

# Modelling the Evolutionary Paths of Multiple Carbon-Free Energy Technologies with Policy Incentives

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**Abstract** In this paper, we establish an economy-energy-environment integrated model by introducing a new technical mechanism, that is, the revised logistic model, to be the technical core of the energy module. This gives the conventional top-down modes more bottom-up features and allows us to model the evolutionary pathways of multiple non-carbon technologies. The model's simulations indicate that the mixed policy of both carbon tax and subsidy plays a significant part in promoting the development of new energy technologies. The shares in total primary energy usage for PV solar, geothermal power and wind energy, for example, will have increased to 24.9, 9.7 and 6.12 %, respectively. Meanwhile, technological progress can be significantly enhanced by introducing research and development (R&D) investment. As a result, the percentages of usage of the above three technologies are likely to increase to 26.2, 12.1 and 7.2 %, respectively, in that case. Besides, energy supply market will be locked up by non-fossil energy as early as 2035, or thereabouts, under the current R&D investment regime. Thus, the expansion of R&D may significantly improve the carbon-reducing potential of the mixed policy and perform well in easing the tax burden on businesses and consumers in the long run.

**Keywords** Logistic curve · Learning-by-doing · Learning-by-searching · Carbon tax · Subsidy · Technology evolution

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## 1 Introduction

As the global economy develops rapidly, the consumption of fossil fuels is increasing, which inevitably results in an increase of carbon dioxide emissions, thereby affecting the environment. Effectively reducing CO<sub>2</sub> emissions is widely considered to be the most important approach to controlling atmospheric concentrations of greenhouse gases and preventing our earth from warming.

There are many ways to cut down CO<sub>2</sub> emissions, including improving traditional fossil energy technologies to decrease the carbon intensity per unit of output, changing people's behaviour to save energy and developing low-carbon or non-carbon technologies, such as carbon capture and storage (CCS) and renewables. In fact, developing low-carbon energy technologies to replace fossil fuels is one of the most promising directions in responding to the issue of emission abatement in the long run. As shown in McKinsey [28], the low-carbon energy substitution may contribute to 25.5 % of the total CO<sub>2</sub> abatement opportunities in 2030, at which time around 70 % of global electricity supply is provided by low-carbon alternatives. Meanwhile, the CO<sub>2</sub> abatement contribution of low-carbon alternatives will account for about 56 % in 2035 for achieving the 450-ppmv carbon concentration stabilization target [18]. However, most of the low-carbon technologies (such as PV solar and Tide) are too expensive currently to deploy on a large scale in the absence of financial incentives, this may block the shift process of energy supply from fossil fuels to low-carbon alternatives. Policies are important to promote not only diffusion of alternatives but also innovations in technologies themselves [10, 22]. For example, with respect to the current policy case, the increment of non-fossil energy will reach 604 Mtoe under the International Energy Agency (IEA) new policies scenario, which yields annual emission savings of around 5 GtCO<sub>2</sub> in 2035 [18]. Based on this, the first intention of this paper is to explore the

long-term evolutionary pathways of multiple carbon-free technologies and determine the role of policy incentives in promoting the development of low-carbon alternatives.

The second intention of this work is to consider the interaction between learning-by-doing (LBD) effect and research and development (R&D)-based learning effect in the process of technological evolution and explore the complementary effect of the strength of R&D activities in promoting technological penetration. In fact, the public R&D activities provide an important option to supplement the knowledge (or experience) accumulated by LBD process and contribute a lot to accelerate the cost-reduction of non-carbon innovations. These are very critical for the development of new technologies, especially in their early stages [19]. Furthermore, induced R&D will lower the cost of achieving a given abatement target [12].

In this paper, we establish a one-region energy-economy-environmental (E3) integrated model that allows us to introduce multiple new energy technologies and address the proposed issues. This model builds on the framework of top-down models, like DICE [32], RICE [33], MERGE [23], DEMETER [8] and ENTICE [36], but our model differs from these models at least in two aspects. First, we introduce a new technical mechanism that theoretically allows us to couple as many technologies as we need. Energy technical structure in the pioneering top-down models are usually oversimplified, which makes the models weak in incorporating multiple new energy technologies and determining the long-term competitive relationship between fossil and non-fossil technology [36]. This may largely be because the constant elasticity substitution (CES) function method has been widely used to model energy technological substitution in conventional top-down models, while this method gets limited potential in combining multiple technologies [34, 37]. To be specific, a substitution elasticity parameter is indispensable when we try to describe the substituting relations between any two technologies by employing the CES method; hence, for considering multiple technologies, lots of elasticity parameters are essential. The problem lies in that the elasticity parameters for new energy technologies are often difficult to estimate (largely due to the unavailability of data), and this might bring plenty of uncertainty to the model results.<sup>1</sup> In this work, we attempt to introduce a new revised logistic technical model into the energy module of our E3 framework to replace of the conventional CES method. The introduction of this new technical mechanism allows us to incorporate multiple carbon-free energy technologies, cutting down the number of elasticity

<sup>1</sup> Gerlagh and van der Zwaan [9] give sensitivity analysis of substitution elasticities between fossil fuels and zero-carbon energy based on their DEMETER model. When the value of elasticity is set to be 2.0, 3.0 and 4.0 respectively, the carbon emissions in 2020 will range from 7.6 to 7.8 GtC, and the reductions will be in the interval 36–73 %; shares of non-fossil energy demand will change from 9 to 16 %.

parameters to be estimated and, to some extent, releasing the dependence on data. Besides, this mechanism allows the conventional top-down models to feature more bottom-up technical characteristics, which provides a feasible option to bridge these two types of model frameworks.<sup>2</sup>

Second, technological progress is endogenized in our model by means of two-factor learning curve, directly incorporating links between policy and technological change. Research on endogenous technological change started at the 1990s when S. Messner first endogenized technological change in the system-engineering model called MESSAGE [29]. In general, endogenous technological advancement comes through knowledge (or experience) that can be accumulated by the LBD process or investment in research and development (R&D).<sup>3</sup> Despite a substantial work on studying endogenous technological change in E3 models, majority of them endogenize technological change by one-factor learning curve.<sup>4</sup> For example, Messner [29], Van der Zwaan et al. [41], Gerlagh et al. [8], Kypreos et al. [21] and Manne et al. [24] endogenize technological improvement by LBD process, while many other papers consider it based on LBS process, including Grübler et al. [14], Goulder et al. [12], Buonanno et al. [7], Popp [36] and Gillingham et al. [11]. However, knowledge accumulated no matter by LBD process or LBS process becomes obsolete as time goes, i.e. there exists so-called forgetting-by-not-doing phenomenon (FBND), which would weaken the effect of learning on technological advancement. R&D efforts (or LBD) act as a complementary channel for knowledge accumulation; it can mitigate the effect of FBND and provide long-term forces to drive technical improvement [4]. On this basis, the two-factor learning curve (both LBD and LBS) is employed in the top-down model framework to describe endogenous technological change, and this provides us a feasible option to discuss the interaction between LBD and LBS in the process of technological evolution and explores the complementary effect of the strength of R&D activities on technological penetration.

<sup>2</sup> Top-down models focus on macroeconomy, in which output is given by a production function, with capital, labour to be the inputs. Sometimes, energy or electricity is also input to be the complemented production factor, leaving energy technology advancement exogenized by automatic energy efficiency improvement (AEEI). Bottom-up models always get relatively rich set of specific energy technologies, making technological progress an exogenous process of cost and efficiency improvements. That is why the bottom-up models are often called “energy-system model” [8, 36].

<sup>3</sup> Arrow [3] is regarded as the first to discuss learning curves to which he refers as “learning-by-doing” (LBD), while the R&D-driven learning curve is often called “learning-by searching” (LBS) process. More information about learning curves can be attributed to Ibenholt [15] and Mattsson [25].

<sup>4</sup> Kouvaritakis et al. [20] and Barreto and Kypreos [4] have done some research on the two-factor learning method, but they did not discuss it in the scope of E3 models, and their study intention is different from ours as well.

The remainder of this paper is organized as follows. Section 2 presents the framework of the model established in this paper and characterized by its technical core of logistic curves. Data sources and processing will be showed in Section 3. Section 4 is dedicated to exhibit the modelling results, as well as the corresponding analysis. Robustness analysis of some key technical parameters is shown in Section 5. Conclusions will be drawn in the last Section 6.

## 2 Model Description

In this paper, we establish an economy-energy-environment integrated model that we call the E3METL model, as an acronym for “economy-energy-environment model with endogenous technological change by employing logistic curve”. Our purpose is to study the evolutionary paths of carbon-free technologies in the policy context and the effects of R&D on the economic and technical systems. E3METL views the world as a single region and embraces three modules of macroeconomy, technological change and climate. The model framework can be seen in Fig. 1.

### 2.1 Macroeconomy Module

Similar to the DICE and MERGE models, we optimize the model by maximizing gross social welfare, which is presented by the discounted sum of the population-weighted utility of consumption per head, subject to a budget constraint:

$$Max \sum_t \left( L(t) \cdot \log \left( \frac{C(t)}{L(t)} \right) \prod_{\tau=0}^t (1 + \sigma(\tau))^{-\Delta t} \right), \quad (1)$$

where  $C(t)$  and  $L(t)$  presents consumption and population, respectively;  $\sigma(t) = \sigma_0 \cdot e^{-d_\sigma t}$  is the pure time preference, with initial value  $\sigma_0$  and decline rate  $d_\sigma$ .<sup>5</sup> The production processes relies on the inputs of capital  $K(t)$ , labour  $L(t)$  and energy  $E(t)$ , which can be expressed as follows:

$$Y(t) = \left[ A(t) \left( K(t)^\gamma \cdot L(t)^{1-\gamma} \right)^\kappa + B(t) E(t)^\kappa \right]^{1/\kappa}, \quad (2)$$

where  $A(t)$  presents the technical progress level of capital and labour,  $\gamma$  is share of capital in capital-labour composition, and  $B(t)$  shows the autonomous energy efficiency improvement (AEEI), which includes all the energy technical progress induced by price changes. Also,  $\kappa$  gives the substitution elasticity between capital-labour mix and energy inputs.

<sup>5</sup> Debates on discount rate have never ceased; for more details on how to set depreciation rates appropriately in environmental problems, see [38]. In this paper, we give the value by referring to Nordhaus [32].

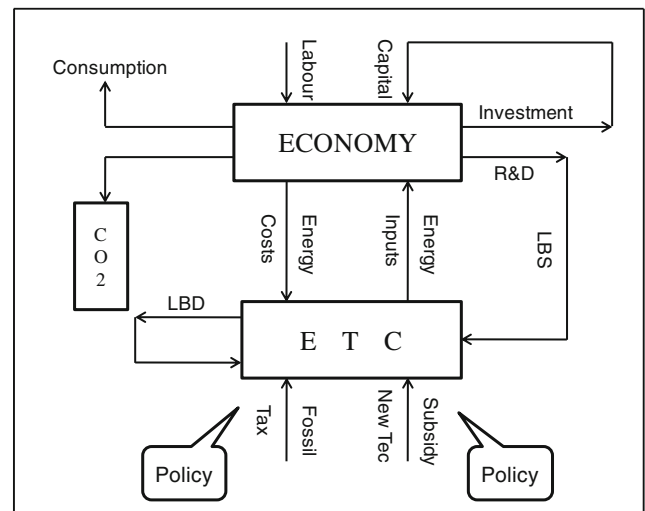


Fig. 1 The framework of the E3METL model

Capital  $K(t)$  can be formulated in terms of current and past capital stock adjusted by the depreciation rate:

$$K(t) = (1-\delta)K(t-1) + I(t), \quad (3)$$

The outputs  $Y(t)$  are made by the production department and will be used to pay for consumption, investment, energy costs and R&D activities; the balance relationship is as follows:

$$Y(t) = C(t) + I(t) + EC(t) + ARD(t), \quad (4)$$

where  $I(t)$  and  $ARD(t)$  are the investments and gross R&D expenditures, respectively, and  $EC(t)$  gives the energy cost, which is expressed as the product of composite price and energy usage,

$$EC(t) = Pe(t) \cdot E(t), \quad (5)$$

$Pe(t)$  is the composite price of fossil fuels, and  $E(t)$  presents energy consumption. For simplicity and convenience in calculating carbon emissions, the consumption of fossil fuels will be measured by equivalent tons of carbon (tC) in this paper; as for non-fossil fuels, we measure them by transforming equivalently in terms of their calorific value to carbon-based energy.

### 2.2 Energy Technology Module

#### 2.2.1 Experience Curve Based on Learning-by-Doing

Considering both LBD-based and LBS-based ITC in energy technology modelling is one of the main features of this paper; thus, it is necessary to define the learning curves. Earlier research on ITC is mainly based on the learning-by-doing

process, and the one-factor learning curve (OFLC) can be expressed as follows:

$$C_i(t) = a_i \cdot (KD_i(t))^{-b_i}, \quad (6)$$

where  $C_i(t)$  is the cost per unit energy for technology  $i$  and  $b_i$  is the learning index. The relation between the learning index and learning rate takes the following form:

$$1 - LR_i = 2^{-b_i}, \quad (7)$$

$LR_i$  is the so-called learning rate, which is the rate at which the cost declines each time the accumulative production or installed capacity doubles.<sup>6</sup> Knowledge stock  $KD_i(t)$  based on learning-by-doing is usually measured by the accumulation amount of energy consumption, including the “obsolete effect” of knowledge, i.e.

$$KD_i(t) = (1 - \delta_1)KD_i(t-1) + S_i(t) \cdot E(t), \quad (8)$$

where  $S_i(t)$  is the share of technology  $i$  in total primary energy demand, and  $\delta_1$  is the obsolete rate for knowledge.

### 2.2.2 Two-Factor Experience Curves by Introducing R&D Efforts

R&D activity has been proven to provide fundamental driving forces towards economic growth and technological progress, especially at the early development stages of carbon-free technologies [13]. On this basis, we endogenized energy technological change by both R&D-based LBS and LBD

process. The two-factor learning curve (TFLC) that incorporates both LBD and R&D-based LBS can be formulated as follows [4, 20]:

$$C_i(t) = a_i \cdot (KD_i(t))^{-b_i} \cdot (KS_i(t))^{-c_i}, \quad (9)$$

where  $C_i$ ,  $b_i$  and  $KD_i$  have been defined above,  $c_i$  is the learning index for learning-by-searching process, with the expression similar to Eq. 7,

$$1 - lr_i = 2^{-c_i}, \quad (10)$$

$lr_i$  is the learning rate for LBS.  $KS_i$  presents the knowledge stock accumulated by R&D efforts, which can be measured in terms of current and past R&D investments adjusted by depreciation rate  $\delta_2$ ,

$$KS_i(t) = (1 - \delta_2) \cdot KS_i(t-1) + ARD_i(t), \quad (11)$$

$ARD_i$  is the R&D expenditure,  $a_i$  in Eq. 9 can be easily figured out by substituting the initial point  $(C_{i0}, KD_{i0}, KS_{i0})$ , and Eq. 9 becomes,

$$C_i(t) = C_{i0} \cdot \left( \frac{KD_i(t)}{KD_{i0}} \right)^{-b_i} \cdot \left( \frac{KS_i(t)}{KS_{i0}} \right)^{-c_i}. \quad (12)$$

It is easy to see from Eq. 12 that technology costs will decrease as knowledge grows. However, cost cannot be reduced infinitely, so it is necessary for us to consider the possible minimal cost  $C_{imin}$ , then Eq. 12 can be transformed into the following formula [2]:<sup>7</sup>

$$C_i(t) = C_i(t-1) - (C_i(t-1) - C_{imin}) \cdot \left( b_i \cdot \left( \frac{KD_i(t) - KD_i(t-1)}{KD_i(t)} \right) + c_i \cdot \left( \frac{KS_i(t) - KS_i(t-1)}{KS_i(t)} \right) \right). \quad (13)$$

### 2.2.3 Modelling for Fossil Energy Technology

The issue on how the cost of fossil fuels will change has long been a bone of contention; the main viewpoints are as follows: some researchers believe that the proven reserves of carbon-based energy will increase as the exploitation technology advances, which implies that the costs of fossil fuels would keep declining for quite a long time; others hold the opinion that fossil energy is one of the non-renewable resources that will be exhausted with the total amount given, and the costs of

fossil fuel are destined to rise due to scarcity. To the best of our knowledge, Nordhaus W.D. is one of supporters for the second point; based on his idea, we describe the changes of cost for fossil fuels as follows [35]:

$$C_F(t) = Q_F(t) + Markup, \quad (14)$$

where  $C_F(t)$  is the cost of fossil energy per unit, and  $Markup$  is the sum of all the external costs, including the cost of transportation, distribution cost and energy tax cost, and we assume that  $Markup$  keeps constant during the entire projection

<sup>6</sup> Rubin et al. [39] did much research on the learning rates of multiple energy technologies, suggesting that the costs of the technologies are declining in the past few decades, with learning rates ranging from 10 to 12 %.

<sup>7</sup> We replace  $C_i(t)$  with  $C_i(t-1) - C_{imin}$  after taking some simple derivative and difference operations to Eq. 12, then we get  $C_i(t) \rightarrow C_{imin}$ , as  $t \rightarrow \infty$ , and the learning effect tends to zero, which fits in with the reality (see Appendix 2).

period.  $Q_F(t)$  presents the marginal cost for exploration of fossil fuels and can be formulated as below:

$$Q_F(t) = \xi_1 + \xi_2(CumC(t)/CumC^{\max})^4, \tag{15}$$

Here,  $CumC(t)$  presents the exploitation accumulation till period  $t$ , and  $CumC^{\max}$  is the global maximum possible extraction;  $\xi_1$  and  $\xi_2$  are given cost parameters. Moreover, we describe the process of accumulative exploitation as follows:

$$CumC(t) = CumC(t-1) + S_F(t) \cdot E(t), \tag{16}$$

where  $S_F$  is the share of fossil energy in gross primary energy use.

### 2.2.4 Revised Logistic Curves and Multiple Energy Technologies Modelling

E3METL employs logistic curves to describe the competitive relationships between different technologies, and the original logistic curve is revised mainly based on the following two facts: first, technology development is closely related to its cost (cost per unit energy or price). Generally speaking, the market competitiveness and demand of some technology would increase as its price declines, so it is necessary for us to incorporate the changes of prices in modelling technological evolution; second, policy intervention is important for promoting technical penetration, so we introduce the revised logistic curve by taking policy variables into account [2]. The revised logistic technological mechanism can therefore be presented as

$$\frac{dS_i(t)}{dP_i(t)} = \chi_i S_i(t) \left( \bar{S}_i \left( 1 + S_i(t) - \sum_i S_i(t) \right) - S_i(t) \right), \tag{17}$$

where rate of change in market share is expressed with respect to the change of relative prices rather than changes in time, and  $P_i$  is the ratio of marker technology that is presented by fossil energy technology in E3METL to alternative

technologies that consist of all the non-carbon technologies; the formulation is

$$P_i(t) = \frac{C_F(t)(1 + T_f(t))}{C_i(t)(1 - G_i(t))}. \tag{18}$$

Here,  $C_F$  and  $C_i$  denote the costs per unit of energy for the marker technology and alternative technology (the ratio  $C_F/C_i$  may show a wide frequency distribution, the value here should be understood as the mean values, and the relative price  $P_i$  is also the mean value of the price ratio). The effects of carbon taxes and subsidies on prices are also included in Eq. 18;  $T_f$  and  $G_i$  represent the tax rate for fossil energy and the subsidy levels for alternative energy, respectively.  $\chi_i$  is a substitution parameter, and  $\bar{S}_i$  means the maximum possible share of technology  $i$  in energy supply market, with  $0 \leq S_i \leq \bar{S}_i \leq 1$ . The relative prices have a great influence on technology substitution, and the share of alternative technology will increase as  $P_i$  closes to 1. An increase of the price ratio  $P$  can be brought about in two ways. One is to increase the carbon taxes levied on the marker technology but not on the substitutes or alternatively to subsidize the substitute technology but not the marker. The second is through innovation that reduces the costs of the alternatives relative to the marker.

The term  $dS_i/dP_i$  in Eq. 17 captures the exponential growth of the alternatives in the early phases of expansion and diminishing possibilities as market saturation levels are approached. In general, the relative price  $P_i$  shows a wide frequency distribution; hence,  $dS_i/dP_i=f(P)$  can be viewed as the frequency distribution of relative prices, this implies that we might estimate the substitution parameter  $\chi_i$  based on the standard deviation of frequency distribution. In fact, there exists an inverse relationship between  $\chi_i$  and the standard deviation of the frequency distribution of the relative prices [2].<sup>8</sup>

For the convenience of inter-temporal simulation, we convert Eq. 17 into a different form:

$$S_i(t) = S_i(t-1) + \chi_i S_i(t-1) \cdot \left( \bar{S}_i \left( 1 + S_i(t-1) - \sum_i S_i(t-1) \right) - S_i(t-1) \right) (P_i(t) - P_i(t-1)). \tag{19}$$

It is worth noting that Eq. 19 will regress to the original form as long as the changes of relative prices in each period are constant and equal to the duration per period, that is,  $\Delta P_i = \Delta t$ .

By embedding logistic curves into technical sub-module, as we have observed above, it becomes much more convenient to inducing carbon tax and subsidy policy variables,

<sup>8</sup> In the one-dimension case, the relationship between parameter  $\chi$  and the standard deviation can be described as  $\chi^2 = \pi^2/3\sigma^2 \approx 1.81\pi^2/\sigma^2$ , when turning to the multi-dimension case, the relationship becomes more complex [2]. Overall, the dynamics of logistic curve is sensitive to the parameter value  $\chi$ , for the formulation,  $S_t = \alpha S_{t-1}(1 - S_{t-1})$ , if  $\alpha \geq 3.57$ , the long run solution starts to become chaotic; if  $\alpha \geq 3.83$ , there will be unaccountable number of asymptotically  $\alpha$ -periodic trajectories, as well as cycles for every integer period [26].



which is beneficial to investigate the influences of various policy instruments on our system. In fact, the most important thing is that we may consider energy technologies as many as possible by means of the revised logistic technical model, with no need to worry about the harsh problems of elasticity estimation and optimal calculation compared to the common constant elasticity substitution method (CES). Besides, by transforming the logistic differential Eq. 17 into a different one Eq. 19, we can easily overcome the nonlinearity problem.

In addition, the composite prices of energy inputs can be defined as follows:

$$Pe_i(t) = C_F(t) \left( 1 - \sum_i S_i(t) \right) (1 + T_f(t)) + \sum_i S_i(t) C_i(t) (1 - G_i(t)). \quad (20)$$

### 2.3 Climate Change Module

CO<sub>2</sub> emission in E3METL is classified into two parts; one is anthropogenic emission, which is mainly attributed to the burning of fossil fuels, and the other is natural emission, which includes all the external emissions. We assume the natural emissions stay unchanged during the entire horizon, so the emission equation can be shown as follows:

$$EMIS(t) = \theta_F S_F(t) E(t) + EMIS0, \quad (21)$$

where  $\theta_F$  is the emission factor, that is, CO<sub>2</sub> emissions per unit of energy consumption, and  $EMIS0$  means natural emissions.  $S_F$  gives the share of fossil energy, which can be expressed as follows:

$$S_F(t) = 1 - \sum_i S_i(t).$$

Carbon concentration in the atmosphere is the sum of current emissions and past emissions adjusted by the sinking rate,

$$AC(t) = (1 - \eta) AC(t-1) + EMIS(t), \quad (22)$$

where  $AC(t)$  denotes atmospheric CO<sub>2</sub> concentration, and  $\eta$  is the sink rate that describes the Earth's carbon absorption level.

Our simulation starts in 2000 and terminates in 2150, with 30 5-year periods. The model can be solved numerically by CONOPT algorithm in GAMS on a standard PC. By maximizing the social welfare objective, the model will choose optimal consumption flows, then we can get the optimal solution. Several minutes are enough to get the solution under the business-as-usual (BAU) case.

### 3 Data and Calibrations

In this work, the fossil energy is the composite of all the carbon-base energy, including coal, oil and natural gas, and we divide non-fossil energy technology into seven types, that is, combustible renewables and waste power (CRW), nuclear (NUC), hydropower (HYD), geothermal energy (GEO), solar power (SOL), wind energy (WIND) and tide (TIDE).

According to the World Bank [43], the gross world product (GWP) in 2000 is \$29.07 trillion, and the world's entire population is 6.68 billion.<sup>9</sup> The maximum size of the world's population is assumed to be 11.4 billion [31]. In addition, energy consumption is 6.63 GtC in 2000 [9].

The initial market shares for various energy technologies considered originate in IEA's key world energy statistics [16]. The gross energy R&D expenditure is estimated to be \$10.54 billion in 2000, with new energy accounting for around 10 % [1]. The initial R&D shares of various alternative technologies stem from renewable energy statistics reported by IEA [17].<sup>10</sup> The R&D investment path is assumed to grow exogenously, with the 5-year growth rate to be 10 % for CRW, NUC and HYD versus 30 % for GEO, WIND, SOL and TIDE. The atmospheric CO<sub>2</sub> concentration for the starting year is set to be 386 GtC, based on the research of Gerlagh and van der Zwaan [10] and Nordhaus and Boyer [35]. For more parameters and initial values, refer to Table 1.

Learning rates for alternative energy technologies and substitution parameters in logistic curves are very important parameters that have great influence on the results of a simulation [39]. McDonald and Schrattenholzer [27] conducted extensive research on estimating the learning rates of different technologies; they explain that emerging technologies may take up a larger amount of the development space, and the corresponding learning rates will range from 12.9 to 18.7 %. Mature technologies may get a lower learning rate than the emerging technologies, with the values from 9.8 to 12.9 %, and there are very limited spaces left for the old technologies, so the learning rates are often evaluated to be about 7 %. The learning indexes for the considered technologies are presented in Table 2 in detail.<sup>11</sup>

The substitution parameters  $\chi_i$  in the revised logistic curves could be comprehended as the capability of replacing fossil fuels with carbon-free technologies. Thus,  $\chi_i$  will grow as time goes by and as the exhaustion of fossil energy continues,

<sup>9</sup> The monetary figures in this paper are in 1990 USD.

<sup>10</sup> Data for R&D are only available for IEA countries (<http://www.iea.org/stats/index.asp>), data for the rest of world is not given in detail. Then we adopt the estimation of total public R&D expenditures for the entire world in 2000, and the share the R&D relates to energy is set to be 2 %, referring to Popp [36].

<sup>11</sup> The learning ratio is the rate at which the specific cost declines each time the cumulative capacity doubles, the relationship between the learning rate and the learning index is described by Eq. 7 [4].

**Table 1** Description for parameters and initial values

Parameter	Value	Description	Reference source
$\sigma_0$	0.03	Initial pure time preference	[32, 34, 35]
$d_\sigma$	0.003	Annual decline rate of pure time preference	Ditto
$\delta$	0.07	Annual capital depreciation rate	Ditto
$\gamma$	0.31	Share of capital's value in capital-labour mix	Ditto
$\kappa$	0.40	Elasticity between energy and capital-labour mix	Ditto
$AEEI$	0.70	Initial automatic energy efficiency improvement	Ditto
$d_a$	0.002	Annual decline rate for AEEI	Ditto
$\zeta_1$	113.00	Cost parameter for fossil energy extraction (\$/tC)	Ditto
$\zeta_2$	700.00	Cost parameter for fossil energy extraction (\$/tC)	Ditto
$\theta_F$	1.00	CO <sub>2</sub> emission factor <sup>a</sup>	[36, 37]
$\eta$	0.006	Natural sink rate	[8–10]
$CumC^{\max}$	6,000.00	The maximum exploitation of fossil fuels (GtC)	[33, 34]
$Markup$	163.29	External cost parameter (\$/tC)	Ditto
$emis0$	1.33	The global natural emissions per year (GtC)	Ditto
$C_F$	276.29	Initial cost of carbon-based energy (\$/tC)	Ditto
$C_C$	830.00	Initial cost of biomass energy (\$/tC)	Estimated <sup>b</sup>
$C_N$	470.00	Initial cost of nuclear power (\$/tC)	Ditto
$C_H$	550.00	Initial cost of hydro power (\$/tC)	Ditto
$C_G$	550.00	Initial cost of geothermal energy (\$/tC)	Ditto
$C_S$	1,380.00	Initial cost of PV solar power (\$/tC)	Ditto
$C_W$	1,100.00	Initial cost of wind energy (\$/tC)	Ditto
$C_T$	1,100.00	Initial cost of tide energy (\$/tC)	Ditto

<sup>a</sup> In this paper, fossil fuel is measured in tons of carbon, then the price of fossil fuels is the price per ton of carbon (\$/tC); non-carbon energy is measured by carbon ton equivalent which can be converted in terms of the equivalent calorific value between fossil and non-fossil energy (Fossil energy in this paper is not subdivided; thus, it is a composited energy consisting of coal, oil and nature gas, and the calorific value of the composited fossil energy is therefore the average value of coal, oil and nature gas); thus, \$/tC can also be the price of non-fossil energy [36]. Since this definition, the carbon emission factor of fossil fuel is equal to 1

<sup>b</sup> Anderson and Winne [2] believes that the cost of nuclear power may be at least 70 % higher than that of fossil fuels; the extent for biomass, offshore wind and tide energy will reach 100 %; and the cost of photovoltaic solar energy is even higher, that is, 2~7 times that of fossil energy. Meanwhile, Gerlagh and van der Zwaan [8] indicates that the cost of biomass might be close to conventional energy, cost of some other new energy, such as offshore wind and onshore wind may be 2~8 folds of fossil fuels, and the cost for solar power may be even higher

while we assume that the parameter values keep constant during our simulation for simplicity. Anderson and Winne [2] suggest that the parameters be valued at the interval of 4 to 15. The technologies that can be replaced easily will certainly get a higher substitute rate, ranging from 10 to 15, and the substitution relationships among fossil fuels may fall into this category. The replacement level for the new energy technologies, such as wind power and biomass energy, may be

lower than 10, with 7 to be the lower boundary. It is difficult for the technologies with wider application cost gaps to substitute for each other, and the parameter values might be even lower; then a range of 4 to 7 is often set. We give the parameters in E3METL by summarizing the information above, and they are presented in Table 2.

## 4 Scenario Setting and Simulation Results

### 4.1 Scenarios

In order to investigate the long-term evolutionary pathways of multiple new energy technologies in the policy context and explore the impacts of R&D activities, we set six other policy scenarios in addition to the benchmark case (business-as-usual, BAU). Policy scenarios are provided in the light of the strength of policy signals and

**Table 2** Assumptions of learning indexes and substitution parameters

Parameter	CRW	NUC	HYD	GEO	SOL	WIND	TIDE
L-index $b_i^a$	0.20	0.10	0.10	0.20	0.30	0.25	0.20
S-index $\chi_i$	5.00	10.00	7.00	5.00	9.00	8.00	6.00

<sup>a</sup> For simplicity, we assume the learning effect of LBD process is the same with that of LBS process, i.e.  $c_i=b_i$

**Table 3** Scenario descriptions for simulation

Scenarios	Endogenous TC		Policy instrument	
	LBD	LBS	Tax rate <sup>a</sup>	Subsidy rate <sup>b</sup>
BAU	√	×	0.00	0.00
LBSN1	√	×	1.10	CRW 0.10 NUC 0.10 HYD 0.10 GEO 0.50 SOL 0.50 WIND 0.50 TIDE 0.50
LBSN2	√	×	1.25	Subsidy rates for all the non-fossil technologies are the same with LBSN1
LBSN3	√	×	1.40	Ditto
LBSY1	√	√	1.10	Ditto
LBSY2	√	√	1.25	Ditto
LBSY3	√	√	1.40	Ditto

<sup>a</sup> Generally, the revenues resulting from carbon tax can be used to subsidized non-carbon technologies, making the net payments be zero. However, our intention is not to find the optimal carbon tax or subsidy policy but to consider the impact of policy intervention, we thus do not implement it in this model, assuming that the tax neutrality be met by adjusting other tax out of our system instead [10]

<sup>b</sup> In this paper, we give fixed scenario parameters during the entire time horizon for convenience of simulation; for the purpose of supporting the development of smaller-share non-carbon technologies, we give them high subsidy rates. In addition, carbon tax and subsidy are implemented by means of ad valorem

whether R&D investment is included in reaching the given climate stabilization targets (Three targets of 450, 500 and 550 ppmv are given in this paper). As we have reviewed in Section 2, research concerning the learning effect of LBD process has grown to a substantial size; thus, we imply the LBD effect in every scenario, and the emphasis of this work is put on R&D-based endogenous technological change. It is worth noting that we only consider the policy mix of carbon taxes and subsidies instead of each one separately, on the basis of the following two facts. Firstly, revenues from a carbon tax can be used to pay for subsidies in the policy mix, which is helpful for meeting the condition of tax neutrality [40]. Secondly, the combination policy is the most cost-effective way of curbing CO<sub>2</sub> emissions with respect to the pure carbon tax policy or subsidy policy, especially when the “spillover effect” in R&D activities is considered [10, 12]. Scenario descriptions are listed in Table 3.

## 4.2 Simulation Results and Analysis

### 4.2.1 Benchmark Case

In the case of BAU, the GWP will grow from \$29.07 trillion in 2000 to \$272.55 trillion in 2100, with the growth close to tenfold. The gross primary energy consumption in 2000 is

6.63 GtC that increases nearly 400 % as compared to 33.14 GtC in 2100. Moreover, by the end of the twenty-first century, the total CO<sub>2</sub> emissions for the entire world will have grown to 23.71 GtC.<sup>12</sup> The energy supply market is dominated by fossil fuels during the entire projection period under the BAU case, and non-fossil energy grows slowly from 20.61 % in 2000 to 30.32 % in 2100 (see Fig. 2).

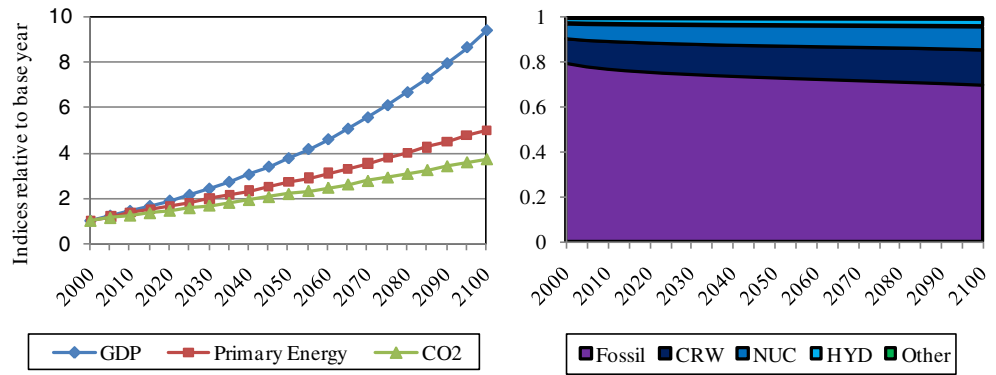
### 4.2.2 Pathways of CO<sub>2</sub> Emission and the Effect of R&D Policy

Figure 3 gives the paths of CO<sub>2</sub> emissions and that of CO<sub>2</sub> abatement, respectively, under the various scenarios given in this paper. In BAU, carbon emissions will keep growing without an inflection point throughout our simulation. Carbon emissions begin to decline in 2030 under the strictest case of LBSY3; by the end of the twenty-first century, the emissions will have been reduced to 67 % of that in 2000, with the atmospheric CO<sub>2</sub> concentration being stabilized at 400 ppmv.

<sup>12</sup> The CO<sub>2</sub> emission in this model in 2100 is much lower than in the RICE model (38 GtC) while approaches to the projection in the DICE model (21 GtC), but the carbon projections in both E3METL and DICE model are in the IPCC’s projection interval of 5 to 35 GtC [33, 42]. The comparisons of the main results in this work to that of the existing models are listed in Table 4 in Appendix 1.



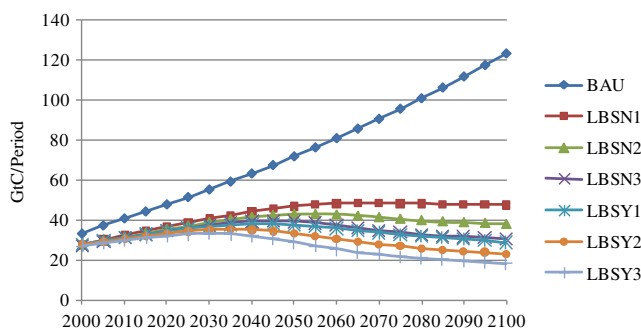
**Fig. 2** (Left) Basic indicators for the BAU case relative to 2000 (index, 2000=1); (right) shares of fossil and non-carbon energy technologies



Ceteris paribus, the peak point of carbon emissions will occur sooner as carbon tax increases. This point first appears in 2045, with the peak value to be 39.35 GtC, corresponding to the case of LBSN3. The implementation of a carbon tax will increase the costs of fossil fuels, which in turn cuts its demand, and emissions are reduced accordingly. Therefore, a carbon tax is an effective way of reducing carbon dioxide.

By comparing LBSY1, LBSY2 and LBSY3 with LBSN1, LBSN2 and LBSN3, respectively, we can observe that R&D-based technological progress plays a significant role in CO<sub>2</sub> reduction, and the peak point of carbon emissions will occur in 2030, with an even lower peak value of 18 GtC, which is in line with the corresponding finding in Gerlagh and van der Zwaan [8]. In fact, R&D activities have no direct influence on CO<sub>2</sub> abatement, but they will help to reduce the cost of non-fossil energy technologies and promote its development, which in turn releases our dependence on fossil fuels and results in carbon abatement.

Under the scenario of LBSN3, in which the rate of carbon tax is set at 140 %, we get the accumulation of tax revenues and subsidy expenditures from 2000 to 2100 to be \$24.52 trillion and \$11.97 trillion, respectively, while in the LBSY3 case, in which we keep the carbon tax rate unchanged and incorporate R&D investment, the corresponding carbon tax revenues and subsidy expenditures are \$19.11 trillion and \$14.09 trillion; by deducting the 50 billion R&D expenditure, we could get a surplus of 4.98 trillion. In other words, 50



**Fig. 3** Carbon-emission paths for the scenarios analyzed

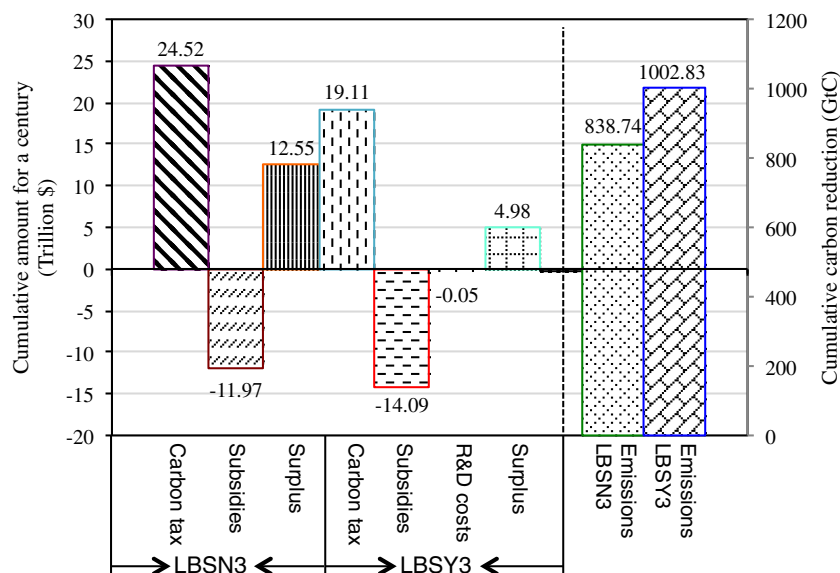
billion of R&D investment could hedge 7.57 trillion of carbon tax loss for the enterprises. In addition, the accumulative CO<sub>2</sub> reduction under the R&D case for the ten decades is 164.1 GtC more than the no R&D case (see Fig. 4). Thus, lower carbon tax is needed to achieve the same carbon reduction target if R&D activity is induced. In summary, the introduction of R&D investments plays an important role in reinforcing the effects of the policy mix, which is not only helpful in cutting down CO<sub>2</sub> emissions but also in easing the tax burden on businesses and consumers in the long run.

4.2.3 Evolutionary Paths of Market Shares for Various Energy Technologies

The mixed policy of combining carbon tax with subsidies will promote the development of zero-carbon technologies to a large extent, while R&D investment enhances the policy effect. Market shares for all the technologies in 2050 and 2100 under various given scenarios are depicted in Fig. 8, in which the horizontal lines show the various scenarios, the tab “2000” presents the shares of technologies in the beginning year and the vertical axis gives the market shares. Under the scenario of BAU, the share of alternative technologies grows slowly from 20.61 % in 2000 to 30.3 % in 2100, which suggests that fossil fuels will dominate the energy supply during the entire projection period. In BAU, the geothermal, solar and wind energy would be underdeveloped without policy instruments taken into account, and the relative shares would be 0.8, 0.1 and 0.06 % by 2100, respectively. Note that by the end of the twenty-first century, the shares of geothermal, solar and wind will have increased to 7, 19.5 and 4.8 %, respectively, in the LBSN1 case, with the total share of new energy to be 24.75 %, versus 9.7, 24.9 and 6.1 %, respectively, in the LBSN3 case, with the total share of non-fossil energy to be 14.28 % (see Fig. 5).<sup>13</sup> Hence, taxing fossil fuels as well as

<sup>13</sup> The results here are in line with that of most of the relevant studies; for example, Gerlagh and van der Zwaan [10] believed that at least half of the world’s energy supply would be provided by alternative technologies at the end of the century.

**Fig. 4** Comparisons of cumulative amounts of carbon emissions and policy costs between the scenarios of LBSN3 and LBSY3



subsidizing carbon-free technologies has a fundamental effect on the penetration of new energy technologies; alternative technologies will develop more rapidly, depending on the strength of the policy signals.

Specifically, the non-fossil technologies will develop to different extents under the case of LBSN3 (see Fig. 6—left). It is known that the energy embedded in sediments and macro-phytes (generated by photosynthesis) is 10 to 20 times the world's energy demand; the part that is currently available to us for development, however, is less than 3 %. This implies that there is a lot of potential for humans to develop energy from combustible materials and waste. The simulated analysis indicates that the share of biomass will reach 23.3 %, with a growth of 112 % by the end of 2100. Hydropower is one of the technologies that have been significantly developed in some countries; there are 24 countries, such as Norway and Brazil, in which the share of hydropower is more than 90 % of the energy mix. There are 55 nations, including Canada and Switzerland, in which hydropower accounts for 50 % of energy consumption and 62 states in which more than 40 % of the energy supply is provided by hydropower. In sum, more than 60 % of the hydropower in developed countries has been developed, which implies a limited space for the world to exploit it.<sup>14</sup> In the case of LBSN3, the share of hydropower will double from 2000 to 2100, reaching 4.5 %. Nuclear power has suffered a lot in recent years because of security issues, but it has in fact gained a great deal of potential. In the long term, nuclear energy will likely be one of the main energy sources we depend on to support the economic development,

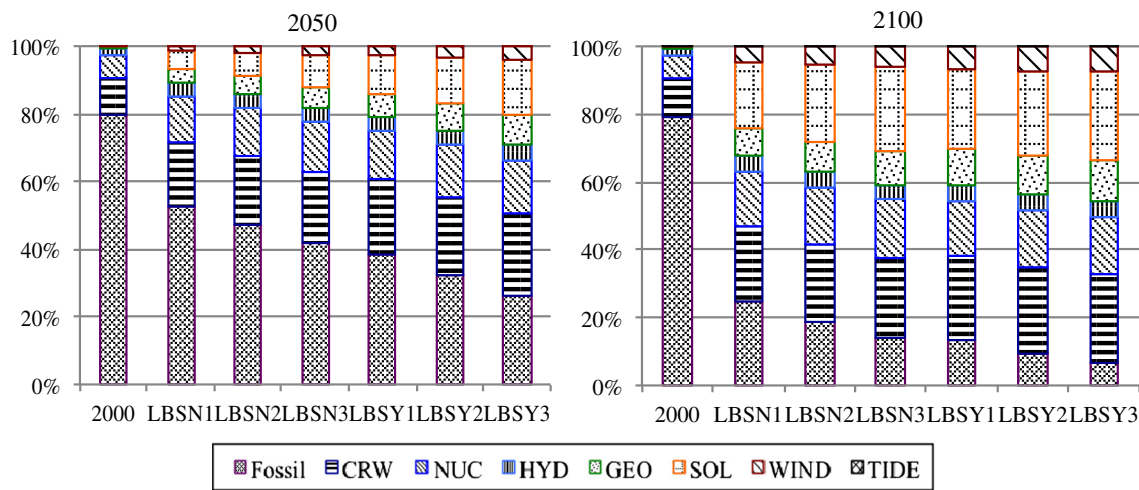
especially if nuclear waste is handled properly and if breakthroughs in nuclear fusion technology occur in the future. According to the above analysis, nuclear technology will develop to a large extent; in the LBSN3 case, its share of total primary energy consumption will increase from 6.8 % in 2000 to 17 % in 2100, with its growth rate be over 150 %.

Solar and geothermal are viewed as the technologies with the greatest potentials on earth. According to the forecast of the IEA [17], a majority of the world's electricity consumption will be supplied by photovoltaic and thermal power plants by 2060, with the rest being supported by wind, hydropower and biomass. Under the scenario of LBSN3, the shares of solar, wind and geothermal in 2060 will reach 15, 3.7 and 7.4 %, respectively, by our calculation, and they will have expanded to 24.9, 6.1 and 9.7 %, respectively, by the end of the twenty-first century. It can be observed from Fig. 5 that tide power is the only technology that maintains a lower share during the entire simulation, which might largely attribute to the stricter constraints supporting its development; the share of tide energy will only be 0.011 % by the end of 2100.

Figure 6—right indicates competitive evolutionary paths of various carbon-free technologies in the scenario of LBSY3, with R&D investments incorporated. Under the incentives of R&D-based technological change, the competitiveness of various energy technologies will be improved as their costs decline. The share of non-fossil energy will reach 85.72 % in 2100 by LBSN3 versus 93.1 % by LBSY3. Similar to the situation in the LBSN3 case, the zero-carbon energy market will be dominated by solar, wind and geothermal, which contribute 26.2, 7.2 and 12.1 %, respectively, to total primary energy demand.

In addition, the timing of “lock-up” points for carbon-free energy is affected by policy incentives to a large extent, and

<sup>14</sup> Data resources: Dams and Development, the report of the World Commission on Dams, Nov. 2000, Earthscan Publications Ltd.



**Fig. 5** Shares of primary energy use in 2050 and in 2100 by scenarios

this point may appear in 2055 or thereabouts (Fig. 7). Strengthening the policy signal by raising the carbon rate from 110 to 140 % could result in moving up the lock-up point to 2045 or thereabouts. The energy supply market could be locked up by the non-fossil energy as early as 2035 if R&D investment is incorporated.<sup>15</sup> Hence, the development of carbon-free technologies relies heavily on the strength level of the policy incentives, and R&D activities provide great driving forces towards energy technological progress—revealing a complementary impact on the combination policy.

#### 4.2.4 Effects on Energy Consumptions and Outputs

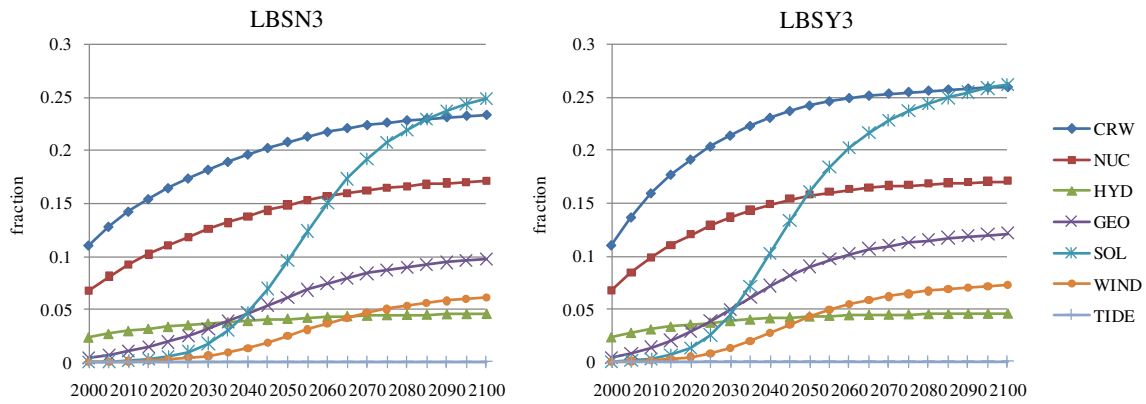
Changes for energy consumptions and GWP are depicted in Figs. 8 and 9, respectively. It can be observed that energy consumption is reduced significantly, beginning in the year when the mixed policy of both carbon tax and subsidy is implemented, which implies that the earlier carbon reduction targets are achieved mainly by reducing the consumptions of fossil fuels. In the beginning of policy implementation, the carbon-free technologies do not have enough time to develop sufficiently to replace fossil energy and support the energy supply, which leads to a significant decrease in energy consumption. After a while, the carbon-free energy sector will grow to a substantial size and offset the decreased use of fossil fuels, allowing energy consumption to return to the primary level. We can also observe that the strength of the policy signal determines the decrease of energy consumption as well as the time it will take for energy demand to catch up with the BAU line. For example, energy consumption will at most be reduced by 21.06 % in LBSN1 and may recover to its primary level by the end of the twenty-first century, versus 24.72 % in LBSY3, with recovery 30 years earlier.

<sup>15</sup> The “lock-up” points define the first time when the share of non-carbon technologies surpasses that of fossil fuels.

Under the shock of policy instruments, the total energy demand will be strongly reduced, especially when substitution possibilities with zero-carbon technologies are not yet available in the short term. This will undoubtedly be a great blow to the global economy—the stricter the climate policies, the greater the blow. For instance, the maximum loss in LBSN1 will be limited to 3.76 % under the BAU case, while the loss will increase to 4.68 % when turning to LBSN3 (Fig. 9). As non-carbon technologies develop, the economy will return to its primary level at the end of the twenty-first century; the inclusion of R&D investment may lower the GWP loss and move up the date that the economy catches up to the BAU trajectory to 2080, which indicates that R&D activities may reduce the GWP loss triggered by climate policies. The inherent ration is that R&D activities provide driving forces to promote the penetration of non-fossil technologies, which then enhances the role of carbon-free energy in the energy supply and in turn supports the development of the global economy.

## 5 Sensitivity Analysis

This section is devoted to a sensitivity analysis. The learning rates (learning indexes) for both LBD and LBS are crucial for the penetration of carbon-free energy technologies; thus, it is of great importance to examine how the choices of these parameters affect the diffusion of non-fossil technologies. The base values of LBD and LBS learning indexes for the considered technologies are presented in Table 2; we implement the sensitivity analysis by reducing or increasing the base values by 30 %. As the sensitivities of learning effects for both LBD and LBS are to be examined, here we focus on one of the R&D policy cases, i.e. LBSY1 case.



**Fig. 6** Comparisons of for shares of non-fossil energy between LBSN3 and LBSY3

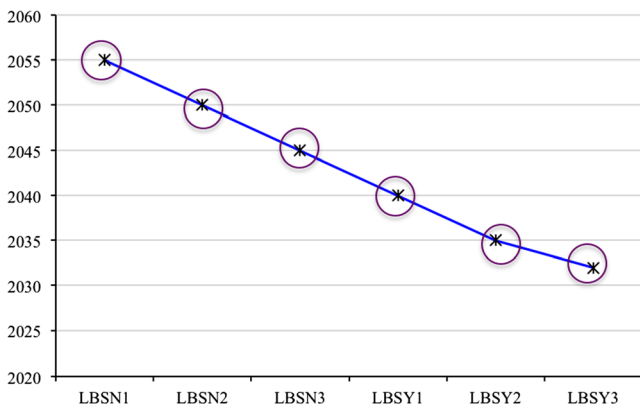
Figure 10 summarizes the percentage deviation of market shares for various non-carbon technologies. Overall, the trajectories of percentage changes for the given technologies are hump-shaped over time, that is, the effects of the learning rates increase first and then decrease. An increase or a decrease of LBS learning effect by 30 % has approximately symmetric impacts on the technological shares, and the changes of percentage for all the given technologies will be lower than 25 %. Meanwhile, the percentage deviations for wind and solar are much larger than the other technologies, with their highest values reach 20.71 and 23.7 %, respectively. As for the LBD case, the symmetric effects could not be observed any more, when the learning indexes increase or decrease by 30 %. The impacts of the increase of LBD learning rates by 30 % are substantially larger than that of the decrease by the same percentage. In addition, the technical shares of solar, wind and geothermal energy are significantly sensitive to the changes of LBD learning rates, and their percentage deviations will reach as high as 147.1, 148.3 and 76.7 %, respectively, if the LBD learning indexes increase by 30 %; Meanwhile, the changes of percentage

will also surpass 50 %, if the learning indexes decline by the same percentage.

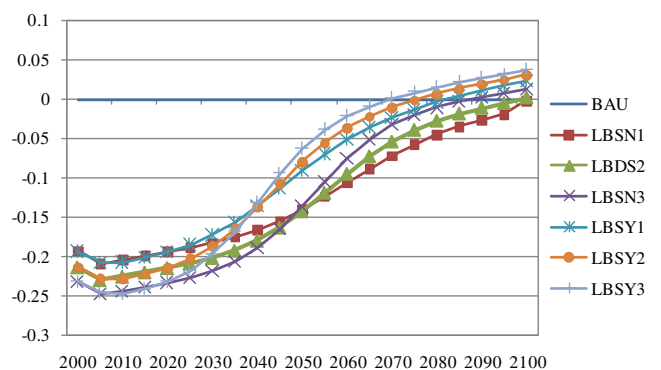
### 6 Concluding Remarks

In this paper, we establish an economy-energy-environment integrated model by employing revised logistic curves as the heart of the technology module; by employing the new technical mechanism, we have successfully introduced multiple non-carbon energy technologies into the conventional E3 model framework, and this provides a feasible option to enrich the technical details of top-down models. The emphases of this paper are to investigate the evolutionary paths of various energy technologies, explore the competitive relations between the conventional fossil and new non-fossil technologies in the policy context and determine the impacts of R&D activities. The key conclusions can be drawn as follows:

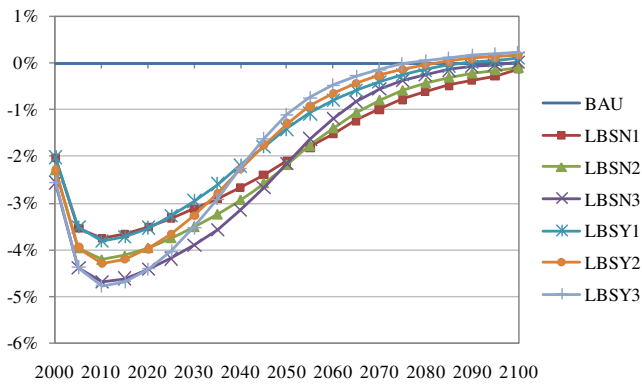
Firstly, R&D is not only helpful in cutting down CO<sub>2</sub> emissions but also in easing the tax burden on businesses and consumers in the long run. The results reveal that 50



**Fig. 7** The timing of “lock-up” points for non-carbon technologies by cases



**Fig. 8** Changes of energy consumption under various scenarios relative to BAU



**Fig. 9** Changes of GWP under various scenarios relative to BAU

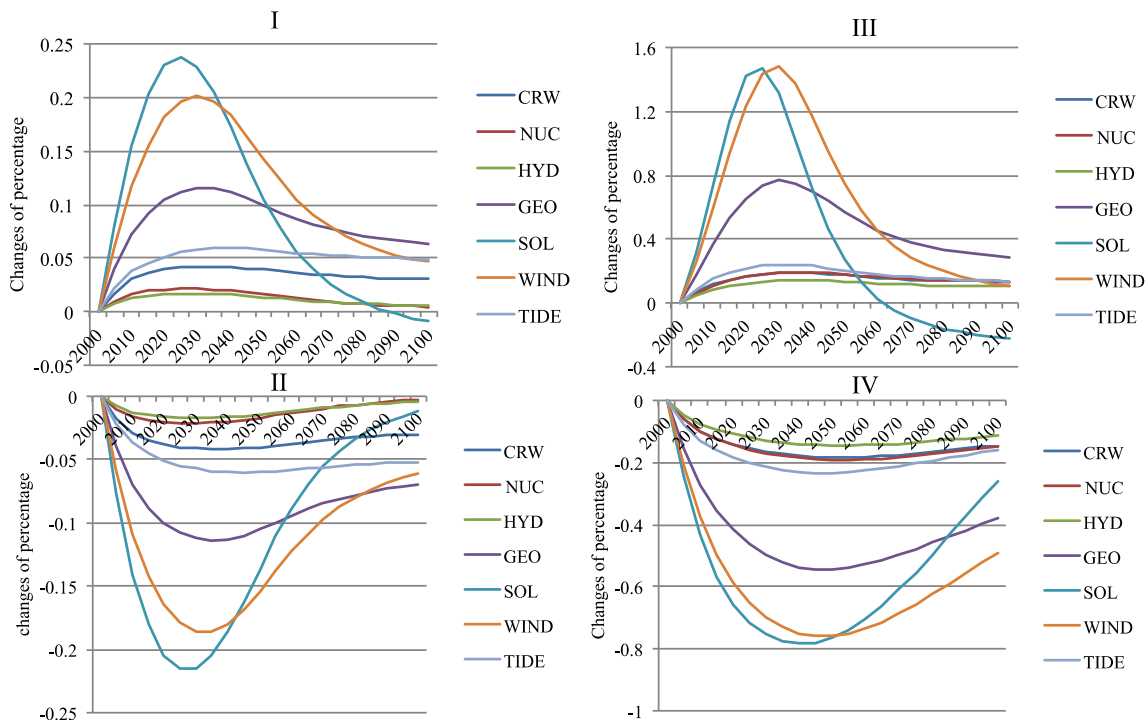
billion of R&D investment could hedge 7.57 trillion of carbon tax loss for the enterprises, while the accumulative CO<sub>2</sub> reductions of the R&D case for the ten decades is 164.1 GtC more than the no R&D case.

Secondly, energy consumption will be strongly reduced immediately upon implementation of the mixed policy, especially if substitution possibilities with non-carbon technologies are not yet available in the short term, which may in turn negatively impact the global economy. However, the energy demand and the macroeconomy will recover to their primary level with the development of non-carbon technologies—the stricter our policy signal, the more energy consumption will decrease and the earlier energy demand will catch up

with the BAU line. Furthermore, R&D investment will effectively ease the negative effect of the policy instruments on the macroeconomy.

Thirdly, the mixed policy of both carbon tax and subsidy plays a significant part in promoting the development of new energy technologies. The non-carbon energy technologies will develop sufficiently in the presence of policy incentives, especially for solar, wind and geothermal power, which account for 24.9, 6.1 and 9.7 %, respectively, of the total primary energy demand under the 140 % carbon rate case, versus 0.1, 0.06 and 0.8, respectively, under the case of BAU. Meanwhile, solar, wind and geothermal will expand their contributions of the total energy usage to 26.2, 7.2 and 12.1 %, respectively in the R&D case, by the end of the twenty-first century, which suggests that R&D investment for carbon-free technologies will dramatically improve their market competitiveness. In addition, including of R&D investment would largely strengthen the substitution of non-carbon technologies for fossil fuels, and the energy supply market will be locked up by non-fossil energy as early as 2035 or thereabouts.

Limitations of this model and directions for future research should be discussed here. First, the E3METL model is a one-sector model; this type of model has great flexibility in studying the evolutionary paths of various energy technologies from a global point of view, but it overlooks regional differences. In fact, there



**Fig. 10** (I, II) Percentage deviations for an increase or a decrease of LBS learning indexes by 30 %; (III, IV) percentage deviations for an increase or a decrease of LBD learning indexes by 30 %



is a great deal of discrepancy on economic situation, climate change policies and public pressure to curb carbon emissions among different nations, which may lead to completely different technological development paths. Hence, expanding E3METL to a multi-regional version will be necessary to investigate the evolution of various energy technologies inter-regionally, and this should be a challenging research project. Second, we assume that the learning effect of LBD process is the same with that of LBS process for simplicity in this paper, and it is a rather rough way to deal with this parameter [30]. We hope to estimate the LBS-based learning rates in detail for renewables in the near future, given more available technical cost and R&D expenditure data. Finally, the R&D investment is assumed to be deterministic, ignoring of the uncertainty in R&D-based technological advancement, which might yield higher investments in innovation and lower policy costs [6]. Therefore, introducing stochastic R&D and considering the robustness of R&D activities could be another potentially interesting aspect of future research.

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## Appendix 1

The following table compares the GWP, CO<sub>2</sub> emissions, energy demand and CO<sub>2</sub> concentration for various models by the end of 21st century.

**Table 4** Comparisons of key results among various E3 models by 2100

Model	GWP (Tri\$)	CO <sub>2</sub> (GtC)	Energy (EJ)	Concentration (ppmv)	Reference
RICE	≈390	38.0	–	≈708	[34]
MERGE	321	17.7	1,279	693	[21, 23]
DEMETER	232	19.9	1,244	640	[41]
WITCH	240	20.0	1,146	–	[5]
E3METL	273	23.7	1,570	–	Model in this paper

‘–’ means the data is unavailable or the result cannot be obtained based on the present resources

## Appendix 2

The differential Eq. 12 is equivalent to the difference Eq. 13, and the derivation is as follows:

$$\begin{aligned}
 \Delta C_i(t+1) &= \frac{\partial C_i(t+1)}{\partial KD_i} \Delta KD_i(t+1) + \frac{\partial C_i(t+1)}{\partial KS_i} \Delta KS_i(t+1) \\
 &= C_i(0) \cdot \frac{-b_i}{(KD_i(0))^{-b_i}} \cdot (KD_i(t+1))^{-b_i-1} \cdot \Delta KD_i(t+1) \\
 &\quad + C_i(0) \cdot \frac{-c_i}{(KS_i(0))^{-c_i}} \cdot (KS_i(t+1))^{-c_i-1} \cdot \Delta KS_i(t+1) \\
 &= C_i(0) \cdot \frac{-b_i}{KD_i(t+1)} \cdot \left( \frac{KD_i(t+1)}{KD_i(0)} \right)^{-b_i} \cdot \Delta KD_i(t+1) \\
 &\quad + C_i(0) \cdot \frac{-c_i}{KS_i(t+1)} \cdot \left( \frac{KS_i(t+1)}{KS_i(0)} \right)^{-c_i} \cdot \Delta KS_i(t+1) \\
 &= -b_i \cdot C_i(t+1) \cdot \left( \frac{KD_i(t+1) - KD_i(t)}{KD_i(t+1)} \right) \\
 &\quad - c_i \cdot C_i(t+1) \cdot \left( \frac{KS_i(t+1) - KS_i(t)}{KS_i(t+1)} \right) \\
 &= -b_i \cdot (C_i(t) - C_{i\min}) \cdot \left( \frac{KD_i(t+1) - KD_i(t)}{KD_i(t+1)} \right) \\
 &\quad - c_i \cdot (C_i(t) - C_{i\min}) \cdot \left( \frac{KS_i(t+1) - KS_i(t)}{KS_i(t+1)} \right)
 \end{aligned}$$

$$\Rightarrow C_i(t+1) = C_i(t) - (C_i(t) - C_{i\min})$$

$$\left( b_i \cdot \left( \frac{KD_i(t+1) - KD_i(t)}{KD_i(t+1)} \right) + c_i \cdot \left( \frac{KS_i(t+1) - KS_i(t)}{KS_i(t+1)} \right) \right)$$

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