdot,T+1}. \tag{10}$$

In this form, superscripts 1 and 2 indicate eastern and inland provinces. W^1 is obtained by replacing rows corresponding to inland provinces in W with zeros. W^2 is obtained by replacing rows corresponding to eastern provinces in W with zeros.

The reduced form of the group-specific spillover effects model S_{con-g} is:

$$\Delta\text{ln}c_{\cdot,T+1} = (1 - \varphi^1 W^1 - \varphi^2 W^2)^{-1}(\rho\Delta\text{ln}c_{\cdot,T} + \Delta\boldsymbol{x}'_{\cdot,T+1}\boldsymbol{\beta} + \sum_{g=1}^{2}\lambda^g\Delta t^g + \Delta\epsilon_{\cdot,T+1}). \tag{11}$$

After obtaining the forecast of $\ln c$, which is the logarithm of carbon intensity, the forecast of carbon intensity can be obtained by taking exponents. Then CO_2 emission forecasts can be obtained by using different scenarios for GDP. While producing point forecasts of emissions are straightforward, it is complicated to derive the standard errors for the spatial models. We use the

Monte Carlo simulation to obtain the standard errors. The coefficients of the above model follow an asymptotic joint normal distribution, and the error term ϵ follows a normal distribution. The expectation and covariance matrix of these distributions are produced by the GMM estimation. By sampling from these distributions, we can simulate the distribution of the forecasted carbon intensity and CO_2 emissions. The standard errors are then computed from the simulated distributions. We conduct 10,000 simulations for each model.

4.3 Model Selection

We would like to compare the forecasting performance of the baseline model and the four types of spatial models described above. Because our goal is to choose a model with the superior out-of-sample predictive ability, we use out-of-sample prediction criterion instead of in-sample criterion (Auffhammer and Steinhauser, 2012). We conduct the one-, two-, up to six-year-ahead out-of-sample prediction experiments for each model. All the out-of-sample prediction experiments use the samples up to year 2000 to conduct the earliest experiments. This means the forecast range is 2001 to 2011 for the one-year-ahead prediction, 2002 to 2011 for the two-year-ahead prediction, and 2006 to 2011 for the six-year-ahead prediction.

The out-of-sample forecast error is based on the aggregate emissions. Model k's root mean squared forecast error (RMSFE) is defined as:

$$RMSFE_k = \frac{1}{t_2 - t_1} \sum_{t=t_1}^{t_2} RMSFE_{k,t} = \frac{1}{t_2 - t_1} \sum_{t=t_1}^{t_2} \sqrt{\frac{1}{30} \sum_{i=1}^{30} (\hat{E}_{k,i,t} - E_{i,t})^2}, \tag{12}$$

where $\hat{E}_{k,i,t}$ is model k's forecast of province i's CO_2 emissions in year t, and $E_{i,t}$ is the actual realization. t_1 to t_2 is the year range for which we calculate the out-of-sample prediction. We denote the model with the lowest RMSFE as the "best forecasting model."

5 Estimation Results

We have five types of models including one baseline and four spatial models. Within each type of model, we can derive a number of variations by selecting different combinations of explanatory variables $\boldsymbol{x}$ and time trend. We denote each variation within a certain type of model as a sub-model. For example, for each type of model, the explanatory variables $\boldsymbol{x}$ can be any combination from the four variables including *Inc*, *Ind*, *Popden*, *Car*, and the trend variable t can be the linear time trend (T), the logarithm time trend (ln$T$) or none. Therefore there are 48 ($= 2^4 \times 3$) sub-models for each type of model and 240 ($= 48 \times 5$) sub-models in total.

We do not present the estimation results for all sub-models here.[12] Our strategy is that, for each type of model, we select the sub-model with the lowest one-year-ahead RMSFE among sub-models within this type of model, or in other words, we are selecting the sub-model representing the best forecasting performance for the corresponding type of model. These selected sub-models are then used to compare the forecasting accuracy of different types of models. In the remainder of the paper, we use the "best forecasting model" to denote the model with the lowest one-year-ahead RMSFE. Later we will show that in most cases these best forecasting models also have the lowest RMSFE when the forecasting horizon gets longer.

The estimation results are summarized in Table 1. We present the estimation results for the selected sub-models representing the best forecasting performance of each type of model. Note that we use two different spatial matrices, i.e., rook contiguity weight matrix and inverse distance matrix. Therefore the results of each type of spatial model take up two columns.

For all specifications in Table 1, the Sargan test and auto-correlation test for error terms suggest that the GMM estimator is valid. The coefficients of the lagged dependent variable are significant in all cases, supporting the dynamic emissions models. The coefficients of spillover effects, no matter contemporaneous or with one-period lag, are significant and positive, suggesting the existence of spillovers in emissions across provinces. Moreover, by considering group-specific spillover effects between eastern and inland provinces, the spatial dependence across the two region groups are different when using the inverse distance matrix, but are close when using the rook contiguity weight matrix. All the selected sub-models contain logarithm time trends with negative and significant coefficients. In three out of four cases with the group-specific time trend, the coefficient of the time trend for eastern provinces is lower than that for the inland provinces, reflecting the fact that eastern provinces have experienced faster declines in carbon intensity than inland provinces. Finally, although we considered four additional explanatory variables, only population density *Popden* is chosen in the selected baseline model.

[12] All sub-model results are available in an online appendix.

The bottom six rows of Table 1 report the results of the out-of-sample forecasting experiment. Compared with the baseline model, it is evident that spatial models improve forecasting significantly. The best forecasting model, i.e. the model with the lowest one-year-ahead RMSFE, is model S_{lag-g} that uses inverse distance weight matrix as shown in column (4). Its one-year-ahead RMSFE is 8.2% lower than that of the baseline model. The improvement becomes more pronounced as the forecasting horizon gets longer: the best model's six-year-ahead RMSFE is 24.6% lower than that of the baseline model.

We use energy intensity as a robustness check. As shown in Table 2, the estimation results of the energy intensity models are very similar with those of the carbon intensity models. The coefficients of the spatial terms are significant in all four types of spatial models. The logarithm time trend is included in the selected sub-models from the four types of spatial models, while the selected baseline model contains linear time trend. The best forecasting model is S_{lag} that uses inverse distance weight matrix as in column (2). The performance of model S_{lag-g} that uses inverse distance weight matrix in column (4) is very close to that of the best model.

To summarize, we have several major findings here. First, accounting for spatial spillover effects improves forecasting and the improvement is more significant as the forecasting horizon gets longer. Second, it is necessary to consider different specifications of spatial effects, e.g. contemporaneous or one-period lag spillover effects, homogeneous or group-specific spillover effects, and different spatial weight matrices. If the spillover effects are restricted to be of certain form *a priori*, it may lead to the selection of a sub-optimal forecasting model.

6 Prediction Results

6.1 Scenarios

We need socioeconomic scenarios to forecast national and provincial CO_2 emissions. However, future GDP, population, and sectoral compositions are associated with large uncertainties at both national and provincial levels. Rather than arbitrarily assuming these variables, we start from the national and provincial 12$^{\text{th}}$ Five-Year Plans to construct the business-as-usual scenario. In China, government plays a tremendous role in socioeconomic development. The targets set in the FYPs are substantially relevant for building scenarios.

Based on the goals in the provincial 12th FYPs, we form the scenarios for provincial GDP and sectoral compositions. These scenarios are summarized in Table A.2 in Appendix B. We would like to highlight the following aspects:

GDP: The national 12th FYP sets the annual GDP growth target at 7%, much lower than the actual growth rates in 2011 and 2012 (9.3% and 7.8%). Therefore we set the national GDP growth rate at 7.5% from 2012 to 2015, and at 7% from 2016 to 2020. However most provinces especially the least developed ones set the goal above 10% in their 12th FYPs, which reflects their strong desire to catch up. The double-digit GDP growth rate may be not sustainable. We downward adjust the goals of provincial GDP growth rates in the 12th FYPs by the same factor to make them consistent with the national growth target. However, with continued slowdown of the Chinese economy, some studies project even more pessimistic growth for China. For example, Eichengreen, Park, and Shin (2012) predict China's GDP to grow by only 6.1% to 7.0% per year from 2011 to 2020. To test the robustness of our result, we consider an additional economic scenario in which the national GDP growth rate is 7.0% per year from 2012 to 2015, and 6.1% per year from 2016 to 2020.

Sectoral compositions: We need the scenario for the share of the secondary industry in GDP Sine variable *Ind* is used. We can get the sectoral compositions scenario from the provincial 12th FYPs. Since the 13th FYP (2016-2020) is not available yet, we further assume the policy goals in the 12th FYP will be continued in the 13th FYP. At the national level, the share of the secondary industry will decrease by 2.3% for each FYP period.

The FYPs do not have population or migration targets. Following the United Nations (2013), we assume that the national population will increase by 0.53% annually from 2011 to 2020. At the provincial level, we first estimate the historical population growth rate from 1978 to 2011 for each province. We adjust the rate by the same factor for the national growth rate and use it as the population growth scenario. For the variable *Car*, we assume that the growth of the number of cars per capita in each province will follow the historical trends.

6.2 National Emissions

We illustrate the national emission forecast in Figure 2 that uses the "best forecasting model" S_{lag-g}. This S_{lag-g} model predicts that China's CO_2 emissions will grow to 14.79 billion metric tons in 2020, an increase of 56.2% from 2011 to 2020. The simulated standard deviation of the predicted emissions is 1.36 billion metric tons. The ± 2 standard deviation interval for the emission growth rate ranges from 27.6% to 84.9%. The predictions of other models in Table 1 (including the S_{lag} model which is used by Auffhammer and Carson (2008)) are close to that of model S_{lag-g}, ranging from 14.65 to 15.05 billion metric tons. The baseline model predicts the national emission to be only 1.2% higher than the best forecasting model. However, at the provincial level, the difference of forecasts between the two models can reach 24%. As shown before, accounting for spatial spillover effects improves predictive ability from the baseline model, therefore we will put more confidence on the best forecasting model.

As shown in Figure 2 (b), the best forecasting model predicts that China's carbon intensity in 2015 will be 2.14 t $CO_2/10^4$ Yuan with the simulated standard deviation being 0.075 t $CO_2/10^4$ Yuan. Accordingly, China's carbon intensity in 2015 will be 8.8% lower than the 2010 level, with the ± 2 standard deviation interval ranging from 2.4% to 15.2%. This implies that China will not be able to reach the 17% reduction target in carbon intensity in the 12th FYP (2011-2015) under the BAU scenario. In 2020, the best forecasting model predicts China's carbon intensity will be 1.95 t $CO_2/10^4$ Yuan with the simulated standard deviation being 0.18 t $CO_2/10^4$ Yuan. In other words, China's carbon intensity in 2020 will be 32.8% lower than the 2005 level, with the ± 2 standard deviation interval being from 20.4% to 45.1% lower. Therefore, under the BAU scenario China is unlikely to fulfill the 40% to 45% reduction target pledged in the Copenhagen Accord.

We use energy intensity as a robustness check to cast as probability of meeting the Copenhagen commitment. The forecasts of energy consumption and energy intensity are illustrated in Figure 3. The best forecasting model predicts that China's energy consumption in 2020 will be 6.57 billion tons of coal equivalent (ce) with the simulated standard deviation being 0.53 billion metric tons of ce. Correspondingly, it projects emissions will increase by 61.7% from 2011 to 2020. The increase is higher than the previous prediction of 56.2% because it largely ignores the change in China's energy mix. The proportion of non-fossil fuel energy (including hydro power, nuclear power, wind power, etc.) in national energy consumption has been improved from 4.9% in 1985 to 8.0% in 2011. Carbon emissions per unit of energy consumption have been declining 0.25% per annum since 1985. Our prediction suggests that the decline will be accelerated to 0.38% annually from 2011 to 2020. Therefore the forecast of energy consumption is actually consistent with our forecast of emissions. The predicted energy intensity in 2020 will be 30.8% lower than the 2005 level, with the ± 2 standard deviation interval being from 19.8% to 41.9%.

Furthermore, if China's economic growth slows down, we would like to assess how it will affect China's carbon emissions. Following Eichengreen, Park, and Shin (2012), we assume a GDP scenario where the national GDP growth rate is 7.0% from 2012 to 2015, and 6.1% from 2016 to 2020. Under this scenario, China's GDP in 2020 is 6.3% lower than that of the previous scenario. Accordingly, the emission forecast by the best forecasting model is 6.5% lower, which suggests that China's emission growth will decelerate almost proportionally with GDP growth.

6.3 Provincial Emissions

An advantage of using the disaggregated data is that it allows for the prediction of provincial BAU emissions, which is of substantial relevance for the sub-national mitigation policy making. We would like to examine whether provinces will be able to achieve the allocated carbon intensity reduction targets under the BAU scenario. In Table 3, we present the forecasted percentage of reduction in carbon intensity using the best forecasting model. We find that during the 12^{th} FYP, only five provinces can reach the allocated targets as suggested by the point forecasts. By 2020, the point forecasts indicate that only nine provinces will be able to reach at least a 40% reduction in carbon intensity relative to the 2005 level, which is the lower bound of the national reduction target in 2020.

The rich eastern provinces are projected to achieve higher carbon intensity targets by 2020 relative to 2005 levels: many provinces can reduce carbon intensity by more than 30% except for Hainan and Fujian. However, many less developed central and western provinces can only lower carbon intensity to less than 30% below 2005 levels by 2020. One possible reason is that the eastern provinces are now accelerating the development of tertiary and high-tech sectors that are less energy intensive. In comparison, the central and western provinces are still in the process of rapid industrialization, creating pressures on their energy and carbon intensities.

7 Further Discussion

7.1 Data Quality

The accuracy of our forecasts relies on national and provincial data quality. However, a large discrepancy in the historical CO_2 emissions data is found between those using the national statistics and those aggregating from the provincial statistics (Guan et al., 2012). We compute China's CO_2 emissions using these two methods, and compare them with the calculations by other institutions including the Energy Information Administration, the International Energy Agency, and the Oak Ridge National Laboratory.[13]

Figure 4 shows that the historical energy-related CO_2 emissions in China differ dramatically among various sources. These estimates are relatively close before 1995. Since then, the CO_2 emissions aggregated from the provincial statistics have been always higher than those from the national statistics. The gap has widened since the year 2005 and reached 1.8 billion metric tons in 2011. The estimated emissions from the other three institutions lie between the two series of emissions calculated in this paper. The Oak Ridge's estimates are close to the numbers based on the national statistics. The EIA's and IEA's estimates are relatively close to the numbers based on the provincial statistics in the last three years.

Guan et al. (2012) have discussed possible reasons of the discrepancy between the national and provincial statistics in depth. Zhao, Nielsen, and McElroy (2012) argue that the provincial statistics are more reliable than the national statistics for three reasons. First, the production of small coal mines may not be well recorded by the national statistics. Second, studies using satellite observations of air pollutants have confirmed that the provincial energy statistics are better proxies for activity levels. Third, the national energy statistics may be deliberately under-reported by China's National Bureau of Statistics and National Development and Reform Commission.

We are convinced that the provincial statistics are more reliable than the national statistics. In addition, these statistics are the only available information for calculating the provincial-level emissions. However, we should be aware of the large uncertainties in quantifying China's CO_2 emissions. Gregg, Andres, and Marland (2008) pointed out that the uncertainty in estimating

[13] EIA's statistics are available at: www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm, IEA's statistics are available at: www.iea.org/statistics, and Oak Ridge's statistics are available at: cdiac.ornl.gov/trends/emis/overview.html.

China's CO_2 emissions could be as high as 15% to 20%. In this situation, when interpreting and comparing our forecasts with other studies, it would be more appropriate to compare the forecasted growth rate rather than the absolute emission level.

7.2 Comparison with Other Forecasts

In comparing forecasts across studies, it is better to compare growth rates in order to avoid the difference in the calculated base year emissions. Table 4 compares our result with the forecasts by several recent studies. The associated assumptions of GDP growth rate are also reported in the table. Our study predicts the annual growth rate of emissions from 2011 to 2020 is 5.1%, which is the highest among the recent forecasts.

The most recent International Energy Outlook (IEO) 2013 forecasts China's CO_2 emissions to grow by 3.9% annually from 2010 to 2020 and to reach 11.53 billion metric tons in 2020 (EIA, 2013). To compare forecasts at the absolute level, we use EIA's calculation of China's emissions in 2011 as the base year emissions. By multiplying the base year emissions by the forecasted growth rate, we project China's emissions in 2020 to be 13.63 billion metric tons, which is about 2.10 billion metric tons higher than that of EIA. This gap is nearly twice of Japan's current energy-related CO_2 emissions. In fact, EIA itself has already adjusted its forecast upward to 11.53 billion metric tons in IEO 2013 (EIA, 2013) from 10.13 billion metric tons in IEO 2011 (EIA, 2011), suggesting the recent emission trend in China has raised EIA's expectation on China's future emissions. The annual growth rate of China's CO_2 emissions from 2000 to 2010 is 9.3%. However, the newest EIA's forecast suggests that the growth rate of China's CO_2 emissions from 2010 to 2020 will be 58% lower than that of the previous decade. In fact, China's CO_2 emissions still grew by 9.0% in 2011 despite the slowdown in GDP growth. This implies that EIA might have underestimated the driving forces for China's future emission growth.

The predicted growth rate of China's emissions is even lower in the other three studies, including the forecasts by IEA (2012), the Lawrence Berkeley National Laboratory (LBNL) (Zhou et al., 2013), and the Energy Research Institute (ERI) in China (ERI, 2009). IEA (2012)'s prediction of emission growth rate is only about half of our prediction, despite its relatively high assumption of GDP growth. The current policy scenario in IEA (2012)'s study assumes the 17% reduction target of carbon intensity during the 12th FYP will be achieved. However, this contradicts with our previous results that the reduction percentage in China's carbon intensity will be only 8.8% during the 12th FYP under the BAU scenario. Similarly, the Continued Improvement scenario (CIS) in the LBNL's study assumes continued progress in energy efficiency and carbon abatement, thus cannot represent the BAU scenario (Zheng, Zhou, and Fridley, 2010). In contrast, with fewer assumptions, the reduced-form models, including the best forecasting model, the baseline model, and the same model as Auffhammer and Carson (2008), all get much higher forecasts. The different results of reduced-form models and structural models can be partly explained by the assumptions made in the latter.

China's CO_2 emissions in 2011 are 7.66 billion metric tons based on the national statistics, or 9.47 billion metric tons based on the provincial statistics. We treat the two numbers as the lower and upper bounds of China's CO_2 emissions in 2011. Our forecasted emission increase from 2011 to 2020 is 56.2%, which means the absolute increase will be 4.31 to 5.32 billion metric tons. The United States has committed to reduce CO_2 emissions by 2020 by 17% below the 2005 level, and the European Union has committed to reduce emissions by 2020 by 30% below the 1990 level. This suggests that the total emission reductions of the EU and US combined during 2011 and 2020 will be about 1.43 billion metric tons[14]. We forecast that China's emission increase from 2011 to 2020 will be about 3.0 to 3.7 times of the emission reductions from the EU and US combined.

8 Conclusion

China's double-digit economic growth in the last three decades has brought wealth to its population, but also made China the largest CO_2 emitter in the world. To address the challenge of climate change, China has pledged to reduce its carbon intensity by 40-45% below the 2005 level by 2020 in the Copenhagen Accord. This paper assess China's probability of compliance by forecasting China's CO_2 emissions up to 2020 under the business-as-usual scenario. We apply dynamic spatial econometric models to the detailed energy consumption data. We make the best use of China's energy statistics to compute CO_2 emissions at the provincial level. The disaggregated data allow us to exploit provincial heterogeneity in emission forecasting. By selecting from a large set of spa-

[14]Calculated using the EIA statistics.

tial models to account for spatial dependence, we find that incorporating spatial spillover effects can improve forecasting especially for a long time horizon.

Although China has started to transition towards less energy and carbon intensive growth and its GDP growth is slowing down, our best forecasting model suggests that there is still no reason to be optimistic that China's future CO_2 emissions will meet its Copenhagen commitment. Additional mitigation efforts will be needed to ensure compliance. In absolute terms, our study forecasts that China's CO_2 emissions will increase by about 4.31 to 5.32 billion metric tons from 2011 to 2020. At the provincial level, we find most eastern provinces will be able to achieve greater reductions in carbon intensity by 2020 relative to 2005 levels, while the less developed central and western provinces will miss their targets. Flexible mitigation mechanisms should be established and targeted policies are needed to ensure the less developed provinces' compliance as they undergo fast industrialization.

A Appendix

A.1 Calculation of Carbon Dioxide Emissions

Carbon dioxide emissions from fossil fuel consumption are calculated following the IPCC guidelines (IPCC, 2006):

$$E_{CO_2} = \sum_i A_i \times e_i \times c_i \times o_i \times \frac{44}{12}, \tag{13}$$

where i indexes fuel type, E_{CO_2} denotes CO_2 emissions, A_i denotes fuel consumption (kg or m^3), e_i denotes net heat value (kJ/kg or kJ/m^3), c_i is carbon emission factor (kg C/GJ), o_i is carbon oxidation rate. Whenever the data are available, we use 17 types of fossil fuels in the energy balance sheets (Table A.1). Net heat values (e_i) are obtained from the *China Energy Statistical Yearbooks*. Carbon emission factors and carbon oxidation rates are obtained from IPCC (2006). Carbon oxidation rates of different fuels are set at the default value of 1.

Table A.1: Coefficients of various fossil fuels

Fuel type	Net heat value e_i		Carbon emission factor c_i (kg C/GJ)
	Unit	Value	
Raw coal	kJ/kg	20908	25.8
Cleaned coal	kJ/kg	26344	25.8
Other washed coal	kJ/kg	15373	25.8
Briquettes	kJ/kg	17773	26.6
Coke	kJ/kg	28435	29.2
Coke Oven gas	kJ/m^3	17981	12.1
Other coal gas	kJ/m^3	8418	12.1
Other Coking Products	kJ/kg	33453	22.0
Crude oil	kJ/kg	41816	20.0
Gasoline	kJ/kg	43070	18.9
Kerosene	kJ/kg	43070	19.5
Diesel oil	kJ/kg	42652	20.2
Fuel oil	kJ/kg	41816	21.1
LPG	kJ/kg	50179	17.2
Refinery gas	kJ/kg	46055	15.7
Other petroleum products	kJ/kg	40200	20.0
Natural gas	kJ/m^3	38931	15.3

Notes: Net heat values (e_i) are obtained from the *China Energy Statistical Yearbooks*. Carbon emission factors are obtained from IPCC (2006).

The energy balance sheets in the *China Energy Statistical Yearbooks* are available in 1985 and from 1995 to 2011 for all provinces, except for Ningxia (available from 2000 to 2002), Hainan (available in 1985 and 2002), and Chongqing (available in 1985, 1995 and 1996). The energy balance sheets contain detailed consumption data on 17 types of fossil fuels, heat, and electricity. The emissions from burning fossil fuels can be calculated using Equation (13). The emissions from heat and thermal power are calculated according to the energy mix for the generation in the corresponding province. The emissions related to inter-regional electricity transmission are ascribed to the consumption side, following the "consumer responsibility" method in Meng et al. (2011). For provinces that are net electricity exporters, the emissions from the exported electricity are not included in that province's total emissions. For provinces that are net importers, the emissions from the imported electricity are calculated using the national energy mix for the generation. Here we use the national energy mix rather than that of the exporter because the energy balance sheets do not specify the source of the imported electricity.

In case the energy balance sheets are missing, we use the energy statistics in the provincial statistical yearbooks to impute the missing data points. These provincial yearbooks provide final energy consumption data by type including: coal, coke, crude oil, gasoline, kerosene, diesel oil, natural gas, heat, electricity, etc. In order to compute CO_2 emissions from final energy consumption, we need to make assumptions on CO_2 emission factors per unit heat and electricity. We assume the emission factors per unit heat and electricity during the missing period to be the average of the corresponding factor in the year just before and after the missing period. This means, for provinces other than Hainan, Sichuan, and Chongqing, the energy balance sheets are available in 1985 and 1995, therefore we assume the CO_2 emission factor per unit heat and electricity from 1986 to 1994 to be the average of the corresponding factor in 1985 and 1995. Similar treatment is applied to the data points of Ningxia from 2000 to 2002 and Hainan in 2002. Because the energy balance sheet is not available for Hainan in 1985, we have to assume the CO_2 emission factor per unit heat and electricity from 1985 to 1994 to be the same as that in 1995. Because Chongqing was separated out from Sichuan to become a municipal city only after 1997, the energy balance sheets of Sichuan in 1985, 1995, and 1996 contain both Sichuan and Chongqing. Therefore we assume the CO_2 emission factor per unit heat and electricity to be the same for Sichuan and Chongqing in 1985, 1995, and 1996, and the emission factors from 1986 to 1994 as the average of that in 1985 and 1995. In this way we construct a panel data set of provincial emissions from 1985 to 2011 with only ten missing observations. The remaining missing data are imputed by cubic spline interpolation.

A.2 Scenario Setting of Provinces

Table A.2: Scenarios setting from 2011 to 2020

Province	GDP annual growth rate		Change of ratio of the secondary industry in GDP
	2012∼2015	2016∼2020	Each FYP
Whole nation	7.50%	7.00%	-2.30%
Eastern provinces:			
Beijing	6.00%	5.60%	-2.70%
Tianjin	9.00%	8.50%	-3.60%
Hebei	6.40%	6.00%	-1.10%
Liaoning	8.30%	7.80%	-3.40%
Shanghai	6.00%	5.60%	-7.60%
Jiangsu	7.50%	7.10%	-5.40%
Zhejiang	6.00%	5.60%	-3.60%
Fujian	7.50%	7.10%	+0.00%
Shandong	6.80%	6.30%	-6.20%
Guangdong	6.00%	5.60%	-2.00%
Hainan	9.80%	9.20%	+2.30%
Central provinces:			
Shanxi	9.80%	9.20%	-1.70%
Jilin	9.00%	8.50%	-2.00%
Heilongjiang	9.00%	8.50%	-1.00%
Anhui	7.50%	7.10%	+0.90%
Jiangxi	8.30%	7.80%	+1.30%
Henan	6.80%	6.30%	-1.40%
Hubei	7.50%	7.10%	-1.60%
Hunan	7.50%	7.10%	+2.70%
Western provinces:			
Inner Mongolia	9.00%	8.50%	-1.80%
Guangxi	7.50%	7.10%	+1.30%
Chongqing	9.40%	8.80%	+2.00%
Sichuan	9.00%	8.50%	+0.30%
Guizhou	9.00%	8.50%	+5.90%
Yunnan	7.50%	7.10%	+1.40%
Shaanxi	9.00%	8.50%	-3.60%
Gansu	9.00%	8.50%	+1.80%
Qinghai	9.00%	8.50%	-0.10%
Ningxia	9.00%	8.50%	+4.00%
Xinjiang	7.50%	7.10%	+0.20%

Notes: Figures in column "GDP annual growth rate" are based on goals set in provinces' 12th FYP, but adjusted by the same factor to make them consistent with the national growth we set.

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Figures and Tables

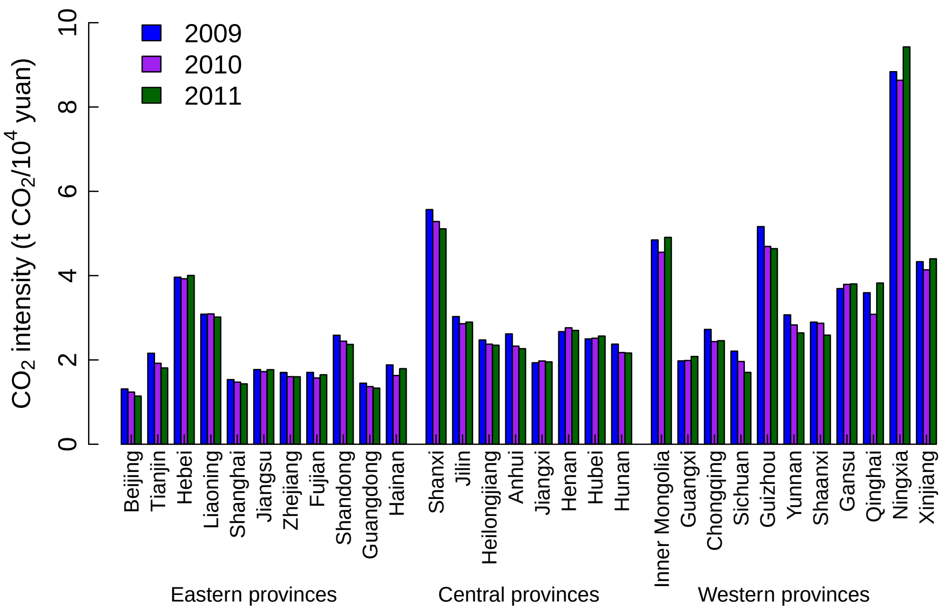
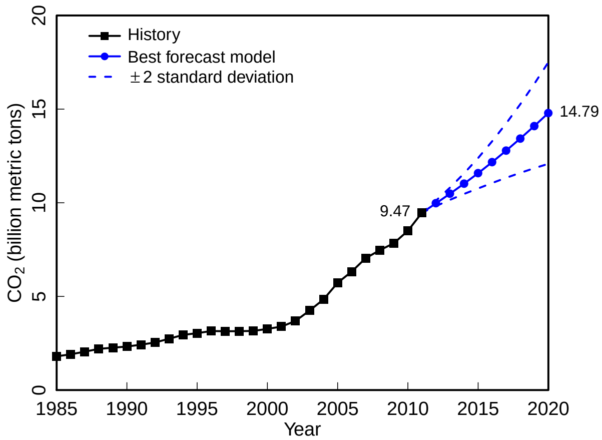
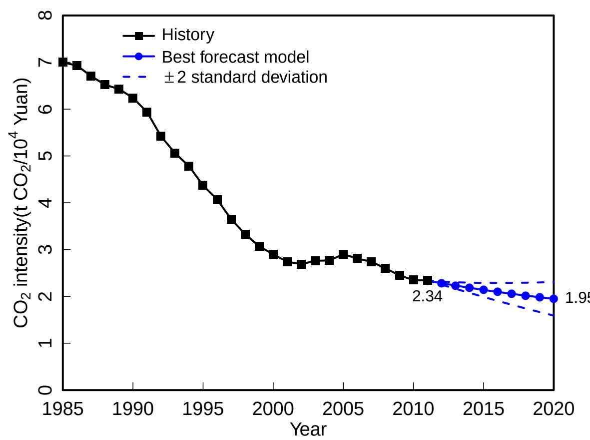


Figure 1: Carbon intensities of provinces from 2009 to 2011. The declining trend of carbon intensities before 2010 slowed down or even reversed in 2011.

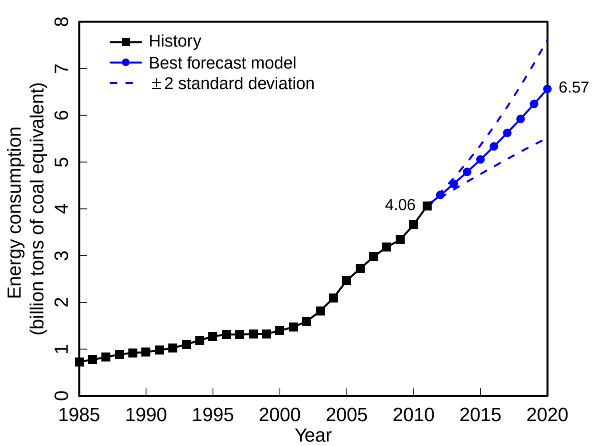


(a) CO_2 emissions

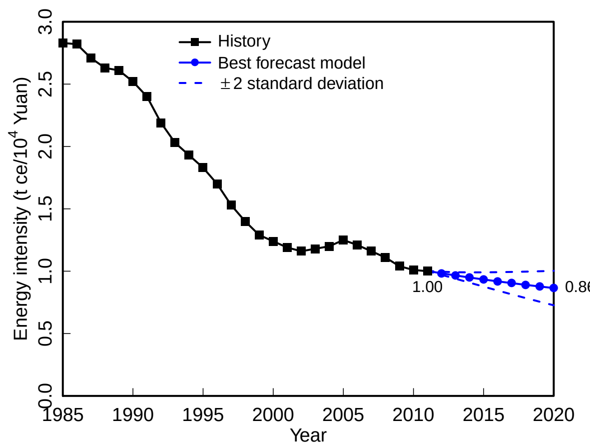


(b) carbon intensity

Figure 2: Emission forecast up to 2020 using the best forecasting model.



(a) Energy consumption



(b) Energy intensity

Figure 3: Energy consumption forecast up to 2020 using the best forecasting model.

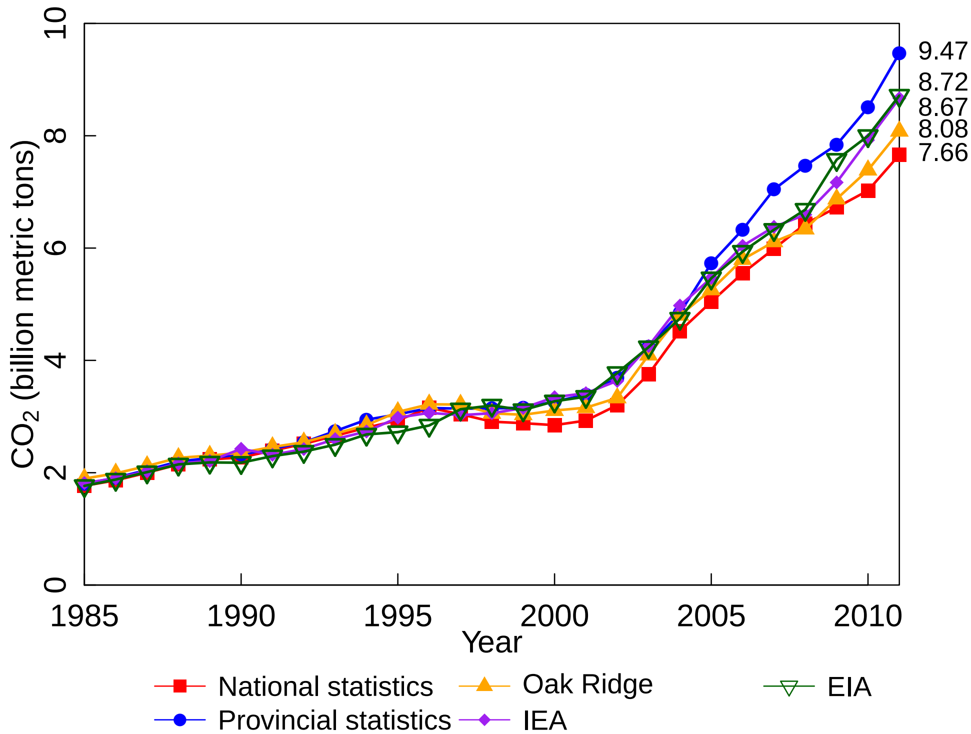


Figure 4: Comparison of estimated China's energy-related CO_2 emissions. All the data from the four sources are energy-related CO_2 emissions, therefore they are comparable. The CO_2 emissions aggregated from the provincial statistics have been always higher than those from the national statistics in the recent decade. The Oak Ridge's estimates are close to the numbers based on the national statistics. The EIA's and IEA's estimates are relatively close to the numbers based on the provincial statistics in the last three years.

Table 1: Estimation results of carbon intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Baseline	S_{lag}		S_{lag-g}		S_{con}		S_{con-g}	
Spatial matrix		W_{inv}	W_{rook}	W_{inv}	W_{rook}	W_{inv}	W_{rook}	W_{inv}	W_{rook}
ρ	0.841***	0.554***	0.654***	0.554***	0.657***	0.695***	0.673***	0.730***	0.680***
	(0.022)	(0.078)	(0.048)	(0.069)	(0.045)	(0.071)	(0.052)	(0.048)	(0.043)
γ		0.332***	0.217***						
		(0.080)	(0.042)						
γ^1				0.264**	0.229***				
				(0.104)	(0.063)				
γ^2				0.365***	0.206***				
				(0.067)	(0.041)				
φ						0.260***	0.253***		
						(0.082)	(0.061)		
φ^1								0.189***	0.248***
								(0.073)	(0.060)
φ^2								0.247***	0.245***
								(0.062)	(0.066)
Popden	-0.190**								
	(0.083)								
ln$T$	-0.053***	-0.056***	-0.060***			-0.018	-0.030**		
	(0.010)	(0.014)	(0.012)			(0.013)	(0.012)		
lnT^1				-0.074***	-0.058***			-0.038**	-0.036**
				(0.019)	(0.018)			(0.017)	(0.015)
lnT^2				-0.048***	-0.061***			-0.006	-0.027*
				(0.016)	(0.015)			(0.016)	(0.016)
Sargan	29.38	29.50	29.26	29.39	28.70	14.51	21.10	10.04	8.65
AR(1)	-3.75***	-3.25***	-3.61***	-3.36***	-3.61***	-3.72***	-3.69***	-3.80***	-3.64***
AR(2)	0.40	0.24	0.39	0.24	0.39	0.39	0.27	0.39	0.28
RMSFE:									
1-year-ahead	1770	1628	1664	**1625**	1672	1664	1659	1681	1660
2-year-ahead	3268	2839	2958	**2828**	2977	2964	2967	3008	2964
3-year-ahead	5052	4175	4418	**4154**	4452	4402	4419	4477	4405
4-year-ahead	7183	5771	6149	**5705**	6209	6169	6157	6261	6119
5-year-ahead	9834	7596	8171	**7453**	8271	8291	8189	8399	8112
6-year-ahead	10877	8415	9008	**8199**	9152	9212	8981	9270	8873

Notes: (1) Meaning of coefficients ρ, γ, and φ can be referred to Equation (1) to (5); (2) In the row "Spatial matrix", W_{inv} represents the inverse distance matrix, W_{rook} represents the rook contiguity weight matrix; (3) Values in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1% level; (4) In the rows corresponding to RMSFE, numbers in bold represent the lowest one.

Table 2: Estimation results of energy intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Baseline	S_{lag}		S_{lag-g}		S_{con}		S_{con-g}	
Spatial matrix		W_{inv}	W_{rook}	W_{inv}	W_{rook}	W_{inv}	W_{rook}	W_{inv}	W_{rook}
ρ	0.840***	0.575***	0.624***	0.589***	0.635***	0.668***	0.596***	0.705***	0.669***
	(0.030)	(0.094)	(0.075)	(0.080)	(0.077)	(0.083)	(0.071)	(0.060)	(0.060)
γ		0.301***	0.239***						
		(0.087)	(0.064)						
γ^1				0.244**	0.225***				
				(0.097)	(0.085)				
γ^2				0.308***	0.232***				
				(0.080)	(0.081)				
φ						0.287***	0.346***		
						(0.088)	(0.067)		
φ^1								0.242***	0.323***
								(0.075)	(0.048)
φ^2								0.268***	0.270***
								(0.062)	(0.067)
Ind	0.168***								
	(0.052)								
T	-0.009***								
	(0.002)								
$\ln T$		-0.060***	-0.062***			-0.014	-0.022**		
		(0.009)	(0.009)			(0.010)	(0.011)		
$\ln T^1$				-0.070***	-0.061**			-0.024	-0.010
				(0.021)	(0.026)			(0.020)	(0.024)
$\ln T^2$				-0.054***	-0.061***			-0.004	-0.019
				(0.013)	(0.014)			(0.011)	(0.011)
Sargan	27.26	29.60	29.53	29.40	29.67	20.29	18.76	13.13	8.71
AR(1)	-3.54***	-3.14***	-3.79***	-3.51***	-3.94***	-2.99***	-3.04***	-3.24***	-3.20***
AR(2)	0.41	0.21	0.37	0.22	0.38	0.47	0.36	0.47	0.39
RMSFE:									
1-year-ahead	628	**576**	585	580	589	591	581	598	592
2-year-ahead	1129	**1004**	1025	1012	1033	1047	1029	1063	1056
3-year-ahead	1708	**1488**	1530	1500	1543	1573	1552	1601	1601
4-year-ahead	2461	**2109**	2167	2119	2187	2282	2238	2329	2331
5-year-ahead	3369	**2811**	2896	2814	2927	3134	3054	3212	3222
6-year-ahead	3673	3078	3165	**3073**	3205	3510	3418	3616	3646

Notes: (1) Meaning of coefficients ρ, γ, and φ can be referred to Equation (1) to (5); (2) In the row "Spatial matrix", W_{inv} represents the inverse distance matrix, W_{rook} represents the rook contiguity weight matrix; (3) Values in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1% level; (4) In the rows corresponding to RMSFE, numbers in bold represent the lowest one.

Table 3: Forecasted percentage of decline in carbon intensity

	Forecasted carbon intensity reduction percentage in 2015 relative to 2010	Allocated goals in 12^{th} FYP	Forecasted carbon intensity reduction percentage in 2020 relative to 2005
Eastern provinces:			
Beijing	**-18%(-10%,-25%)**	-18.00%	**-46%(-35%,-57%)**
Tianjin	**-19%(-11%,-26%)**	-19.00%	**-48%(-38%,-59%)**
Hebei	-5%(3%,-13%)	-18.00%	-31%(-15%,-46%)
Liaoning	-9%(-3%,-15%)	-18.00%	-31%(-18%,-44%)
Shanghai	-11%(-5%,-17%)	-19.00%	-39%(-27%,-50%)
Jiangsu	-6%(2%,-13%)	-19.00%	-36%(-22%,-50%)
Zhejiang	-10%(-3%,-16%)	-19.00%	-35%(-23%,-47%)
Fujian	-6%(2%,-13%)	-17.50%	-29%(-14%,-43%)
Shandong	-13%(-6%,-19%)	-18.00%	**-40%(-29%,-51%)**
Guangdong	-12%(-5%,-18%)	-19.50%	-35%(-23%,-47%)
Hainan	-4%(5%,-13%)	-11.00%	-22%(-4%,-39%)
Central provinces:			
Shanxi	-13%(-6%,-19%)	-17.00%	-31%(-17%,-44%)
Jilin	-9%(-2%,-16%)	-17.00%	**-43%(-32%,-54%)**
Heilongjiang	-10%(-4%,-17%)	-16.00%	-37%(-25%,-50%)
Anhui	-15%(-8%,-22%)	-17.00%	**-40%(-28%,-52%)**
Jiangxi	-7%(-1%,-14%)	-17.00%	-29%(-14%,-43%)
Henan	-8%(-1%,-15%)	-17.00%	-24%(-9%,-40%)
Hubei	-5%(3%,-13%)	-17.00%	-23%(-6%,-39%)
Hunan	-12%(-6%,-19%)	-17.00%	**-41%(-30%,-53%)**
Western provinces:			
Inner Mongolia	-3%(7%,-13%)	-16.00%	-25%(-7%,-42%)
Guangxi	-3%(6%,-12%)	-16.00%	-25%(-8%,-43%)
Chongqing	-13%(-7%,-20%)	-17.00%	-38%(-25%,-51%)
Sichuan	**-26%(-15%,-37%)**	-17.50%	**-44%(-28%,-59%)**
Guizhou	-14%(-8%,-21%)	-16.00%	**-50%(-40%,-60%)**
Yunnan	**-18%(-10%,-26%)**	-16.50%	**-46%(-34%,-58%)**
Shaanxi	**-17%(-9%,-26%)**	-17.00%	-26%(-10%,-43%)
Gansu	-4%(3%,-12%)	-16.00%	-29%(-14%,-44%)
Qinghai	9%(29%,-11%)	-10.00%	-22%(10%,-54%)
Ningxia	1%(13%,-10%)	-16.00%	-11%(13%,-34%)
Xinjiang	-3%(6%,-12%)	-11.00%	-18%(0%,-37%)

Notes: (1) Taking "-18%(-10%, -25%)" as an example: -18% is the point forecast meaning carbon intensity will decrease by 18%, and (-10%, -25%) is the ± 2 standard deviation interval. (2) In column two, numbers in bold font represent the allocated carbon intensity reduction target can be achieved under point forecast. In column four, numbers in bold font represent the point forecast exceeds the 40% reduction percentage, which is the lower bound of national reduction target in 2020.

Table 4: Comparison with other studies

Study	Base Year	Assumption of annual GDP growth rate from 2010 to 2020	Annual growth rate of CO_2 emissions (forecast range)
EIA (2011)	2008	7.5%	3.4% (2008 to 2020)
EIA (2013)	2010	7.5%	3.9% (2010 to 2020)
IEA (2012) [a]	2010	7.9%	2.9% (2010 to 2020)
Zhou et al. (2013) [a]	2005	7.5%	2.5% (2010 to 2020)
ERI (2009) [a]	2005	8.4%	2.7% (2010 to 2020)
This study	2011	7.5% (2011-2015) 7.0% (2016-2020)	5.1% (2011 to 2020)

Notes: [a] The cited results in the table correspond to the current policy scenario in IEA (2012), CIS scenario in Zhou et al. (2013), and baseline scenario in ERI (2009).