Incorporating health impacts into the cost-benefits analysis of achieving China’s INDC targets at province-level

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INTRODUCTION
China’s INDC targets

• Decrease in carbon intensity: 60–65%
• Share of non-fossil Energy: 20%
• Peaking time of CO$_2$ Emission: 2030

Health Impacts

• In 2016, national average of $PM_{2.5}$ concentration was 68$\mu g/m^3$, > 35$\mu g/m^3$ (National) and 10$\mu g/m^3$ (WHO).
• Exposure to $PM_{2.5}$ has ranked as the 4th leading cause of premature mortalities in China in 2016.
• Estimates of the social costs of air pollution in China were 0.5% to 5.9% of GDP.

China is facing the double challenges of climate change and air quality.
Carbon mitigation has AQ co-benefits.

1) GHGs and air pollutants are released simultaneously from emission sources, and consist in emissions controls (Tian et al, 2009).

2) Different low carbon development pathways will lead to different air quality co-benefits.
   • Ji et al (2015) discovered that carbon mitigation by promoting electric vehicles in China will cause more air pollution in western provinces.
   • Thompson et al. (2014) found out that mitigation policies such as CAT, CES and TRN have totally different air quality co-benefits (see figure on the right).
   • Boyce and Pastor (2013) identified the disparities on air quality co-benefits of different sources.
Why incorporating air quality co-benefits into mitigation policies?

- Reducing the social costs of carbon mitigation, gaining policy support from the public.
- Supporting more aggressive near term climate action even in the face of large uncertainty.
- Creating local incentives of climate polices because of location-specific mitigation benefits.
Carbon mitigation policies in China are implemented at provincial level, allocation of mitigation costs are key concern for provincial governments.

### Very ambitious
Provinces with clear emission peaking schedule

<table>
<thead>
<tr>
<th>Province</th>
<th>Peaking at</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beijing</td>
<td>2020</td>
</tr>
<tr>
<td>Shanghai</td>
<td>2025</td>
</tr>
<tr>
<td>Tianjin</td>
<td>2025</td>
</tr>
<tr>
<td>Yunnan</td>
<td>2025</td>
</tr>
<tr>
<td>Shandong</td>
<td>2027</td>
</tr>
<tr>
<td>Chongqing</td>
<td>Around 2030</td>
</tr>
<tr>
<td>Shanxi</td>
<td>Around 2030</td>
</tr>
<tr>
<td>Hainan</td>
<td>Before 2030</td>
</tr>
<tr>
<td>Gansu</td>
<td>Around 2030</td>
</tr>
<tr>
<td>Xinjiang</td>
<td>2030</td>
</tr>
</tbody>
</table>

### Ambitious
Provinces with clear emission peaking schedule for certain cities/sectors

<table>
<thead>
<tr>
<th>Province</th>
<th>Cities/Industries Peaking at</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jiangsu</td>
<td>Suzhou, Zhenjiang, peaking at 2020</td>
</tr>
<tr>
<td>Guangdong</td>
<td>Guangzhou, Shenzhen, peaking at 2020</td>
</tr>
<tr>
<td>Shaanxi</td>
<td>Yanan (2029), Ankang (2028)</td>
</tr>
<tr>
<td>Jiangxi</td>
<td>Certain heavy chemical industries peak around 2020</td>
</tr>
<tr>
<td>Sichuan</td>
<td>Certain heavy chemical industries peak around 2020</td>
</tr>
</tbody>
</table>

### Less ambitious
Provinces encouraging certain cities to peak asap

<table>
<thead>
<tr>
<th>Province</th>
<th>Encouraging</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ningxia</td>
<td>Center cities to peak asap</td>
</tr>
<tr>
<td>Fujian</td>
<td>Encouraging Fuzhou, Xiamen, Quanzhou to peak asap, and Nanping, Putian to raise a peaking target</td>
</tr>
<tr>
<td>Hubei</td>
<td>Wuhan to peak asap</td>
</tr>
<tr>
<td>Anhui</td>
<td>National low-carbon pilot cities to peak asap</td>
</tr>
<tr>
<td>Henan</td>
<td>National low-carbon pilot cities to peak asap</td>
</tr>
<tr>
<td>Hunan</td>
<td>Encouraging Changsha to become national low-carbon pilot city</td>
</tr>
<tr>
<td>Zhejiang</td>
<td>Hangzhou, Ningbo, and Wenzhou to peak asap</td>
</tr>
<tr>
<td>Guizhou</td>
<td>National low-carbon pilot cities to peak asap</td>
</tr>
</tbody>
</table>

### Least ambitious
Provinces still working on peaking plans

<table>
<thead>
<tr>
<th>Province</th>
<th>Working on peaking plan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qinghai</td>
<td></td>
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<tr>
<td>Guangxi</td>
<td></td>
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<tr>
<td>Heilongjiang</td>
<td></td>
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<tr>
<td>Jilin</td>
<td></td>
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<tr>
<td>Inner Mongolia</td>
<td></td>
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<tr>
<td>Hebei</td>
<td></td>
</tr>
</tbody>
</table>

Very ambitious: Provinces with clear emission peaking schedule
Ambitious: Provinces with clear emission peaking schedule for certain cities/sectors
Less ambitious: Provinces encouraging certain cities to peak asap
Least ambitious: Provinces still working on peaking plans
The health benefits consist of 90% of the air quality co-benefits, and the health co-benefits are highly dependent on the local socioeconomic and environmental conditions such as population density, industrial structure and geographic conditions.
Health-CGE: The general analysis framework for province-level costs-benefits analysis

China province level CGE model

Province level mitigation costs
Health-CGE: The general analysis framework for province-level costs-benefits analysis
Health-CGE: The general analysis framework for province-level costs-benefits analysis

CTM (Chemical Transport Model)
- **Pros**
  - CTMs are three-dimensional mechanistic models that predict ambient concentrations of pollutants.
  - Accounting for emissions, transport and dispersion by winds, chemical transformations and atmospheric removal process.
  - They are the most scientifically detailed and rigorous tools available for linking emission to ambient concentrations.
- **Cons**
  - Running full CTMs is very intensive in terms of expertise, time, and computing resources.
- **Examples**
  - CMAx/CMAQ
  - WRF-Chem
  - GEOS-Chem
Health-CGE: The general analysis framework for province-level costs-benefits analysis

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  - WRF-Chem
  - GEOS-Chem

The bottleneck of this framework

They are **over-qualified** for this framework:

- For health impacts evaluations, **annual average province-level** concentrations are enough.
- Running CTM for one turn usually takes up to two weeks, which prevents us from modelling experiments that requires repeated runs such as **uncertainty analysis**, and **marginal damage estimations**.

They are **not easily accessible** to policy study communities.
Health-CGE: The general analysis framework for province-level costs-benefits analysis

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Air Quality Model

The bottleneck of this framework

Is it possible to develop a model that is easy to run and publicly accessible?
INTRODUCTION

CTM (Chemical Transport Model)
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  • They are the most scientifically detailed and rigorous tools available for linking emission to ambient concentrations.
• **cons**
  • Running full CTMs is very intensive in terms of expertise, time, and computing resources.
• **examples**
  • CMAx
  • CMAQ
  • WRF-Chem
  • GEOS-Chem

RCM (Reduced-Complexity Model)
• **pros**
  • They are less demanding on computing resources and time.
  • They are more accessible for detailed policy analysis
    • Source-specific regulations
    • Uncertainty analysis
• **cons**
  • The time and spatial resolutions are lower than CTM models.
• **examples**
  • APEEP /AP2
  • EASIUR
  • RSM
  • InMap
  • Rollback
  • Fixed box
Reliabilities of RCMs: inter-model comparison between different RCMs

• Gilmore et al. compare the marginal pollutants mitigation costs of major pollutants in the US of three RCMs:
  • AP2 (the latest version of APEEP)
  • InMap
  • EASIUR
• Although their modeling mechanisms vary greatly from each other, their marginal damage estimation for PM2.5 reveal high correlations.
Reliabilities of RCMs: inter-model comparison between CTM and RCM

- Muller and Mendelsohn compared the prediction performance of APEEP and CMAQ on multiple pollutants concentrations of 2002, they found that the results were highly correlated.

<table>
<thead>
<tr>
<th>Pollutants</th>
<th>Season</th>
<th>ME</th>
<th>MB</th>
<th>MNE(%)</th>
<th>MNB(%)</th>
<th>correlations</th>
<th>Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOx</td>
<td>Summer</td>
<td>1.1</td>
<td>0.21</td>
<td>42</td>
<td>14</td>
<td>0.86</td>
<td>3110</td>
</tr>
<tr>
<td>SO2</td>
<td>Summer</td>
<td>0.5</td>
<td>0.06</td>
<td>47</td>
<td>19</td>
<td>0.78</td>
<td>3110</td>
</tr>
<tr>
<td>O3(24hr)</td>
<td>Summer</td>
<td>9.2</td>
<td>-1.83</td>
<td>20</td>
<td>-4</td>
<td>0.69</td>
<td>74640</td>
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<tr>
<td>O3(8h)</td>
<td>Summer</td>
<td>6.6</td>
<td>5.8</td>
<td>12</td>
<td>11</td>
<td>0.77</td>
<td>24880</td>
</tr>
<tr>
<td>PM2.5</td>
<td>Annual average</td>
<td>1.8</td>
<td>-0.5</td>
<td>26</td>
<td>-2</td>
<td>0.77</td>
<td>3110</td>
</tr>
<tr>
<td>PM10</td>
<td>Annual average</td>
<td>4.2</td>
<td>3.8</td>
<td>50</td>
<td>27</td>
<td>0.74</td>
<td>3110</td>
</tr>
</tbody>
</table>

- They compared their predictions in 180 samples with the actual monitored value provided by US EPA, and the reliability performances are quite close.

<table>
<thead>
<tr>
<th>Method</th>
<th>ME</th>
<th>MB</th>
<th>MNE(%)</th>
<th>MNB(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>APEEP</td>
<td>4.4</td>
<td>-2.6</td>
<td>35%</td>
<td>-20%</td>
</tr>
<tr>
<td>CMAQ</td>
<td>5.5</td>
<td>-2.1</td>
<td>43%</td>
<td>-16%</td>
</tr>
</tbody>
</table>
## INTRODUCTION

### Overview of RCMs

<table>
<thead>
<tr>
<th>Model</th>
<th>Developer</th>
<th>Spatial Resolution</th>
<th>Model categories</th>
<th>Principles</th>
</tr>
</thead>
<tbody>
<tr>
<td>APEEP/AP2</td>
<td>Robert Mendelsohn, Nicolas Muller</td>
<td>USA, county level</td>
<td>• Mechanistic model</td>
<td>• Source-Receptor Matix</td>
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<td>USEPA</td>
<td>USA, county level</td>
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<td>• Source-Receptor Matrix</td>
</tr>
<tr>
<td>Fixed box</td>
<td>Chen and He</td>
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<td>• Mechanistic model</td>
<td>• Assuming the whole nation as a uniformly dispersion box</td>
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Mechanism-based RCM：S-R matrix
Mechanism-based RCM： S-R matrix

- Gaussian Plume Dispersion Model

\[ C_r = \sum_{s=1}^{S} \left[ \left( \frac{E_s \theta_{sd}}{\pi \mu_s \sigma_y (x_{rs}) \sigma_z (x_{rs})} \right) e^{\left( \frac{-H^2}{2\sigma_z (x_{rs})^2} \right)} \right] \]

**Source parameters**

- \( E_s \): Emissions from source S
- \( \mu_s \): wind speed
- \( \theta_{sd} \): wind direction distribution
- \( x_{rs} \): Distance between source and receptor

**Meteorological conditions**

- Stack height
- Wind speed
- Wind direction distribution
Mechanism-based RCM: S-R matrix

- Gaussian Plume Dispersion Model
- Dry deposition, wet deposition, and chemical reactions

\[ C_r = \sum_{s=1}^{S} \left[ \left( \frac{E_s \theta_{sd} f_w f_d f_c}{\pi \mu_s \sigma_{yd}(x_{rs}) \sigma_{zd}(x_{rs})} \right) \left( \frac{-H^2}{2\sigma_{zd}(x_{rs})^2} \right) \right] \]

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Chemical Reactions
- \( f_w \): Wet decomposition coefficients
- \( f_d \): Dry decomposition coefficients
- \( f_c \): Chemical reaction coefficients
METHODOLOGY

Mechanism-based RCM: S-R matrix

- Gaussian Plume Dispersion Model
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METHODOLOGY

Data Sources

Emission Parameters
\[ E_s : \text{Emissions} \]
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\[ x_{rs} : \text{distance} \]

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\[ \mu_s : \text{wind speed} \]
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Chemical Reactions
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Data Sources
- MIX China (2008, 2010) (MEIC official website)
- China power yearbook
- Greenpeace report on health impacts of China’s CFPPs
- Li et al. (2013)

Haversine function

China meteorological historical daily values (1998-2016) (China Meteorological Data Center)

Lack of these coefficients prevent the development of S-R matrix in China.
Research Goal

• **On methodology**: to develop a reduced-complexity air quality model that fits the health-CGE analysis framework.

• **On policymaking**: to figure out the distribution of mitigation costs and health co-benefits of China’s INDC on province level and give province-specified policy suggestions.
METHOD
The Analysis Framework

- **CHEER-P**
  - Province level mitigation costs

- **CAPIM**
  - Province level health co-benefits

**Province level air pollutants emissions**
METHODOLOGY

**CHEER-P Model** (**China Hybrid Energy and Economic Research Province level model**)

**Energy and Emission**
- CO2 Emission
- Energy Input
  - Coal
  - Natural Gas
  - Crude Oil
  - Oil

**Production & Consumption**
- Household
  - saving
- Government
  - investment
- Capital
- Sectoral Production
- Intermediate Input
- Labor

**Marco Closure**
- Commodity Market Clear
- Labor Market Clear
- Capital Market Clear
- Income/Expenditure Equilibrium
- Investment/Saving Equilibrium
- Interregional Trade Equilibrium

**Interregional Trade**
- Commodity Trade
- Armington Goods
- Service Trade
- Multiregional Interaction
CHEER-P Model (China Hybrid Energy and Economic Research Province level model)

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- CO2 Emission
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- Service Trade

**Diagram**
- Local and Domestic
- Foreign
- Energy Capital Labor Competitive
  - Energy
  - Domestic
  - Labor
  - Capital

**Equilibrium**
- Total Output
- Value Added
- Income/Expenditure
- Investment/Saving
- Interregional Trade
- Commodity Trade
- Armington Goods
- Multiregional Interaction
- Service Trade
**CAPIM (Chinese Air Pollution Impact Model)**

- An interdisciplinary analysis framework that combines the natural science, public health and economic studies
- 95% of the damages related to PM2.5 exposure are health damages, therefore we only cover the health impacts in the impacts evaluation module
- Spatial Resolution: province-level

**Emission Inventory Module**
- Province-level air pollutants concentrations
- Province-level emission inventories

**Air Quality Module**
- Gaussian Plume Dispersion: Atmospheric dispersion of pollutants
- Transformation coefficients: Atmospheric chemical reactions

**Economic Valuation Module**
- VSL datasets for mortality related evaluation
- WTP datasets for hospital admission based on local epidemic WTP studies

**Health Impacts Module**
- Dose-Response functions based on RR factors for both chronic and acute exposure
- Baseline incidences dataset for individual health endpoints

**Concentrations**

**Physical Health Impacts**

**Monetized Health Impacts**
Air quality Module: S-R matrix

- Gaussian Plume Dispersion Model
- Dry deposition, we deposition, and chemical reactions

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Meteorological Conditions

- $\mu_s$: wind speed
- $\theta_{sd}$: wind direction distributions

Chemical Reactions

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- $f_d$: dry deposition coefficients
- $f_c$: Chemical reaction coefficients

Lack of these coefficients prevents the development of S-R matrix in China.
We simulated the province-level overall transformation rate based on the provincial concentration after Guassian dispersion and the actual concentrations.

Provincial concentration after Gaussian Dispersion in 2008

<table>
<thead>
<tr>
<th>Province</th>
<th>AHf</th>
<th>BJf</th>
<th>ZJf</th>
<th>...</th>
<th>Source</th>
<th>Receptor</th>
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<tbody>
<tr>
<td>AN</td>
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<td>BY</td>
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<tr>
<td>ZJ</td>
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</tbody>
</table>

Provincial concentrations in 2008

\[
\begin{align*}
A_H & = A_{HC} \\
B_J & = B_{JC} \\
Z_J & = Z_{JC}
\end{align*}
\]

\[
f_A \times f_B \times f_Z = C_A \times C_B \times C_Z
\]
• Transformation coefficients are higher in the dry northwestern regions, and lower in wet southeastern regions.

• We validate the reliability of the model by comparing the concentrations we predict for 2010 and the actual concentrations.
Health impacts module

- 7 health endpoints are covered
  - Chronic exposure related impacts
    - chronic obstructive pulmonary disease (COPD)
    - ischemic heart disease (IHD)
    - Lung cancer (LC)
    - Stroke
  - Acute exposure related impacts
    - hospital admission due to respiratory disease (RHA)
    - hospital admission due to cardiovascular and cerebrovascular disease (CHA)
    - premature deaths from acute exposure.

**Integrated Exposure-Response Model**

- Increased incidence caused by exposure to PM2.5 are calculated using the Relative Risk model developed by Burnett et al, 2014

\[
RR(C) = \begin{cases} 
1 + \alpha(1 - e^{-\gamma(C - C_0)}) & \text{if } C > C_0 \\
1, & \text{else} 
\end{cases}
\]

- Increased Incidence:
  - Mortality
  - Morbidity
  - Hospital Admission

\[
E = \frac{RR - 1}{RR} \times B \times P
\]

- C: concentration of PM2.5
- C0: concentration of counterfactual PM2.5
- B: Baseline Incidence
- P: Population
## Methodology

The concentration from one point on individual wind direction is:

### WTP and VSL values

<table>
<thead>
<tr>
<th>VSL Value</th>
<th>Source</th>
<th>Study Region</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.2</td>
<td>Gao et al., 2015</td>
<td>Beijing</td>
<td>CV</td>
</tr>
<tr>
<td>0.09</td>
<td>Guo et al., 2006</td>
<td>Chengdu</td>
<td>CV</td>
</tr>
<tr>
<td>0.17-0.21</td>
<td>Zhang et al, 2006</td>
<td>Beijing</td>
<td>CV</td>
</tr>
<tr>
<td>0.17-0.34</td>
<td>Hammit et al, 2006</td>
<td>Chongqing</td>
<td>CV</td>
</tr>
<tr>
<td>0.19</td>
<td>Wang et al, 2006</td>
<td>Beijing, Anqing and Anqing rural areas</td>
<td>CV</td>
</tr>
<tr>
<td>0.21-0.73</td>
<td>Guo et al., 2009</td>
<td>Cities in 11 provinces</td>
<td>Hedonic wage</td>
</tr>
<tr>
<td>1.31</td>
<td>Qin et al., 2013</td>
<td>Sampling cities in 31 provinces</td>
<td>Hedonic wage</td>
</tr>
</tbody>
</table>

**Physical health impacts**

**Monetized health impacts**
METHODOLOGY

• **BaU scenario**

<table>
<thead>
<tr>
<th></th>
<th>2010</th>
<th>2015</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP growth rate</td>
<td>7.3%</td>
<td>6.5%</td>
<td>6%</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>Population (Billions)</td>
<td>1.341</td>
<td>1.376</td>
<td>1.400</td>
<td>1.408</td>
<td>1.403</td>
</tr>
<tr>
<td>LPR</td>
<td>74.3%</td>
<td>73.2%</td>
<td>70.9%</td>
<td>69.9%</td>
<td>68.6%</td>
</tr>
<tr>
<td>AEEI growth rate</td>
<td>1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

• **Policy scenario**

Carbon Intensity Reduction Targets: 60% by 2030
RESULTS
The total economic costs required to achieve China’s INDC target is 0.67% of GDP by 2030.

- To achieve the 60% carbon intensity reduction targets by means of carbon market, the GDP loss compared to BaU scenario is -0.67%.
- The carbon emission peaking time is between 2025-2030.
- The non-fossil fuel ratio in the whole energy structure is 22.6%.
The economic costs vary greatly across provinces, from -11.3% to -0.1%.

- Less developed provinces with relatively high original carbon intensities are the provinces with highest GDP loss rates, examples in these categories include Ningxia, Guizhou, Inner Mongolia, and Shanxi.
- Then among developed provinces, provinces with low carbon intensities like Guangdong, Fujian, Zhejiang, and Jiangsu suffer from lowest GDP loss rates.
- Ranking in the middle are the developed provinces with relatively higher carbon intensities such as Beijing, Shandong, and less developed provinces with relatively lower carbon intensities such as Anhui, Yunnan, and Sichuan et al.
Monetized health impact co-benefits concentrated in southeastern coast regions.

- Regions with high health co-benefits are regions with both high air pollutants reduction co-benefits and high population densities, that’s why provinces located in southeastern coast regions have the highest health co-benefits.
Air pollutants reduction co-benefits are also highly variant across provinces

Regions with higher air pollutants reduction co-benefits can be categorized into three categories:

• High GDP regions such as Guangdong, Shandong and Jiangsu
• Energy production bases such as Inner Mongolia and Shanxi
• Industrial base provinces such as Liaoning.
Benefits-costs ratio distribution demonstrates high disparities between provinces.

Regions with high benefits-costs ratios can be categorized into two groups:

- Southeastern coastal regions such as Guangdong, Shandong and Jiangsu. These provinces are entitled to high GDP, relative clean energy structure and high population density.

- Provinces transforming from coal-dependent industrial structures such as Shanxi, Inner Mongolia et al.
province-level benefits-costs ratio vs. province-level carbon peaking ambitions

<table>
<thead>
<tr>
<th>Very ambitious</th>
<th>Ambitious: provinces with clear emission peaking schedule for certain cities/sectors</th>
<th>Less ambitious: Provinces encouraging certain cities to peak asap</th>
<th>Least ambitious: Provinces still working on peaking plans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beijing</td>
<td>Peaking at 2020</td>
<td>Ningxia Encouraging center cities to peak asap</td>
<td>Qinghai Working on peaking plan</td>
</tr>
<tr>
<td>Shanghai</td>
<td>Peaking at 2025</td>
<td>Fujian Encouraging Fuzhou, Xiamen, Quanzhou to peak asap, and Nanping, Putian to raise a peaking target</td>
<td>Guangxi Working on peaking plan</td>
</tr>
<tr>
<td>Tianjin</td>
<td>Peaking at 2025</td>
<td>Hubei Encouraging Wuhan to peak asap</td>
<td>Heilongjiang Working on peaking plan</td>
</tr>
<tr>
<td>Yunnan</td>
<td>Peaking at 2025</td>
<td>Anhui Encouraging national low-carbon pilot cities to peak asap</td>
<td>Jilin Working on peaking plan</td>
</tr>
<tr>
<td>Shandong</td>
<td>Peaking at 2027</td>
<td>Henan Encouraging national low-carbon pilot cities to peak asap</td>
<td>Inner Mongolia Working on peaking plan</td>
</tr>
<tr>
<td>Chongqing</td>
<td>Peaking around 2030</td>
<td>Hunan Encouraging Changsha to become national low-carbon pilot city</td>
<td>Hebei Working on peaking plan</td>
</tr>
<tr>
<td>Shanxi</td>
<td>Peaking around 2030</td>
<td>Zhejiang Encouraging Hangzhou, Ningbo and Wenzhou to peak asap</td>
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</tr>
<tr>
<td>Hainan</td>
<td>Peaking before 2030</td>
<td>Guizhou Encouraging national low-carbon pilot cities to peak asap</td>
<td></td>
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<tr>
<td>Gansu</td>
<td>Peaking around 2030</td>
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<tr>
<td>Xinjiang</td>
<td>Peaking at 2030</td>
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<tr>
<td>Jiangsu</td>
<td>Suzhou, Zhenjiang, peaking at 2020</td>
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<tr>
<td>Guangdong</td>
<td>Guangzhou, Shenzhen, peaking at 2020</td>
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</tr>
<tr>
<td>Shaanxi</td>
<td>Yanan(2029), Ankang(2028)</td>
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<tr>
<td>Jiangxi</td>
<td>Certain heavy chemical industries peak around 2020</td>
<td></td>
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<tr>
<td>Sichuan</td>
<td>Certain heavy chemical industries peak around 2020</td>
<td></td>
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<tr>
<td>Qinghai</td>
<td>Working on peaking plan</td>
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<tr>
<td>Guangxi</td>
<td>Working on peaking plan</td>
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<td>Heilongjiang</td>
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<tr>
<td>Jilin</td>
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<tr>
<td>Inner Mongolia</td>
<td>Working on peaking plan</td>
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<tr>
<td>Hebei</td>
<td>Working on peaking plan</td>
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</tbody>
</table>
Policy Implications

• Both the costs and benefits of achieving China’s INDC targets have high provincial variations.

• Provinces in the southeastern costs areas are the regions with relative high health co-benefits and low GDP losses, which means they benefit most from the national carbon mitigation actions.

• For provinces with high benefit-cost ratio and low mitigation ambitions (Fujian, Henan, Zhejiang, Guizhou), this result provide policy incentives for them to carry on more ambitious mitigation actions.

• For provinces with low benefit-cost ratio and high mitigation ambitions (Shanghai, Yunnan, Gansu, Shaanxi, Hainan), introducing market-oriented mitigation policies might contribute to reducing mitigation costs.
Contributions

• We develop a reduced-complexity air quality model
  • Based on open-access data
  • Based on simple but transparent mechanisms
  • Flexible on spatial resolutions
  • Open-source (in the future)
EXTENSIONS

We are working on......

1. **Emission Inventories**
2. **Air Quality Module**
3. **Dose-Response Functions**
4. **Morbidity and Mortality Change**
5. **Labor Supply Change**
6. **Air Pollutants Emissions**

**CAPIM**

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Thank you for your attention! Questions?

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