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Economic implications of carbon neutrality in China: A dynamic general equilibrium analysis☆

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ABSTRACT

We utilize a dynamic computable general equilibrium model to analyze the economic implications of carbon neutrality for China. Novel treatments of power generation and carbon capture and storage (CCS) possibilities are a feature of the analysis. We calculate the impact of carbon neutrality by comparing a business-as-usual base-case scenario with results from an alternative carbon neutrality scenario. We discuss the assumptions used in these scenarios and shocks relating to energy efficiency, energy preferences, and the implementation of CCS. Our simulation results show that macroeconomic (especially employment) setbacks are minor, suggesting that China should be able to achieve the joint policy goals of both net carbon neutrality by 2060 and doubling real gross domestic product by 2035. We also test the sensitivity of our core results to changes in key underlying assumptions.

1. Introduction

China has pledged to reach (net) carbon neutrality by 2060. Furthermore, it has set a range of medium- and short-term low-carbon goals, such as peaking carbon dioxide (CO_2) emissions before 2030 and reducing *energy intensity* by 13.5% between 2020 and 2025. China is simultaneously committed to achieving ambitious social-economic development goals, such as doubling its gross domestic product (GDP) between 2020 and 2035. This paper examines the economic implications of China reaching carbon neutrality while remaining true to its development goals.

Our analysis is based on simulations from a dynamic computable general equilibrium (CGE) model of the Chinese economy (CHINAGEM-E), which has an explicit representation of the interactions between the energy and nonenergy systems. As such, it can trace through the economic system the often-complex impacts of mitigation efforts *via* input–output linkages and various price-, technology-, and preference-induced behavioral changes. Therefore, CGE models have been widely used in energy and climate policy analysis (Böhringer and Löschel, 2006; Beckman et al., 2011; Babatunde et al., 2017).

Our study is a scenario analysis. We design a core policy scenario, the carbon neutrality scenario (CNS), with assumptions for the macroeconomic economy, energy efficiency and preferences, and the uptake of carbon capture and storage (CCS) technologies. The CCS assumptions are of particular interest. China has large coal reserves and can produce coal at a moderate cost compared to oil and gas (Fan et al., 2018; Jia and

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Lin, 2021). Coal-fired power is also of great value to the stability of the power system and energy safety and can complement renewable energy. China may continue to use coal-fired power generation; however, future use will implement CCS extensively. We supplement the CNS with alternative scenarios to test the sensitivity of our results to key underlying assumptions.

The rest of the paper is organized as follows. Section 2 contains a literature review in which we identify three gaps in the literature. Section 3 explains the assumptions used in the two core scenarios: the base-case scenario (BCS) and the CNS. The key results from the two core scenarios are given in Section 4, while Section 5 explores the sensitivity of the CNS to changes in assumptions regarding CCS. Concluding remarks and policy implications are presented in Section 6.

2. Literature review and major contributions

The Chinese government's announcement in 2020 of "two carbon goals" (peaking carbon emissions before 2030 and achieving carbon neutrality by 2060) has generated considerable research. Some studies have focused on carbon neutrality within a specific sector. For example, Mu et al. (2021) explore achieving net-zero emissions in China's passenger transport sectors through regionally tailored mitigations strategies. Yu and Tan (2022) combine conventional strategies with innovative technologies, such as CCS and hydrogen metallurgy, to investigate China's pathway to carbon neutrality for the iron and steel industry. Xiang et al. (2023) explore the feasibility of zero carbon production and a transition roadmap for China's ammonia industry.

Other studies have explored the implications of neutrality from an economy-wide perspective (China National Petroleum Corporation Economic and Technology Research Institute, 2020; Energy Foundation China, 2020; Project Synthesis Report Writing Group, 2020; Goldman, 2020; IEA, 2021b; SG and ICCSD, 2021; Kong et al., 2023; Maheen et al., 2023). Their main contributions are projections of the energy and emissions pathways, forming views on total primary energy consumption levels, energy compositions, and so forth.

We have identified several limitations in published studies, which we address in this paper.

2.1. A lack of detailed results

First, there is a lack of dynamic analysis of the detailed economic implications of reaching net-zero emissions in China. Although several studies (Wang et al., 2009; Zhang et al., 2022; Cao et al., 2023) have discussed the implications on GDP, the effects on employment, consumption, trade, or other macroeconomic indicators have not been discussed. At a fine sectoral level, the existing literature focuses primarily on the impacts on China's energy-intensive sectors, especially the power sector. They rarely consider the impacts on nonenergy-intensive sectors; however, our analysis shows that changes in nonenergy-intensive but labor-intensive sectors could have strong implications for aggregate employment levels. Lu et al. (2022) discussed different carbon neutrality paths on China's industrial structures; however, they did not analyze the effects on detailed nonenergy industrial and service sectors.

2.2. Vague consideration of CCS possibilities

A second limitation is a general absence of explicit, endogenous treatment of CCS technologies, including fossil-fuel-based (FFCCS), Bioenergy (BECCS), and Direct Air (DACCS). Maheen et al. (2023), Kong et al. (2023), and Vennemo et al. (2014) are among the few to have explicitly treated CCS in CGE modeling in China; however, they only consider coal-fired power CCS. Similarly, some recent studies have considered BECCS technologies only (Huang et al., 2020; Weng et al., 2021). To our knowledge, no study has combined FFCCS, BECCS, and DACCS to form a CNS. Moreover, existing studies tend to presume a fixed amount of emissions that are extracted by CCS mechanisms, then set the emissions path equal to the total of the targeted emissions level plus the fixed CCS extraction (Project Synthesis Report Writing Group, 2020). This approach has three significant drawbacks. First, neither CCS mitigation nor CCS costs can be attributed to specific emitters. Second, emitters must still bear the cost of carbon prices for all emissions before CCS removals because the emissions that are supposed to be extracted by CCS are still in the system. Hence, when the carbon price is higher than the cost of CCS per unit of CO_2 abatement, there would be an overestimation of mitigation costs, and vice versa. Third, emitters cannot adjust their emissions levels nor CCS uptake levels endogenously according to the ongoing rates of carbon prices and CCS costs.

2.3. Incongruous demand responses

Another limitation of recent literature is the use of inappropriate electricity-generation nesting structures. The term "nesting" refers to the hierarchal structure of demand decisions imposed on industries in the model, with choices at one level based on decisions already made. For example, a common nesting structure for generation demand considers how much of each renewable-generation technology to use based on a prior decision of how much aggregate renewable and aggregate fossil-fuel power will be employed.

Liang et al. (2022) introduced fuel and electricity substitutions and energy and nonenergy substitutions into their model; however, they made no allowance for substitution between energy and capital. Wang et al. (2009) use multilayer interfuel and interfactor nesting structures to explore the economic impact of different Chinese climate policy options; however, they quantify the associated substitution possibilities using data not relevant to the Chinese economy.

While it has long been recognized that interfuel and interfactor substitution parameters are essential to CGE modeling results for different countries (Bhattacharyya, 1996), the literature has only recently begun investigating the implications of different nesting structures in China. Zha and Zhou (2014) first attempted to find an appropriate top-level (the labor-capital-energy nesting level) fuel-factor nesting structure for China; however, their work does not employ a CGE model to test the implications of different nesting structures. Feng and Zhang (2018) were the first to do so; however, their work is confined to analyzing the top nesting level between factor and energy. Cui et al. (2020) extend these studies by comparing a one-layer power generation nest with a two-layer one; however, even with their finest two-layer nest, it is assumed that the elasticity of substitution is the same among coal-fired power, gas-fired power, nuclear power and hydropower technologies. Such a structure means that nuclear power and hydropower would grow substantially to replace fossil-fuel-based power as carbon prices increase. This characterization may not be representative of the Chinese power sector, where long-term growth in hydropower and nuclear power is constrained by environmental factors.

2.4. How are these perceived shortcomings dealt with in this paper?

First, we explicitly model a CNS for China with an end year of 2060. We provide a strong focus on the quantitative economic results at the macro economy and the sector level. Second, we incorporate a new CCS modeling mechanism in CHINAGEM-E, differentiating CCS applications by fuels and fuel users (stationary emitters). Given unit CCS costs and ongoing carbon prices, these emitters can decide their production levels endogenously. Third, we create a three-layer electricity-generation nesting structure by allowing more targeted substitution between fossil-fuel-based power and new clean power (i.e., solar power and wind power). The purpose is to highlight China's intention to use mainly the latter to replace the former.

3. Model summary and core scenarios

3.1. CHINAGEM-E

CHINAGEM-E is based on the CHINAGEM model, itself based on the MONASH dynamic recursive CGE model of the Australian economy. CHINAGEM's database is developed from the 2017 input–output table of China, which has 149 industries. As is common with this class of CGE models, all users (firms, investors, households, government, and exporters) minimize costs subject to technology and resource constraints. Markets are perfectly competitive, and production technology displays constant returns to scale, reflected in pricing equations that set pure profits from all activities to zero and market clearing equations for all primary factors and commodities.

The model is solved sequentially, one year at a time, generating time paths for all variables for all years t = (0, … T). This class of recursive dynamic CGE models incorporates three types of intertemporal links, reflecting physical capital accumulation, financial asset/liability accumulation, and lagged adjustment processes. The first two ensure that the stock of capital and net financial assets at the end of period t are equal to the stock of capital and net financial assets at the start of period t + 1. The latter governs the determination of real wages and real rates of return to capital in response to disequilibrium in employment and investment. Model equations are presented in percentage change form and solved using GEMPACK (Horridge et al., 2019). Complete documentation of the CHINAGEM model can be found in Peng (2023), and details of the MONASH model are presented in Dixon and Rimmer (2002).

CHINAGEM-E provides three critical extensions to the CHINAGEM model. First, CHINAGEM-E has a more detailed representation of the energy sector. The single hydrocarbon sector is split into separate crude oil and gas sectors, using physical quantity data from the China Energy Statistical Yearbook and price data deduced from Chinese Customs and the China Energy Statistical Yearbook.[1] The Electricity sector is split into eight generation technologies and nine industries (eight generation industries plus a single distribution sector) using physical quantity data from the China Electric Power Yearbook and price data from CHINA ENERGY.[2] Furthermore, physical accounts of primary energy and emissions are incorporated into the model. Data for these two new accounts are from The World Energy Outlook (IEA, 2020), China Energy Statistical Yearbook (China National Bureau of Statistics and Press, 2018)), and China Electric Power Yearbook (China Electric Power Yearbook Editorial Commission and Press, 2018).

Second, an explicit, endogenous mechanism of modeling CCS is incorporated into CHINAGEM-E.[3] We set up three new physical accounts for emissions extracted by CCS, from FFCCS, BECCS, and DACCS. We define CCS coverage rates explicitly because we want to control them exogenously, which allows emitters to endogenously determine their production levels and, therefore, their levels of CO_2 emissions and CCS extractions through optimization.

The third extension is a new production nesting structure for power generation, as shown in Fig. 1.[4] Table 1 shows the values for substitution elasticities, which are taken from the literature wherever possible. Values that are not found in the literature are assumed by the authors.

The upper part of Fig. 1 (above the top dashed line) presents a standard representation of production technology in energy CGE models, with intermediate inputs differentiated by source (upper-right) combined with value-added and energy (upper-left). The middle of Fig. 1 (between the two dashed lines) shows an aggregate of nonelectric energy and electricity combined with capital in a capital-energy nest. The nonelectric energy nest is in the lower-left of Fig. 1. To this point, the representation of production technology is similar to that used in other energy CGE models (Zhang et al., 2016). We adopt substitution elasticities for SKEL, SGKE, and SENR from Feng and Zhang (2018) and Feng et al. (2021b), where elasticities are estimated using Chinese data, and those for SNEL and SNCC from GTAP-E (Burniaux and Truong, 2002).

The electricity nest is in the lower right of Fig. 1, where electricity generation (ElecGen) is represented in a novel, three-layer structure. Its top-level aggregates bioelectricity, hydropower, nuclear power, and a "main substitution" nest. The development of hydropower and nuclear power, in particular, is subject to geological, political, and other constraints. We thus assign a relatively small substitution elasticity value (SELG = 0.5) to dampen price-induced substitution. In the middle level of ElecGen, we give a larger elasticity value (SGMS = 1.5) for the "main substitution" nest to allow substantial transformation from fossil-fuel power (represented by the FF nest) to wind and solar power (represented by the WS nest). At the bottom level, we choose a substitution value of 2 between coal-fired and gas-fired power and a value of 0.5 between wind and solar power. The relatively higher value in the former nest reflects the ease of substitution between coal- and gas-fired power generation. The relatively lower value for the latter nest reflects 1) the policy intention to promote strong growth in both technologies and 2) the fact that solar and wind power resources are generally not closely located in China.

3.2. BCS

The BCS illustrates a likely economic development path from 2017 to 2060 based on business-as-usual assumptions for the key drivers of the Chinese economy (population growth, productivity improvement) with government policy directed toward economic growth and relatively little concern for carbon neutrality. The BCS serves as our benchmark to which results from the CNS are compared. Table 2 summarizes some key statistics from the BCS.

The BCS reflects the information in the IMF's World Economic Outlook (IMF, 2021), the IEA's World Energy Outlook (IEA, 2020), and model simulations. Some concern for environmental factors is evident in the BCS, but not to the extent that would lead to carbon neutrality. The carbon price in the BCS reaches 359 Chinese yuan per ton of CO_2 (CNY/tCO_2), well below the 1614 CNY/tCO_2 required to reach carbon neutrality in the CNS (see Section 4).

Under the BCS, the average annual real GDP growth between 2020 and 2035 is 4.77%, making the Chinese economy 101.1% larger in 2035 than in 2020. Although this satisfies China's goal of doubling its economic size by 2035, it leaves little room for mitigation efforts to slow down economic growth.

3.3. Core CNS

The CNS illustrates a likely economic development path leading to carbon neutrality in China in 2060.[5] Comparing the CNS with the BCS shows the impacts of moving to carbon neutrality.

The following common macroeconomic assumptions are adopted in the CNS. First, the real wage is sticky in the short run and becomes

[1] Several facilities exist to disaggregate sectors using input use share data. We used the MSplitCom facility developed at the Centre of Policy Studies: see https://www.copsmodels.com/msplitcom.htm. Please also refer to part A1 in the technical appendix for the assumptions made when splitting crude oil and gas.

[2] Please refer to part A1 in the technical appendix for more details of electricity disaggregation.

[3] The carbon capture and storage equations are explained in part A2 in the technical appendix.

[4] Please refer to part A3 in the technical appendix for a typical three-factor nested constant elasticity of substitution (CES) production function.

[5] We deal specifically with carbon neutrality relative to carbon emissions from fossil fuels. We do not account for emissions from sources like land use change (cutting down or planting forests).

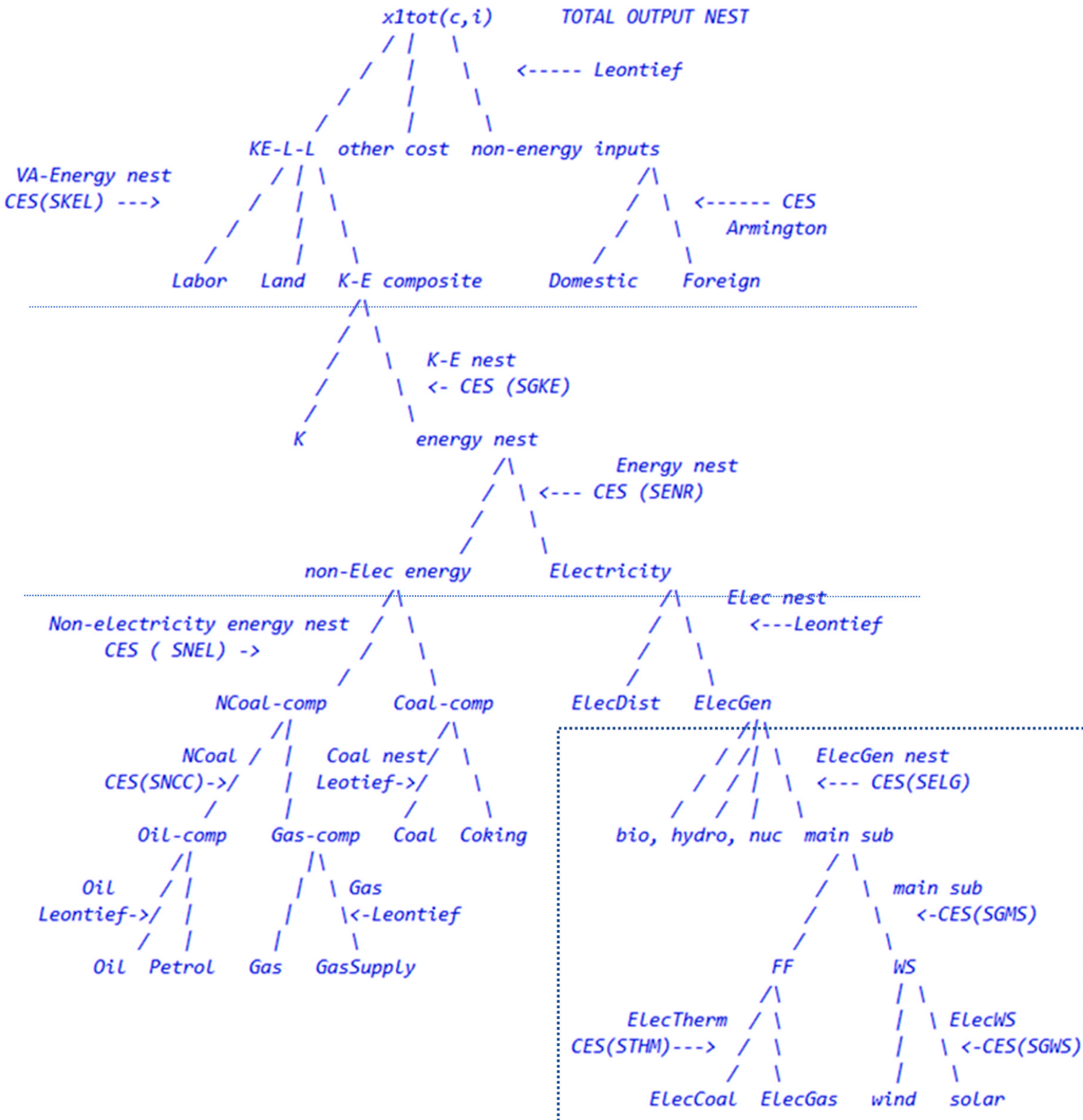

Fig. 1. Multilevel fuel-factor nesting production structure in CHINAGEM-E.

Table 1
Substitution elasticity values in CHINAGEM-E.

	Nonenergy sectors	Energy sectors		Nonenergy sectors	Energy sectors
SKEL	0.78	0.78	SELG	0.5	0.5
SGKE	0.72	0.72	SGMS	1.5	1.5
SENR	1.85	0.5	STHM	2	2
SNEL	0.5	0	SGWS	0.5	0.5
SNCC	1	0			

flexible in the long run; thus, employment in the CNS can deviate from the BCS in the short run but gradually trend back to BCS levels in the long run. Second, aggregate consumption follows household disposable income. Third, investment is a positive function of the expected rate of return on capital. Fourth, Chinese exports face downward-sloping demand curves in the rest-of-the-world. Fifth, import prices are assumed to be exogenously fixed at levels determined in world markets. Sixth, the trade balance as a share of GDP is assumed to be fixed to prevent unrealistic changes in trade balances from distorting domestic economic activities. Seventh, carbon prices are endogenous, with carbon-pricing revenues recycled as a lump-sum transfer to households.

The following subsections detail the energy-related assumptions imposed in the CNS.[6]

3.3.1. Energy efficiency assumptions in the CNS

We give additional autonomous energy efficiency improvement in the CNS relative to that assumed in the BCS. We do not explicitly model the policies necessary to bring this about; we simply postulate that the necessary policies will be in place and will produce the outcome assumed (see Fig. 2). Without information on costs relating to efficiency

[6] Further assumptions regarding exogenous changes in energy preferences (i.e., households using electricity to replace fossil fuels and transport switching from petrol to electricity) are detailed in Feng et al. (2023). These exogenous changes to energy preferences are themselves driven by the endogenous carbon tax.

Table 2
Summary of base-case scenario (selected years, % unless otherwise indicated).

Year	Real GDP growth	Employment growth	Capital stock growth	TFP	Fossil-fuel share in primary energy	Carbon price (CNY/tCO_2)	Carbon dioxide emissions (mtCO2)
2030	4.03	−0.81	5.63	2.02	75	110.9	10,453
2040	3.16	−1.11	4.28	1.94	69	193.7	9830
2050	2.87	−1.26	3.62	2.08	62	276.4	8655
2060	2.60	−1.21	3.11	2.06	55	359.0	7517

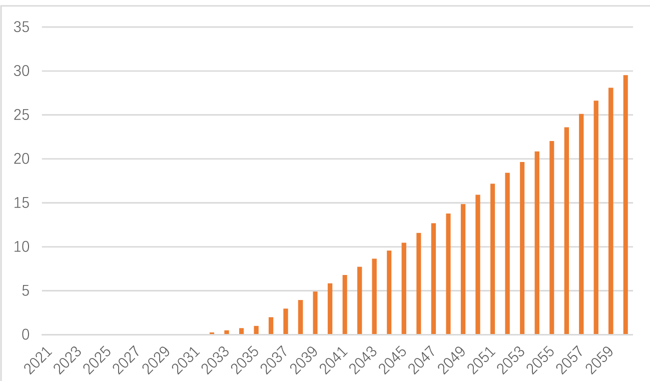

Fig. 2. Energy efficiency improvement in carbon neutrality scenario (Cumulative deviation from BCS, %).

improvement, we enable the commonly used "cost-neutrality condition"[7] by increasing production costs across the board so that efficiency changes do not affect total production costs.

In the CNS, we assume annual efficiency improvements of around 1.2%. In comparison, China reported an efficiency improvement of 2.9% for 2019. Lee (2021) and Zhang et al. (2016) assumed efficiency improvements of 1.7% annually up to 2050, which suggests that our assumed efficiency improvements in the CNS are relatively conservative.

3.3.2. CCS assumptions in the CNS

As Section 3.1 discussed, we exogenously control the CCS coverage rates. Fig. 3 presents our assumptions regarding these rates. We assume coal-based CCS will be utilized at a large scale from 2031. We set the coverage rate for coal-based CCS according to information provided by CHINA ENERGY. The coverage rate increases relatively quickly to 2050, when many coal-based power generation stations reach their life expectancy. The coverage rate increases only slightly from 2051 and reaches 90% by 2060. We assume that oil- and gas-based CCS will be utilized large scale from 2041—their rate of coverage increases by a fixed annual rate that reaches 90% by 2060. We also assume that BECCS will be employed at a large scale from 2041— its coverage will also increase at a fixed annual rate, reaching 80% by 2060. We use the level of bioelectricity to calculate the equivalent CO_2 emissions from coal-fired power generation.

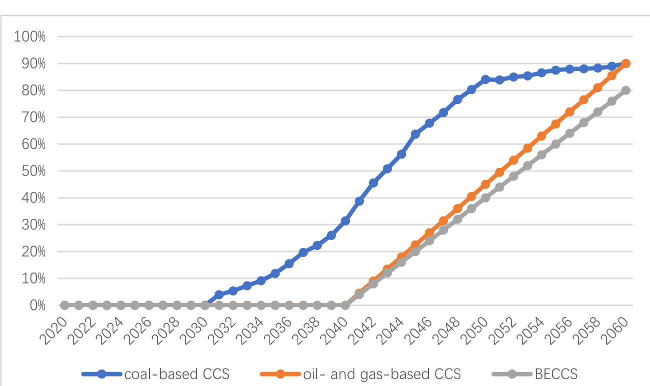

Fig. 3. CCS coverage rate assumptions in the CNS (%). Source: authors' assumptions.

We explicitly model the costs of employing fossil-fuel-based CCS, by assuming a fixed unit cost of 400 CNY/tCO_2 emissions captured and stored by fossil-fuel-based CCS. Wu et al. (2013) estimated CCS costs to be 390 CNY/tCO_2 to 460 CNY/tCO_2 for power generation in China. IEA (2021a) estimated that CCS costs could range between 256 CNY/tCO_2 and 511 CNY/tCO_2 for power generation globally. Our assumed unit cost is consistent with these estimates. Sensitivity tests are performed against this fixed unit cost (see Section 5).

We do not explicitly model BECCS's cost because bioelectricity is emissions-neutral; the emissions it generates are stored in its biomass, which is formed by capturing emissions from the atmosphere. Therefore, BECCS is a negative-emissions technology as it captures these emissions again; hence, without credible cost forecasts, we assume that the gains in selling emissions permits offset the costs of BECCS.

We assume DACCS becomes available at a large scale from 2056. We exogenously set the amount of CO_2 emissions taken by DACCS (see Fig. 4). By 2060, we assume that DACCS will capture 1 gigaton of CO_2 emissions; however, we found little guidance on DACCS in the literature. Again, we performed sensitivity tests against the level of DACCS uptake (see Section 5). Similar to BECCS, we assume DACCS costs are compensated by income from emissions permits.

3.3.3. The carbon neutrality path in the CNS

We impose a path of total CO_2 emissions in the CNS that will reach net-zero in 2060 (see Fig. 5). The path is broadly consistent with many commentators' beliefs (He, 2021; Lin, 2021). In our scenario, CO_2 emissions resemble a "flat peak" at around 10 billion tons of carbon

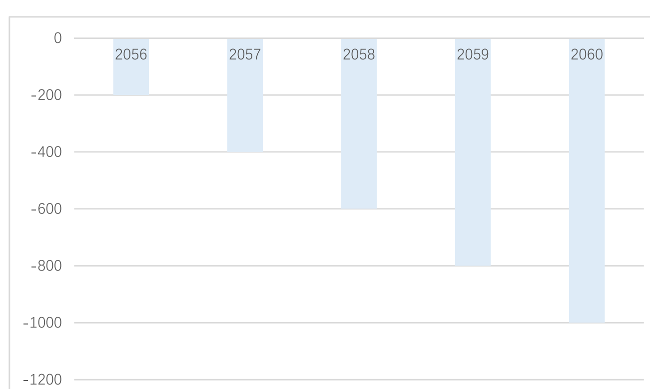

Fig. 4. CO_2 Emissions reduction by DACCS ($mtCO_2$). Source: authors' assumptions.

[7] For a detailed discussion about the implications of this condition, see Cui et al. (2020).

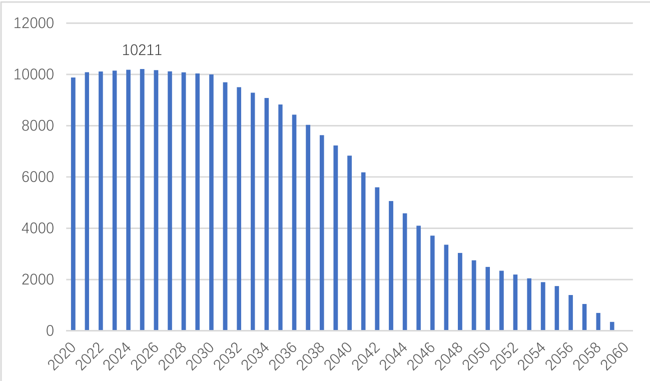

Fig. 5. Net CO_2 emissions in CNS ($mtCO_2$). Source: authors' assumptions.

dioxide ($btCO_2$) over the 2020s. Emissions begin to fall from 2031. The average annual emissions reduction rate between 2030 and 2035 is 2.5%. This reduction rate accelerates to 5% from 2035 to 2040. It further accelerates in the 2040s, averaging 9.6% per annum. The 2040s is the decade of the fastest emissions reduction, primarily due to fossil-fuel-based CCS and BECCS contributions. Although it slows in the early 2050s, the reduction rate increases again in 2056 as large-scale adoption of DACCS commences. In CNS, total cumulative emissions between 2020 and 2060 are 250 $btCO_2$, 65% of total cumulative emissions in the BCS.

4. Core scenario results

This section focuses on reporting economic results. Energy results, including CCS-related results, are available in Feng et al. (2023).

4.1. Carbon price

Fig. 6 reports carbon price levels[8] under the BCS and the CNS. In the CNS, carbon price levels are slightly higher than those in the BCS until the mid-2030s. Before the mid-2030s, extra CO_2 mitigation in CNS is achieved primarily *via* changes in energy efficiency and preferences. After the mid-2030s, carbon price levels begin to increase faster in the CNS. This acceleration is due mainly to the faster reduction in total emissions over this period (see Fig. 5)—the carbon price increases even faster after the mid-2050s. Although the absolute emissions reduction levels are smaller than in earlier years, emissions reduction rates are much faster over this period. Moreover, there is much less room (*i.e.*, coal-fired power generation) for emissions reduction in these later years, while the increase in the CCS coverage rate also decelerates in the 2050s; these factors cause abatement costs to increase faster. By 2060, the carbon price will reach 1614 CNY/tCO_2 (equivalent[9] to 221 USD/tCO_2) in CNS.

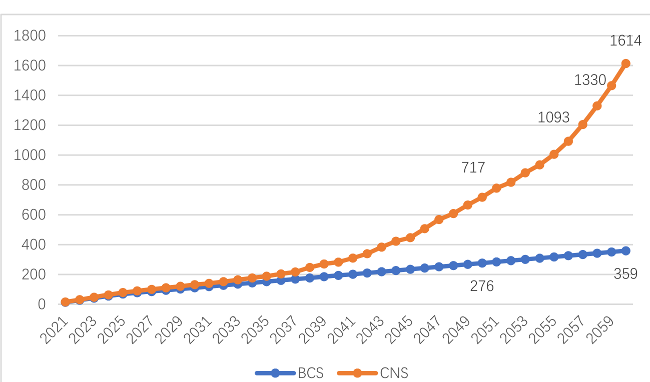

Fig. 6. Carbon price levels (CNY/tCO_2).

4.2. Real GDP and other key economic variables

The left graph of Fig. 7 plots the cumulative growth in real GDP over the simulation period. By 2060, cumulative real GDP has increased by 313% and 308% in the BCS and CNS, respectively. In 2060, real GDP under the CNS will be 1.36% lower than under the BCS (right graph of Fig. 7). The left graph of Fig. 7 also highlights that by 2035, real GDP will be 100.6% higher under the CNS than in 2020. This finding suggests that China can simultaneously achieve the target of doubling real GDP by 2035 and reach the carbon neutrality target in 2060.

Fig. 8 presents the number of employed persons at the national level. By 2060, the total number of employed persons will be 502.1 million and 501.8 million in BCS and CNS, respectively. The CNS leads to 335,000 fewer employed persons in 2060 than the BCS. In an economy with more than 500 million employed persons, this is a very small reduction. Between 2021 and 2060, on average, there are 660.7 million and 660.1 million employed persons per annum in the BCS and CNS, respectively. Therefore, the annual average number of unemployed persons attributed to the CNS is 600,000, a very small figure compared to the total workforce.[10]

Fig. 9 reports expenditure-side GDP results. By 2060, consumption under the CNS is 1.11% lower than under the BCS, compared to a relative drop in real GDP of 1.36%. The transfer of carbon-pricing revenues helps consumption to fall less than real GDP. By 2060, investment will experience the largest decrease under the CNS, 1.51% lower than under the BCS. Export and import changes are smaller, falling by 0.46% and 0.16% from the BCS, respectively, while higher carbon prices increase domestic prices. On the one hand, this increases export prices[11] and thus hurts exports. On the other hand, it leads to domestic appreciation, which hurts the global competitiveness of China's goods and services. By 2060, China's trade balance is 345 billion CNY lower than under the BCS (see Fig. 10).

4.3. Industry results

Individual industry output results are reported in Fig. 11 for energy sectors and Fig. 12 for nonenergy sectors (note the difference in scales on the vertical axis between Figs. 11 and 12). Three clean energy industries, namely offshore wind power (Wind_Offsh), solar electricity (SolarElec), and onshore wind power (Wind_OnSh), are standout winners. Three electricity-related industries, namely bioelectricity (BioElec), electricity distribution (ElecDist) and power transmission equipment (PwrTrnEqp), are also winners. Fossil-fuel energy and related sectors are clear losers, among which, coal (CoalMineProc) and coal-fired power generation (CoalElec) contract the most. The changes in nonenergy industry outputs in Fig. 12 are all relatively smaller than the energy industry output changes, falling within the [–4%, 4%] range.

A few generalizations can be made regarding sector output changes

[8] While these are indicative of carbon prices under emissions trading systems (ETS), the two are not necessarily the same because ETS carbon prices are influenced by factors (such as permit supply) not explicitly accounted for in current simulations. Please also refer to part A4 in the technical appendix for detailed explanations of the carbon-pricing mechanism in the CHINAGEM-E model.

[9] Adopting an exchange rate of 1 USD = 7.3 CNY.

[10] Some industries will hire less, and some will hire more. Industrial level employment results are reported at the end of Section 4.3.

[11] Since import prices are assumed fixed, this amounts to an improvement in the terms of trade (see Fig. 11).

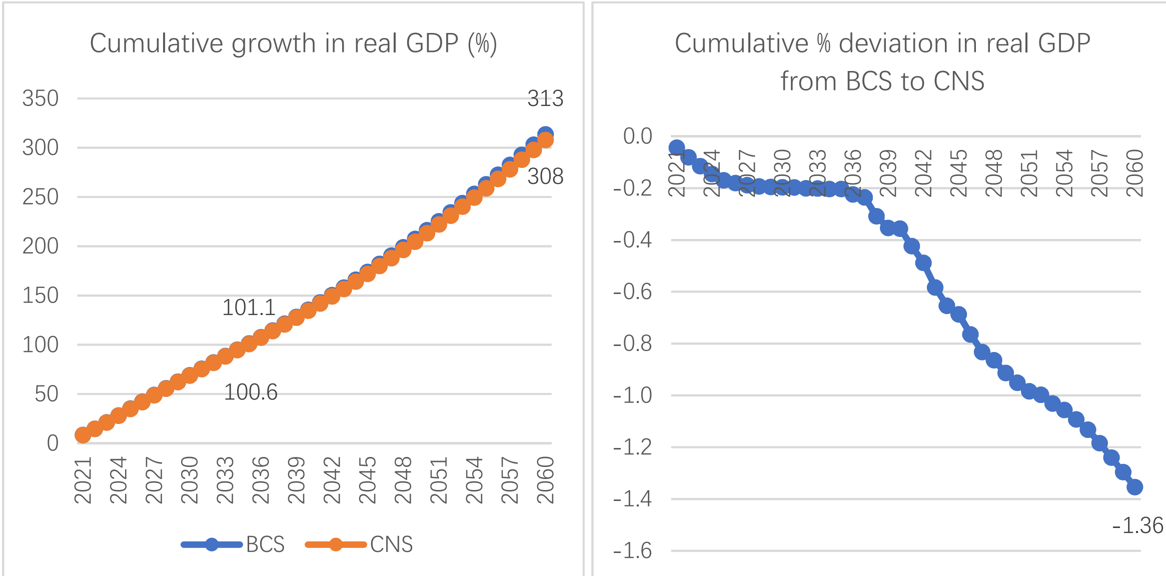

Fig. 7. Real GDP results.

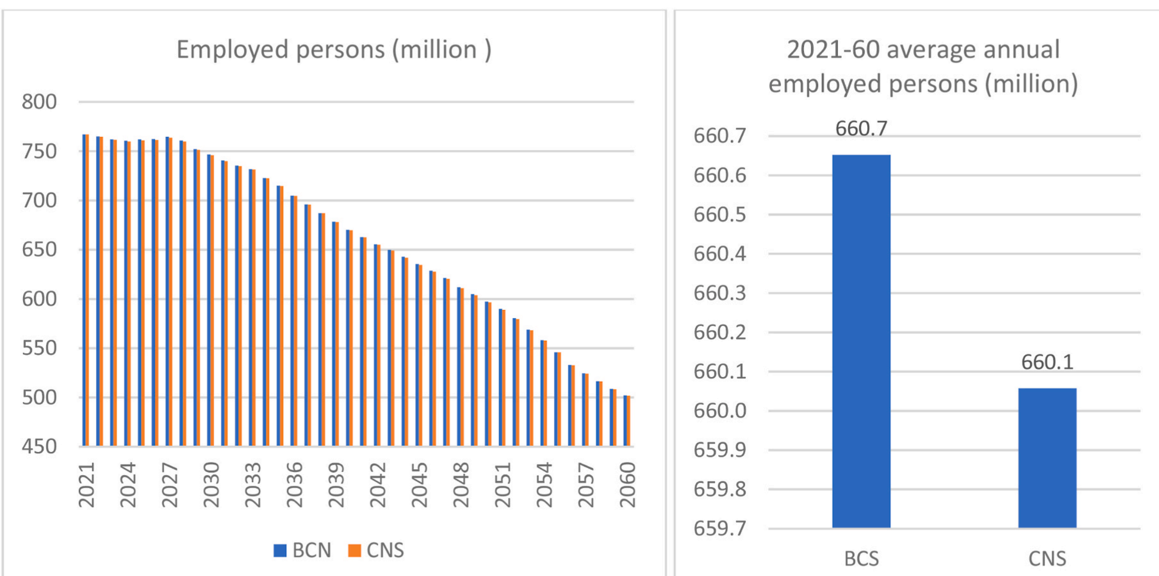

Fig. 8. Employed persons—national level results.

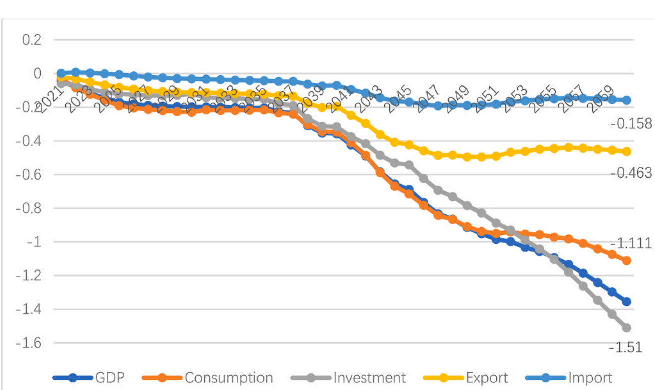

Fig. 9. Demand side GDP results in CNS—cumulative deviations from BCS (%).

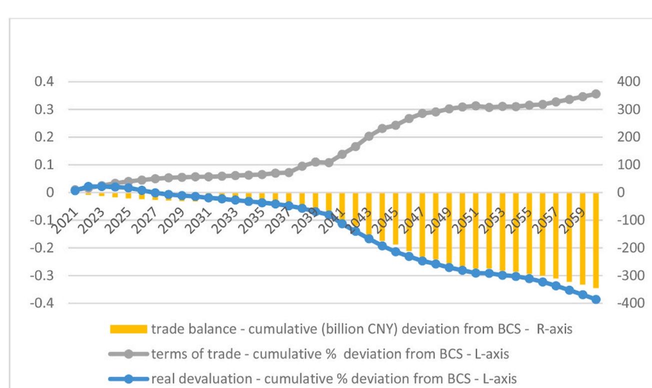

Fig. 10. Terms of trade, real exchange rate, and trade balance.

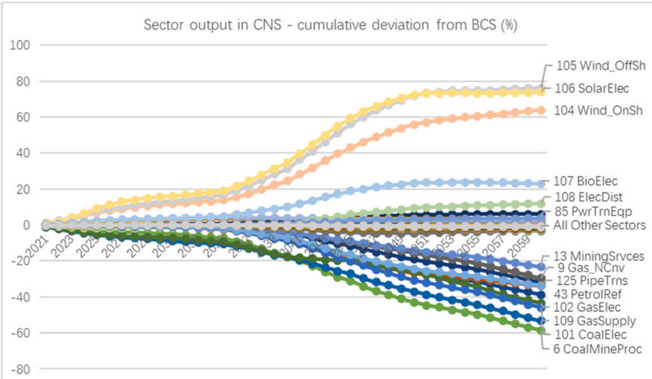

Fig. 11. Energy sector output in CNS—cumulative deviations from BCS (%).

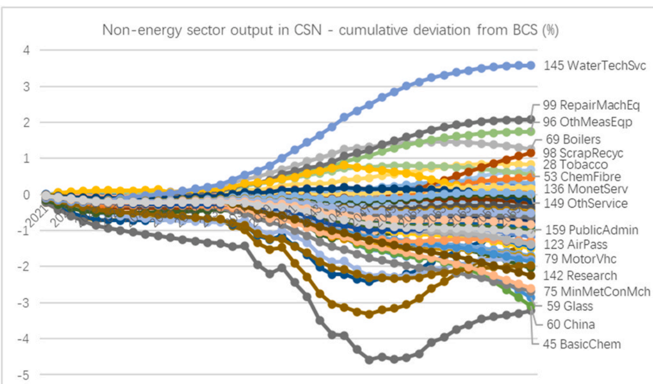

Fig. 12. Nonenergy sector output results in CNS.

in China's pursuit of carbon neutrality. First, carbon neutrality mainly affects energy-related industries; thus, clean energy industries will gain at the expense of fossil-fuel energy industries.

Second, regarding upstream–downstream structures, industries that sell a large proportion of output to electricity sectors (except fossil-fuel electricity sectors) will gain because electricity output increases. The most notable case is the power transmissions equipment (PwrTrnEqp) industry.

Third, CCS technologies help carbon-intensive sectors to continue to produce. Basic Chemical (BasicChem), brick and stone (BrickStone), and nonmetallic mineral products (NMtlMinPr) are some of the most carbon-intensive sectors. The output of these industries may be expected to fall much more relative to less carbon-intensive industries; however, the application of CCS reduces the carbon emissions from these industries. As a result, they pay the CCS costs instead of the carbon prices for these avoided emissions. Notably, the carbon price in CNS will become larger than the fixed unit CCS cost in 2044 and will quadruple CCS by 2060.

Fourth, carbon-intensive industries are nonetheless affected negatively. BasicChem, China, and Glass contract relatively more than others among nonenergy industries. Recall that the CCS technologies do not absorb all CO_2 emissions; their coverage rates peak at 90% in our simulation years; hence carbon-intensive industries may still have positive net emissions subject to carbon prices. These costs negatively affect their output.

Fifth, nonenergy industries, whose costs are composed of more imported materials, suffer less. Computers, communication equipment, and electronic parts are three large electronic equipment industries with high shares of imported inputs. By 2060, the output of the first two industries will fall by much less than real GDP relative to BCS (0.29% and 0.18%, respectively). The output from the electronic parts industry increases by 0.2% relative to the BCS. These industries suffer less from the higher domestic prices caused by higher carbon prices since they rely more on imports, whose prices are unaffected by domestic carbon prices.

Six, investment-led industries suffer more. Investment falls the most of all components of final demand (recall Fig. 9). Industries like residential construction and installation construction that sell a large share of their output to investment demand thus tend to contract more. The real output of these two industries will fall by 1.4% and 1.9% relative to BCS levels by 2060, respectively.

We report changes in employed persons by 19 aggregated sectors in Fig. 13.[12] By 2060, the total number of job losses caused by carbon neutrality efforts is 335,000, among which the mining sector suffers the most (484,000); however, not all industries suffer job losses. Nine of the 19 aggregated industries employ more people in 2060 under the CNS than under the BCS. The electricity, gas, and water (ElcGasWater) sector employs 378,000 more people, showing that the increase in solar and wind power can compensate for job losses in fossil-fuel-based energy sectors.

5. Alternative policy scenarios

We restrict our analysis of alternative policy scenarios to those illustrating the impacts of changes in CCS costs and the impact of border adjustment mechanisms. Other scenarios that focus on the timing of tax cuts, different elasticities, and assumptions regarding the impact of the carbon tax on preferences are available in Feng et al. (2021a).

5.1. Higher and lower CCS costs scenarios (HCC & LCC)

HCC and LCC are designed to test the sensitivity of results regarding

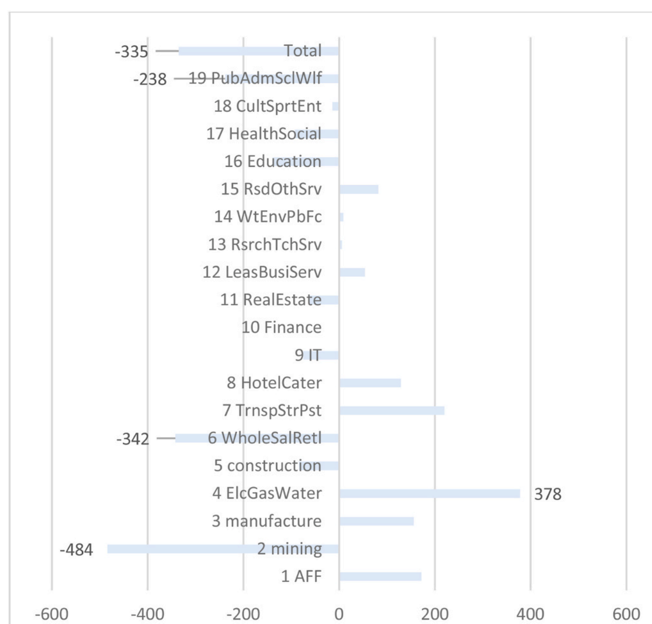

Fig. 13. Employed persons in CNS, 2060—deviations from BCS (1000 persons).

[12] We do not show results for employed persons at the 158-industry level. Our current employment data were sourced from the 2015 National 1% Population Sample Survey and the 2018 China Labor Statistical Yearbook and do not support such detailed results. The 19 aggregated industry results are in accord with the 2015 survey. The mapping between the 158 individual and 19-aggregated industries is available in the Appendix of Feng et al. (2021a).

changes in CCS[13] cost assumptions. Without cost information, we assumed the unit costs of fossil-fuel-based CCS abatement would be 400 CNY/tCO_2 throughout the policy years. In HCC and LCC, we increase and decrease the unit abatement costs by 20%, respectively, to 480 and 320 CNY/tCO_2, respectively.

The macroeconomic results under the HCC and LCC scenarios are virtually identical to those under the CNS. By 2060, cumulative real GDP under HCC or LCC will be within 0.001% of the CNS. To achieve the same level of cumulative CO_2 emissions, the carbon price in 2060 will remain between 1613 and 1615 CNY/tCO_2, compared to 1614 CNY/tCO_2 under CNS. Modeling results are very insensitive to these changes in CCS costs.

5.2. More and less DACCS contribution scenarios (MDC & LDC)

MDC and LDC test the sensitivity of results to DACCS assumptions. In MDC and LDC, we assume DACCS's contribution to emissions reduction in 2060 is 20% higher and lower than under the CNS scenario, respectively. Therefore, in 2060, we set DACCS to reduce CO_2 emissions by 1200 $mtCO_2$ and 800 $mtCO_2$, respectively.

Changes to DACCS contribution result in notable impacts on real GDP. Under the MDC (LDC), cumulative real GDP is 0.2% higher (−0.25% lower) compared to the CNS. To achieve the same level of cumulative CO_2 emissions by 2060, MDC (LDC) requires a lower (higher) carbon price: 1180 CNY/tCO2 (2226 CNY/tCO2) compared to 1614 CNY/tCO2 under CNS.

5.3. Border adjustment mechanisms scenario (BAM)

In this scenario, we assume China implements import taxes on energy-intensive imports (chemicals, cement, and steel) to maintain the price competitiveness of its domestic goods. Recall that import prices are assumed to be fixed in our core simulation scenarios. China's carbon neutrality efforts will increase the prices of its energy-intensive outputs and reduce their price competitiveness globally. In this scenario, we continue to assume world prices are fixed but maintain domestic and import price ratios at the BCS levels by endogenizing import tariffs for energy-intensive commodities. Recall that CHINAGEM-E is a single-country model. Although a global model is arguably a better choice to model BAM, it would be impractical to use a global model to reflect the high level of industry detail and other model features built into CHINAGEM-E. Nonetheless, this experiment helps to gain insights on the potential implications of China implementing a border tax should global mitigation efforts not reach China's levels.

Relative to the CNS, macroeconomic results under the BAM scenario are virtually unchanged. Cumulative real GDP by 2060 in BAM is 0.004% lower than CNS, and to achieve the same level of cumulative CO_2 emissions by 2060, the carbon price in 2060 is 1644 CNY/tCO_2 under the BAM compared to 1614 CNY/tCO_2 under the CNS; however, relative to the CNS, imports of energy-intensive goods in the BAM scenario are significantly lower. This result is to be expected, as under BAM, the competitiveness of domestic goods is restored by adjusting the tax on imported goods.

6. Concluding remarks and policy implications

China is the world's largest emitter of CO_2, and the country's energy-related carbon emissions have grown significantly over the past decade, accounting for 28% of the global total before the onset of the COVID-19 pandemic. The immense scale of China's energy consumption and its ambitious economic growth targets, present substantial challenges to achieving net-zero emissions by 2060. Therefore, a comprehensive study is essential to offer valuable insights into this policy problem. Using a dynamic CGE model (CHINAGEM-E), we analyze the economic implications of reaching carbon neutrality in China. To do so, we modified CHINAGEM-E to include updated data representing production activity in over 150 sectors in the Chinese economy, a new CCS modeling mechanism, and a new power generation nesting structure where the hydrocarbon sector has a separate representation of coal, oil, and gas, and with detailed representation of eight separate electricity-generation technologies. We clearly described the key assumptions characterizing our two core scenarios: a business-as-usual scenario and a CNS. Comparing these two scenarios leads to the following key results.

Most importantly, we showed that China could reach its 2020 announced carbon goals, peaking carbon emissions before 2030 and achieving carbon neutrality by 2060, as well as its economic development goal of doubling GDP between 2020 and 2035. The CNS was characterized by very small reductions in real GDP and real household consumption (−1.36% and −1.11% by 2060, respectively) compared to the business-as-usual scenario. These findings should give the Chinese government added confidence in pursuing its carbon neutrality objectives.

Furthermore, our results align with broader findings in the literature, indicating that robust mitigation efforts do not necessarily derail economic development objectives in the long term, even before considering positive social benefits. The carbon price under the CNS could be around 1600 CNY/tCO_2 (equivalent to around 220 USD/tCO_2) in 2060, comparable to the carbon price estimated for other major economies pursuing net-zero carbon emissions.

Our simulation results also showed that China's carbon neutrality efforts should not cause large-scale unemployment. Labor moves across sectors; thus, clean energy sectors will expand and employ more persons, compensating for the job losses that result from contracting fossil-fuel-related sectors. Our CNS projected a relatively modest net job loss of approximately 600,000 individuals in the annual average, relative to business-as-usual. While this figure is comparatively small, our results suggest that appropriate policies can be implemented to smooth the employment transition for affected workers. For example, providing training programs for skills specific to occupations in clean energy sectors can equip the workforce with the skills needed for emerging green industries, fostering a smoother transition.

Industry detail is a feature of the CHINAGEM-E model, which allows us to highlight how carbon neutrality efforts affect industries differently. Energy and related industries are significantly affected, with fossil-fuel (especially coal)-related industries contracting while renewables (wind and solar) expand by between 60% and 80% relative to baseline levels. Upstream and downstream industries in the electricity-generation supply chain (power transmission equipment and electricity distribution) simultaneously expand due to the electrification of the Chinese economy, while industries selling more to investment suffer relatively significant losses in line with projected falls in overall investment spending.

In constructing our carbon neutrality and business-as-usual scenarios, we detailed several key assumptions regarding the behavior of accelerated advancements in energy efficiency, the affordability of renewable electricity, expanded electrification, the successful implementation of negative emission technologies, such as FFCCS, BECCS, and DACCS, and features of the carbon tax including revenue recycling. These assumptions underscore the necessity for China to make substantial efforts in driving technological advancements, particularly in the energy sector. It is essential to highlight the vital role of CCS technologies in successfully implementing policies to achieve carbon neutrality, and these technologies are integral to achieving this goal. Our simulations demonstrate that CCS, encompassing fossil-fuel-based CCS, BECCS, and DACCS, can contribute to a 20% reduction in total emissions between 2020 and 2060. Therefore, strategic investments in CCS technology and ongoing efforts to reduce associated costs will be instrumental in China's pursuit of carbon neutrality.

While CHINAGEM-E allows us to highlight the policy implications of

[13] In this case, we consider only fossil-fuel-based CCS as we do not make explicit assumptions regarding BECCS or DACCS cost.

China's carbon neutrality policy at the national level, it would be interesting to decompose these economic impacts to the regional level. Some regions in China will be more adversely affected upon adopting China's carbon neutrality policy, while others might gain, especially regions over-representing renewable energy sources. Analysis of the economic impacts of the move to net-zero emissions using a regional CGE model would be an important avenue for future research.

Nonetheless, the computation burden of our focus on a highly detailed representation of the Chinese economy using CHINAGEM-E precluded more detailed modeling of the global economy. Future research could use a more aggregated model that properly represents China's major trading partners to analyze the country's net-zero emissions policy in a global context. Such work could enable an analysis of the potential expansion of a global CO_2 emissions trading system to include China's entry into an international permit trading scheme.

Credit author statement

Shenghao Feng: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Original draft, Review, Editing, Visualization, and Funding acquisition.

Xiujian Peng: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Review, Editing, Supervision, Project administration.

Philip Adams: Methodology, Software, Validation, Formal analysis, Review, and Editing.

Dalin Jiang: Conceptualization, Resources, Review, and Project administration.

Robert Waschik: Review and Editing.

Declaration of competing interest

We declare no conflict of interest of this research.

Data availability

We are able to share our model code and software. But we do not have permission to share data because they are commercial products.

ECMODE-D-23-00523 (Original data) (Mendeley Data)

Technical Appendix

This study utilized a dynamic computable general equilibrium model (CHINAGEM-E) to examine the economic implications of achieving carbon neutrality in China. The key features of the CHINAGEM-E model include the following.

(1) Updated data representing production activity across over 150 sectors in the Chinese economy, with particular disaggregation of energy sectors
(2) Integration of a new carbon capture and storage (CCS) modeling mechanism
(3) Introduction of a new power generation nesting structure where the hydrocarbon sector has separate representation of coal, oil, and gas, and with detailed representation of eight separate electricity-generation technologies

This appendix provides the technical details of these key features. Furthermore, recognizing the importance of carbon pricing, we also provide the technical details of the carbon-pricing mechanism integrated into the CHINAGEM-E model.

A1. Disaggregation of energy sectors

Split crude oil and gas sector.

When splitting the original crude oil and gas (CrudeOilGas) sector from China's input–output table into two distinct ones (crude oil and gas), we employ value shares to allocate both commodities and industries. When splitting commodities, we operate under two key assumptions: (1) crude oil only sells to the petroleum refinery industry; (2) gas is sold to all users except petroleum refinery.

Split electricity sector.

In the CHINAGEM-E model, we expanded upon the original CHINAGEM framework by disaggregating the electricity sector. First, we split the electricity sector into electricity generation and distribution. For the electricity generation, we further disaggregated it into eight technologies: coal-fired power, gas-fired power, onshore wind power, offshore wind power, solar power, nuclear power, hydroelectricity, and bioelectricity. Each type of electricity generation is treated as a separate industry with a unique output, except for onshore wind and offshore wind industries, both producing the same output: wind power. This disaggregation of electricity generation recognizes that electricity generated from different technologies may vary in price. Furthermore, all electricity-generation industries exclusively sell their output to the electricity distribution industry. The electricity distribution sector is the end-use supplier, purchasing electricity from generation and distributing it to users.

When intermediate users purchase electricity, a nested, multilayer substitution exists between various generation technologies in response to changes in generation costs, as shown in the lower right of Fig. 1. Such substitution is price-induced, with the elasticity of substitution between the technologies outlined in Table 1.

A2. Carbon capture and storage (CCS)

Achieving carbon neutrality without CCS would necessitate carbon prices to escalate to levels where fossil-fuel utilization becomes economically unviable; however, integrating CCS technologies will help reduce the cost of carbon neutrality significantly. Therefore, we incorporated three types of CCS technologies, namely conventional CCS, bioelectricity with CCS (BECCS), and direct-air CCS (DACCS) into the CHINAGEM-E model. We identify four broad sectors (i.e., chemicals, cement, steel, and thermal power) to host conventional CCS installations, with further distinctions made between coal-, oil-, and gas-based facilities. BECCS installations are implemented in bioelectricity stations.

We establish three new emissions accounts for CCS, defined as follows.

1) FFCCS(*f,i*), representing emissions extracted by sector *i* from the utilization of fuel *f*, where $i \in$ *[chemicals, cement, steel, thermal power]*, and $f \in$ *[coal, oil, gas]*
2) BECCS, indicating emissions captured by bioelectricity

3) DACCS, where the captured emissions are not attributed to any specific industry

Net carbon dioxide emission (NetCO_2) is expressed in Equation (A1) as follows:

$$NetCO_2 = \sum_{f,i} CO_2(f,i) + \sum_{f,i} FFCCS(f,i) + BECCS + DACCS \tag{A1}$$

Our fossil-fuel-based CCS (FFCCS) and BECCS mechanisms do not necessitate the disaggregation of existing sectors. We presume a given percentage of carbon dioxide emissions from a given industry is removed by CCS technologies, defined as the fossil-fuel CCS coverage rate (FFCOV) and BECCS coverage rate (BECOV). This situation is illustrated in Equations (A2) and (A3), respectively:

$$FFCOV(f,i) = \frac{FFCCS(f,i)}{CO_2(f,i)} \tag{A2}$$

$$BECOV = \frac{BECCS}{CO_2(bioelec)} \tag{A3}$$

We assume a fixed cost per unit of CO_2 removed for fossil-fuel-based CCS.

BECCS is a negative-emissions technology because biomass absorbs carbon from the atmosphere, while burning biomass puts the absorbed carbon back into the atmosphere. Capturing these emissions leads to a net reduction of CO_2 in the atmosphere; therefore, BECCS endeavors should benefit from emissions permit sales. Instead of assigning specific costs, we presume the costs of BECCS efforts to be equivalent to the benefits from permit sales.

While DACCS is also featured in our scenarios, we treat it as a residual. In other words, we assume that DACCS removes the remaining CO_2 emissions after CCS and BECCS mitigation. Analogous to BECCS, we assume the benefits from selling emissions permits fully offset the costs of DACCS efforts.

A3. Multilevel fuel-factor nesting production structure

We create a new fuel-factor nesting structure to allow substitutions between production factors and various energy types. CES functions are employed to construct our nesting structure. Equation (A4) exemplifies a typical three-factor nested production function as follows:

$$Y = Ae^{\lambda}\left[\beta(\alpha K^{-\rho_{KE}} + (1-\alpha)E^{-\rho_{KE}})^{\rho_{KE_L}/\rho_{KE}} + (1-\beta)L^{-\rho_{KE_L}}\right]^{-m/\rho_{KE_L}} \tag{A4}$$

where Y represents total output, and K, L, and E denote the total input of capital, labor, and energy, respectively. A and λ are an efficiency parameter and the rate of technological change, respectively, with $A, \lambda \geq 0$. The share parameters α and β are input factor contributions to output, with $0 < \alpha, \beta < 1$. ρ_{KE} and ρ_{KE_L} are inner and outer nested substitution parameters, respectively, while m is the return to scale parameter, where $m = 1(>1, <1)$ stands for constant (increasing, decreasing) return to scale. Thus, Equation (A4) represents a nesting structure where the upper level comprises a CES nest between labor and a capital-energy bundle, formed by a lower-level CES nest between capital and energy.

A4. The carbon-pricing mechanism

We integrated a carbon-pricing mechanism into the CHINAGEM-E model. A carbon price is a specific tax that collects a given amount of monetary value from a given amount of physical CO_2 emissions; however, the input–output (I/O) database is based on value rather than physical quantities. To reconcile this, we must translate the specific tax on CO_2 emissions into an ad valorem tax that aligns with the model database (expressed in CNY 10 million). To achieve this translation, we adopt the methodology that Adams and Parmenter (2013) utilized. The method utilizes carbon-pricing revenues to establish a connection between an ad valorem tax (sales tax) and a specific tax (emissions tax), as depicted in Equation (A5):

$$S \times Q \times I = \frac{P \times X \times V}{100} \tag{A5}$$

The left-hand side (LSH) of Equation (A5) represents the carbon-pricing revenues from a specific tax. S is the specific carbon price (CNY per ton of CO_2), Q is the volume of CO_2 emissions (in millions of tons), and I is a price index for preserving nominal homogeneity. The right-hand side (RHS) of Equation (A5) represents the carbon-pricing revenues from an ad valorem tax. V is the (percent) ad valorem tax rate, and $P \times X$ is the basic value of the taxed flow (P and X denote price and quantity, respectively). Since the monetary value in the model is in 10 million and emission is in millions, for the LHS of Equation (A5) to be in 10 million, $I = 0.1$ is needed.

The equations for the ordinary change of the LHS and RHS of Equation (A5) are depicted in Equations A6 and A7, respectively.

$$LHS = Q \times I \times delS + \frac{S \times Q \times I}{100} \times (q + i) \tag{A6}$$

$$RHS = \frac{P \times X}{100} \times delV + \frac{P \times X \times V}{10,000} \times (p + x) \tag{A7}$$

where $delS$ and $delV$ denote ordinary changes in S and V, respectively. Lower-case q, i, p, and x denote percentage changes in their respective upper-case variables. Combining Equations (A6) and (A7) and solving for $delV$ gives Equation (A8):

$$delV = \frac{S \times Q \times I}{P \times X} \times (q + i - p - x) + 100 \times \frac{Q \times I}{P \times X} \times delS \tag{A8}$$

Ordinary changes in carbon-pricing revenues ($delR$) can thus be expressed as Equation (A9):

$$delR = Q \times I \times delS + \frac{S \times Q \times I}{100}(q+i). \tag{A9}$$

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