The unintended dilemma of China's target-based carbon neutrality policy and provincial economic inequality

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0. Abstract

Target-based carbon mitigation could be an essential strategy for achieving carbon neutrality. However, how carbon reduction will affect economic balance across different regions remains unclear. Here, with a newly developed dynamic multi-region computable general equilibrium model for China's 31 provincial economies, we examine the regional economic impacts of different carbon quota arrangement schemes. It is found that without fostering new growth engines driven by low-carbon industries, the national stringent carbon restrictions will bring an 'economic sabotage' with deteriorated regional equity and polarized the industrial structures, especially in the fossil-fuel reliant north China. Carbon shadow prices and costs play a prominent role and cause rippling effects in this regionally imbalanced recession, depending on energy, industrial structures and endowments. Furthermore, no prevailing carbon quota arrangements, either by historical, intensity, or capacity rules, could resolve the dilemma between equality and effectiveness in our simulation. By contrast, to offset the regionally unbalanced shock of decarbonization, it is important to cultivate low-carbon industries timely to compensate for the potential transition costs in the long run.

Keywords: Carbon Neutrality; Regional economic inequality; General equilibrium; China; IMED Model

1. Introduction

In response to the Paris Agreement, China announced its ambitious goal of achieving a carbon peak by 2030 and carbon neutrality by 2060, commonly known as the "3060" target. Despite notable progress in transitioning to low-carbon practices(Guan et al., 2018; Xu et al., 2014; Zhao et al., 2022), the current advancements still fall behind the global need(UNEP, 2021). Numerous studies(Duan et al., 2021; Xiliang et al., 2022) have emphasized the challenge of reconciling the "3060" target with China's fossil fuel-driven economic growth. For instance, transitioning to renewable energy sources necessitates a significant increase from less than 15% to over 75% by 2060, while reducing thermal power generation from 68% to below 10%, requiring substantial long-term investments based on some multi-model practices (Kong et al., 2023; Zheng et al., 2021).

Various approaches to decarbonization have been considered, such as limiting the quantity of carbon emissions by strict regulation, allocating carbon permits to stakeholders, levying a carbon

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tax and allowing emitters to trade their carbon permits (Chen and Nie, 2020; Sugandha et al., 2014). Traditional environmental economics categorized these into two aspects: quantity-based and price-oriented policies (Weitzman, 1974). Studies have shown that these policies have global mitigation benefits in both ex-ante (Böhringer and Welsch, 2004; Lin and Jia, 2018) and ex-post cases(Huang et al., 2022; Zhang and Wei, 2010). **However, because of the high dependence on fossil fuels and inelastic energy demand, price-oriented policies might be ineffective in China**. For instance, over the past 20 years, the price elasticities of fossil fuel demand ranged from -0.2 to -0.7, which means a 1% increase in price only reduces 0.2% to 0.7% in energy demand (Burke and Liao, 2015; Lin and Zeng, 2013). This phenomenon indicates that a carbon trading system or carbon tax alone cannot be a perfect choice in the past. Therefore, since 2005, one of the main agendas of the Chinese government has been to directly limit both energy consumption and intensity, commonly used as “energy consumption and intensity dual control system” (Congress, 2006, 2010), leading to significant impacts on climate mitigation, energy and industrial structural change, and economic expansion (Meng et al., 2011; Mi and Sun, 2021; Zhang and Wang, 2022).

In light of China's resolute commitment to the "3060" targets, a quantity-based policy prevails, both in the present and foreseeable future, following the government's transition from the "energy consumption and intensity dual control system" to "carbon dual control"(Xi, 2022). However, the allocation of these substantial national mitigation targets among diverse emission stakeholders remains an unresolved challenge. Given that a significant portion of emissions originates from state-owned companies under the regulation of central or provincial governments, policymakers must find a viable way to scale down the national carbon neutrality target to different levels without unduly disrupting local development agendas. Failure to consider these local interests will achieve the national targets, albeit widening the regional gap and weakening public support (Konc et al., 2022). Researchers quoted this predicament as "one-size-fits-all" (Jörgensen et al., 2015; Paul and Milman, 2017). For instance, China's energy capping policy, primarily focused on ensuring the national feasibility of caps, places a disproportionate economic burden on the Western regions, thereby impeding their local development (Guo et al., 2019; Shi et al., 2020). This imbalance arises from the disparity between ambitious policy targets and regionally limited capabilities (Liu et al., 2022b; Mi and Sun, 2021). However, prioritizing local interests over the efficiency of achieving mitigation targets may lead to a reduction in overall effectiveness. In this regard, Jin et al. (2020) pointed out the carbon trading scheme in China, which allocates more permits to regions with more production, would be an ideal solution due to its fewer economic losses. Goulder et al. (2022) used an equilibrium model to explain that this scheme implicitly subsidy the existing production, thereby compromising cost-effectiveness. Many researchers concluded this as the trade-off between the efficiency of policy achievements and regional equity (Lange et al., 2007; Zhou and Wang, 2016).

Looking forward, the ambitious "3060" target holds considerable promise, and it is likely that governance will continue to be quantity-based. So far, few studies have explored these uneven regional or sectoral impacts. Specifically, the dynamics of industrial structural changes along inter-regional and inter-sectoral economic chains remain inadequately understood, given their intricate interplay involving multilateral trade, relative price adjustments, and spillover effects. Therefore, evaluating these potential impacts and underlying mechanisms can provide valuable policy insights for the central and local governments in formulating long-term decarbonization strategies and garnering public support.

In this paper, we propose an analytical framework using a dynamic multi-region and multi-sector computable general equilibrium (CGE) model validated with 2017 data of China' provincial economies. This model enables us to examine how carbon neutrality policies will affect industrial outputs and structures across 31 provinces in China. We consider six policy scenarios with different rules for provincial carbon permit allocation, categorized as equity-based and efficiency-based rules, which are included in Table 1. To facilitate the understanding of the complex results, we first demonstrate the results of SaCI in sections 3.1-3.3, which is relatively close to the current carbon policy arrangement, as a central and starting point for analyzing potential effects. We then introduce the multi-scenario experiments in section 3.4 to see whether multiple rules of carbon permit allocation can alleviate the unintended inequalities. In section 3.5, the CGE model is sharpened by coupling with an econometric model to analyze the pass-through rippling effects of the multiple policy shock. Based on the enlightenment of simulation results contrasted against reality, thoughtful policy implications are put forward to find equity-efficiency solutions. More details about the methodology are described in Section 2.

2. Methods

2.1 Overview of the methods

A multi-province and multi-sector computable equilibrium (CGE) model is built to simulate the carbon policy to reach China's 2060 carbon neutrality pledge at the provincial level. A guideline of the CGE model can be seen in section 2.2, and the policy scenarios in this study are introduced in section 2.3. To further explain subsequent impacts and uneven effects, we evaluate the regional and sectoral inequalities using statistical indices, such as the Gini coefficient and Theil coefficient, and compare their changes across scenarios (section 2.4.1). Regression models based on the CGE results are used to uncover how the policy would result in inequality and to show the effects of price signals triggered by carbon mitigation (section 2.4.2).

2.2 Computable general equilibrium (CGE) model

The IMED|CGE (Integrated Model of Energy, Environment and Economy for Sustainable Development | Computable General Equilibrium) model used in this study is a recursive-dynamic CGE model, covering 25 aggregated economic sectors of 31 provinces in mainland China. Based on the general equilibrium theory, the CGE model solves the optimized level of supply, demand, and prices that support equilibrium in interrelated marketplaces under a set of constraints. The capacity of the CGE model to examine the implications of low-carbon-related policies for macroeconomic indicators, such as industrial structure, employment, and social fairness, makes it valuable in the quantitative analysis of environmental and climate policies.

As shown in Fig. 1, four blocks in the IMED|CGE model interact with each other simultaneously: the production block, the market block covering domestic and international transactions, and the blocks covering the income and expenditure of the government and household. Solved at a one-year time step, the model generates the parameters of interest based on the recursively dynamic behavior and results of previous periods.

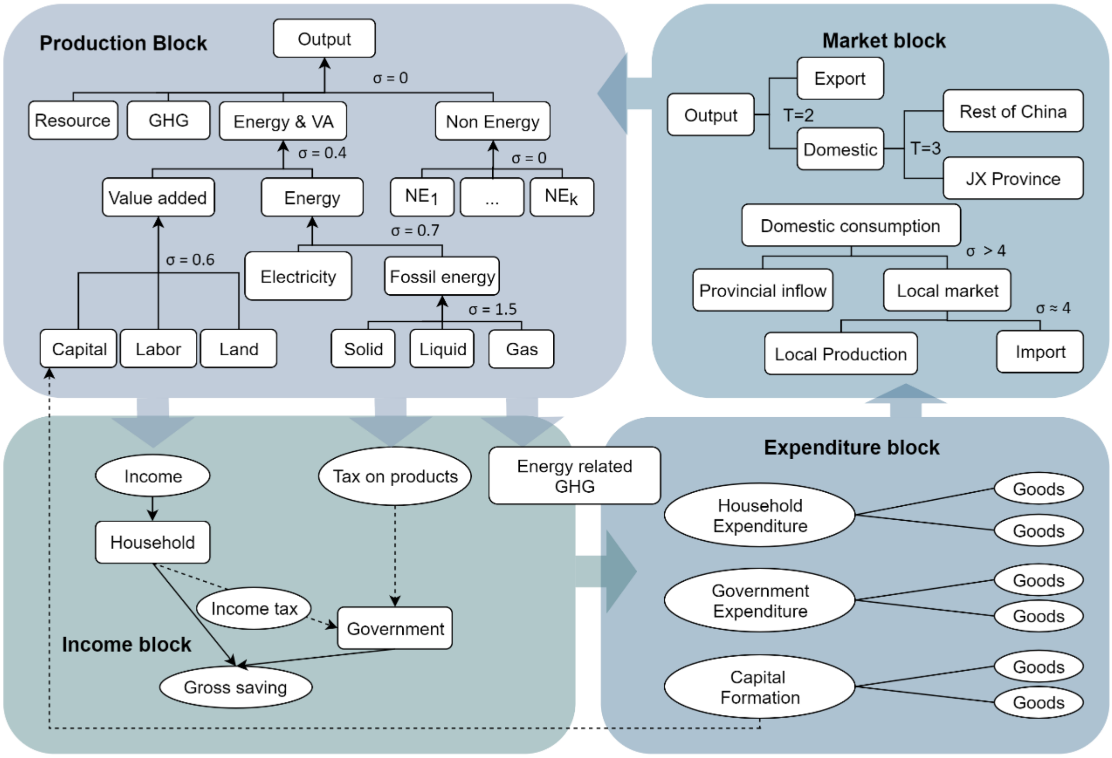

Fig. 1 The four interacting blocks in the IMED|CGE model framework

In this study, we use the IMED|CGE model to assess the effects of achieving the carbon neutrality target on the 31 provinces in China during 2017-2060. The input data of the base year is collected through the inter-regional input-output table (IOT) and the energy balance tables (EBT). In addition, Tibet's data in 2017 are derived from the available data in 2014, referring to Ou et al. (2019) and Shan et al. (2017). As the IOT and EBT follow inconsistent formats, the energy consumption data from the IOT is converted into EBT order, which is believed to be more reliable in energy consumption to achieve consistency. Furthermore, to simulate provincial competition due to carbon intensity constraints in a CGE model, it is assumed that under the assumption of market clearance, the price of a commodity in any province is determined by three indices, which are the supply to the local market of the same province, the outflow to the domestic markets of other provinces, and the export to the international market. Suppose the carbon reduction target causes more burden on the target province than on others, either through imposing more stringent emission constraints or levying a higher carbon tax. In that case, the commodity prices in the target province will increase more significantly, making the province a "loser" in the provincial competition, resulting in a lowered demand for its products and, thus a decreased output.

Fig. 2 shows how the carbon policy affects the production block in the CGE model and uncovers which variables are the prominent causes of the output loss. Leontief functions are adopted to mimic the physical thermal laws that govern the relationship between carbon emissions ($CO2_{r,j}$) and different fossil fuel combustion ($FOS_{r,j}$). Therefore, by acting on the endpoints of carbon emissions, the target-based carbon policy will directly influence the energy input and accordingly change the equilibrium results.

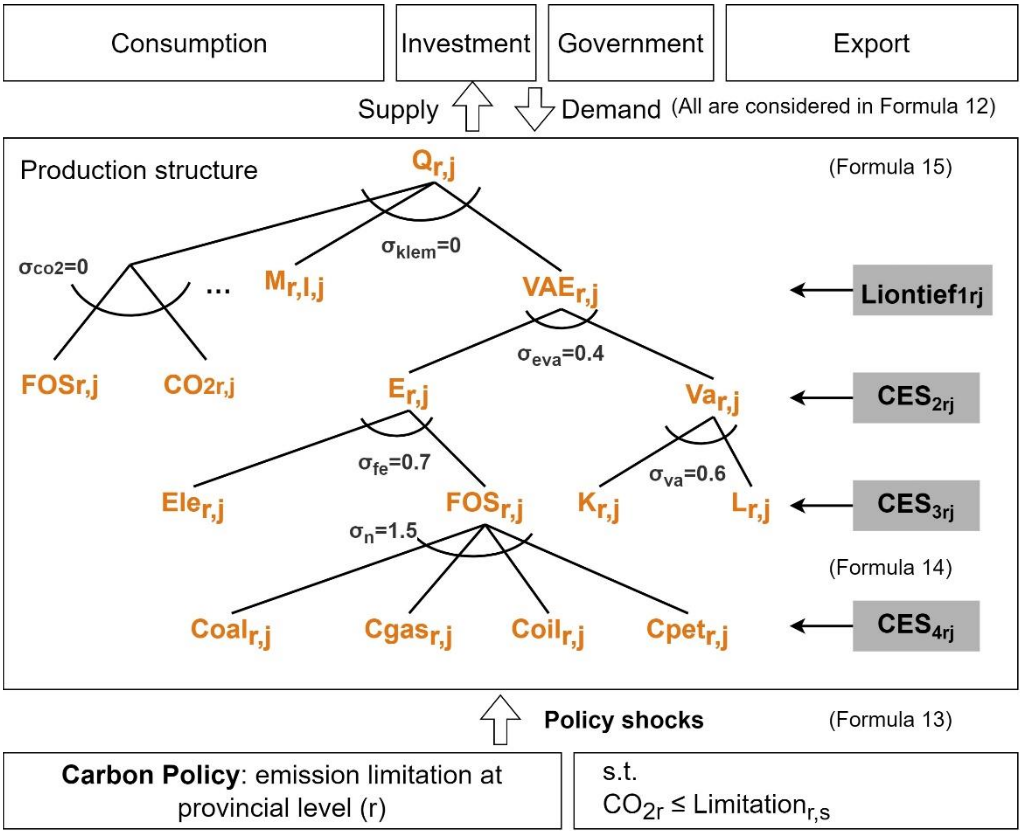

Fig. 2 The detailed nesting structure of a representative producer in the IMED|CGE model and the relationships between total demand, production, and carbon policy shock (r, j, s stand for region, sector, and scenario.). Formulas 5-8 are described in section 2.4.2, and it is clear that the regression setting and variables choices are derived from the CGE model setting.

2.3 Policy scenario setting

To testify whether different carbon allocations will change the uneven effects, six carbon neutrality policies are designed in this study: (1) Business as usual (BaU), (2) efficiency-based policies, including SaCI, E, F scenarios. (3) equity-based policies, including CA, DE, and HS scenarios. The detailed assumptions are listed in Table 1.

Before allocating carbon permits among provinces, we must set a national emission cap in 2060, considering China's carbon budget under the neutrality pledge. As the negative emission technologies (NETs) will provide spaces for 'the last mile' emissions for industries or other necessary carbon emitters, the potentials from NETs such as bioenergy with carbon capture and storage (BECCS) and afforestation (or land carbon sink) should be carefully considered in the national emission cap. Referring to the BECCS evaluation by Weng(2021), Huang(2020), and Jiang(2018), and the land carbon sink estimation by Fang(2018), Wang(2022b), and other studies on the global carbon budget(Bednar et al., 2021; Friedlingstein et al., 2020), we found that BECCS and terrestrial carbon sink could each provide approximately 0.8~1.5 Gt/CO_2 yr in China in 2060. For simplicity, we assume their combined neutralized potential as 2.1 Gt/CO_2 in 2060, as the national carbon budget allocated to all provinces. The emission trajectories of each scenario are shown in Fig. S1.

Table 1 The detailed scenario setting in this study

Basic rule	Scenarios	Descriptions

Business as usual	**BaU**	Business as usual
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	SaCI	Requiring all provinces to achieve the same carbon intensity in 2060
Efficiency-based	**E**	Requiring all provinces to reduce their emission with the same yearly decline rate
	F	Requiring all provinces To achieve the same per capita emission in 2060
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	HS	Provinces with higher historical accumulated emissions will have more carbon permits
Equity-based	**CA**	Provinces with higher GDP per capita in 2060 will have fewer carbon permits
	DE	Provinces with higher GDP per capita in 2020 will have fewer carbon permits

2.3.1 SaCI

$$C_{i,SaCI,2060} = CI_{China,SaCI,2060} \times GDP_{i,BaU,2060} \quad (1)$$

$$CI_{China,SaCI,2060} = \frac{C_{\text{china,SaCI,2060}}}{GDP_{China,BaU,2060}} = 0.036\ tCO_2\ /\ million\ USD \quad (2)$$

Where, $C_{i,SaCI,2060}$ is the carbon emission permits of province i in 2060 under the SaCI scenario, $C_{\text{china,SaCI,2060}}$ is the national carbon emissions, $CI_{China,SaCI,2060}$ is the national carbon intensity, which is 0.036 tCO_2/million USD, estimated by GDP and the carbon emission budget under the neutrality targets above. Smooth linear projection is used to calculate the emission trajectory from 2018 to 2059.

2.3.2 E

$$V_{i,t} = V_{China,t} \quad (3)$$

Where, $V_{i,t}$ is the carbon emission reduction rate of province i in year t. The emissions are set to peak in around 2025 and then decline by -1% to -7% yearly rate.

2.3.3 F

$$C_{i,\text{F},2060} = C_{\text{china,F,2060}} \times \frac{POP_{i,\text{SSP2,2060}}}{\sum_{i=1}^{31} POP_{i,\text{SSP2,2060}}} \quad (4)$$

Where, $C_{i,\text{F},2060}$ is the carbon emission permits of province i in 2060 under the F scenario, $C_{\text{china,F,2060}}$ is the national carbon emission in 2060 under the F scenario, $POP_{i,2060}$ is the projected population of province i in 2060 based on the SSP2 (Chen et al., 2020). Smooth linear projection is used to get the emission limitation from 2018 to 2059. This equivalent per capita emission principle is referred from Liu et al. (2022a).

2.3.4 HS

$$C_{i,HS,2060} = C_{\text{china,HS,2060}} \times \frac{\sum_{1997}^{2019} C_{i,t}}{\sum_{i=1}^{31}\sum_{1997}^{2019} C_{i,t}} \quad (5)$$

Here, $C_{i,t}$ is the provincial emission from 1997 to 2019. Because Tibet only has the emission data in 2014 (Zheng et al., 2019), we used the national emission growth rate to fulfill the emission of Tibet from 1997 to 2019.

2.3.5 DE

$$C_{i,DE,2060} = C_{\text{china,DE,2060}} \times \frac{POP_{i,\text{SSP22060}} \times (GDP_{i,2020}/POP_{i,2020})^{-\alpha}}{\sum_{i=1}^{31} POP_{i,\text{SSP2,2060}} \times (GDP_{i,2020}/POP_{i,2020})^{-\alpha}} \quad (6)$$

Here, $\frac{POP_{i,2060} \times (GDP_{i,2020}/POP_{i,2020})^{-\alpha}}{\sum_{i=1}^{30} POP_{i,2060} \times (GDP_{i,2020}/POP_{i,2020})^{-\alpha}}$ represents the carbon permits fraction of province i. α is the adjustment parameter, ranging from 0 to 1. A smaller α could narrow the emission permit gap among provinces. In this paper, we take α as 0.5. This indicates that the DE scenario arranges the carbon permits mainly based on the current development level.

2.3.6 CA

$$C_{i,CA,2060} = C_{\text{china,CA,2060}} \times \frac{POP_{i,\text{SSP2,2060}} \times (GDP_{i,\text{BaU,2060}}/POP_{i,\text{SSP2,2060}})^{-\alpha}}{\sum_{i=1}^{31} POP_{i,\text{SSP2,2060}} \times (GDP_{i,\text{BaU,2060}}/POP_{i,\text{SSP2,2060}})^{-\alpha}} \quad (7)$$

Similar to the DE scenario, we use $GDP_{i,\text{BaU,2060}}/POP_{i,\text{SSP2,2060}}$, GDP per capita in 2060 as a reference to allocate the carbon permits. It indicates that regions with higher development potential will have less future emission space. In this case, we take α as 0.5 as well.

2.4 Empirical strategy

2.4.1 Inequality indicators

This study uses multiple statistical indices, including the Gini coefficient, Theil coefficient, and the range to quantitatively measure the regional disparity in various macroeconomic indicators. In general, each index can represent the gap and inequality with advantages and disadvantages that are complementary to each other. The simplest one is the range between the highest and lowest value (formula 8).

$$Exm_{i,t} = \left(\max_i y_{i,t} - \min_i y_{i,t}\right) \quad (8)$$

$y_{i,t}$ is GDP or other macroeconomics variables at the per-capita level in province *i* and year *t*. Formulas 10 and 11 show the general framework of the Gini and Theil coefficients and their unique set in this study.

$$Gini = \left(\frac{1}{2n^2\mu}\right) \sum_{i=1}^{n} \sum_{j=1}^{n} \left|y_i - y_j\right| \quad (9)$$

Where, both i and j are regions and $\left|y_i - y_j\right|$ means all possible pair-wise. Originally, y is a person-based index like income per capita, but some studies also use region-based indices. For instance, Lin and Zhou (1998); Lin et al. (1998) implemented per capita industrial output to calculate the Gini coefficient for the analysis of the regional development gap in China, and Miaojing and Hongmin (2013) reviewed the literature that uses the Gini to analyze the inequality of carbon emissions. The other comprehensive inequality indicator is the Theil index, which can be seen in the following formula:

$$Theil = \sum_i^n f_i \frac{y_i}{\mu} \ln \frac{y_i}{\mu} \quad (10)$$

f_i is the fraction of y_i in aggregated value of 31 provinces. More details about the indices above can be seen in Sen et al. (1997), Guanghua (2009) and Xu(2003).

2.4.2 Regression model

To further explain how and why carbon policies influence provincial and sectoral production that leads to inequality, we have built up a multi-stage regression framework, as shown in Fig. 3 and formulas 12-15. This regression strategy is initiated from the nesting structure of the production process under CGE modeling, explaining how we connect fossil fuel use and carbon emission with economic activities and how the carbon policy will affect the following economic, energy, and emissions inside IMED|CGE model, which can refer to Dai (2018).

In order to explain the scenario changes of per capita output, formula 12 has been built up, using scenario changes of capital price ($CapitalPrice_{r,t}$), labor price ($LaborPrice_{r,t}$), demand-side variables ($DemandSide_{r,t}$), energy and industry structure at BaU ($Structure_{BaU_{r,t}}$) as explanatory variables. Regarding this regression, consumption and net export loss are used to be proxy of demand-side variable, the fraction of coal in primary energy use and the fraction of EITE (energy-intensive sector, Table S1) production in total production under the BaU scenario is used as the variable of energy and industrial structure. The core focus of our analysis is the parameter $\gamma_{1,j}$, which represents the extra marginal effects of carbon policy, differentiated by regional heterogeneity. Here, we use $EmissionGap_{t,r}$or $CarbonCost_{t,r}$ to represent the carbon policy. The former is the percentage emission differences between BaU and policy scenarios, while the latter is calculated by emissions multiplying carbon shadow price. In addition, r, t, and j denote regions, time, and sectors, respectively.

$$OutputLoss_{r,t,j} = \alpha_1 + \beta_{1,j} \cdot CarbonPolicy_{r,t} + \gamma_{1,j} \cdot CarbonPolicy_{r,t} \times RegionDummy + \theta_1 \cdot LaborPrice_{r,t} + \vartheta_1 \cdot CapitalPrice_{r,t} + \iota_1 \cdot DemandSide_{r,t} + \delta_1 \cdot Structure_{BaU_{r,t}} + \sigma_r + \varphi_t + \varepsilon_{r,t}$$

(11)

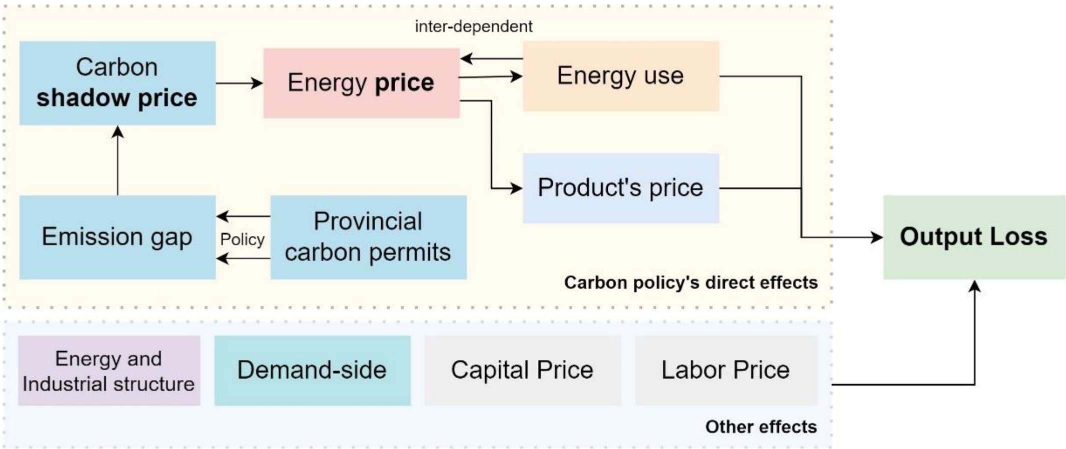

Fig. 3 The ideal framework of the regression model

The first step is to explain the formation of the carbon shadow price. Instead of a carbon tax or emission trading, in the CGE model used for this study, we implemented a carbon emission constraint for each province each year. According to the Kuhn-Tucker condition(Kuhn and Tucker, 1951), the shadow price is the following multiplayer λ, which is directly correlated with the percentage difference between emissions in BaU and the policy scenarios, which is defined as the $EmissionGap_{t,r}$ in Formula 13, which also gives a complete picture of the regression framework to explain this correlation:

$$\boldsymbol{log}\ (\boldsymbol{CarbonPrice_{t,r}}) = \alpha_2 + \beta_2 \cdot log\ (EmissionGap_{t,r}) + \boldsymbol{\theta_2} \cdot log\ (EmissionGap_{t,r}) \times RegionDummy + \sigma_{2_r} + \varphi_{2_t} + \varepsilon_{2_{t,r}} \quad (12)$$

Where $CarbonPrice_{t,r}$ stands for the shadow price in year *t* and province *r*. α, β and ε are parameters in the regression model. We anticipate that a wider emission gap will lead to a higher carbon shadow price, significantly raising production costs. Θ evaluates the different emission gaps in different regions.

Then, the energy price, especially the fossil fuel energy price, will change, which will, in turn, influence energy use. However, the change in energy price and energy use are interdependent in both model and reality. Accordingly, we build up a three-stage least squares (3SLS) regression, which consists of a two-stage least squares (2SLS) and a seemingly unrelated regression (SUR). 3SLS helps to effectively estimate the parameters when formulas are interrelated (Qiang, 2014). Meanwhile, it has been widely used for such quantity-price problems(Kamerschen and Porter, 2004).

$$\begin{cases} \boldsymbol{EnergyPrice_{r,t}} = \alpha_3 + \beta_3 \cdot EnergyUse_{r,t} + \gamma_3 \cdot CarbonPolicy_{r,t} + \boldsymbol{\eta_3} \cdot CarbonPolicy_{r,t} \\ \qquad \times RegionDummy + \vartheta_3 \cdot otherEnergyPrice_{r,t} + \sigma_{3_r} + \varphi_{3_t} + \varepsilon_{3_{t,r}} \\ \boldsymbol{EnergyUse_{r,t}} = \alpha_4 + \beta_4 \cdot EnergyPrice_{r,t} + \boldsymbol{\lambda_4} \cdot EnergyPrice_{r,t} \times RegionDummy \\ \quad + \theta_4 \cdot EnergyIntensity_{r,t} + \vartheta_4 \cdot PE_{Coal_{r,t}} + \iota_4 \cdot GDP_{Consum_{r,t}} + \sigma_{4_r} + \varphi_{4_t} + \varepsilon_{4_{t,r}} \end{cases} \quad (13)$$

The endogenous variables in this simultaneous equation are $\boldsymbol{EnergyPrice_{r,t}}$ and $\boldsymbol{EnergyUse_{r,t}}$, and the others are exogenous variables or the lists of Instrumental variables (IV). The changes in energy prices are driven by energy use, carbon policy, regional heterogeneity, and substitute energy prices. The changes in energy use are driven by energy price, regional heterogeneity, and changes in energy intensity ($EnergyIntensity_{r,t}$), changes in coal fraction in primary energy use ($PE_{Coal_{r,t}}$), changes in household consumption ($GDP_{Consum_{r,t}}$).

Then, the energy price will finally influence the production price, as energy is one of the essential materials product's output, especially in energy-intensive sectors such as electricity. Formula 15 gives the estimations between production price, energy price, and regional heterogeneity, changes in labor and capital price, and household consumption change.

$$ProductPrice_{j,r,t} = \alpha_5 + \beta_{5_j} \cdot EnergyPrice_{r,t} + \boldsymbol{\psi}_{5_j} \cdot EnergyPrice_{r,t} \times RegionDummy + \theta_{5_j} \cdot SubstituteEnergyPrice_{r,t} + \kappa_5 \cdot LaborPrice_{r,t} + \vartheta_5 \cdot CapitalPrice_{r,t} + \iota_5 \cdot GDP_{Consum_{r,t}} + \sigma_{5_r} + \varphi_{5_t} + \varepsilon_{5_{j,r,t}} \quad (14)$$

In addition, all the above formulas have been estimated by considering σ_r and φ_t as the regional and time-fixed effects and intercept α will be removed when the panel effects have been implemented.

3. Results

3.1 The economic impacts of carbon intensity convergence

When the national net-zero restriction target requires the carbon intensity of each province to converge to the same level by 2060, as assumed in the SaCI scenario, the provincial industrial activities and economies will be hurt to different extents. **Meanwhile, those with tremendous absolute losses may not be the ones bearing the deepest pain** (**Fig. 4**). For instance, compared to the BaU scenario, Shandong and Guangdong would suffer the most absolute negative output loss of 3.7 and 1.2 trillion US dollars (USD, 2017 constant price) in 2060, respectively. However, their relative losses (19.0% and 6.2%) are not the highest. By contrast, Inner Mongolia and Gansu would suffer nearly half of their production in 2060, by 49.6% and 39.5%, respectively. Furthermore, it can be seen from **Fig. 4**a that the policy shocks would heavily cut production in northern and eastern China, which are China's core industrialized zones. However, the relative pains are minor in these well-developed regions. The percentage loss is around 1.1% and 6.5% in Jiangsu and Zhejiang, much less than that in the northern regions like Shanxi and Hebei, where the relative losses head to 33.9% and 31.5%. The exceptions are in several central developing provinces like Hubei and Jiangxi, where the absolute and relative losses are milder compared to their neighboring provinces to the south and North.

When it comes to sectoral loss, **it is found that the provincial economic loss is mainly caused by the shrinkage of the traditional industrial output that makes up the backbone of the current local economies**. Compared to BaU, the national output value of **manufacturing** sectors is projected to reduce by the most (4.7 trillion USD, 12.1%), followed by 2.6 trillion USD (25.3%) in metal smelting and 1.8 trillion USD (3.5%) in service (**Fig. 4**d), which is higher than most other sectors across all provinces. By contrast, even though fossil-fired power generation does not have to undertake such an absolute reduction as massive as manufacturing, its declining rate compared to BaU will head to 41.5%, implying that such fossil-fired power generation loss ought to be compensated by zero-carbon power sources such as renewables. More detailed results in Fig. 4b-d show that **provinces relying more on fossil fuel and a highly carbon-intensive industrial system**

will experience a more painful low-carbon transition. For instance, coal accounted for 96.1%, 95.4%, and 84.3% of total primary fossil energy use in Shanxi, Inner Mongolia, and Hebei in 2017. Consequently, chemicals, metal smelting, and manufacturing are the most suffering sectors in 2060 in Shanxi, Inner Mongolia, and Hebei, accounting for 20.6%, 27.1%, and 37.6% of the total loss, respectively. On the contrary, the situation in provinces driven by low-carbon and high-tech industries such as Guangdong and Shanghai are pretty different. These regions consume much less coal, only 55.8% and 42.4% in their primary fossil energy mix. Hence, the most shrinking sectors are not heavy industry but electronics, service, and transport. For instance, 86.3% of the output loss in Guangdong is caused by its electronics, 53.9% of which is due to the decline in overseas exports (**Fig. 4**a and **Fig. 4**b).

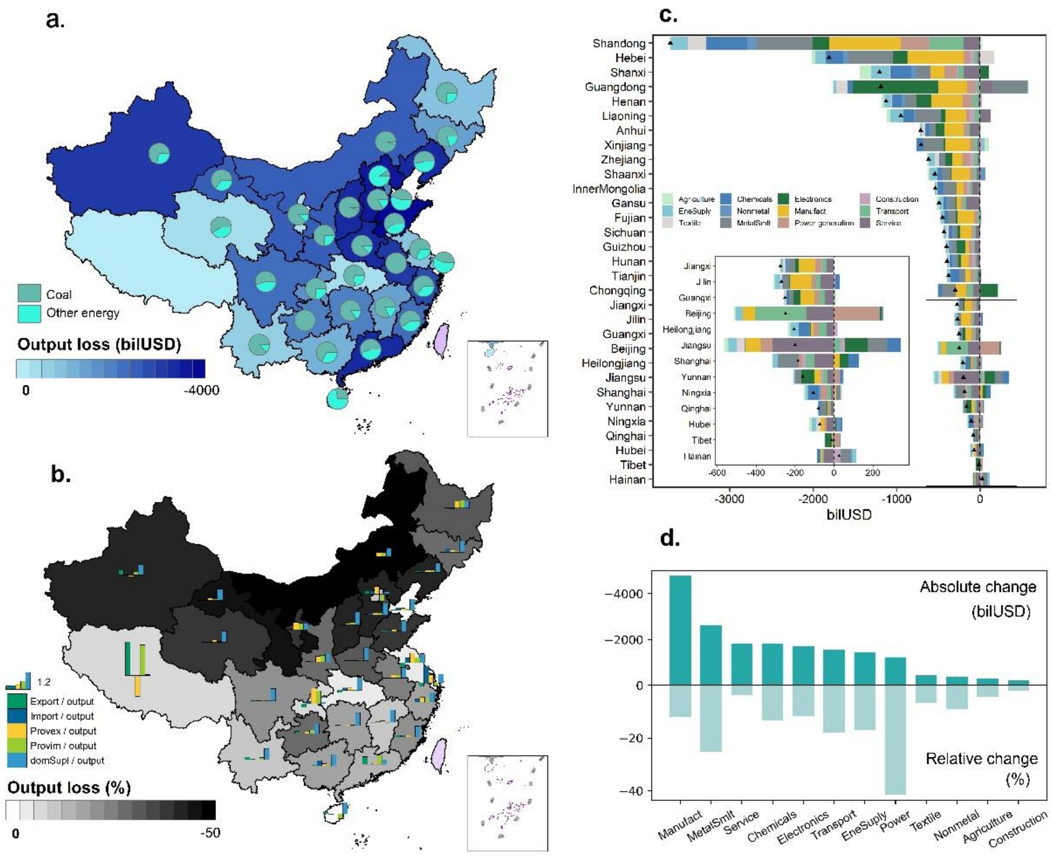

Fig. 4. Absolute and relative output loss in China at the provincial and sectoral level from BaU to SaCI scenario in 2060. (a). Absolute output loss at the provincial level. The pie chart shows the fraction of coal use in the primary fossil energy mix in 2017; (b). Relative output loss at the provincial level. The bar chart shows the percentage of trade and domestic supply loss in the total output loss in 2060; (c). Absolute loss in different sectors at the provincial level; (d). Absolute (upper panel) and relative (lower panel) loss at the sectoral level in China. In addition, '**Export**' in (b) means the export to other countries, '**Provex**' means outflow from one province to other provinces, '**Import**' means import from foreign countries, and '**Provim**' means inflow from other provinces. '**domSupl**' means the supply of commodity produced in a certain province to its own domestic provincial market. The details about the abbreviation of sectors are included in Table S1.

3.2 The inequality effects on provincial macroeconomics

Whether the heterogeneities of negative impacts in section 3.1 improve or worsen provincial economic inequality is a matter of concern. **Fig. 5**a demonstrates that carbon emission restriction not only lowers economic development but also widens the macroeconomic gap among provinces over time. The Gini coefficients of GDP per capita in China are projected to increase from 0.25 in BaU to 0.29 in SaCI in 2060. In the BaU scenario in 2060, Beijing has the highest per capita GDP at 98.5 thousand USD/capita, while Gansu lies on the other end of the economic spectrum with 19.8 thousand USD/capita, and Anhui (39.3 thousand USD/capita) falls in the middle zone. However, these values are lowered significantly to different extents under the SaCI scenario, especially in the most undeveloped regions. Inner Mongolia replaces Gansu as the poorest province with a per capita GDP of 11.1 thousand USD, yet Beijing's per capita GDP falls only slightly by 1.32% to 97.2 thousand USD/capita. Additionally, the median province switches to Hunan, which decreases by 4.6% to 36.9 thousand USD/capita (**Fig. 5**b). The other macroeconomic indicators, such as the components of GDP, household or governmental consumption, export, and import, also exhibit similar characteristics. In particular, provinces show more disparities in export and import behaviors, as indicated by higher Gini coefficients, although the annual increase of the Gini coefficients is not significant. For instance, the Gini coefficient of exports in the SaCI scenario is projected to increase from 0.48 to 0.51 and that of imports increases from 0.47 to 0.50 (**Fig. 5**a). It is noted that those uneven effects on trade and industrial transfer might further alter the economic structures. Consequently, it implies that the backward provinces will face even more significant challenges in catching up with well-developed provinces when undertaking deep decarbonization in the future.

Furthermore, in **Fig. 6**, we use the Gini coefficient to concisely depict the uneven effects on sectoral outputs and their components. The level of inequality in overall output is expected to increase slightly from 2017 to 2060 in BaU (0.26 to 0.28), but the carbon neutrality policy will significantly raise the level of inequality from 0.28 in BaU to 0.32 in SaCI in 2060. The Gini coefficient of domestic supply is also expected to increase from 0.28 to 0.31 from the BaU to SaCI in 2060. Most importantly, the sectoral Gini coefficients reveal that **when implementing deep decarbonization, energy supply sectors will have more severe regional disparities and be concentrated in one or two regions, especially the southwestern regions**. For instance, the Gini coefficient of power generation output is projected to increase from 0.48 in the BaU scenario to 0.79 under SaCI in 2060, with power generation predominantly shifting to southwestern China, such as Yunnan. Similarly, a similar trend is observed in gas production, which will be significantly concentrated in Chongqing and Sichuan, accounting for 26.0% of the national output in 2017 and projected to reach 55.7% by 2060 in the BaU scenario. This proportion is expected to increase further to 80.9% by 2060 in the SaCI scenario. The Gini coefficients for the energy supply sector, such as coal, coke, crude oil, petrol oil, power generation, and gas are higher compared to any other sector. This shift is also reflected in the Gini coefficients of sectoral exports and imports. For example, in power generation, the scenario change in the Gini coefficient of exports is expected to increase from 0.76 to 0.91, which is the highest. However, despite the influence of the carbon neutrality policy, the absolute production in these energy sectors is projected to decline by over 70% compared to the BaU scenario. This indicates that the geographical shift in production will significantly have negative economic consequences.

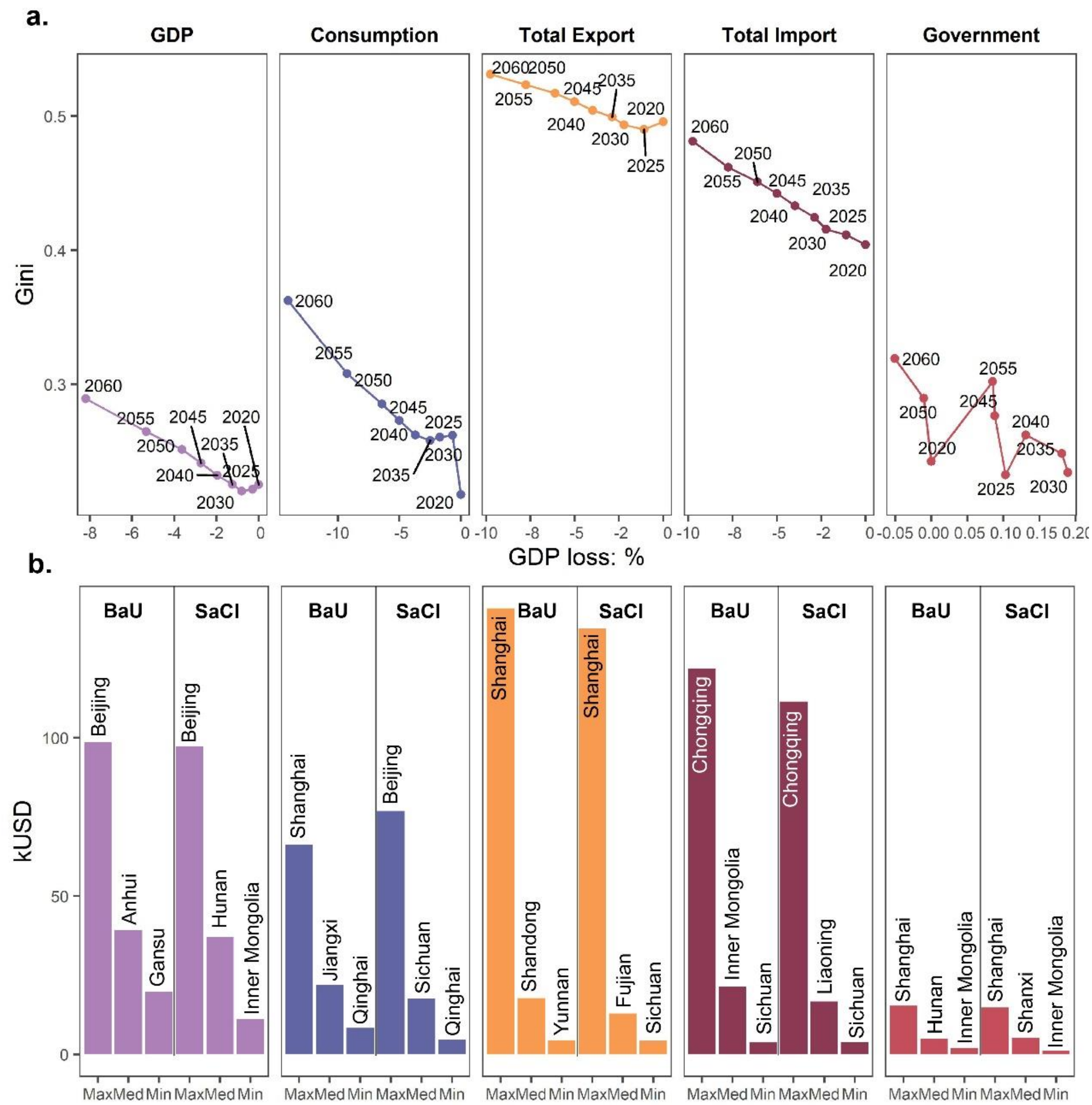

Fig. 5 The Gini coefficients and the range of macroeconomics indicators at the provincial level under BaU and SaCI scenarios (a). The interactions between macroeconomics loss (x-axis) and Gini coefficients (y-axis). **(b).** The maximum, median, and minimum values of each macroeconomic indicator under BaU and SaCI in 2060. It is noted that all macroeconomic indicators are at the per capita level. The calculation of Gini and the range value are included in section 2.4.1. Investment is not included because IMED|CGE treats it as exogenous input, which doesn't vary across scenarios. More details can be seen at https://www.jianguoyun.com/p/DZnI8a8QlL7CBhi913M.

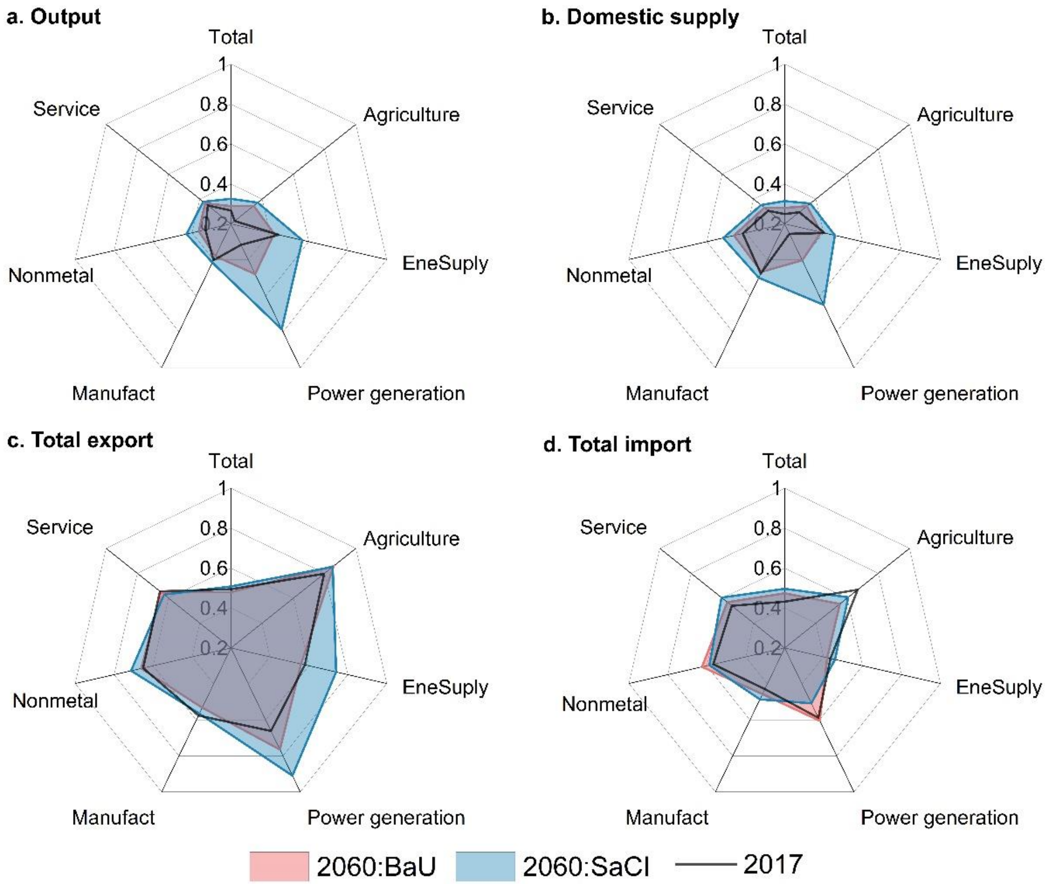

Fig. 6 Gini coefficients of sectoral output in 2017 and 2060 under BaU and SaCI scenarios. (a) Gini coefficients of per capita output; (b) Gini coefficients of per capita domestic supply, which is calculated by total output minus provincial export and international export; (c) Gini coefficients of per capita export, which is calculated by provincial domestic outflow to other provinces plus international export; (d) Gini coefficients of per capita import, which is calculated by provincial domestic inflow from other provinces plus international import. In addition, we implement the Gini coefficient to describe inequalities among 31 provinces in China by different macroeconomic variables, and more details about the calculation method are described in section 2.4.1.

3.3 More polarized industrial structure in the North of China driven by decarbonization

Without compensation for the output loss in traditional industries by new low-carbon industries, carbon neutrality restrictions will lead to a more polarized industrial structure, particularly in northern parts of China, including North, Northeast and Northwest China. As shown in **Fig. 7**, Theil coefficients, an indicator measuring the polarization magnitude of industrial structure, will increase in nearly all provinces. The **North** will be dependent more on service instead of carbon-intensive sectors from BaU to SaCI, whose share of the service industry rises from 34.19% to 41.12% in 2060, whereas the share of the energy supply sector decreases from 9.25% in 2017 to 2.03% (BaU) in 2060, and 0.49% (SaCI) in 2060. Meanwhile, the production of traditional energy and carbon-intensive industries in provinces like Liaoning, Inner Mongolia, Shanxi, and Hebei, will no longer have competitive advantages and will be wiped out due to accelerated carbon abatement actions (Fig. S2 and Fig. S5). It should be alerted that the essential energy and manufacturing industries cannot simply fade out in these regions because they provide most of the key commodities and many jobs.

When adding the dimension of carbon productivity changes into the picture, we find that the production in all provinces will be ‘cleaner’ due to the deep decarbonization, but the degree is hugely different. **Well-developed eastern regions usually have higher carbon productivity, fewer changes in their internal industrial structure, and lower carbon mitigation cost than the northern part of China**. For instance, in Shanghai, 1-ton carbon emissions can produce $85348.5 under the policy scenario in 2060. However, the same amount of carbon emission only creates $20448.7 in Inner Mongolia. The costs per ton of carbon emission in these two places are $2262.91 and $5871.22 in 2060, respectively. When it comes to industrial structure adjustment, eastern China is obviously more effective than the North. The low-carbon transformations in northern China are passively caused by the output loss in carbon-intensive industries (**Fig. 4** and **Fig. 7**). In contrast, eastern China has greater endurance and resilience to withstand the low-carbon transition pressure and can swiftly initiate industrial transformations with fewer costs. Consequently, the provincial development gaps inside China would be widened.

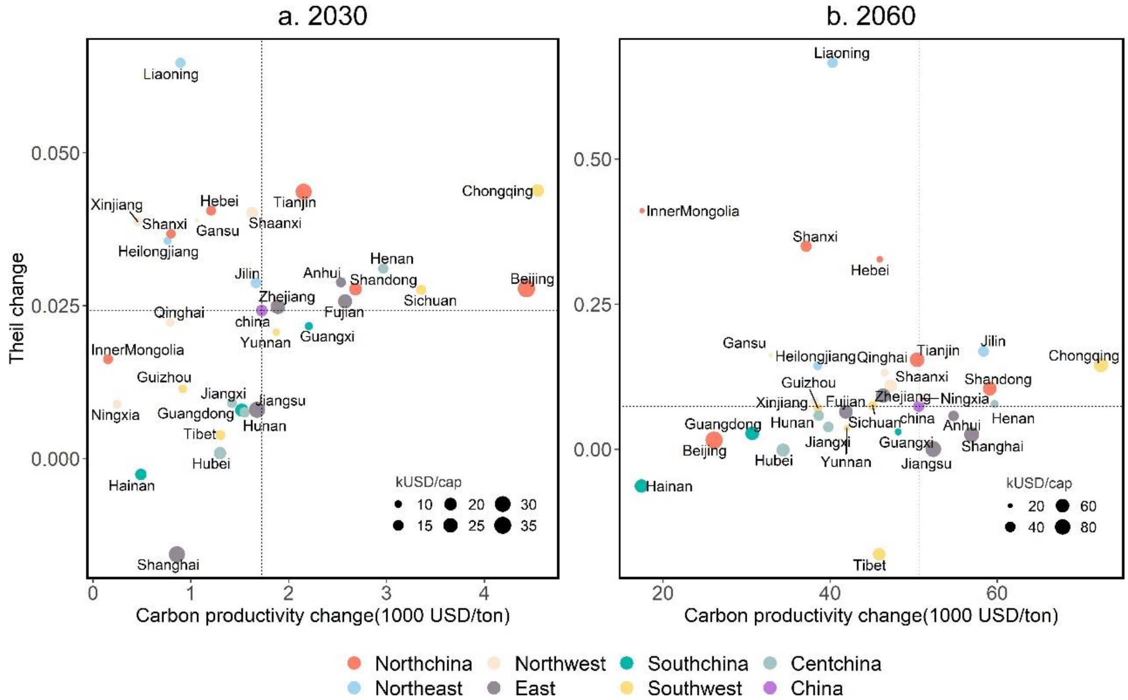

Fig. 7 Change in the Theil coefficient and carbon productivity at the provincial level in 2030 (a) and 2060 (b) in SaCI compared with the BaU scenario. The size of the bubble means the per capita GDP in BaU in 2060. The x-axis shows the change in carbon productivity in each province, representing the production per unit of carbon emissions. The y-axis shows the effects of carbon policy on the Theil coefficient, which illustrates the balance of industrial structure. Higher Theil value stands for a more unbalanced industrial fraction, which means the production becomes more concentrated in some sectors (Section 2.4.1). Carbon productivity is calculated by dividing output by carbon emissions. The whole figure is divided into four quadrants, with China at the origin. Provinces located in the top right corner mean that their industry systems are cleaner than the national average level but more concentrated on certain specific sectors; provinces in the top left corner mean that they are less clean and more reliant on certain specific sectors; provinces in the bottom left corner mean although they are less clean but have a more balanced industrial structure, and provinces in the bottom right corner mean they are much cleaner than most of the provinces and have a more balanced and solid industrial industry than other provinces.

The auxiliary results of carbon productivity in each province and year are included in Fig. S6.

3.4 The thirst for limited residual carbon permit: allocating to the East or the North?

Differential treatments in carbon permit allocation based on the economic development level of different provinces could help narrow the regional gap. Carbon cap allocation towards intensity convergence in the SaCI scenario leads to the highest regional inequalities for most sectors. In such a case, the developed eastern provinces could achieve this national target relatively easily, while the northern regions will hit the target much more painfully due to higher reliance on carbon-intensive industries. This gives rise to a policy debate that if more emission permits are allocated to provinces with lower GDP per capita for equity concerns, as assumed in the CA and DE scenarios, provincial inequalities can be alleviated because carbon permits are transferred from the East to the North. It turns out true. For instance, the Gini coefficient of the overall output is 0.289 in the CA scenario (**Fig. 8**), which is even lower (and better) than BaU. Moreover, the Gini coefficient of the energy supply sector in CA is 0.431, close to 0.421 in BaU, and much smaller than 0.566 in the SaCI scenario.

Nevertheless, **CA and DE have their imperfections, in which the eastern provinces will suffer more output loss and fall in polarized industrial structure, leading to higher national mitigation costs and raising the dilemma of maintaining national efficiency and provincial equity**. For example, even though Shandong has higher GDP per capita, it relies so extensively on traditional high-carbon manufacturing and chemicals that CA and DE will be economically unfavorable for them (Fig. 9). In comparison, HS and E scenarios provide some of the northern and western provinces with more emission rights than CA or DE so that their economic losses will be limited, and regional inequalities can be alleviated (**Fig. 8**). **But in eastern and central China, especially the regions with less historical cumulative carbon emissions but relatively large annual emissions and industrial output such as Guangdong, Chongqing, and Hunan, will be hurt badly in HS and E**. For instance, compared with BaU, the output loss decreases from 537.91 billion USD in the SaCI scenario to 208.50 billion USD in the HS scenario in the northern province of Inner Mongolia. By contrast, the loss would increase from 1189.27 to 2094.35 billion USD in Guangdong, suggesting that the economic losses are highly unmatched between the North and the East under different permit allocation scenarios.

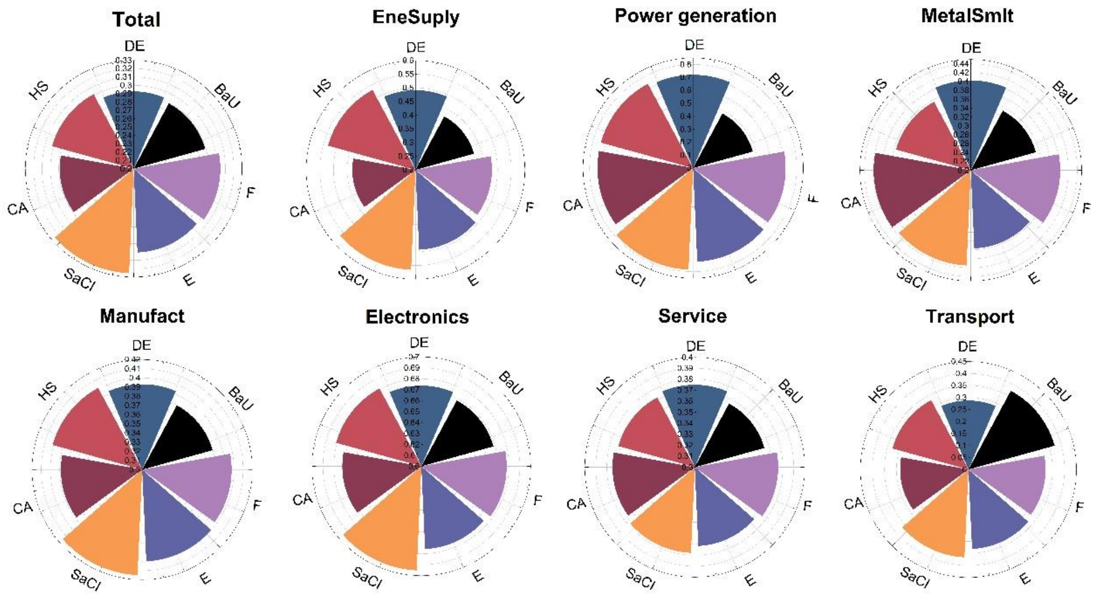

Fig. 8 Gini coefficients of per capita output in key sectors in 2060 under different scenarios. Each circle represents a sector with the inner pie in different colors, denoting seven carbon permit allocation scenarios. The value of each pie means the Gini coefficients of output at the per capita level. **BaU** represents the current policy trend. **SaCI** asks all provinces to achieve the same carbon intensity target in 2060. **CA** and **DE** assume that regions with higher GDP per capita will have fewer emission permits. **HS** assumes regions with more accumulated historical emissions will have more emission permits. **F** requires all provinces to reach the same emission per capita level in 2060, and **E** requires all provinces to reduce their emission at the same annual decline rate. More details about the scenario assumption can be seen in Section 2.3 and Table 1.

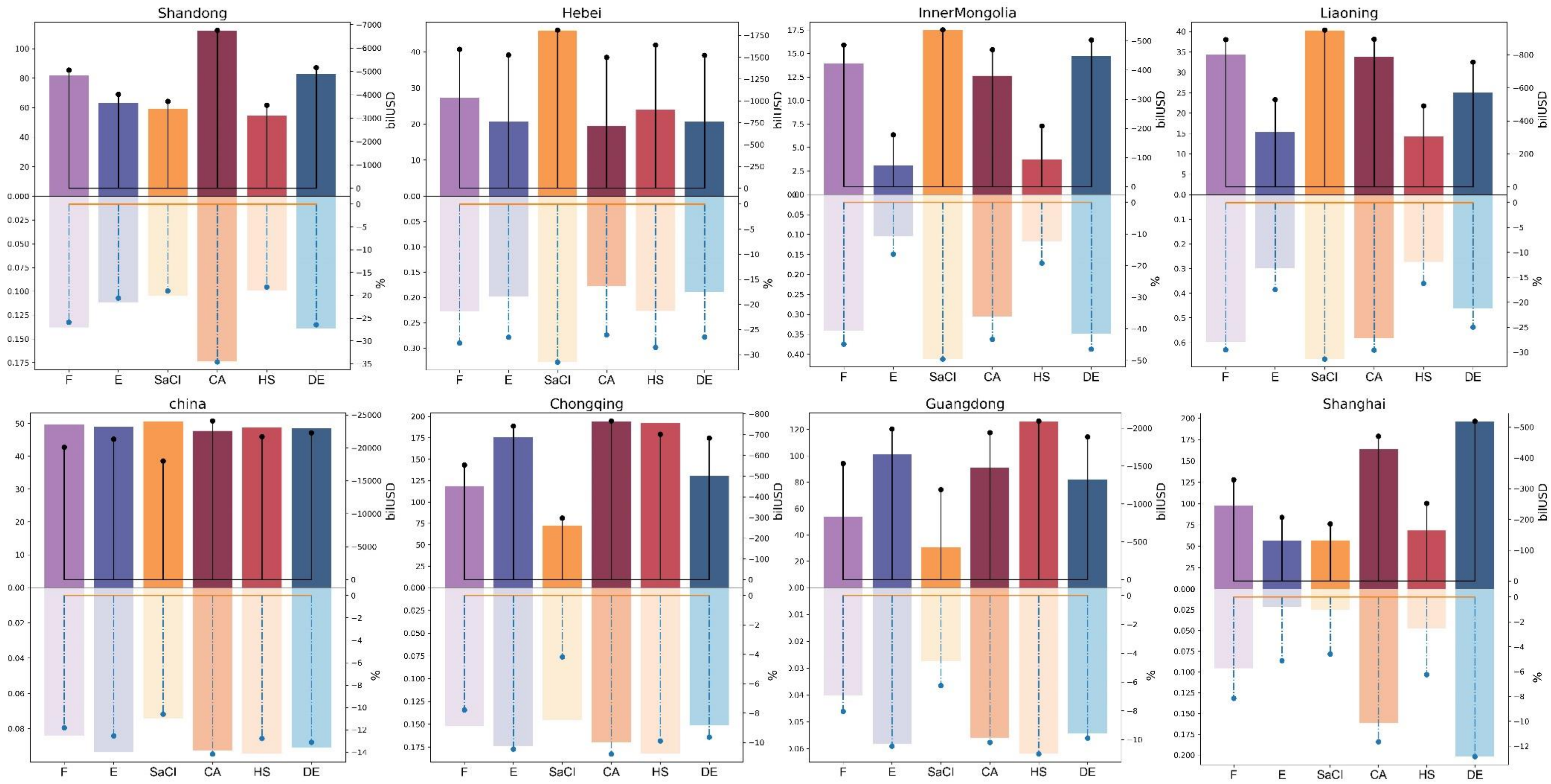

Fig. 9 **Changes in carbon productivity, Theil coefficients, output loss in 2060 under different scenarios**. Each frame represents a representative province, covering all the geographical classifications except for Central China. The upper panels with dark color represent the carbon productivity and the lower panels with light colors represent the Theil coefficient. Moreover, the solid line in the upper panels is the total output loss in absolute value and the dotted line in the lower panels is relative loss.

3.5 Uncovering the hidden rippling effects of carbon policy across sectors and regions

With an econometric model in which fixed effects and inter-dependent problems are considered (section 2.4.2), the impacts of carbon policy on overall output loss (Table 2) and, more importantly, the pass-through rippling effects of the carbon policy shock are uncovered (**Fig. 10**), revealing that **the regionally distinguished effects of carbon policy on energy costs and industrial production are mediated by different carbon prices originated from the provincial carbon permission arrangement**.

Per capita output loss in northern regions will be larger as the carbon limitations tighten and the abatement costs rise. For instance, for every 100% increase in the emission gap between BaU and SaCI scenarios, the per capita output will extra decrease by 23 dollars in North China (Table 2), including the Jing-jin-ji region, Shanxi, Inner Mongolia, and Shandong, but only decrease by 6.3 dollars in the eastern provinces such as Jiangsu, Zhejiang and Shanghai. Moreover, the equity-based rule, such as DE, seems to have less negative marginal effects by 15 dollars in northern China. When using carbon cost as the policy explanatory instead of emission gap, the results are mostly similar. Technically, as the dependent variable is the output change across scenarios, the positive estimator does not mean the output will increase but indicates that the output losses would be relatively slower. Combining the auxiliary results in Table S2, we can conclude that the embodied price effects of the carbon permission policy will be severe in the North, but relatively mild in Central, South and East China, which is jointly determined by the production scale, industrial bases, energy intensity, labor and capital price.

When separating the rippling effects passing through the CGE modeling process (Fig. 2), **it is clear to see the extent to which regional heterogeneities shape each process of the impact flow of the carbon policy** (**Fig. 10**). First, more stringent carbon limitations will basically come up with a higher carbon shadow price, and the regional difference here is slight. Next, the carbon shadow price will marginally raise the coal price, and the effects in the East and South are slightly higher than in the North, because the coal use in the East and the South mainly comes from imports. **The exception is the Southwest, whose coal and power price are relatively lower than in other places**. Sequentially, higher fuel prices will generally moderate its consumption, primarily captured in central and northeast China, partly because their energy-intensive sectors would lose competitiveness, leading to declining fossil fuel use. Eventually, all the changes will somehow uplift the related production price. In the real world, it could be seen as climate change actions raise the production cost of traditional industries. It is worth calling back that equity-based allocation will aggravate the abatement cost in the East, as every unit uplifting in energy price will much more enhance the production price in CA and DE scenarios compared with the SaCI and HS scenarios.

Table 2 The marginal effects γ of carbon policy on output loss at the per capita level

	Formula 12											
	γ: EmissionGap × RegionDummy						γ: CarbonCost × RegionDummy					
	F	E	SaCI	CA	HS	DE	F	E	SaCI	CA	HS	DE
Policy×Northchina	-24.0***	-48.0***	-23.0***	-31.0***	-35.0***	-15.0***	-0.74***	-0.22***	-0.71***	-0.46***	-0.34***	-0.47***
Policy×Northeast	3.30	-5.90*	-16.00***	-1.10	6.20*	9.70***	-1.100***	-0.270**	-0.880***	-0.70***	-0.23*	-0.61***
Policy×Northwest	9.6**	-8.70***	-6.0	-6.8*	9.6***	15.0***	-1.4***	-0.5***	-1.6***	-0.97***	-0.580***	-1.1***
Policy×East	-8.40**	-22.0***	-6.30*	-11.0***	-16.0***	-2.50	0.110	0.62***	-0.088	0.080	0.33***	-0.018
Policy×Southchina	5.90	-4.20*	16.0***	-17.0***	5.2**	5.0	-0.41***	0.087	-0.86***	-0.15	-0.082	-0.19
Policy×Southwest	5.10	19.0***	1.90	15.0***	11.0***	7.40**	0.23	0.03	0.63***	0.17	0.27***	0.17
Policy×Centchina	25.0***	0.22	11.0***	15.0***	5.80**	30.0***	-0.088	0.44***	-0.52***	-0.057	0.26***	0.002
Fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200
Adjusted R2	0.59	0.54	0.46	0.74	0.46	0.69	0.96	0.95	0.94	0.97	0.94	0.96
F Statistic	140.0***	114.0***	84.0***	265.0***	84.0***	208.0***	2015.0***	1868.0***	1462.0***	2830.0***	1538.0***	2015.0***

Notes: γ is the estimator of the cross-term between carbon policy and regional dummy variable (The carbon policy is represented by the emission gap and carbon cost. A negative value means that the total regional output per capita will lose an extra γ for every unit increase in emission gap or carbon cost, from 2017 to 2060. In addition, the emission gap is the percentage difference in emissions between BaU and policy scenarios. Carbon cost is the total amount by multiplying carbon emission and carbon shadow price. Section 2.4.2 shows the details. The statistical significance: **p<0.1; **p<0.05; ***p<0.01*).

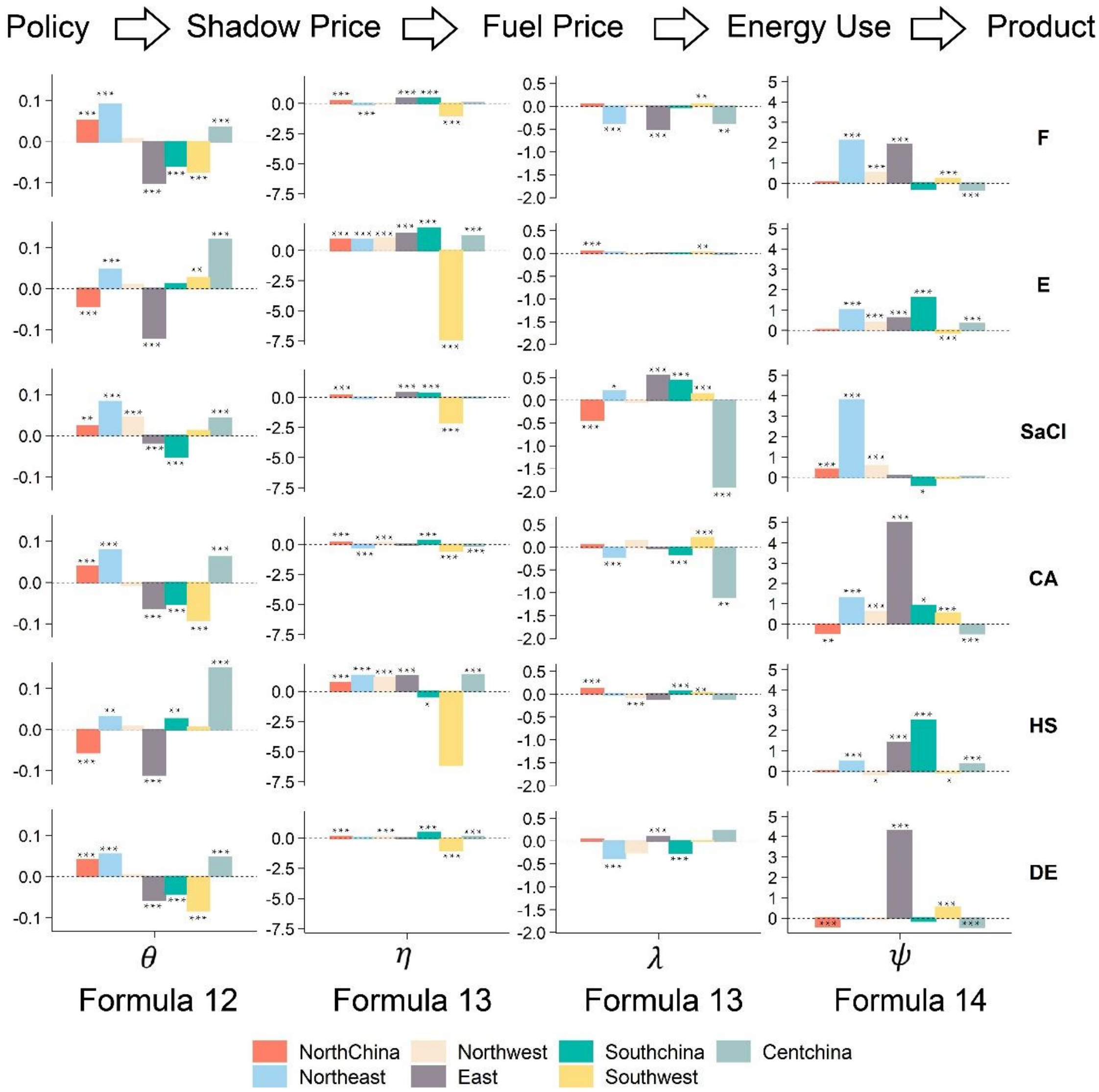

Fig. 10 The impact flow of carbon policy and its statistical significance in the CGE model (results in each column are the cross-term estimator between key explanatories and regional dummy variables in formula 12-14 in section 2.4.2. $\boldsymbol{\theta}$ means the marginal impact of the emission gap on carbon shadow price, $\boldsymbol{\eta}$ represents the marginal impacts of the emission gap on coal price, $\boldsymbol{\lambda}$ evaluates the marginal impacts of coal price on coal consumption, $\boldsymbol{\psi}$ estimates the marginal impacts of energy on product's price. Here we use the production price of the power sector as an example. All the variables are the formation of scenario loss. The statistical significance: *$*p<0.1$; $**p<0.05$; $***p<0.01$*. The four parameters here correspond to the formulas in section 2.4.2)

4. Discussion

4.1 Sensitivity analysis

In this paper, we undertake a systematic sensitivity analysis to assess the robustness of our study by examining four sets of parameters: Total Factor Productivity (TFP), Energy Efficiency Indicators (EEI), the elasticity of substitution between energy and other factors (referred to as 'VABE'), and national carbon permits for the year 2060 (referred to as 'EMS'). Changes in TFP and

EEI are conventionally regarded as external shocks within the realm of CGE analysis (Bataille and Melton, 2017; Bezabih et al., 2011). For instance, an unexpected technical advancement in the energy system could be a beneficial shock to the prevailing economic conditions (Wiser et al., 2021; Yuan et al., 2020), becoming a major source of uncertainty in the model. To explore this, we introduced ±5% variations in TFP and EEI within the IMED|CGE model. The VABE has significant implications for formulating output and diversifying model outcomes (Wang and Chen, 2006). Drawing inspiration from established practices in multi-model project (Cao et al., 2021), we opted for alternative values of 0.2 and 1.2 for VABE, contrasting with the default value of 0.4 in the IMED model. Furthermore, the national carbon emission cap constitutes a pivotal factor, shaped by trading markets (Jin et al., 2020) and advancements in scientific understanding pertaining to carbon sinks, bioenergy, and carbon capture and sequestration (Piao et al., 2022). To gauge sensitivity, we selected national cap values of 2.5 and 3.0 billion tons of CO_2. Our calculations and analysis rest upon the elasticity of GDP loss and CO_2 reduction in response to parameter variations, following the 'one at a time' methodology (Ren et al., 2023).

The model results, particularly concerning GDP loss, exhibit a high degree of sensitivity to exogenous variations in TFP, while showing a moderate sensitivity to changes in EEI, VABE, and EMS (as shown in **Fig. 11**). A mere 1% alteration in TFP across six distinct policy scenarios prompts adjustments in GDP loss exceeding 10%, and even approaching 20%, in comparison to the benchmark policy scenarios. Conversely, the resulting changes in CO_2 reduction are notably marginal. Similarly, a 1% adjustment in EEI corresponds to changes in GDP loss and CO_2 reduction that surpass 0.2% and 0.00004%, respectively. Regarding VABE and EMS, 1% fluctuations in these variables yield changes in GDP loss and CO_2 reduction of less than 1.2%, or even as low as 1%. While variations in impacts are observable across the six policy scenarios and the degree of parameter changes, our findings indicate that no single permit scheme can simultaneously drive equitable and efficient economic development, which holds a substantial degree of validity. However, the marked sensitivity to TFP adjustments underscores a cautionary note: the external propagation of productivity enhancements may potentially reshape the uneven impacts stemming from the pursuit of carbon neutrality.

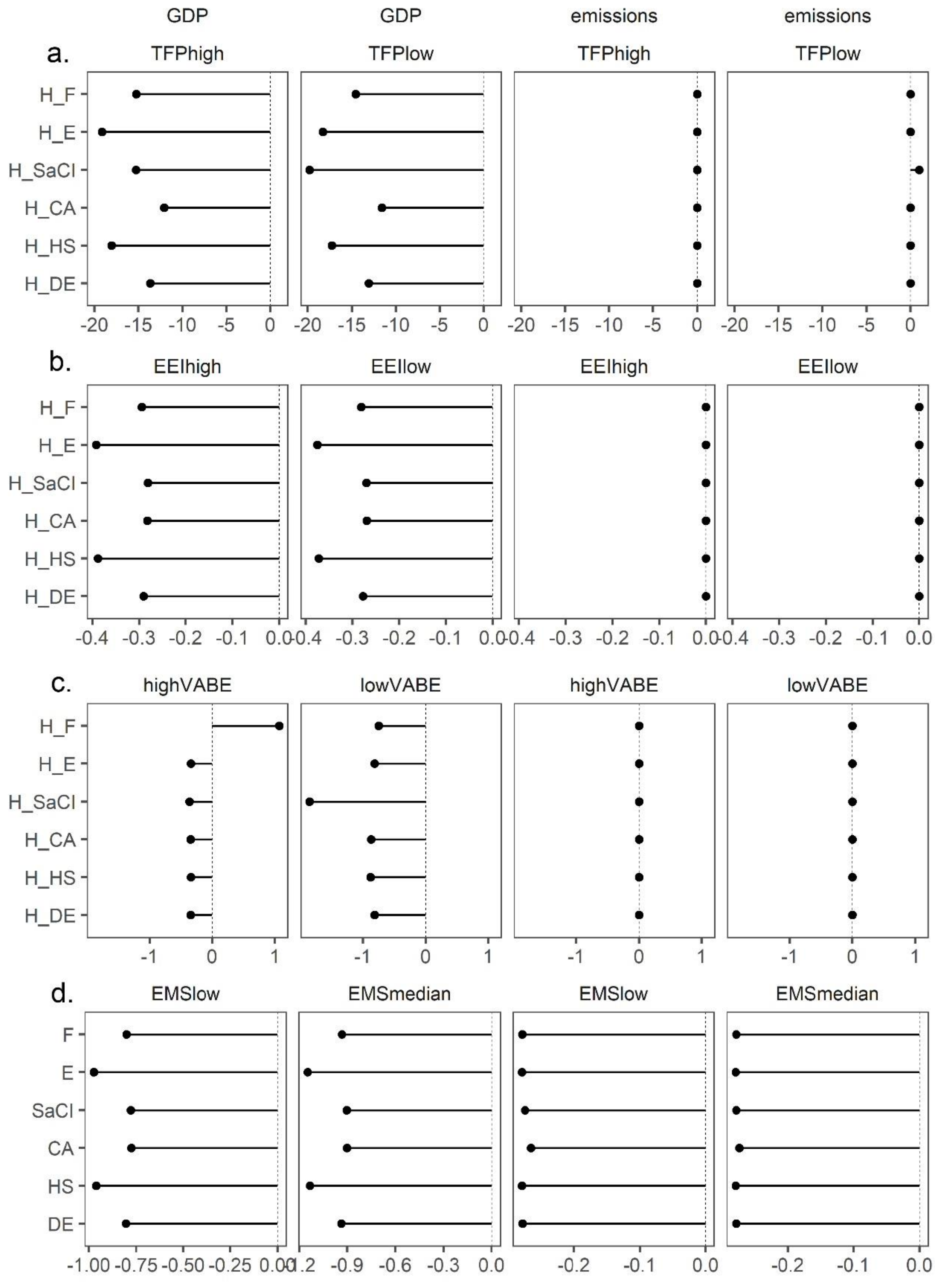

Fig. 11 The elasticities of **GDP loss** and **CO_2 reduction** in 2060 under the changes of (a) total factor productivity (TFP), (b) Energy Efficiency Index (EEI), (c) the subsititution elasticity between energy input and other inputs ('VABE'), (d) the total amount of carbon restriction in 2060 ('EMS'). We use the results from 2059 under H_SaCI_lowVABE and H_SaCI_TFPlow, as the model cannot find an optimal solution under these two scenarios in 2060.

4.2 Research limitation

Nonetheless, our analytical process encompasses certain limitations. Most notably, the current model doesn't explicitly represent or project how ground-breaking low-carbon technologies and industries would be endogenously induced by the transformative carbon neutrality revolution. Such an omission may lead to an overestimation of the macroeconomic loss and a relatively conservative projection of future economic resilience. In reality, waves of low-carbon technologies in the power generation and transportation sectors have emerged and made significant inroads in recent years, substantially reducing carbon mitigation costs and compensating for output loss in traditional industries. Moreover, state-of-the-art model-based studies (Fujimori et al., 2016; Wang et al., 2022a; Yuan et al., 2023) strive to bridge the substantial discrepancies between projections and reality by identifying gaps and refining the energy production settings. Therefore, it should be aware that the key insights generated by this study primarily pertain to the impending challenges faced by traditional industries.

5. Conclusion and policy implications

Our study has delved into the ramifications of stringent carbon restriction policies on regional economies and industrial structures, uncovering the potential unintended uneven shocks. It has been found that traditional industries will unavoidably witness contraction, thereby exacerbating regional disparities due to varying carbon costs, particularly noticeable between northern and other parts of China. Notably, Inner Mongolia and Shandong may confront significant economic setbacks if they persist in adhering to carbon-intensive traditional industries without fostering alternative sources of economic growth. Conversely, well-developed regions like Chongqing and Jiangsu are poised for resilience, given their advanced low-carbon industries and robust economic foundations, enabling them to navigate the transition costs adeptly. Methodologically, we have devised an innovative regression approach to unveil the "black box" of the CGE model, often criticized for its intricate and ambiguous model structure and configurations. By circumventing inherent endogeneity through multi-stage regression, the regression series uncovers the profoundly non-linear, latent ripple effects of carbon policies across sectors and regions, empowering policymakers to gain a clearer grasp of the intricate behaviors inherent in integrated assessment models.

Furthermore, this paper has illuminated a commonplace yet pressing issue: how to determine the effective and equal allocation of mitigation obligations among provinces. Especially with the nascent launch of the national carbon trading market, central and local governments have introduced a succession of "3060" policies, such as the "1+N" policy framework for carbon neutrality. Several studies have highlighted tensions between the North, West, and well-developed provinces. Various proposals have emerged, including prioritizing historical output (Jin et al., 2020), flexible adjustments based on technical requirements (Chen et al., 2022), arrangements involving border tax adjustments (Li et al., 2021), and the consideration of geo-economic ties (Zhang et al., 2019). However, we contend that these strategies might offer limited assistance in averting substantial economic costs when aiming for ambitious objectives like carbon neutrality. Suppose a nation adheres to a growth pattern characterized by high-carbon, export-oriented industries, investment-driven approaches, and dominance of heavy industries, the pursuit of carbon neutrality will inevitably result in economic recession across regions, exacerbated by heightened social issues stemming from exacerbated regional inequalities.

In conclusion, the insights provided in this paper should serve as a catalyst, compelling both the central government and industry leaders to promptly transition their economic growth patterns and business models. Additionally, the scale of the new economy should match or exceed the potential losses stemming from carbon mitigation, as evidenced by the model's findings. For provincial and local decision-makers, it is imperative to take decisive actions in developing industries that can support low-carbon transitions and cultivate sustainable growth engines, exemplified by electronics in Chongqing and semiconductors as well as new energy vehicles in the Jiangsu-Zhejiang-Shanghai regions.

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Appendix A. Supplementary materials

See Supplementary materials.docx: