China's Nationwide CO_2 Emissions Trading System: A General Equilibrium Assessment

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ABSTRACT

China recently introduced a nationwide CO_2 emissions trading system that has become the world's largest and is expected to contribute importantly to the nation's goal of achieving carbon neutrality before 2060. The new system is a tradable performance standard (TPS), a rate-based emissions allowance trading system under which each covered facility receives free allowances from the government equal to the product of its intended output (e.g., electricity) and an assigned "benchmark" (emissions-output ratio). The TPS includes provisions for allowance trading.

Because the government's allowance allocation to a given covered facility is proportional to the facility's output, it is endogenous to the facility's output supply decisions. This is a key difference from cap and trade (the most frequently used CO_2 emissions trading system in other parts of the world), where a facility's allowance allocation is generally exogenous from the facility's perspective. This difference from cap and trade (C&T) has important implications for the TPS's aggregate costs and the distribution of its impacts across sectors and regions.

This paper presents and interprets results over the interval 2020-2035 from a multi-sector, multi-period general equilibrium model designed to evaluate China's new effort. The model differs from earlier studies because of its general equilibrium framework, its attention to changes in impacts over time, its recognition of differences between the TPS and C&T in terms of their incentives and impacts, and its ability to consider a range of potential future TPS designs – designs that are currently under consideration by China's planners. The potential designs include alternative specifications for the variation and average stringency of benchmarks, the introduction of an allowance auction as a supplementary source of allowance supply, and the possible transition from the TPS to a C&T system.

The results from our analysis yield unique insights into the potential impacts of China's new and evolving policy effort. First, we find that the TPS's environmental benefits are likely to be well above its economic costs, with benefits exceeding costs by a factor of five if only the climate-related benefits are considered and by a significantly higher factor if health benefits from reduced emissions of local pollutants are also considered. Second, the currently planned stringency of China's TPS is considerably weaker than the efficiency-maximizing level. Third, the relative costs per ton of the TPS versus C&T change significantly over time: China's pre-existing taxes help explain this dynamic pattern. Fourth, introducing an auction as a complementary source of allowance supply can lower the economic costs of the TPS by 24-40 percent relative to the no-auction case, depending on the revenue-recycling methods employed. Finally, there are significant trade-offs between the goals of low aggregate cost and evenness of impacts across provinces; for example, employing a single benchmark for the electricity sector would lower costs by 30 percent relative to the four-benchmark system that is actually in place, but would increase the standard deviation of percentage income losses across provinces by about 50 percent.

1. Introduction

China has launched an ambitious nationwide program to reduce emissions of CO_2 and address climate change. Introduced in 2021, the program has already become the world's largest emissions trading system. It is expected to make a major contribution toward meeting China's pledge to peak its emissions before 2030 and achieve net-zero CO_2 emissions before 2060.

The new system is a tradable performance standard (TPS), a rate-based system under which each covered facility receives from the government in each compliance period a certain number of emissions allowances based on its output and the government's assigned "benchmark" ratio of emissions per unit of output. In general, the benchmarks are set below the average initial emissions intensities across the covered facilities, which implies that the TPS will require an overall reduction in the emissions-output ratio.

China's TPS is an example of an output-oriented emissions intensity standard, as it imposes a ceiling on the ratio of emissions to output.[1] It can be contrasted with input-oriented rate-based standards, which impose floors on the ratio of "clean" (low-polluting) to "dirty" (high-polluting) inputs to production. Examples include low-carbon fuel standards, which have been introduced in several US states, and renewable portfolio standards, which establish a floor on the ratio of renewables-generated to fossil-generated electricity purchased by electric utilities. These standards implicitly subsidize the cleaner inputs and tax the dirtier ones.[2]

China's TPS includes provisions under which covered facilities may trade emissions allowances. Such trades alter the distribution of abatement efforts across

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[1] Fischer (2001) offered a seminal theoretical study of the efficiency properties of TPS. Subsequent studies examining TPS in the US include Fischer *et al.*(2017), Bushnell *et al.* (2017), Zhang *et al.* (2018), and Chen *et al.* (2018). Recent studies of China's TPS include Pizer & Zhang (2018), Goulder *et al.* (2022), Wang *et al.* (2022), and Karplus & Zhang (2017).

[2] Studies of low-carbon fuel standards include Holland *et al.*(2009), Holland *et al.*(2015), and Bento *et al.* (2020). Analyses of renewable portfolio standards include Fischer (2010), Fischer & Preonas (2010), and Bento *et al.*(2018). A close cousin to a renewable portfolio standard is a clean electricity standard, which imposes a floor on the ratio of "clean" electricity to fossil-generated electricity used by utilities, where "clean" may include energy from nuclear power plants as well as renewable sources. Goulder *et al.*(2016) and Borenstein & Kellogg (2022) examine such standards. Fullerton & Metcalf (2001), Fischer & Newell (2008), Goulder & Parry (2008), Parry *et al.*(2016), Fischer *et al.*(2017), Metcalf (2019) and Dimanchev & Knittel (2020) survey the efficiency attractions and limitations of a wide range of climate policy instruments, including intensity standards and cap and trade.

facilities and bring about more abatement efforts by facilities that can achieve emissions reductions at the lowest cost. In this respect, the TPS shares a key feature of cap and trade (C&T), the principal type of emissions trading program used in other countries.

However, a TPS differs from C&T in important ways. Under C&T, a covered facility's compliance is based on the absolute quantity of its emissions over the compliance period. Compliance requires that this quantity not exceed the facility's allocated emissions allowances, an amount that usually is exogenous from the covered facility's perspective.[3] In contrast, under the TPS's intensity-based approach, the number of allowances granted to a covered facility is proportional to its output level: it is the product of its output level and assigned benchmark. This intensity-based allocation method offers the covered facility just enough allowances to justify the emissions it would generate if its actual emissions-output ratio matched its benchmark. Since a facility's allowance allocation is proportional to its output, the allocation is not exogenous, as the facility can influence its allocation through its choice of output during the compliance period. This is an important difference from C&T, a difference with important implications for the costs of achieving the nation's overall emission-reduction targets and the distributional impacts.

This paper presents the structure and results from a multi-sector, multi-period general equilibrium model designed to evaluate China's new effort. We apply the model to assess the TPS's impact on output levels, production costs, prices, and CO_2 emissions over the interval 2020-2035.

The model has several distinguishing features. First, it pays close attention to the structure and compliance obligations of China's TPS. Much of the earlier literature on China's emissions trading system did not consider the significant differences between the TPS and C&T. Some relatively recent studies of China's nationwide climate policy efforts recognize these differences[4], but the analysis in the present paper extends this analysis by taking into account the significance of pre-existing taxes and energy-related regulations such as the administered pricing of electricity. The paper shows that these features influence the TPS's costs and their differences from the costs of C&T.

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[3] A few C&T systems include provisions for output-based allocation, in which case a facility's allowance allocation is connected to the facility's chosen level of output and thus is endogenous.

[4] See, for example, Geng & Fan (2021), Goulder *et al.*(2022), IEA (2022), Ma & Qian (2022), Wang *et al.* (2022), Zhang *et al.*(2023), and Yu *et al.*(2022).

Second, the model employs a general equilibrium framework, which enables it to consider interactions among sectors covered by the TPS as well as between the covered and uncovered sectors. Earlier studies examining China's TPS have tended to employ partial equilibrium models.[5] We are aware of only one general equilibrium model that studied China's TPS – Yu *et al.* (2022). Our model differs from that model in two ways. First, it incorporates plant-level data, which enables it to account for heterogeneous production technologies within sectors and to consider the TPS with multiple benchmarks within each covered sector – which is consistent with the actual benchmark design of China's TPS. Second, while Yu *et al.* focus only on the first phase of China's TPS when it covers only the electricity sector, our analysis also considers the later phases during which the TPS's coverage extends to several other sectors.

Third, the model is intertemporal, so it can capture changes in policy stringency and impacts over time. The few existing TPS studies that incorporate intertemporal dynamics tend to focus on individual sectors.[6] Our model's dynamic general equilibrium framework can assess how the absolute and relative costs of the TPS and C&T change over time with the changes in sector coverage and policy stringency.

Finally, the model has considerable flexibility in terms of the range of future TPS policy designs it can examine, dimensions that have not been comprehensively analyzed in the prior literature. These include alternative specifications for the variation and average stringency of benchmarks, the introduction of allowance auctioning, and the possible transition from the TPS to a C&T system. Although China has already introduced the first phase of the TPS, the Ministry of Environment and Ecology (MEE) – the ministry responsible for the design and implementation of the program – is continuing to make important decisions about the design of later phases. The model can incorporate the alternative potential policy designs, which have differing implications for aggregate costs, their distribution across sectors and regions, and the scale of emissions reductions. The flexibility makes this model poised to offer important policy recommendations for China's continually evolving carbon emissions trading system.

[5] The partial equilibrium studies include Geng & Fan (2021), Goulder *et al.*(2022), IEA (2022), Ma & Qian (2022), Wang *et al.*(2022), and Zhang *et al.*(2023).

[6] See, for example, Fischer & Springborn (2011), Becker (2020), and Yu *et al*.(2022).

The results from our analysis yield several insights into the potential impacts of China's new nationwide climate policy effort. First, we find that the TPS's environmental benefits are likely to be well above its economic cost. Our central estimate is that the climate-related benefits from the TPS's emissions reduction over the interval 2020-2035 would exceed its cost by a factor of five. Taking account of the health benefits from improved local air quality increases the TPS's benefit-cost ratio to 25.[7]

Second, the planned stringency of China's TPS is less than the efficiency-maximizing level. Efficiency maximization requires that marginal abatement cost equal marginal environmental benefit. Over the interval 2020-2035, the average discounted marginal cost of abatement in the 2020-2035 interval (in year-2020 constant prices) is 124-158 RMB (or 18-23 US dollars) per ton of CO_2.[8] This is below the Biden Administration's central estimate of the average discounted marginal climate benefit from abatement (i.e., the average discounted social cost of carbon, or SCC) over this interval. Our numerical model indicates that efficiency maximization would require the use of benchmarks that are 16-22 percent tighter than the current benchmarks and the ones projected for the next phases of the TPS. We estimate that the use of efficiency-maximizing benchmarks would lead to emissions reduction over the interval 2020-2035 around 2.5-3.2 times what seems likely to result from the current and projected benchmarks over this interval.

Third, the TPS's cost is generally higher than those of an equivalently stringent C&T system. The TPS's method for allowance allocation implicitly introduces a subsidy to intended output, since covered facilities receive free allowances for each additional unit of production. The implicit subsidy causes covered firms to rely too little (from an efficiency point of view) on output reduction to achieve compliance, as reducing output

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[7] The climate-related benefits from CO_2 reductions range from 8 trillion to 49 trillion RMB under a plausible range of values for the SCC, model parameters and policy stringency over the 2020-2035 interval. The central estimate is 12 trillion RMB. When health co-benefits are considered, the TPS's total environmental benefits range from 19 to 106 trillion RMB, with 53 trillion RMB as the central estimate. The economic costs range from 2 trillion to 3 trillion under the same range of model parameters and policy stringency. We offer details in Section 6.2.

[8] Under assumptions of pure competition and a well-functioning allowance market, the price of emissions allowances is the marginal abatement cost for covered facilities. This marginal cost is different from the economy-wide marginal cost of abatement. The latter is larger, as it includes the costs to firms in uncovered industries. We obtain the economy-wide marginal cost by evaluating the cumulative economy-wide cost from an incremental tightening of benchmarks relative to their values under the TPS in the central case. Specifically, the average marginal cost per ton is the present value of cumulative change in GDP during 2020-2035 divided by the associated cumulative change in emissions relative to the baseline, using a discount rate of 5%.

implies a reduction in the allowance allocation. This accounts for the TPS's higher cost than those of C&T, which includes no such subsidy. We also find that the excess cost of the TPS relative to those of C&T increases with the stringency of the emissions-reduction target, as increased stringency leads to higher allowance prices and thereby gives greater importance to the implicit subsidy. Accordingly, our simulations indicate a growing gap in the marginal cost of abatement between the TPS and that of an equivalently stringent C&T system, a reflection of the planned increase in stringency of the TPS over time. On the other hand, we find that the TPS's implicit output subsidy has the *beneficial* effect (in terms of efficiency) of reducing the distortionary effect of pre-existing taxes on labor and capital. This effect offsets what otherwise would be a larger disadvantage of the TPS in terms of cost-effectiveness.

Fourth, supplying some allowances under the TPS via an auction can lower the economic costs of achieving given emissions-reduction targets.[9] Our central estimate is that introducing an allowance auction would lower the economy-wide cost by 24-40 percent relative to the no-auction case, depending on how auction revenues are recycled. The cost reduction is especially large when the auction revenue is used to finance cuts in pre-existing capital and labor tax rates; over the 2020-2035 simulation interval, this reduces the cost by 17 percent relative to a scenario where the revenue is returned in a lump-sum fashion, because reducing pre-existing tax rates lowers the distortionary effects of pre-existing taxes on production decisions. Also, using the revenue to finance output subsidies for wind- and solar-generated electricity leads to a significant increase in the market penetration by renewables-based electricity. Devoting the revenues toward compensation to the sectors that could suffer the largest profit losses (the coal and mining sectors) can fully offset their profit losses.

Fifth, the simulation results reveal important trade-offs between cost-effectiveness and distributional equity. Distributional concerns can be addressed through the use of varying benchmarks, but greater variation in benchmarks raises aggregate costs by widening the disparities in the marginal costs of production. The TPS currently in place has four different benchmarks for the electricity sector, and it is plausible that this will

[9] Strictly speaking, the system is no longer a TPS once an auction is introduced, because a covered facility's compliance will no longer depend on achieving an assigned emissions-output ratio. Rather, compliance will require that its total emissions not exceed the *level* of emissions authorized by its total allowance holdings – the sum of the allowances received free as a function of the prescribed benchmark and the allowances purchased at the auction or on the trading market.

continue to be the case for this sector over the rest of the 2020-2035 interval. We find that employing a single benchmark for this sector over this interval would imply economy-wide costs 30 percent lower than in the four-benchmark case. At the same time, the one-benchmark case increases the standard deviation of percentage income losses across provinces by more than 50 percent.

The rest of this paper is organized as follows. Section 2 describes the basic features of the TPS and provides a simple analytical model of the incentives it yields for covered facilities' choices of inputs, levels of output, and purchases or sales of emissions allowances. Section 3 presents the numerical model's structure, and Section 4 indicates its data and parameters. Section 5 describes the policies examined, and Section 6 presents and interprets the outcomes from policy simulations. Section 7 provides a sensitivity analysis, and Section 8 offers conclusions.

2. The TPS

2.1 Basic Features

Under the TPS, covered facilities can utilize three channels to minimize costs of compliance: (a) reducing emissions intensity (emissions per unit of output), (b) reducing output supply, and (c) purchasing or selling allowances.

China's TPS allows for allowance trading across provinces and sectors. The opportunity to trade allowances helps reduce compliance costs. In the absence of provisions for trading, a performance standard would require each covered facility to achieve an emissions-output ratio not exceeding its assigned benchmark. With allowance trading as a possibility, the covered facility's initial allocation of allowances, plus (minus) any allowances it purchases (sells) on the trading market, must be sufficient to justify its emissions during the compliance period. As was noted above, under the TPS a covered facility's initial allowance allocation is proportional to its output. This is a key difference from C&T – a difference with important implications for output choices, emissions, and economy-wide policy costs.

The TPS will be introduced in phases. The first began in 2021 and covers only the power sector. The compliance is based on emissions performance in the previous year. In the second phase, which is likely to begin in late 2023 or early 2024, the TPS's coverage will expand to include the cement and aluminum sectors and possibly the iron & steel sector as well.[10] At least one further phase is expected, under which the TPS will expand to cover additional manufacturing sectors. The expected additional sectors are pulp & paper, other non-metal products, other non-ferrous metals, chemicals, and petroleum refining.

2.2 Producer Behavior and Efficiency Implications

The following framework indicates how covered facilities will employ three channels – input-substitution (leading to reduced emissions intensities), changes in production levels, and emissions trading – to minimize costs of compliance under the TPS and C&T. We start with a focus on the electricity sector, which faces administered prices for some of the electricity supplied.[11] We then briefly discuss the framework for other sectors, which is simpler because administered prices do not apply.

We assume that firms are price takers in both the product market and allowance trading market.[12] Under the TPS, the profit function π for electricity generators is:[13]

$$\pi_{ELEC}^{TPS} = \overline{pq} + p(q-\overline{q}) - C(q,e) - t(e-\beta q) \tag{1}$$

where p denotes the market price, q the level of output, C the total cost of production, t the market price of carbon allowances, and β the benchmark. In China's electricity market, generators sell a fixed amount of their electricity $\overline{q}$ at a government-administered

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[10] At the time of this writing, there remains uncertainty as to whether the iron & steel sector will be covered under Phase 2. The simulations in this paper assume coverage of this sector in that phase.

[11] The structure of the analytical model is similar to that in Goulder *et al.* (2022), a partial equilibrium study of the electricity sector.

[12] There is no evidence suggesting the existence of market power in the national emission trading system. Some studies, e.g., Wang *et al.*, (2021) and Zhu *et al.* (2020), obtained evidence of the limited exercise of market power in the earlier regional pilots programs. We anticipate negligible exercise of market power in the national market in light of the market's greater scope and much larger number of participants.

[13] The profit function could be expressed as a function of input choices denoted by a vector x. That is, expression 2 could be re-written as: $\pi_{ELEC}^{TPS} = pq(x) + (\overline{p} - p)\overline{q} - C(x) - t(e(x) - \beta q(x))$, where emissions and output levels are functions of input choices. In this case the first-order condition with respect to x_i (with i indexing inputs) yields: $\partial \pi^{TPS} / \partial x_i :\ p \partial q / \partial x_i = C_{x_i} + t(\partial e / \partial x_i - \beta \partial q / \partial x_i)$, which indicates that the marginal benefit of input x_i must equal its marginal cost. Since the $\partial e / \partial x_i - \beta \partial q / \partial x_i$ term in the right-hand side differs across inputs, the TPS induces input substitution. The more emissions-intensive input has a higher $\partial e / \partial x_i$ than a less emissions-intensive one. Hence the TPS causes the low-intensity input's marginal cost (left-hand side) to decline relative to that of a high-intensity input, leading firms to substitute away from the emission-intensive inputs.

price $\overline{p}$ and sell the electricity beyond that production level at market prices. The profit function can be rewritten as:

$$\pi_{ELEC}^{TPS} = pq + (\overline{p} - p)\overline{q} - C(q,e) - t(e - \beta q) \tag{2}$$

For sectors other than electricity, outputs are sold at market prices, and thus the profit function is:

$$\pi_{NON-ELEC}^{TPS} = pq - C(q,e) - t(e - \beta q) \tag{3}$$

Under TPS, the number of allowances allocated to the covered facility is βq. Covered facilities with relatively low initial emissions intensities – that is, with intensities below their benchmarks – will receive allocations of allowances in excess of what is needed for compliance. For these facilities $t^*(e - \beta q)$ is negative. These facilities have incentives to increase output, as this will expand their allowance allocation, giving them additional allowances to sell.

In contrast, the facilities with relatively high initial emissions intensities will have emissions above the levels authorized by their allowances. For these facilities $t^*(e - \beta q)$ is positive. Such facilities can reduce the costs of allowance purchases $t^*(e - \beta q)$ by reducing output. Importantly, the fact that reducing output leads to a reduction in allowance allocation means that the firm faces an implicit tax on the reduction in output. As a result, under the TPS the high-intensity facilities tend to exploit output-reduction less than under an equivalent C&T system to reduce emissions. The numerical results displayed in Section 4 show that the differences between the TPS and C&T in terms of reliance on output-reduction are quite large.

Since the electricity generators sell the marginal electricity at the market price, as shown in Expression (2), the profit-maximizing first-order conditions with respect to the two decision variables e and q for both electricity generators and non-electricity firms are:

$$\partial\pi^{TPS} / \partial e: \; -C_e = t \tag{4}$$

$$\partial\pi^{TPS} / \partial q: \; C_q = p + \beta t \tag{5}$$

where $-C_e$ and C_q represent the private marginal cost of emissions reductions and production, respectively.

Condition 4 indicates that profit maximization requires that the marginal cost of abatement be equated to the marginal benefit of abatement. Condition 5 indicates that the marginal cost of production must equal the marginal benefit of production. The marginal benefit is the price of output plus βt, the increment to profit from selling the β additional allowances generated by a unit increase in output. The βt term is the implicit subsidy to an increase in output under the TPS. This term is also the implicit tax on a reduction in output under the TPS.

Under the C&T, the profit function for electricity generators is:

$$\pi_{ELEC}^{C\&T} = \overline{pq} + p(q - \overline{q}) - C(q,e) - t(e - \overline{a}) \tag{6}$$

where $\overline{a}$ denotes the fixed number of allowances allocated to the firm. The difference from the TPS's profit function is in the far-right term, in which the allowance allocation is the exogenous quantity $\overline{a}$. The profit function is equivalent to:

$$\pi_{ELEC}^{C\&T} = pq + (\overline{p} - p)\overline{q} - C(q,e) - t(e - \overline{a}) \tag{7}$$

For non-electricity sectors, the profit function is:

$$\pi_{NON-ELEC}^{C\&T} = pq - C(q,e) - t(e - \overline{a}) \tag{8}$$

The profit-maximizing first-order conditions under C&T for both electricity generators and non-electricity firms are:

$$\partial\pi^{C\&T} / \partial e: \; -C_e = t \tag{9}$$

$$\partial\pi^{C\&T} / \partial q: \; C_q = p \tag{10}$$

Conditions 4 and 9 are identical: under both the TPS and C&T, profit-maximization requires that the marginal cost of emissions equals the allowance price t.

Conditions 5 and 10 are different, however. In contrast with C&T, the TPS introduces the implicit subsidy to output (or tax on output-reduction) βt. For any given allowance price, the subsidy gives firms incentives for higher output than under C&T. It is straightforward to show that the first-order conditions of the C&T match those of a social planner (Tietenberg, 1985), whereas the TPS encourages output levels above the socially optimal level. Correspondingly, the TPS does not make sufficient use of output-reduction as a channel for achieving compliance and instead relies excessively (from the perspective of cost-effectiveness) on reductions in emissions intensities. This underlies the lower cost-effectiveness of the TPS relative to C&T.

The magnitude of the difference between TPS and C&T also depends on the variation of benchmarks. Higher variation leads to greater differences in the implicit output subsidy, which in turn tends to cause greater variation in the marginal cost of production across firms. This leads to a further sacrifice of cost-effectiveness.

The above analysis has conveyed a handicap of the TPS relative to C&T in terms of cost-effectiveness. It should be recognized, however, that the TPS has some attractions relative to C&T. First, it would likely give rise to lower emissions leakage. The implicit output subsidy under the TPS leads to smaller increases in the prices of the output of the covered facilities than under C&T. As a result, the TPS induces a smaller shift in demand toward the output of firms in the non-covered industries and less associated leakage. Second, TPS's endogeneity of allowance allocation to output level makes it responsive to macroeconomic conditions. When the economy is booming (contracting), the production levels increase (decrease) as a response to the demand change, and the number of allowances allocated automatically increases (decreases), helping moderate the potential changes in the allowance price. Third, the TPS's rate-based structure capitalizes on China's historical experience with intensity-based environmental regulation.

3. The Numerical Model

3.1 Main Features

For this study, we have developed and applied a multi-sector dynamic computable general equilibrium (CGE) model. As Figure 1 shows, the model captures the interactions among the production, household, and government sectors of China. Representative firms in each of the 31 production sectors employ inputs of primary factors (capital, labor, and natural resources) along with intermediate inputs (energy and material goods) to produce goods for the domestic market and export. A representative household earns income from returns to the factors of production and devotes that income to consumption and savings. The government receives tax revenues, which are devoted to government consumption, public savings, and transfers to households. Private and public savings finance investment. The final demand for goods and services consists of household consumption demand, public and private investment demand, and the government's demand for goods and services. The model also includes emissions allowance trading, which applies under the TPS and the alternative policy of C&T.

The model solves for equilibrium prices and production levels of all the commodities, factor prices, and allowance prices at yearly intervals from the year 2020 to 2035.

The model differs from many other CGE models in recognizing the heterogeneity in production methods within sectors. Here it exploits information from a unique firm-level dataset on emissions, output, and energy use obtained from the MEE. Thus, the model can be used to analyze the impacts of the national emissions trading system on firms of different emissions intensities within a given sector.

3.2 Production

3.2.1 Primary Factors

The primary factors in the model are labor, capital, and "natural resources." Labor and capital are employed in production in all sectors. Labor is perfectly mobile across sectors. Capital is imperfectly mobile: there are costs to its reallocation across sectors or subsectors. Natural resources are directly employed only in wind, solar, hydro, and nuclear electricity production and are not mobile across sectors or subsectors.

3.2.2 Sectors and Subsectors

Table 1 identifies the model's 31 production sectors. The outputs from these sectors divide into two major categories: materials and energy goods. The first 24 outputs in the table are in the first category, the remaining seven in the latter. As indicated below, some sectors subdivide into subsectors. The model recognizes the presence of a national market for produced goods and services.

In the electricity sector, the model distinguishes renewable electricity (solar, wind, and hydro) and nuclear electricity from fossil-based electricity. Within the group of fossil-based electricity generators, the model recognizes heterogeneity across the fossil-electricity plants by distinguishing eleven technology categories. The cement, aluminum, and iron & steel sectors also have subsectors with differing production technologies and associated input intensities. Notwithstanding the differences in input intensities across subsectors, the outputs from subsectors of a given sector are treated as homogeneous and face the same market price. The rationale and method for subsector classifications are offered in Appendix A.

Production in the model is represented by nested constant elasticity of substitution (CES) functions. Each sector (and subsector in the electricity, cement, aluminum, and iron & steel sectors) employs material inputs, energy, and factor inputs for production. Additional detail is provided in the electricity sector to capture elements of renewable and nuclear electricity supply in China. Details on the production structure and functional forms and on the data and calibration methods mentioned above are in Appendixes B and C.

3.3 Household Behavior

A representative household's consumption choices reflect its utility maximization subject to a budget constraint. A nested CES utility function governs the allocation of consumption expenditure across specific consumer goods.

The household receives income from labor, capital, and natural resource rents, and devotes its income to consumption and private savings. The model assumes an exogenous private saving rate: the ratio of the value of saving to the value of after-tax income is fixed in each period.

Private savings, together with government savings (assumed to be a fixed share of tax revenue within one period), constitute total savings. The value of total savings in each period and the price of capital goods determine real investment, the quantity of new capital goods purchased in each period.

The government sector comprises government behavior at all levels: national, regional, and municipal. The model's taxes include output taxes and subsidies, intermediate taxes and subsidies, factor taxes and subsidies, final demand taxes, import tariffs, export subsidies, and subsidies for wind and solar electricity generation. Government expenditure consists of government savings, public consumption, and transfers to households. Public consumption is set as a fixed share of GDP and is characterized by a CES preference function defined over the material-energy composite. The government must balance its budget in each period. In each period, government transfers are endogenously determined and are adjusted to meet the government's budget balance requirement.

Appendix B offers details of the three CES preference structures for consumption, investment, and government spending, respectively.

3.4 Foreign Trade

The model has a simple treatment of China's trade with the rest of the world (ROW). We regard China as a price-taker on the world market, so the foreign-currency prices of imports are exogenous, as are the foreign-currency prices at which exports can be sold. In all scenarios, the exchange rate adjusts to yield a time-path of the trade balance consistent with historical trends. The model does not include international capital flows. Domestically produced and imported goods in a given sector category are regarded as imperfect substitutes; hence their market prices can differ.

3.5 Equilibrium

The general equilibrium requires supply-demand balance in each period for each factor and produced good. Under policies with emissions allowance trading, the allowance supply and demand must match as well. In each period, these requirements determine (a) the prices for the 31 sectors' produced goods; (b) the wage rate; (c) the rental prices of capital, which differ across sectors (as well as subsectors in the electricity, cement, aluminum, and iron &steel sectors); (d) the four different rental prices of the natural resources, for these resources employed in the solar, wind, hydro, and nuclear electricity production subsectors, respectively; and (e) the carbon allowance price.

3.6 Dynamics

The model solves at one-year intervals from 2020 through 2035.[14] Changes in equilibria from one period to the next depend on the increments to the stocks of labor and capital. There is one aggregate capital stock. The stock in the next period is aggregate real investment in the current period net of depreciation over that period. The stocks of the four kinds of natural resources (wind, solar, hydro, and nuclear) are treated as fixed at the base year level.

The model incorporates technological progress as exogenous improvements in energy factor productivity in production sectors. Additionally, for the wind electricity and solar electricity subsectors, the model incorporates Hicks-neutral technological progress

[14] The model is solved as a mixed complementarity problem (MCP) with a Newton-based solver.

as exogenous improvements in total factor productivity. Details can be found in Appendix C.

4. Data and Parameters

4.1 Data

We employ data from several sources to create a consistent database for inputs, outputs, and emissions. Data on inputs and outputs of production sectors are obtained from China's 2017 input-output table (National Bureau of Statistics, 2018). The data on household consumption, government consumption, and investment (which equals total savings) are also obtained from China's 2017 input-output table. The pre-existing tax and subsidy rates are obtained from the Global Trade Analysis Project (GTAP 10) database (Aguiar *et al.*, 2019). Data on CO_2 emissions for different production sectors and the consumption sector are calculated from the sectoral energy use data in the 2017 China energy balance table (National Bureau of Statistics, 2018). We update the input and output data so that the GDP, the total CO_2 emissions, the value-added shares of the service sector and agriculture sectors, and the total tax revenue net of subsidies match the published statistics in 2020 (National Bureau of Statistics, 2021).

Subsector-level data on production, fossil fuel energy use, electricity use, and CO_2 emissions are compiled from an administrative firm-level dataset for electricity, cement, aluminum, and iron & steel sectors collected by the MEE. The sectoral data are then disaggregated into subsectors for electricity, cement, aluminum, and iron & steel sectors according to the subsector-level information, which is obtained by aggregating the firm-level MEE data. The processing steps are detailed in Appendix A.

4.2 Parameters

The elasticities employed in the production and utility functions are adopted from the GTAP database (Aguiar *et al.*, 2019), the MIT EPPA model (Chen *et al*., 2017), the RTI-ADAGE model (RTI International, 2015), the DIEM model (Ross, 2014), and other relevant studies (Cossa, 2004; Hertel *et al.*, 2007; Hertel & Mensbrugghe, 2019; Jomini *et al.*, 1991).

The data sources and processing described in the previous section yield a consistent dataset for 2020. To complete the dataset, we obtain the remaining “free” parameters through calibration. One calibration requirement is that the model’s solution in 2020 must match the benchmark data in terms of costs, production levels, and prices. Parameters for the dynamics of the model are calibrated so that the baseline outcomes during the period 2020-2035 match the projections in government documents and literature.[15] For example, the time profile of effective labor is exogenously specified and calibrated so that the model’s GDP growth rate in the baseline matches some official projections in China.[16]

Further details about parameter sources, values, and calibration methods are in Appendix C.

5. Scenarios

The first TPS phase begins in 2020 and covers only the electricity sector (about 43% of China’s total CO_2 emissions in 2020). For the future phases, the model’s specifications follow closely the approaches endorsed in discussions by decision-makers in the MEE and other administrative bodies. The second phase is assumed to begin in 2023, with the TPS expanding to also cover the iron & steel, aluminum, and cement sector (about 67% of China’s CO_2 emissions). The third phase begins in 2026, with coverage expanding further to include pulp & paper, other non-metal products, other non-ferrous metals, raw chemicals, and petroleum refining industries, which currently account for nearly 75% of China’s CO_2 emissions.[17]

Table 2 indicates the main features of the various policy cases considered. We consider cases that differ in terms of the number and stringency of benchmarks. We also consider cases in which some of the emissions allowances are supplied via auction.

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[15] We abstract from any new policy interventions that might occur between 2020 and 2035.

[16] These projections are in *Medium and Long-term Goals, Strategies, and Paths of China's Economic and Social Development* (The State Information Center, 2020). We calibrate the model to yield a GDP growth rate of 5.5% in 2020-2025, 4.5% in 2026-2030, and 3.5% in 2031-2035, consistent with these projections.

[17] Other non-metal products include ceramics, bricks, and glasses; other non-ferrous metals include copper and tin; raw chemicals include ethylene, methanol, synthetic ammonia, caustic soda, soda ash, synthetic fiber, and plastic; refined petroleum products include gasoline and diesel fuels.

6. Results

6.1 Central Case

6.1.1 Emissions Reductions

Figure 2 displays the policy-induced emissions reductions in Case 1 relative to the baseline. As indicated in the figure, the reductions in CO_2 emissions relative to the same year of the baseline become progressively larger as the system's coverage expands and benchmarks are tightened in later phases. The average annual reduction over the Phase 2 interval is about 550 million tons, more than three times the average annual reduction under Phase 1; the average annual reduction over the Phase 3 interval is about 2.2 billion tons, about four times the average annual reduction during Phase 2.[18]

In Phase 1, by far the largest changes in emissions are in the one covered sector (electricity), where emissions decline annually by about 184 million tons, or four percent from the baseline. Emissions from uncovered sectors increase slightly -- by two million tons annually. This increase mainly reflects the slightly higher use of coal in these sectors because of the lower coal prices stemming from the significant reduction in coal demand by the electricity sector.

Over the entire interval 2020-2035, the cumulative emissions reduction amounts to 24 billion tons, or 12 percent of the cumulative baseline emissions.

Figure 3 shows the covered sectors' relative contributions to emissions reductions over the interval 2020-2035. The largest reductions are from the electricity sector and the sectors that were added in Phase 2, with the former accounting for 57 percent and the latter accounting for 30 percent of the total. Over the 2020-2035 interval, the TPS gives rise to a slight (0.5 percent) increase in emissions from uncovered sectors, reflecting the aforementioned increase in the demand for coal by these sectors.

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[18] Under China's TPS, the emissions associated with electricity production are priced twice: the electricity sector faces the price of emissions from its generation of electricity, and non-electricity sectors are also charged for the emissions from the generation of the electricity they use as an input in production. This deliberate double-counting is intended to encourage high-electricity consuming industries to further reduce emissions, to offset the reduced incentives to improve electricity-use efficiency because of the free allocation of allowances and the presence of administered prices for some electricity. The simulations in this study incorporporate the administered pricing and double-counting. The emissions reductions reported are the actual economy-wide reductions.

6.1.2 Aggregate Costs

1) Impacts under the TPS

Table 4 presents the aggregate costs of the TPS, measured both by the change in GDP and by the equivalent variation measure of the change in household utility. The GDP cost in Phase 1 is relatively small (less than 0.01 percent), but costs expand significantly over time, a consequence of increased benchmark stringency and broader sector coverage. The present value of the GDP cost over the period of 2020-2035 is 2.1 trillion RMB, 0.13 percent of the baseline GDP. When measured via the equivalent variation, the cost is smaller, largely because this measure is based on changes in consumption and disregards the significant declines in investment. The TPS's negative impacts on investment are substantial because the main inputs into the production of the composite investment good are iron&steel and cement, which are emissions-intensive and covered by the TPS. In subsection 6.2 below we compare these costs with estimates of the environmental benefits.

Figure 4 displays the allowance price under the TPS over time in Case 1 under central values for parameters. In Phase 1, the allowance price increases from 44 RMB/ton in 2020 to 62 RMB/ton in 2022. This is close to the observed prices, which ranged from 40-60 RMB/ton. The rising allowance price pattern reflects the combination of benchmark tightening and broader coverage of the TPS over time.[19]

2) Comparison with C&T

Figure 5 compares the economic costs under the TPS and C&T. The TPS's costs are close to those of an equally stringent C&T system during the first eight years of the program, but rise significantly above the C&T costs in later years.[20] Three factors underlie this pattern.

First, as was noted in Section 2, the TPS introduces an implicit subsidy to output, which causes covered facilities to make relatively inefficient use of the output-reduction channel to reduce emissions. Figure 6 displays the relative contributions of the three key

[19] The slight dip in the price from 2022 to 2023 reflects a short-term reduction in the overall stringency of the TPS during the transition from Phase 1 to Phase 2.

[20] In the simulations of C&T, emissions allowances are allocated for free and the total supply matches those under the TPS in Case 1. The allocations for sectors and subsectors are proportional to those under the TPS.

channels for emissions reductions over the interval 2020-2035 under the TPS and the equally stringent C&T system. Compared with C&T, covered facilities rely less on the output-reduction channel and more on reduced emissions-intensities in order to achieve emissions reductions. The analytical model indicated that the inefficiency associated with the TPS's implicit subsidy is proportional to the product of the benchmark and the allowance price. Figure 5's results suggest that the magnitude of this inefficiency is not great until Phase 3, when higher allowance prices cause this product to be considerably higher than in earlier years.[21]

A second factor explaining the TPS's relatively small initial cost-disadvantage relates to pre-existing taxes. As in other economies, there are significant taxes on the labor, capital, and intermediate inputs used in production in most of China's sectors. Although the TPS's implicit output subsidy leads to inefficiently high output relative to C&T, it also has the *beneficial* effect (in terms of efficiency) of reducing the distortionary effect of pre-existing taxes on labor and capital. This "tax-interaction" effect has been examined theoretically and numerically in the prior environmental economics literature.[22] This impact from the subsidy helps improve the cost-effectiveness of the TPS and offsets what otherwise would be a larger disadvantage relative to C&T.[23] In the first years of the TPS, the two effects on cost-effectiveness are comparable. However, over time, as the product of the allowance price and benchmark increases, the adverse impact from this product becomes significantly more important than the beneficial impact of pre-existing taxes, and the gap between the TPS and C&T costs widens.

A third factor is a slightly faster rate of capital accumulation under the TPS. The TPS's implicit output subsidy results in relatively low prices of new capital goods. This promotes faster investment. The higher associated capital stock implies a lower rental

[21] See, Fischer (2001) and Goulder *et al.* (2022), for further discussion of the inefficiency associated with the TPS's implicit subsidy. In our simulations of the TPS, allowance prices rise over time by a larger percentage than the percentage by which the benchmarks decline. Hence the product of the allowance price and benchmark grows, increasing the associated distortion.

[22] See, for example, Goulder *et al*. (1999), Parry and Bento (2000), and Parry and Williams (2010).

[23] To confirm the significance of pre-existing taxes for the relative costs of the TPS and C&T, we have performed counterfactual simulations in which the magnitudes of pre-existing taxes on capital and labor are different. As indicated in Appendix D, the ratio of the present value of TPS's costs to the costs under C&T is lower when the levels of pre-existing taxes are higher.

price of capital, which in turn implies lower future costs of CO_2 abatement: covered facilities can switch at a lower cost from fuel inputs to capital.[24]

The TPS's lower reliance on output-reduction also explains why allowance prices rise more under the TPS than under C&T (see Figure 4). The higher output relative to C&T is associated with a higher demand for allowances, which leads to higher allowance prices despite the TPS's lower emissions intensity.

6.1.3 Sector Impacts

1) Sector and Subsector Prices, Outputs, and Profits

Table 5 displays for each sector and in each of the three phases the percentage change in the output price, level of production, and profit.[25] Prices and profit are expressed in real terms, with the price of a composite consumption good employed as the price index.

As expected, the covered sectors tend to experience the largest reductions in output, reflecting the use of output-reduction as a channel for reducing compliance costs. The reduction in output is highest in the electricity sector. This sector's carbon intensity is relatively high and its benchmarks are stringent relative to those of other sectors.[26] As a result, unit costs of electricity production increase significantly, prompting a significant reduction in electricity demand.

In all three phases, all of the covered sectors experience increased profits. This reflects the economic rents associated with the value of the free allowances these sectors receive under the TPS.[27] The rents are significant, as the demands for the products of these sectors are relatively inelastic. The low elasticity in part reflects the fact that these sectors are not highly trade-exposed; hence they are less vulnerable to imported

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[24] China's planners are contemplating a transition from the TPS to C&T, which could begin a decade or so in the future. The capital accumulation effect plays a key role in this scenario. We offer details about this case in Appendix E.

[25] We measure the sectors' profit by the total after-tax return to the sectors' capital and the value of free allowances.

[26] The emissions intensities by sector are provided in Table A10 in Appendix F.

[27] Goulder *et al.* (2010) offer a detailed discussion of how free allowance allocation yields economic rents. Under the TPS, free allocation is an intrinsic characteristic of the system: a covered facility with benchmark β receives the quantity βq of free allowances. These have a value of $t\beta q$. As an example, in the TPS simulations here, the value of the allowances offered free to the electricity sector in 2021 is 220 billion RMB. This is enough to offset the increased production cost of this sector in 2021, which is about 216 billion RMB.

substitutes. (Appendix F indicates trade exposure for each sector in terms of the ratio of traded goods to total output.)

In the uncovered sectors, impacts on profits and output reflect changes in demand and production cost. The coal sector suffers the highest percentage losses of output and profit, reflecting a significant reduction in demand for coal by the contracting electricity sector. In contrast, the natural gas sector experiences large percentage increases in prices, profits and output. The increased output reflects increased demand for natural gas, which has a lower emissions factor than coal and can substitute for coal in some covered sectors as a way to reduce emissions intensity. Also, the MEE sets less stringent benchmarks (measured by the difference between the benchmark and the baseline emissions intensity) for gas-fired plants than coal-fired plants, which contributes to the substitution of natural-gas-fired for coal-fired electricity.

For many other uncovered sectors, the TPS raises the costs of production by increasing the prices of their inputs. In Phase 1, this is especially important in the aluminum sector, which is intensive in its use of electricity.

2) Impacts on Renewables

Many policymakers and citizens hope that China's climate policies will help spur the transition away from fossil fuels and toward renewables-based energy. Both the TPS and C&T promote the substitution of renewables-based electricity for fossil-based power. This reflects the fact that both policies raise the prices of carbon-intensive fuel inputs, which raises the marginal costs of fossil-based generation relative to renewables-based generation.[28]

Figures 7a and 7b show the impacts of the two policies on renewables generation, as changes relative to the baseline (7a) and as shares of total generation (7b).[29] The shifts toward renewable electricity sources are smaller under the TPS than under C&T. The difference is due to the TPS's implicit output subsidy, which mitigates the increase in

[28] Over the interval 2020-2035, the profits of fossil-based electricity increase by 5%, and the profits of wind- and solar electricity increase by 13%. The higher profits of fossil-based electricity seem surprising, given the sector's higher production costs. As explained earlier in this subsection, the free allowances received by the fossil-based generators yield economic rents large enough to offset the cost increase and yield an increase in profits.

[29] The extent of hydroelectric and nuclear electricity generation is mainly determined by government planning in China. Accordingly, the model assumes their outputs remain at the base year levels and are not influenced by the TPS and C&T policies.

fossil-based electricity prices and moderates the substitutions toward renewables-based power.

6.2 Net Benefits

The TPS's climate-related benefits are estimated to be well above its economic costs. This conclusion holds under a plausible range of values for the climate-related benefits from CO_2 abatement (as implied by alternative assumed values for the social cost of carbon), for production parameters[30], and for assumed future levels of stringency of the TPS.[31]

For the SCC, we consider three paths[32]: one path starting at 307 RMB/ton and increasing at 3% annually (following Nordhaus (2017)), one starting at 353 RMB/ton and increasing by 3% annually (following the Biden Administration (2021)), and one starting at 1,304 RMB/ton and increasing by 2% annually (following Rennert *et al.* (2022)).

Figure 8a shows the ranges and the central estimates of TPS's costs and climate benefits under Case 1. The estimated benefits from the cumulative CO_2 reductions over the 2020-2035 interval are in the range of 8-49 trillion RMB, 4-23 times the cumulative costs. The central estimate of the climate benefit is 12 trillion RMB, more than five times TPS's costs.

Figure 8b displays the costs and benefits when health benefits from reduced local pollution are taken into account. The health benefits are measured as the estimated values of avoided premature deaths. To estimate these benefits, we apply an emissions-inventory model (described in Zheng *et al.* (2019)), an air-quality model (Polynomial function-based Response Surface Model, pf-RSM, described in Xing *et al.*(2018)), and the Global Exposure Mortality Model (GEMM) developed by Burnett *et al.* (2018) to calculate

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[30] These include elasticities of substitution in production, elasticities of capital transformation, saving rate, and rates of exogenous improvement in energy factor productivity. Section 7 below indicates the parameters we alter in the sensitivity analysis.

[31] To address the uncertainty about future benchmark tightening rates, we consider a low stringency scenario in which benchmarks are 0.5 percentage points lower than in Case 1 and a high stringency scenario with benchmarks 0.5 percentage points higher than in Case 1. Section 7 below offers related details.

[32] The SCC at time *t* is the cost to the economy, from time *t* into the indefinite future, from the change in climate stemming from an incremental increase in the CO_2 emissions. It reflects the value of climate change impacts, including changes in net agricultural productivity, human mortality related to heat, energy expenditures for heating and cooling buildings, and the coastal impacts of rising sea levels, etc. (Rennert *et al.*, 2022).

$PM_{2.5}$-related pre-mature mortalities under the baseline and the TPS.[33] Details are provided in Appendix G. The mortality impacts are then monetized by considering three sets of assumptions for the value of a statistical life (VSL).[34]

Accounting for health benefits raises the benefit-cost ratio substantially. The central estimate is that under Case 1, the TPS could avoid 2.2-2.4 million $PM_{2.5}$-related deaths in total over the 2020-2035 interval, relative to the baseline.[35] Under plausible ranges of the parameters determining the benefits and costs, the present value of the TPS's climate and health benefits are in the range of 19-106 trillion RMB over the 2020-2035 interval. The central estimate is 53 trillion RMB, 25 times the central estimate for the TPS's costs.

A related and important issue is how the TPS's abatement path over the 2020-2035 interval compares with the path that would maximize net benefits over this interval. This requires attention to marginal (rather than total) costs and benefits from abatement. We consider the marginal benefits and costs here.

Efficiency maximization requires that marginal costs per ton of emissions reduction equal the SCC. We assess the efficiency of the stringency level of the TPS by comparing average marginal costs and benefits over the 2020-2035 interval. The average marginal benefits are the average values of the SCC over the interval. The average marginal costs are based on marginal costs in each period. These are derived by decrementing the Case 1 benchmarks each year and noting the associated incremental increase in costs per ton. The results are shown in Figure 9. We find that efficiency maximization would require benchmarks approximately 16-22 percent lower than the Case 1 benchmarks. In the model, efficiency-maximizing benchmarks would give rise to

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[33] Studies indicate that $PM_{2.5}$ is a major contributor to premature mortality from air pollution (Burnett *et al.*, 2018; Zhou *et al.*, 2019; Wang *et al.,* 2021). For this reason we focus on the benefits from reduced $PM_{2.5}$.

[34] We assume a constant elasticity of the VSL with respect to income: $VSL_t = VSL_0(INC_t \,/ INC_0)^{\sigma_{VSL}}$, where INC_t and INC_0 are the per capita income in year t and in the base year 2020, and are calculated from the model's output. VSL_0 and σ_{VSL} are the estimated VSL for base year 2020 and the income elasticity of the *VSL*, which are obtained from the literature. The three sets of assumptions for the VSL_0 and σ_{VSL} are: 6.5 million RMB in 2020 with an elasticity of the VSL with respect to per-capita GDP of 0.22, based on Hoffmann *et al.* (2017); 10.3 million RMB in 2020 with the elasticity of 1, based on OECD (2012); and 18.4 million RMB in 2020, with the elasticity of 0.8, based on the U.S. EPA (2010).

[35] The range reflects uncertainties associated with the GEMM functions. See Appendix G for details.

emissions reductions of around 28-37 percent relative to the baseline, about three times the scale of the reductions in Case 1.

6.3 Impacts of Auctioning

China's policymakers are seriously contemplating revising the allowance allocation method so that a share of allowances is supplied via auction rather than offered for free. Here we present results from simulations in which auctioning serves as a source of supply of some of the allowances. The policy simulations span a range of auctioning cases, differing in the ways that the auction revenues are recycled back to the economy. For comparability, the total number of allowances supplied in each year is the same in the cases with and without auctioning. To maintain the same allowance supply in the auctioning case, the benchmarks (which determine the amounts supplied outside of the auction) are reduced by a common factor across sectors and technology types.

Figure 10 shows the economic costs in cases involving auctioning and in Case 1, which involves no auction. In all of the auctioning cases, the costs are lower than in Case 1. Introducing auctioning lowers costs because supplying by auctioning does not involve the TPS's implicit output subsidy and its associated distortions. In addition, in the cases where the auction revenues are recycled through cuts in marginal rates of pre-existing income taxes, the costs are reduced further, since lowering the marginal tax rates reduces the economic distortions from such taxes. These results provide support for introducing auctioning as part of China's national emissions trading system.

Among all the auctioning cases, the highest costs are in the case where all of the auction revenues are recycled as output subsidies for wind and solar electricity generation. The cost in this case is higher than in the other cases because the subsidies introduce new distortions (holding fixed aggregate reductions in emissions). The lowest cost is in the case in which auction revenues are recycled to finance cuts in taxes on capital and labor, which lower the distortions from pre-existing capital and labor taxes. In the case where auction revenues are recycled as a lump-sum transfer, the cost lies between those of the other two auctioning cases.

The present value of the gross revenue from the auction is about 2.6 trillion RMB over the 2025-2035 interval. If used as compensation for the coal and mining sectors (the two sectors with the largest percentage profit losses), this revenue would fully offset their losses of profit over the same interval, which amounts to 0.9 trillion RMB.

Figure 11 shows the electricity produced from wind and solar electricity generators under the different revenue-recycling options. With auctioning, electricity prices increase more than in Case 1, as auctioning reduces the TPS's output subsidy. The higher prices promote greater substitution of renewables-based power generation for fossil-based generation and imply higher production of wind- and solar-based generation. Among the auctioning cases, the case involving recycling in the form of subsidies to renewables-based electricity generation yields the greatest increase in wind and solar electricity generation.

6.4 Trade-offs between Efficiency and Distributional Impacts

As indicated in the analytical model, the TPS's cost-effectiveness depends on the variation of benchmarks. Figure 12 displays the economic costs in cases that differ in terms of such variation. It also shows the cost under an equally stringent C&T system. The smaller the number (and greater uniformity) of benchmarks, the lower the cost. Greater uniformity lowers the aggregate cost by reducing the variation in the implicit subsidy and associated wedge between the price of output (or marginal value to consumers) and its private marginal cost of production. This leads to a more efficient allocation of production across generators. Under the one-benchmark TPS, the economy-wide cost is sufficiently low to fall below that of C&T. We noted earlier that the TPS's implicit output subsidy and the policy's impacts on capital accumulation partly offset the distortions of pre-existing taxes. In the one-benchmark case, the combination of these partial offsets and the lower distortions associated with the uniformity of the benchmarks are enough to cause the TPS's overall cost to fall below the cost under C&T.[36]

The use of multiple benchmarks can serve distributional objectives, however. Table 6 presents the cumulative income change of all sectors by province.[37] In the period 2020-2035, the percentage losses of income are much more unevenly distributed in the one-benchmark case than in the four-benchmark case. The red (green) font identifies the five provinces with the largest (smallest) percentage income losses in a given benchmark

[36] To confirm the underlying determinants of this outcome, we performed a counterfactual simulation with no pre-existing taxes and with exogenous capital growth. In this case, the cost of the one-benchmark TPS exceeds that of C&T.

[37] Details of the estimation method are in Appendix H.

case. Under the one-benchmark case, the difference in income percentage change between the best-off province and the worst-off province is 2.68, higher than that under the four-benchmark case, which is 2.14. The standard deviation of percentage losses across provinces in the one-benchmark case is 0.578. This is more than 50 percent higher than the standard deviation of 0.378 in the four-benchmark case.

These results reveal a trade-off between cost-effectiveness and distributional equity (and associated political acceptability) in the choice of TPS design. Table 6 shows that the average percentage loss of income in the one-benchmark case is a third lower than that of the four-benchmark case. This advantage must be weighed against its disadvantage in terms of a higher variation in costs across sectors.

7. Sensitivity Analysis

Here we examine the sensitivity of the model's results to input substitution elasticities, capital transformation elasticities, the parameters that determine the model's dynamics, and the assumed rates of increase in policy stringency.

The significance of input substitution and transformation elasticities is examined in Table 7. A higher elasticity of substitution between energy and other inputs lowers the cost of reducing emissions intensities through the substitution of material inputs for high-carbon fuels. Similarly, a higher capital transformation elasticity implies lower costs of reallocating capital from the low-efficiency subsectors to the high-efficiency subsectors in response to a changing policy environment. Thus, costs per ton decline with a higher value for this elasticity.

Table 8 focuses on parameters that directly influence the dynamics. The autonomous energy efficiency improvement (AEEI) rate is the growth rate of exogenous energy factor productivity in production. The central case employs an AEEI of 0.7 %/year. A higher AEEI rate implies faster growth of energy efficiency and lower baseline emissions. Thus, the economic costs per ton decline with a higher AEEI rate.

The savings rate determines the share of income devoted to purchases of new capital goods. In the central case, the savings rate starts at 42 percent in 2020 and declines linearly to 32 percent in 2035. We consider two alternative specifications for the savings rate. In one, the baseline savings rate time-profile is shifted up by five percentage points. This yields a baseline with higher capital accumulation and GDP growth, leading to higher emissions over time than in the central baseline. Greater capital accumulation makes it easier for firms to substitute carbon-intensive inputs with capital inputs, thus in this alternative scenario, the TPS has a slightly lower cost per ton than in the central case.

In the other case, the savings rate does not decline over time but instead remains at the first-year rate of 42%. This implies greater capital accumulation and GDP growth as well as higher demand for new capital goods than the central case. These goods intensively use inputs from the construction, iron & steel, and cement sectors – inputs that are relatively emissions-intensive. As a result, the average emissions intensity of the economy in the baseline in this scenario is higher than in the central case, implying that the TPS necessitates a larger reduction in intensities and higher costs-per ton of abatement than in the central case.

Table 9 examines the significance of assumptions about the future extent of policy stringency, as determined by the rate of benchmark tightening after 2022. In the central case, benchmarks are tightened by 1.5% and 2.5% annually for the electricity and non-electricity sectors, respectively. We consider two alternative scenarios. In the low (high) stringency scenario, electricity sector benchmarks are tightened by 1% (2%) annually and non-electricity sectors' benchmarks by 2% (3%). The cumulative emissions reductions in the high stringency case are approximately 25 percent higher than in the central case. Costs per ton of abatement are higher, the greater the level of stringency, reflecting rising marginal costs of abatement.

The bottom row in tables 7, 8, and 9 indicates how the ratio of the TPS's costs to those under C&T depends on key parameters. As discussed in Section 2, the TPS's implicit output subsidy is the product of the allowance price and the applicable benchmark. Hence a lower carbon price implies a smaller implicit output subsidy and thus a smaller associated distortion under the TPS. A higher energy-factor substitution elasticity, higher AEEI rate, and lower benchmark tightening rate all work toward lower allowance prices by implying lower costs of reducing emissions and lower demands for allowances. Hence they lead to a lower ratio of TPS costs to C&T costs. In contrast, the influence of capital transformation elasticity on the ratio of TPS costs to C&T is ambiguous. It depends on differences in the two policies' reliance on capital reallocation as a channel for reducing emissions. In Phase 1, the TPS relies more than the C&T on changes in sector composition, while in Phases 2 and 3 C&T relies more on this channel.[38] Such changes are dependent on the ease of capital transformation, that is, the extent of capital mobility across sectors. Correspondingly, easier capital transformation benefits the TPS more than the C&T in Phase 1, and benefits C&T more in Phases 2 and 3.

Overall, our main findings on the impacts of the TPS are robust to changes in these parameters. This includes the findings that the TPS's environmental benefits significantly exceed its economic costs, that the planned stringency of China's TPS is less than the efficiency-maximizing level, and that the TPS's costs become higher than those of an equivalently stringent C&T system once the system reaches a critical level of stringency.[39]

8. Conclusions

This paper presents and interprets results from a multi-sector, multi-period general equilibrium model designed to evaluate the impacts of China's recently implemented nationwide tradable performance standard to reduce CO_2 emissions. The model indicates this new venture's potential costs and benefits over the interval 2020-2035, both in the aggregate and across sectors and provinces, and identifies the relative attractions and limitations of alternative specific policy designs.

The model differs from earlier studies because of its general equilibrium framework, its attention to changes in impacts over time; its recognition of differences between the TPS and C&T in terms of structure, incentives, and impacts; and its ability to consider a range of potential future TPS designs. The potential designs include alternative specifications for the variation and average stringency of government-specified benchmarks, the introduction of an allowance auction as a supplementary source of allowance supply, and the possible transition from the TPS to a C&T system. With this

[38] In Phase 1, the relative contributions of the changed sector composition (see Section 6.1.2 for the definition) under the TPS and C&T is 55% and 43%. In Phase 2, this relative contributions under the TPS and C&T is 34% and 37%. In Phase 3, they are 30% and 37%. The extent of sector composition change depends on the heterogeneity of subsectors' marginal cost of emissions reduction. The benchmarks under the TPS may increase or decrease this heterogeneity, depending on the benchmarks introduced.
[39] As shown in tables 8 and 9, when the benchmark tightening rate is slight (1% for electricity and 2% for the non-electricity sector) or the AEEI rate is high (1.4%), the TPS can have smaller costs than C&T during all three phases. Under these conditions, the tax-interaction and capital accumulation effects noted in Section 6.1.2 outweigh the distortions from the implicit output subsidy.

flexibility, the model can offer useful information to China's planners as they continue to make decisions about the design of later phases of the TPS.

The results from our analysis yield unique insights into the potential impacts of China's new and evolving policy effort. First, we find under plausible parameters and levels of policy stringency over the 2020-2035 interval, the TPS's environmental benefits are well above its economic costs. Our central estimate is that the benefits exceed costs by a factor of five when only the climate-related benefits are considered and by a much higher factor when health benefits from reduced emissions of local pollutants are also considered.

Second, the currently planned stringency of China's TPS is considerably weaker than the efficiency-maximizing level. Based on distributions of marginal environmental benefits and economic costs, we find that efficiency maximization would require using benchmarks approximately 16-22 percent tighter than the current and projected benchmarks over the interval 2020-2035 interval.

Third, the relative cost of the TPS and an equivalently stringent C&T system depends importantly on the level of stringency of the system and on pre-existing taxes. While earlier literature has identified a cost-effectiveness handicap of the TPS relative to C&T because of its implicit subsidy to output, we extend the earlier findings by showing that the TPS's implicit output subsidy also has the *beneficial* effect of reducing the distortionary impact of pre-existing taxes on labor and capital. Indeed, in the short run, when the stringency of the system is relatively low, pre-existing taxes effectively eliminate what would otherwise be the TPS's disadvantage in terms of cost-effectiveness.

Fourth, introducing an auction as a complementary source of allowance supply can lower the economic costs of the TPS by 24-40 percent relative to the no-auction case. Auctioning lowers costs because there is no implicit subsidy to allowances introduced via auction. A further cost advantage arises to the extent that the auction revenues are used to finance cuts in pre-existing distortionary taxes.

Finally, the simulation results reveal important trade-offs between cost-effectiveness and distributional equity. Distributional concerns can be addressed through the employment of varying (customized) benchmarks, but greater benchmark variation raises aggregate costs by widening the disparities in marginal costs of production. Employing a single benchmark for the electricity sector would lower costs by 30 percent relative to the four-benchmark system that is in place but would increase the standard deviation of percentage income losses across provinces by roughly 50 percent.

References

Aguiar, A., Chepeliev, M., Corong, E., & van der Mensbrugghe, D. (2019). The GTAP Data Base: Version 10. *Journal of Global Economic Analysis 4*(1): 1–27.

Becker, J. M. (2020). Tradable performance standards in a dynamic context. Working Paper 2020–03.

Bento, A. M., Garg, T., & Kaffine, D. (2018). Emissions Reductions or Green Booms? General Equilibrium Effects of a Renewable Portfolio Standard. *Journal of Environmental Economics and Management*, *90:* 78–100.

Bento, A. M., Jacobsen, M. R., Knittel, C. R., & van Benthem, A. A. (2020). Estimating the Costs and Benefits of Fuel-Economy Standards. *Environmental and Energy Policy and the Economy*, *1:* 129–157.

Borenstein, S., & Kellogg, R. (2022). Carbon Pricing, Clean Electricity Standards, and Clean Electricity Subsidies on the Path to Zero Emissions. Working Paper No. 30263, National Bureau of Economic Research.

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C. A., Apte, J. S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S. S., Kan, H., Walker, K. D., Thurston, G. D., Hayes, R. B., … Spadaro, J. V. (2018). Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences*, *115*(38): 9592–9597.

Bushnell, J. B., Holland, S. P., Hughes, J. E., & Knittel, C. R. (2017). Strategic Policy Choice in State-Level Regulation: The EPA's Clean Power Plan. *American Economic Journal: Economic Policy*, *9*(2): 57–90.

Chen, Y., Tanaka, M., & Siddiqui, A. S. (2018). Market Power with Tradable Performance-Based CO_2 Emission Standards in the Electricity Sector. *The Energy Journal 39*(01).

Chen, Y.-H. H., Paltsev, S., Reilly, J. M., & Karplus, V. (2017). *The MIT Economic Projection and Policy Analysis (EPPA) Model, Version 5.* Joint Program Technical Note TN #16.

Cossa, P. F. (2004). *Uncertainty analysis of the cost of climate policies.* PhD thesis, Massachusetts Institute of Technology.

Dimanchev & Knittel. (2020). Trade-offs in Climate Policy: Combining Low-Carbon Standards with Modest Carbon Pricing. Working paper, MIT Center for Energy and Environmental Policy Research, November.

Fischer, C. (2001). Rebating Environmental Policy Revenues: Output-Based Allocations and Tradable Performance Standards. Resources for the Future Discussion Paper dp-01-22.

Fischer, C. (2010). Renewable Portfolio Standards: When Do They Lower Energy Prices? *The Energy Journal 31*(1).

Fischer, C., & Newell, R. G. (2008). Environmental and technology policies for climate mitigation. *Journal of Environmental Economics and Management 55*(2): 142–162.

Fischer, C., & Preonas, L. (2010). Combining Policies for Renewable Energy: Is the Whole Less than the Sum of its Parts? *International Review of Energy and Resource Economics 4*(1): 51-92.

Fischer, C., Preonas, L., & Newell, R. G. (2017). Environmental and Technology Policy Options in the Electricity Sector: Are We Deploying Too Many? *Journal of the Association of Environmental and Resource Economists 4*(4): 959–984.

Fischer, C., & Springborn, M. (2011). Emissions targets and the real business cycle: Intensity targets versus caps or taxes. *Journal of Environmental Economics and Management*, *62*(3): 352–366.

Fullerton, D., & Metcalf, G. E. (2001). Environmental controls, scarcity rents, and pre-existing distortions. *Journal of Public Economics 80*(2): 249–267.

Geng, W., & Fan, Y. (2021). Emission trading in an imperfectly competitive product market: A comparison of social welfare under mass- and rate-based schemes. *Computers & Industrial Engineering 162*.

Goulder, L. H., Hafstead, M. A. C., & Dworsky, M. (2010). Impacts of alternative emissions allowance allocation methods under a federal cap-and-trade program. *Journal of Environmental Economics and Management 60*(3).

Goulder, L. H., Hafstead, M. A. C., & Williams III, R. C. (2016). General Equilibrium Impacts of a Federal Clean Energy Standard. *American Economic Journal: Economic Policy 8*(2): 186–218.

Goulder, L. H., Long, X., Lu, J., & Morgenstern, R. D. (2022). China's unconventional nationwide CO_2 emissions trading system: Cost-effectiveness and distributional impacts. *Journal of Environmental Economics and Management 111*.

Goulder, L. H., & Parry, I. W. H. (2008). Instrument choice in environmental policy. *Review of Environmental Economics and Policy 2*(2): 152–174.

Goulder, L. H., Parry, I. W. H., Williams III, R. C., & Burtraw, D. (1999). The cost-effectiveness of alternative instruments for environmental protection in a second-best setting. *Journal of Public Economics*, *72*(3): 329–360.

Hertel, T., Hummels, D., Ivanic, M., & Keeney, R. (2007). How confident can we be of CGE-based assessments of free trade agreements? *Economic Modelling 24*(4): 611–635.

Hertel, T., & van der Mensbrugghe, D. (2019). Chapter 14: Behavioral Parameters, Center for Global Trade Analysis, *Global Trade Analysis Project (GTAP),* Purdue University.

Hoffmann, S., Krupnick, A., & Qin, P. (2017). Building a Set of Internationally Comparable Value of Statistical Life Studies: Estimates of Chinese Willingness to Pay to Reduce Mortality Risk. *Journal of Benefit-Cost Analysis 8*(2): 251–289.

Holland, S. P., Hughes, J. E., & Knittel, C. R. (2009). Greenhouse Gas Reductions under

Low Carbon Fuel Standards? *American Economic Journal: Economic Policy 1*(1): 106–146.

Holland, S. P., Hughes, J. E., Knittel, C. R., & Parker, N. C. (2015). Some Inconvenient Truths About Climate Change Policy: The Distributional Impacts of Transportation Policies. *The Review of Economics and Statistics 97*(5), 1052–1069.

IEA. (2022). *Enhancing China's ETS for Carbon Neutrality: Focus on Power Sector*.

Jomini, P., Zeitsch, J. F., McDougall, R., Welsh, A., Brown, S., Hambley, J., & Kelly, J. (1991). *SALTER: A General Equilibrium Model of the World Economy, vol. 1, Model Structure, Database and Parameters.* Industry Commission, Canberra.

Karplus, V. J., & Zhang, X. (2017). Incentivizing firm compliance with China's national emissions trading system. *Economics of Energy & Environmental Policy 6*(2): 73–86.

Ma, R., & Qian, H. (2022). Plant-level evaluation of china's national emissions trading scheme: Benchmarks matter. *Climate Change Economics*, *13*(01), 2240009.

Metcalf, G. E. (2019). On the Economics of a Carbon Tax for the United States. *Brookings Papers on Economic Activity*, 405–458.

National Bureau of Statistics. (2018). *China Energy Statistic Yearbook 2017*.

National Bureau of Statistics. (2018). *2017 China Input-Output Table*.

National Bureau of Statistics. (2021). *Statistical Bulletin of the People's Republic of China on National Economic and Social Development in 2020*.

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences 114*(7).

OECD. (2012). *Mortality risk valuation in environment, health and transport policies*. OECD.

Parry, I. W. H., & Bento, A. M. (2000). Tax Deductions, Environmental Policy, and the "Double Dividend" Hypothesis. *Journal of Environmental Economics and Management 39*(1):67–96.

Parry, I. W. H., & Williams III, R. C. (2010). Moving U.S. Climate Policy Forward: Are Carbon Taxes the Only Good Alternative? In R. Hahn and A. Ulph (eds.), *Climate Change and Common Sense: Essays in Honour of Tom Schelling,* Oxford University Press.

Parry, I. W., Shang, B., Wingender, M. P., Vernon, N., & Narasimhan, T. (2016). Climate Mitigation in China: Which Policies Are Most Effective? International Monetary Fund.

Pizer, W. A., & Zhang, X. (2018). China's New National Carbon Market. *AEA Papers and Proceedings 108*: 463–467.

Rennert, K., Errickson, F., Prest, B. C., Rennels, L., Newell, R. G., Pizer, W., Kingdon, C., Wingenroth, J., Cooke, R., Parthum, B., Smith, D., Cromar, K., Diaz, D., Moore, F. C., Müller, U. K., Plevin, R. J., Raftery, A. E., Ševčíková, H., Sheets, H., and Anthoff, D. (2022). Comprehensive evidence implies a higher social cost of CO2. *Nature 610:* 687–692.

Ross, M. T. (2014). *Structure of the Dynamic Integrated Economy/Energy/Emissions*

Model: Computable General Equilbrium Component, DIEM-CGE. (NI WP 14-12).

RTI International. (2015). *The Applied Dynamic Analysis of the Global Economy (RTI ADAGE) model* (U.S. Regional Module Final Release). RTI International.

State Information Center. (2020). *Medium and long-term goals, strategies, and paths of China's economic and social development.* The State Information Center.

Thomas H. Tietenberg. (1985). *Emissions Trading, an Exercise in Reforming Pollution Policy*. Resources for the Future.

U.S. EPA. (2010). *Guidelines for Preparing Economic Analyses*. U.S. Environmental Protection Agency.

Wang, B., Pizer, W. A., & Munnings, C. (2022). Price limits in a tradable performance standard. *Journal of Environmental Economics and Management*, 102742.

Wang, X., Zhu, L., & Liu, P. (2021). Manipulation via endowments: Quantifying the influence of market power on the emission trading scheme. *Energy Economics 103*, 105533.

Wang, Y., Hu, J., Zhu, J., Li, J., Qin, M., Liao, H., Chen, K., & Wang, M. (2021). Health Burden and economic impacts attributed to PM2.5 and O3 in China from 2010 to 2050 under different representative concentration pathway scenarios. *Resources, Conservation and Recycling 173*, 105731.

Xing, J., Ding, D., Wang, S., Zhao, B., Jang, C., Wu, W., Zhang, F., Zhu, Y., & Hao, J. (2018). Quantification of the enhanced effectiveness of control from simultaneous reductions of VOC and NH3 for reducing air pollution in the Beijing–Tianjin–Hebei region, China. *Atmospheric Chemistry and Physics 18*(11).

Yu, Z., Geng, Y., Calzadilla, A., & Bleischwitz, R. (2022). China's unconventional carbon emissions trading market: The impact of a rate-based cap in the power generation sector. *Energy 255*.

Zhang, D., Chen, Y., & Tanaka, M. (2018). On the effectiveness of tradable performance-based standards. *Energy Economics 74:* 456–469.

Zhang, H., Zhang, D., & Zhang, X. (2023). The role of output-based emission trading system in the decarbonization of China's power sector. *Renewable and Sustainable Energy Reviews*, *173*: 113080.

Zheng, H., Zhao, B., Wang, S., Wang, T., Ding, D., Chang, X., Liu, K., Xing, J., Dong, Z., Aunan, K., Liu, T., Wu, X., Zhang, S., & Wu, Y. (2019). Transition in source contributions of PM2.5 exposure and associated premature mortality in China during 2005–2015. *Environment International 132*: 105111.

Zhou, M., Wang, H., Zeng, X., Yin, P., Zhu, J., Chen, W., Li, X., Wang, L., Wang, L., Liu, Y., & Liu, J. (2019). Mortality, morbidity, and risk factors in China and its provinces, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *The Lancet* 394: 1145-1158.

Zhu, L., Wang, X., & Zhang, D. (2020). Identifying Strategic Traders in China's Pilot Carbon Emissions Trading Scheme. *The Energy Journal 41*(2).

Table 1. Sectors

Name	Description
Cement[1]	Cement
Iron & steel[2]	Iron and steel
Aluminum[3]	Aluminum products
Pulp & paper	Pulp and paper
Other non-metal products	Non-metal processing other than cement
Other non-ferrous metals	Non-ferrous metals other than aluminum
Raw chemicals	Raw chemical materials, chemical products
Agriculture	Crop cultivation, forestry, livestock and livestock products, and fishery
Mining	Metal minerals mining and non-metal minerals, and other mining
Food	Food and tobacco
Textile	Textile
Clothing	Clothing
Log & furniture	Log and furniture
Printing & stationery	Printing and stationery
Daily chemical products	Chemical fibers, medicines, rubber & plastics products
Metal products	Metal products
General equipment	General equipment manufacturing
Transport equipment	Transport equipment manufacturing
Electronic equipment	Electronic equipment manufacturing
Other manufacturing	Other manufacturing
Water	Water
Construction	Construction
Transport	Transport and post
Services	Services
Electricity[4]	Electricity generation
Petroleum refining	Petroleum refining
Heat	Heat distribution
Coal	Coal mining and processing
Crude oil	Extraction of crude oil
Natural gas	Primary production of natural gas
Gas manufacture & distribution	Manufacture, processing, and distribution of natural or synthetic gas

[1] The cement divides into 3 subsectors: high, medium, and low-efficiency cement production.

[2] The iron&steel sector divides into 6 subsectors: high, medium, and low-efficiency basic oxygen steel production, and high, medium, and low-efficiency electric-arc furnace steel making.

[3] The aluminum sector divides into 3 subsectors, including high, medium, and low-efficiency aluminum production.

[4] The electricity sector divides into 15 subsectors, distinguishing the following generation technologies: LUSC (1000MW Ultra-supercritical); SUSC (600MW Ultra-supercritical); LSC (600MW Supercritical); SSC (300MW Supercritical); LSUB (600MW Subcritical); SSUB (300MW Subcritical); OTHC (Installed capacity less than 300MW); LCFB (Circulating Fluidized Bed Units with installed capacity greater than or equal to 300MW); SCFB (Circulating Fluidized Bed Units with installed capacities less than 300MW); HPG (Gas fired plants, F-class); LPG (Gas fired plants, Pressure lower than F-class); Wind power; Solar power; Hydropower; and Nuclear power.

Table 2. Policy Cases Considered

Case 1: Central case	- **Number of benchmarks**. Four benchmarks apply to the electricity sector: three for coal-fired and one for gas-fired generators. Two benchmarks apply to the iron & steel sector.[1] One benchmark applies to each of all other covered sectors. - **Initial benchmarks**. Initial benchmarks for the electricity sector are set according to the MEE's released documents. Initial benchmarks for other sectors are set to be 2.5% below their emissions intensity in the year before they are included in the TPS. - **Tightening rates of benchmarks**. The tightening rate for the electricity sector is 0.5 %/year during Phase 1 according to the MEE. We assume the tightening rate for the electricity sector in Phases 2 and 3 is 1.5%, and the rate for other sectors is 2.5%.[2]
Case 2: Fewer benchmarks for the electricity sector	- ***Case 2a***: **Two-benchmark case**: One benchmark for coal-fired generators; a different benchmark for gas-fired generators. All other benchmark assumptions are the same as in Case 1. The coal-fired generators' benchmark is the weighted average of their differing benchmarks in Case 1. All benchmarks are scaled by a common factor to match Case 1's economy-wide emissions each year. - ***Case 2b***: **One-benchmark case:** A single benchmark applies to all generators. The settings of all other benchmark assumptions are the same as in Case 2a.
Case 3: Allowance auction	- **Auction share.** The auction starts in 2025. The initial share of auctioned allowances is 10% for the electricity sector and 0% for others. The auction share increases by a constant rate in the electricity sector and a different constant rate in the other sectors, reaching 100% for the electricity sector and 30% for other covered sectors by 2035. The benchmarks that determine free allowances are lowered to match Case 1's economy-wide emissions in each year. - **Recycling of auction revenues.** ***Case 3a:*** recycled as output subsidies for wind and solar electricity. ***Case 3b:*** recycled as lump-sum transfers. ***Case 3c:*** recycled to finance cuts in capital and labor taxes in all sectors.

[1] One for the basic oxygen process and one for the electric arc furnace process.
[2] The lower tightening rate for the electricity sector is consistent with the MEE's view that there is less room for future energy-efficiency improvements in this sector than in others.

Table 3. Initial Benchmarks in the Policy Cases

Sectors	Subsectors	Initial benchmarks*					
		Case 1	*Case 2a*	*Case 2b*	*Case 3a*	*Case 3b*	*Case 3c*
Electricity (tCO_2/MWh)	Coal-fired generators with capacity < 300 MW (SSC, SSUB, and OTHC)	0.882	0.859	0.843	0.882	0.882	0.882
	Coal-fired generators with capacity >= 300 MW (LUSC, SUSC, LSC, and LSUB)	0.824	0.859	0.843	0.824	0.824	0.824
	Circulating fluidized bed generators (LCFB, SCFB)	0.940	0.859	0.843	0.940	0.940	0.940
	Gas-fired generators (HPG, LPG)	0.394	0.394	0.843	0.394	0.394	0.394
Cement (tCO_2/ton)	Low (L), medium (M), and high (H) efficiency	0.848	0.848	0.846	0.848	0.848	0.848
Iron & steel (tCO_2/ton)	Basic oxygen furnace – L, M, H	0.017	0.017	0.016	0.017	0.017	0.017
	Electric arc furnace – L, M, H	0.004	0.004	0.004	0.004	0.004	0.004
Aluminum (tCO_2/ton)	L, M, H	7.941	7.936	7.914	7.941	7.941	7.941
Other non-metal products (tCO_2/*k*RMB)	All facilities	0.055	0.055	0.055	0.054	0.054	0.054
Other non-ferrous metals (tCO_2/*k*RMB)	All facilities	0.049	0.049	0.048	0.048	0.048	0.048
Pulp & paper (tCO_2/*k*RMB)	All facilities	0.048	0.048	0.047	0.047	0.047	0.047
Petroleum refining (tCO_2/*k*RMB)	All facilities	0.042	0.042	0.041	0.041	0.041	0.041
Raw chemicals (tCO_2/*k*RMB)	All facilities	0.087	0.087	0.086	0.086	0.085	0.085

* "Initial benchmarks" refers to the benchmark values when they are first introduced under the TPS. For the electricity sector, the initial benchmarks apply to 2020. For sectors first covered in Phase 2, they apply to 2023. For the sectors firs covered in Phase 3, they apply to 2026.

Table 4. Summary of Costs of Case 1

	Cost (billion RMB)		CO_2 Emissions Abatement (billion tons)	Cost per ton of CO_2 abatement (RMB/t)	
	Measured by the change in GDP	Measured by the equivalent variation of consumption		Measured by the change in GDP	Measured by the equivalent variation of consumption
Phase 1 (2020-2022)	23	12	0.5	43	22
Phase 2 (2023-2025)	81	26	1.7	49	15
Phase 3 (2026-2035)	2,016	771	21.7	93	35
Overall (2020-2035)	2,121	808	24.0	89	34

Table 5. Price, Quantity, and Profit Impacts of the TPS

Percentage Changes from the Baseline[1]

Sectors	Price Change (%)				Output Change (%)				Profit Change (%)		
	Phase 1	Phase 2	Phase 3		Phase 1	Phase 2	Phase 3		Phase 1	Phase 2	Phase 3
Electricity	0.412	0.840	4.805		-0.302	-0.828	-6.380		1.428	3.635	9.949
Cement	-0.019	0.759	9.759		-0.024	-0.114	-0.315		-0.050	5.285	17.893
Iron & steel	-0.008	0.173	0.681		-0.055	-0.322	-0.553		-0.075	2.802	9.798
Aluminum	0.179	0.594	4.568		-0.199	-0.654	-1.687		-0.098	2.526	6.835
Pulp & paper	0.013	0.018	0.280		-0.024	-0.051	-0.177		-0.016	-0.042	2.445
Petroleum refining	0.006	0.020	0.270		-0.056	0.033	-0.023		-0.066	0.044	0.661
Raw chemicals	0.011	0.011	0.632		-0.045	-0.085	-0.467		-0.048	-0.104	1.720
Other non-metal products	0.012	0.063	0.761		-0.030	-0.109	-0.303		-0.029	-0.128	1.161
Other non-ferrous metal	0.030	0.073	0.620		-0.093	-0.267	-0.679		-0.101	-0.311	0.691
Coal	-0.284	-0.700	-2.284		-2.181	-5.370	-11.06		-3.266	-7.970	-26.24
Natural Gas	0.308	0.506	2.535		0.620	1.020	2.076		1.008	1.693	9.613
Mining	0.016	0.010	0.151		-0.069	-0.368	-0.708		-0.078	-0.502	-2.167
Agriculture	-0.007	-0.029	-0.172		-0.005	0.002	0.008		-0.006	0.003	-0.005
Uncovered manufacturing sectors[2]	0.004	0.009	0.069		-0.028	-0.086	-0.176		-0.035	-0.119	-0.625
Construction	0.003	0.042	0.360		-0.010	-0.050	-0.147		-0.018	-0.087	-0.694
Service sectors [3]	-0.004	-0.020	-0.158		-0.015	-0.033	-0.067		-0.027	-0.073	-0.408

[1] The figures are weighted average percentage changes relative to the baseline in the corresponding period, with annual output levels used as weights. The blue font identifies the covered sectors in the applicable phase.
[2] Elements in this row are percentage changes for the aggregate of all the manufacturing sectors not covered by the TPS. These sectors include Food, Textile, Clothing, Log furniture, Printing and stationery, Daily chemicals, Metal products, General equipment, Transport equipment, Electronic equipment, and Other manufacturing.
[3] Here we display the results after aggregating the results from the specific service sectors: gas manufacture and distribution, heat distribution, water, transport, and other services.

Table 6. Cumulative Income Change by Province, 2020-2035[1]

Region	Provinces[2]	Four-Benchmark (Case 1)		Two-Benchmark (Case 2a)		One-Benchmark (Case 2b)	
		Absolute change (billion RMB)	Percent change (%)	Absolute change (billion RMB)	Percent change (%)	Absolute change (billion RMB)	Percent change (%)
East	Hebei	90	0.14	12	0.02	-184	-0.28
	Shandong	-70	-0.05	-170	-0.12	-685	-0.49
	Liaoning	-21	-0.05	-25	-0.06	-143	-0.31
	Jiangsu	-192	-0.12	-184	-0.12	-102	-0.06
	Hainan	7	0.08	-4	-0.04	-14	-0.15
	Zhejiang	-122	-0.13	-60	-0.06	133	0.13
	Fujian	14	0.02	56	0.09	206	0.33
	Shanghai	-101	-0.17	-65	-0.11	116	0.19
	Guangdong	-239	-0.14	-247	-0.15	39	0.02
	Tianjin	16	0.05	28	0.08	318	0.90
	Beijing	-72	-0.12	-71	-0.12	323	0.54
	Regional Total	**-690**	**-0.078**	**-731**	**-0.082**	**9**	**0.001**
Central	Shanxi	-371	-1.21	-423	-1.38	-419	-1.32
	Heilongjiang	-137	-0.42	-159	-0.48	-194	-0.57
	Henan	-151	-0.18	-137	-0.16	-182	-0.21
	Anhui	-211	-0.40	-92	-0.17	-267	-0.49
	Jilin	-46	-0.17	-40	-0.15	-26	-0.09
	Hubei	29	0.04	18	0.03	-28	-0.04
	Hunan	-79	-0.13	-62	-0.10	-14	-0.02
	Jiangxi	30	0.08	58	0.16	30	0.08
	Inner Mongolia	-209	-0.74	-217	-0.76	-299	-1.03
	Regional Total	**-1146**	**-0.269**	**-1053**	**-0.247**	**-1398**	**-0.319**
West	Ningxia	-11	-0.18	-13	-0.20	-89	-1.36
	Guizhou	-168	-0.67	-153	-0.61	-251	-0.97
	Shaanxi	-223	-0.55	-232	-0.57	-15	-0.04
	Yunnan	11	0.04	2	0.01	-55	-0.17
	Guangxi	0	0.00	11	0.03	-38	-0.10
	Xinjiang	71	0.30	61	0.26	167	0.70
	Chongqing	-59	-0.16	-49	-0.13	-30	-0.08
	Gansu	91	0.58	41	0.26	-75	-0.47
	Sichuan	-44	-0.06	-28	-0.04	206	0.27
	Qinghai	49	0.93	55	1.04	71	1.32
	Regional Total	**-284**	**-0.096**	**-305**	**-0.103**	**-110**	**-0.036**
National Total		**-2121**	**-0.132**	**-2089**	**-0.130**	**-1499**	**-0.091**
Standard deviation			**0.378**		**0.386**		**0.578**

[1] The red font identifies the five provinces with the largest percentage income losses in a given benchmark case; the green font identifies the five with the smallest percentage losses (or largest percentage increases).
[2] Hong Kong, Macao, Tibet and Taiwan are not included in this table due to input-output data limitations.

Table 7. Sensitivity Analysis - I
Significance of Production and Transformation Elasticities

	Energy-factor substitution elasticity			Capital transformation elasticity		
	0.3	**0.4** (central case)	**0.5**	**2**	**3** (central case)	**4**
Cumulative emissions reduction (billion tons)						
Phase 1 (2020-2022)	0.53	0.55	0.56	0.54	0.55	0.55
Phase 2 (2023-2025)	1.63	1.66	1.69	1.65	1.66	1.67
Phase 3 (2026-2035)	21.80	21.75	21.79	21.76	21.75	21.76
Present value of cumulative cost (billion RMB)						
Phase 1 (2020-2022)	23	23	24	26	23	22
Phase 2 (2023-2025)	84	81	79	87	81	77
Phase 3 (2026-2035)	2,216	2,016	1,866	2,146	2,016	1,914
Economic cost per ton (RMB/ton)						
Phase 1 (2020-2022)	44.1	42.9	41.9	47.7	42.9	39.2
Phase 2 (2023-2025)	51.5	48.9	47.0	52.3	48.9	46.2
Phase 3 (2026-2035)	101.7	92.7	85.6	98.6	92.7	88.0
Average allowance price (RMB/ton)						
Phase 1 (2020-2022)	60	54	49	60	54	49
Phase 2 (2023-2025)	97	86	78	91	86	80
Phase 3 (2026-2035)	459	382	326	401	382	360
Wind- and solar- electricity increase (%)						
Phase 1 (2020-2022)	0.49	0.48	0.48	0.66	0.48	0.37
Phase 2 (2023-2025)	1.17	1.06	0.98	1.28	1.06	0.90
Phase 3 (2026-2035)	7.10	6.02	5.22	6.67	6.02	5.51
Ratio of TPS cost to C&T cost						
Phase 1 (2020-2022)	1.03	0.98	0.95	1.01	0.98	0.97
Phase 2 (2023-2025)	1.06	1.02	0.99	1.01	1.02	1.03
Phase 3 (2026-2035)	1.15	1.11	1.07	1.08	1.11	1.13

Table 8. Sensitivity Analysis - II
Significance of Key Dynamic Parameters

	AEEI rate			Saving rate		
	0.35%	0.7% (central case)	1.4%	47% in 2020 to 37% in 2035	42% in 2020 to 32% in 2035 (central case)	Remain 42% in all years
Cumulative emissions reduction (billion tons)						
Phase 1 (2020-2022)	0.55	0.55	0.54	0.56	0.55	0.55
Phase 2 (2023-2025)	1.74	1.66	1.50	1.75	1.66	1.71
Phase 3 (2026-2035)	23.80	21.75	17.89	23.83	21.75	24.30
Present value of cumulative cost (billion RMB)						
Phase 1 (2020-2022)	24	23	23	24	23	24
Phase 2 (2023-2025)	87	81	70	85	81	84
Phase 3 (2026-2035)	2,367	2,016	1,428	2,200	2,016	2,289
Economic cost per ton (RMB/ton)						
Phase 1 (2020-2022)	42.9	42.9	42.8	42.9	42.9	42.9
Phase 2 (2023-2025)	50.2	48.9	46.4	48.4	48.9	49.0
Phase 3 (2026-2035)	99.5	92.7	79.8	92.3	92.7	94.2
Average allowance price (RMB/ton)						
Phase 1 (2020-2022)	54	54	54	54	54	54
Phase 2 (2023-2025)	90	86	78	84	86	86
Phase 3 (2026-2035)	433	382	292	377	382	389
Wind- and solar- electricity increase (%)						
Phase 1 (2020-2022)	0.48	0.48	0.48	0.48	0.48	0.48
Phase 2 (2023-2025)	1.09	1.06	1.00	1.03	1.06	1.05
Phase 3 (2026-2035)	6.30	6.02	5.36	5.90	6.02	5.95
Ratio of TPS cost to C&T cost						
Phase 1 (2020-2022)	0.99	0.98	0.98	0.99	0.98	0.99
Phase 2 (2023-2025)	1.05	1.02	0.98	1.02	1.02	1.03
Phase 3 (2026-2035)	1.16	1.11	0.99	1.11	1.11	1.12

Table 9. Sensitivity Analysis - III
Significance of Policy Stringency

	Benchmark Annual Tightening Rate		
	1% for electricity; 2% for other sectors	**1.5% for electricity; 2.5% for other sectors** (central case)	**2% for electricity; 3% for other sectors**
Cumulative emissions reduction (billion tons)			
Phase 1 (2020-2022)	0.55	0.55	0.55
Phase 2 (2023-2025)	1.42	1.66	1.91
Phase 3 (2026-2035)	16.19	21.75	27.57
Present value of cumulative cost (billion RMB)			
Phase 1 (2020-2022)	23	23	23
Phase 2 (2023-2025)	63	81	102
Phase 3 (2026-2035)	1,185	2,016	3,104
Economic cost per ton (RMB/ton)			
Phase 1 (2020-2022)	42.9	42.9	42.9
Phase 2 (2023-2025)	44.5	48.9	53.7
Phase 3 (2026-2035)	73.2	92.7	112.6
Average allowance price (RMB/ton)			
Phase 1 (2020-2022)	54	54	54
Phase 2 (2023-2025)	70	86	104
Phase 3 (2026-2035)	243	382	579
Wind- and solar- electricity increase (%)			
Phase 1 (2020-2022)	0.48	0.48	0.48
Phase 2 (2023-2025)	0.76	1.06	1.42
Phase 3 (2026-2035)	2.98	6.02	10.89
Ratio of TPS cost to C&T cost			
Phase 1 (2020-2022)	0.98	0.98	0.98
Phase 2 (2023-2025)	0.95	1.02	1.09
Phase 3 (2026-2035)	0.98	1.11	1.18

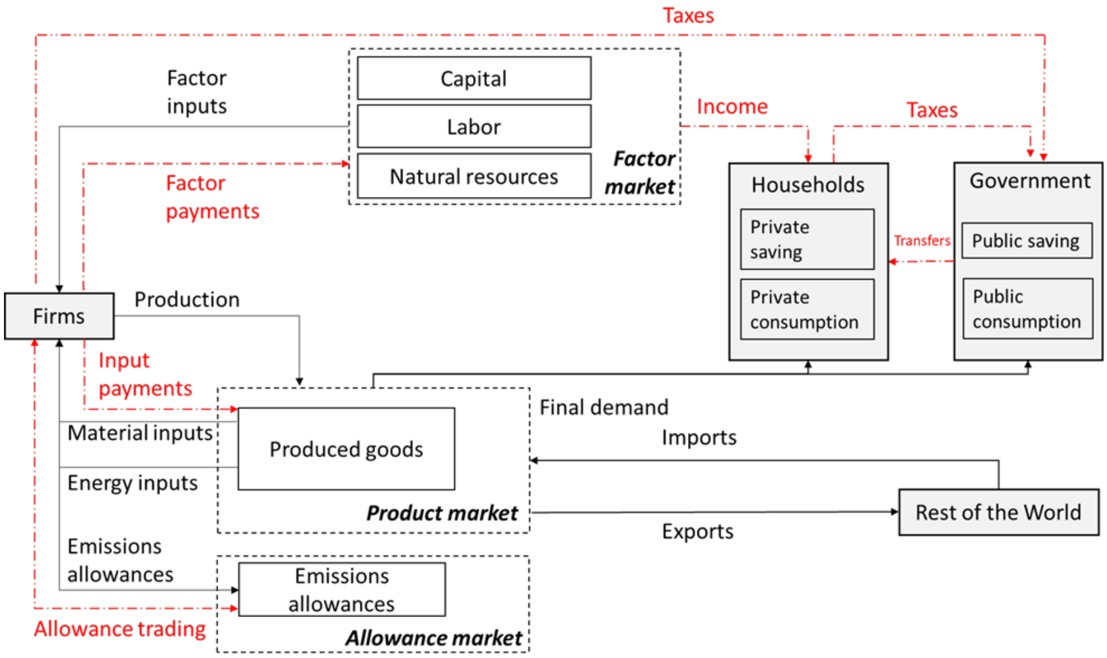


Figure 1. Goods and Financial Flows*

* The solid and dashed lines with arrows indicate the material flow and cash flow in the economy, respectively.

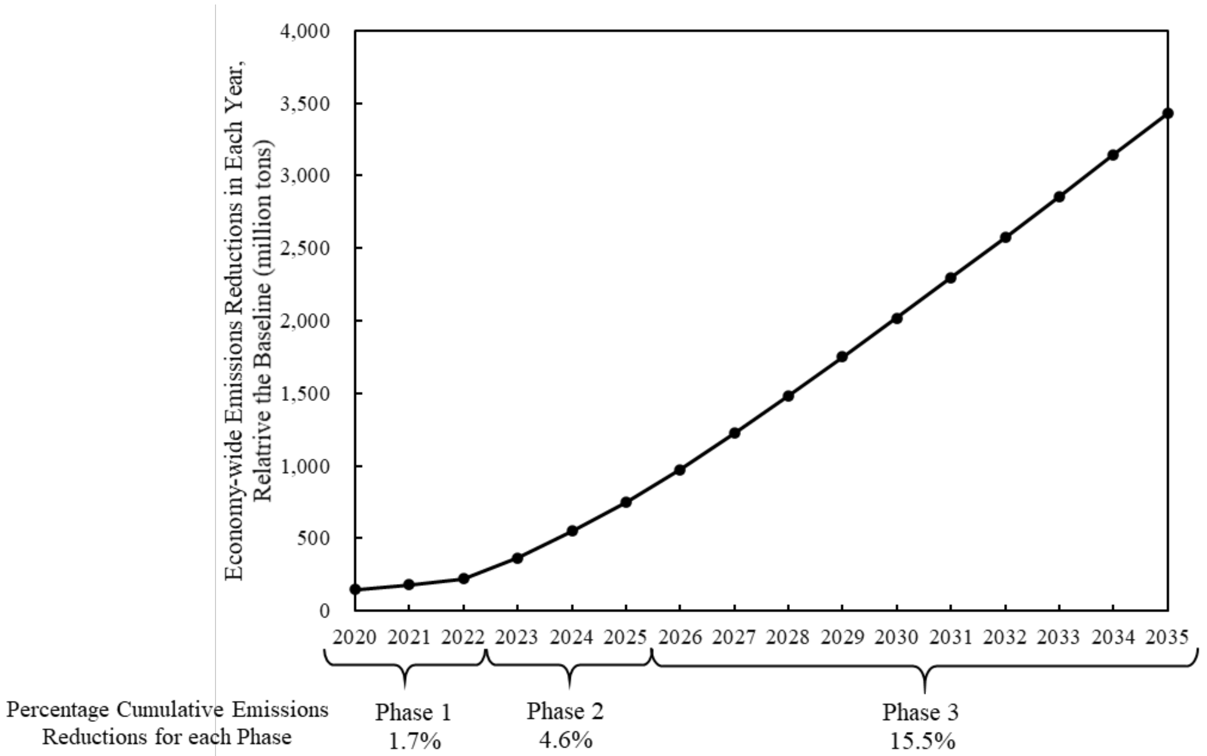


Figure 2. Emissions Reductions Relative to the Baseline, Over Time

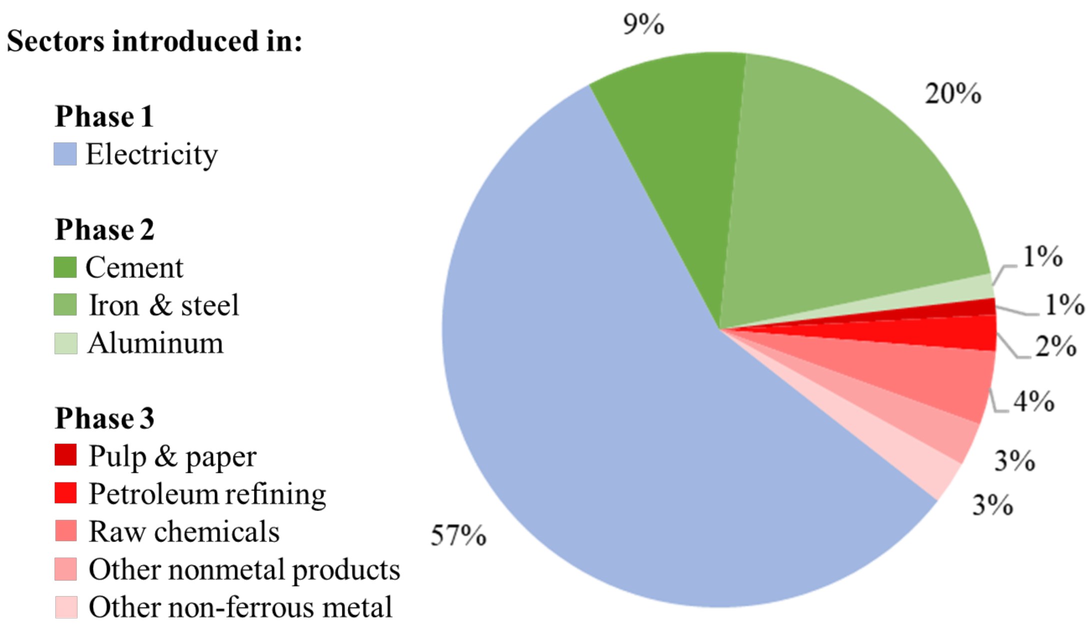


Figure 3. Covered-Sectors' Cumulative Emissions Reductions Over the Interval 2020-2035

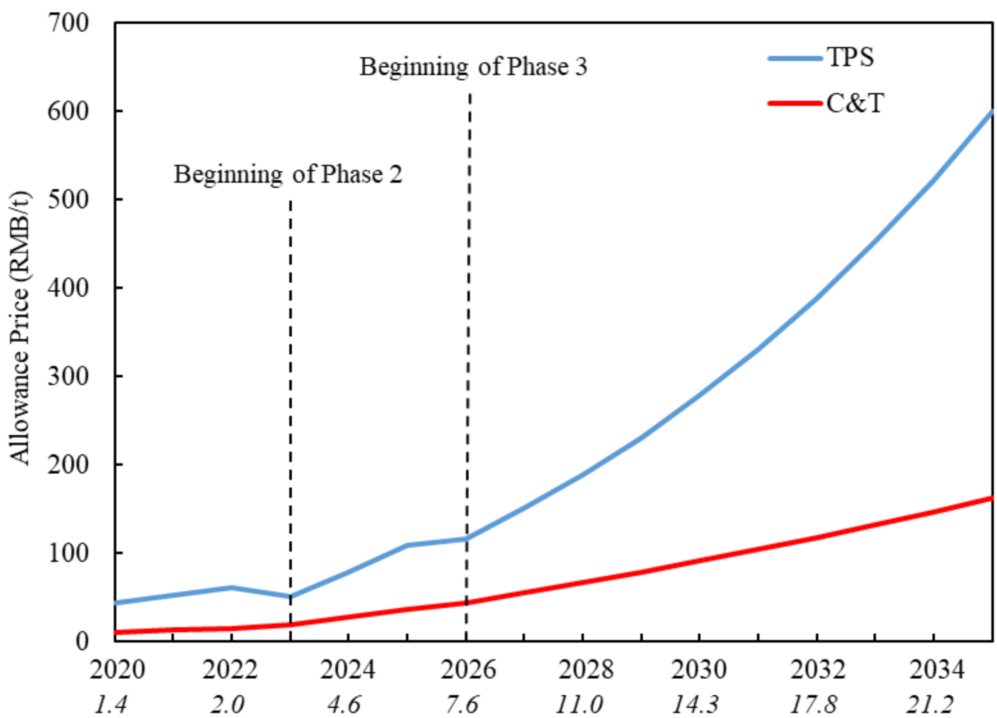


Figure 4. Allowance Prices Over Time

Numbers in italics are percentage emission reductions from the baseline

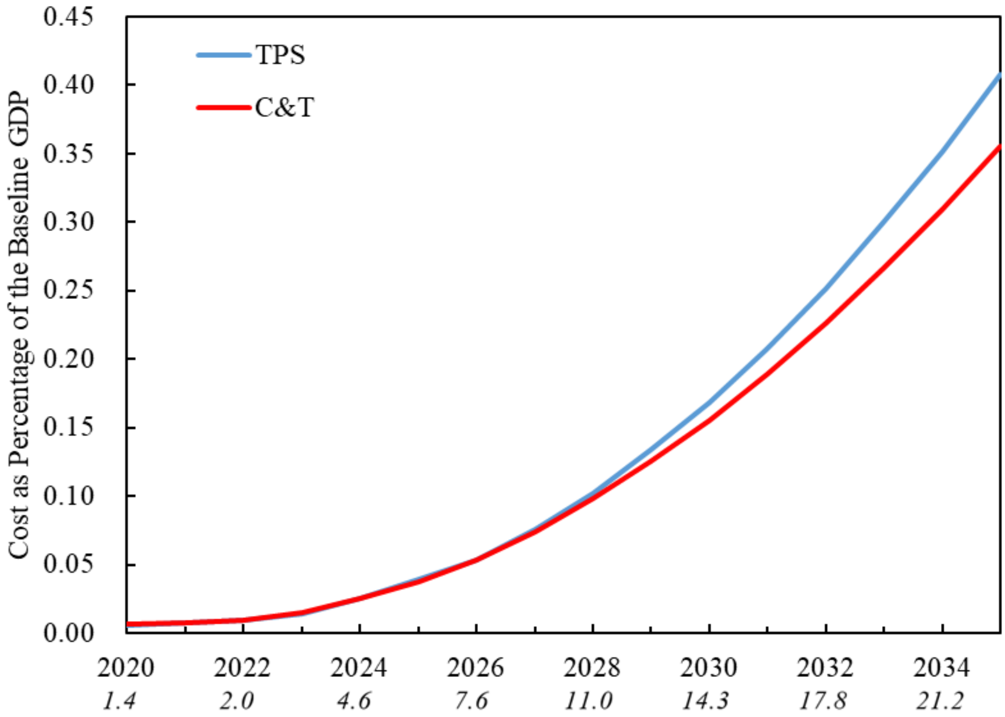


Figure 5. TPS and C&T Economic Costs Over Time
Numbers in italics are percentage emission reductions from the baseline

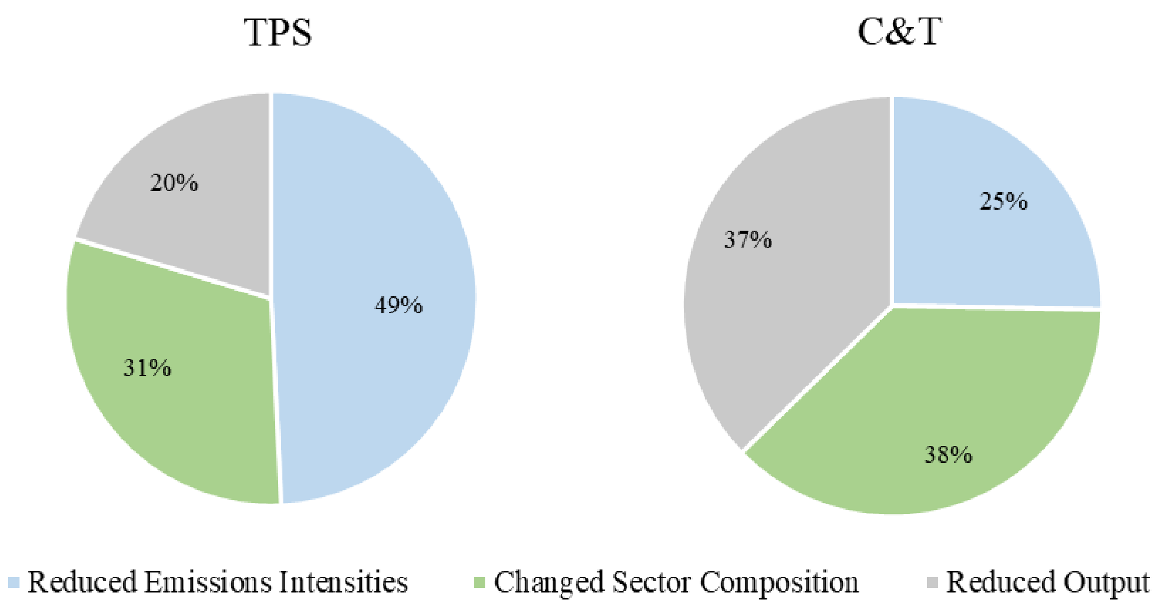


Figure 6. Sources of Emissions Reductions Under the TPS and C&T, 2020-2035

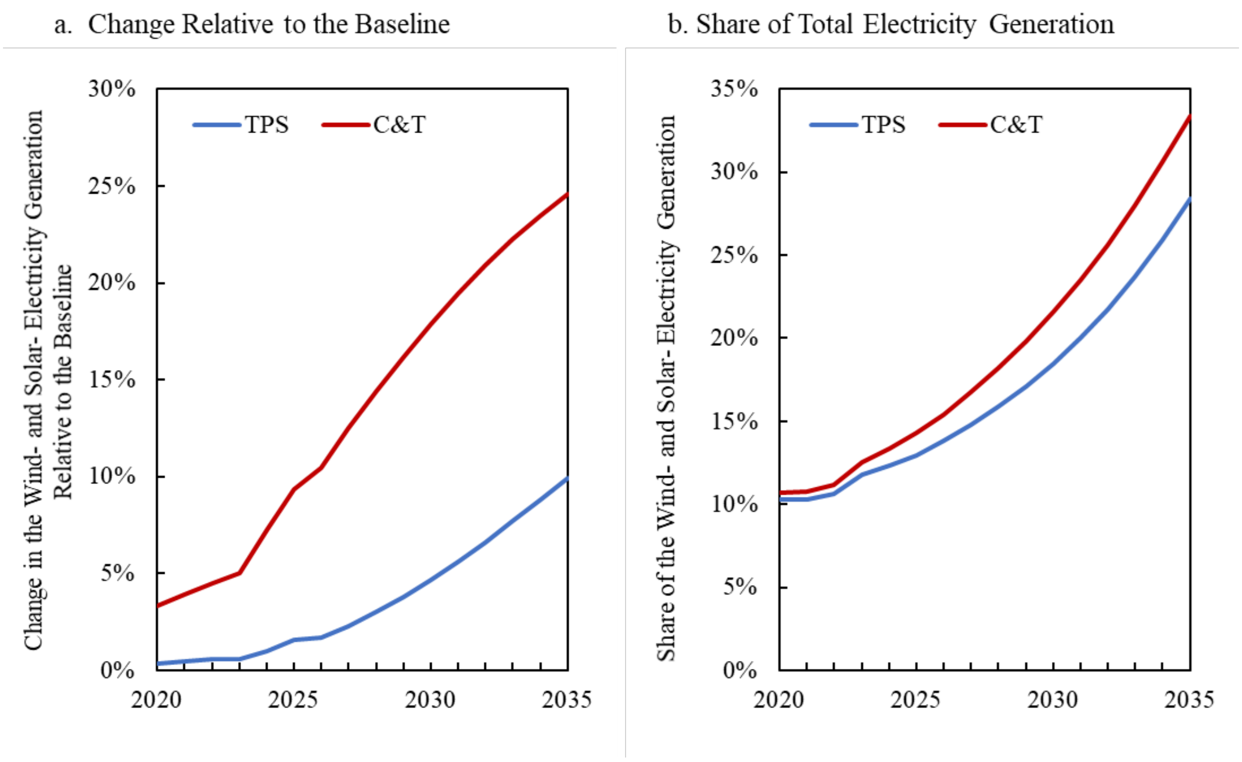
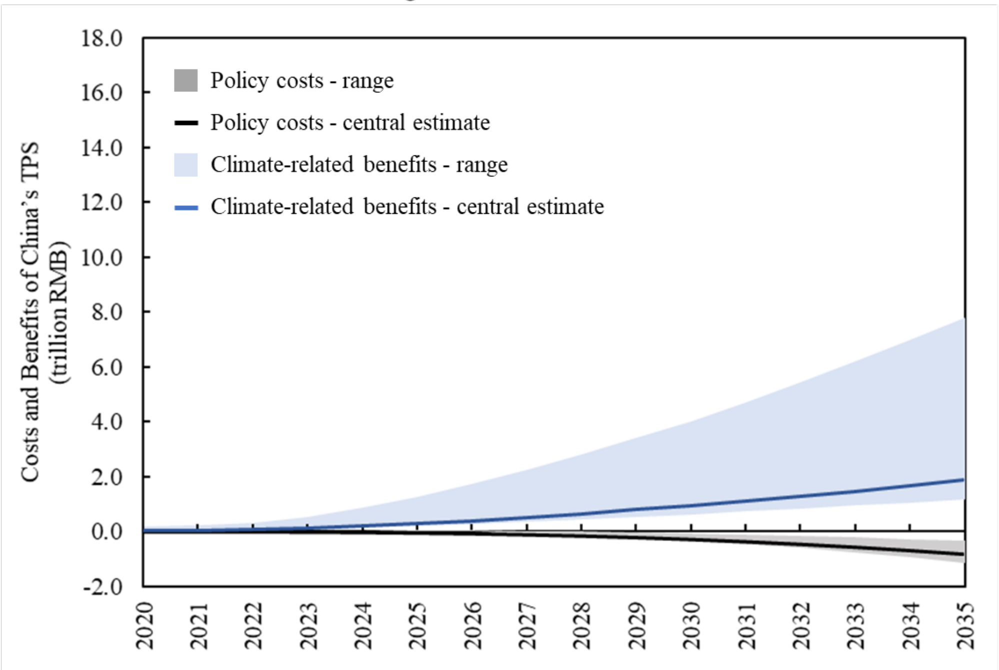


Figure 7. Change in Wind- and Solar- Electricity Generation Relative to the Baseline

Figure 8. Costs and Benefits of China's TPS

a. Costs and Benefits, Excluding Health Benefits



b. Costs and Benefits, Including Health Benefits

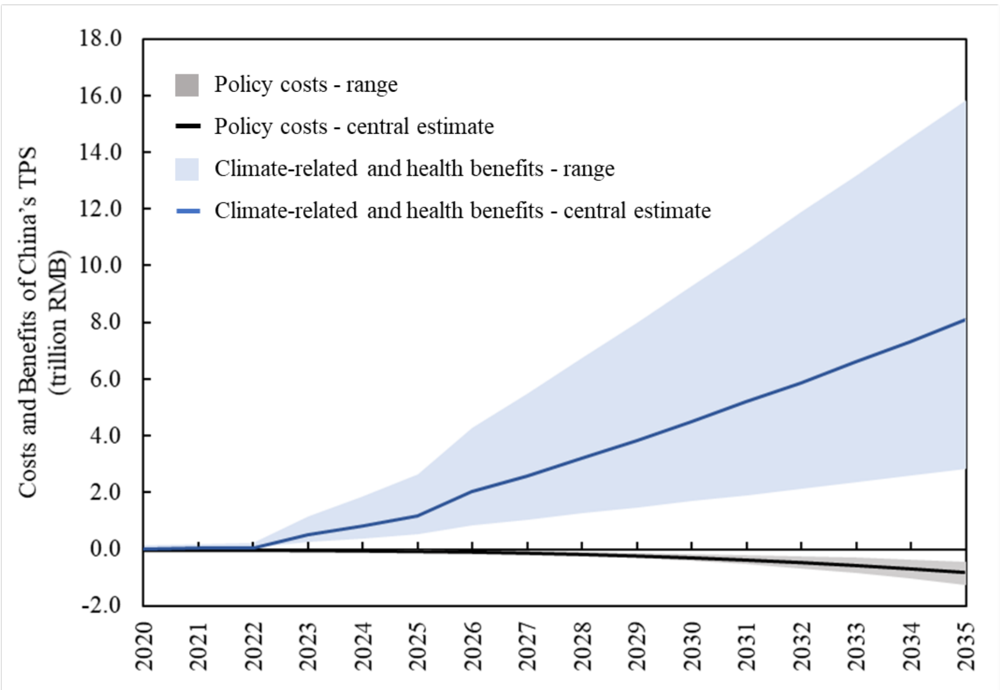
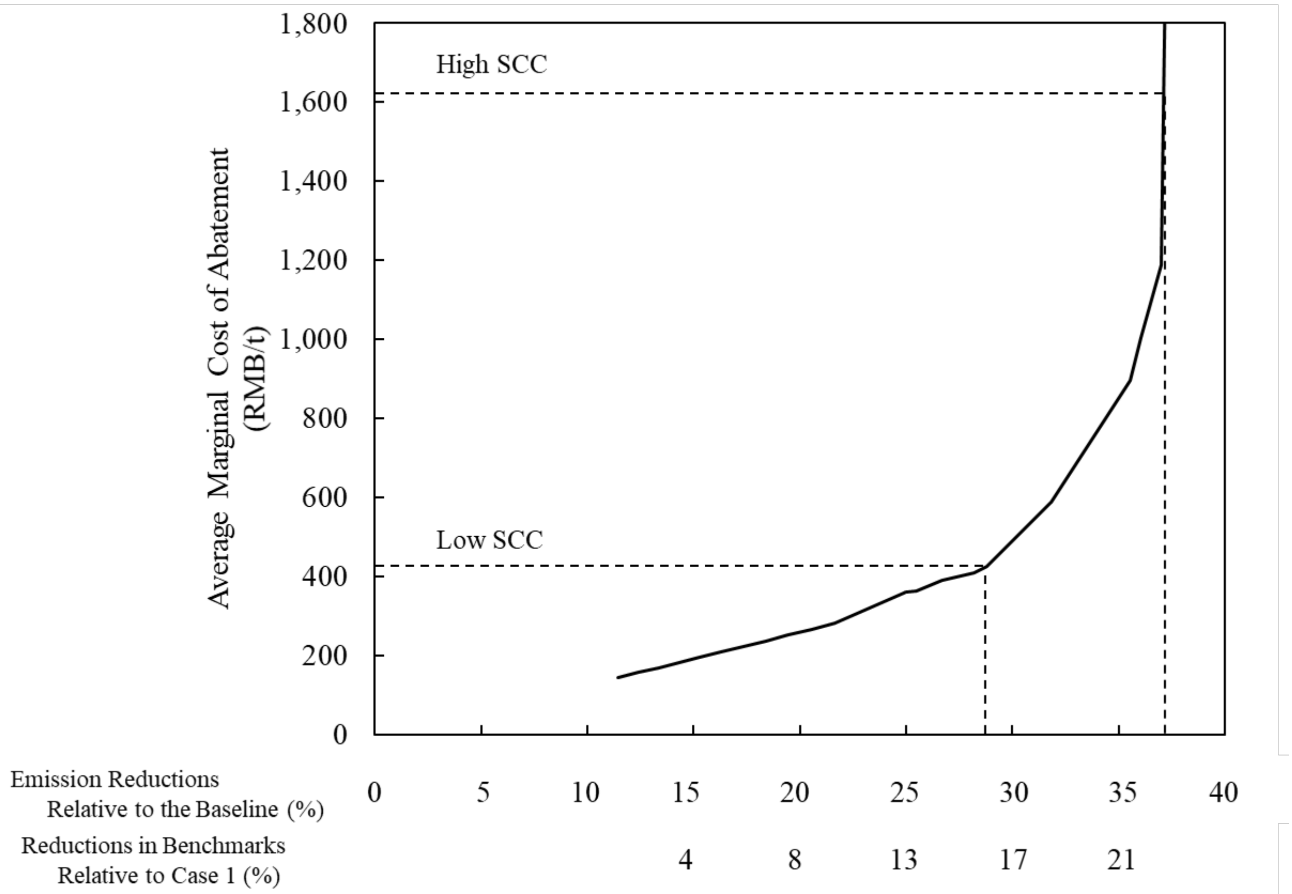


Figure 9. Average Marginal Cost of Abatement
Under Alternative Benchmark Stringencies



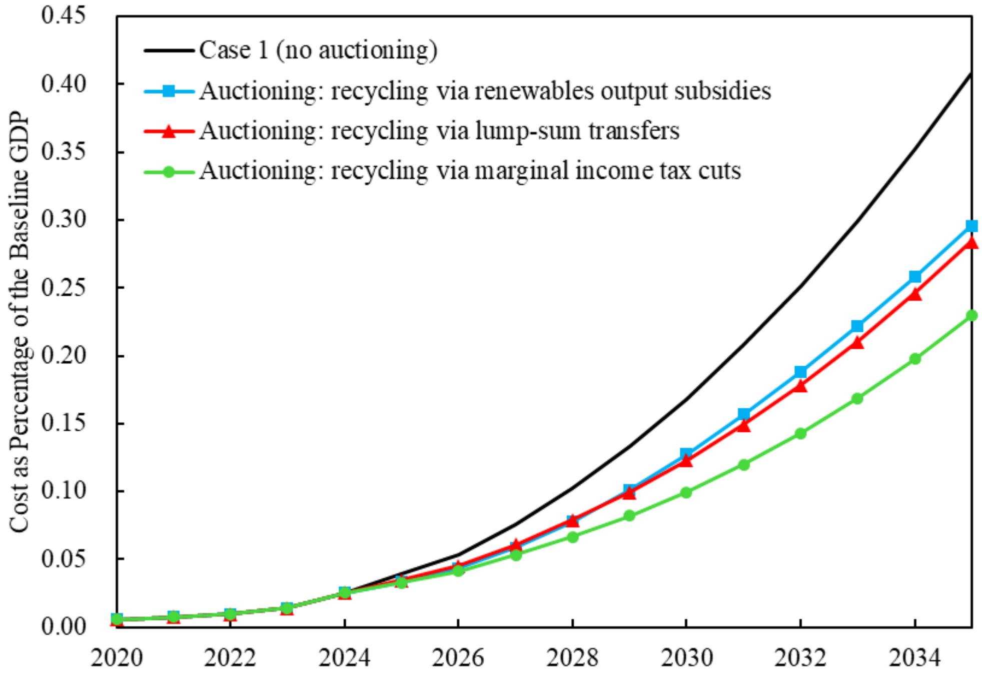


Figure 10. Economic Costs under Different Auction Revenue Recycling Options, 2020-2035

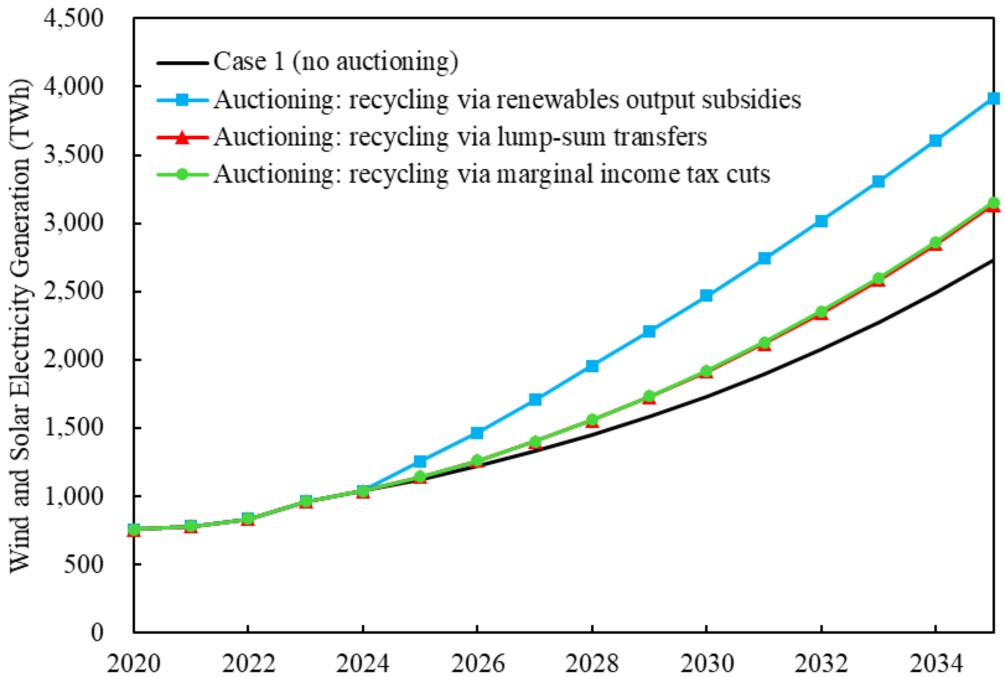


Figure 11. Wind and Solar Electricity Generation Under Different Auction Revenue-Recycling Options, 2020-2035

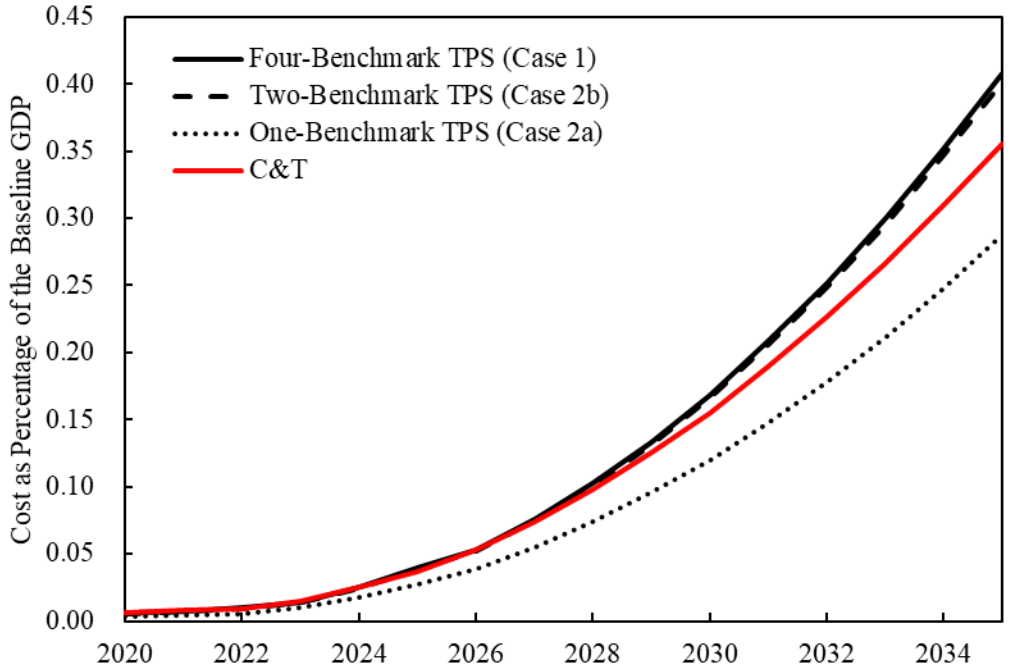


Figure 12. Economic Cost under Scenarios Differing in the Variation of Benchmarks

China’s Nationwide CO_2 Emissions Trading System:
A General Equilibrium Assessment

APPENDIXES

Table A1. Notation

Symbol	Definition
Y	Output
R	Tax revenue
T	Lump-sum transfer
E	CO_2 emissions
p	Price of goods and factors
t	Price of allowances
x	Material inputs
e	Energy inputs (electricity and fuels)
s	Electricity inputs
f	Fuel inputs
d	Domestic intermediate inputs
n	Imported intermediate inputs
m	Labor inputs
w	Capital inputs
res	Natural resources inputs
$\overline{m}, \overline{w}$	Endowment of factor
σ	The elasticity of substitution between inputs
α	Parameters of CES function
i,j,l	Sectors
k	Subsectors

Appendix A. Data and method for subsector classification and data processing

In the model, the electricity, cement, aluminum, and iron & steel sectors include subsectors distinguished by technology or emissions-intensity considerations.

Electricity Sector

For the electricity sector, there are 15 subsectors, with each subsector representing a distinct technology used for electricity generation. The first 11 technologies differ in terms of fuel input (coal or gas), capacity (300MW, 600MW, etc.), and temperature & pressure (subcritical, supercritical, etc.). The 12th - 15th technologies are low-carbon (wind, solar, hydro, and nuclear power) generation. The differing fuel input intensities imply different emissions intensities.

In our data, there are 1,929 coal-fired and gas-fired units, generating 23 billion kWh in 2017, covering 49.7% of China's coal- and gas-fired electricity generation.

Table A2. Subsectors of the Electricity Sector

Technology Category	Subsector
Coal-fired (other than circulating fluidized bed)	LUSC- 1000MW Ultra-supercritical SUSC - 600MW Ultra-supercritical LSC - 600MW Supercritical SSC - 300MW Supercritical LSUB - 600MW Subcritical SSUB - 300MW Subcritical OTHC - install capacity less than 300MW
Circulating Fluidized Bed	LCFB - Circulating Fluidized Bed Units (with installed capacity greater than or equal to 300MW) SCFB - Circulating Fluidized Bed Units (with installed capacity less than 300MW)
Gas-fired	HPG - F-class LPG - Pressure lower than F-class
Other	Wind power Solar power Hydropower Nuclear power

Cement

For the cement sector, the subsectors reflect heterogeneity in emissions intensity, rather than along a technology dimension. We cluster by their base year emissions intensity.

In our data, there are 797 cement production lines from 631 cement firms, covering 57% of China's cement production. We have the CO_2 emissions intensity data for each production line.[40] We apply a clustering algorithm to group the production lines into five clusters, which are described in the section below. The lowest and highest clusters have very few production lines, so we include them in the closest intermediate groups. Each of the resulting three clusters represents a subsector of the cement sector. The clusters are indicated in Table A3 below. Figure A1 shows the cumulative density function that captures the relationship between the emissions intensities of the three emissions-intensity groups and cumulative cement production.

Table A3. Subsectors of the Cement Sector

Subsector	**CO_2 emissions intensity**
High-efficiency cement production	CO_2 emissions intensity < 0.845 tCO_2/ton cement production
Medium-efficiency cement production	$0.914 >$ CO_2 emissions intensity $\geqslant 0.845$ tCO_2/ton cement production
Low-efficiency cement production	CO_2 emissions intensity $\geqslant 0.914$ tCO_2/ton cement production

[40] We do not have emissions data for the full cement production, but we have emissions data for cement clinkers for each production line of cement firms. Cement is produced by grinding cement clinker into a fine powder. Since emissions from the "clinker grinding" process accounts for only a small portion of the total emissions of producing cement, using the emissions intensity of cement clinker to define subsectors approximates fairly closely the emissions intensity of cement production.

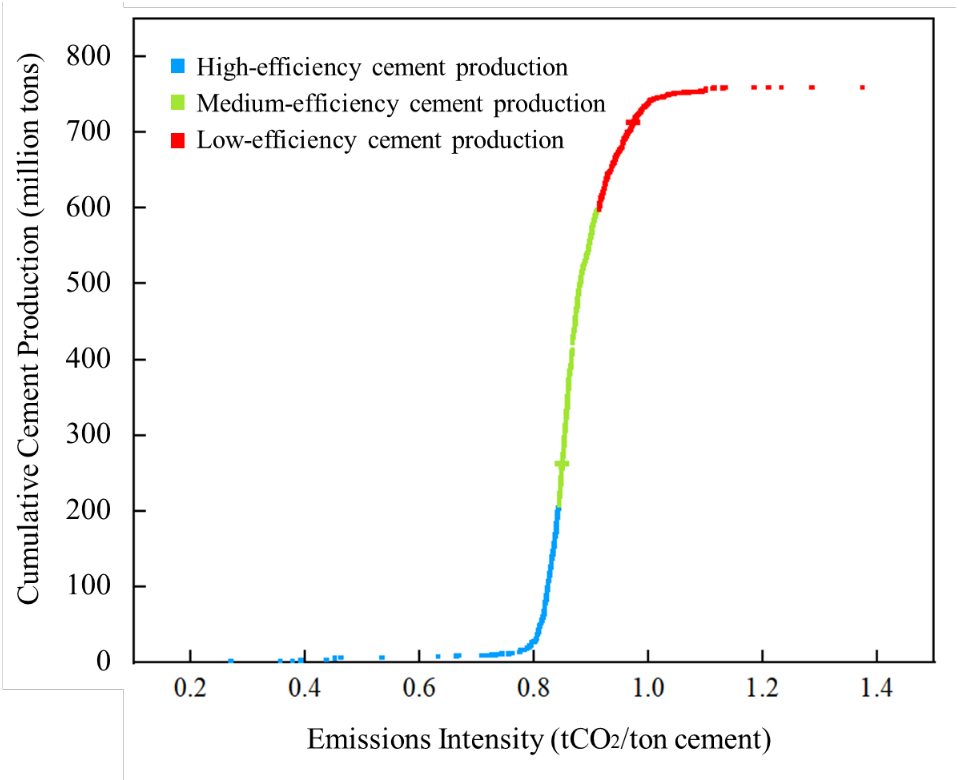


Figure A1. Clustering of Cement Sector by Emissions Intensity

Aluminum

As with cement, we cluster aluminum firms by their base year emissions intensity. In our data, there are 116 aluminum production lines from 64 aluminum firms, covering 42% of China's aluminum production. We use the same clustering method as cement – we take the logarithm of emissions intensities before using K-means to group the 116 production lines into 5 clusters, and then regroup the lowest and highest clusters to their closest groups, respectively. We end up with three clusters, each representing one subsector in the aluminum sector.

Table A4. Subsectors of the Aluminum Sector

Subsector	**CO_2 emissions intensity**
High efficiency	CO_2 emissions intensity < 8.00 (tCO_2/ ton aluminum)
Medium efficiency	8.33 > CO_2 emissions intensity ⩾ 8.00 (tCO_2/ ton aluminum)
Low efficiency	CO_2 emissions intensity ⩾ 8.33 (tCO_2/ ton aluminum)

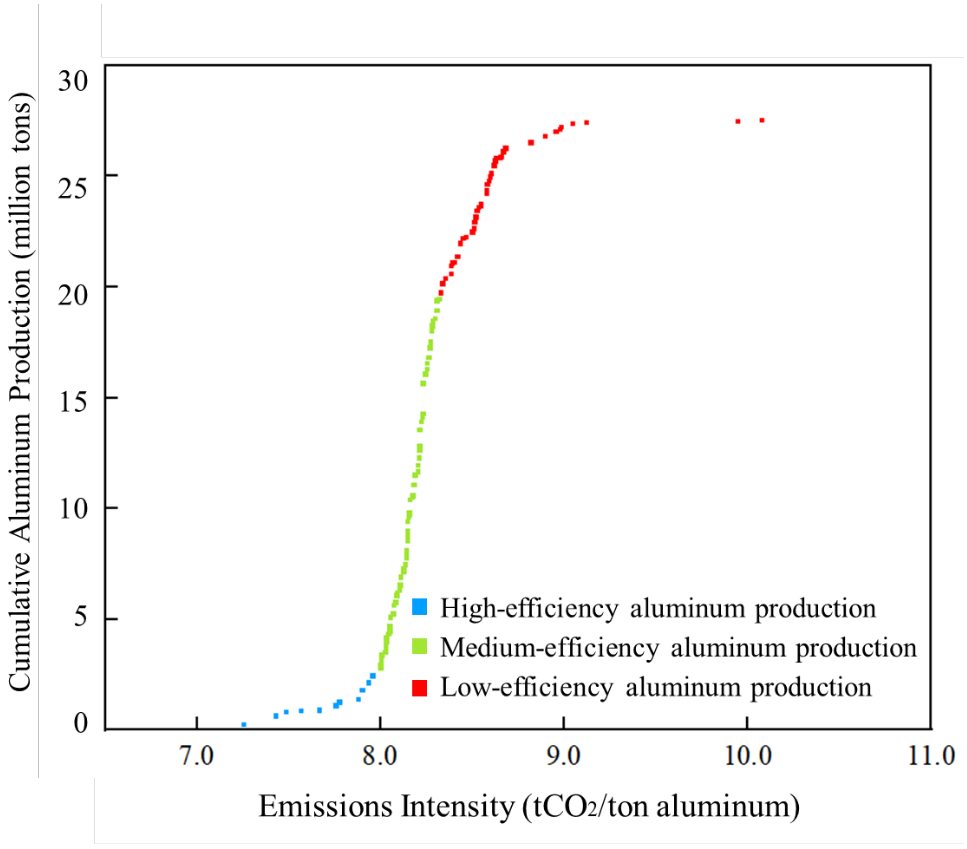


Figure A2. Clustering of Aluminum Sector by Emissions Intensity

Iron & Steel

We first classify iron & steel units into two technology categories: basic oxygen (BO) steelmaking and electric arc (EA) furnace steelmaking. Each technology category is further classified into subcategories based on its base-year emissions intensities.

There are 187 BO steelmaking units with a total production of 600 million tons of crude steel, and 262 EA steelmaking units with a total production of 133 million tons of crude steel. In total, our data cover 88% of the national crude steel production in 2017.

We use the same clustering method as cement and aluminum. We use K-means to cluster the 187 BO steelmaking units into 5 clusters, and then regroup the lowest and highest ones to their closest groups, respectively. We end up with three clusters, each representing one subsector in BO steelmaking units. Similarly, we cluster the 259 EA steelmaking units into 5 clusters, and then regroup the lowest and highest clusters to their closest groups, respectively, and we end up with three clusters, each representing one subsector in EA steelmaking units.

Table A5. Subsectors of the Iron & Steel Sector

Subsector	CO_2 emissions intensity
Basic oxygen steelmaking	CO_2 emissions intensity < 1.41 (tCO_2/t)
	1.98 > CO_2 emissions intensity ⩾ 1.41 (tCO_2/t)
	Carbon emissions intensity ⩾ 1.98 (tCO_2/t)
Electric arc furnace steelmaking	CO_2 emissions intensity < 0.125 (tCO_2/t)
	0.235 > CO_2 emissions intensity ⩾ 0.125 (tCO_2/t)
	CO_2 emissions intensity ⩾ 0.235 (tCO_2/t)

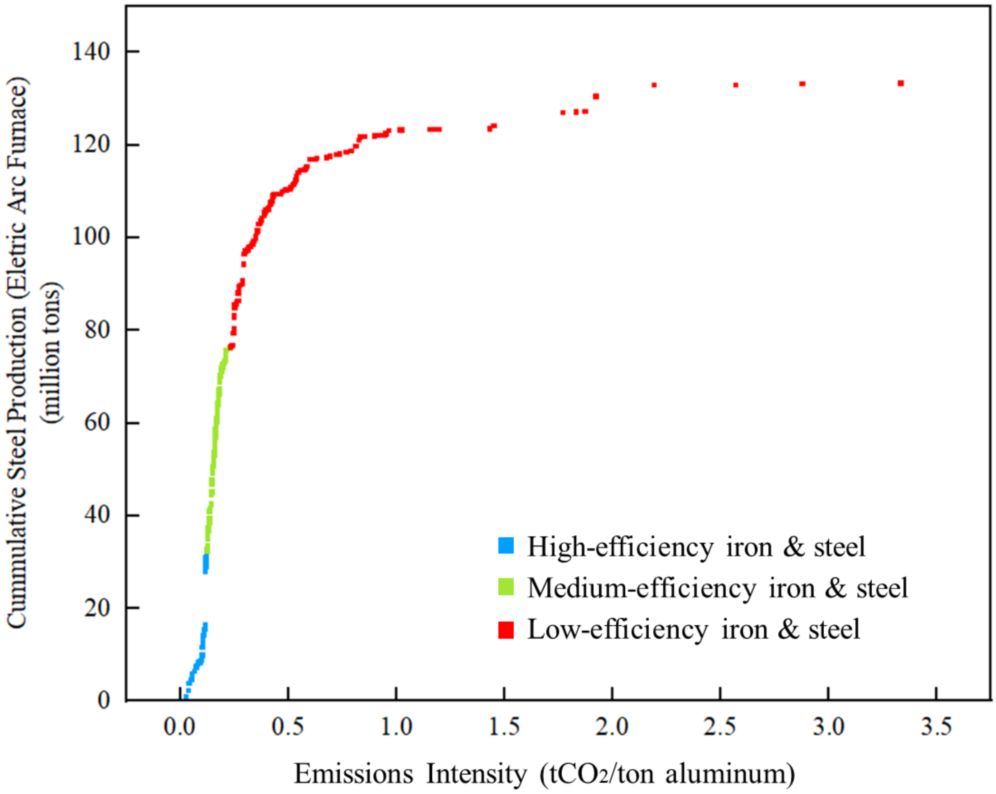


Figure A3. Clustering of Iron & Steel (EA) Sector by Emissions Intensity

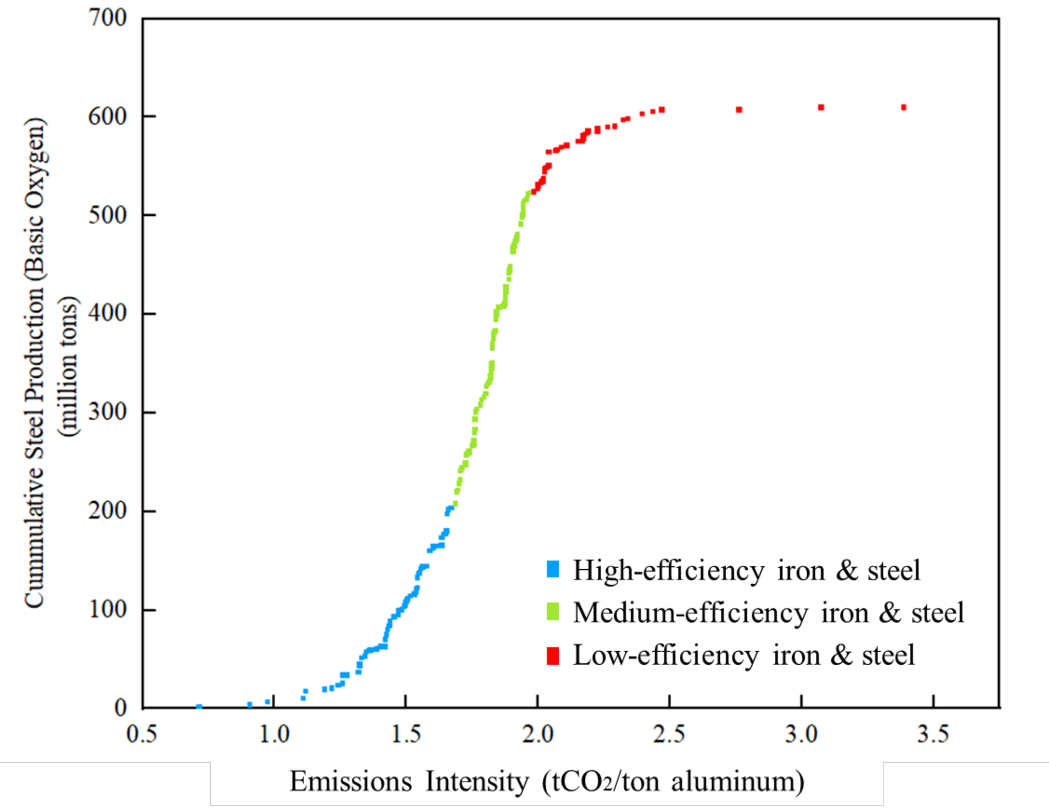


Figure A4. Clustering of Iron & Steel (BO) Sector by Emissions Intensity

The Clustering Algorithm

The clustering algorithm applies a machine-learning technique that groups data points into clusters. We cluster plants within a given sector into subsectors based on their base-year emissions intensities. The first step is to choose the sector to be disaggregated and the resulting number of subsectors. The second step is to employ the clustering algorithm to find cluster centers and assign plants to each cluster such that the distance (i.e., the difference between the center's emissions intensity and the plant's emissions intensity) is minimized. Various clustering algorithms differ in how "cluster center" and "distance" are defined. K-means clustering defines the center as the mean of all data points in the cluster, distance as the squared Euclidean deviation from the mean, while K-medians clustering defines the center as the median of all data points in the cluster, and distance as the Manhattan distance. Therefore, clustering is subject to the researcher's choice of the number of clusters (i.e., the number of subsectors) and the choice of the distance metric.

Data Processing

The data are processed in four steps. First, the 149 sectors' input-output data from China's 2017 input-output table are aggregated to the 31 production sectors in our study and scaled to 2020, the first simulation year. We use three scalars to translate these input and output data to 2020: one for the service sector, one for the agriculture sector, and one for other sectors. The data are scaled so that the GDP, as well as the value-added shares of the service sector and agriculture sectors, match the published statistics in 2020 (National Bureau of Statistics, 2021). Second, the sectors are then disaggregated into subsectors for electricity, cement, aluminum, and iron & steel according to the subsector-level information, which is obtained by aggregating the firm-level Ministry of Ecology and Environment (MEE) data. The disaggregation method is described in the next paragraph. Third, we scale all tax and subsidy rates reported in GTAP for 2014 (the latest version) by a common factor so that the total tax revenue net of subsidies matches that in 2020 (National Bureau of Statistics, 2021). Lastly, we re-balance the input-output data after these adjustments, as described in the subsection "Input-Output Table Rebalance" below.

Disaggregating Sector-level Data to Subsectors

The input-output table provides sector-level data on economic value variables. The sectors are then split into subsectors (for electricity, cement, aluminum, and iron & steel sectors) according to the subsector-level information, which is obtained by aggregating the firm-level data from the MEE. The disaggregation method is described below.

For factor inputs (m_j, w_j), material inputs (d, n), and exports (Y_{ex}), sector-level electricity, cement, and aluminum data are split into subsectors by assuming that each subsector's share of a corresponding input (or export) equals the subsector's output share. As for the material inputs of iron & steel, we consider the different technical properties of the basic oxygen (BO) steelmaking and electric arc furnace (EA) steelmaking subsectors: BO steelmaking converts iron ore into pig iron and then into steel, while the EA steelmaking directly converts scrap or direct reduced iron to steel by electric arcs. Therefore, we assume that the BO steelmaking subsector uses all the iron ore and mineral material inputs in the iron & steel sector. We also assume that the self-inputs of the EA steelmaking subsector account for 60% of its total input, while the self-inputs of the BO steelmaking subsector only account for 20%, according to Lu *et al.* (2015). Other material inputs, factor inputs, and exports of the iron & steel sector are split in the same way as the electricity, cement, and aluminum sectors.

For energy inputs in the electricity sector, the MEE data provides each coal-fired subsector's share of coal use, and each gas-fired subsector's share of gas usage. For energy inputs in the cement and the iron & steel sector, the MEE data provides each subsector's share of electricity, heat, and fuel composite. We assume that a subsector's share of the fuel composite applies to each fuel. For energy inputs in the aluminum sector, the MEE data provides each subsector's share of electricity input. We assume this share also applies to other energy inputs.

The MEE data provides the emissions in electricity, cement, iron & steel, and aluminum sectors. Note that the cement sector, in addition to emissions from consuming energy inputs, also emits CO_2 in the process of carbonate decomposition ($CaCO_3$ decomposed to CaO and CO_2). The data only covers a subset of the whole sector. For example, data on the cement sector covers 57% of China's cement production. We scale the emissions data up by the share of coverage for each of the three sectors. Then, for the electricity, cement, iron & steel, and aluminum sectors, the emissions data at the sector level are split into subsectors in the same way as we split energy inputs.

Input-Output Table Rebalance

After the processing of the original data, the original input-output table becomes unbalanced – the total inputs and total outputs of a sector may be different. We thus apply a least-square optimization method to obtain a balanced input-output table following Zhang *et al.*(2013). Specifically, Equation (A1) is applied to adjust the factor inputs and intermediate inputs so that the input and output of a sector are balanced.

$$
\begin{aligned}
&\min_{\{x_{ijk}, e_{ljk}, w_{jk}, m_{jk}\}} \sum_{i,j,k} \{(x_{ijk} - \overline{x_{ijk}})^2 + (w_{jk} - \overline{w_{jk}})^2 + (m_{jk} - \overline{m_{jk}})^2 + (e_{jk} - \overline{e_{jk}})^2\} \\
&s.t. \\
&\sum_i (x_{ijk} + w_{jk} + m_{jk} + e_{ljk}) \cdot (1 + \overline{\theta_{res_{jk}}}) = (\sum_{i,k} x_{jik} + \sum_{i,k} \overline{Y_{ex_{ijk}}}) \cdot \psi_{jk}, \forall j, k \\
&x_{ijk}, w_{jk}, m_{jk}, e_{ljk} > 0, \\
&x_{ijk} \equiv 0, \forall \overline{x_{ijk}} = 0 \\
&w_{jk} \equiv 0, \forall \overline{w_{jk}} = 0 \\
&m_{jk} \equiv 0, \forall \overline{m_{jk}} = 0 \\
&e_{ljk} \equiv 0, \forall \overline{e_{ljk}} = 0,
\end{aligned}
\qquad (A1)
$$

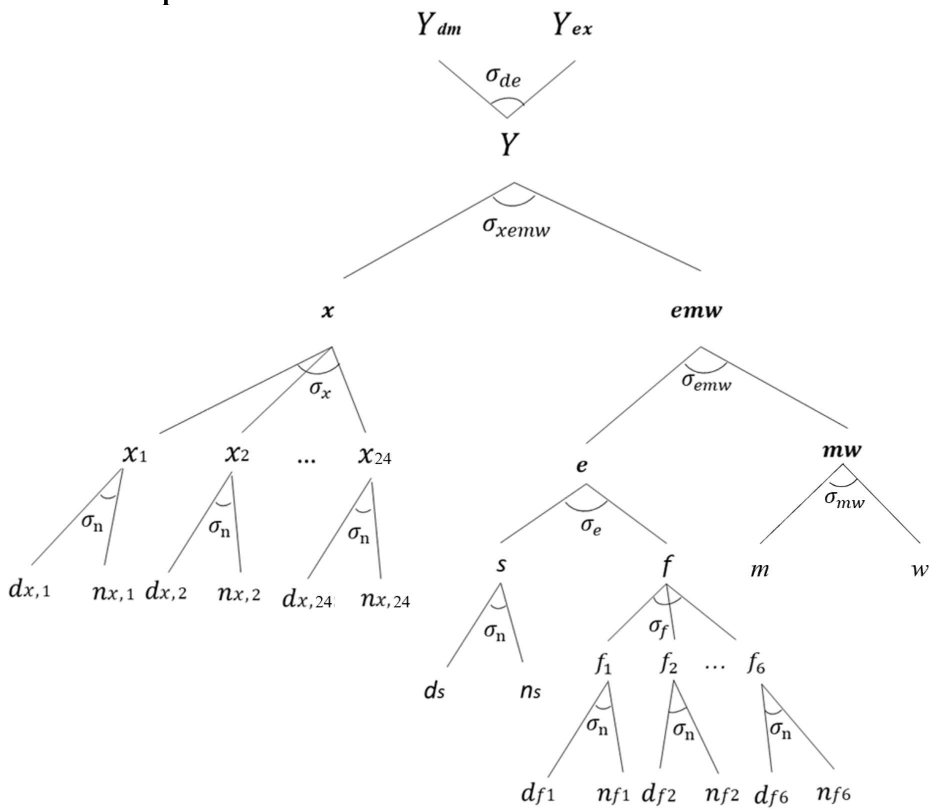
In Equation (A1), $x_{ijk}, e_{ljk}, w_{jk}, m_{jk}$ represent the adjusted material *i*, energy *l*, capital, and labor input of sector *j*, subsector *k*. $\overline{x_{ijk}}, \overline{e_{ljk}}, \overline{w_{jk}}, \overline{m_{jk}}$ represent the corresponding accounts before the rebalance. The objective function is to minimize the difference between the adjusted and unadjusted original value. The constraints for the objective function are the balance of the input and output of sector j, subsector k. The left-hand side represents the total inputs of sector j, subsector k. $\overline{\theta_{res_{jk}}}$ is the share of natural resources for renewable and nuclear electricity production subsectors. Appendix C provides the details. The right-hand side is the total output of sector j, subsector k, of which ψ_{jk} represents the subsector k's output share in sector j.

Appendix B. Production structure and functional forms

Production

Production in each of the sectors in each modeling period is represented by a nested structure shown in Figure A5. The σ's in the nesting structure are elasticities that govern the ease with which inputs can be substituted for each other. This nesting structure includes a large number of distinct parameters, which allows the model to incorporate considerable variation in the ease of input substitution for differing inputs.

a. Fossil-fuel based power sector and other sectors



b. Solar, wind, hydro, and nuclear power subsectors

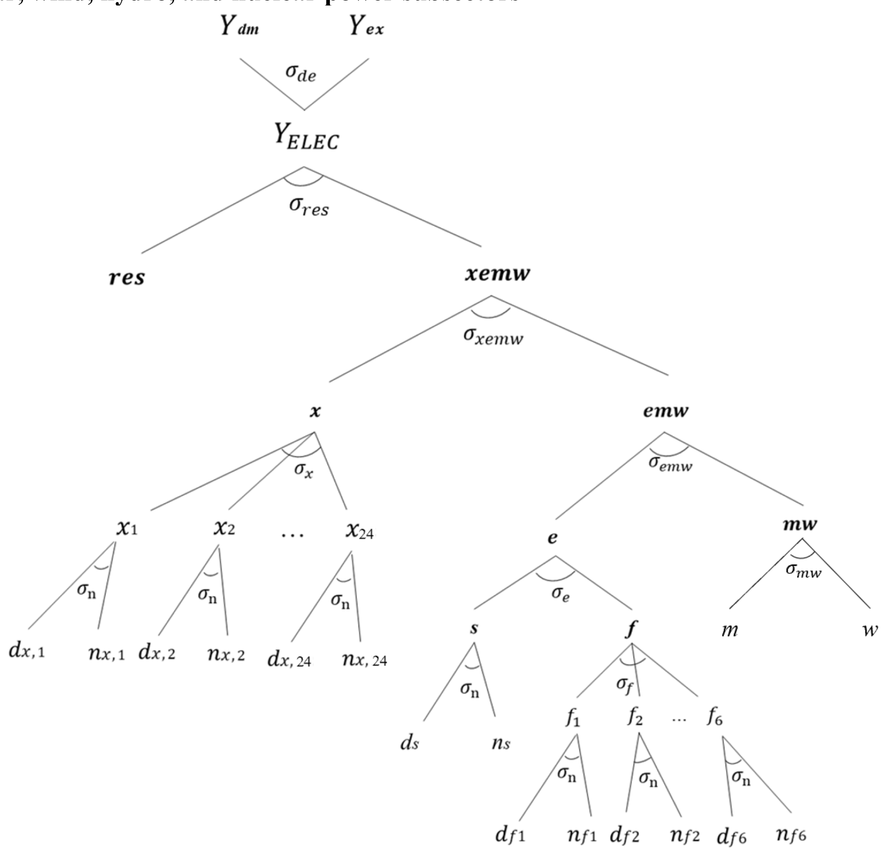


Figure A5. Nested CES Production Structure for Each Sector

Below we use fossil-based power sector and other sectors as an example to illustrate the production structure. The structure for solar, wind, hydro, and nuclear power subsectors are similar, except that they have natural resources (*res*) as their inputs.

In each sector, producers employ material inputs (***x***), energy inputs (***e***), and factors (***mw***) to produce output. As indicated in the left portion of the nested structure, the material inputs x_1, x_2, …, x_{24} combine to produce the composite material input ***x***. Each of the material inputs x_i is a composite of a domestically produced material input $d_{x,i}$ and, if any, a foreign-produced material input $n_{x,i}$.

The energy composite (*e*) is produced from electricity (*s*) and non-electricity fuels (*f*), and the non-electricity fuel is a composite of six fuel inputs $f_1, f_2, \ldots, f_6$ (coal, crude oil, natural gas, gas manufacture & distribution, petroleum products, and heat). Distinguishing electricity from non-electricity fuels allows flexibility in setting different elasticities of substitution with regard to fuels and electricity, as a more realistic representation of the production technologies. Energy inputs f_i (*s*) is also a composite of a domestically produced energy $d_{f,i}$ (d_s) and, if any, a foreign-produced input $n_{f,i}$ (n_s)

Producers also employ factors of production labor (*m*) and capital (*w*). As discussed further below, labor is represented as perfectly mobile across sectors, while the other factors are imperfectly mobile. These factors combine to form the composite factor ***mw***. Additionally, producers of renewable and nuclear electricity employ a special factor of production, natural resource (***res)***, as Figure A5(b) above shows.

The composite ***mw*** combines with the energy composite ***e*** to produce the energy-factor composite ***emw***. The elasticity of substitution between ***e*** and ***mw*** controls the energy efficiency improvements achieved by substituting capital and labor for energy. The composite ***emw*** then combines with ***x*** to produce gross output (*Y*). The output *Y* is allocated toward the domestic market or the export market. Y_{dm} and Y_{ex} represent the output devoted to each of these markets.

The model employs the constant-elasticity-of-substitution (CES) functional form for the production functions at each stage of the production nest. A general equation for this functional form is:

$$V = \left[\sum_{i=1}^{n} \alpha_i v_i^{\rho} \right]^{\frac{1}{\rho}} \tag{A2}$$

where $\sum_{i=1}^{n} \alpha_i = 1$. The parameter ρ is equal to $1 - \frac{1}{\sigma}$, where σ is the elasticity of substitution among v_i in producing V.

Equation (A2) indicates the relationship, at any given point of the nest, between a given composite and its underlying elements. For example, the function that combines $\boldsymbol{x}$ and $\boldsymbol{emw}$ to produce Y is expressed by:

$$Y = \left[\alpha_x \boldsymbol{x}^{\rho_{xemw}} + \alpha_{emw} \boldsymbol{emw}^{\rho_{xemw}}\right]^{\frac{1}{\rho_{xemw}}} \tag{A3}$$

where $\alpha_x + \alpha_{emw} = 1$, $\rho_{xemw} = 1 - \dfrac{1}{\sigma_{xemw}}$, and σ_{xemw} is the elasticity of substitution between $\boldsymbol{x}$ and $\boldsymbol{emw}$.

A constant elasticity of transformation (CET) function maps the total output Y into the domestic supply Y_{dm} and export Y_{ex}.

$$Y_{dm} = \alpha_{dm}^{\sigma_{de}} \left[\frac{p_{dm}}{p}\right]^{-\sigma_{de}} Y \tag{A4}$$

$$Y_{ex} = \alpha_{ex}^{\sigma_{de}} \left[\frac{p_{ex}}{p}\right]^{-\sigma_{de}} Y \tag{A5}$$

where $\alpha_{dm} + \alpha_{ex} = 1$, and σ_{de} is the elasticity of transformation between Y_{dm} and Y_{ex}. p_{dm}, p_{ex} and p denote the domestic price, export price, and composite price of the produced good, respectively. As these functions indicate, the fraction of Y devoted to the domestic market and exports is a function of the real prices of goods sold to the domestic and foreign markets. Throughout, wherever there is a tax or subsidy, the price in all equations is the gross-of-tax price.

Factor Types and Supply

Labor (*m*) is perfectly mobile across sectors, capital (*w*) is imperfectly mobile, and natural resource (*res*) is immobile. The supplies of the imperfectly mobile factor capital in every single period to the 31 sectors are based on a transformation function. The transformation function allocates capital to the model's sectors. Changes in relative prices alter its allocation across sectors. The marginal returns to capital generally will differ across sectors, a reflection of its imperfect mobility. Consequently, the market price of capital will generally differ across sectors.

The transformation function, $\Gamma_{w_i}(\bullet)$, has the CET functional form and is expressed by:

$$\overline{w} = [\sum_{j=1}^{31} \alpha_{w,j} w_j^{S\,\rho_w}]^{1/\rho_w} \tag{A6}$$

where $\sum_{j=1}^{31}\alpha_{w,j}=1$ and $\rho_w = 1-\frac{1}{\sigma_w}$, where σ_w is the elasticity of transformation among sectors. The element $\bar{w}$ denotes the fixed endowment of capital and w_j^S the allocation of $\bar{w}$ to sector j.

Capital is allocated to maximize the return to their owners. The maximization problem is expressed by the following:

$$\begin{aligned} &\max_{w_j^S} \sum_{j=1}^{j=31} w_j^S P_{wj} \\ &s.t. \Gamma_w\left(w_{\mathrm{j}}^{\mathrm{S}}\right)=w \end{aligned} \tag{A7}$$

where w_j^S denotes the allocation of capital to sector j and p_{wj} is the sector-specific price of the factor w. $\Gamma_W(\cdot)$ is the CET function for capital. As indicated earlier, the model distinguishes subsectors of the electricity, cement, aluminum, and iron & steel sectors, to reflect within-sector differences in technology or emissions intensities. The same maximization problem determines the allocation of capital across subsectors.

Inputs and Outputs

In each sector, managers of firms are assumed to aim to maximize profit. This objective determines firms' choices of input and output levels. Optimal choices of inputs and outputs are shown below. The sector subscript has been suppressed in this subsection.

Optimal input intensities

For any CES function of the form in Equation (A2), the Lagrangian equation for obtaining the composite V at minimum cost is given by:

$$L=\sum_{i=1}^{n} p_i v_i + \lambda\left\{\left[\sum_{i=1}^{N}\alpha_i v_i^{\rho}\right]^{\frac{1}{\rho}} - V\right\} \tag{A8}$$

where p_i the price of input v_i.

The first-order conditions can be summarized as:

$$\frac{v_i}{v_j}=\left[\frac{\alpha_j}{\alpha_i}\frac{p_i}{p_j}\right]^{\frac{1}{\rho-1}} \tag{A9}$$

for all i and j in 1, … ,n.

From the first-order conditions and the CES production function, the optimal demand of input v_i per unit of the composite V is derived as:

$$\frac{v_i}{V} = \alpha_i^{\sigma} \left[\frac{p_i}{P} \right]^{-\sigma} \tag{A10}$$

where σ is the constant elasticity of substitution equal to $\frac{1}{1-\rho}$. P is the price of the composite V:

$$P = \left[\sum_{i=1}^{n} \alpha_i^{\sigma} p_i^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{A11}$$

The formulas in equations (A10) and (A11) apply at every level of the production nest. As an example, the intensity of domestic material input d_{xl}, imported material input n_{xl} in the domestic-import material composite x_l, and the price of the composite x_l are:

$$\frac{d_{xl}}{x_l} = \alpha_{d_{xl}}^{\sigma_n} \left[\frac{p_{d_{xl}}}{p_{x_l}} \right]^{-\sigma_n} \tag{A12}$$

$$\frac{n_{xl}}{x_l} = \alpha_{n_{xl}}^{\sigma_n} \left[\frac{p_{n_{xl}}}{p_{x_l}} \right]^{-\sigma_n} \tag{A13}$$

$$p_{x_l} = \left[\alpha_{d_{xl}}^{\sigma_n} p_{d_{xl}}^{1-\sigma_n} + \alpha_{n_{xl}}^{\sigma_n} p_{n_{xl}}^{1-\sigma_n} \right]^{\frac{1}{1-\sigma_n}} \tag{A14}$$

Optimal output

The profit function is:

$$\begin{aligned} \Pi &= pY - C \\ &= pY - p_{\boldsymbol{x}}x - p_{\boldsymbol{emw}}emw \end{aligned} \tag{A15}$$

$$\Pi_k = pY - p_x x - p_{emw} emw - p_{rk} res_k \tag{A16}$$

where the C is the cost of production inputs, which equals the payment to ***x*** and ***emw***. For renewable and nuclear electricity supply, Equation (A16) is applied, where p_{rk} and $\boldsymbol{res_k}$ denote the price and endowment for natural resources in renewable and nuclear subsectors (wind, solar, hydro, and nuclear). The p denotes the composite price of the produced good:

$$p = \left[\alpha_{dm}^{\sigma_{de}} p_{dm}^{1-\sigma_{de}} + \alpha_{ex}^{\sigma_{de}} p_{ex}^{1-\sigma_{de}} \right]^{\frac{1}{1-\sigma_{de}}} \tag{A17}$$

where p_{dm} is the domestic price, p_{ex} the export price, σ_{de} the elasticity of transformation between domestic and export supply, and $\alpha_{dm} + \alpha_{ex} = 1$. Thus, the composite price is a function of the market prices for the sale of the output to the domestic and export markets.

Differentiating the profit function with respect to $\boldsymbol{x}$ gives the first-order condition for $\boldsymbol{x}$, where the left-hand side represents the marginal revenue of $\boldsymbol{x}$ and the right-hand side represents the marginal cost of $\boldsymbol{x}$:

$$p \frac{\partial Y}{\partial \boldsymbol{x}} = p_{\boldsymbol{x}} \tag{A18}$$

From the first-order condition, we can solve the optimal quantity of $\boldsymbol{x}$ as a function of output.

$$\boldsymbol{x} = \alpha_{\boldsymbol{x}}^{\sigma_{\boldsymbol{xemw}}} \left[\frac{p_{\boldsymbol{x}}}{p} \right]^{-\sigma_{\boldsymbol{xemw}}} Y \tag{A19}$$

Similarly, differentiating the profit function with respect to ***emw*** gives the first-order condition for ***emw***. And from the first-order condition, we have the optimal quantity of ***emw*** as a function of output.

$$p \frac{\partial Y}{\partial \boldsymbol{emw}} = p_{\boldsymbol{emw}} \tag{A20}$$

$$\boldsymbol{emw} = \alpha_{\boldsymbol{emw}}^{\sigma_{\boldsymbol{xemw}}} \left[\frac{p_{\boldsymbol{emw}}}{p} \right]^{-\sigma_{\boldsymbol{xemw}}} Y \tag{A21}$$

Under the model's production structure, each firm's production exhibits constant returns to scale. The optimal output level, *Y*, is determined such that, when market equilibrium is achieved, price equals the constant marginal cost.

Applying the optimal $\boldsymbol{x}$ and optimal ***emw*** in equations (A19) and (A21) to the optimal input intensities, we get the optimal levels of all inputs. As an example, the optimal level of $d_{x,l}$ is:

$$d_{x,l} = \frac{d_{x,l}}{x_l}\frac{x_l}{\boldsymbol{x}}\boldsymbol{x}$$

$$= \alpha_{d_{x,l}}^{\sigma_n}\left[\frac{p_{d_{x,l}}}{p_{x_l}}\right]^{-\sigma_n} \alpha_{x_l}^{\sigma_x}\left[\frac{p_{x_l}}{p_{\boldsymbol{x}}}\right]^{-\sigma_x} \alpha_{\boldsymbol{x}}^{\sigma_{xemw}}\left[\frac{p_{\boldsymbol{x}}}{p}\right]^{-\sigma_{xemw}} Y \tag{A22}$$

Final Demand

Consumption

In the model, a representative household makes consumption choices to maximize utility. The nested structure of the utility function is below. The household chooses between material goods (*x*) and energy goods (*e*). At the next level, the material composite is a CES combination of material goods, $x_1, x_2, \ldots, x_{24}$. The energy composite is a CES function of electricity (*s*) and fuel composite (*f*). The fuel composite is a CES function of six fuel goods, $f_1, f_2, \ldots, f_6$. Each x_l, f_l, and *s* is a composite based on the domestically and foreign supplied component.

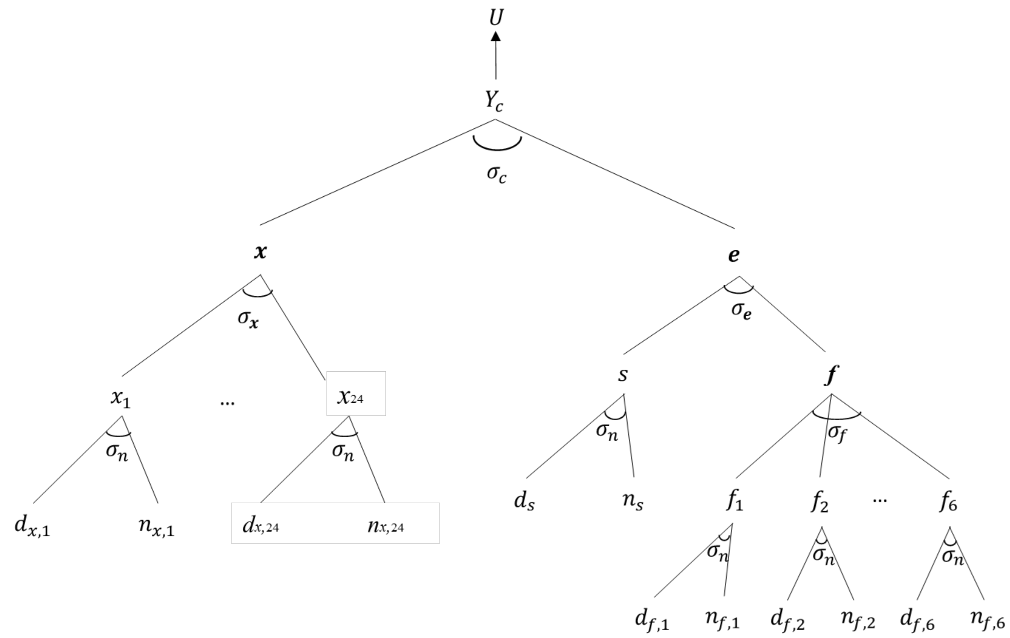


Figure A6. Household Demand Structure

The generalizable CES function form in Equation (A2) applies to all nests in the household demand structure. For example, the top level is expressed by

$$Y_C = \left[\alpha_{x_C} \boldsymbol{x}_C^{\rho_{xe}} + \alpha_{e_C} \boldsymbol{e}_C^{\rho_{xe}} \right]^{\frac{1}{\rho_{xe}}} \tag{A23}$$

where Y_C, $\boldsymbol{x}_C$, and $\boldsymbol{e}_C$ are the demand of the final private good, material composite, and energy composite, respectively. The distribution shares α_{x_C} and α_{e_C} sum to 1, and $\rho_{xe} = 1 - \frac{1}{\sigma_{xe}}$, where σ_{xe} is the elasticity between $\boldsymbol{x}$ and $\boldsymbol{e}$.

The generalizable form of the price function in Equation (A11) applies to the composite prices for all nests of the household demand structure. For example, the composite price of the final consumption good is a combination of the material composite price and energy composite price expressed as:

$$p_C = \left[\alpha_{x_C}^{\sigma_{xe}} p_{x_C}^{1-\sigma_{xe}} + \alpha_{e_C}^{\sigma_{xe}} p_{e_C}^{1-\sigma_{xe}} \right]^{\frac{1}{1-\sigma_{xe}}} \tag{A24}$$

where p_C, p_{x_C}, and p_{e_C} are the price of the final consumption good, the material composite, and energy composite, respectively.

The household maximizes utility subject to its budget constraint. The utility maximization problem is:

$$\begin{gathered} \max U\left(Y_C\right) = Y_C \\ s.t. \;\; p_C Y_C \leq p_m \overline{m} + p_w \overline{w} + p_{res} res + T - p_I Y_I \end{gathered} \tag{A25}$$

where $p_C Y_C$ is the household expenditure,

$p_m \overline{m}$ is the income from the endowments of labor,

$p_w \overline{w}$ is the income from the endowments of capital,

$p_{res} res$ is the income from the endowments of natural resources,

T is the income from transfer from the government, and

$p_I Y_I$ is the private savings, which we discuss below.

Investment

In the model, the level of real investment is determined by the total savings and the price of investment goods of the economy. It is composed of private investment (i.e., investment by the household) and public investment (i.e., investment by the government). Private savings are determined by a fixed fraction of total after-tax households' income. Public savings are specified as a fixed share of government income.

Real investment is the quantity of a new capital good that is produced at minimum cost. The production of the capital goods derives from the nested structure in Figure A7 below. The intensities of the inputs used to produce the capital goods change in response to changes in their prices. The capital good is a CES aggregation of material and energy composites, and the material (energy) composite is a CES aggregation of material (energy) goods. Each material (energy) good is a domestic-import composite.

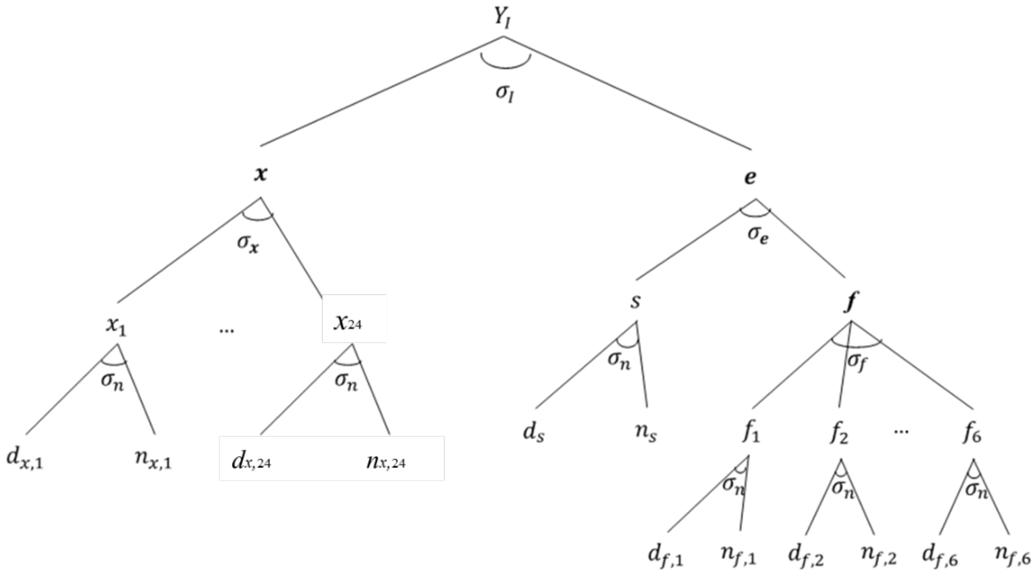


Figure A7. Nested Structure for Investment

The generalizable CES function form in Equation (A2) applies to all nests in the capital good production structure. For example, the top level is expressed by

$$Y_I = \left[\alpha_{x_I} \boldsymbol{x}_I^{\rho_{xe}} + \alpha_{e_I} \boldsymbol{e}_I^{\rho_{xe}}\right]^{\frac{1}{\rho_{xe}}} \tag{A26}$$

where Y_I, $\boldsymbol{x}_I$, and $\boldsymbol{e}_I$ are the investment composite, the material composite, and the energy composite, respectively. $\alpha_{x_I} + \alpha_{e_I} = 1$. $\rho_{xe} = 1 - \dfrac{1}{\sigma_{xe}}$, where σ_{xe} is the elasticity between $\boldsymbol{x}$ and $\boldsymbol{e}$.

The investment good is produced at the minimum cost. The minimum cost problem has the same form as that of the cost minimization problem of commodity goods. Hence the generalizable form in Equation (A11) applies to the investment good. The composite price of the final good is expressed as:

$$p_I = \left[\alpha_{x_I}^{\sigma_{xe}} p_{x_I}^{1-\sigma_{xe}} + \alpha_{e_I}^{\sigma_{xe}} p_{e_I}^{1-\sigma_{xe}} \right]^{\frac{1}{1-\sigma_{xe}}} \tag{A27}$$

where p_I, p_{x_I}, and p_{e_I} are the price of the final investment good, the material composite, and energy composite, respectively.

Plugging the equations for investment into the household's budget constraint in Equation (A25) yields:

$$\begin{aligned} p_C Y_C \leq\ & p_m \overline{m} + p_w \overline{w} + p_{res} res + \mathrm{T} \\ & - \left[\alpha_{x_I}^{\sigma_{xe}} p_{x_I}^{1-\sigma_{xe}} + \alpha_{e_I}^{\sigma_{xe}} p_{e_I}^{1-\sigma_{xe}} \right]^{\frac{1}{1-\sigma_{xe}}} \mathrm{Y}_I \end{aligned} \tag{A28}$$

Government Spending

Government spending in the model is characterized by a CES preference function defined over the material-energy composite. The structure is the same as the structure for household consumption, with the only difference being the values of the elasticities.

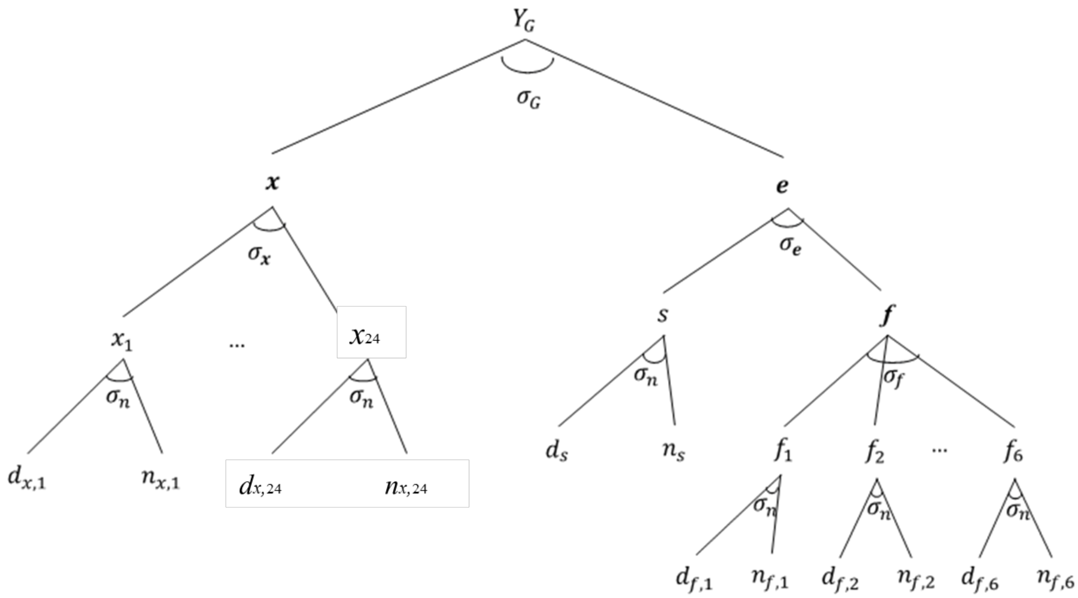


Figure A8. Nested Structure for Government Spending

The government's budget balance is:

$$p_G \overline{Y_G} = R - T - I_G \tag{A29}$$

where the left side is the expenditure on public consumption, and the right side is the total tax revenue R (consists of output taxes, intermediate demand taxes, factor taxes, and final demand taxes) minus transfer income to household T and public saving I_G.

The transfer T is endogenously determined by the government's budget balance requirement. Government consumption is set as a fixed share (17%, in 2017) of GDP and is characterized by a CES preference function defined over the material-energy composite. The transfer to households is then endogenously determined by the government's budget balance requirement.

The generalizable CES function form in Equation (A2) applies to all nests in the government demand structure. For example, the top level is expressed by

$$Y_G = \left[\alpha_{x_G} \boldsymbol{x}_G^{\rho_{xe}} + \alpha_{e_G} \boldsymbol{e}_G^{\rho_{xe}} \right]^{\frac{1}{\rho_{xe}}} \quad \text{(A30)}$$

where Y_G, $\boldsymbol{x}_G$, and $\boldsymbol{e}_G$ are the government's demand for the final good composite, the material composite, and the energy composite, respectively.

The composite government-provided final good is produced at minimum cost. The minimum cost problem has the same form as that of the cost-minimization problem for the outputs of the model's various sectors. Hence the generalizable form in Equation (A11) applies to the government's composite good. For example, the composite price of the final good is expressed as:

$$p_G = \left[\alpha_{x_G}^{\sigma_{xe}} p_{x_G}^{1-\sigma_{xe}} + \alpha_{e_G}^{\sigma_{xe}} p_{e_G}^{1-\sigma_{xe}} \right]^{\frac{1}{1-\sigma_{xe}}} \quad \text{(A31)}$$

where p_G, p_{x_G}, and p_{e_G} are the price of the final composite, the material composite, and the energy composite, respectively.

Appendix C. Parameters and calibration methods

- **Parameters for the static part of the model**

Most elasticities employed in the production and utility functions are adopted from the GTAP database (Aguiar *et al.*, 2019), the MIT-EPPA model (Chen *et al.*, 2017), the RTI-ADAGE model (RTI International, 2015), the DIEM model (Ross, 2014), and literature (Cossa, 2004; Hertel *et al.*, 2007; Hertel & Mensbrugghe, 2019; Jomini *et al.*, 1991). Values for these parameters are presented in Table A6.

Table A6. Elasticities

Parameter	Source	Values[1]
Production elasticities		
σ_r	Calibrated	Solar: 0.27; Wind: 0.28; Hydro, Nuclear: 0
σ_{xemw}	GTAP, EPPA, RTI-ADAGE, DIEM	0
σ_{emw}	EPPA	0.40
σ_e	Cossa (2004), RTI-ADAGE	Non-ELEC: 0.50; ELEC: 0.10
σ_f	Cossa (2004), RTI-ADAGE	Non-ELEC: 1.00; ELEC: 0.10
σ_{mw}	Jomini *et al.* (1991)	AGR: 0.24 COL, OIL, GAS, OMN: 0.20 FBT: 1.12 SER: 1.36 TRN: 1.48 Other sectors: 1.26
σ_x	GTAP, EPPA, DIEM	0
σ_n	Hertel *et al.* (2007)	OMN: 1.80 CON, TRN, SER: 3.80 OIL: 4.20 AGR: 4.84 FBT: 5.09 CMT, OTHNMP: 5.80 WTR, GDT, ELEC, HEAT: 5.60 PAP, IAS: 5.90 COL: 6.10 TEM: 6.31 CHP: 6.60 LOG: 6.80 TXT, MTP, OEM: 7.50 CLO: 7.63 GEM: 8.10 ALU, OTHNFM: 8.40 ELQ: 8.80 CRU: 10.40 GAS: 16.00
σ_{ds}	GTAP	Same as σ_n
Consumption elasticities		
σ_{xs}	GTAP	0
σ_s	DIEM	0.7
σ_f	DIEM	0.5
σ_x	GTAP	Household consumption: 1.00 Government consumption, investment: 0
Transformation elasticities[2]		
σ_{w}	GTAP	1.5 for capital, $+\infty$ for labor
σ_{w_k}	GTAP	3 for capital, $+\infty$ for labor

[1] We assume the elasticities are the same across subsectors within a sector.

[2] σ_w represents the factor transformation elasticities between sectors; σ_{w_k} represents the factor transformation elasticities between subsectors within a sector.

The elasticity of substitution between the resource input and other input, σ_r, as well as the share of natural resource input, θ_{res}, are calibrated to incorporate a detailed representation of renewable and nuclear electricity supply in China. Below we describe the rationale and procedure of the calibration.

The supply curves of solar and wind electricity demonstrate the marginal cost of wind or solar electricity increases as the share of wind or solar increases. The marginal cost of wind or solar electricity is its marginal generation cost plus the cost of integration. The generation cost depends on technology-specific investment and operation costs, as well as site-specific wind and solar conditions. It is usually calculated using annualized investment costs and operating costs (Levelized Cost of Electricity, LCOE). The integration cost stems from grid integration, balancing services, more flexible operation of thermal plants, reserve costs, etc., and rises as the wind and solar penetration level (share of wind/solar in the total electricity supply) rise (Hirth et al., 2015).

The increase in marginal cost associated with increasing penetration of wind or solar has been investigated in many studies, but these empirical studies mainly focus on European countries and states of the US. The integration cost of wind or solar is complex and highly context-specific. It is nonlinearly related to the renewables' penetration level and depends on other characteristics of a power system, e.g., the share of flexible power sources, regulatory practices, and so on. Therefore, the existing empirical studies may not be suitable for China. We thus use a China power system model, Renewable Electricity Planning and Operation (REPO) Model, to derive the unit cost increase associated with increasing renewable electricity supply.

The REPO model is a capacity expansion and operation model for China's power system that includes sub-provincial level details. It has been developed to conduct in-depth energy and environmental analysis for relevant policy designs for China's power sector (Cassisa *et al.*, 2021; Zhang *et al*., 2023). By using the REPO model, we simulated the power system cost when the wind (or solar) penetration level increases, respectively, from 7% (5% for solar) to 10%, 15%, 20%, 30%, and 40%. The total electricity generation is assumed to remain the same throughout the simulation. Then, the marginal cost is calculated from the system cost differences when wind (or solar) penetration level varies. We then construct the marginal cost step curve shown below.

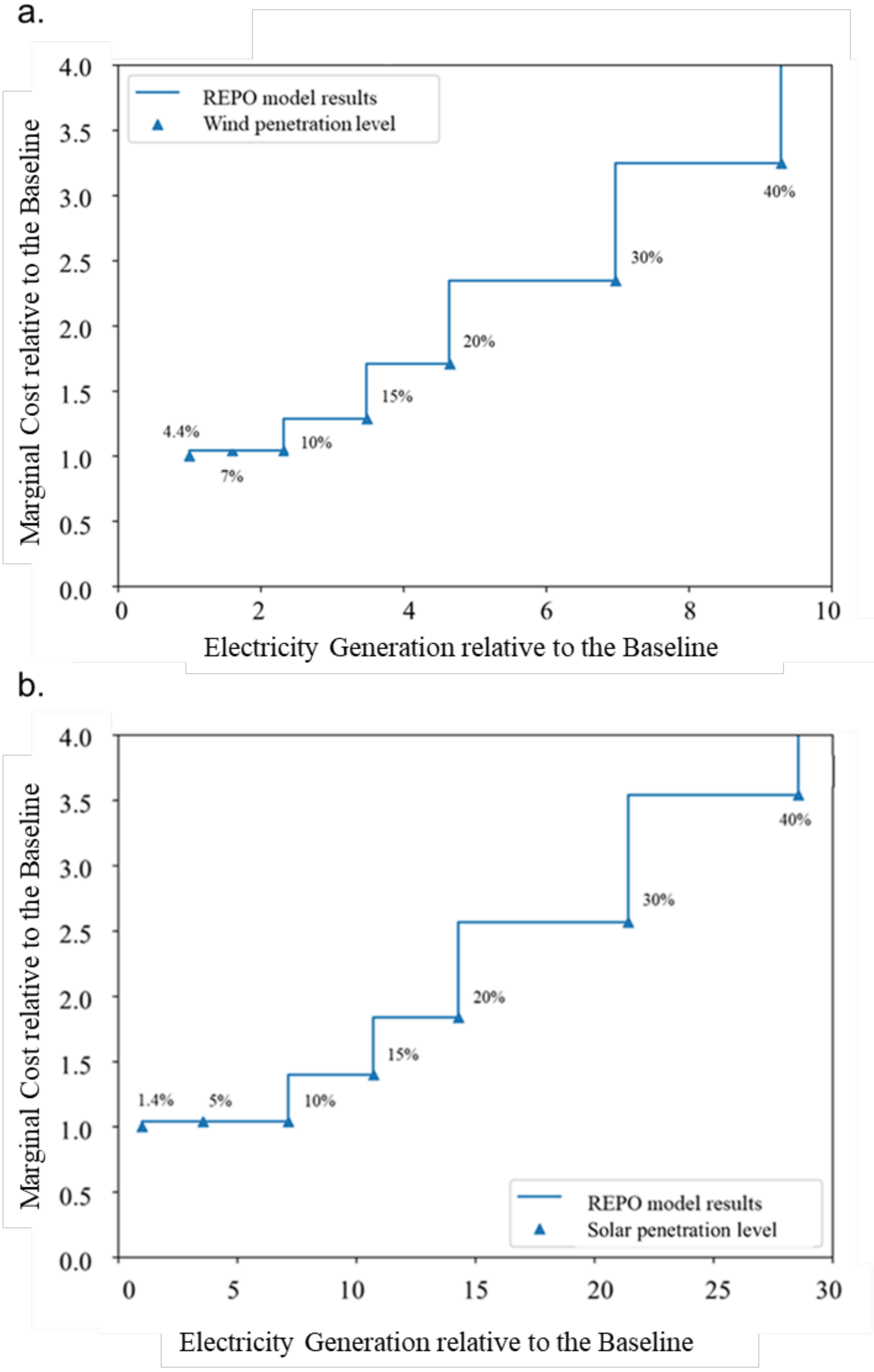


Figure A9. Marginal Cost for Wind and Solar from the REPO Model

The aim of the calibration is to have a CES function closely dictate the targeted supply curve at different electricity price levels in the CGE model. We adopt a CES production function with a fixed factor (*res*) at the top level of the nested CES production function in calibrated share form suggested by Rutherford (1998).

$$\tilde{p}_{Y_e} = (\theta_{res}\tilde{p}_{res}{}^{1-\sigma_{res}} + (1-\theta_{res})\tilde{p}_{emwx}{}^{1-\sigma_{res}})^{\frac{1}{1-\sigma_{res}}} \tag{A32}$$

In the cost function, Y_e denotes the output of renewable and nuclear electricity; ***res*** and ***emwx*** denote resource input and aggregate of other inputs, respectively. We assume that the resource supply is fixed at its initial value ($\boldsymbol{res} \equiv 1$), and the ***emwx*** price is assumed to be stable $\tilde{p}_{emwx} \equiv 1$, we can solve for output:

$$Y_e = \left(\frac{1-(1-\theta_{res})\tilde{p}_{Y_e}{}^{\sigma_{res}-1}}{\theta_{res}} \right)^{\frac{\sigma_{res}}{1-\sigma_{res}}} \tag{A33}$$

We then use Equation (A33) and two free parameters in the CES function (θ_{res} and σ_{res}) to fit the shape of the targeted supply curve in Figure A9. We use the range of 0 to 20% penetration level for curve fitting, as the wind or solar penetration does not exceed 20% in any of the cases in our study period. We adopt the ordinary least-square fitting method, as suggested in Rausch & Zhang (2018). The fitted curves are shown in Figure A10.

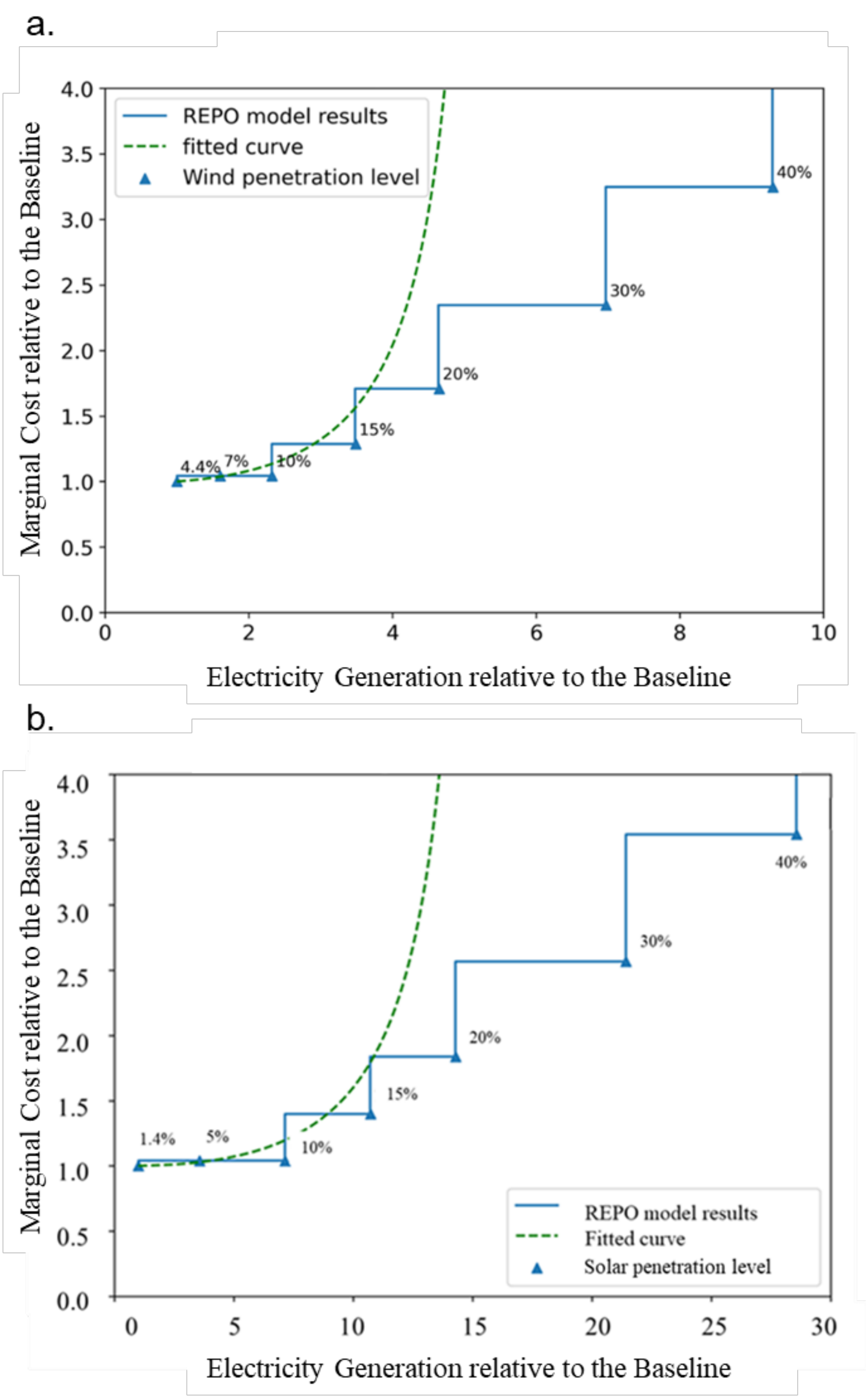


Figure A10. Fitted Supply Curves for Wind and Solar Electricity

For hydroelectricity and nuclear power, we use the Leontief production function since the amount of hydro and nuclear electricity generation in China is mainly constrained by planning and does not change with electricity price. Therefore, for hydroelectricity and nuclear power, $\sigma_{res} = 0$. θ_{res}, as a representation of resource-related input that isn't captured by other intermediate goods input and capital or labor input, can be derived from existing literature.

The θ_{res} associated with hydroelectricity is calculated as the price difference between the hydroelectricity on-grid price (258.93 yuan/MWh) and the average on-grid electricity price (376.28 yuan/MWh) (NEA, 2018). The resulting hydroelectricity θ_{res} is 0.3119 ($= \frac{376.28 - 258.93}{376.28}$).

Since the nuclear power on-grid price in China is higher than the average on-grid electricity price, we cannot use the above method to calculate θ_{res} for nuclear power. By definition, θ_{res} should be small for nuclear power. Thus, we set $\theta_{res} = 0.006$ for nuclear power, which equals the share of "payment for regional society" in its total cost (IAEA,2018).

- **Parameters for the model's dynamics**

The parameters for the model's dynamics include the growth rate of effective labor, the rate of autonomous energy efficiency improvement, the saving rate, the reproducible capital depreciation rate, and the interest rate. Values for these parameters are displayed in Table A7.

The growth of capital derives from savings decisions. The saving consists of private savings and government savings. Private savings are assumed to be a fixed fraction of total after-tax household income, and public savings are specified as a fixed share of government income. Public savings takes account for about 5% of total savings in China, according to Zhang *et al.* (2018). We use this information and the total investment data from the China IO table to calculate private and public savings in the base year (2020). We calculate the two savings rates so that the resulting public and private savings match the data of the base year. For the following years, we assume the private saving rate decreases from 42% in 2020 to 32% in 2035 according to the projection by the People's Bank of China (2021). The public saving rate is assumed to remain constant at the level of 15%.

The total savings are used to buy the investment goods. The real investment level in period *t* is thus determined by the total savings and the unit price of the investment goods. The growth of capital from period *t* to *t*+1 is calculated as the investment of period *t* net of depreciation during period *t*. We apply a depreciation rate of 5% per year according to Herd (2020). The capital stock of the base year (2020) is adopted from Holz & Sun (2018).

The model incorporates technological progress. We assume a 0.7% annual autonomous energy efficiency improvement rate (AEEI) for production sectors but energy production sectors following Duan *et al.* (2014). The energy production sectors (Oil refinery, Coal, Natural Gas, Gas manufacture & distribution, Electricity) are unique in that they convert fossil fuel to produce other energy products. We assume zero AEEI rates in these sectors.

The model also considers the cost reduction of wind electricity and solar electricity and assumes Hicks-neutral technological change. Currently, wind and solar electricity have higher unit cost than fossil-based electricity. Therefore, China's government gives them subsidies to lower the unit cost of wind and solar electricity to a comparable level of conventional generation technologies, i.e., fossil-based electricity. We obtain the subsidy rates from Direct Trading Pilots of Green Power[41]. The model assumes technological progress in the production of wind- and solar-powered electricity generation through an exogenously specified productivity factor. This factor is calibrated to be 1 in the base year 2020. It linearly increases to 1.56 (= 1/(1-36%)) for wind and solar electricity by 2035, respectively, as the unit cost is projected to decrease by 36% according to IRENA (2019a, 2019b). Correspondingly, the subsidies are projected to decrease, too. Studies have projected that these existing subsidies will decrease to zero before 2025 (Tu *et al.*, 2019; Zhang *et al.,* 2021). Therefore, we assume the subsidy rates for wind and solar electricity will decrease linearly to zero in 2025.

We also incorporate important structural changes in China in the calibration of the reference scenario, i.e., the sectoral transition towards the service sector. This structural change is the result of differences in factor productivity growth between the service sector and other sectors. The manufacturing sector is projected to have the highest productivity growth rate while the service sector has the lowest, due to sector-biased technological change (Święcki, 2017). The lowest factor productivity growth rate in the service sector implies it would need more factor inputs per unit output, and as a result, driving factors to flow from industrial sectors to service sectors (Święcki, 2017). We use a multiplier on the factor input in the service sector to simulate this structural change and calibrate it to match the projection by the State Information Center (2020). During 2020-2035, the share of agriculture, industry, and service sector in GDP is calibrated to change from 7%, 37%, and 56% to 6%, 30%, and 64%.

[41] According to the statistics from Direct Trading Pilots of Green Power, the wind and solar electricity has a price markup of around 0.03-0.05 yuan/kWh over fossil fuel electricity, which implies an existing subsidy to the renewable electricity of about 8-13%. Therefore, in this study, we assume the pre-existing subsidy on wind and solar electricity to be 10%.

Table A7. Sources and values of dynamic module parameters

	Value	Method/Reference
Effective labor annual growth rate	Average level 3% /year	Calibrated
Autonomous energy efficiency improvement rate	0 for the energy production sectors 0.7% for other sectors	Duan *et al.* (2014)
Household saving rate	42% in 2020 and decreases to 32% in 2035 linearly	People's Bank of China (2021)
Government saving rate	15% and fixed over time	Calibrated
Factor productivity for wind and solar electricity	1-1.56 for wind and solar	IRENA (2019a, 2019b, 2020)

Appendix D. The significance of pre-existing taxes and policy stringency

To confirm the significance of pre-existing taxes for the relative cost of the TPS and C&T, we have performed counterfactual simulations in which there the magnitudes of pre-existing taxes on capital, labor, and intermediate inputs to production are different. As indicated in Table A8, the ratio of the TPS's cost to the cost under C&T is lower, the higher the level of pre-existing taxes.

Table A8. Ratios of TPS's Cost to C&T's Cost with Different Assumptions of the Extent of Pre-Existing Taxes in 2020-2035.

Pre-existing taxes	Ratios of TPS's Cost to C&T's Cost
0% of the central case	1.16
20% of the central case	1.15
40% of the central case	1.13
60% of the central case	1.12
80% of the central case	1.11
Central case	1.10
120% of the central case	1.09
140% of the central case	1.08
160% of the central case	1.07
180% of the central case	1.06
200% of the central case	1.05

Appendix E. Dynamics of potential transition from the TPS to C&T

In Section 6.1.2 we compared the costs of the TPS and an equally stringent C&T system when each policy is introduced in 2020 and maintained over the entire simulation interval. Here we consider a scenario in which the TPS converts to C&T at some future time. Such a transition is being contemplated by China's planners.

In the transition scenario, the system is a TPS system before 2028 and a C&T system since 2028. That is, the transition is completed in one year, and there is no transition period during which the TPS and C&T co-exist.[42]

Figure A11 shows the cost of the central case TPS, the central case C&T and the transition case. As Figure A11 shows, the transition case has a lower cost than the TPS and C&T since 2028. Its economic cost is lower than the TPS because of the absence of the implicit output subsidy. Its economic cost is lower than the C&T because of the differences in capital accumulation before the transition. Prior to the transition year, when the TPS system applies in the transition case, aggregate investment is higher than in the central C&T case. The higher investment reflects the TPS's implicit output subsidy, which implies lower prices of the more emission-intensive capital goods relative to the prices under C&T. As a result, during and after the transition, the economy's capital endowment is higher than in the same years under C&T in the central case. The higher capital endowment implies a lower rental price of capital, which in turn implies a lower cost of CO_2 abatement, as covered facilities can switch at a lower cost from carbon-based fuels to capital in production.

[42] In an alternative scenario, we assume the transition is more gradual, starting in 2028 and completed by 2030. The TPS and C&T are both in place in 2028 and 2029, and C&T is the only ETS starting in 2030. During the transition period, the free allowances allocated by TPS's benchmarks account for 2/3 and 1/3 of total free allowances in 2028 and 2029. This scenario yields similar results with the immediate transition case.

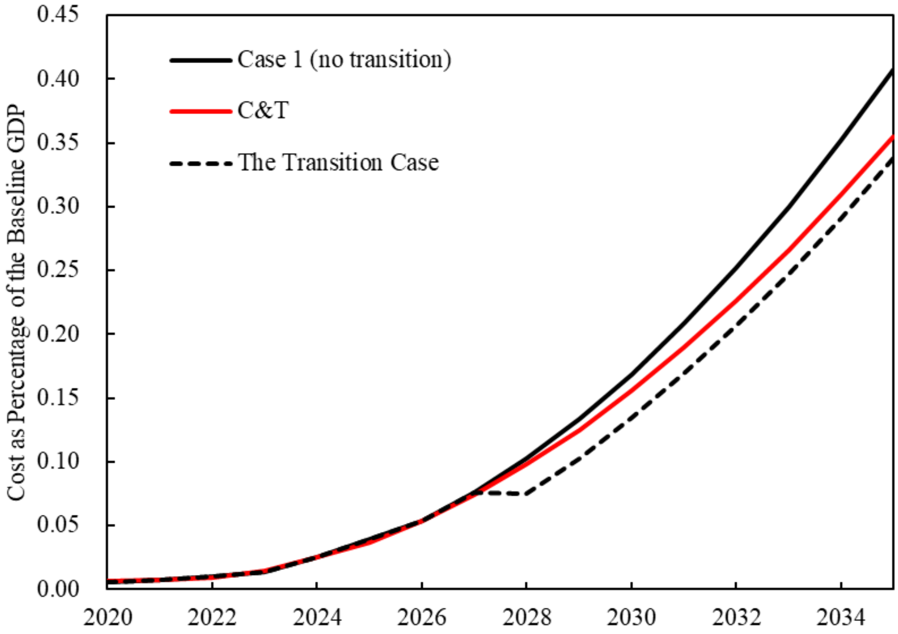


Figure A11. Economic Cost under Transition to a Full C&T System, 2020-2035

Appendix F. Data detail

Table A9. Import and export as ratios to sectors' total output

	Gross export to total output (%)	Gross import to total output (%)
Clothing	36	4
Electronic	36	23
Printing and	24	3
Log furniture	18	4
Textile	15	5
General equipment	15	16
Transport	14	6
Metal products	12	4
Other manufacturing	11	27
Daily chemicals	9	7
Aluminum	8	1
Raw chemicals	7	14
Transport equipment	7	17
Iron & steel	5	4
Other non-metal	5	2
Pulp & paper	4	6
Natural gas	4	21
Services	4	3
Food	3	4
Other non-ferrous	3	14
Petroleum refining	2	6
Mining	1	63
Agriculture	1	7
Coal	1	12
Crude oil	1	238
Construction	0	0
Cement	0	0
Electricity	0	0

Table A10. Emissions Intensity of Sectors

	Emissions Intensity (t/kRMB)
Cement[1]	1.940
Electricity	0.874
Heat	0.835
Aluminum	0.442
Iron & steel	0.235
Raw chemicals	0.092
Transport	0.062
Other non-metal products	0.058
Pulp & paper	0.051
Other non-ferrous metals	0.051
Petroleum refining	0.043
Crude oil	0.043
Water	0.038
Coal	0.028
Mining	0.016
Agriculture	0.011
Food	0.007
Textile	0.006
Natural gas	0.006
General equipment	0.004
Daily chemical products	0.003
Metal products	0.003
Other manufacturing	0.003
Construction	0.003
Gas manufacture & distribution	0.003
Log & furniture	0.002
Transport equipment	0.002
Clothing	0.001
Printing & stationery	0.001
Electronic equipment	0.001
Services	0.001

[1] Cement has a higher emissions intensity in value terms than that of electricity. However, it has not been covered by the TPS until the second phase, so their benchmarks are relatively less stringent than that of electricity. Also, it has a lower demand elasticity than electricity: electricity, as an energy input, can be more easily substituted through energy saving. Therefore, in section 6.1.3, the output quantity change of cement is less significant than electricity.

Appendix G. Methodology for calculating $PM_{2.5}$ concentrations and corresponding health co-benefits

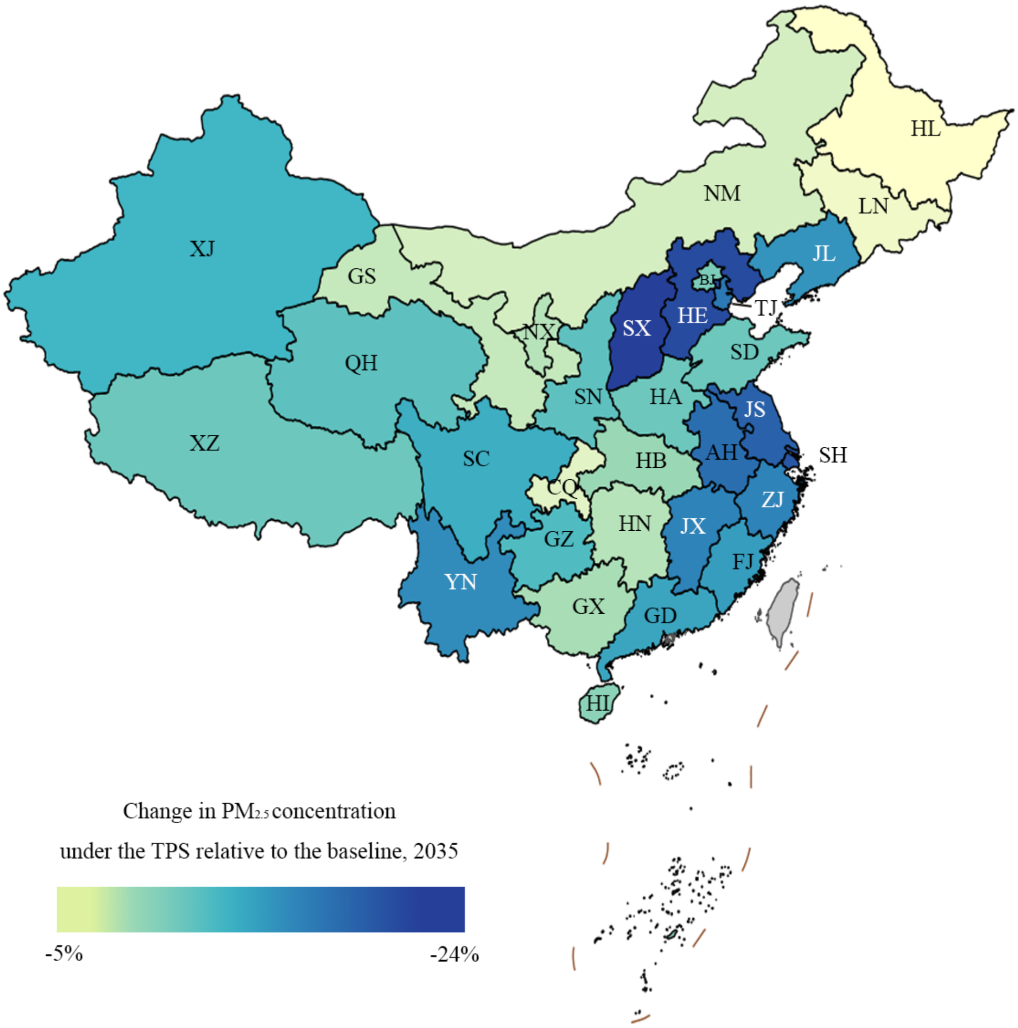
To calculate the health co-benefits from avoided pre-mature deaths, we apply an emission-inventory model (described in Zheng *et al.* (2019)), an air-quality model (Polynomial function-based Response Surface Model, pf-RSM, described in Xing *et al.* (2018)), and the Global Exposure Mortality Model (GEMM) developed by Burnett *et al.* (2018) to calculate $PM_{2.5}$-related pre-mature mortalities under the baseline and the TPS.

The emissions inventory model is the Air Benefit and Cost and Attainment Assessment System – Emission Inventory (ABaCAS-EI) model, which was jointly developed by the School of Environment at Tsinghua, the Southern China University of Technology, and the University of Tennessee. It is widely used in China's air quality research. It covers six major categories of anthropogenic emissions sources, each of which is further divided top-down into industry-level, fuel-level, and technology-level subsectors.

The air quality model is the Polynomial function-based Response Surface Model (Pf-RSM), which was developed by the School of Environment at Tsinghua. Pf-RSM combines mathematical and statistical methods and performs stable and rapid emissions concentration-response simulation.

To link the dynamic general equilibrium model to the air quality model, we first run the dynamic general equilibrium model to obtain the results for sectoral fuel consumption and sectoral outputs. These results are then multiplied by the pollutants emissions factors in the ABaCAS-EI emissions inventory to yield sectoral pollutant emissions at the provincial level.[43] The air pollutants we consider include SO_2, NOx, NH_3, non-methane volatile organic compounds (NMVOCs), and primary PM. Then, the provincial sectoral pollutant emissions are employed as inputs to the RSM model. Using these inputs, the RSM model simulates the local air pollution concentrations for each province. Changes in provincial $PM_{2.5}$ concentration in 2035 relative to the baseline are shown in Figure A12.

[43] We assume that over the interval 2020-2035, the spatial distribution of firms within an industry and the pollutant emission factors do not change.



Abbreviation:	AH	BJ	CQ	FJ	GS	GD	GX	GZ
Province:	Anhui	Beijing	Chongqing	Fujian	Gansu	Guangdong	Guangxi	Guizhou
HI	HE	HL	HA	HB	HN	JS	JX	JL
Hainan	Hebei	Heilongjiang	Henan	Hubei	Hunan	Jiangsu	Jiangxi	Jilin
LN	NM	NX	QH	SN	SD	SH	SX	SC
Liaoning	Inner Mongolia	Ningxia	Qinghai	Shaanxi	Shandong	Shanghai	Shanxi	Sichuan
TJ	XJ	XZ	YN	ZJ				
Tianjin	Xinjiang	Tibet	Yunnan	Zhejiang				

Figure A12. Change in $PM_{2.5}$ concentration under TPS relative to the baseline, 2035

We then use these concentration results to calculate the health-related benefits. We apply the up-to-date GEMM NCD+LRI method (Burnett *et al.*, 2018) to estimate avoided pre-mature death related to reductions in chronic exposure to outdoor fine particulate matter ($PM_{2.5}$) under different scenarios. This approach is adopted in many recent cost-benefit analyses. The GEMM

NCD+LRI quantifies the relationship between the hazard ratio (RR) and ambient $PM_{2.5}$ concentration (c) with the following equation:

$$RR(c) = \exp\left(\theta \times \frac{\ln\left(\frac{\max\left(0, c - c_f\right)}{\alpha} + 1 \right)}{1 + \exp\left(- \frac{\max\left(0, c - c_f\right) - \mu}{\nu} \right)} \right) \tag{A34}$$

where θ, α, μ, ν, and c_f are all shape parameters and are adopted from Burnett *et al.* (2018). Then, the avoided death can be calculated using Equation (A35) below.

$$\Delta \mathrm{M}_t = \sum_{m,p} M_m^B \times pop_{p,t} \times \left(\frac{1}{RR\left(c_{TPS,t}\right)} - \frac{1}{RR\left(c_{BS,t}\right)} \right) \tag{A35}$$

where $c_{\mathrm{BS,t}}$ and $c_{\mathrm{TPS,t}}$ are the $PM_{2.5}$ concentration under the baseline scenario and TPS policy case, in period t. The mortality rates with the lowest level of exposure to $PM_{2.5}$ for age group m in China, M_m^B, are retrieved from the Global Health Data Exchange. We follow the convention to divide the national population into 12 subgroups (adults with ages 25 to 85 and above in five-year intervals). $pop_{p,t}$ is the baseline provincial population projection period t and is sourced from Chen *et al.* (2020).

We also consider the uncertainties related to Equation (A34) by adopting the assumption that θ has a normal distribution following Burnett *et al.* (2014). We can then sample 1,000 points from the normal distribution and calculate the mean and 95% confidence interval of avoided death using Equation (A35). The results of avoided deaths are presented in Table A11. The total avoided pre-mature deaths during the period 2020-2035 is 2.2-2.4 million, or an average annual avoided death of 136,000-153,000.

Table A11. Average annual avoided deaths under the TPS by provinces, 2020-2035

Provinces	**Annual Avoided deaths under the TPS (1,000)** (95% confidence interval)	**Provinces**	**Annual Avoided deaths under the TPS (1,000)** (95% confidence interval)
Beijing	1.9	Hubei	6.6
	(1.8, 2)		(6.2, 6.9)
Tianjin	2	Hunan	6.2
	(1.9, 2.1)		(5.8, 6.5)
Hebei	10.8	Guangdong	11.2
	(10.3, 11.3)		(10.4, 11.8)
Shanxi	5.4	Guangxi	5.4
	(5.1, 5.7)		(5.1, 5.7)
Inner Mongolia	1.5	Hainan	0.6
	(1.4, 1.6)		(0.6, 0.6)
Liaoning	5	Chongqing	2.3
	(4.7, 5.3)		(2.2, 2.4)
Jilin	1.8	Sichuan	7.3
	(1.7, 1.9)		(6.9, 7.7)
Heilongjiang	0.8	Guizhou	1.9
	(0.8, 0.9)		(1.7, 2)
Shanghai	2.8	Yunnan	3.1
	(2.7, 3)		(2.9, 3.2)
Jiangsu	9.6	Xizang	0.1
	(9.1, 10.2)		(0.1, 0.1)
Zhejiang	5.5	Shaanxi	4
	(5.1, 5.8)		(3.8, 4.2)
Anhui	6.7	Gansu	1.7
	(6.3, 7.1)		(1.6, 1.8)
Fujian	3.6	Qinghai	0.3
	(3.4, 3.8)		(0.3, 0.4)
Jiangxi	5.1	Ningxia	0.4
	(4.8, 5.4)		(0.4, 0.4)
Shandong	12.8	Xinjiang	1.7
	(12.1, 13.4)		(1.6, 1.7)
Henan	14.6		
	(13.8, 15.3)		

Appendix H. Estimation of the geographical distribution of cost-impacts

For the geographic distributional impacts, we use the following method. Let INC_{ikp} be the income of sector *i* subsector *k* in province *p*, and INC_p be the income of all sectors in province *p*.

$$INC_p = \sum_{ik} INC_{ik} \frac{INC_{ikp}}{INC_{ik}} \tag{A36}$$

In Equation (A36), the term $\frac{INC_{ikp}}{INC_{ik}}$ represents the share of the income from sector *i* subsector *k* in province *p* in the national income from sector *i* subsector *k* in province *p*. We assume these shares are the same and remain at the base year's level for all years and in all scenarios. $\frac{INC_{ikp}}{INC_{ik}}$ in the base year can be calculated from the provincial input-output tables and the firm-level MEE data as we described in section 4.1.

Let ΔINC_P be the change of income of province p, then

$$\Delta INC_p = \sum_{ik} \Delta INC_{ik} \frac{INC_{ikp}}{INC_{ik}} \tag{A37}$$

Equation (A37) is used to calculate the absolute change of the provincial income presented in Table 6, section 6.4. The percentage change can then be calculated by $\frac{\Delta INC_p}{INC_p}$.

Appendix References

Aguiar, A., Chepeliev, M., Corong, E., & van der Mensbrugghe, D. (2019). The GTAP Data Base: Version 10. *Journal of Global Economic Analysis*, *4*(1), 1–27.

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C. A., Apte, J. S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S. S., Kan, H., Walker, K. D., Thurston, G. D., Hayes, R. B., … Spadaro, J. V. (2018). Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences*, *115*(38), 9592–9597.

Burnett, R. T., Pope III, C. A., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., Shin, H. H., Singh, G., Hubbell, B., Brauer, M., & others. (2014). An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental Health Perspectives*, *122*(4), 397–403.

Cassisa, C., Chen, X., & Zhang, D. (2021). *The Role of China's ETS in Power Sector Decarbonisation* (p. 86). IEA.

Chen, Y., Guo, F., Wang, J., Cai, W., Wang, C., & Wang, K. (2020). Provincial and gridded population projection for China under shared socioeconomic pathways from 2010 to 2100. *Scientific Data*, *7*(1), 83.

Chen, Y.-H. H., Paltsev, S., Reilly, J. M., & Karplus, V. (2017). *The MIT Economic Projection and Policy Analysis (EPPA) Model: Version 5* (Joint Program Technical Note TN #16, p. 32p).

Cossa, P. F. (2004). *Uncertainty analysis of the cost of climate policies* [PhD Thesis]. Massachusetts Institute of Technology.

Duan, H.-B., Zhu, L., & Fan, Y. (2014). Optimal carbon taxes in carbon-constrained China: A logistic-induced energy economic hybrid model. *Energy*, *69*, 345–356.

Herd, R. (2020). *Estimating Capital Formation and Capital Stock by Economic Sector in China: The Implications for Productivity Growth*. World Bank, Washington, DC.

Hertel, T., Hummels, D., Ivanic, M., & Keeney, R. (2007). How confident can we be of CGE-based assessments of Free Trade Agreements? *Economic Modelling*, *24*(4), 611–635.

Hertel, T., & van der Mensbrugghe, D. (2019). Chapter 14: Behavioral Parameters (Center for Global Trade Analysis). *Purdue University, West Lafayette, IN: Global Trade Analysis Project (GTAP).*

Hirth, L., Ueckerdt, F., & Edenhofer, O. (2015). Integration costs revisited – An economic framework for wind and solar variability. *Renewable Energy*, *74*, 925–939.

Holz, C. A., & Sun, Y. (2018). Physical capital estimates for China's provinces, 1952–2015 and beyond. *China Economic Review*, *51*, 342–357.

National Energy Administration.(2018). *2017 Regulatory report on national electricity pricing*.

IAEA. (2018). *Economic Assessment of the Long Term Operation of Nuclear Power Plants: Approaches and Experience*.

IRENA. (2019a). *Future of Solar Photovoltaic: Deployment, investment, technology, grid integration and socio-economic aspects* (A Global Energy Transformation: Paper). International Renewable Energy Agency.

IRENA. (2019b). *Future of wind: Deployment, investment, technology, grid integration and socio-economic aspects* (A Global Energy Transformation: Paper). International Renewable Energy Agency.

IRENA. (2020). *Renewable Power Generation Costs in 2019* (p. 144). International Renewable Energy Agency.

Jomini, P., Zeitsch, J. F., McDougall, R., Welsh, A., Brown, S., Hambley, J., & Kelly, J. (1991).

SALTER: A General Equilibrium Model of the World Economy, vol. 1, Model Structure. *Database and Parameters, Industry Commission, Canberra*.

Lu, M., Zhu, R., & Lu, W. (2015). Optimization of material structure in converter steelmaking. *Chinese Journal of Engineering*, *S1*, 70–73.

The State Information Center. *Medium and long-term goals, strategies, and paths of China's economic and social development.* (2020).

People's Bank of China (PBC). (2021). *Research on the calculation of China's potential output and growth momentum during the 14th Five Year Plan Period*. No.2021/1 PBC Working Paper.

Rausch, S., & Zhang, D. (2018). Capturing natural resource heterogeneity in top-down energy-economic equilibrium models. *Energy Economics*, *74*, 917–926.

Ross, M. T. (2014). *Structure of the Dynamic Integrated Economy/Energy/Emissions Model: Computable General Equilbrium Component, DIEM-CGE.* (NI WP 14-12).

RTI International. (2015). *The Applied Dynamic Analysis of the Global Economy (RTI ADAGE) model* (U.S. Regional Module Final Release). RTI International.

Rutherford, T.F. (1998). *CES preferences and technology. GAMS MPSGE Guide. GAMS Development Corporation, Washington, pp. 89–115.* _

Święcki, T. (2017). Determinants of structural change. *Review of Economic Dynamics*, *24*, 95–131.

Tu, Q., Betz, R., Mo, J., Fan, Y., & Liu, Y. (2019). Achieving grid parity of wind power in China – Present levelized cost of electricity and future evolution. *Applied Energy*, *250*, 1053–1064.

Xing, J., Ding, D., Wang, S., Zhao, B., Jang, C., Wu, W., Zhang, F., Zhu, Y., & Hao, J. (2018). Quantification of the enhanced effectiveness of control from simultaneous reductions of VOC and NH3 for reducing air pollution in the Beijing–Tianjin–Hebei region, China. *Atmospheric Chemistry and Physics*, *18*(11), Article 11.

Zhang, D., Rausch, S., Karplus, V. J., & Zhang, X. (2013). Quantifying regional economic impacts of CO2 intensity targets in China. *Energy Economics*, *40*, 687–701.

Zhang, H., Zhang, D., & Zhang, X. (2023). The role of output-based emission trading system in the decarbonization of China's power sector. *Renewable and Sustainable Energy Reviews*, *173*, 113080.

Zhang, L., Du, Q., & Zhou, D. (2021). Grid Parity Analysis of China's Centralized Photovoltaic Generation under Multiple Uncertainties. *Energies*, *14*(7), 1814.

Zhang, M. L., Brooks, M. R., Ding, D., Ding, H., He, H., Lu, J., & Mano, R. (2018). *China's high savings: Drivers, prospects, and policies*. International Monetary Fund.

Zheng, H., Zhao, B., Wang, S., Wang, T., Ding, D., Chang, X., Liu, K., Xing, J., Dong, Z., Aunan, K., Liu, T., Wu, X., Zhang, S., & Wu, Y. (2019). Transition in source contributions of PM2.5 exposure and associated premature mortality in China during 2005–2015. *Environment International*, *132*, 105111.