Hongbo Duan, Jianlei Mo, Ying Fan, Shouyang Wang

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Achieving China's energy and climate policy targets in 2030 under multiple uncertainties

Hongbo Duan[1], Jianlei Mo[2,3*], Ying Fan[4], Shouyang Wang[1,5]

[1] School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China.

[2] Center for Energy and Environmental Policy research, Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China.

[3] Grantham Research Institute for Climate Change and the Environment, London School of Economics and Political Science, Houghton Street, London, U.K. WC2A 2AE.

[4] School of Economics and Management, Beihang University, Beijing 100191, China.

[5] Academy of Mathematics and System Science, Chinese Academy of Sciences, Beijing 100190, China.

[*] Corresponding author. E-mail: mo_jianlei@126.com, mojianlei@casipm.ac.cn

Abstract

The stringency of China's energy and climate targets in 2030 and the policy needed to realize these targets are full of controversy, mainly as a result of multiple future uncertainties. This study has developed a stochastic energy-economy-environment integrated model, to assess China's energy and climate targets in 2030, with a particular focus on the carbon intensity reduction, carbon emission peaking, and non-fossil energy development. The probabilities of realizing the targets are obtained, and the nexus among different targets is explored. It's argued that carbon emission management and policy-making should be implemented from the perspective of risk management, and policy makers can take corresponding policy measures based on the degree of confidence required under multiple future uncertainties. It is found that the probabilities of realizing carbon emission-peaking target and non-fossil energy target are low, with the business-as-usual efforts, and additional policies may still be needed. More specific, carbon pricing plays a major role in curbing and peaking carbon emissions, while the policy mix of carbon pricing and non-fossil energy subsidies can peak the carbon emission with relatively low cost compared to the single carbon pricing policy. It is also found that the carbon intensity reduction target is most likely to be attained, followed by the carbon-peaking target, and then the non-fossil energy target, given the same policy efforts. This indicates that, China may not deliberately increase carbon emissions rapidly over the next decade to make the carbon emission peak as high as possible; otherwise, it may be difficult to achieve the non-fossil energy target.

Key words: Integrated assessment model; Uncertainty; INDC target; China; Carbon emission peaking; Carbon pricing; Renewable energy subsidy

1 Introduction

With the Paris Agreement in force, the focus of the global response to climate change shifts to the implementation and credibility of the Paris pledges. As the world's largest greenhouse gas (GHG) emitter, China plays a critical and formidable role in reducing GHGs and in coping with global climate change. Especially against the background that the US administration has decided to withdraw from the Paris agreement, what China does next, and how, will have significant implications for the trend and direction of the global response to climate change. According to the U.S.-China Joint Announcement on Climate Change in 2014[1], China is committed to peaking its carbon emissions in 2030, at which time the share of non-fossil energy in China will reach over 20%; China's Intended Nationally Determined Contributions (INDC) plan, which was submitted to the United Nations in 2015, reaffirms this commitment and proposed the 60-65% carbon intensity reduction target. Although plenty of work has been done to prove the rationality and feasibility of these targets for economic development and energy consumption, as well as for energy restructuring, there remain different opinions on the commitments at home and abroad. Some argue that these targets are pretty ambitious, and that China has to deal with very daunting challenges (He, 2013; Elzen etal. 2016), while others believe that the goals committed to may not be so difficult to reach, costing less than expected (CERS, 2016; Green and Stern, 2016). In addition, as China has no absolute target of carbon emission before 2030, some even suspect that China may deliberately increase its carbon emission over the next decade in order to make the 2030 peak as high as possible (Malakoff, 2014). It is likely that the multiple uncertainties embedded in the process of carbon mitigation are largely responsible for this divergence of opinion. There remain around 15 years for China to deliver on its commitments, during which time a great many uncertainties involving economic growth, energy efficiency enhancement and low-carbon transition, etc., will commingle and significantly affect the feasibility, policy options and costs of fulfilling the goals, and make judgments about future carbon emission projections and energy transition trends complicated and difficult (Webster et al., 2002; Babonneau et al., 2012; Kriegler et al., 2014).

Several studies have discussed the trends of energy consumption and CO_2 emissions in China

[1]https://obamawhitehouse.archives.gov/the-press-office/2014/11/11/us-china-joint-announcement-climate-change.

(ERI, 2009; Wang and Watson, 2010; Zhou et al., 2013; BP, 2016). The summarized results reveal that, without any policy intervention, China's carbon emissions will continue increasing until 2050, with emission amounts ranging from 11.9 to 16.2 $GtCO_2$; this amount may decrease and fall into the interval of 4.3-9.5 $GtCO_2$ when certain decarbonization policies are carried out. Further, it would be difficult for China to peak its CO_2 emissions before 2040 under the business-as-usual case; only via policy can China deliver on its carbon-peaking goal by or before 2030, depending on the stringency of policy implementations. Actually, across different studies the pricing interval of CO_2 emissions to peak China's carbon emissions on schedule appears to be wide, ranging from 100 to 500 USD/tC, and the corresponding peak values differ even more significantly, from 6 to 13 $GtCO_2$. It is easy to observe that big divergences exist among the carbon emission projections from different research, which could be largely explained by the future uncertainties involving the economic growth, the energy intensity of the economy, and the carbon intensity of energy consumption (Kaya, 1990; Webster et al., 2002; Webster et al., 2008; Peters et al., 2013; Lewandowsky et al., 2014; Golub, 2014).

Although some previous research works have explored China's energy and carbon emission projections in the medium and long term future (ERI, 2009; Wang and Watson, 2010; Zhou et al., 2013; He, 2013; BP, 2016; Elzen etal. 2016; Liu et al., 2017), there are few quantitative studies explicitly focusing on the multiple uncertainties affecting China's energy consumption and carbon emission. In addition, there are three main targets in China's INDC pledge, involving the carbon intensity reduction, carbon emission peaking and non-fossil energy share. Under multiple uncertainties, it may be difficult to determine the relationship among different targets and coordinate the three targets and the corresponding policy measures, which has been rarely explored. In this work, the key uncertainties affecting China's future energy consumption and carbon emissions are identified, including the economic uncertainties and technological uncertainties, based on which a stochastic version of China energy-economy-environment (3E) system model were developed. Using this model, China's energy and climate targets in 2030 under multiple uncertainties were assessed, especially focusing on the impacts of relevant policies, i.e. carbon pricing and renewable energy subsidy, on the time distribution of carbon emission peaking, distribution of peaking levels and the non-fossil energy share. The probabilities of realizing these targets under different policy scenarios are obtained, and specifically, the nexus among different policy targets are explored.

2 Model and methods

The proposed stochastic 3E-integrated model in this work is essentially based on the prior 3E system model, CE3METL, a Chinese version of the E3METL model (Duan et al., 2013; Duan et al., 2014). Characterized by its core technology diffusion mechanism, i.e., multi-logistic curves instead of the conventional constant elasticity substitution (CES) method, the E3METL model consists of macro economy, energy technology and climate sub-modules, which is consistent with the typical frameworks of 3E-integrated models (Nordhaus, 2007). The E3METL and CE3METL models have been employed to conduct energy and climate-relevant research since they were built in 2013 (Duan et al., 2015; Duan et al., 2016). By incorporating multiple uncertainties and employing Monte Carlo simulation methods (Babonneau et al., 2012; Hu et al., 2012), we have extended the framework of the CE3METL model and developed a stochastic 3E-integrated model, the skeleton of which is depicted in Fig. 1; furthermore, we give the corresponding optimum algorithm of this large-scale system model, based on the GAMS software platform. For convenience of understanding the proposed stochastic model, we first briefly introduce the CE3METL model, from both model structure and running rationales, and then the randomization of the model.

[INSERT Fig. 1 HERE]

2.1 Description of the CE3METL model

We assume that the central planner of CE3METL has perfect-foresight expectations, taking the maximum social utility (welfare) as its target. This social welfare is accumulated by the increase of intertemporal consumption per capita; the welfare-maximization goal is therefore governed by the dynamic consumption flows and the population evolution. Further, the intergenerational distribution of utility is contingent on the pure time preference rate and the marginal consumption elasticity, which determine the depreciation factor of utility accumulation as well (Duan et al., 2013; Duan et al., 2014). Specifically, given L_t and c_t the population as well as labor input and consumption per capita in t respectively, and σ_t the discount factor, then the utility objective can be expressed as follows,

$$U = Max \sum\nolimits_{t \epsilon T} \left(L_t log(c_t) \prod\nolimits_{\tau=0}^{t} (1+\sigma_\tau)^{-\Delta t} \right) \quad (1)$$

Aggregated production or gross output Y is produced with a single CES production function in capital (*K*)-labor (*L*) complex and energy (*E*), with capital and labor combined via Cobb-Douglas (CD) function, i.e.,

$$Output_t = \left(\alpha_t \left(K_t^{\eta} L_t^{1-\eta} \right)^{\rho} + \beta_t E_t^{\rho} \right)^{\frac{1}{\rho}} \quad (2)$$

where α_t is the technological progress level for the capital-labor composite, and β_t covers the technological progress level of the energy sector.

Like other 3E-integrated models, we view the output as a single complex commodity that is allocated to investment, consumption, ex- and imports and payment for energy input and carbon reduction (Duan et al., 2013; Duan et al., 2016). As for inputs, population is assumed to grow exogenously over time, while the capital stock is determined by optimizing the dynamic consumption flows; furthermore, energy input is made up of two parts: conventional energy (fossil fuels) and non-fossil energy, of which the fossil fuels consist of coal, oil and natural gas, while non-fossil technologies involve biomass, hydropower, nuclear, wind power, solar power, tide and geothermal power.

The economy-wide technological change and energy efficiency improvement depend on the exogenous autonomous energy efficiency improvement (AEEI). Closure conditions are indispensable to a regional 3E-integrated model, which could effectively avoid unreasonable economy fluctuation due to imperfect market closure (Kumbaroğlu et al., 2008). In the CE3METL model, we assume the ex- and imports dynamically follow the optimal trajectory of GDP growth, and this is achieved by introducing a lower bound and an upper bound, respectively, for the changes of ex- and imports.

The CE3METL model features a multi-technology evolution mechanism and an endogenous technological improvement mechanism. As compared to the CES method, which is commonly used to describe technology replacement, we have introduced multi-logistic curves into the CE3METL model instead, which greatly enrich the technology details of 3E model frameworks. According to the multi-logistic technology mechanism, market share of the targeted technology is contingent on changes in the relative cost (cost ratio of the target technology and the marker technology) and policy intervention effects. In specific terms, let $P_{i,t}$ denote the ratio of the price of the marker technology (e.g. coal) to that of the new technology i, including the effects of carbon pricing and subsidies on prices. That is,

$$P_{i,t} = \frac{C_{coal,t}\left(1 + Tax_{coal,t}\right)}{C_{i,t}\left(1 + Sub_{i,t}\right)} \tag{3}$$

where $C_{coal,t}$ and $C_{i,t}$ denote the unit costs of the marker technology and alternative technology i; $Tax_{coal,t}$ and $Sub_{i,t}$ present the rate of carbon price for the marker technology and subsidy for alternative i, respectively.

We then get the relationship between technology share $S_{i,t}$ and $P_{i,t}$ by revising the classical logistic model; specifically, the rate of change in market share is expressed with respect to the change in relative prices rather than the change in time, which provides greater economic appeal to us. The term $\mathrm{d}S_{i,t}/\mathrm{d}P_{i,t}$ is shown to indicate the effects of a per unit change in prices on the share of the new technology in use. Hence, we have

$$\frac{\mathrm{d}S_{i,t}}{\mathrm{d}P_{i,t}} = a_i S_{i,t}\left(\tilde{S}_i\left(1 - \sum\nolimits_{j \neq i} S_{j,t}\right) - S_{i,t}\right) \tag{4}$$

which captures the exponential growth of opportunities in the early phases of expansion and diminishing possibilities as market saturation levels are approached. In this way, the technical cost and incentive policy, which are considered to play an important role in affecting the technological development, are embedded in the technical diffusion process (see detail in Appendix A).

The other technology characteristic, i.e., the endogenous technological improvement mechanism, mainly refers to the one-factor learning curve, i.e. learning-by-doing (LBD). Generally, define $C_{k,t}$ and $KD_{k,t}$ the unit cost for alternative technology i and knowledge capital stock, respectively; we then get the relationship between cost evolution and the LBD process,

$$C_{k,t} = C_{k,0}\left(\frac{KD_{k,t}}{KD_{k,0}}\right)^{-b_k} \tag{5}$$

in which $C_{k,0}$ and $KD_{k,0}$ represent the initial technology cost and knowledge capital, and b_k is the learning index (Appendix A for details). As production proceeds, the production experience (or knowledge) accumulates, which in turn promotes technological change and finally reduces technology costs. It is worth noting that a depreciation effect should be taken into account when accumulating knowledge capital intertemporally due to experience obsolescence; thus, the current knowledge stock is the sum of the vintage and the net knowledge stock in the previous period. The learning rate is the core parameter describing the learning effect in the process of technology diffusion, which refers to the ratio of cost reduction when output (or cumulative installed capacity) doubles (Barreto and Kaassen, 2004).

Unlike the global 3E system model, in which climate system dynamics such as the carbon cycle, the dynamics of radiative forcing flows, warming responses and climate damages are well described, we simplify the climate module of the regional CE3METL model. Specifically, the emphasis of climate modeling is placed on the estimation of anthropogenic CO_2 emissions, and it amounts to the sum of the products of the carbon content of all types of carbon-based energy and the corresponding energy consumption. For more model details, please refer to the equations listed in Appendix A.

2.2 Randomization of the model

There are many uncertain factors influencing the future evolution of the energy-economy-environment (3E) system (Kaya, 1990; Webster et al., 2002; Webster et al., 2008; Peters et al., 2013; Lewandowsky et al., 2014; Golub, 2014). The economy is one of the major parts of the 3E system, directly influencing future energy consumption and carbon emissions; economic uncertainty is, therefore, an important aspect of climate-related research (Kriegler et al., 2014). In most 3E models, economic growth is derived from the growth of production factors (labor, capital, energy) and from the technical progress associated with each factor. Among them, the most important factors are the growth of the labor force and the evolution of labor productivity, according to many existing relevant studies (Webster et al., 2002; Babonneau et al., 2012; Webster et al., 2008; Duan et al., 2014). The population growth of China has long been stabilizing due to family planning (World Bank, 2012), and this trend is not likely to change much despite the recent change to the one-child policy (Zeng, 2016; Wang et al., 2016). Considering this, we overlook the uncertainty in population growth, assuming it increases exogenously based on the World Bank's recent projection, and the uncertainty involving the labor productivity growth (LPG) is taken into account in our study. Moreover, energy efficiency improvement plays a key role in lowering energy intensity and carbon emission (Grubb, 2002; Babonneau et al., 2012; Duan et al., 2014), and future projections for China are full of uncertainty. So this uncertainty, represented by the autonomous energy efficiency improvement (AEEI), is taken into account following many relevant studies (Webster et al., 2002; Gerlagh et al., 2004; Webster et al., 2008; Babonneau et al., 2012). Besides the AEEI, the substitution between the energy and other input factors also has a significant effect on future energy consumption, as well as the flexibility of economic production, and the uncertainty of elasticity between energy and capital-labor combination is also considered (Webster et al., 2002; Babonneau et al., 2012). The future carbon intensity of energy consumption is closely related to the energy structure evolution, especially the development of non-fossil energy. The long-term diffusion of the non-fossil energy is affected mostly by the cost competiveness relative to the fossil fuels, which in turn closely relates to the learning rates and the potential of cost reduction in future. Generally, the learning rates vary over time as the stages of technology change; meanwhile, their variation ranges are fairly large, and differences in power plants' geographic locations and scales will also lead to different learning rates (Rout et al., 2009). In our study, the learning rate uncertainties of seven non-fossil energy technologies, i.e. wind, solar, hydro, biomass, geothermal, tides, and nuclear, are incorporated.

In this work, the uncertainties referred above are grouped into two categories, i.e. economic uncertainty and technological uncertainty, of which the former involves labor productivity growth (LPG), elasticity of substitution between the capital-labor complex and energy and AEEI, while the latter is essentially the uncertainty related to the technology learning effect. Different assumptions are made regarding the probability distributions and evolutionary trends of different uncertainty factors based on the relevant studies, and the sampling procedures are achieved by employing a large-scale Monte Carlo simulation method. Generally, cutting down the sample size is beneficial for simplifying the computation and optimization; on the other hand, a large sample is required to better fit the assumed distribution function. In order to cope with this contradiction, we use the Latin hypercube technique to generate 2000 set of values for the chosen uncertain parameters. For each set of parameters sampled, they are treated as the average of the parameters in the whole time herizon and held fixed throughout the whole simulation period as we run the model to get the optimal path.

1) LPG, elasticity and AEEI uncertainty

For LPG uncertainty, we first calibrate the LPG level under the deterministic BAU scenario, in which economic growth and energy demand fit future expert expectations well (see the detailed BAU results in the Appendix B); then, we assume a bounded normal distribution, normalized to a mean of 1.0 and a standard deviation of 0.3 and use the positive sampled value as a multiplicative factor, following Babonneau et al.(2012) and Webster et al. (2008); finally, the product of the multiplicative factor in conjunction with the LPG in the deterministic case is employed to portray the LPG uncertainty. The frequency distribution and probability density of the multiplicative factor for LPG are shown in Fig. 2.

Based on the characteristic of the production function of the CE3METL model, our emphasis is placed on the uncertainty analysis of substitution elasticity between the capital-labor combination and the energy input. Similar to Webster et al. (2008) and Babonneau et al. (2012), we first calibrate this elasticity in the deterministic BAU scenario (see the detailed BAU results in the Appendix B); then, a normal distribution, being normalized to a mean of 1.0 and a standard deviation of 0.3, is assumed, and we regard the positive sampled value as a multiplicative factor. The uncertainty on this elasticity of substitution is now measured by the product of the multiplicative factor and the substitution elasticity calibrated in the deterministic BAU scenario (see Fig. 2).

The energy efficiency improvement in the CE3METL model is given exogenously by the AEEI coefficient, which is consistent with other typical 3E-integrated models, such as DICE, DEMETER and GEMINI-E3 (Gerlagh and van der Zwaan, 2004; Babonneau et al., 2012). Generally, the AEEI covers the entire energy efficiency enhancement that is independent of economy-related and energy market factors, and it proves to greatly affect the trajectories of energy consumption and CO_2 emissions (Duan et al., 2014). Similar to the uncertainty processing of LPG and substitution elasticity, the first step is to calibrate the AEEI level under the deterministic BAU scenario (see the detailed BAU results in the Appendix B); then, we assume a normal distribution, normalized to a mean of 1.0 and with a standard deviation equal to 0.3, which is also in line with the prior assumptions on LPG and elasticity of substitution. Finally, with the sampled value of the random variable as a multiplicative factor (Fig. 2), the AEEI uncertainty is then measured by the product of the multiplicative factor and the calibrated AEEI value.

[INSERT Fig. 2 HERE]

2) Energy technology learning uncertainty

In recent years, the learning curve method has been frequently used to portray the evolutionary trends of technology costs (Weiss et al., 2010). Generally, the learning curves feature a simple form and convenient application; besides, it is a feasible option for us to incorporate the inherent learning effect of technology change, which contributes more to fitting the real cost trends. However, the learning curve method is highly dependent on data quality, while the data available for most of the alternative technologies are usually of lower quality in the present, which may increase errors when estimating the learning parameters and, to some extent, further reduce the reliability of this method (Alberth, 2008). Actually, the uncertainty on learning rates not only directly influences the technology cost trends and market diffusion, but negatively affects the entire technology development environment, which in turn interferes with the estimation of technology floor costs and policy-making for technology deployment (McDonald and Schrattenholzer, 2001; Rout et al., 2009). The above considerations indicate the great importance of incorporating the uncertainty of the learning effect into our model.

There have been several works estimating and reviewing the learning rates of various alternative technologies. McDonald & Schrattenholzer (2001) estimate learning rates of both fossil and non-fossil technologies across regions, Di et al. (2012) discuss the learning effect of wind power in China, while Rout et al. (2009) review intervals of learning rates for biomass, wind, nuclear and solar PV etc., and Rubin et al. (2015) systematically report the one-factor and two-factor learning rates of electricity supply technologies. By combining these data sources, we obtain the interval boundaries of learning rates for all the considered alternatives, as given in Table 1. On this basis, we assume all the learning rates follow a uniform distribution (Rout et al. 2009; Babonneau et al., 2012), and the ensemble of scenarios is generated via the Latin hypercube sampling method.

[INSERT Table 1 HERE]

To further check how the uncertain factors affect our results, we make a sensitivity analysis of the key indexes, e.g. GDP, energy consumption, carbon emission and renewable energy development, to the uncertain parameters, which can be found in the Appendix C.[2]

[2] In the current work, the twelve parameters are combined together and assumed to be uncorrelated for simplicity. In fact, there may exist complex correlation between these parameters, positive or negative, which may affect the non-fossil energy development and carbon abatement path and the relevant policy making. This issue can be further explored in future work.

3 Policy scenario setting

During the past few years, many command-and-control policy instruments have been adopted by the Chinese government to realize its energy saving targets, e.g. raising the entry threshold of energy efficiency in the energy-intensive sectors, developing large units and suppressing small ones, closing outdated capacity, compulsory purchase of energy-efficient products, etc. Although great achievements have been made in reducing energy intensity and greenhouse gas emissions, China has also paid a giant cost (Lo, 2012). Given this experience, China is becoming more interested in market-based instruments for GHGs control. In addition, the Chinese government has been committed to further market-oriented reform since 2013, allowing the market to play a more important role in the allocation of resources. In this situation, market-based policy instruments have been increasingly employed in the practice of combating climate change, e.g., carbon pricing policy and subsidies for renewable energy (Zhang et al., 2013; Cui et al., 2014; Wu et al., 2016; Mo et al., 2016). In this circumstance, the carbon pricing is adopted as one of main policy instruments in our study. Besides, the alternative subsidy policy is also taken into account, as the feed-in tariff (FIT) policy, adopted during the 12th Five-Year Plan (2011-2015), plays an important role in promoting China's renewable energy development.

Based on the discussion above, two sets of scenarios have been formulated: the business-as-usual (BAU) scenario, and the policy scenarios, including the single carbon pricing policy, the single subsidy policy for renewable energy, and the policy combination of carbon pricing and renewable energy subsidies. In the BAU scenario, the policy measures aimed at improving energy efficiency during 12th Five-Year Plan (2011-2015) are incorporated through setting the exogenous initial AEEI, which means that energy intensity would continue decreasing in this scenario, but the potential of energy efficiency improvement may become limited over time with the opportunities being explored (Wang et al., 2014) by setting a positive decline rate of AEEI, given that China has made a great effort and progress on deployment of energy-saving technology during the past decade. For the policy scenarios, we set different levels of the carbon price and subsidy. Economic theory and previous study suggest that optimal carbon prices may increase over time, with the annual average growth rate approaching the discount rate (Duan et al., 2013; Duan et al., 2014; Duan et al., 2016); hence the increasing carbon price is adopted in our scenario setting, and the corresponding increasing rate is assumed to be 5%. The current average carbon price in China's pilot carbon markets is about 30 USD/tC and it's expected to increase, with the climate policy becoming more stringent in future; on this basis, the lower bound of the initial carbon price is set as 30 USD/tC, and the other two higher levels are assumed to be 60 USD/tC and 90 USD/tC, respectively. In addition, the current subsidy rate for renewable energy (mainly in the form of FIT) in China mainly falls between 20% and 30% based on the development stage of different technologies, and it may decrease as the renewable energy costs become lower. Accordingly, the subsidy rate levels are set as 0, 20% and 30%, respectively.

Thus, we can obtain 12 (3×4) simulation scenarios, including the BAU. The details of the policy scenarios are shown in Table 2. Our model starts running in 2010 and terminates in 2070, with 12 five-year periods; in the policy scenarios, carbon prices or subsidies or the policy mix of both, are introduced from 2015. In order to avoid the end of period effects, we report the simulation results from 2015 to 2050, as many relevant studies have done.

[INSERT Table 2 HERE]

4 Results

We first calibrate our model in the BAU scenario, and the detailed results can be found in the Appendix B. The main results in the policy scenarios are presented as follow.

4.1 Carbon emission peak

As shown in Fig. 3, in the BAU scenario with carbon mitigation efforts made during the 12th Five-Year Plan (2011-2015), the probability for carbon emissions to peak before 2030 is low, only about 14.5%, and it does not reach 50% until 2040. This means that it seems unlikely for China to realize its carbon-peaking target in or before 2030 without making further efforts. With the carbon price and subsidy increasing, the distribution of the time for carbon emissions to peak moves to the left, and the peaking time becomes earlier. Specifically, with a subsidy of 30% being introduced, carbon emissions mainly peak between 2035 and 2040, and the probabilities are 26.5% and 28.7%, respectively; when moving to the single carbon tax of 90 USD/tC, the carbon emissions mainly peak in 2030, 2035 and 2040, with probabilities of 21.2%, 31.0% and 23.9%, respectively (Fig. 3 (a)). It follows that the carbon pricing policy has a more significant effect on carbon emissions than does the subsidy policy. Specifically, the probability of carbon emission peaking before 2030 is 39.7% with a carbon price of 90USD/tC, while this probability is only 25.4% with the subsidy of 30% being implemented (Fig. 3 (c)). In addition, the results show that the single carbon pricing or subsidy policy cannot guarantee that carbon emissions will peak before 2030 with a high probability, i.e. 50%, and some mix policies may therefore be indispensable. More specifically, with the policy mix of a carbon price of 30 USD/tC and 30% subsidy (T30S30), the probability to peak China's carbon emission before 2030 can reach more than 40%, and with that of carbon price of 60 USD/tC and 30% subsidy, or that of 90 USD/tC and 20% subsidy, the probability can reach more than 50%, i.e. 54.8% and 54.1% respectively (Fig. 3 (c)). Under the policy mix scenarios, e.g. the T30S30 scenario and T60S20 scenario, some curves almost overlap with each other (Fig. 3 (b)), which means that different combination policies may have more or less the same effect on peaking carbon emissions. Under the most stringent policy scenario (T90S30), carbon emissions would peak before 2030 with a high probability of 66.2% (Fig. 3 (d)). In summary, carbon emission management and policy-making should be implemented from the perspective of risk management under multiple future uncertainties (Rogelj et al., 2013), and policy makers can take corresponding measures based on the degree of confidence required; if they hope to realize the target with a higher degree of confidence or a higher probability, a more stringent policy will be needed.

[INSERT Fig. 3 HERE]

Fig. 4 presents the distribution of carbon peak value. The carbon emission peak value falls between 2.11 GtC and 3.7 GtC in the BAU case with a probability of 95%, and the corresponding median is 2.75 GtC. With carbon pricing introduced and increasing, the distribution curve moves to the left, and the carbon emission peak value decreases. Pricing carbon at 30USD/tC, 60USD/tC and 90USD/tC decreases the median values of the carbon emission peak to 2.64 GtC, 2.53 GtC and 2.39 GtC, respectively (Fig. 4 (a)). In addition, the distribution of the carbon emission peak values would become more concentrated as the carbon pricing effort enhances, and the uncertainty of the carbon emission peak value would decrease (Fig. 4 (a) and (b)). With the subsidy policy being introduced and increasing, the distribution curves of emission peak value seem to move to the right. However, it should be noted that this result does not mean that the introduction of a subsidy policy would increase the total long-term carbon emissions, and this effect could be better understood as a temporary phenomenon. A possible explanation is that the implementation of the subsidy policy may affect the global optimal path of the carbon emission abatement; on this basis, it may be optimal to delay carbon mitigation actions in the short term, while reducing more carbon emissions in the mid- and long-term future when the non-fossil energy costs are becoming lower as a result of the learning effect. This explanation can be verified by the results of the cumulative carbon emissions in different periods. As shown in Fig. 4 (c), the cumulative distribution curves of carbon emission with subsidy policy between 2015 and 2030 almost overlap with that in the BAU scenario, which implies that the effect of the alternative subsidy on cumulative carbon emissions is not significant in the short period; when turning to the longer period 2015-2050, the movements of the probability distribution curves become more significant (Fig. 4 (d)), which indicates a much more remarkable carbon-reducing effect of the subsidy policy. It follows that the effect of the subsidy on carbon mitigation often lags behind its initial introduction, which has also been observed by Grimaud et al. (2009). Generally, the learning effect and cost evolution of energy technologies are path-dependent, and time is still needed for the cost of the non-fossil energy to decrease to a point lower than that of fossil fuels, even after the subsidy policy is introduced, as a result of the inertial effect of the initial energy system (Kriegler et al., 2014).

[INSERT Fig. 4 HERE]

4.2 Non-fossil energy development

Fig. 5 shows the energy consumption evolution and energy structure under different policy scenarios. As shown in the left panel of Fig. 5, the carbon pricing plays a dominant role in restraining the fossil energy consumption growth, and subsidy policy dominate in promoting the non-fossil energy development. In addition, it seems unlikely for China to realize the non-fossil energy deployment target in 2030 in the absence of additional carbon pricing or subsidy, as shown in the right panel of Fig. 5, and the contribution of the single subsidy policy or the single carbon pricing policy to achieving the 20% non-fossil energy target also seems to be limited. The policy mix has a more significant effect on energy transformation and decarbonization. To be specific, with the subsidy of 30% and the carbon price of 30 USD/tC being implemented, the probability reaches 26.3%. This means that the current carbon price level in China’s carbon trading pilots and the subsidy rate for alternative energy sources cannot ensure the achievement of the non-fossil energy target with a high probability. When doubling the carbon price level, i.e. 60 USD/tC, combined with the 30% subsidy, the corresponding probability increases to 73.1%. Therefore, one single policy may be insufficient to realize the 20% non-fossil energy target, and a more stringent policy mix is necessary to restrain the fossil energy consumption growth and promote the deployment of non-fossil energy technologies. By comparing the probabilities of achieving the carbon peaking target (Fig. 3(d)) and non-fossil energy target (Fig. 5) across all the targeted policy scenarios, it can be inferred that the policy effect on the carbon emission peaking is more remarkable than that on the non-fossil energy development, and China's carbon-peaking goal seems to be more likely to be realized with the same policy efforts.

[INSERT Fig. 5 HERE]

4.3 Carbon intensity evolution

Besides the carbon-peaking and non-fossil energy targets, the carbon intensity reduction goal, i.e., reducing carbon intensity by 60~65% in 2030 relative to the 2005 level, is another important aspect of the INDC. The simulation results of carbon intensity evolution across different policy scenarios are shown in Fig. 6. In the BAU scenario, the median of carbon intensity would decrease by 63.4% in 2030, relative to that in 2005 (Fig. 6 (a)). This means that the lower limit of the target in 2030 could be realized without additional efforts; however, to realize the upper limit of the target, more policy efforts are still needed. With the 20% renewable subsidy being introduced, the median of carbon intensity in 2030 does not change significantly relative to that in the BAU scenario, and it decreases by 64.5% (Fig. 6 (a)); while in the scenario of 30% subsidy, the upper limit of China's carbon intensity goal in 2030 could be achieved, with the decline rate reaching 65.3% (Fig. 6 (a)). The carbon-pricing policy has a more significant effect on the carbon intensity reduction. For example, the median of carbon intensity decreases by 66.7% in 2030 when a 30 USD/tC of initial carbon tax is introduced (Fig. 6 (a)); moving to the policy mix scenarios, the distribution curves of the carbon intensity would move to the right more significantly, indicating a much more remarkable decrease in carbon intensity (Fig. 6 (b)). Overall, the lower bound of China's carbon intensity target in 2030 can be realized with high probability, i.e. more than 50%, even without any additional policy; the achievement of the upper bound requires more policy efforts (Fig. 6 (c) and Fig. 6 (d)). More specifically, with the implementation of some single policies, such as 30 USD/tC carbon tax or 30% alternative subsidy, China can realize the 65% target with a probability of more than 50% (Fig. 6 (d)). By contrasting the probabilities to reach the carbon-peaking and non-fossil energy deployment goals under the same policy scenarios, we may conclude that the carbon intensity target seems easier to achieve.

[INSERT Fig. 6 HERE]

4.4 Carbon abatement cost

The economic cost of reaching China's energy and climate targets is of great concern to policy makers; we therefore calculated the probability distribution across various GDP losses, and the probability distribution of the cumulative net present value of the GDP during the period of 2015-2030, as portrayed in Fig. 7. With the subsidy policy being introduced, the probability distribution curves of cumulative GDP change slightly, which indicates that the subsidy policy has little effect on economic output[3]; while in the presence of increasing carbon pricing, the probability distribution curves move significantly to the left relative to the BAU curve. More specifically, the median values of the cumulative GDP in the period of 2015–2030 under the three considered carbon pricing policy scenarios are 137.7, 135.9, and 134.3 trillion USD, respectively, and compared to the cumulative GDP under the BAU scenario, i.e. 139.8 trillion USD, the GDP losses reach 1.5%, 2.7% and 3.9%, respectively. Thus, the single carbon pricing policy, especially the high carbon price, has a significant negative effect on economic output, and to peak China's carbon emissions in 2030 with a probability of 50%, the cumulative GDP loss would approach 4% (relative to the BAU case). However, if the combined policy of carbon price and renewable subsidy were implemented instead, the corresponding GDP loss would decrease significantly. Specifically, the total GDP under the mixed policy scenarios of T30S30, T60S30, and T90S30 are 138.54, 136.77, and 135.3 trillion USD, and the relative GDP losses decline to 0.90%, 2.12% and 3.2%, respectively. Through the above cost analysis and the probability distribution results given

[3] There seems to be a tiny increase of the total GDP from 2015 to 2030 under the subsidy policy. However, it should not be understood that the subsidy policy can surely promote the economic growth, and the tiny GDP increase may be just a short-period temporary phenomenon. There are several possible reasons for this result. First, with the subsidy policy being implemented, the overall cost of the energy input would decrease, which may increase the GDP. Second and more important, with the subsidy policy being introduced, the energy cost in distant future may become much lower as a result of more significant learning effect, and part of the carbon abatement may be delayed to the future, which may increase the GDP in short period, e.g. from 2015 to 2030. In addition, the discount rate used may also have effect on the total GDP. Overall, whether the renewable subsidy policy could increase the total GDP in longer period is determined by many factors, e.g. the potential of learning effect and the cost reduction of the renewable energy, the time horizon we concerned, the discount rate used, etc., which should be further explored in furure work.

in Fig. 1, we find that the introduction of a mixed policy can avoid excessive dependence on carbon pricing, which is largely in agreement with the finding of Acemoglu et al. (2012). As a result, the carbon-peaking goal can be realized with higher probability in the presence of a mixed policy, and the corresponding policy cost (GDP loss) can be reduced by up to 3%, compared to the pure carbon pricing policies. Further, to achieve the carbon-peaking target with more or less the same probability, the mixed policy costs may also be remarkably different. For instance, the probabilities of achieving the carbon-peaking target are 54.8% and 54.0% respectively for the policy mix scenarios of T60S30 and T90S20, while the GDP loss under the former scenario is 2.1%, versus 3.6% under the latter. Thus, from the perspective of cost-control, the combination of the policy instruments should be sufficiently optimized in practice to realize the carbon-peaking target.

[INSERT Fig. 7 HERE]

In addition to the total economic cost discussed above, how the annual GDP loss will change over time is also of concern to us. It’s found that the annual GDP loss under the policy scenarios will first increase slightly before 2035 and then decrease rapidly. For example, under the mixed policies of T30S30 and T60S30, the GDP loss curves from 2015 to 2050 are hump-shaped, as portrayed in Fig. 5 (c) and Fig. 5 (d). In addition, the total GDP losses during the period of 2015-2050 for T30S30 and T60S30 are 0.87% and 2.01% respectively. This implies that the economic cost of attaining the carbon-peaking goal will become lower in the mid- and long-term future, owing to the decreasing cost of the non-fossil energy resulting from the leaning effect and the gradual transformation from carbon-based fuels to low carbon energies.

5 Conclusion and discussion

The projections on China’s future energy consumption and carbon emission are full of uncertainty, due to the uncertainties of economic growth, energy efficiency improvement and non-fossil energy development. As a consequence, carbon emission control and policy making should be implemented from the perspective of risk management, and the policy measures should be taken in terms of the required degree of confidence that a policy target can be realized.

Our simulation results show that without taking any further policy measures, the probability of China's emissions peaking before 2030 is low, and it does not reach 50% until 2040. To achieve the carbon-peaking target with a high probability, additional policy efforts, e.g. carbon pricing and renewable energy subsidy are necessary. Our conclusion is in accordance with the recent study of Elzen et al. (2016), which made a systematic assessment of the impact of current and enhanced policies on China's future GHG emissions through two different methods, i.e. bottom-up model framework and FAIR/TIMER model respectively. In the current policy scenario, the policy that has been adopted during the 12th Five-Year Plan (2011-2015) continues, and in the enhanced policy scenario, higher building efficiency standards, increase of the share of renewables, and further fuel efficiency improvement in the transport sector are implemented. Their simulation results reveal that the current policy is likely not sufficient for achieving a peak in CO_2 emissions by or before 2030, and the enhanced policy is necessary to fulfill this task. In addition, they also stress that the carbon emission projections are closely related to the future economic growth projections. Unlike our study and Elzen et al. (2016), Green and Stern (2016) conclude that China's CO_2 emissions will probably grow much more slowly than before, and are likely to peak even at some point before 2025. However, it should be noted that the conclusion drawn by Green and Stern (2016) is based on a relatively conservative estimate of future economic growth, and optimistic estimates on both energy efficiency improvement and energy structure adjustment. Specifically, the economic growth rate is set as 6.5% per year during the period 2014-2020, which may be the lower bound of the economic growth rate needed to assure that China can achieve its target of building a comprehensive well-off society during the 13th Five-Year Plan (2016-2020). As for the energy efficiency enhancement, the energy intensity decrease rate is set to be 4% during 2014-2030, which is higher than the average decrease rate (3.8%) during the past two decades (1990-2015). However, the potential for a further decline in energy-intensity may become limited over time given that China has made a great effort and progress on deployment of energy-saving technology during the past decade (Wang et al., 2014; Liu et al., 2017); and the extent to which energy efficiency can be further improved largely depends on an economic restructuring away from the energy-intensive industry in future (World Bank, 2015), which is full of uncertainty currently. Moving to the carbon intensity of energy consumption, the annual decline rate is set as 1% during 2014-2020, and further increases to 1.5% during 2020-2030 in Green and Stern's study, while actually it was only 0.5% during the past decade (2005-2015). In effect, whether significant decrease of carbon intensity could be achieved greatly relies on future renewable energy development (Liu et al., 2017), and the road ahead is full of challenges. For example, the restriction of the connection to the grid still heavily blocks the sustainable capacity expansion of the renewable energy, and China will restrict rapid capacity expansion in the regions where the curtailment of wind and solar power are serious, e.g. northwest regions of China, during the 13th Five-Year Plan (2016-2020).

The carbon pricing policy plays a key role in China realizing its carbon-peaking target by 2030. However, the economic cost caused by the single high carbon price is also significant. The introduction of the policy mix, i.e., combining carbon pricing with a renewables subsidy, effectively lowers the dependence on the high carbon price, and significantly reduces the associated GDP loss for reaching the carbon-peaking target. Specifically, a carbon price of 30-60 USD/tC accompanied by a 30% non-fossil energy subsidy may ensure the achievement of the carbon-peaking target before 2030 with a high probability, and the median of the corresponding GDP loss falls between 0.91%-2.12% during the period of 2015-2030, which further decreases in the longer period, e.g. to 0.87%-2.01% during the period of 2015-2050. Our cost estimates are more or less the same with the results from WITCH and MERGE and higher than that from GCAM and DNE21+ (Aldy et al., 2016). Thus, from the perspective of cost-effectiveness, it's recommended that a policy mix of carbon pricing and renewable subsidy policy is more acceptable and feasible in practice to realize China's carbon-peaking goal before 2030. Additionally, different policy mixes may yield a similar policy effect, while differing largely in economic costs, and effective policy optimization is therefore very important to achieving China's energy and climate targets at low cost in reality.

It is found that the carbon intensity goal for 2030 committed to by China is most likely to be achieved, followed by the carbon-peaking target and then the non-fossil energy development goal, given the same policy strength. This result indicates that it seems not likely that China will deliberately increase emissions rapidly over the next decade to make the 2030 peak as high as possible, despite China having no definite target of carbon peak level, since otherwise it may be difficult to achieve the non-fossil energy target. In addition, this result may also have an important implication for the coordination between different policy targets and the future carbon price evolution of China's national carbon market (Mo et al., 2016). Specifically, as the non-fossil energy target is more difficult to achieve than the carbon mitigation target, more policy effort would be needed to realize the non-fossil energy target. In this situation, renewable development may contribute more to the carbon emission mitigation than in the single-carbon-mitigation target situation, and the demand for the carbon allowance from the power sector would be lower, which may lead to a lower carbon price and undermine the effectiveness of the future national carbon market (Fan and Mo, 2015). The policy implication is that if the carbon intensity target is chosen as the basis for determining the carbon emission cap of the national carbon trading system in future, this target should be set higher than that in the current INDC, to avoid a possible carbon price collapse.

It should be pointed out that the carbon abatement progress under the Paris is iterative, and there will be successive rounds of NDCs to increase effort and ambition to meet the global target. For China, once it succeeds in peaking carbon emissions, those emissions must begin to decrease, or stay at a certain level for some time and then decrease. Our model framework can be employed to design China's long term carbon abatement targets in view of the global decarbonization target. In specific, after the carbon emission peaks at around 2030, different remaining carbon emission budgets until 2050 or 2100 can be incorporated into the model as new emission constraint. By running the model under different constraints of carbon emission budgets, the optimal path of economic growth and carbon emission can be obtained, and subsequently the optimal carbon abatement targets at different time. Alternately, given certain policies, e.g., carbon pricing, subsidy or policy mix, the distribution of the future carbon emission path and the corresponding cumulative carbon emission until some time (2050 or 2100) can be obtained from the modelling results. By comparing the cumulative carbon emission on each simulated path with the given carbon budget (target), the probability of realizing the target can be obtained. With different target setting, we can get the corresponding probability. Based on this mapping from the target to probability, the policy makers can select the target according to the probability required.

Our model framework can also be further extended in several ways. First, in our current model, the feature of the sequential decision was not incorporated. In reality, the decision-making under uncertainty may be sequential, which means that the decision makers can learn with new information of the economy and technology arriving, and adapt the policy to the new information accordingly. Our model can be extended to adapt to this more complex situation in the following way. On the one hand, the future uncertainties about the economy and technology can be depicted using dynamic stochastic process, and the evolution of the uncertain factors can be observed by the decision makers. On the other hand, the behavior of the decision makers should be flexible, and they can re-optimize the future path in the remaining time herizon and update their decision based on the new information. Second, in the current model framework, we just consider one-factor learning curve, i.e. learning-by-doing, and in future work, the two-factor learning curve, which includes both learning-by-doing and learning-by-searching can be incorporated into our model. In this situation the endogeneity effect may emerge, that is, the learning parameter distribution may be affected by the R&D subsidy for certain technologies, which should be carefully dealt with. At last, neither carbon capture and storage (CCS) nor negative emission technologies (e.g. BECCS) are considered in the current model, although they are projected to play important roles in mitigating carbon emissions for China (Mo et al., 2015), particularly in the mid- to long-term future, and it should be a promising area for exploration in future works.

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Appendixes

Appendix A. The key parameters, variables and formulas of CE3METL model

A.1 Main equations

The objective of CE3METL is to maximize the welfare, given σ_t the discount factor, i.e.,

$$Utility = Max \sum_t (L_t log(c_t) \prod_{\tau=0}^{t} (1+\sigma_\tau)^{-\Delta t}) \quad \text{(Eq.A1)}$$

$$\sigma_t = \sigma_0 e^{-d_\sigma t} \quad \text{(Eq.A2)}$$

$$c_t = C_t / L_t \quad \text{(Eq.A3)}$$

Production proceeds by means of a single CES production function. Specifically, with inputs capital K_t, labor L_t and energy E_t, we have

$$Output_t = \left[\alpha_t \left(K_t^\eta L_t^{1-\eta}\right)^\rho + \beta_t E_t^\rho\right]^{1/\rho} \quad \text{(Eq.A4)}$$

To calculate the parameter α_t and β_t, we first give the reference values of $Output_t$, K_t and E_t for the given initial values $Output_0$, K_0 and E_0, that is

$$\begin{cases} Output_t^{REF} = Output_0\, LPG_t L_t / L_0 \\ K_t^{REF} = K_0\, LPG_t L_t / L_0 \\ E_t^{REF} = E_0\, AEEI_t L_t / L_0 \end{cases} \quad \text{(Eq.A5)}$$

LPG_t follows exponential pattern by giving initial labor productivity growth LPG_0 and its decrease rate per period (five-year) $derat_l$; $AEEI_t$ is determined by initial energy efficiency enhancement $AEEI_0$ and decline rate per period $derat_{\mathrm{e}}$, that is

$$LPG_t = (LPG_0 / derat_l)(1 - e^{-derat_l t}) \quad \text{(Eq.A6)}$$

$$AEEI_t = AEEI_0 (1 - derat_e t) \quad \text{(Eq.A7)}$$

Through first-order optimality condition of Eq.A4, and marginal productivity of energy MPE_0, we could get

$$\begin{cases} \alpha_t = ((Output_t^{REF})^\rho - \beta_t (E_t^{REF})^\rho) / (K_t^{REF})^{\eta\rho} (L_t)^{(1-\eta)\rho} \\ \beta_t = MPE_0\, (Output_t^{REF})^{\rho-1} / (E_t^{REF})^{\rho-1} \end{cases} \quad \text{(Eq.A8)}$$

The capital stock K^t equals the sum of depreciated previous capital stock and current investment,

$$K_t = (1-\delta_1) K_{t-1} + I_t \quad \text{(Eq.A9)}$$

GDP that consists of investment, consumption, ex- and imports, is the current output net of energy costs and carbon abatement costs, i.e.,

$$GDP_t = Output_t - EC_t - AC_t \quad \text{(Eq.A10)}$$

$$C_t = GDP_t - I_t - X_t + M_t \quad \text{(Eq.A11)}$$

$$EC_t + AC_t = E_t (PF_t + PNF_t) \quad \text{(Eq.A12)}$$

To close up the regional 3E-integrated model, we assume the ex- and imports dynamically follow the optimal trajectory of GDP growth, and this is achieved by introducing a lower bound and an upper bound, respectively, for the changes of ex- and imports,

$$X_t \geq \theta_x GDP_t \quad \text{(Eq.A13)}$$

$M_t \leq \theta_m GDP_t$ (Eq.A14)

The core technological evolution mechanism, i.e., the revised multi-logistic curves, is coupled to the 3E-integrated model framework. In specific, the dynamic competitive relationship between conventional energy technologies and non-fossil alternatives is determined by the relative price $P_{i,t}$ and policy intervention of carbon prices and subsidies, i.e.,

$$\frac{dS_{i,t}}{dP_{i,t}} = a_i S_{i,t}\left(\tilde{S}_i\left(1 - \sum_{j \neq i} S_{j,t}\right) - S_{i,t}\right) \quad \text{(Eq.A15)}$$

$$P_{i,t} = C_{coal,t}\left(1 + tax_{coal,t}\right) / C_{i,t}\left(1 + sub_{i,t}\right) \quad \text{(Eq.A16)}$$

$$tax_{i,t} = \begin{cases} tax_{coal}\frac{\xi_i}{C_{i,t}}, & i \neq k \\ 0, & i = k \end{cases} \quad \text{(Eq.A17)}$$

Non-fossil energy technology advancement is endogenized by so-called learning-by-doing process, i.e., the unit costs $C_{k,t}$ will decrease with the cumulative production experience $KD_{k,t}$ accumulating, that is,

$$C_{k,t} = C_{k,0}\left(\frac{KD_{k,t}}{KD_{k,0}}\right)^{-b_k} \quad \text{(Eq.A18)}$$

$$1 - lr_k = 2^{-b_k} \quad \text{(Eq.A19)}$$

and knowledge capital $KD_{k,t}$ is measured in terms of current production and previous knowledge stock adjusted by depreciation rate δ_2,

$$KD_{k,t} = (1 - \delta_2) KD_{k,t-1} + S_{k,t} E_t \quad \text{(Eq.A20)}$$

The composited prices for fossil and non-fossil energy are the sums of fossil and non-fossil energy costs, respectively, weighted by the corresponding technological shares and policy intervention,

$$PF_t = \sum_f C_{f,t} S_{f,t}\left(1 + tax_{f,t}\right) \quad \text{(Eq.A21)}$$

$$PNF_t = \sum_k C_{k,t} S_{k,t}\left(1 - sub_{k,t}\right) \quad \text{(Eq.A22)}$$

Total carbon emissions equals to the sum of industrial CO_2 emissions and exogenous natural emissions (mainly refer to the emissions associated with the change of land use),

$$Emis_t = \sum_f\left(\xi_f S_f E_{f,t}\right) + Emis_0 \quad \text{(Eq.A23)}$$

and the carbon emission stock is accumulated by the annual CO_2 emissions and the past emission stock adjusted by the sinking rate, i.e.,

$$CumE_t = (1 - sr) CumE_{t-1} + Emis_t \quad \text{(Eq.A24)}$$

A.2 Indices

t	time period
i, j	technology type except for coal
k	non-fossil energy technologies
f	fossil fuels

A.3 Variables

C_t	consumption of goods and services

K_t capital stock

E_t energy input

$Output_t^{REF}$ reference output

K_t^{REF} reference capital input

E_t^{REF} reference energy input

I_t investment flow

L_t population as well as labor input

c_t per capita consumption

GDP_t gross domestic production

X_t export

M_t import

EC_t energy costs

AC_t abatement cost

PF_t composited price of fossil energy

PNF_t composited price of non-fossil energy

$S_{i,t}$ market share of technology i

$\tilde{S}_i$ the maximal possible potential of technology i

$P_{i,t}$ the relative prices of coal and alternative i

$C_{coal,t}$ unit cost of coal

$C_{i,t}$ unit cost of the other types of energy except coal

$tax_{coal,t}$ carbon price level imposed on coal

$tax_{i,t}$ carbon price level imposed on the other fossil fuels

$sub_{i,t}$ subsidy level for alternatives

$KD_{i,t}$ knowledge stock of learning-by-doing

$Emis_t$ carbon emissions

$CumE_t$ cumulative carbon emissions

A.4 Parameters

σ pure rate of social time preference (per year)

d_σ annual declining rate of σ

η capital value share

ρ elasticity of substitution

α_t, β_t technological progress parameters which include LPG and $AEEI$

δ_1, δ_2 rates of depreciation for conventional capital and knowledge capital

θ_x, θ_m bounds of export and import

a_i substitution capability parameter of alternatives to coal

b_k learning index for learning curve

lr_k learning rate

sr sink rate of carbon in nature

ξ_f carbon contents of fossil fuels (carbon emission factors)

MPE_0 marginal productivity of energy

LPG_0 initial labor productivity growth

$AEEI_0$ initial autonomous energy efficiency improvement

$derat_l$ per period decrease rate of LPG_0

$derat_e$ per period decrease rate of $AEEI_0$

[INSERT Table A1 HERE]

A.5 Variable initial values

$Output_0$ initial output in the base year

K_0 initial capital stock

E_0 initial energy input

$Emis_0$ exogenous initial carbon emissions from land use change

Appendix B. The Results in the BAU scenario

In this section, the simulation results in the BAU scenario were presented, based on which we calibrated the model by making some comparisons with other relevant studies.

B.1 GDP growth

Energy consumption and CO_2 emissions are closely related to future economic growth; gross domestic product (GDP) and its growth rates are shown in Fig. B1. There is still great potential for future economic growth in China. For the median result, the GDP increases from 5.97 trillion USD in 2010 to 21.98 trillion USD in 2030, i.e., 3.68 times that of 2010, and it further reaches 48.6 trillion USD in 2050, i.e., 8.1 times that of 2010. Although economic growth will continue, the GDP growth rate is likely to decrease over time, from 7.0% during the period of 2010–2020 to 4.7% during the period of 2030–2040, and further to 3.3% for the period of 2040–2050.

[INSERT Fig. B1 HERE]

Given the future uncertainties, we make a statistical analysis of the simulation results of economic growth in particular, and we get 60%, 80%, 90% and 100% confidence intervals for the GDP growth paths, as shown in Fig. B1. The uncertainty of the GDP amount is still significant, and it will further increase over time. More specifically, for the 60% confidence level, the GDP amount falls between 19.07 and 25.49 trillion USD in 2030, versus 38.27 and 62.07 trillion USD in 2050; and for the 90% confidence level, the GDP amount falls into the interval of 16.67 and 29.24 trillion USD in 2030, while in 2050 it ranges from 30.40 to 77.85 trillion USD. This situation changes when moving to the GDP growth rate, i.e., the uncertainty would decrease over time. For example, for the 60% confidence level, the GDP growth rate ranges from 6.50% to 8.09% in the period of 2010-2020, and the range would decrease to the interval of 2.97% and 3.82% for the period of 2040-2050.

We also summarize the results of economic growth in other related studies, as shown in Fig. B2. Our results for GDP growth rates are lower than those of the ERI (2009), more or less the same as the moderate scenario of Tsinghua University (THU-M) (THU, 2014) and LBNL (Zhou, 2013), and a bit higher than those of the IEA (2010) and the UNDP (2009).

[INSERT Fig. B2 HERE]

B.2 Energy consumption

Future carbon emissions are determined by the total energy consumption and the change in carbon intensity. As a result, controlling energy consumption by enhancing energy conservation and improving energy efficiency is still China's current priority strategy to combat climate change. In the BAU scenario, the median of the energy consumption would continue growing until 2050, as shown in Fig. B3. Specifically, the energy consumption in 2010 is 3.25 Gtce, and it will increase to 5.72 Gtce in 2030, i.e., 1.76 times that of 2010, and will further reach 6.98 Gtce in 2050. This result is more or less the same as the results of the BAU scenario of the IEA (2010), reference scenario of the UNDP (2009) and the energy-saving scenario of the ERI (2009). Although energy consumption would continue increasing in the mid- to long-term future, the energy consumption growth rate would decrease, from 3.2% in the period of 2010-2020 to 0.53% in the period of 2040-2050, and then the total energy consumption would become stable.

[INSERT Fig. B3 HERE]

Also, we note that the uncertainty of the energy consumption is significant. For the 60% confidence level, energy consumption ranges from 4.63 to 7.09 Gtce in 2030, versus 4.72 to 10.23

Gtce in 2050. However, the uncertainty of the energy consumption growth rates would decrease over time. For the 60% confidence level, the confidence interval would decrease from (2.09%, 4.37%) in the period of 2010-2020 to (1.47%, 3.59%) in the period of 2020-2030, and further to (−0.31%, 1.31%) in the period of 2040- 2050.

Besides the total energy consumption amount, the change of energy structure also has a fundamental effect on the future carbon emission. Fig. B4 (a) and Fig. B4 (b) show the evolution of the energy structure under the BAU scenario. Coal is still China's top energy source currently and may continue dominating the whole energy consumption market until 2050, although its share seems to have temporarily peaked in 2015. The consumption of less carbon-intensive fossil energy, i.e. oil and gas, will also increase, and especially the share of gas. Currently, non-fossil energy only accounts for about 11% of the total energy consumption; however, the diffusion of non-fossil energy is significant both in terms of the amount and the share, mainly as a result of the learning effect. To be specific, the cost of non-fossil energy will decrease with cumulative energy consumption increasing, and the cost disadvantages with the fossil energy diminish in future gradually, as shown in Fig. B4 (c). Hydropower is the most important non-fossil energy, and it will continue increasing in our simulation. In addition, nuclear, wind and biomass will contribute much of the non-fossil energy increase in future.

[INSERT Fig. B4 HERE]

B.3 Carbon emissions and intensity

Fig. B5 (a and b) shows the carbon emission evolution. The median result shows that the carbon emissions in China in 2010 were 2.1 GtC, and they increase continuously until 2040. In 2030, the carbon emissions are 3.55 GtC, which is 1.67 times that in 2010, and they further increase to 3.91 GtC in 2040, when they peak. From 2040 to 2045, carbon emissions relatively stabilize at the peak level in 2040, and after that they gradually decrease. Similarly, the increase rate of carbon emissions during the period of 2010–2020 is 2.97%, and it decreases gradually to 0 and turns negative during the period of 2040–2050. The median results under the BAU scenario are similar to those in the energy-saving scenario of the ERI (2009), where carbon emissions peak in 2040, but the peak value of the ERI (2009), i.e., 3.55 GtC, is a little lower than our results. In addition, our estimation of CO_2 emissions is more conservative compared with the results of the baseline scenario of the IEA (2010) and the reference scenario of the UNDP (2009), in which CO_2 emissions would not peak before 2050 and reach 4.36 GtC in 2050. Future CO_2 emissions are also full of uncertainty, and the uncertainty would further increase over time. In 2030, for the 60% confidence level, carbon emissions fall between 2.87 and 4.40 GtC, versus 2.32 and 5.35 GtC for the 90% confidence level. In 2040, the confidence interval for the 60% confidence level is (2.8, 5.29) GtC, and further expands to (2.13, 7.04) GtC for the 90% confidence level. In contrast, the uncertainty of the growth rate decreases over time, and for the 60% confidence level, the confidence interval of the growth rate from 2010 to 2020 is (1.83%, 4.13%), and it reduces to (−1.21%, 0.42%) during the period of 2040–2050.

The simulation results show that there is still great potential for China to reduce its carbon intensity, as shown in Fig. B5 (c and d). For the median results in the BAU scenario, the carbon intensity decreases from 0.36 tC/thousand USD in 2010 to 0.24 tC/thousand USD in 2020, i.e., a 33.3% reduction, and further decrease to 0.16 tC/thousand USD in 2030, i.e., a 51.4% reduction. Besides, the carbon intensity in 2020 and 2030 decrease by 46.0% and 63.4%, respectively (relative to that in 2005), given that the carbon intensity reduction is about 19% during the 11th Five-Year Plan (2005–2010). In addition, the decrease rate is full of uncertainty according to the results for carbon intensity distribution shown in Fig. B5 (c and d); despite that, the distribution curves moves downward and the carbon intensity decreases over time.

[INSERT Fig. B5 HERE]

Appendix C. Sensitivity analysis of the key indexes to the uncertain parameters

In this section, we make a sensitivity analysis of the key uncertain parameters, involving exogenous energy efficiency improvement (AEEI), labor productivity growth (LPG), and elasticity of substitution between capital-labor complex and energy (EOS). By using different percentile values of the uncertain parameters, i.e., 5%, 40%, 60% and 95%, and holding the other parameters at the BAU level, we test how the variation of the key parameters would affect the relevant results, including cumulative GDP, carbon emissions, and energy consumption during 2015 to 2050 (Fig. C1).

As for the considered parameters, labor productivity growth (LPG) is the most important factor that affects cumulative GDP, followed by energy efficiency enhancement (AEEI) and elasticity of substitution between capital-labor and energy (EOS). For example, the changes in cumulative GDP from 2015 to 2050 are −19.09% and 20.10% for the percentile values of 5 and 95 for LPG, respectively. The energy consumption results are also sensitive to changes to the LPG and AEEI parameters. For the 5 and 95 percentile values of the LPG, the variations are −20.04% and 20.99%, and for the AEEI, the variations are 37.61% and −28.11% respectively. Moving to the cumulative CO_2 emission, the results are more sensitive to the energy efficiency improvement than the other two parameters. More specifically, the cumulative CO_2 emissions changes are 35.94% and −27.10%, respectively, given the 5 and 95 percentile values for AEEI; when moving to the EOS, the corresponding variation ranges decrease to 15.10% and −10.69% (Fig. C1). In addition, the comparison of the results for the 5 and 95 percentile values referred to above also indicates that the effects of the positive and negative parameter deviations relative to the BAU on the main outcome are asymmetric in some cases.

[INSERT Fig. C1 HERE]

To further explore the impact of the learning parameters on the non-fossil energy deployment, we also obtain the results across different learning percentile values chosen according to the uncertainty distribution reported in Table 1. As shown in Fig. C2, different energy technologies encounter different effects of learning uncertainty. To be specific, the current low-market-share technologies, such as wind, PV solar, tide, geothermal and biomass, may be more sensitive to the uncertainty of learning effect, but this situation changes when turning to the better-developed technologies, e.g., nuclear and hydropower. For example, under the 5 percentile case, the consumption of wind and PV solar increases by 44.3% and 24.3% respectively, while the variation for hydropower and nuclear are just 0.39% and 4.10% correspondingly; even under the 40 percentile case, the change of wind energy consumption is still as high as 8.61%, while the corresponding value for hydro-power further lowers to 0.085% (Fig.C2).

[INSERT Fig.C2 HERE]

Table 1 Uncertainty information for learning parameters (b_k).

	GEO	PVSOL	WIND	TIDE	BIO	NUC	HYD
MIN	0.82	0.72	0.81	0.73	0.89	0.91	0.95
MAX	0.92	0.85	0.96	0.86	0.95	0.97	0.99

Sources: McDonald & Schrattenholzer (2001), Rout et al.(2009), Di et al.(2012), Rubin et al. (2015).

Table 2 Policy scenario design details.

		Initial carbon price level (USD/tC)			
		0	30	60	90
Subsidy Rate (%)	0	BAU	T30	T60	T90
	20	S20	T30S20	T60S20	T90S20
	30	S30	T30S30	T60S30	T90S30

Table A1. The value of key parameters in our model

Parameter	Value	Notes
Capital value share	0.31	Gerlagh and van der Zwaan (2004), Nordhaus (2007)
Elasticity between capital-labor and energy	0.40	
Depreciation rate	5.0%	Duan et al. (2013), Aldy et al. (2016)
Initial time preference ratio	0.03	Gerlagh and van der Zwaan (2004), Kumbaroglu et al. (2009)
Decrease rate of preference ratio per annum	0.30%	
Upper bound of export share in GDP	40%	Calibrated according to the historical data from 2000 to 2012 (Duan et al., 2014)
Upper bound of import share in GDP	30%	
Discount rate for knowledge capital	5.0%	Duan et al. (2013), Aldy et al. (2016)
Initial labor productivity growth (LPG)	6.1%	Gerlagh and van der Zwaan (2004), Kumbaroglu et al. (2009), Duan et al. (2013), Nordhaus and Sztorc (2013)
Decline rate of LPG	0.30%	
Basic initial energy efficiency improvement	0.76%	
Decline rate of AEEI	0.20%	
Marginal productivity of energy	0.34	Calibrated in this work
Carbon contents for coal (tC/tce)	0.756	IPCC Greenhouse Gas (GHG) Emission Inventory (IPCC, 2006)
Carbon contents for oil (tC/tce)	0.586	
Carbon contents for natural gas (tC/tce)	0.448	
Natural sink rate of carbon emissions	0.006	IPCC (2006), Nordhaus (2007)

Note: The other key parameters, such as learning indexes for all the alternative technologies, are the main concerns of uncertainty analysis, we therefore do not list them here again.

Highlights

- China's energy and climate targets in 2030 under multiple uncertainties are assessed using a stochastic energy-economy-environment integrated model.
- The probabilities to realize the targets are obtained, and the nexus among different targets is explored.
- Carbon emission management and policy-making should be implemented from the perspective of risk management.
- Carbon pricing plays a major role in curbing and peaking China's carbon emissions.
- The carbon intensity reduction target is most likely to be attained, followed by the carbon-peaking target, and then the non-fossil energy target.

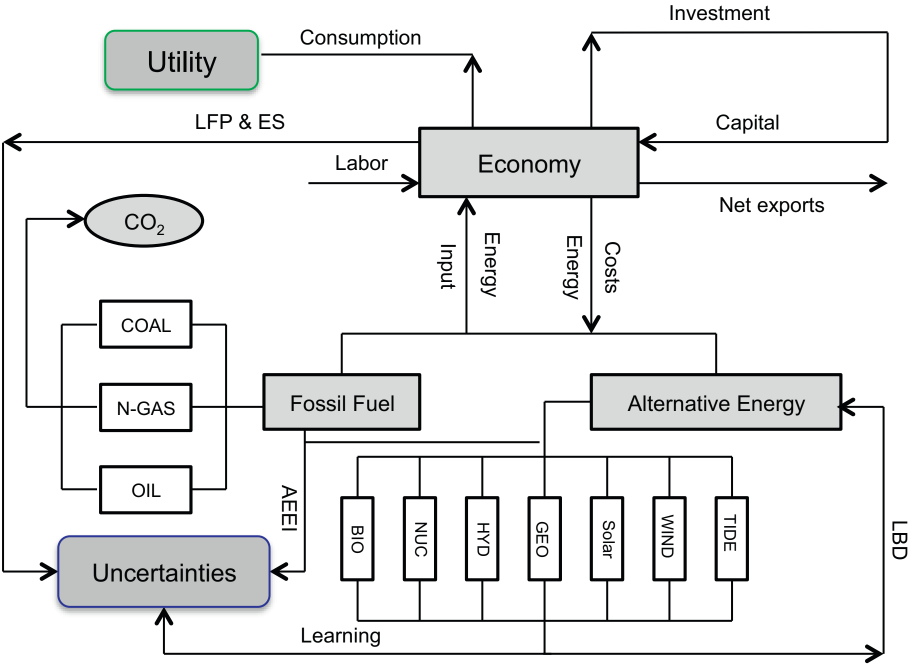

Utility
Consumption
Investment
Capital
LFP & ES
Labor
Economy
Net exports
CO_2
Input
Energy
Energy
Costs
COAL
N-GAS
OIL
Fossil Fuel
Alternative Energy
AEEI
BIO
NUC
HYD
GEO
Solar
WIND
TIDE
LBD
Uncertainties
Learning

Figure 1

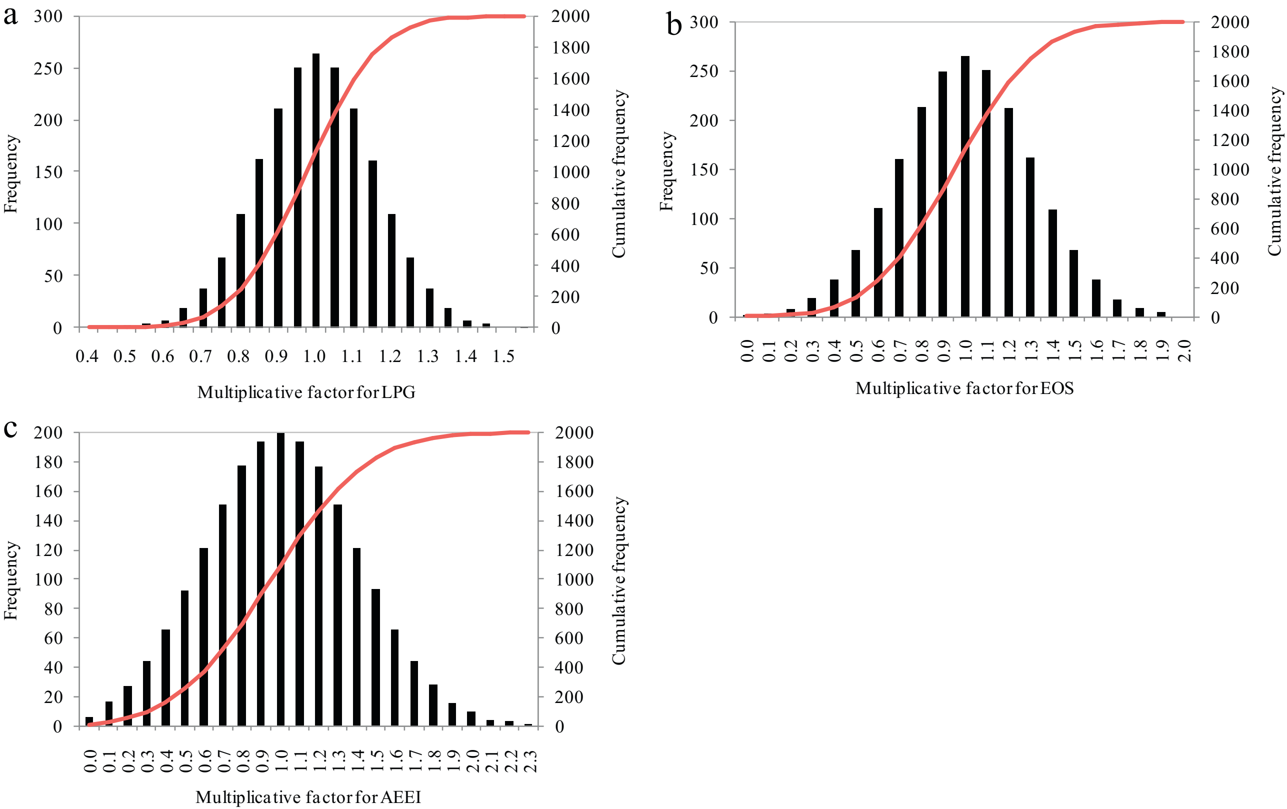
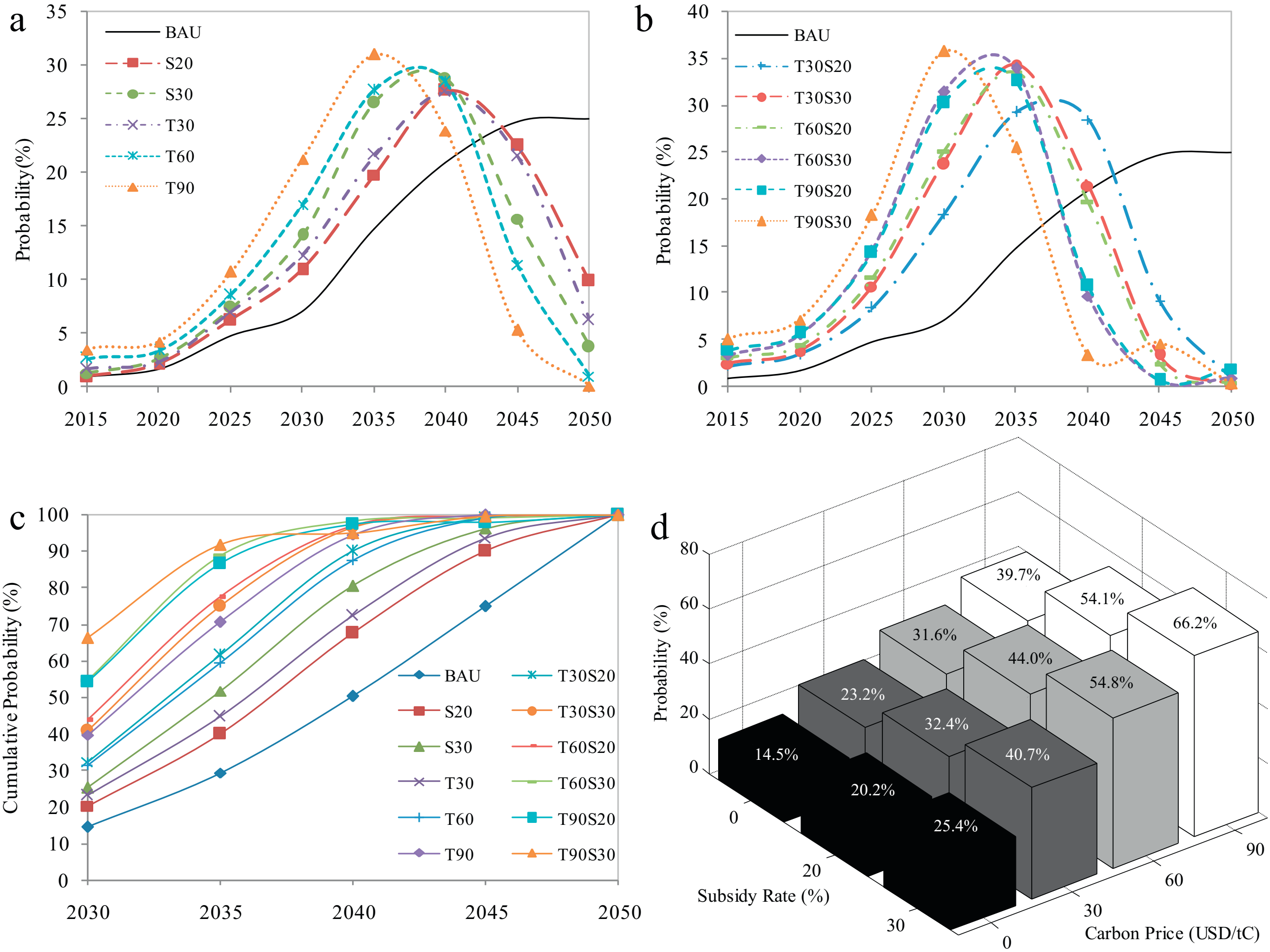
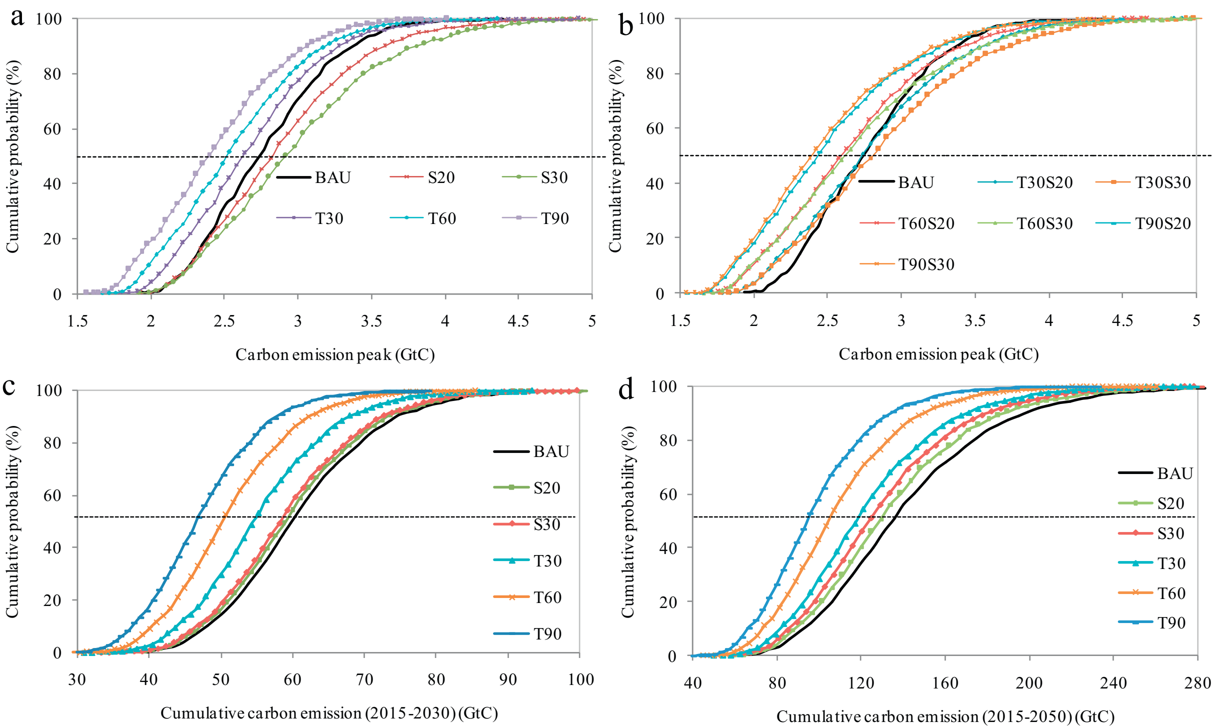

a
Frequency
Cumulative frequency
Multiplicative factor for LPG
b
Frequency
Cumulative frequency
Multiplicative factor for EOS
c
Frequency
Cumulative frequency
Multiplicative factor for AEEI

Figure 2



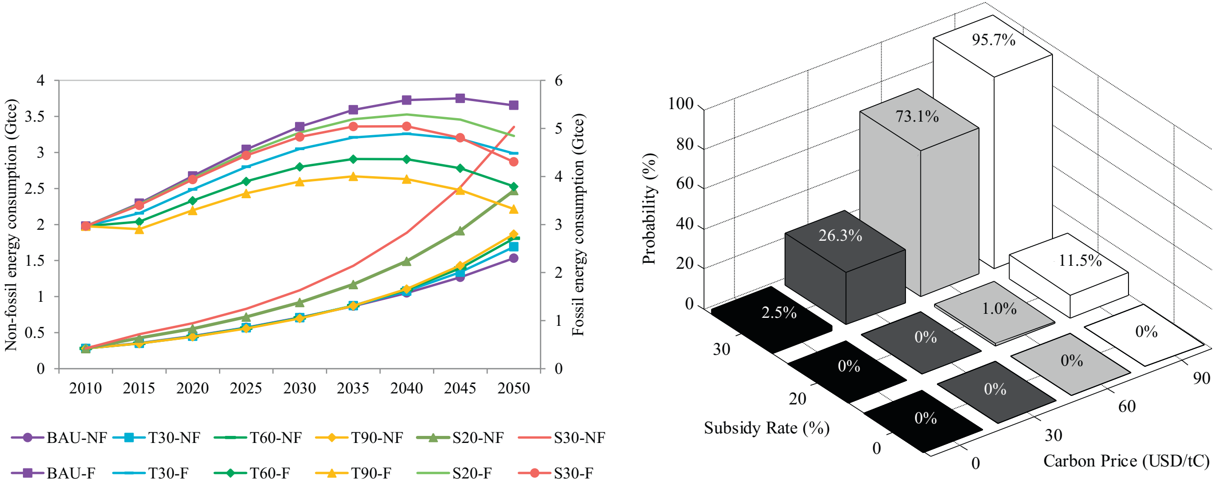
a
Probability(%)
BAU
S20
S30
T30
T60
T90
b
Probability (%)
BAU
T30S20
T30S30
T60S20
T60S30
T90S20
T90S30
c
Cumulative Probability (%)
BAU
S20
S30
T30
T60
T90
T30S20
T30S30
T60S20
T60S30
T90S20
T90S30
d
Probability (%)
39.7%
54.1%
66.2%
31.6%
44.0%
54.8%
23.2%
32.4%
40.7%
14.5%
20.2%
25.4%
Subsidy Rate (%)
Carbon Price (USD/tC)

Figure 3



a
b
c
d
Cumulative probability (%)
Carbon emission peak (GtC)
Cumulative carbon emission (2015-2030) (GtC)
Cumulative carbon emission (2015-2050) (GtC)
BAU
S20
S30
T30
T60
T90
T30S20
T30S30
T60S20
T60S30
T90S20
T90S30

Figure 4



Non-fossil energy consumption (Gtce)
Fossil energy consumption (Gtce)
0
0.5
1
1.5
2
2.5
3
3.5
4
0
1
2
3
4
5
6
2010
2015
2020
2025
2030
2035
2040
2045
2050
BAU-NF
T30-NF
T60-NF
T90-NF
S20-NF
S30-NF
BAU-F
T30-F
T60-F
T90-F
S20-F
S30-F
Probability (%)
0
20
40
60
80
100
95.7%
73.1%
26.3%
11.5%
2.5%
1.0%
0%
0%
0%
0%
0%
0%
Subsidy Rate (%)
30
20
0
Carbon Price (USD/tC)
0
30
60
90

Figure 5

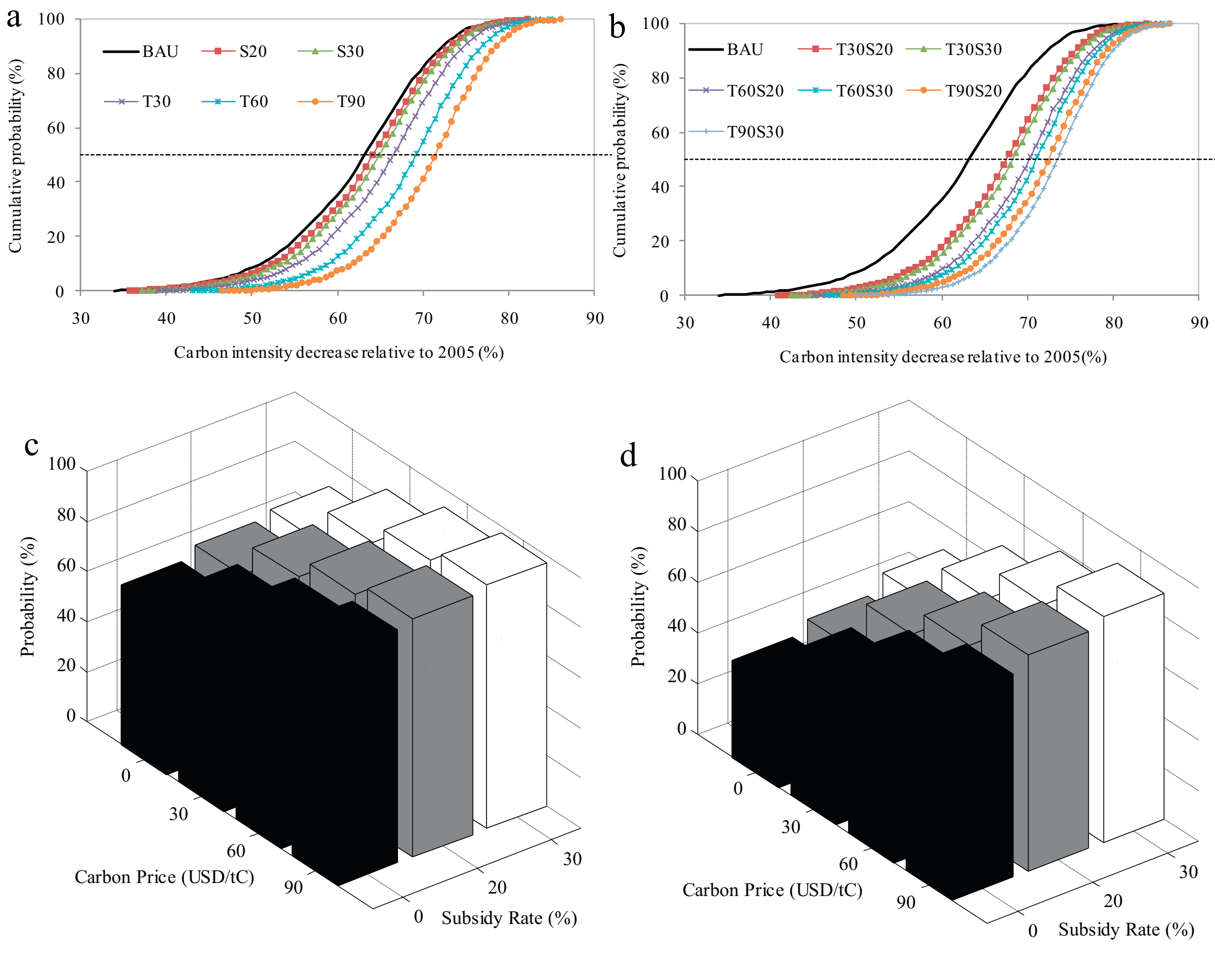

a
b
c
d
BAU
S20
S30
T30
T60
T90
T30S20
T30S30
T60S20
T60S30
T90S20
T90S30
Cumulative probability (%)
Carbon intensity decrease relative to 2005 (%)
Probability (%)
Carbon Price (USD/tC)
Subsidy Rate (%)

Figure 6

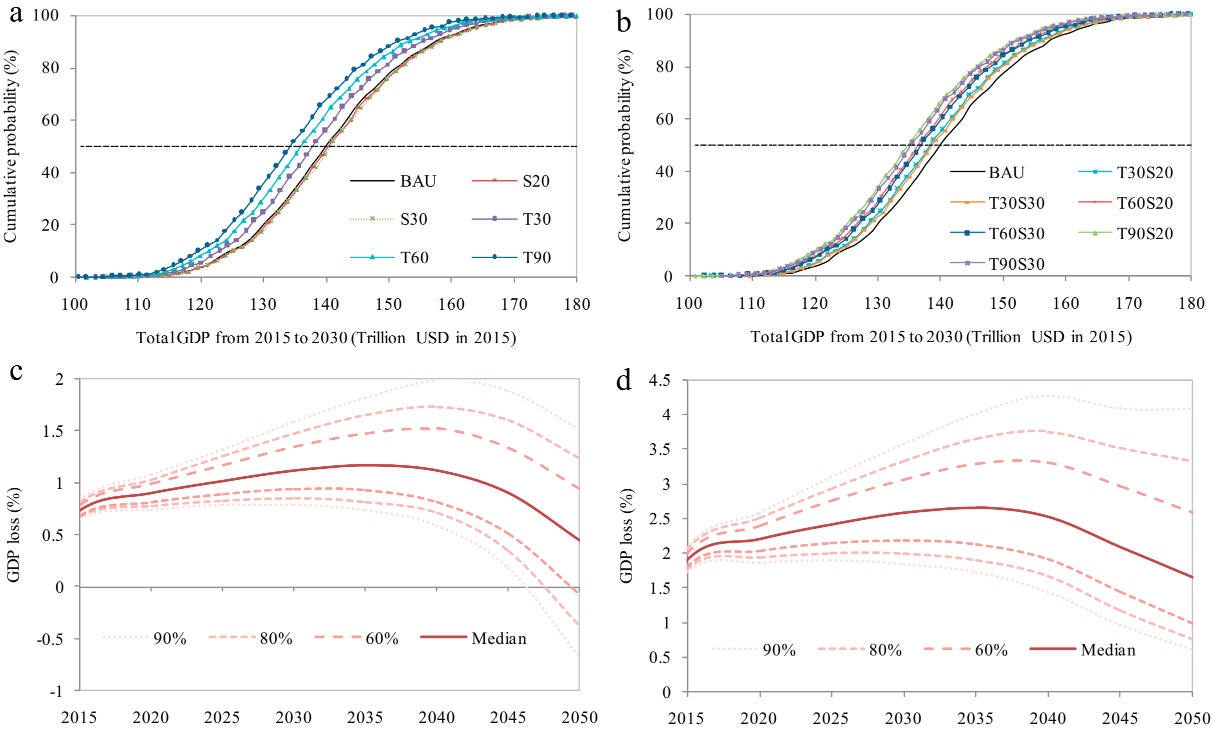
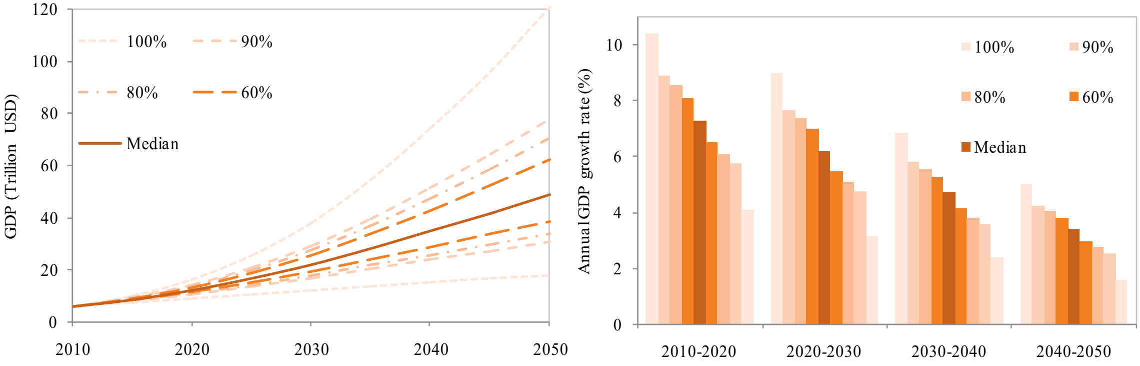
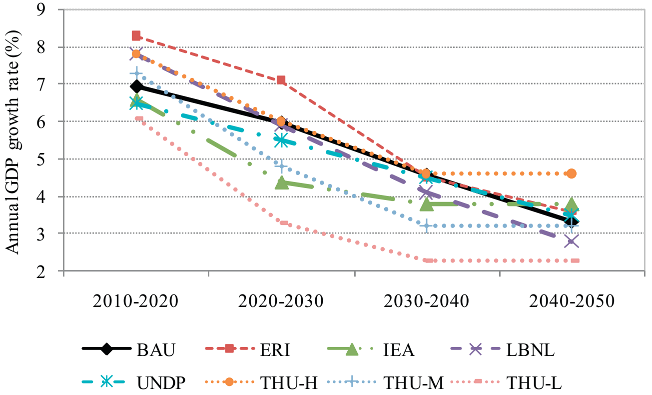

a
b
c
d
Cumulative probability (%)
Tota1GDP from 2015 to 2030 (Trillion USD in 2015)
BAU
S20
S30
T30
T60
T90
T30S20
T30S30
T60S20
T60S30
T90S20
T90S30
GDP loss (%)
90%
80%
60%
Median

Figure 7



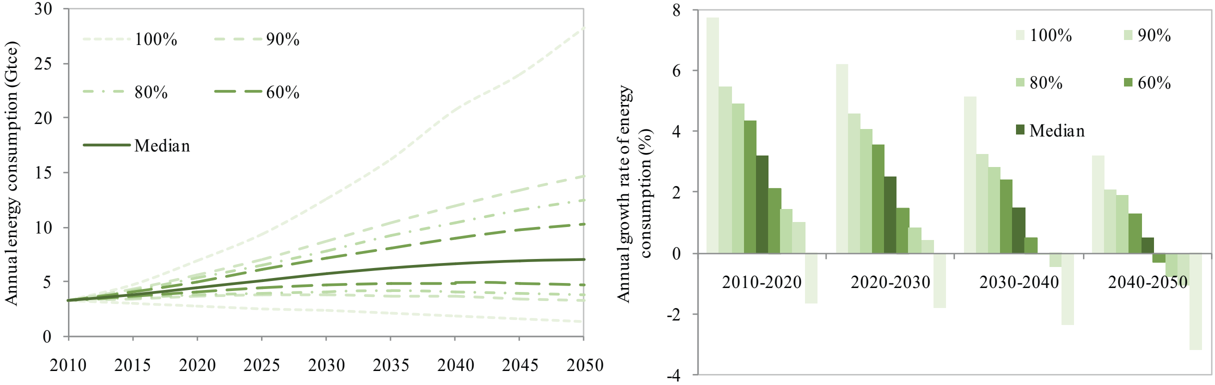
120
100
80
60
40
20
0
GDP (Trillion USD)
100%
90%
80%
60%
Median
2010
2020
2030
2040
2050
10
8
6
4
2
0
Annual GDP growth rate (%)
100%
90%
80%
60%
Median
2010-2020
2020-2030
2030-2040
2040-2050

Figure 8



Annual GDP growth rate (%)
9
8
7
6
5
4
3
2
2010-2020
2020-2030
2030-2040
2040-2050
BAU
ERI
IEA
LBNL
UNDP
THU-H
THU-M
THU-L

Figure 9



30
25
20
15
10
5
0
Annual energy consumption (Gtce)
100%
90%
80%
60%
Median
2010
2015
2020
2025
2030
2035
2040
2045
2050
8
6
4
2
0
-2
-4
Annual growth rate of energy consumption (%)
2010-2020
2020-2030
2030-2040
2040-2050

Figure 10

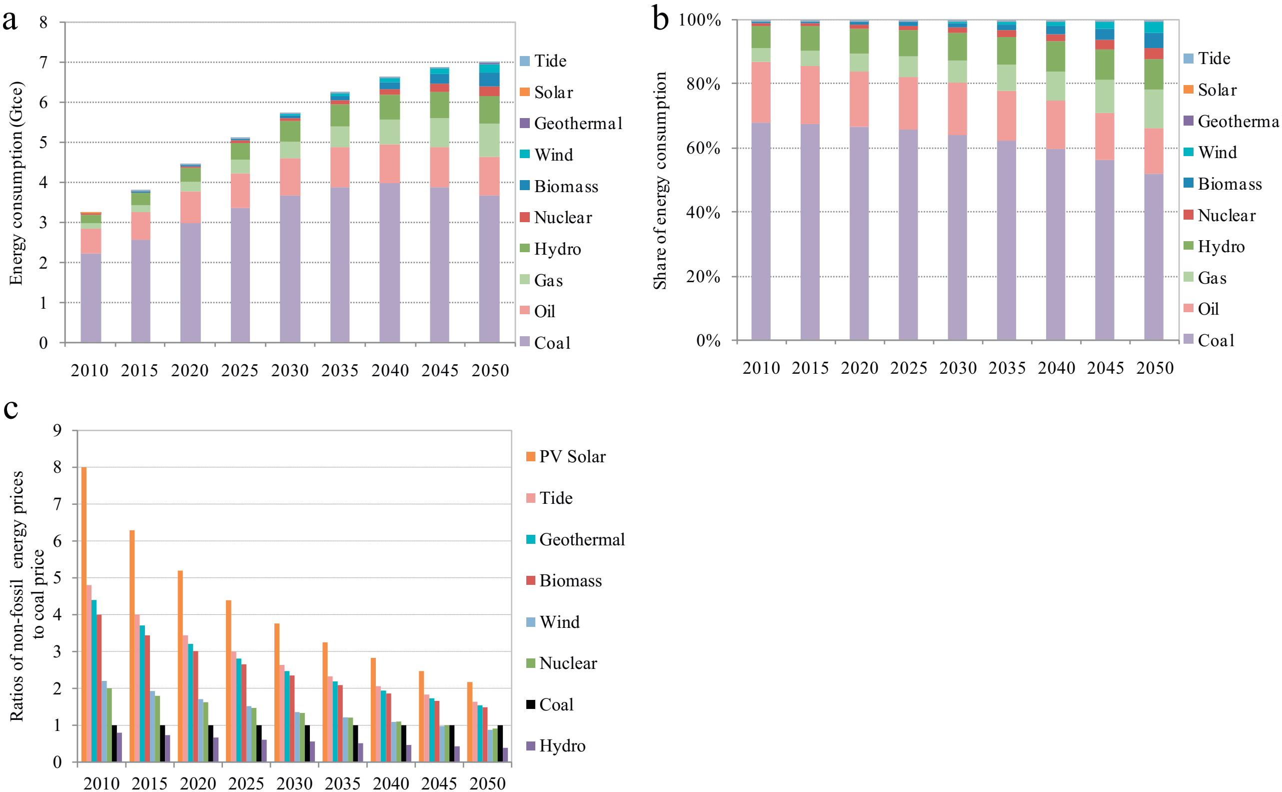
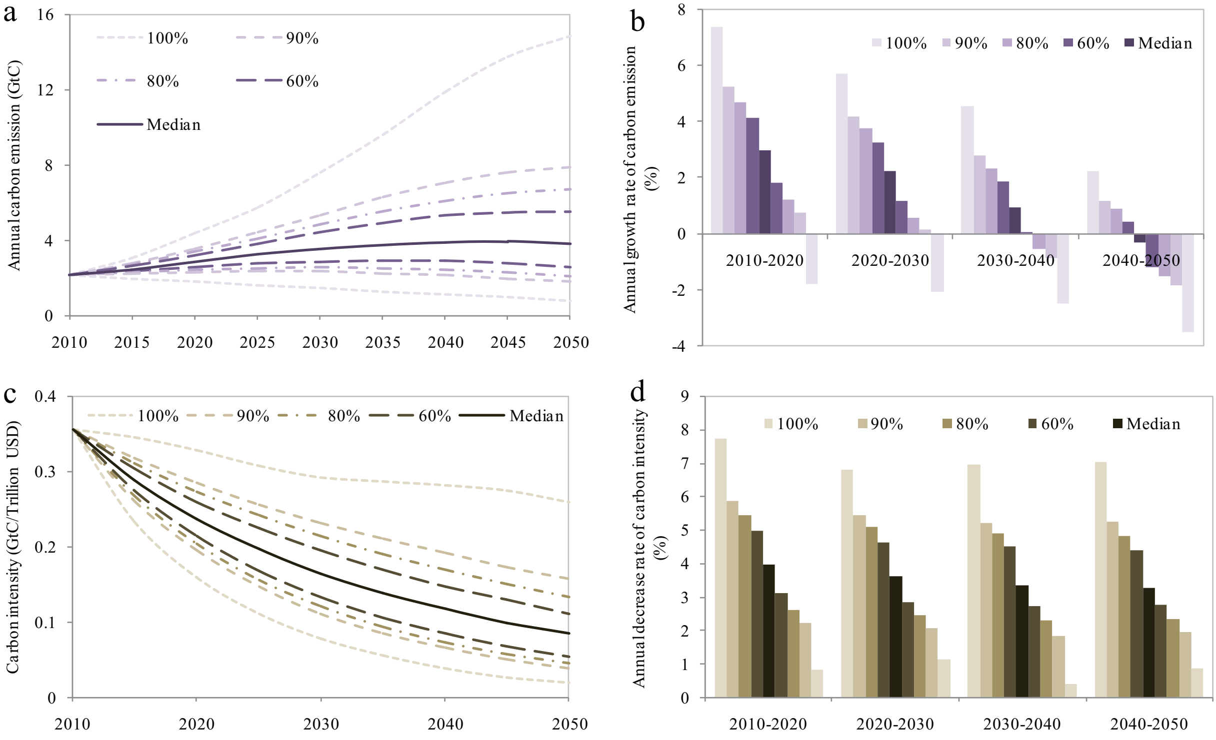
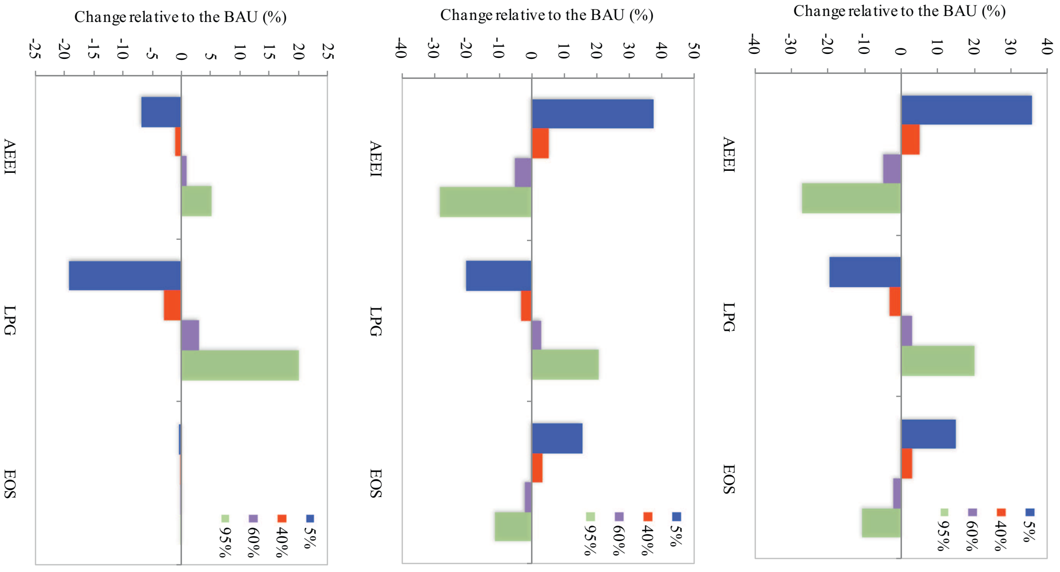

a
Energy consumption (Gtce)
0
1
2
3
4
5
6
7
8
2010
2015
2020
2025
2030
2035
2040
2045
2050
Tide
Solar
Geothermal
Wind
Biomass
Nuclear
Hydro
Gas
Oil
Coal
b
Share of energy consumption
0%
20%
40%
60%
80%
100%
2010
2015
2020
2025
2030
2035
2040
2045
2050
Tide
Solar
Geothermal
Wind
Biomass
Nuclear
Hydro
Gas
Oil
Coal
c
Ratios of non-fossil energy prices to coal price
0
1
2
3
4
5
6
7
8
9
2010
2015
2020
2025
2030
2035
2040
2045
2050
PV Solar
Tide
Geothermal
Biomass
Wind
Nuclear
Coal
Hydro

Figure 11



a
b
c
d
Annual carbon emission (GtC)
100%
90%
80%
60%
Median
Annual growth rate of carbon emission (%)
2010-2020
2020-2030
2030-2040
2040-2050
Carbon intensity (GtC/Trillion USD)
Annual decrease rate of carbon intensity (%)

Figure 12



Total GDP 2015-2050 | Total energy consumption 2015-2050 | Total CO_2 emissions 2015-2050

Figure 13

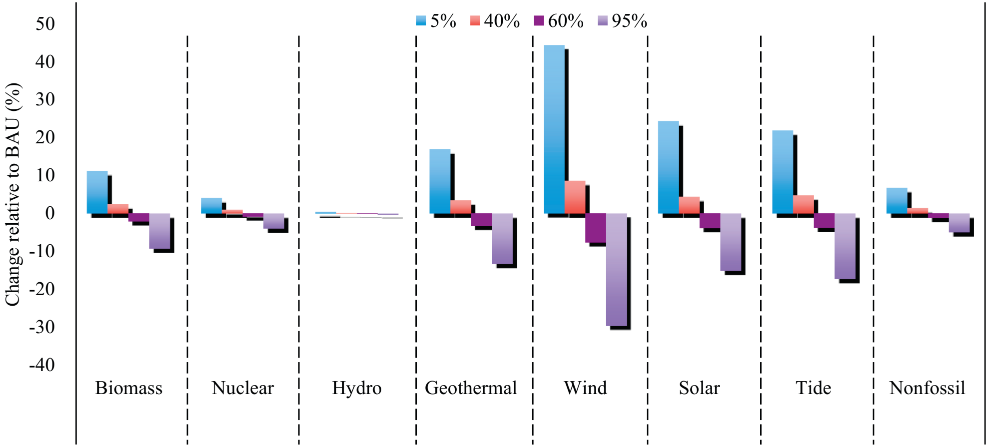

5%
40%
60%
95%
50
40
30
20
10
0
-10
-20
-30
-40
Change relative to BAU (%)
Biomass
Nuclear
Hydro
Geothermal
Wind
Solar
Tide
Nonfossil

Figure 14