Uncovering the key mechanisms of how deep decarbonization benefits air pollution alleviation in China

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Abstract

Addressing climate change and air pollution goals in conjunction would be efficient and cost-effective. Dealing with these two challenges is a common issue for urban clusters pursuing sustainable development. Expected to become the fourth international first-class bay area, the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) takes the lead in exploring a green and low-carbon transition path as a key element of being a pioneering economic reform demonstration zone. Based on an integrated modeling framework that couples an energy-economy model (IMED|CGE), decomposition analysis, and regression methods, the potential contribution of achieving the climate mitigation target to air pollutant reduction in the GBA by 2050 was quantified. The results showed that the transport sector has the most significant potential for carbon reduction. Energy intensity and structural transformations are the main contributors to reducing carbon emissions, with the latter becoming increasingly important over time. Climate policy can effectively reduce air pollutant emissions; however, this effect varies for different pollutants and sectors. Based on the assessment of the synergy index and cost of abatement, sectors with priority for synergic governance were identified. The regression results indicated that the carbon shadow price would be significantly more effective in reducing air pollutant emissions in the post-2030 period than before 2030, except for SO$_2$ and NH$_3$, partially because of the existing actions that cause the synergistic effects to decline. In addition, end-of-pipe removal measures still play a relatively significant role in reducing air pollutants, particularly VOC, NH$_3$, and primary PM$_{2.5}$. Thus, the findings suggest that priority should be given to sectors with huge synergistic benefits, such as transportation and power generation while paying attention to possible trade-offs.

Abbreviations

GBA Guangdong-Hong Kong-Macao Greater Bay Area
ROC Rest of China
LMDI Logarithmic mean Divisia index
SPD Structural path decomposition
PM$_{2.5}$ Particulate matter less than 2.5 µm in diameter
VOC Volatile organic compound
AGR Agriculture
PET Petroleum and nuclear fuel processing industry
COA Coal mining and dressing
FOD Food production
TEX Textile industry
PPP Papermaking and paper products
CHM Chemical industry
ONM Non-metal industry
MET Metal melting industry
MPD Metal product
L$_S$ Iron steel manufacturing

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1. Introduction

In the last decade, China has made initial achievements in addressing climate change and air pollution but still faces the dual pressures of carbon emission reduction and air quality improvement, and the potential for air pollutant reduction still needs to be further released [1]. Given the homogeneity of traditional greenhouse gases and air pollutant emission sources, climate policies will undoubtedly help accelerate air pollution improvements [2–6]. The contribution of climate policies and economic structural transformation to PM$_{2.5}$ exposure alleviation has become increasingly prominent in recent years in China [7]. Although climate change mitigation alone is insufficient to fully address air pollution [8], such co-benefits will become increasingly important as climate change mitigation actions advance [9].

Understanding the drivers of carbon emissions will facilitate the development of targeted emissions reduction policies. Decomposition methods, including the LMDI [10, 11] and structural decomposition analysis (SDA) [12, 13], are widely used to elucidate how various factors drive changes in energy consumption and carbon emissions in ex-post evaluation. Based on such approaches, it has been found that energy efficiency improvements, economic slowdowns, and shifts in consumption patterns have slowed the average annual growth rate of carbon emissions in China from 10% in 2002–2012 to 0.3% in 2012–2017 [14]. Most existing studies are based on historical data, while few studies have incorporated decomposition into future scenario analyses. Su et al found that the inhibition effect of structural changes on carbon emissions presented an increasing marginal trend in China from 2010–2035 using LMDI decomposition [15]. However, these studies ignore changes in carbon emissions caused by industrial chains and inter-provincial trade. Therefore, it remains unclear how to identify the key contributing nodes for emissions and the key pathways along the industrial chain to cut emissions.

Meanwhile, many studies have quantified the air quality co-benefits of climate policies [2, 16–20]. These studies have shown that these co-benefits can partially cover or even offset the cost of mitigation [2, 18], while there is significant regional and sectoral heterogeneity [2, 18]. Nevertheless, there is a lack of in-depth exploration of the marginal impact of climate policies on air pollutants. Only a few studies have quantified this marginal impact. Tan et al found that a 1% increase in the price of CO$_2$ was associated with a 0.13% reduction in SO$_2$ emissions in the Shanghai carbon market from 2014–2016 [21]. Zirogiannis et al found that a 1% decrease in electricity output from coal power plants would reduce SO$_2$ by 0.6% and NO$_x$ by 0.8% in power plants from 1998–2014 in the US [22]. However, Tan et al ignored the direct factors affecting the end-of-pipe removal of air pollutant emissions, and Zirogiannis et al did not consider the indirect effects of changes in industrial structure, which may cause bias.

The above literature review shows a strong need to analyze how to achieve carbon emission and air pollutant reduction simultaneously and effectively by diagnosing the key economic channels of how deep decarbonization benefits air pollution alleviation. Therefore, by taking the GBA and the ROC as an example, this study aims to answer the following questions: (a) how will climate goals affect the economy by altering energy and industrial structures? (b) What will be the quantitative contributions of the driving factors to carbon reduction by 2050? (c) What are the key mechanisms of carbon reduction in cutting air pollutant emissions simultaneously through the economic channels of price effects and structural effects? To address these multi-faceted questions, we propose an integrated assessment framework consisting of a multi-region and multi-sector computable general equilibrium model (IMED|CGE), LMDI decomposition, SPD, and regression analysis methods. This integrated framework is innovative in three aspects. First, it allows for analyzing the economic and environmental impacts of carbon emission reduction policies from the forward-looking and sector-wide perspectives with the help of the dynamic CGE model. Second, it enables us to understand the pathways of carbon emission drivers along the industry chain through the lens of the SPD approach. Third, it provides a simple and transparent framework for quantifying the marginal contribution of climate policies and other key explanatory variables to air pollutant reduction supported by the regression models.

The GBA was selected as a typical case study for the following reasons. As one of the largest and most economically dynamic urban agglomerations in China [23], which is expected to be the fourth largest world-class bay area, it is also the front-runner in harmonious economic development and protection of the ecological environment [24–29]. The carbon intensity of the GBA is already among the lowest in China and the GBA is the first region to exit the three key regions of air pollution prevention and control [19, 30, 31]. However, it is still far from sufficient to
achieve the carbon neutrality target, and there is still a gap between the GBA and the WHO guideline values [32]. With the continuous promotion of emission reduction, regional climate and environmental governance is facing increasing difficulties and rapidly growing costs, and there is an urgent need for innovation and collaborative governance systems. The GBA has entered a critical period and window of opportunity and collaborative governance systems. The GBA is also a major international land and sea corridor connecting countries along the Silk Road Economic Belt and the Maritime Silk Road, playing an important role in promoting global low-carbon and sustainable development and having a demonstration effect on other bay areas and city clusters.

2. Methods

2.1. Overview
Based on the IMED|CGE (Integrated Model of Energy, Environment and Economy for Sustainable Development, computable general equilibrium) model, this study combines decomposition analysis and regression methods (figure 1) to analyze the energy-economic-environmental impacts of different climate targets and end-of-pipe air pollutant control magnitudes.

We first construct a two-region CGE model for the GBA and ROC for the first time in the literature, which is used to project the future industry-level carbon emission pathways, air pollutants, and relevant socioeconomic trends up to 2050. Furthermore, by innovatively combining the CGE model with decomposition analysis and regression methods that are frequently applied in retrospective studies, we identify major drivers and emission reduction mechanisms. Using the LMDI method, the trends in CO₂ emissions are decomposed into effects from five drivers, including carbon intensity, energy structure, energy intensity, industrial output, and household consumption. We also use SPD to further analyze the impact of coal consumption on air pollutant emission reduction and the underlying direct and indirect impact mechanisms.

2.2. Social-economic and energy model
The two-region IMED|CGE model in this study is developed by the Laboratory of Energy & Environmental Economics and Policy at Peking University, which includes the GBA and ROC. The input-output (IO) table and energy balance table of the base year 2015 were used as the database for the socioeconomic energy aspects, and air pollutant emission inventory data were combined to form the base year data. The model covers 29 sectors (table S1), and this sectoral classification provides a relatively detailed portrayal of energy-intensive and high-emission sectors to better model low-carbon transition pathways. The model dynamically simulates industrial structure changes, energy consumption, CO₂, and air pollutant emission trends from 2015 to 2050 in 1 year step. More information can be found on the website (http://scholar.pku.edu.cn/hanchengdai/imedcge).

2.3. Decomposition analysis

2.3.1. Logarithmic mean Divisia index
The LMDI analysis compares a set of indices between the base and final year of a given period and explores the effects of these indices on the trend of emissions over that period [33]. We can decompose the total CO₂ emissions as

\[ C = \sum_i \sum_j C_{ij} = \sum_i \sum_j O_i \times \frac{I_j}{O_j} \times \frac{E_{ij}}{E_{ij}} + \frac{C_{ij}}{E_{ij}} \]

\[ = \sum_i \sum_j O_i \times I_j \times M_{ij} \times T_{ij} + \Delta C_{H1}. \] (1)

Here, \( \Delta C_{H1} \) is the CO₂ emissions change caused by household consumption. \( O_i \) is sector \( j \)'s total output; \( I_j = E_j/O_j \) is the energy intensity in sector \( j \) and measures the energy consumption per unit of gross domestic product (GDP), which indicates the energy efficiency; \( M_{ij} = E_{ij}/E_j \) is the proportion of fuel type \( i \) in sector \( j \) and represents the energy mix effect; \( M_{ij}, M_{ij}, M_{ij}, M_{ij} \) and \( M_{ij} \) in equation (1) describe the proportion of coal, oil, natural gas and electricity in the production. \( T_{ij} = C_{ij}/E_{ij} \) is the emission intensity of fuel type \( i \) in sector \( j \), reflecting changes in fuel carbon content upgrades (for example, replacing brown coal with anthracite) within any broad fuel type (that is, coal consumption).

According to the LMDI model, the change in energy-related industrial CO₂ emissions in year \( t \) compared with the year \( t - 1 \) is calculated as

\[ \Delta C_{\text{tot}} = \sum_i \sum_j L \left( \omega_{ij}^t - \omega_{ij}^{t-1} \right) \ln \left( \frac{O_{ij}^t}{O_{ij}^{t-1}} \right) \]

\[ + \sum_i \sum_j L \left( \omega_{ij}^t - \omega_{ij}^{t-1} \right) \ln \left( \frac{M_{ij}^t}{M_{ij}^{t-1}} \right) \]

\[ + \sum_i \sum_j L \left( \omega_{ij}^t - \omega_{ij}^{t-1} \right) \ln \left( \frac{T_{ij}^t}{T_{ij}^{t-1}} \right) \]

\[ = \Delta C_O + \Delta C_M + \Delta C_I + \Delta C_T. \] (2)

Here, \( L(x, y) = \begin{cases} \frac{(x - y)}{(\ln x - \ln y)}, & x \neq y > 0 \\ x, & x = y > 0 \end{cases} \)
2.3.2. Structural path decomposition analysis

We also use SDA to measure the driving factors on the industrial scale. We use additive decomposition, and the change in carbon emissions $d(E)$ is decomposed into three factors that denote the change in carbon emissions, which are carbon emissions intensity change (CI), intermediate input structure change (IO) and the final demand (FD) change:

$$d(E) = d(CI) LFD + CI d(L) FD + CIL (dFD).$$  \hspace{1cm} (3)

As carbon emissions change in the two scenarios and various factors change at the same time, weighting is needed when using discrete decomposition. We adopt the average weighted decomposition method, and the three factors obtained can be expressed as follows:

$$\Delta E_{CI} = \frac{1}{3} \times \Delta CI_0 LFD_1 + \frac{1}{6} \times \Delta CI_1 LFD_0$$
$$+ \frac{1}{6} \times \Delta CI_0 LFD_1 + \frac{1}{3} \times \Delta CI_1 LFD_1$$

$$\Delta E_{IO} = \frac{1}{3} \times CI_0 \Delta LFD_0 + \frac{1}{6} \times CI_0 \Delta LFD_1$$
$$+ \frac{1}{6} \times CI_1 \Delta LFD_0 + \frac{1}{3} \times CI_1 \Delta LFD_1$$

$$\Delta E_{FD} = \frac{1}{3} \times CI_0 L_0 \Delta FD + \frac{1}{6} \times CI_0 L_1 \Delta FD$$
$$+ \frac{1}{6} \times CI_1 L_0 \Delta FD + \frac{1}{3} \times CI_1 L_1 \Delta FD. \quad (4)$$

The SPD method is generated by combining SDA and structural path analysis [34], which can explore the change in carbon emissions in each supply chain and the corresponding influencing factors. Combining the discrete structure decomposition formula (4)
with the expansion formula of the Leontief matrix (5), the decomposition formula of SPD can be obtained. Such as Cl0, ∆FD = Cl0(1 + A + AA) ∆ FD = Cl0 ∆ FD + Cl0A ∆ FD + Cl0AA ∆ FD.

\[ L = (I - A)^{-1} = I + A + A^2 + \ldots \]  \hspace{1cm} (5)

\[ \Delta E \approx \frac{1}{2} \times \Delta CI (FD_0 + FD_t) + \frac{1}{2} \times (CI_0 + CI_t) \Delta FD \\
+ \frac{1}{6} \times \Delta CI[A_0 (2FD_0 + FD_t) + A_1 (FD_0 + 2FD_t)] \\
+ \frac{1}{6} \times [CI_0DA (2FD_0 + FD_t) \\
+ CI_1DA (FD_0 + 2FD_t)] \\
+ \frac{1}{6} \times [(2CI_0 + CI_t)A_0 \Delta FD \\
+ (CI_0 + 2CI_t)A_1 \Delta FD] \\
+ \frac{1}{6} \times [CI_0DA_0 (2FD_0 + FD_t) \\
+ CI_1DA_1 (FD_0 + 2FD_t)] \\
+ \frac{1}{6} \times [CI_0DA (2FD_0 + FD_t) \\
+ CI_1DA (FD_0 + 2FD_t)] \\
+ \frac{1}{6} \times [(2CI_0 + CI_t)A_0A_0 \Delta FD \\
+ (CI_0 + 2CI_t)A_1A_1 \Delta FD]. \hspace{1cm} (6)

2.4. Regression model

To further explain the impacts of carbon policy on air pollutant emissions, we conduct a regression model to estimate the pass-through effects, which would benefit the analysis of comprehensive model results [35–37]. As figure 1 shows, carbon policy (represented by carbon shadow price), structural change, as well as end-of-pipe control measures are the main explanatory variables influencing air pollutants emissions. Putting carbon policy as the critical explanatory can also represent the changes in energy price and energy use, based on the estimations of formulas (7) and (8). In terms of using energy structure and industrial structure to partially explain the differences in air pollutants emission, we build up formulas (9) and (10) to derive the residual of these regressions (‘res’ in formula (11), hereafter), which are the values unrelated to energy price and use. Then we can use the residuals of energy structure and industrial structure in formula (11) to capture the impacts of natural structural changes on air pollutants emissions. Finally, in formula (11), we take the fraction of coal and oil in total primary energy use as energy structure, the fraction of selected energy-intensive sectoral production in total production as industrial structure, the removal rate of specific end-of-pipe technology as end-of-pipe, and carbon shadow price in the CGE model as carbon price.

\[ \log(\text{energy price}_m, t) = \alpha_0 + \beta_{m,0} \cdot \log(\text{carbon price}_t) + \varepsilon_{0,t} \]  \hspace{1cm} (7)

\[ \log(\text{energy use}_m) = \alpha_1 + \gamma_1 \cdot \log(\text{carbon price}_t) + \varepsilon_{1,t} \]  \hspace{1cm} (8)

\[ \log(\text{energy structure}_m, t) = \alpha_2 + \beta_2 \cdot \log(\text{energy price}_m, t) + \gamma_2 \cdot \log(\text{energy use}_m, t) + \varepsilon_{2,t} \]  \hspace{1cm} (9)

\[ \log(\text{ind structure}_m, t) = \alpha_3 + \beta_3 \cdot \log(\text{energy price}_m, t) + \gamma_3 \cdot \log(\text{energy use}_m, t) + \varepsilon_{3,t} \]  \hspace{1cm} (10)

\[ \log(\text{air pollutants}_m, t) = \alpha_4 + \beta_4 \cdot \log(\text{carbon price}_t) + \gamma_4 \cdot \log(\text{end-of-pipe}_m, t) + \delta_4 \cdot \text{res(energy structure)} + \theta_4 \cdot \text{res(ind structure)} + \mu_{4,t} \]  \hspace{1cm} (11)

where \( m \) and \( n \) distinguish the different energy items (coal, oil, gas, and electricity) and specific end-of-pipe technology (PM2.5, SO2, VOC, NOx, NH3). \( \alpha \) is the intercept, and \( \beta, \gamma, \delta \) and \( \varepsilon \) are marginal effects of their explanatory. \( \varepsilon \) and \( \mu \) are residuals of the corresponding regression model. \( t \) defines the different time stage that we take 2030 as a watershed because the Chinese government’s pledge aims to achieve peak carbon emission by 2030. So, in each formulas (9)–(11), we regress twice based on the two-time ranges. From all the above steps, we quantitatively specify how much the reduction of air pollutant emissions can be achieved by a unit carbon shadow price. Besides, the marginal effects of other essential variables, including structural change and end-of-pipe technology, are also estimated.

2.5. Scenario setting and data

As shown in table 1, six scenarios are set up in this study to explore the impact of carbon emission reduction and end-of-pipe air pollution control in two dimensions. The climate policy dimension includes the baseline scenario without any emission cap (BaU), a 2-degree scenario, and a 1.5-degree climate target scenario. The air pollution control dimension consists of a frozen scenario and a current legislation (CLE) scenario.

In terms of climate scenarios, based on the global carbon emission pathways under the 1.5-degree and 2-degree global climate targets [38, 39], the future carbon emission constraint pathways for the GBA are downscaled based on the principle of convergence of per capita emissions.

In terms of air pollutant control, for the setting of end-of-pipe removal rates for each air pollutant,
Table 1. Scenario setting with two dimensions of climate mitigation and air pollution control.

| Scenario       | Definition                                                                 | Climate target                                                                 | End-of-pipe pollution control                                      |
|----------------|----------------------------------------------------------------------------|--------------------------------------------------------------------------------|---------------------------------------------------------------------|
| BaU_frozen     | BaU_frozen offers the reference point for other scenarios. It presumes China will achieve its Nationally Determined Contributions (NDCs) pledges, and the air pollutant end-of-pipe control will remain at the 2020 level. | CO₂ emissions peak in 2030 that in line with NDC pledges               | End-of-pipe removal rate control frozen at the 2020 level          |
| BaU_CLE        | BaU_CLE shares the same energy and socioeconomic development with BaU_frozen, but will deploy stronger end-of-pipe control technologies. |                                                                                   | Current released and upcoming policies                              |
| 2-degree_frozen| 2-degree_frozen is designed to pursue the 2-degree climate target and assumes a faster rate of electricity substitution and a higher level of technological progress than BaU. The air pollutant end-of-pipe control would remain at the 2020 level. | 2-degree                                                                   | End-of-pipe removal rate control frozen at the 2020 level          |
| 2-degree_CLE   | 2-degree_CLE shares the same energy and socioeconomic development with 2-degree_frozen, but will deploy stronger end-of-pipe control technologies. | 2-degree                                                                   | Current released and upcoming policies                              |
| 1.5-degree_frozen| 1.5-degree_frozen is designed to pursue the 1.5-degree climate target and assumes a faster rate of electricity substitution and a higher level of technological progress than 2-degree. The air pollutant end-of-pipe control would remain at the 2020 level. | 1.5-degree                                                                   | End-of-pipe removal rate control frozen at the 2020 level          |
| 1.5-degree_CLE | 1.5-degree_CLE shares the same energy and socioeconomic development with 1.5-degree_frozen, but will deploy stronger end-of-pipe control technologies. | 1.5-degree                                                                   | Current released and upcoming policies                              |

this study calibrated the reduction rate according to emission inventories in 2017 and made projections based on existing policies (table S4). For future simulation years, the frozen scenario assumes that end-of-pipe removal rate control is frozen at the 2020 level. In contrast, the CLE scenario assumes a continuation of the existing control effort. Therefore, carbon emissions are the same between CLE and frozen scenarios, and in sections 3.1–3.3, which focus on the results of energy and CO₂, we do not distinguish between CLE and frozen scenarios for simplicity.

The total population, investment rate, and total factor productivity are the same for six scenarios. See appendix p 5 for the setting. All currency units are at constant 2015 prices for the base year. It is noteworthy that this study made innovative adjustments in the parameter of energy efficiency improvement exogenously by sector and energy type. Many CGE modeling studies modify the autonomous energy efficiency improvement (AEEI) by taking a constant value for simplicity. Moreover, the AEEI parameter only distinguishes between different energy types, which leads to an inability to portray changes in the consumption of crucial energy in key sectors and thus may underestimate the rate of the energy transition. Therefore, this study takes a different approach, adjusting direct input coefficients in the IO table for the power generation and end-use sectors to simulate energy efficiency improvements to address these shortcomings. Table S3 and appendix p 6 briefly show how we adjusted it.

3. Results

3.1. Energy consumption pattern and CO₂ emissions trajectory

In the BaU scenario, the scale effect of economic development and population growth will spur an increase in energy demand, which will lead to a continuous increase in carbon emissions before 2030 under an energy mix dominated by fossil fuels (figure 2(a)). With the decarbonization of power generation and a slowdown in population growth, CO₂ emissions will peak at 540.8 million and 11.7 billion tons for the GBA and ROC in 2030, respectively. The number will decline thereafter (figure 2(b)), which is consistent with China’s NDCs pledge. By 2050, transport will be the main contributor to carbon emissions in the GBA, accounting for 31.2% of the total emissions, followed by power generation (16.1%) and manufacturing (16.0%) (figure 2(b)). By contrast, in ROC, power generation is predicted to be the main contributor to carbon emissions, accounting for 25.2% of the total emissions by 2050, followed by metal smelting
Figure 2. Final energy consumption pattern and CO$_2$ emissions of the Greater Bay Area and the rest of China. (a) Final energy demand. (b) CO$_2$ emissions by sector in the BaU. (c) Total CO$_2$ emissions trajectories. (d) Emission reduction contribution by sector in 2050 (sorted by the amount of emission reduction).

including iron steel and non-ferrous metal smelting, 17.6%) and transportation (16.0%).

The 1.5-degree scenario requires reducing carbon emissions to half of 2020 levels approximately by the year 2037, which implies a profound transformation of the energy system (figure 2(a)). In 2050, the proportion of electricity in the total energy consumption for the GBA will increase from 36.6% in the BaU to 79.3% in the 1.5-degree scenario. Similarly, electricity consumption in the ROC will increase from 24.5% to 78.4%. The service sector accounts for the highest share, and road transportation will have the highest growth rate of electricity demand among all sectors in the GBA, reflecting the large-scale penetration of electric vehicles. The metal smelting sector accounts for the highest share in the ROC, with services having the highest growth rate.

In 2050, in terms of sectoral contribution to carbon reduction compared to the BaU (figure 2(d)), under the 2-degree target, transportation will be the most crucial sector in the GBA, contributing to 26.6% of the reduction (62.0 Mt), followed by manufacturing (23.4%, 54.5 Mt). Under the 1.5-degree target, transport remains the largest emission reduction sector (41.8%, 39.9 Mt), and deep decarbonization of the power generation sector will make a further significant contribution, reducing the total emissions by 25.0% (39.9 Mt) compared with the 2-degree scenario. By contrast, the ROC has a different sectoral abatement pathway. In comparison to the BaU, under the 2-degree scenario, metal smelting is the largest contributor to reduction (1419.0 Mt, 21.3%), followed by the power generation sector (1355.4 Mt, 20.4%) in 2050. However, in the 1.5-degree scenario, the power generation sector reduces emissions by 364.7 Mt (28.6%) compared with the 2-degree scenario.

3.2. Industrial structure change and economic impact

In the BaU, the total industrial output of the GBA and ROC will be 6.5 and 5.4 times the 2015 level, and GDP per capita will increase to 98.0 and 47.1 kUSD (constant price in 2015) in 2050, respectively. In the GBA, the share of the tertiary sector will increase from 61.6% in 2015 to 67.1% in 2050 (figure S5), approaching the levels in developed countries. Unlike other international bay areas, the advanced manufacturing industry is still an important part of the GBA and will account for more than 30% by 2050. This may imply that the GBA is under greater environmental pressure than other bay areas.

Under climate policy scenarios, the price of fossil fuel energy will increase, making energy-intensive industries costlier and less productive, resulting in varying degrees of decline in output and GDP (figures 3(a) and (b)). For instance, compared to the BaU, the total output of the GBA and ROC is reduced by 2.3%–3.7% and 3.6%–4.9%, and GDP per capita will increase to 98.0 and 47.1 kUSD (constant price in 2015) in 2050, respectively. In the GBA, the share of the tertiary sector will increase from 61.6% in 2015 to 67.1% in 2050 (figure S5), approaching the levels in developed countries. Unlike other international bay areas, the advanced manufacturing industry is still an important part of the GBA and will account for more than 30% by 2050. This may imply that the GBA is under greater environmental pressure than other bay areas.
will be 6.2% and 3.0%, while in the ROC, it will be 1.5% and 0.3%, respectively. This is because we assumed faster industrial restructuring, more rapid energy transition, and higher energy efficiency in the 1.5-degree scenario (appendix p 6). However, government spending, an essential pillar of the economy in the face of disaster, shows an increase.

Carbon and energy intensity can be used to measure efficiency. These two indicators will continue to decline as the economy and technology develop. The energy efficiency of the GBA was found to be higher than that of the ROC. Moreover, energy efficiency will be further improved in the climate scenario. Meanwhile, in 2050, the carbon intensity of the GBA and ROC under the 1.5-degree scenario will be further reduced by 11.6% and 14.8%, respectively, compared to 2015. In terms of trade under the 1.5-degree scenario compared to the BaU (figure 3(d)), increased exports of textiles and electronics in the GBA, which have lower carbon intensity and higher added value, could mitigate GDP losses. The increase in imports and decrease in provincial exports by waterways, aviation, and road transportation, which are more carbon-intensive, could help ease the pressure for carbon emission reduction because carbon emissions in this model are from the producer’s perspective.

3.3. Key contributions to carbon emission reduction

This study defines the future trends of the different emission driving forces through LMDI analysis (figure 4(a)). The output expansion is a critical driver of the increase in carbon emissions in the two regions, which can be offset by the decrease in energy intensity under the 1.5-degree scenario. In addition, the contribution of changes in the energy structure to carbon reduction will become more important over time. Specifically, energy intensity could reduce emissions by 284, 148, and 79 million tons in the 2015–2030, 2030–2040, and 2040–2050 periods in the GBA, respectively.

This study further uses the SPD method to determine the changes in CO₂ emissions of the core inter-industry supply chain between 1.5 degrees and BaU in 2050 (figure 4(b)). The most crucial emission reduction factor in both regions is the reduction in CO₂ intensity (emissions per unit output, or CI effects in figure 4(b)). In addition, a significant
Figure 4. The key factors contributing to decarbonization based on (a) the LMDI approach from 2015 to 2050 in the 1.5-degree_frozen scenario, and (b) the SPD approach from the perspective of the industrial chain in the 1.5-degree_frozen compared to the BaU scenario. In panel (b), the node on the left side is the supply sector that supplies the raw materials (different colors distinguish supply chains with different numbers of sectors), and the numerical symbols represent the industry’s position in the supply chain (specifically, the number ‘2’ or ‘3’ represents that the sector is in the second or third position in the supply chain), the sector at the end of the supply chain is the final demand sector, and the term ‘CI’ represents the carbon intensity effect, the ‘IO’ represent the Input-Output coefficients changes effect, and ‘FD’ represents the final demand effect.

A difference is found between the two regions in other critical paths for reducing emissions. In the GBA, textiles (TEX), road transportation (TRD), and aviation (TAR) are the core reduction sectors. The direct CO$_2$ emission reductions triggered by changes in CO$_2$ emission intensity are 13.5, 11.7, and 11.6 million tons, respectively. Conversely, in the ROC, the power (ELE, 380 million tons), service (CSS, 247), chemical (CHM, 175), and construction (CNS, 137) sectors contribute the most to direct carbon emission reduction. Due to the reduction of carbon emission intensity in the power sector, the supply chain from the power sector to the service sector could reduce carbon emissions by 5.3 million tons in the GBA. On the contrary, in the ROC, the supply chain from the power sector to the CNS reduces carbon emissions by 195 million tons. In addition, a critical third-order supply chain, from the power sector to non-metals to construction (ELE-ONM-CNS), reduces carbon emissions by 125 million tons. Compared with the key contribution of the carbon intensity effects, the influences of the industrial IO factors on the supply side and FD factors on the demand side is relatively insignificant in both regions. The impact of IO factors on emissions is only 2.7% and 16.4% of the impact of CI factors in the GBA and ROC, respectively. The impact of FD factors on emissions is only 9.4% and 1.4% of the impact of CI factors in the GBA and ROC regions, respectively. For instance, in the ROC, the intermediate demand of the service sector for electricity increases, resulting in a 99 million ton increase in the carbon emissions of this supply chain.
3.4. Synergistic reduction effects of carbon reduction on air pollutant abatement in the GBA

Without additional climate policies and end-of-pipe controls (BaU_frozen), NO\textsubscript{x}, SO\textsubscript{2}, VOC, NH\textsubscript{3}, and primary PM\textsubscript{2.5} emissions in 2050 in the GBA will be 0.73, 0.81, 3.91, 2.66, and 1.10 times the 2015 levels, respectively, owing to the increase in energy consumption and socioeconomic activity (figure 5(a)). The implementation of climate policy can help reduce air pollutant emissions, but the effects vary depending on the type of pollutant. NO\textsubscript{x} and SO\textsubscript{2} have a relatively higher degree of synergy along with carbon abatement, mainly from the combustion of fossil fuels in the transportation and power generation sectors. In contrast, VOC, NH\textsubscript{3}, and primary PM\textsubscript{2.5} are less synergistic because they are mainly from process emission sources. NH\textsubscript{3} mainly originates from the agricultural sector and is less influenced by climate policies, while primary PM\textsubscript{2.5} mainly originates from the emissions created in the production process of non-metals. Therefore, VOC, NH\textsubscript{3}, and primary PM\textsubscript{2.5} are more dependent on end-of-pipe abatement controls, especially in the absence of a climate policy. As climate targets and end-of-pipe controls become stricter, the sectoral emissions shares of different air pollutants would also change (figures 5(b))

(ELE-CSS). In the GBA, the increase in intermediate inputs from electricity to other sectors also leads to a slight increase in carbon emissions.
and S9–S11). For example, if we rely solely on climate policy but without efforts from end-of-pipe technologies under the 1.5-degree_frozen scenario, the proportion of VOC industrial process emissions in the total emissions will increase from 67.9% in 2015 to 98.4% in 2050, with the main contributing sector changing from road transportation (30.9%) to chemical production process emissions owing to the electrification of the transport sector. For NOx, with additional efforts from end-of-pipe technologies under the 1.5-degree_CLE scenario in 2050, the contribution from the power sector increases significantly with a decline in emissions from the transport sector.

Several high-ranking sectors for implementing synergic governance are identified in the blue shadow considering synergistic co-reduction effects and unit abatement costs (figure 5(b)). It is found that sectors contributing more than 5% of the emissions would have a higher degree of effective synergistic reduction effects and lower emission reduction costs. For instance, for NOx, the transport sector, including water transport (corresponding to TWT) and road transport (TRD), is found to have the highest synergies and lowest costs in the 1.5-degree_frozen scenario, while aviation (TAR) and metal smelting (MET) sectors incur the highest costs. Conversely, textiles (TEX), railway (TRL), food production (FOD), and power generation (ELE) sectors have negative abatement costs owing to increased production. For SO2, the water transport sector has the highest synergies and lowest abatement costs, while non-metals (ONM) and textiles sectors are also the key sectors that contribute more and have lower abatement costs. For VOC, road transport is the most synergistic and least costly, while it is noted that there are some trade-offs between CO2 and VOC, with an increase in the production of electronics (ELP) potentially leading to an increase in VOC. For NH3, the agricultural sector (AGR) has a higher contribution, a higher degree of synergy, and a lower cost. For primary PM2.5 emissions, synergistic benefits exist for non-metals, transport, and construction (CNS).

3.5. Differentiated stagewise marginal effects of climate policy on air pollutant emissions
The regression results for the impacts of carbon shadow price on energy price and energy use (table S2) suggest that a 1% increase in carbon shadow price will stimulate a 0.1% increase in coal price and a slight decrease in other energy prices, which leads to a 0.09% decrease in final energy use and affects energy-intensive industrial activities. Consequently, air pollutant emissions will be affected since fossil fuels and energy-intensive sectors are the main sources of most air pollutants emissions.

As shown in tables 2 and 3, the marginal impacts of the carbon shadow price and other explanations are detected for the emissions of five air pollutants under the 1.5-degree and 2-degree scenarios. Most
5. Discussion and conclusions

Achieving ambitious climate mitigation targets will have profound impacts on the economy, energy, and environment, especially in rapidly developing regions, which deserve in-depth investigation. Based on a recursive dynamic two-region CGE model accompanied by decomposition analysis and regression methods, industry-level carbon and air pollutant

remarkably, a more stringent climate policy will have a greater effect on the annual air pollutant reduction. For instance, from 2030 to 2050, the 1.5-degree scenario could bring more obvious co-benefits than the 2-degree scenario. A 1% increase in carbon shadow price could bring a reduction of 0.51% in the 1.5-degree scenario but an even higher reduction of 0.63% in NOX emissions in the 1.5-degree scenario. Furthermore, from the medium- and long-term perspectives, it is found that the carbon shadow price will reduce the emissions of air pollutants quite differently from 2030 to 2050 as compared to before 2030 periods.

For instance, in the 1.5-degree scenario, the marginal increase per 1% in the shadow price of carbon could result in a much more significant decrease in primary PM2.5 emissions in the 2030–2050 periods (0.51%) than that (0.25%) in the 2015–2030 periods. The same trend is observed for VOC and NOX. However, the effect of the policy on SO2 is reversed with other air pollutants. Its co-benefits are stronger during 2015 and 2030, partially due to adequate pre-actions on mitigating sulfur, which causes marginal effects to decline. However, the results show that the marginal effect of shadow price on VOC emissions is −0.5% after 2030, with no significant effects between 2015 and 2030, indicating a trade-off with carbon reduction, as mentioned in section 3.4. In addition, the marginal effects of carbon policy on NOX and NH3 emissions only exist statistically after 2030, and surprisingly, a 1% increase in the carbon shadow price could also increase NH3 by 0.01%. It may be that higher mitigation costs hinder co-benefits in the context of figure 5.

By examining the contribution of the end-of-pipe technologies, it is concluded that their removal rates play more essential roles in reducing primary PM2.5, SO2, NOX, and NH3 emissions in the post-2030 era, especially under the weaker 2-degree scenario. For instance, from 2030 to 2050, under the stronger 1.5-degree scenario, a 1% increase in the end-of-pipe removal rate will reduce SO2 emissions by 1.8%, NOX emissions by 1.8%, and NH3 emissions by 0.35%. However, when climate ambitions are not so strong in the 2-degree scenario, the effects will become 2.5%, 2.1%, and 0.48%, respectively. In addition, the effects of end-of-pipe technology on VOC are ambiguous, probably because the GBA still participates in large chemical production, so the emissions forecast for 2030 is nearly unchanged compared to 2015 (figure 5).

Table 3. Marginal effects of carbon policy on air pollutants emission in CLE in 2030–2050 in the GBA, based on formula (11).

| Climate target | Variable | Primary PM2.5 | SO2 | VOC | NOX | NH3 |
|----------------|----------|---------------|-----|-----|-----|-----|
| 1.5 °C         | Carbon shadow price | −0.51*** | −0.07*** | −0.50*** | −0.63*** | 0.02*** |
|                | End of pipea | 1.60 | −1.80*** | −1.10 | −1.80* | −0.35*** |
|                | Energy structure | 0.82 | 0.05 | 0.13 | 1.4 | 0.04 |
|                | Ind structure | 3.90** | 0.67 | 3.3 | 0.67 | 1.00** |
|                | Constant | −0.14 | 12.00*** | 14.00*** | 17.00*** | 6.20*** |
|                | Observations | 20 | 20 | 20 | 20 | 20 |
|                | Adjusted $R^2$ | 0.99 | 1.00 | 0.94 | 0.98 | 0.92 |
|                | F Statistic | 478.0*** | 2016.0*** | 71.0*** | 247.0*** | 56.0*** |
| 2 °C           | Carbon shadow price | −0.16*** | −0.06*** | −0.55*** | −0.51*** | 0.03*** |
|                | End of pipea | −6.20*** | −2.50*** | −0.67 | −2.10*** | −0.48*** |
|                | Energy structure | 4.3 | 1.1 | 5.50 | 7.10* | 0.00 |
|                | Ind structure | 2.5 | 0.06 | −0.18 | −1.60 | −0.86* |
|                | Constant | 31.00*** | 15.00*** | 12.00*** | 17.00*** | 6.70*** |
|                | Observations | 20 | 20 | 20 | 20 | 20 |
|                | Adjusted $R^2$ | 0.98 | 0.99 | 0.97 | 0.99 | 0.96 |
|                | F statistic | 255.0*** | 586.0*** | 151.0*** | 533.0*** | 122.0*** |

Notes: values in the first line are estimators of $\beta$, $\gamma$, $\delta$, and $\theta$. Values in parentheses are standard errors. Stars are the level of significance in the t-test. The $p$-value classification are: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. 

...
emission pathways were simulated in the GBA and the ROC, and the key influencing factors, sectoral contributions, and impact mechanisms underlying the joint emission reduction were analyzed in this study. In literature, there are three mainstreams, but disconnected ways of analyzing the effectiveness and impacts of climate policies: (a) through complex system simulation tools such as the top-down CGE model or bottom-up technology optimization model; (b) based on retrospective data-driven decomposition analysis approaches such as LMDI and SPD methods; and (c) based on empirical approaches such as statistical or econometric models. Traditionally, combining these approaches in a single study or paper is rare, if not absent, despite the fact that they are complementary to each other. In such a context, in addition to integrating the up-to-date, realistic energy-environment-economic dataset from various authoritative local institutions into the two-region CGE model dedicated to the GBA region, this study makes remarkable methodological contributions to the literature by innovatively combining the decomposition, econometric and general equilibrium simulation approaches to maximize the strength of each method. By doing so, this study overcomes the shortcomings of the retrospective approaches in their inability to analyze the future climate policy shocks while opening the ‘black box’ criticized for the conventional CGE model-based studies.

The results of our modeling analysis show that climate policies will have a profound impact on the conventional economy, leading to a decrease in total output by 2.3%–3.7% and 3.6%–4.9%, and GDP losses of 3.3%–4.3% and 1.8%–3.2% in the GBA and ROC in 2050, respectively. Furthermore, faster industrial restructuring, more rapid energy transitions, higher energy efficiency, and restructuring of export and import structures can effectively counteract the economic impact of climate policies. However, the foreseeable economic loss mitigation actions should be immediately implemented to curb the increase in carbon emissions if the 1.5 °C target is to be met.

Reducing energy intensity and restructuring the energy mix of key sectors are essential for reducing carbon emissions. It was found that a reduction in energy intensity can offset the increase in carbon emissions due to economic output expansion. Further, the contribution of the energy mix transition will become increasingly more important over time. Meanwhile, there are apparent regional differences in the sectors that contribute to carbon emission reduction. Transport and power generation contributed the largest carbon reductions in the GBA and ROC, respectively. In addition, from the perspective of the secondary industrial chain, power generation, as the main end-use energy and intermediate input, plays a core role in emission reduction in both regions.

Climate policies can effectively reduce the emissions of air pollutants, but this effect varies for different pollutants and sectors. NO\textsubscript{x} and SO\textsubscript{2} emissions have a relatively higher degree of synergy with carbon emission reduction, mainly from the combustion of fossil fuels in the transportation and power generation sectors. In contrast, VOC, NH\textsubscript{3}, and primary PM\textsubscript{2.5} are less synergistic because they are mainly from process emission sources, suggesting the continued importance of end-of-pipe control measures. The sectors with priority for synergic governance dependent on the air pollutant type were further identified, highlighting the importance of key sectors such as power generation, transport, and non-metal processes. The carbon shadow price is significantly more effective in reducing air pollutant emissions in the post-2030 era than before 2030, except in the case of SO\textsubscript{2} and NH\textsubscript{3}, partially because of the existing adequate desulfurization and denitrification actions that cause the synergistic effects to decline.

This study also encompasses some limitations. First, the IMED|CGE model used in this study does not explicitly consider discrete power generation technologies. Instead, they are represented as an aggregated category that does not adequately model the substitution effects between energy sources for power generation. Second, non-energy combustion-related air pollutant emissions from industrial processes driven by output are simplified as a function of economic output value rather than physical output and specific technologies, which is a classical treatment and weakness of top-down type economic models. Third, the cost of controlling air pollutants is not considered in the model used in the study, although the technical costs of end-of-pipe control measures are typically minor compared with the transition costs of deep decarbonization in the long-run. Finally, this study only deals with synergies in terms of energy consumption and industrial processes and does not include the potential change in air pollutant emissions that may result from the implementation of specific low-carbon measures.

In conclusion, the analysis of this study uncovers the impact mechanisms of climate policy and air pollution and provides valuable insights into their synergistic governance, which is applicable to other city clusters facing the dual challenges and cost dilemmas of climate change mitigation and air pollution control. The findings indicate that economic losses in reducing carbon emissions can be partially offset by exporting high-value-added, low-carbon products. However, attention must be paid to air pollutant emission sources beyond the reach of synergistic effects, such as VOC emissions from the manufacture of electronic products. Meanwhile, a well-developed transport network is an accelerator of economic development in the GBA, but it is also the highest carbon-emitting sector as well as the key emission source of NO\textsubscript{x}, SO\textsubscript{2}, and VOCs. Therefore, such insights from the GBA could provide invaluable lessons for other urban agglomerations facing
similar situations, such as the Beijing–Tianjin–Hebei region in China [40] and the United States [41]. To reduce emissions in the transport sector, various measures are required, including enhancing emission standards, increasing the electrification rate, promoting public transport, and accelerating low-carbon and clean power generation. At the same time, reducing energy intensity, which involves improving energy-use efficiency and optimizing the industrial structure, is another important driver for reducing carbon emissions. From the cost-effectiveness perspective, to maximize the synergistic emission co-reduction effects of climate policy on air pollutants, attention should be paid to coordinated control and prioritization of key sectors with lower costs and higher efficiency of emission reduction, as identified in this study. Last but not least, it is critical to focus on adopting end-of-pipe control technologies for air pollutants, where process emissions dominate, especially for VOCs, NH$_3$, and primary PM$_{2.5}$. 

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare that they have no conflict of interest.

Author contributions

Xiaorui Liu designed the outline and wrote the manuscript. Chaoyi Guo did a regression model, wrote the corresponding text, and calibrated the IMED|CGE model with Kai Wu. Xiaotian Ma developed the decomposition method and wrote the corresponding text. Peng Wang constructed the input-output table and energy balance table of 2015 for the Greater Bay Area. Zhijiong Huang constructed the air pollutant inventory for the years 2015 and 2017. Chen Huang, Ziqiao Zhou, and Silu Zhang were involved in the interpretation of the results. Minghao Wang was involved in visualization. Hancheng Dai designed the overall study, developed the IMED|CGE model and reviewed the whole manuscript.

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