Energy and Climate Management, 2025, 1(1): 9400003
https://doi.org/10.26599/ECM.2024.9400003

Review

Endogenous technological change in IAMs: Takeaways in the E3METL model

Yixin Sun, Hongbo Duan✉

School of Economics and Management, University of the Chinese Academy of Sciences, Beijing 100190, China

Received: 15 December 2023; Revised: 27 February 2024; Accepted: 20 March 2024

ABSTRACT

Due to the critical role of technical innovation in transitioning from fossil fuel energy to carbon-free alternatives, there is a widespread consensus among IAM teams regarding the necessity of modeling endogenous technical change (ETC). This paper systematically demonstrates current techniques and theoretical foundations for handling ETC in both demand-side and supply-side, using the E3METL model as an example. Modeling technological progress and innovation in IAMs is essential for understanding technology competition and evolution, leading to more reasonable and insightful results. However, IAMs still lack a systematic framework for the development of ETC, requiring sectoral innovation mechanisms to develop endogenous technology modules and support the economic and social changes of technological innovation. Meanwhile, emerging techniques such as the socio-technical approach, innovation diffusion, and agent-based interactions show promise for ETC when integrated with IAMs. Furthermore, it is important to recognize that ETC interacts more extensively with non-energy systems, such as land, biological systems, and human health, than commonly assumed. This underscores the need for assessments within a more realistic framework and redesigning in conjunction with international cooperation.

KEYWORDS

Endogenous technical change, IAMs, energy restructuring, economic decarbonization.

1 Introduction

Curbing the confirmed human influence on the climate system and mitigating climate change will require profound transformation of global energy system. Technical progress is critical for lowering renewable energy costs and accelerating the transition of energy services away from fossil fuels and toward low-carbon energy sources. Meanwhile, it is a significant uncertain factor influencing the implementation of mitigation investment and activities of carbon dioxide reduction, thus causing the uncertainty of climate damage[1]. The economic growth of sector output, decrease of energy cost and scale economy arousing by technological change and diffusion of new technology could effectively increase the returns on energy-related investment[2, 3]. Therefore, modeling technical progress and innovation in integrated assessment models (IAMs) are of the essence as it provides insights about the consequences of possible strategies for long term greenhouse gas (GHG) emission reductions, by simultaneously capturing the development of several interacting systems and technical evolution process.

In the early stages of integrated assessment modeling, energy technology development controlled by exogenous technological change was predominant: In top-down models, the constant elasticity substitution (CES) function has been widely used to model energy technological substitution in those conventional models, leaving energy technology advancement externalized by autonomous energy efficiency improvement (AEEI). It implicitly assumes technological change does not alter the marginal substitution rate of labor and capital. For bottom-up models, they always modeled as a range of specific energy technologies with competitive relationships, treating technological progress as an exogenous process of cost and efficiency improvements. However, both bottom-up and top-down modeling approaches have their own advantages and drawbacks. For instance, the former describes macro-economy and interactions among sectors in more detail but lacks a specific depiction of energy technology in variety, which probably fails to capture the technological transformation in the energy system. The latter is quite noted for its detailed description of dynamic characteristics in technological improvement and advanced technology diffusion by introducing learning curves. However, its macroeconomic structure is too simple to capture the close interdependence between the energy sector and other sectors.

Due to gradually deepening cognition of both energy system and social transition, modelers have recognized that IAMs with induced endogenous technical change produce more reasonable and explanatory outcomes in pathways assessment of climate policy and damage estimation work, which makes endogenous technical change (ETC) becomes the consensus of model communities. Messner and Strubegger was the earliest work that introduced technological change into an energy system model named MASSAGE[4], which inferred that the investment cost of energy technology decreases with an increase in installed capacity, inducing the increase of investment in new energy technology and ultimately leading to the earlier emergence of zero-carbon technology. Afterwards Bosetti et al. (2006)[5] conducted a technological learning mechanism with double learning curves LBD (learning by doing) and LBS (learning by searching), which confirms that R&D investment is also an important factor affecting technological progress and cost reduction, broadening the way of knowledge accumulation. The accumulated experience shows that it is the interaction of these two effects of technological progress that makes the long-term cost of technology decrease significantly. In addition to endogenous learning rate, other

✉Address correspondence to Hongbo Duan, E-mail: hbduan@ucas.ac.cn, honper.dunn@gmail.com

common techniques for modeling ETC include endogenous energy efficiency and knowledge capital[6, 7], which have also been applied in different IAMs.

During the past years, IAMs have evolved gradually from simple structure to detailed complex module structure[8–11], accompanied by the transformation from exogenous to endogenous technological progress. Up to now, embracing quantitative modeling of technological change is still regarded as one of the ambitious challenges that must be faced in the third wave of climate change economics[12]. The need arises from the fact that only radical technological innovation can bring about a shift in the way energy is produced and consumed, ultimately achieving net-zero goals in the second half of this century. Acknowledging that energy transition is essentially a process of social structural transition, we will quickly notice that advanced technology is developed through endogenous competition, which changes the direction of evolution in the energy system[13]. This ultimately leads to the transformation of innovation and the economy[14, 15].

In recent years, several new strands of theories and methods have emerged that aim to contribute valuable insights towards technical transitions in climate policy assessment. This includes studies that directed technical change theory (DTC) originated from endogenous economic growth[16], socio-technical approach focusing on the evolution of technology diffusion[17], technology choice model based on discrete choice model (DCM)[18] as well as agent-based IAM model characterized by heterogeneity and bounded rationality[19]. Odenweller (2022)[20] conducted a coupled model combined with the technology diffusion model and the multi-regional economic climate model systematically elaborated on the expected prospects of the future development of IAM to the direction of socio-technical modeling, as an attempt to expand the existing optimization model to the socio-technical system. Koch et al. (2023)[21] developed an IAM focused on global-scale structural transformation to study the interaction between sectoral reallocation of economic activities and climate mitigation policies. It is argued that the structural transformation of the economy should be compatible with climate change goals. Therefore, it should be pointed out that modeling endogenous technological change (ETC) within a broader social system will be one of the core tasks in future model development. More modeling of technological innovation, diffusion, and transition dynamics should be included in IAMs to be consistent with the actual development dynamics of technology.

Although there exist great differences in the methods of innovation modeling in studies[22, 23], one common problem is the increasing returns to scale caused by technical progress, which brings difficulties in finding an optimal solution. Due to the fact that innovation is a path-dependent process, the core problem behind it is that the initial state and incentive intensity towards innovation play an essential role in the transition from dirty to green energy[24]. If the innovation level and technical capacity are large enough, then it is foreseeable that the energy system will move towards a clean future. This is also consistent with the reality that solar power capacities are currently about to or have already gone across the tipping point of cost and entered the era of parity[25]. Unfortunately, few models capture characteristics of this. Path dependence and complementarities in technological diffusion and adoption are also currently poorly dealt with in IAMs[12]. In particular, technological improvement is usually modeled using worldwide learning curves (e.g. Imaclim-R & REMIND), which imposes strong assumptions about perfect diffusion and spillovers[26]. In this regard, DTC theory, DSGE method, and ABMs may provide unique insights into climate assessment of technological change for the well descriptions about state dependence of innovation, lock-in effect, and network diffusion effects. However, DSGE models may also encounter problems with multiple solutions due to non-convexity.

Here we explore these issues in the context of a specific application: the Energy-Economy-Environment Model with Endogenous Technological change by employing Logistic curves model (E3METL). This model has been designed to systematically assess socio-economic and energy technology development under the background of climate change and energy transition, which has made significant contributions to issues in the environmental and climate change economics area after multi-generational development. The paper is organized around the updated avenues of modeling endogenous technical change (ETC), elucidating these approaches within the context of specific models and examining the implications and limitations of each. E3METL model, a global dynamic intertemporal optimization IAM based on endogenous economics growth theory, introduces a new technical mechanism, the revised logistic model, to be the technical core of the energy module. It inherited the structure of the classical DICE model, consisting of macroeconomics, energy technology, and climate modules. E3METL-R, the global multi-regional directed technical changed IAM with detailed demand sectors, is underdeveloped. It models endogenous technical transition in a wider social system, which is also a signal of the E3METL model in the next stage.

Like all models of complex systems, E3METL reflects a number of compromises among the details of economic sectors and their technologies, the levels of complexity in mathematical specification, and computational feasibility. It is a progressive developing model structure with a consistent theme of endogenous technical progress, which incorporates new perspectives on energy technology and empirical outcomes into the model. We describe various modeling techniques on ETC and highlight the anticipated effect of ongoing developing model.

The rest of this paper is arranged below: Section 2 reviews the modeling of endogenous technical change in IAMs, dividing technical change modeling into two different types. Section 3 briefly introduces the structure of the proposed E3METL-R model, consist of the economy, energy, and climate module. Section 4 describes the demand-side modeling that incorporates technological change. Section 5 then turns to supply mechanisms dealing with multiple energy technologies based on a bottom-up approach. Finally, Section 6 lays out key challenges in understanding technology in climate policy, as well as research opportunities for deploying technological advances in optimization-type IAMs.

2 Endogenous technical change in IAMs

2.1 Endogenous technical change and innovation in economic theory

One of the two common techniques used in modeling technical change is the learning by doing (LBD) strategy in bottom-up models, the other technique involves the concept of knowledge stock accumulating with R&D expenditure in top-down models. The discrepancy between these techniques is the difference of opinion on knowledge innovation. In the long term, scholars specializing in technology believe that energy efficiency can be improved at a low cost as long as active interventions are conducted toward the market for energy-using equipment. This perspective suggests that substantial reduction of greenhouse gas (GHG) emissions can be achieved at a low cost by employing specific marketing tools focused on technical solutions. The view is similar to that presented in Arrow (1962)[27] who notes that the accumulation of knowledge is not the result of deliberate effort, but rather a side effect of traditional economic activities. This implies that knowledge can be acquired through the accumulation of experience[4, 28, 29]. Hence, that is why there are significant increasing returns to scale in sectors critical for climate policy, such as power generation. The forms in which learning curves are used, however, have relatively weak theoretical underpinnings.

Other scholars focusing on markets place more emphasis on utilizing market-based GHG control policies by minimizing system costs and achieving optimal energy efficiency. They argue that there is a trade-off between energy efficiency and economic efficiency. Prices coordinate the behavior of all agents so that the market for production factors (labor, capital, knowledge, etc.) reaches equilibrium[27, 30–33]. Endogenous technology change, as proposed by Romer based on the micro-market theory, suggests that innovations can be enhanced through increasing the variety of goods. This supports the idea that research activities play a crucial role in the development of new types of machines and that a wider variety of machines leads to a more efficient "division of labor", ultimately resulting in improved productivity of the final product[32,34].

Other researchers[31, 35] apply analogous ideas on aspects of progressive enhancement of existing products. For example, Grossman and Helpman (1991)[35] propose that research leads to the invention of new goods, which means they argue that households obtain greater utility from consuming a greater variety of products because they prefer variety. Grossman and Helpman (1994)[36] also points out that international interdependence through trade produces spillover effects of R&D innovation. Following endogenous growth theory, Acemoglu developed directed technical change (DTC) theory based on the ideological basis of Romer, that is, endowment resources devoted to different types of innovations reflect the market power on a large scale[30]. Recently, the DTC theory has been applied in climate change economics due to it could well explain the relationship between substitutions among sectors and innovation bias[24,37].

The concept of knowledge stock being engaged in production function, inherited from the theory of endogenous technical change, has been applied in modeling technology transformation in climate policy. Endogenous technical change (ETC) has been incorporated into some top-down integrated assessment models (IAMs), with the common thread being technical progress rooted in the accumulation of R&D investments. Duan et al. (2017)[7] corrected the model's deviation from single exogenous handling methods by incorporating endogenous energy efficiency. This study contends that targeted R&D policy is the primary force driving endogenous energy efficiency improvement and that R&D investment can promote the formation and accumulation of energy-related knowledge capital, of which the substitution effect on traditional energy enables emissions-free production.

2.2 Modelling technical change in demand sectors

In integrated assessment models, the primary source of total energy demand is that from economic sectors. The technical transition embodied in the energy sector, underpinning both economic growth and emission reduction, is one of the major drivers of change in demand sector activities. Given the significance of demand sectors in terms of energy demands and CO_2 emissions, accurate modeling within the context of the law of technical change implied for economic growth is critical for reflecting the extensive structural revolution against climate change in global economic activities.

The CES function is commonly used as the sectoral production function in IAMs, where the subject model is a macroeconomic model. Total factor productivity is used as the primary indicator of technological progress, and the level of energy efficiency progress is determined by the parameter of autonomous energy efficiency improvement (AEEI) [5, 9, 38]. In general, AEEI includes energy efficiency enhancement associated with energy consumption behavior and energy structure transformation, excluding those induced by price factors. The common limitation of these models is that their mechanism of energy efficiency cannot distinguish between endogenous and exogenous energy efficiency, which makes them unable to accurately describe the improvement in energy efficiency triggered by R&D policies. In fact, any attempt to distinguish energy efficiency based on R&D may probably involve other factors affecting energy efficiency at the same time, which leads to carbon intensity being simulated by a model higher than the true level[10]. The introducing of endogenous energy efficiency can well make up for the lack of an exogenous energy efficiency handling mechanism, thereby correcting the bias that an exogenous treatment into the model results[39].

Targeted R&D policies are critical in driving energy efficiency improvements. R&D investment can encourage the creation and accumulation of knowledge capital related to energy use, and the substitution of such capital for traditional energy allows for lower-emission production. Gillingham et al. (2008)[22] developed an ETC model with an endogenous technical framework (see Table 1) that incorporates feedback from endogenous technology learning, which occurs through channels such as energy prices, additional R&D activity, or the accumulation of production experience to reduce production costs (learning by doing). Gillingham et al. (2008)[22] also state that there is no available framework that can directly match the theory model and existing numerical modeling for the real world.

As a commonly used approach to endogenize technological change, R&D-induced technological change has been widely applied in IAMs. From the early theoretical work of Kennedy (1964)[40] and Kamien and Schwartz (1968)[41] in developing the innovation possibility frontier (IPF) and induced technological innovation, there is a long-standing theoretical foundation for endogenous R&D-based technological change. Nordhaus (2002) introduced technical innovation into the R&DICE model (see Table 1). These models indicate that endogenous technological innovation is conducive to developing low-carbon production technologies and using low-carbon energy products for enterprises, although its impact on climate change policy is weaker than that of substitution among energy, capital, and labor. Buonanno et al. (2003)[42] found that the introduction of endogenous technology has a significant effect on reducing abatement costs and this result is not influenced by the implementation of a carbon emission trading mechanism. Furthermore, Gillingham et al. considered whether ETC can reduce the optimal abatement cost is related to whether the assumed technology in the baseline scenario reaches the optimum. When the innovation market is imperfect and the technology supply is insufficient, ETC can lead to lower abatement costs, as found in many studies[43]. However, assuming that the level of technology is already optimal in the baseline, the envelope theorem suggests that technological changes under the policy may not have a significant impact on abatement costs if other relative prices do not change significantly.

In addition, the impact of energy prices on technological progress and consumer behavior has been confirmed in numerous empirical studies. This relationship has been captured and modeled as a price-induced form in IAMs. Popp (2001)[44] empirically concluded that there is a negative correlation between the change in energy intensity of the US industrial sector and the change in energy price. Approximately two-thirds of the change in energy consumption came from price-induced factor substitution, while only one-third of that came from policy-induced technological innovation. The higher price of fossil fuel energy is expected to encourage investment in energy efficiency improvement and promote a shift in energy consumption behavior. Price-induced technology change assumes that energy efficiency or technological progress in energy is greatly affected by energy prices. According to the Hicks-induced innovation hypothesis, changes in relative prices can stimulate innovation, leading to a reduction in the use of more expensive inputs, such as energy. As described in Table 1, both the EPPA model and IAMGE model attempt to model price induction[45, 46]. However, this modeling method oversimplifies the relationship between innovation stimulation and price mechanism. It lacks consideration for other market influences, such as the scale effect, and relies heavily on empirical results. Hence, this implicit modeling method has not been widely used in IAMs and is gradually being replaced by modeling methods based on R&D.

Introducing R&D investment into the IAMs partially solves the problem of technological path solidification caused by completely exogenous technology change. However, it lacks the description of knowledge externalities and the micro foundations of modern endogenous growth theory. As Nordhaus points out, it is unclear who is responsible for R&D activities and how they are funded and valued. Acemoglu (2002)[30] demonstrated that the trade-off between innovation in various directions in IPF is generated internally through the dynamic optimization problem faced by firms. There have been limited attempts by IAMs to address this issue. Smulders and de Nooij (2003)[47] proposed an economic growth model driven by energy utilization and the ETC, in which the speed and direction of technological progress are endogenous. The model captures the stylized facts of total energy use growth, energy efficiency improvement, and energy intensity decline. However, it has limited capability in modeling the dynamic changes in the energy technology mix.

2.3 Endogenous technological changes on the supply side

In historical context, the utilization of coal and oil energy technologies has resulted in the influence of anthropogenic industrial activities on climate change, and vice versa, the shift to a low-carbon society requires the widespread advancement and extensive implementation of innovative low-carbon technologies. Thus, low-carbon technologies on the energy supply side offer the potential to overcome barriers to climate change mitigation. Endogenous modeling of energy technologies is particularly important for the economic analysis of climate change mitigation. There are numerous ways in which technology learning can be used in energy transition modeling[48, 49], which through these approaches presents us with a future of cost reduction, efficiency improvement, and infrastructure service capability enhancement through technology learning.

At present, the most common approach in IAMs is to conduct endogenous learning curves[50–52]. This approach aims to improve technical efficiency by leveraging the two effects: Learning-by-Doing (LBD) and Learning-by-Searching (LBS). LBD refers to the investment cost for energy technology decreases as the total installed capacity increases, reflecting the accumulation of experience in practical application, whereas LBS represents the decrease in investment for energy technology as the accumulated R&D capital increases. Unlike endogenous learning by capacity accumulation, the level of R&D activity relies more on policy support. In the early stages of new technology deployment, private enterprises often encounter challenges in becoming the main sponsors of R&D activities due to the uncertainties in technology development and the associated investments risks. Therefore, the allocation of government public funds becomes crucial. The learning curve that only considers Learning-by-Doing (LBD) is referred to as the One-Factor Learning Curve (OFLC), while the process of technological progress that comprehensively incorporates both LBD and LBS is termed the Two-Factor Learning Curve (TFLC). This solution is pivotal in IAM applications and serves as the mechanism for addressing technology endogeneity in nearly all energy system modules. However, it is worth noting that energy models using linear programming as the optimal solution often encounter significant computational costs when incorporating endogenous learning curves. Consequently, externally fitting cost curves become an alternative solution.

Although endogenous learning can lead to cost reductions in technology development, the effects of multiple technology curves can sometimes be uncertain. Manne and Richels (1992)[53], based on the MERGE model, integrated a top-down economic perspective with a bottom-up energetic approach to establish endogenous technical learning curves. They found that for each doubling of accumulated experience, the learning cost decreases by 20%. It was observed that LBD significantly affects the time and cost of abatement. Moreover, incorporating both LBD and LBS into the POLES model[54] resulted in complex simulation properties. The results indicated that the learning efficiency of R&D was slower in the accelerated abatement scenario due to the faster deployment of technology, resulting in less cumulative research and R&D learning. Nevertheless, in the accelerated abatement scenario, learning efficiency improved as targeted accumulated capacities and costs were reached in a shorter time.

In addition to considering the learning characteristics of technology, it is also important to take into account technology diffusion, the speed of energy transition, and the technical dynamic process[55]. For example, technology co-evolution and innovation spillovers are crucial in technology diffusion but are rarely explicitly modeled in IAMs, making it difficult to capture path dependence, innovation behaviors, market drivers, and inertia in technical substitution[56, 57]. In fact, due to the high investment cost and long lifetime characteristics, infrastructure construction has been shown to create lock-in path dependence. Socio-technical approaches rooted in evolutionary economics and focused on temporal transformation dynamics have emerged and been applied in IAMs[25, 58]. The social-technical perspective of technological change revolves around technology diffusion and technological lock-in, which are portrayed in the wider co-evolutionary understanding of society and technology. Duan et al. (2015)[59] proposed the E3METL model, constructed using the logistic curve as the core of the technology module and accounting for ETC. Logistic curves were used to describe the substitution and evolution laws among various technologies in the model. In addition, the variables of carbon tax and subsidy are introduced into the traditional logistic curve as powerful tools to depict the evolution of multiple energy technologies.

A typical IAM focused on technical diffusion is E3ME-FTT[60], a simulation model derived from the parameterizing of historical data and the trajectory of technical diffusion. Unlike traditional IAMs, it extends from a single representative consumer and decision maker to include heterogeneous consumers and suppliers. The industrial, transportation, and electricity sectors are represented by different FTT sub-models, characterized by the typical S-shaped curve of technology adoption. This perspective shift leads to a policy orientation from the traditional energy modeling community[25] and offers a better depiction and prediction of the future based on reality. Nijsse et al. argue that the dynamics of cost competition between renewable energy and fossil energy have undergone a significant shift. They suggest that the focus should no longer be on achieving a carbon price balance, but rather on addressing challenges related to grid resilience, financing channels, material supply chain management, and other factors crucial for achieving net- zero emissions. In contrast, Odenweller (2022)[20] provides an example of two-way coupling between the MIND macro model and the power model of FTT technology diffusion. Odenweller points out that the linear optimization method of cost minimization may lead to overly optimistic results of technology evolutio due to the path-anchoring bias introduced by the initial state of the model. This bias is caused by the lack of calibration updates for the current cost of the latest energy technology in the IAM.

Table 1 The way endogenous technological progress modeled in IAMs.

Model	Type	Representation of ETC	Reference
R&DICE	Optimization model	R&D	[9]
ENTICE	Optimization model	R&D	[61]
ETC-RICE	Optimization model	R&D	[42]
E3METL	Optimization model	R&D; LBD&LBS	[62]
WITCH	Optimization model	R&D; LBD&LBS	[63]
REMIND	Optimization model	LBD	[64]
MIT-EPPA	CGE	Price-indued; LBD	[46]
Sue Wing-EPPA	CGE	R&D	[65]
GEM-E3	CGE	Price-indued; LBD	[66]
MARKAL	Energy system model	LBD	[67]
MESSAGE	Energy system model	LBD	[29]
POLES	Energy system model	LBD&LBS	[54]
IAMGE	Simulation model	Price-induced	[45]
E3ME-FTT	Simulation model	Technical diffusion	[60]
ENGAGE	ABM	Technical diffusion	[68]

Note: Model abbreviations and other abbreviations can be found in Table A1 and Table A2 in Appendix.

3 Structure of the E3METL-R model

The E3METL model (Energy-Economy-Environment Model with Endogenous Technological change by employing Logistic curves) is an Integrated Assessment Model (IAM) designed to incorporate the ETC. Constructed upon logistic curves as the fundamental framework of the technology mode, it comprises three main modules: economy, energy technology, and carbon emissions. The E3METL-R model, the global multi-regional version of E3METL, inheriting the assumption of the Ramsey intertemporal optimization framework, which aims to maximize global discounting utilities determined by the social planner. In other words, the model is forward-looking rather than myopic. The utility function at any time and region is based on constant relative risk aversion (CRRA), which guarantees the balanced growth path of the economy. E3METL models series have exploited single-region (China), global single-region, and global multi-region versions. In this example, we will focus on the latter (E3METL-R) due to its relative completeness, which makes it convenient to study the long-term evolution of various energy technologies.

3.1 Macroeconomic module

The optimizing objective is maximizing intertemporal discounted reginal utility function U_r, which is calculated with consumption $C(t,r)$ and labor $L(t,r)$, $\rho(\tau)$ is the pure time preference. $U_r(\cdot)$ represents regional instantaneous utility function as an expesion of utility per capita at the given moment. $U_r(\cdot)$ in benchmark model employes CRRA utlilty with $U_r'(\cdot)>0$, $U_r''(\cdot)<0$ and constant relative risk aversion coefficient θ.

$$\mathrm{Max}\sum_t\left(L(t,r)\frac{\left(\dfrac{C(t,r)}{L(t,r)}\right)^{1-\theta}-1}{1-\theta}\prod_{\tau=0}^{t}\left(1+\rho(\tau)\right)^{-tstep}\right) \tag{1}$$

where $\rho(t)=\rho_0\cdot e^{-d_\rho\cdot t}$ represents discounting factor to measure time preference, specificly ρ_0 is initial time preference, and d_ρ is decline rate of time preference rate. $\rho(t)$ declining with time represents a less impatience with the future and more attention to cliamte change issue. The time scale of the model is $tstep$ and $\rho(t)$ presents average discout level in each period.

In the E3METL-R model, there are specialized production sectors for consumer goods, and the production process is represented by a constant elasticity substitution production function:

$$Y(t,r)=\left[\alpha\left(A_{t,r}K(t,r)^{\omega}\cdot L(t,r)^{1-\omega}\right)^{\kappa}+(1-\alpha)(ES(t,r))^{\kappa}\right]^{1/\kappa} \quad (2)$$

where $Y(t,r)$ presents total output, $K(t,r)$ presents capital stock in t year, and $L(t,r)$ is labor element input detemined by exogenous growth rate. $A_{t,r}$ is technical progress level in the mix of capital and labor, ω means the share of captical in capital-labor mix, $ES(t,r)$ is energy service level, and α is the share of production element. Final good Y is generated by nest CES function combined with KL and ES, and κ represents elasiticity of substitusition between them. Capital stock K can be formulated in terms of current and past capital stock adjusted by the depreciation rate:

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

where δ presents yearly depreciation rate of capital and $I(t,r)$ presents investment level. Regional consumption per capita is the only decision vaiable in utility function and controlled by budget constraint with taking cliamte damage feeback, investment, net-export and energy cost into account. The outputs $Y(t,r)$ are made by the production department and will be used to pay for consumption $C(t,r)$, investment $I(t,r)$, net-export $MG(t,r)-XG(t,r)$, energy costs $EC(t,r)$, trading cost $cxtrade_j$ and $cmtrade_j$, adaption investment $IAdap(t,r)$, abatement cost $CAbate(t,r)$, R&D activities expenditure $TRD(t,r)$, agriculture cost $CAgri(t,r)$ and pollution expendeture $CPollution(t,r)$. The balance relationship is as follows:

$$\begin{aligned}C(t,r)=&\frac{Y(t,r)}{\Omega_{t,r}}+(1-\varepsilon_r^G)MG(t,r)-XG(t,r)-I(t,r)\\&-TRD(t,r)-IAdap(t,r)-EC(t,r)-CAbate(t,r)\\&-cxtrade_j\cdot X_j(t,r)-cmtrade_j\cdot M_j(t,r)\\&+pxEl_j\cdot\sum_k ElX_j(t,r,k)-pmEl_j\cdot\sum_k ElX_j(t,k,r)\\&-CAgri(t,r)-CPollution(t,r)\end{aligned} \quad (4)$$

where $MG(t,r)$ presents import of region r and $XG(t,r)$ prensents export with ε_r^G as trade cost of composite goods. $\sum_k ElX_j(t,r,k)$ and $\sum_k ElX_j(t,k,r)$ are imports and exports of region r in electricity bilateral trade respectively with import electricity price $pmEl_j$ and export electricity price $pxEl_j$.

3.2 Energy technology module

Based on the consideration of the scarcity of exhaustible resources, E3METL-R incorporates the updates and explanation of Rogner's cumulative extraction cost curve (CECC) to model fossil fuel price changes[69,70]. The extraction cost of oil, coal, and gas is as follows:

$$\begin{aligned}Fos_{excost}(t,r)=&\alpha_{0,r}+\alpha_{1,r}CumExfos(t,r)+\alpha_{2,r}CumExfos(t,r)^2\\&+\alpha_{3,r}CumExfos(t,r)^3\end{aligned} \quad (5)$$

$$CumExfos(t,r)=CumExfos(t-1,r)+tstep\cdot Fos_{\mathrm{extr}}(t,r) \quad (6)$$

where $Fos_{excost}(t,r)$ is long-term extraction cost of fossil fuel in region r, $\alpha_{0,r}$, $\alpha_{1,r}$, $\alpha_{2,r}$ and $\alpha_{3,r}$ are the coefficients of the polynomial function (5). Eq.(6) describes the accumulation of fossil fuel extractions $CumExfos(t,r)$ with yearly extraction $Fos_{\mathrm{extr}}(t,r)$. In addition, the model introduces short-term adjustment costs, which are used to simulate the penalty markup caused by excessive fluctuations in short-term extraction.

$$Fos_{\mathrm{adjust}}(t,r)=1-\varphi+\varphi\left(\frac{Fos_{\mathrm{extr}}(t,r)}{\zeta_r}\right)^{\chi} \quad (7)$$

$$COSTFos_{\mathrm{extr}}(t,r)=Fos_{excost}(t,r)+Fos_{\mathrm{adjust}}(t,r) \quad (8)$$

where $Fos_{\mathrm{adjust}}(t,r)$ presents the short-term adjustment costs with threshod parameters φ, χ. $COSTFos_{\mathrm{extr}}(t,r)$ presents total extraction cost of fossil fuels, which equals the sum of long-term cost and short-term cost.

3.3 Carbon emission module

Total CO_2 emissions are the sum of CO_2 emissions from fossil-fuel combustion in industries $EMIS_{\mathrm{INDUS}}(t,r)$, from land-use change $EMIS_{\mathrm{LAND}}(t,r)$ minus emissions from avoided deforestation $EMIS_{\mathrm{REDD}}(t,r)$. Total emissions and industrial emissions can be expressed as:

$$EMIS(t,r)=EMIS_{\mathrm{INDUS}}(t,r)+EMIS_{\mathrm{LAND}}(t,r)-EMIS_{\mathrm{REDD}}(t,r) \quad (9)$$

$$EMIS_{\mathrm{INDUS}}(t,r)=\sum_f emif_f\cdot PROD_f(t,r)-\sum_{f'}CCS_{f'}(t,r) \quad (10)$$

$$CCS_{f'}(t,r)=PROD_{f'}(t,r)\times capture\_rate_{f'} \quad (10')$$

here $emif_f$ is carbon emissions per unit of fossil fuel consumption (carbon emission factor), while f and f' encompasse all energy technologies and technologies with CCS, respectively. $PROD_f(t,r)$ and $PROD_{f'}(t,r)$ denote the annual regional energy production without and with CCS, respectivel. The quantity of carbon captured, $CCS_{f'}(t,r)$, is computed from all CCS technologies according to a specific capture rate $capture\_rate_{f'}$.

3.4 Global multi-regional demand sectors and trade mechanisms

The level of energy input of the economic module depends on the energy demand of the economic sectors. These sectors are divided into three categories: construction, industry, and transportation. The CES functional form is still used for the energy input levels of construction, industry, and transportation. The energy input of the economic sector is as follows:

$$\begin{aligned}E(r,t)=&(\alpha_{Indus}(r)Indus(t,r)^{\kappa_E}+\alpha_{Build}(r)Build(t,r)^{\kappa_E}\\&+\alpha_{Trans}(r)Trans(t,r)^{\kappa_E})^{1/\kappa_E}\end{aligned} \quad (11)$$

$Indus(t,r)$, $Build(t,r)$, and $Trans(t,r)$ represents industry, construction and tranport sectors inputs respectively, α_i stands for input share of sectors, $\alpha_i\in\{\alpha_{Indus},\alpha_{Build},\alpha_{Trans}\}$. The energy used by conventional economic sectors, such as the industry and construction sectors, is divided into electric energy and non-electric energy. Electric energy is generated through various energy technologies, which include renewable energy sources and fossil fuels (primarily coal, oil, and natural gas). Non-electric energy includes the use of coal, oil, natural gas, biomass fuels, and some backstop technologies in the construction and industrial sectors. The CES functions of electric and non-electric energy are aggregated as follows:

$$Indus(r,t) = (\alpha_{E,indus}(r)EL_{indus}(t,r)^{\kappa_{E,indus}} + (1-\alpha_{E,indus}(r))NEL_{indus}(t,r)^{\kappa_{E,indus}})^{1/\kappa_{E,indus}} \quad (12)$$

$$Build(r,t) = (\alpha_{E,build}(r)EL_{build}(t,r)^{\kappa_{E,build}} + (1-\alpha_{E,build}(r))NEL_{build}(t,r)^{\kappa_{E,build}})^{1/\kappa_{E,build}} \quad (13)$$

where $EL(t,r)$ and $NEL(t,r)$ stands for the electricity and nonelectricty input level with the share of two inputs $\alpha_E(r)$ and substitution elasticity κ_E between two elements. The input of tranport sector divides into passengers transport $Pass(t,r)$ and freight transport $Freight(t,r)$. $\alpha_{E,trans}(r)$ is the share of passenger traffic in the energy input of the transport sector and $\kappa_{E,trans}$ represents the elasticity of substitution between the two inputs. Energy inputs in the transport sector are as follows:

$$Trans(r,t) = (\alpha_{E,trans}(r)Pass(t,r)^{\kappa_{E,trans}} + (1-\alpha_{E,trans}(r))Freight(t,r)^{\kappa_{E,trans}})^{1/\kappa_{E,trans}} \quad (14)$$

The E3METL-R model explicitly models the trade of final composite goods, primary energy, and emission quotas, making it suitable for intertemporal investment and trade analysis in the long run. The model allows for intertemporal trade, which complements capital mobility in multi-regional trade. The clearing condition for intertemporal trade must be satisfied in period T (T is the last period in which the model is solved), which corresponds to the consumer's intertemporal budget constraint or the Walrasian rule. Capital flow is defined as the cash flow accompanied by unrestricted trade of composite commodities. However, it does not encompass capital flow on a broader scale, such as the influx of foreign investment, so it can be regarded as weak capital mobility[71]. Capital flows and intertemporal trade lead to the equalization of the rate of capital return and ensure intertemporal and cross-regional trade equilibrium.

In the composite commodity trade, primary energy trade, and carbon quota trade, it is assumed that the imports and exports of the regions come from a common pool, and there is no bilateral trade between the two regions. This means that for a given commodity j, there is a corresponding unique market price P_j. The trade equilibrium in period t is as follows:

$$\sum_r (X_j(t,r) - M_j(t,r)) = 0 \quad \forall j, \forall t \quad (15)$$

The physical trade volume of primary energy, including coal, oil, natural gas, and biomass energy, conforms to the budget constraint of primary energy supply:

$$PE_j(t,r) = EX_j(t,r) - X_j(t,r) + M_j(t,r) \quad (16)$$

where $PE_j(t,r)$ represents regional energy supply, $EX_j(t,r)$ represents the amount of domestic primary energy extraction, $X_j(t,r)$ is the primary energy export volume of region r, and $M_j(t,r)$ is the primary energy import volume of region r. Any trade in goods and energy implies trade in financial capital and a net flow of financial capital. This relationship is characterized by the intertemporal budget constraint, and the net foreign assets (NFA) of each region converge to 0 in period T:

$$B(r) = N(r) + \sum_t \sum_j P_j(t)\,[X_j(t,r) - M_j(t,r)] \quad \forall r \quad (17)$$

4 Demand-side technical change in typical IAMs

4.1 Endogenous energy efficiency mechanism in E3METL-R

The exogenous efficiency trajectory significantly influences macroeconomic growth and carbon emissions. However, relying on historical data to calibrate the AEEI may not ensure its effectiveness because setting AEEI too high or too low can result in underestimating or overestimating the energy demand and abatement cost[1, 43, 72]. The introduction of endogenous energy efficiency can mitigate the shortage of exogenous energy efficiency mechanisms and correct biases introduced by a single exogenous treatment in the model results[39]. The energy service consists of two parts: carbonaceous fossil energy and energy-related knowledge capital.

$$ES(r,t) = [\beta_1(\alpha_{ee,r}KDE(r,t))^{\kappa} + (1-\beta_1)(E(r,t))^{\kappa}]^{1/\kappa} \quad (18)$$

where $E_{r,t}$ stands for energy inputs, β_1 stands for the share of knowledge capital in energy service, and κ is representation of ease of substitution of knowledge $KDE_{r,t}$ and energy $E_{r,t}$. The scale factor of knowledge $\alpha_{ee,r}$ is used to represent the energy-saving effect resulting from R&D knowledge.

The dynamic accumulation equation of $KDE_{r,t}$ gives

$$KDE(r,t) = (1-\delta_{ee})\,KDE(r,t-1) + IPF(r,t) \quad (19)$$

where δ_{ee} is the decay rate of knowledge. $IPF(r,t)$ is called the innovation possibility frontier, which is used to describe the process of R&D investment generating knowledge. It can be expressed as:

$$IPF(r,t) = aRD_{ee,r,t}^{\varphi_1} KDE_{r,t}^{\varphi_2} \quad (20)$$

Total R&D input (TRD) includes R&D expenditure (RD_i) from carbon-free energy (biomass BIO, nuclear NUC, hydroelectricity HYD, and other renewable energy $OTHRE$) and R&D investment from energy efficiency improvement (RD_{ee}).

$$TRD_{r,t} = \sum_{i\in I} RD_{i,r,t} + RD_{ee,r,t} \quad i \in I = \{BIO,\ NUC,\ HYD,\ OTHRE\} \quad (21)$$

The modeling of energy efficiency improvement in RICE, ENTICE, WITCH, and EPPA, given in Table 2, adopts a similar way, that is, the modeling approach based on R&D capital. The introduction of endogenous energy efficiency has a significant positive impact on the gross world product (GWP). However, this positive effect gradually weakens with the implementation of emission control policies, particularly in the middle and late stages of emission reduction policies[7]. The improvement of endogenous energy efficiency is primarily driven by R&D investment, leading to more efficient production with an economic rate of return on R&D, ultimately improving the production value per unit of

Table 2 The comparison between E3METL and other IAMs in demand-side technical change.

Model	exogenous AEEI	R&D capital modeling	Endogenous economic growth	Multi-regional model	Reference
RICE	√	√		√	[9]
ENTICE		√			[61]
ETC-RICE		√		√	[42]
FUND	√			√	[75]
E3METL	√	√			[62]
WITCH	√	√		√	[63]
REMIND	√		√	√	[76]
AIM	√			√	[77]
MIT-EPPA		√		√	[46]
GEM-E3		√		√	[66]

energy. The study by Wang et al. (2019)[73] examined the relationship between energy share and energy cost, indicating a 1% increase in the energy share results in a 1.2% improvement in energy efficiency over the next 20 years. This relationship has been modeled in an IAM and a carbon price intervention could lead to a 30% energy savings compared to a scenario without an endogenous energy efficiency induction mechanism in 2120. This finding suggests that higher carbon prices incentivize investments in renewable energy and result in an increased share of green energy.

4.2 Directed technical progress mechanism in E3METL-R

Based on modern endogenous growth theory[31, 32], the characteristic of the directed technological change (DTC) model is that innovation is built on the shoulders of giants. This means that innovators not only improve current technologies but also enable future innovators to build upon their innovations[15]. The earliest example of DTC was proposed by Aghion and Howitt (1992)[31], who modeled research and development separately and analyzed the incentives of researchers to allocate their efforts to both. Afterward, Acemoglu developed the typical DTC model, which showed that innovation could increase the demand for either low-skilled or high-skilled labor. Several studies have explored the impact of DTC between energy-saving and energy-consuming technologies[74] while DTC between clean and dirty technologies in energy production has also been investigated[16]. Insights from DTC have been integrated into fields such as environmental economics and labor economics, yet no IAM has thus far explicitly modeled directed technological innovation. The productivity of endogenous fossil energy and renewable energy in this model is as follows:

$$A_{f,t} = (1+\gamma\eta n_{ft}^{1-\psi})A_{f,t-1} \tag{22}$$

$$A_{g,t} = (1+\gamma\eta n_{gt}^{1-\psi})A_{g,t-1} \tag{23}$$

$$n_{f,t} + n_{g,t} = 1 \tag{24}$$

where $A_{f,t}$ and $A_{g,t}$ represents productivity of fossil fuel and clean energy technology, $n_{f,t}$ and $n_{g,t}$ stands for the proportion of research input targeted innovation activities in two sectors. ψ is the diminishing returns to scale, η is probability of successfully innovation, and γ is innovation scale. The innovation possibilities frontier is as follows. At the beginning of every period, innovation input need to determined whether devoted in renewbale or fossil fuel technology. Innovation inputs is then randomly allocated to at most one machine and is successful in innovation with probability $\eta \in (0,1)$, where innovation increases the quality of a machine by a factor $1+\gamma n_{g,t}^{1-\psi}$ and $1+\gamma n_{f,t}^{1-\psi}$, that is, from $A_{f,t}$ and $A_{g,t}$ to $(1+\gamma n_{f,t}^{1-\psi})A_{f,t}$ and $(1+\gamma n_{g,t}^{1-\psi})A_{g,t}$.

E3METL-R, the global regional version of E3METL model (see Table 2), endogenously models the productivity of energy technology in demand sectors according to the theoretical mechanism of DTC, which fundamentally changes the mode of economic growth and forms an economic structure change driven by ETC. More detailed comparisons between E3METL and other IAMs in demand-side technical change are shown in Table 2.

5 Multiple energy technology diffusion mechanisms in IAMs

5.1 Diffusion of multiple energy technologies

The E3METL-R model's primary feature is the systematic integration of induced technical change, with a focus on the endogenous learning curve for renewables. The return on R&D investment depends on previously accumulated knowledge capital that is conducive to lower energy investment costs, resulting in a learning-by-searching (LBS) effect in undeveloped technologies such as wind and solar. Notably, E3METL, WITCH, and POLES models in Table 1 incorporate the LBS mechanism. Additionally, learning-by-doing is extensively employed in energy system optimization models (e.g., MARKAL, MESSAGE, POLES models in Table 1 and Table 3), where renewables are integrated with alternative energy technologies. Over time, knowledge and experience may become obsolete due to the depreciation rate of knowledge, impacting the speed of forgetting[59]. Our model applies two-factor learning curves[78,79]. The form is as follows:

$$IC_j(t,r) = \alpha_j(r)\cdot\left(\frac{\sum_r RD_j(t,r)}{\sum_r RD_j(0,r)}\right)^{lbr\_factor}\left(\frac{\sum_r CCAP_j(t,r)}{\sum_r CCAP_j(0,r)}\right)^{lbd\_factor} \tag{25}$$

where $IC_j(t,r)$ is the investment cost of energy tchnology j, $RD_j(t,r)$ is the R&D capital stock, $CCAP_j(t,r)$ is total installed capcacity of energy technology j, and $\alpha_j(r)$ is the difference between initial investment cost and least cost price. Technological learning is assumed to be global, and the knowledge capital stock

Table 3 The comparison between E3METL and other IAMs in supply-side technical change

Model	LBD	LBS	Diffusion of technologies	Diffusion across regions	Reference
E3METL	√	√	√		[62]
WITCH	√	√		√	[63]
REMIND	√				[76]
MARKAL	√				[67]
MESSAGE	√				[29]
POLES	√	√			[54]
MIT-EPPA	√				[46]
GEM-E3	√				[66]
E3ME-FTT	√		√		[17]
ENGAGE			√		[68]

and installed capacity of each region are pooled to reduce the cost of technology. *lbr_factor* and *lbr_rate* measure the intensity of the learning effect. They are based on the relationship below, *lbr_rate* measures the rate at which unit costs fall for doubling of the stock of knowledge or capacity.

$$lbr\_factor = \frac{\ln(1 - lbr\_rate)}{\ln 2} \tag{26}$$

It is easy to see from Eq. 25 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, then Eq. 26 can be transformed into Eq. 27:

$$\begin{aligned} IC_j(t,r) =& IC_j(t-1,r) - (IC_j(t-1,r) - IC_{j\min}(r)) \\ & \cdot \left(lbs\_factor_j \cdot \left(\frac{\sum_r RD_j(t,r) - RD_j(t-1,r)}{\sum_r RD_j(t,r)} \right) \right. \\ & \left. + lbd\_factor_j \cdot \left(\frac{\sum_r CCAP_j(t,r) - CCAP_j(t-1,r)}{\sum_r CCAP_j(t,r)} \right) \right) \end{aligned} \tag{27}$$

Eq. 28 describes the equation of installed capacity accumulation for technology j, based on yearly depreciation and installed capacity increment:

$$CCAP_j(t+1,r) = CCAP_j(t,r) \cdot (1-\delta_j)^{tstep} + tstep \cdot ADDCAP_j(t,r) \tag{28}$$

The influence of incorporating the learning curve into energy modules in IAMs is evident, particularly given the background of the cost of alternative energy technology is much higher than traditional technologies, due to R&D activities requiring incentives from relevant policies[6, 80]. Duan et al. (2015)[59] explored the evolutionary process of renewable technologies with R&D inputs using two learning curves, revealing that R&D investment can effectively mitigate adverse shocks associated with the implementation of a mix of carbon taxes, thereby increasing the flexibility of emission reduction policies. Based on CE3METL and the plate ocean climate model[81], the study concentrated on the radiative forcing and temperature benefits of electricity technologies substitution and found that the learning effect enhances the competitiveness of photovoltaic power by contributing to a more competitive price.

5.2 Knowledge diffusion across regions

The diffusion of emerging knowledge is influenced by the accumulation of knowledge capital in energy technologies, known as the diffusion effect of knowledge. In endogenous economic growth theory, knowledge diffusion effects vary across specific modeling frameworks: sometimes expressed as state dependence on alternative technology[30], while other times characterized by the productivity growth rate depending on the distance to the frontier. Despite these variations, these modeling techniques commonly establish knowledge diffusion based on productivity gains without considering the source of these productivity gains from knowledge diffusion.

Indeed, knowledge diffusion effects across technologies are the foundation of many new technological innovations. For example, Tesla's first product prototype was developed by reconfiguring a fuel-powered car by removing the internal combustion engine and filling the engine compartment with batteries. Consequently, the relative reduction in R&D costs is a significant driving force behind directed technical innovation. Specifically, the accumulation of R&D capital lies on innovating investment in the region at time t, existing R&D capitals stock, and diffusion effect from other regions. Modeling the knowledge diffusion effect as an amplification proportion of R&D investment, taking the product of the diffusion effect and R&D investment as the increment of R&D capital means that the greater the technological gap with developed regions, the greater the increase in R&D capital per unit of investment corresponding to more effective R&D investments. Energy technologies accord with this rule include PV, wind, hydrogen, biomass, and others.

$$RD(t+1,r) = RD(t,r)(1-\delta_{RD})^{tstep} + tstep \cdot I_{RD} \cdot SPILL_{RD}(t,r) \tag{29}$$

$$SPILL_{RD}(t,r) = \left(\frac{\sum_{r \in \{OECD\}} RD(t,r)}{RD(t,r)} \right)^{\phi_{RD}} \tag{30}$$

where $RD(t,r)$ is the R&D capital stock, δ_{RD} is depreciation coefficient of R&D capital and ϕ_{RD} is the sclae factor of spillover effects. $SPILL_{RD}(t,r)$ is the knowledge spillover effect and the scale is expressed as the gap in knowledge stock between this region and OECD regions.

Knowledge diffusion effects across technologies are crucial for understanding the role of policy in the transition of the economy towards cleaner production. Studies by Donald (2023)[82], Liu and

Ma (2021)[83] have demonstrated that technology spillover is equally important as the substitution effect, and it has a profound impact on the speed of long-term goals, in other words achieving a clean energy future. Unfortunately, this spillover effect is usually excluded from current models. Leimbach and Edenhofer (2007)[84] analyzed the impact of climate policy characterized by technology spillovers using the REMIND model, which was the first to apply a model with technology spillovers within the context of climate policy. The study found that spillover effects could smooth emission reduction costs across regions and provide stronger incentives for developing economies to engage in climate agreements. A recent study[85] combined the WITCH model and GEM-E3 model, incorporating the R&D learning rate, diffusion mechanism, and GEM-E3's distinctive low-carbon technology financing mechanism to offer insights into the selection of energy technology mix and the optimal timing for R&D investment. In a regional context, Zhang et al. (2020)[80] found that the diffusion effects of technical learning have different influences on global and regional aspects based on various control settings for diffusion effects using the REMIND model. This study emphasizes explicitly modeling the manufacturing and trade of equipment components to link energy system modeling with innovation research that integrates innovation, deployment, and diffusion dynamics to regional patterns.

5.3 Multiple energy technologies diffusion

In the E3METL model, logistic curves are employed to represent the substitutional and evolutionary dynamics of various energy technologies, while also incorporating carbon taxes and subsidies into the conventional logistic curve framework. Furthermore, considering the inverse correlation between energy technology costs and the proportion of energy technologies, we propose a novel approach to substitute the proportion of technical change relative to time with the proportion relative to price in logistic curves. The revised equation is as follows:

$$\frac{dS_j(t)}{dP_j(t)} = a_j S_j(t)\left[\overline{S}_j\left(1+S_j(t)-\sum_j S_j(t)\right)-S_j(t)\right] \tag{31}$$

here $P_j(t)$ 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

$$P_j(t) = \frac{C_f(t)\,(1+Tax_f(t))}{C_j(t)\,(1-Sub_j(t))} \tag{32}$$

here, $C_f(t)$ and $C_j(t)$ denote the costs per unit of energy for the marker technology and alternative technology. $Tax_f(t)$ and $Sub_j(t)$ represent the tax rate for fossil energy and the subsidy levels for alternative energy, respectively. a_j is a substitution parameter, and $\overline{S}_j$ means the maximum possible share of technology j in energy supply market, with $0 \leqslant S_j \leqslant \overline{S}_j \leqslant 1$.

Incorporating the mechanism of multi-technological competition into the E3METL model[59] further confirms the effectiveness of logistics curves as a powerful tool for illustrating the alternative evolution of multi-technologies. By employing simulation techniques, the findings revealed that solar energy, wind power, and geothermal power have been developed more sufficiently rather than fossil fuels. Under the combined carbon tax scenario with a 140% increase, the proportion of solar, wind, and geothermal energy is 24.9%, 6.1%, and 9.7% respectively. In contrast, these energy sources account for only 0.1%, 0.06%, and 0.8% in the baseline scenarios. In another study of optimal carbon tax within carbon constraints by using the CE3METL model[1], it was discovered that it is increasingly essential for the learning rate to describe the penetration of non-carbon technologies and determine the optimal carbon tax. In the BAU scenario, for every 3% increase in the learning rate, the share of renewable energy will only increase by 3.23%, which contrasts with 26.33% of renewable energy share in the mitigation scenario.

Socio-technical approaches, characterized by the interaction between technology diffusion and technological lock-ins, offer distinct advantages in comprehensively capturing the energy technology revolution[86]. The estimations of technology diffusion derived from empirical studies are progressively integrated into energy system models[87]. Duan et al. (2014)[62] employed the modified Lotka-Volterra model to compare development patterns and diffusion laws related to wind and photovoltaic technologies on a national level, which revealed that the scale dependence effect is prevalent in wind power markets across different countries, whereas it is not common in photovoltaic energy markets. In the context of the cross-border diffusion of technology, Duan et al. (2018)[88] proposed a two-dimensional framework to analyze the theoretical and empirical aspects of cross-country diffusion effects on technical innovation. However, the aforementioned research is more concentrating on wind energy and photovoltaic energy separately, while disregarding the influence of other renewable energy technologies and fossil energy sources. The FTT model[85] has been increasingly involved in the evaluation of energy systems by simulating the diffusion competition among multiple energy technologies. Mercure et al. (2021)[17] conducted a re-evaluation of the geographical pattern of energy under the decreasing costs of renewable energy and the economic consequences of the post-pandemic era. Their study utilized the E3ME-FTT-GENIE model and revealed that energy systems experience a wider range of impacts under the technology diffusion and path dependence perspective than in previous research findings. Photovoltaic (PV) will become the dominant energy technology, electric vehicles are also experiencing a winner-take-all trend in the transportation sector. Additionally, heating technologies are undergoing significant advancements as households strive to reduce their carbon footprint.

5.4 Other ETC modeling techniques

IAMs are often criticized for their failure to capture the dynamic processes of technology diffusion and technology transition[89, 90], for example, co-evolution between technologies, mutual learning between agents, network spillover effects, and reinforcing feedback. While previous sections have discussed the systematic integration of technological progress and evolution components into intertemporal IA models, certain modeling techniques are better suited for simulation models rather than optimization models. Hence, this section primarily delves into the remaining modeling techniques for ETC and provides examples of their application in existing research.

Demand sectors in macroeconomics-IAMs are often represented by simplified CES function structures, lacking an endogenous selection process from energy service to final energy use. This limitation hinders the ability to provide specific recommendations for decarbonizing demand sectors. Due to the discrete choice model (DCM) can easily determine the utilities of purchasing or using products and services for customers in a group, as well as simulate the competitive circumstances of the energy market, DCM has been gradually engaged in the sector modeling of IAMs. Widely utilized in transportation studies, DCMs analyze individual behavior regarding destination and transportation mode to forecast demand for transport technologies[18].

The underlying principle of DCM is based on random utility theory, which involves selecting fixed utility factors and a random utility distribution. This allows the mathematical expression of the probability of selecting each alternative as a function of the fixed utility. The cost of energy technology can be modeled as the perceived cost, encompassing both monetary and non-monetary factors, such as consumer preferences. Vehicle choice is determined by the polynomial logit equation in IMAGE's vehicle choice model[91], allocating the market share of various types of vehicles each year, to ensure that the cheapest vehicle captures the largest share of the market. The variation in vehicle types is influenced by factors such as regional energy costs, technological investment costs, regional loading factors, and energy efficiency[92]. Based on this model, Edelenbosch et al. (2018)[18] employed a combined technological and social learning model to examine the interaction between these two factors and their impact on the transition dynamics of electronic vehicles, which demonstrated how early adopters promote technical innovation by stimulating market demand. In addition, the methodological principle behind models such as FTT-transport and FTT-power is also based on DCM. What they have in common is not optimizing the entire system, but rather being partly based on the observed technical diffusion trajectory and partly based on the characteristics of customers, including agent heterogeneity, social influence, and non-monetary factors.

Social learning about the benefits and risks associated with new technologies is at the core of technical diffusions, which could be defined as the process of innovations spread over time among members of a social system and can be effectively captured by an agent-based model[93]. Agent-based model (ABM) is a promising field that addresses the aspect of individual heterogeneity within social systems in integrated assessment models. This type of model analyzes the dynamics of climate, energy, and macroeconomics based on agents[94], representing climate damage and its cross-sector penetration from a bottom-up perspective and explains the role of finance in sustaining the economy and shaping the dynamics of the energy transition. The outstanding advantage of ABM is that it allows us to explicitly characterize individual heterogeneous consumers, instead of relying on aggregate equations. As the first generation of ABM-IAMs, ENGAGE model, shown in Table 1, focuses on the diffusion of technology over time, in which technical change is simulated as a process of endogenous evolution and probability, allowing for the simulation of future scenarios with different technologies[68]. However, the simulation of ABM models, such as ENGAGE, is still quite stylized and has many obvious shortcomings. For example, it completely ignores population growth and only uses a limited number of representative sectors and all these features greatly reduce the realism and comparability of the model.

In recent years, ABM-based IAMs are still emerging. Multi-agent model for transition risk (MATRIX) is a multi-sectors and multi-agents macroeconomic model[19], using different climate models, damage functions, and carbon cycle models to simulate different climate policy scenarios, which aims to assess the economic impacts of climate change and abatement policies in the context of uncertainty and heterogeneity. The model endogenously incorporates firms' investment in emission reduction efforts based on updated information, but unfortunately, the MARTIX model does not account for endogenous technological progress. The ABM-IAM model[95] describes how interactions between heterogeneous consumers, firms, power plants, and banks within the network drive the economy. By introducing climate cycles and damage functions in traditional IAMs, the model captures the complex interaction among the economy, electricity, and financial markets and provides more detailed insights into the heterogeneity of the inequality issue.

6 Conclusions

Technical cost changes brought about by innovation are one of the decisive factors in the long-term mitigation costs of climate change, as a result systematically modeling the structure of endogenous technical change has been a consensus among the majority of IAM teams. Due to the scope and complexity of the climate change problem, as well as the trade-off between model intelligibility and complexity, modeling endogenous technical change requires both skill and difficulty to achieve. This paper attempts to systematically demonstrate current techniques and theoretical basis for handling ETC and uses the E3METL model as an example, in which showing the outcomes of energy technology development path, economic output impacts, and abatement cost changes by introducing R&D investment, LBD&LBR learning curves, and logistic technical mechanism into the model. The integration of IAM combined with a macroeconomic module and a bottom-up energy module offers several advantages in addressing the issue of technical change problem, so it is conducive to the expansion of modeling methods for different techniques.

For modeling technical change in demand sectors, taking R&D investments into the economic structure, which is also called induced innovation, is the most common technique in top-down macroeconomic IAMs[36]. The knowledge capital associated with specific energy technologies can be developed and accumulated through innovative inputs, gradually expanding in competition with traditional energy capital, and ultimately facilitating the adoption of carbon-free energy. The method similar to induced innovation is price-induced technical progress, constructing the paths of technical progress through the quantitative relationship between energy price and technical efficiency. Considering the particularity and significance of carbon reduction potentials in demand sectors, developing endogenous technical innovation mechanisms in demand sectors has the potential for future expansion. For example, developing a detailed technology choice model for demand sectors, addressing knowledge externalities, and examining the relationships between technologies and innovations.

For modeling technical change from the supply side, the concept of ETC can be well represented by learning curves, which illustrate the internal factors driving technical progress. The learning process specifically manifests as the LBD effect, which means that production costs decrease exponentially as cumulative production increases, and the LBS effect, which means that production costs decrease exponentially as knowledge capital increases. Two-factor learning curves have been applied gradually in many researches with increasing consideration of endogenous technical progress in energy system models. Nogueira et al. (2023)[96] linked three IAMs in a macroeconomic framework

(WITCH, MERGE-ETL, and GEM-E3) with a bottom-up, technology-rich energy system model (TIAM-ECN), examining technological learning in macroeconomic sectors and the cost-reducing effects of energy systems, so as to quantitatively explore how R&D investments can support deep decarbonization.

With the reexamination of technological learning in the context of economic structural and social transformation, more and more modern endogenous growth theories and socio-technical methods have been engaged in IAMs, for instance E3METL is a preliminary attempt to incorporate the S-shaped logistic curve into the competition mechanism and its optimization effect is evident. There is currently an important body of research in the field of IAM addressing this issue. For instance, Mercure et al. (2015)[60] investigated alternative modeling approaches based on complex dynamics and agent heterogeneity to represent technology adoption and diffusion. Beyond that, modeling based on discrete choice and agent-based plays a significant role in technical diffusion and transition dynamics[42, 44]. We point out that IAM still lacks a systematic framework for the development of endogenous technological progress, to which more and richer theories and methods are needed to develop the endogenous technology modules and support the economic and social changes of technological innovation.

E3METL-R, the global multi-regional version of E3METL currently being developed, features its detailed economic and trade modules, and demand sectors with DTC mechanisms. Meanwhile, as one of key sources that hinders the reliability of model outcomes on energy technological progress, model uncertainty has been a public concern of policy research communities. Multi-model comparisons are effective methods for exploring reliable scientific findings and drawing robust policy conclusions[97, 98]. The current multi-model research has high model requirements, especially for climate economics and policy research based on IAMs. Further multi-model work at both the global and regional levels remains meaningful and challenging.

We retraced the approaches of technology change modeling in order to shed light on the processes and challenges in developing the mechanism of ETC in IAMs and its contribution to international cooperation on climate change. In reality, emission scenarios have always been a crucial part of IPCC reports. To enhance diversity and transparency, models consisted with a wider range of sectors and more detailed deep climate mitigation policies are called for in developing future-focused scenario databases and implementing international climate cooperation[99, 100]. In fact, it is difficult and unfair to discuss economic growth separately without considering the impact of technological progress on productivity, as technological progress is the determinant of long-term economic growth. A reasonable modeling framework for endogenous economic growth is crucial to address the widely criticized limitation of IAMs, which is their lack of realism. Therefore, a redesign of current policy mixes consisting of more coherent policies under a ETC framework, such as clarifying the intervene time of carbon taxes and renewable energy subsidies, may respond to the current call for strengthened policies. Additionally, through redesigning in combination with international cooperation, it is possible to prevent carbon leakage to other sectors and countries, avoiding stranded assets, and strengthening the regulatory capacity of governments[99].

Further, exploring the global impacts of non-energy systems driven by technological advancements is also an promising direction for future research. While all decarbonization approaches offer environmental benefits, the scale of these benefits and potential trade-offs is largely determined by the technologies chosen endogenously[101]. For example, rapid development of bioenergy can pose risks to the environment, food markets, and biodiversity, especially considering regional disparities. Even though IAMs typically incorporate constraints on land use, such as protecting biodiversity-rich areas, real-world implementation requires corresponding regulatory frameworks[102]. Efforts should also be made to mitigate leakage effects in international bioenergy markets and prevent free-riding behavior. Therefore, ETC interacts more profoundly with non-energy systems[103], such as land, biological systems[104], and human health, than commonly assumed, leading to increasing uncertainty in technology developments over longer time horizons.

Acknowledgements

We acknowledge the anonymous referees for their valuable comments. This study is financially supported by the National Natural Science Foundation of China (Nos. 72325008, 72274188, and 72243011), the National Key Research and Development Program of China (2020YFA0608603), and the Fundamental Research Funds for the Central Universities in China.

Appendix

Table A1 Abbreviations.

Abbreviation	Definition	Abbreviation	Definition
ABM	Agent-based model	GWP	Gross world product
AEEI	Autonomous energy effiency improvement	IAMs	Integrated assessment models
CCS	Carbon capture and storage	IPF	Innovation possibility frontier
CECC	Cumulative extraction cost curve	LBD	Learning by doing
CES	Constant elasticity substitution	LBS	Learning by searching
CGE	Computable general equilibrium	NFA	Net foreign assets
CRRA	Constant relative risk aversion	OFLC	One-factor learning curve
DCM	Discrete choice model	PV	Photovoltaic
DTC	Directed technical change	R&D	Research and development
ETC	Endogenous technical change	TFLC	Two-factor learning curve
GHG	Greenhouse gas		

Table A2 Model abbreviations and names.

Abbreviation	Model's name
AIM	Asia-Pacific Integrated Model
DICE	Dynamic Integrated Climate-Economy
E3ME-FTT	Energy-Environment-Economy Macro-Econometric-Future Technology Transformations
E3METL	Energy-Economy-Environment Model with Endogenous Technological change by employing Logistic curves
ENTICE	ENdogenous Technological Integrated Climate-Economy
EPPA	Economic Projection and Policy Analysis
ETC-RICE	Endogenous Technical Change-Regional Integrated model of Climate and the Economy
FUND	Framework for Uncertainty, Negotiation and Distribution
GEM-E3	General Equilibrium Model for Energy-Economy-Environment interactions
IAMGE	Integrated Model to Assess the Global Environment
MARKAL	MARKet ALlocation
MERGE	Model for Evaluating Regional and Global Effects
MESSAGE	Model for Energy Supply System Alternatives and their General Environmental Impact
POLES	Prospective Outlook on Long-term Energy Systems
REMIND	REgional Model of INvestments and Development
TIAM	TIMES Integrated Assessment Model
WITCH	World Induced Technical Change Hybrid

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

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

[2] Hsu, C. C., Quang-Thanh, N., Chien, F., Li, L., Mohsin, M. (2021). Evaluating green innovation and performance of financial development: Mediating concerns of environmental regulation. *Environmental Science and Pollution Research*, 28: 57386–57397.

[3] Popp, D., Newell, R. G., Jaffe, A. B. (2010). Energy, the environment, and technological change. In: Handbook of the Economics of Innovation, Volume 2. Amsterdam: Elsevier: 873–937.

[4] Messner, S., Strubegger, M. (1995). User's Guide for MESSAGE III.

[5] Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., Tavoni, M. (2006). WITCH—A world induced technical change hybrid model. *SSRN Electronic Journal*: 13–37.

[6] Duan, H. B., Fan, Y., Zhu, L. (2013). What's the most cost-effective policy of CO_2 targeted reduction: An application of aggregated economic technological model with CCS. *Applied Energy*, 112: 866–875.

[7] Duan, H., Zhang, G., Fan, Y., Wang, S. (2017). Role of endogenous energy efficiency improvement in global climate change mitigation. *Energy Efficiency*, 10: 459–473.

[8] Emmerling, J., Reis, L. A., Bevione, M., Berger, L., Bosetti, V., Carrara, S., Marangoni, G., Sferra, F., Tavoni, M., Witajewski-Baltvilks, J., et al. (2016). The WITCH 2016 model —Documentation and implementation of the shared socioeconomic pathways. *SSRN Electronic Journal*: https://doi.org/10.2139/ssrn.2800970.

[9] Nordhaus, W. D., Yang, Z. (1996). A regional dynamic general-equilibrium model of alternative climate-change strategies. *The American Economic Review*, 86: 741–765.

[10] Popp, D. (2004). ENTICE: Endogenous technological change in the DICE model of global warming. *Journal of Environmental Economics and Management*, 48: 742–768.

[11] Stehfest E., van Vuuren, D., Kram, T., Bouwman, L., Alkemade, R., Bakkenes, M., Bouwman, A., den Elzen, M., Janse, J., Lucas, P., et al. (2014). Integrated assessment of global environmental change with IMAGE 3.0: Model description and policy applications. Report. PBL Netherlands Environmental Assessment Agency.

[12] Farmer, J. D., Hepburn, C., Mealy, P., Teytelboym, A. (2015). A third wave in the economics of climate change. *Environmental and Resource Economics*, 62: 329–357.

[13] Mathias, J. D., Debeljak, M., Deffuant, G., Diemer, A., Dierickx, F., Donges, J. F., Gladkykh, G., Heitzig, J., Holtz, G., Obergassel, W., et al. (2020). Grounding social foundations for integrated assessment models of climate change. *Earth's Future*: https://doi.org/10.1029/2020EF001573.

[14] Hémous, D. (2012). Environmental policy and directed technical change in a global economy: Is there a case for carbon tariffs? Harvard University. http://cowles.econ.yale.edu/conferences/2012/sum12/ma_hemous.pdf.

[15] Hémous, D., Olsen, M. (2021). Directed technical change in labor and environmental economics. *Annual Review of Economics*, 13: 571–597.

[16] Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, 102: 131–166.

[17] Mercure, J. F., Salas, P., Vercoulen, P., Semieniuk, G., Lam, A., Pollitt, H., Holden, P. B., Vakilifard, N, Chewpreecha, U., Edwards, N. R., et al. (2021). Reframing incentives for climate policy action. *Nature Energy*, 6: 1133–1143.

[18] Edelenbosch, O. Y., McCollum, D. L., Pettifor, H., Wilson, C., van Vuuren, D. P. (2018). Interactions between social learning and technological learning in electric vehicle futures. *Environmental Research Letters*, 13: 124004.

[19] Bazzana, D., Rizzati, M., Ciola, E., Turco, E. M., Vergalli, S.

(2023). Warming the MATRIX: A climate assessment under uncertainty and heterogeneity. *SSRN Electronic Journal*: https://doi.org/10.2139/ssrn.4445332.

[20] Odenweller, A. (2022). Climate mitigation under S-shaped energy technology diffusion: Leveraging synergies of optimisation and simulation models. *Technological Forecasting and Social Change*, 178: 121568.

[21] Koch, J., Leimbach, M., Marcolino, M. (2023). A structural transformation integrated assessment model of climate change.

[22] Gillingham, K., Newell, R. G., Pizer, W. A. (2008). Modeling endogenous technological change for climate policy analysis. *Energy Economics*, 30: 2734–2753.

[23] Skea, J., Shukla, P., Al Khourdajie, A., McCollum, D. (2021). Intergovernmental panel on climate change: Transparency and integrated assessment modeling. *WIREs Climate Change*, 12: https://doi.org/10.1002/wcc.727.

[24] Acemoglu, D., Aghion, P., Barrage, L., Hemous, D. (2023). Climate change, directed innovation, and energy transition: The long-run consequences of the shale gas revolution. *SSRN Electronic Journal*: https://doi.org/10.2139/ssrn.4567661.

[25] Nijsse, F. J. M. M., Mercure, J. F., Ameli, N., Larosa, F., Kothari, S., Rickman, J., Vercoulen, P., Pollitt, H. (2023). The momentum of the solar energy transition. *Nature Communications*, 14: 6542.

[26] Waisman, H., Guivarch, C., Grazi, F., Hourcade, J. C. (2012). The Imaclim-R model: Infrastructures, technical inertia and the costs of low carbon futures under imperfect foresight. *Climatic Change*, 114: 101–120.

[27] Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, 29: 155–173.

[28] Anderson, D., Bird, C. D. (1992). Carbon accumulations and technical progress—A simulation study of costs. *Oxford Bulletin of Economics and Statistics*, 54: 1–30.

[29] Arnulf, G., Sabine, M. (1998). Technological change and the timing of mitigation measures. *Energy Economics*, 20: 495–512.

[30] Acemoglu, D. (2002). Directed technical change. *Review of Economic Studies*, 69: 781–809.

[31] Aghion, P., Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60: 323.

[32] Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98: S71–S102.

[33] Romer, P. M. (1986). Increasing returns and long-Run growth. *Journal of Political Economy*, 94: 1002–1037.

[34] Romer, P. M. (1987). Growth based on increasing returns due to specialization. *The American Economic Review*, 77: 56–62.

[35] Grossman, G. M., Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European Economic Review*, 35: 517–526.

[36] Grossman, G. M., Helpman, E. (1994). Endogenous innovation in the theory of growth. *Journal of Economic Perspectives*, 8: 23–44.

[37] Acemoglu, D., Aghion, P., Hémous, D. (2014). The environment and directed technical change in a North–South model. *Oxford Review of Economic Policy*, 30: 513–530.

[38] Van der Zwaan, B. C. C., Gerlagh, R., G, Klaassen, Schrattenholzer, L. (2002). Endogenous technological change in climate change modelling. *Energy Economics*, 24: 1–19.

[39] Barker, T., Ekins, P., Foxon, T. (2007). The macro-economic rebound effect and the UK economy. *Energy Policy*, 35: 4935–4946.

[40] Kennedy, C. (1964). Induced bias in innovation and the theory of distribution. *The Economic Journal*, 74: 541–547.

[41] Kamien, M. I., Schwartz, N. L. (1968). Optimal "induced" technical change. *Econometrica*, 36: 1.

[42] Buonanno, P., Carraro, C., Galeotti, M. (2003). Endogenous induced technical change and the costs of Kyoto. *Resource and Energy Economics*, 25: 11–34.

[43] Grubb, M., Köhler, J., Anderson, D. (2002). Induced technical change in energy and environmental modeling: Analytic approaches and policy implications. *Annual Review of Energy and the Environment*, 27: 271–308.

[44] Popp, D. C. (2001). The effect of new technology on energy consumption. *Resource and Energy Economics*, 23: 215–239.

[45] Hordijk, L., Arnell, N., Gerten, D., van Ittersum, M., Klaassen, G., Riahi, K., Scharlemann, J., Janssen, P. (2014). International Review of IMAGE 3.0. 45. http://www.pbl.nl/sites/default/files/cms/publicaties/pbl-2015-international-review-of-image-3.0_01799.pdf.

[46] Jacoby, H. D., Reilly, J. M., McFarland, J. R., Paltsev, S. (2006). Technology and technical change in the MIT EPPA model. *Energy Economics*, 28: 610–631.

[47] Smulders, S., de Nooij, M. (2003). The impact of energy conservation on technology and economic growth. *Resource and Energy Economics*, 25: 59–79.

[48] Creutzig, F., Agoston, P., Goldschmidt, J. C., Luderer, G., Nemet, G., Pietzcker, R. C. (2017). The underestimated potential of solar energy to mitigate climate change. *Nature Energy*, 2(9): 17140. https://doi.org/10.1038/nenergy.2017.140.

[49] Savona, M., Ciarli, T. (2019). Structural changes and sustainability. A selected review of the empirical evidence. *Ecological Economics*, 159: 244–260.

[50] Bauer, N., Baumstark, L., Leimbach, M. (2012). The REMIND-R model: The role of renewables in the low-carbon transformation—First-best *vs*. second-best worlds. *Climatic Change*, 114: 145–168.

[51] Kypreos, S. (2005). Modeling experience curves in MERGE (model for evaluating regional and global effects). *Energy*, 30: 2721–2737.

[52] De Vries, B., van Vuuren, D., den Elzen, M., Janssen, M. (2001). Targets IMage energy regional (TIMER) model. Technical Documentation. RIVM. http://rivm.openrepository.com/rivm/handle/10029/9512.

[53] Manne, A. S., Richels, R. G. (1992). Buying greenhouse insurance: The economic costs of CO_2 emission limits. https://api.semanticscholar.org/CorpusID:152554443.

[54] Criqui, P., Mima, S., Menanteau, P., Kitous, A. (2015). Mitigation strategies and energy technology learning: An assessment with the POLES model. *Technological Forecasting and Social Change*, 90: 119–136.

[55] Keppo, I., Butnar, I., Bauer, N., Caspani, M., Edelenbosch, O., Emmerling, J., Fragkos, P., Guivarch, C., Harmsen, M., Lefèvre, J., et al. (2021). Exploring the possibility space: Taking stock of the diverse capabilities and gaps in integrated assessment models. *Environmental Research Letters*, 16: 053006.

[56] Geels, F. W., Kern, F., Fuchs, G., Hinderer, N., Kungl, G., Mylan, J., Neukirch, M., Wassermann, S. (2016). The enactment of socio-technical transition pathways: A reformulated typology and a comparative multi-level analysis of the German and UK low-carbon electricity transitions (1990–2014). *Research Policy*, 45: 896–913.

[57] Hirt, L. F., Schell, G., Sahakian, M., Trutnevyte, E. (2020). A review of linking models and socio-technical transitions theories for energy and climate solutions. *Environmental Innovation and Societal Transitions*, 35: 162–179.

[58] Mercure, J. F., Lam, A., Billington, S., Pollitt, H. (2018). Integrated assessment modelling as a positive science: Private passenger road transport policies to meet a climate target well below 2 ℃. *Climatic Change*, 151: 109–129.

[59] Duan, H. B., Zhu, L., Fan, Y. (2015). Modelling the evolutionary paths of multiple carbon-free energy technologies with policy

incentives. *Environmental Modeling & Assessment*, 20: 55–69.

[60] Mercure, J., Mercure, J., Pollitt, H., Bassi, A., Viñuales, J., Edwards, N. (2016). Modelling complex systems of heterogeneous agents to better design sustainability transitions policy. https://api.semanticscholar.org/CorpusID:1114137.

[61] Popp, D. (2006). ENTICE-BR: The effects of backstop technology R&D on climate policy models. *Energy Economics*, 28: 188–222.

[62] Duan, H. B., Zhu, L., Fan, Y. (2014). A cross-country study on the relationship between diffusion of wind and photovoltaic solar technology. *Technological Forecasting and Social Change*, 83: 156–169.

[63] Bosetti, V., Eni, F., Mattei, E., et al. (2007). CIP—Climate impacts and policy division the WITCH model. Structure, 10.

[64] Baumstark, L., Bauer, N., Benke, F., Bertram, C., Bi, S., Gong, C. C., Dietrich, J. P., Dirnaichner, A., Giannousakis, A., Hilaire, J., et al. (2021). REMIND2.1: transformation and innovation dynamics of the energy-economic system within climate and sustainability limits. G*eoscientific Model Development*, 14(10): 6571–6603. https://doi.org/10.5194/gmd-14-6571-2021.

[65] Wing, I. S. (2004). Computable general equilibrium models and their use in economy-wide policy analysis. Working Paper, 33(SUPPL.): 17–20.

[66] Van Regemorter, D., Perry, M., Capros, P., Ciscar J., Paroussos, L., Pycroft, J., Karkatsoulis, P., Abrell, J., Saveyn, B. GEM-E3 model documentation. JRC Scientific and Policy Reports (Vol. 26034). https://doi.org/10.2788/47872.

[67] Loulou, R., Goldstein, G., Noble, K. Documentation for the MARKAL family of models. Energy Technology Systems Analysis Programme: 65–73.

[68] Gerst, M. D., Wang, P., Roventini, A., Fagiolo, G., Dosi, G., Howarth, R. B., Borsuk, M. E. (2013). Agent-based modeling of climate policy: An introduction to the ENGAGE multi-level model framework. *Environmental Modelling & Software*, 44: 62–75.

[69] Bauer, N., Hilaire, J., Brecha, R. J., Edmonds, J., Jiang, K., Kriegler, E., Rogner, H. H., Sferra, F. (2016). Assessing global fossil fuel availability in a scenario framework. *Energy*, 111: 580–592.

[70] Leimbach, M., Baumstark, L. (2010). The impact of capital trade and technological spillovers on climate policies. *Ecological Economics*, 69: 2341–2355.

[71] Leimbach, M., Bauer, N. (2022). Capital markets and the costs of climate policies. *Environmental Economics and Policy Studies*, 24: 397–420.

[72] Dowlatabadi, H., Oravetz, M. A. (2006). US long-term energy intensity: Backcast and projection. *Energy Policy*, 34: 3245–3256.

[73] Wang, R., Saunders, H., Moreno-Cruz, J., Caldeira, K. (2019). Induced energy-saving efficiency improvements amplify effectiveness of climate change mitigation. *Joule*, 3: 2103–2119.

[74] Hassler, J., Krusell, P., Olovsson, C. (2021). Directed technical change as a response to natural resource scarcity. *Journal of Political Economy*, 129: 3039–3072.

[75] Waldhoff, S., Anthoff, D., Rose, S., Tol, R. S. J. (2014). The marginal damage costs of different greenhouse gases: An application of FUND. *Economics*, 8: https://doi.org/10.5018/economics-ejournal.ja.2014-31.

[76] Hübler, M., Baumstark, L., Leimbach, M., Edenhofer, O., Bauer, N. (2012). An integrated assessment model with endogenous growth. Discussion Paper No. 12-054. https://ftp.zew.de/pub/zew-docs/dp/dp12054.pdf.

[77] Fujimori, S., Hasegawa, T., Masui, T. (2017). AIM/CGE V2.0: Basic feature of the model. In: Post-2020 Climate Action: Global and Asian Perspectives. Fujimori, S., Hasegawa, T., Masui, T. Eds. Springer Singapore: 305–328. https://doi.org/10.1007/978-981-10-3869-3_13.

[78] Castrejon-Campos, O., Lu, A., Hui, F. K. P. (2022). Effects of learning curve models on onshore wind and solar PV cost developments in the USA. *Renewable and Sustainable Energy Reviews*, 160: 112278.

[79] Klaassen, G., Miketa, A., Larsen, K., Sundqvist, T. (2005). The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. *Ecological Economics*, 54: 227–240.

[80] Zhang, S., Bauer, N., Yin, G., Xie, X. (2020). Technology learning and diffusion at the global and local scales: A modeling exercise in the REMIND model. *Technological Forecasting and Social Change*, 151: 119765.

[81] Duan, H. B., Zhang, G. P., Zhu, L., Fan, Y., Wang, S. Y. (2016). How will diffusion of PV solar contribute to China's emissions-peaking and climate responses. *Renewable and Sustainable Energy Reviews*, 53: 1076–1085.

[82] Donald, E. (2023). Spillovers and the direction of innovation: An application to the clean energy transition.

[83] Liu, E., Ma, S. (2021). Innovation networks and R&D allocation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3994285.

[84] Leimbach, M., Edenhofer, O. (2007). Technological spillovers within multi-region models: Intertemporal optimization beyond the Negishi approach. *Economic Modelling*, 24: 272–294.

[85] Aleluia Reis, L., Vrontisi, Z., Verdolini, E., Fragkiadakis, K., Tavoni, M. (2023). A research and development investment strategy to achieve the Paris climate agreement. *Nature Communications*, 14: 3581.

[86] Achakulwisut, P., Erickson, P., Guivarch, C., Schaeffer, R., Brutschin, E., Pye, S. (2023). Global fossil fuel reduction pathways under different climate mitigation strategies and ambitions. *Nature Communications*, 14: 5425.

[87] Uidhir, T. M., Gallachóir, B. Ó., Curtis, J., Rogan, F. (2022). Achieving the unprecedented: Modelling diffusion pathways for ambitious climate policy targets. *Energy and Climate Change*, 3: 100073.

[88] Duan, H., Zhang, G., Wang, S., Fan, Y. (2018). Peer interaction and learning: Cross-country diffusion of solar photovoltaic technology. *Journal of Business Research*, 89: 57–66.

[89] Köhler, J., Geels, F. W., Kern, F., F., Markard, J., Onsongo, E., Wieczorek, A., Alkemade, F., Avelino, F., Bergek, A., Boons, F., et al. (2019). An agenda for sustainability transitions research: State of the art and future directions. *Environmental Innovation and Societal Transitions*, 31: 1–32.

[90] Pindyck, R. S. (2017). The use and misuse of models for climate policy. *Review of Environmental Economics and Policy*, 11: 100–114.

[91] Girod, B., van Vuuren, D. P., Deetman, S. (2012). Global travel within the 2 ℃ climate target. *Energy Policy*, 45: 152–166.

[92] Pettifor, H., Wilson, C., McCollum, D., Edelenbosch, O. Y. (2017). Modelling social influence and cultural variation in global low-carbon vehicle transitions. *Global Environmental Change*, 47: 76–87.

[93] Rogers, E. M., Singhal, A., Quinlan, M. M. (2019). Diffusion of innovations 1. In: An Integrated Approach to Communication Theory and Research. Routledge, 415–434.

[94] Lamperti, F., Mandel, A., Napoletano, M., Sapio, A., Roventini, A., Balint, T., Khorenzhenko, I. (2019). Towards agent-based integrated assessment models: Examples, challenges, and future developments. *Regional Environmental Change*, 19: 747–762.

[95] Safarzyńska, K., van den Bergh, J. C. J. M. (2022). ABM-IAM: Optimal climate policy under bounded rationality and multiple inequalities. *Environmental Research Letters*, 17: 094022.

[96] Nogueira, L., Dalla Longa, F., Reis, L. A., Drouet, L., Vrontisi, Z., Fragkiadakis, K., Panos, E., van der Zwaan, B. (2023). A multi-model framework to assess the role of R&D towards a decarbonized energy system. *Climatic Change*, 176: 82.
[97] Duan, H., Zhang, G., Wang, S., Fan, Y. (2019). Robust climate change research: a review on multi-model analysis. *Environmental Research Letters*, 14(3): 033001.
[98] Duan, H., Zhou, S., Jiang, K., Bertram, C., Harmsen, M., Kriegler, E., van Vuuren, D. P., Wang, S., Fujimori, S., Tavoni, M., et al. (2021). Assessing China's efforts to pursue the 1.5 ℃ warming limit. *Science*, 372: 378–385.
[99] Cointe, B. (2024). The AR6 scenario explorer and the history of IPCC scenarios databases: Evolutions and challenges for transparency, pluralism and policy-relevance. *NPJ Climate Action*, 3: 3.
[100] Dekker, M. M., Daioglou, V., Pietzcker, R., Rodrigues, R., de Boer, H. S., Dalla Longa, F., Drouet, L., Emmerling, J., Fattahi, A., Fotiou, T., et al. (2023). Identifying energy model fingerprints in mitigation scenarios. *Nature Energy*, 8: 1395–1404.
[101] Luderer, G., Pehl, M., Arvesen, A., Gibon, T., Bodirsky, B. L., de Boer, H. S., Fricko, O., Hejazi, M., Humpenöder, F., Iyer, G., et al. (2019). Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies. *Nature Communications*, 10: 5229.
[102] Bauer, N., Rose, S. K., Fujimori, S., van Vuuren, D. P., Weyant, J., Wise, M., Cui, Y., Daioglou, V., Gidden, M. J., Kato, E., et al. (2020). Global energy sector emission reductions and bioenergy use: Overview of the bioenergy demand phase of the EMF-33 model comparison. *Climatic Change*, 163: 1553–1568.
[103] Soergel, B., Kriegler, E., Weindl, I., Rauner, S., Dirnaichner, A., Ruhe, C., Hofmann, M., Bauer, N., Bertram, C., Bodirsky, B. L, et al. (2021). A sustainable development pathway for climate action within the UN 2030 Agenda. *Nature Climate Change*, 11: 656–664.
[104] Kozicka, M., Havlík, P., Valin, H., Wollenberg, E., Deppermann, A., Leclère, D., Lauri, P., Moses, R., Boere, E., Frank, S, et al. (2023). Feeding climate and biodiversity goals with novel plant-based meat and milk alternatives. *Nature Communications*, 14: 5316.