The role of technology diffusion in a decarbonizing world to limit global warming to well below 2 °C: An assessment with application of Global TIMES model

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Abstract

Low-carbon power generation technologies such as wind, solar and carbon capture and storage are expected to play major roles in a decarbonized world. However, currently high cost may weaken the competitiveness of these technologies. One important cost reduction mechanism is the "learning by doing", through which cumulative deployment results in technology costs decline. In this paper, a 14-region global energy system model (Global TIMES model) is applied to assess the impacts of technology diffusion on power generation portfolio and CO_2 emission paths out to the year 2050. This analysis introduces three different technology learning approaches, namely standard endogenous learning, multiregional learning and multi-cluster learning. Four types of low-carbon power generation technologies (wind, solar, coal-fired and gas-fired CCS) undergo endogenous technology learning. The modelling results show that: 1) technology diffusion can effectively reduce the long-term abatement costs and the welfare losses caused by carbon emission mitigation; 2) from the perspective of global optimization, developed countries should take the lead in low-carbon technologies' deployment; and 3) the establishment of an effective mechanism for technology diffusion across boundaries can enhance the capability and willingness of developing countries to cut down their CO_2 emission.

Keywords

Global TIMES model, technology diffusion, Endogenous technology learning, long-term climate mitigation target

1. Introduction

In order to limit global warming to 2 °C or even 1.5°, both energy supply side and demand side need to be changed. The core of such transformation lies in the large-scale use of low-carbon technology on the supply side and the improvement of energy efficiency and fuel- and technology- switching on the end-use side. The advancement in low-carbon technologies can improve energy efficiency, reduce the cost of energy-saving technologies and non-fossil energy technologies, reduce

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dependency on fossil fuels, and avoid the rapid growth of CO_2 and other greenhouse gases. The IPCC 5th Assessment Report also highlights the importance of technological advances for stabilizing greenhouse gas concentrations [1]. In the current world of economic globalization, the exchange of capital, products and materials across boundaries has created a ground for international technology progress and diffusion [2]. The global spill-over of knowledge and technology allow a country to take advantage of international resources to build its own technological reserves and develop low-carbon technologies effectively and rapidly. The *Paris Agreement* stressed the importance of technical cooperation in achieving emission reductions, "*the urgent need to enhance the provision of finance, technology and capacity-building support by developed country Parties, in a predictable manner, to enable enhanced pre-2020 action by developing country Parties*."[3]

In energy system models, technological change is currently modelled either endogenously or exogenously [4]. The way in which the technological changes (cost and efficiency) are modelled in energy system models, often influence the model results, i.e., energy system development pathways and resulting energy system costs. Therefore, more and more models are beginning to consider endogenous technology learning (ETL), to investigate the impact of technology progress on energy systems [5-13]. Mattsson and Wene (1997) [5] modelled technology learning endogenously to solar photovoltaic (PV) and fuel cell in the GENIE model to assess the technology lock-in effect. The main conclusion is that early research investment is nee ded to reduce production costs. Seebregts et al. (2000) [6] attempt to introduce ETL in Western European MARKAL model. Their study focuses on technology learning and spillover effects of new technologies, such as wind and fuel cell. Model results show that technology learning and spillover significantly reduce policy costs. Gritsevskyi and Nakicenovic (2000) [7] explored ETL in MESSAGE model with consideration of scale effects and clusters effects of linked technologies. Their study also focused on technology uncertainty and long-term cost and benefit. Iyer et al. (2015)[11] applied technology learning and spillover endogenously in wind power and solar PV in GCAM model to explore the global and regional technology development strategies to achieve a long-term climate mitigation target. Their model results show that international cooperation in the deployment of low-carbon technologies can lead to substantial gains when achieving the global goal.

Technology learning is usually applied to a set of technologies which are competing or potentially complementary. Sano et al (2005) [8] modelled ETL of fuel cell, wind and PV power in DNE21+ model. Rao et al. (2006) [9] included wind, PV and hydrogen production technologies in a hybrid model MESSAGE-MACRO. Barreto and Kypreos (2004) [10] have estimated learning by doing for PV, fuel cells and wind turbine. Iyer et al. (2015) [11] assessed wind and solar PV only. In this study, learning is applied to a set of low-carbon power generation technologies - wind, solar and CCS, which are important technology options in future low-carbon technology portfolio.

Most studies apply ETL to technologies individually. Several studies have examined the "cluster learning" phenomenon, which a cluster of technologies shares a common component that linked and learn together [6, 12, 13]. De Feber et al. (2002) [13] modelled ETL in fuel cell which leads to cost decline in transportation technologies. Seebregts et al. (2000) [6] applied learning to five clusters:

wind turbines, solar PV, fuel cells, gasifiers and gas turbines. Anandarajah et al. (2013) [12] modelled multi-cluster learning in key vehicle components, namely automotive batteries, fuel cells, and electric drivetrains, which are shared across different transportation modes (buses, HGVs, cars). In Global TIMES model, several CCS generation technologies can obviously comprise multiple clusters. We incorporate a multi-cluster learning approach, applying learning for four types of coal- and gas-fired generation technologies, namely post-combustion coal CCS, oxyfuel combustion coal CCS, integrated gasification combined cycle with CCS (IGCC CCS) and natural gas combined cycle with CCS (NGCC CCS).

In this paper, technology learning is endogenously modelled in three different approaches into a 14-region energy system model Global TIMES to analyze the impact of technology progress and technology diffusion under the Shared Socio-economic Pathways (SSPs)[14-17], which provides a systematic scenario framework differentiated by socio-economic challenges to climate change mitigation and adaptation. It seems to be unique to model different endogenous technology learning mechanism under SSPs framework. The rest of the paper is organized as follows: Section 2 is a methodological section that describes the framework of Global TIMES model integrated with endogenous technology learning module; Section 3 provides the basic assumptions and scenario definition; Section 4 presents and discusses the model results and the conclusions are provided in Section 5.

2. Methodology

2.1 Overview of Global TIMES model

The TIMES (The Integrated MARKAL and EFOM System) is a combination of the MARKAL (Market Allocation Model) and EFOM (Energy Flow Optimization Model) developed and maintained by the ETSAP (Energy Technological System Analysis Program) of IEA (International Energy Agency) [18] . The Global TIMES, which is developed based on China MARKAL[19-21] and China TIMES [22-30], is a 14-region global energy system model built on TIMES framework with a modelling period of 40 years from 2010 to 2050 with 5-year reporting period. It is a powerful and reliable technology rich bottom-up tool to study energy system development and carbon mitigation assessment for each of the regions. Global TIMES incorporates the whole energy system, including energy supply, energy conversion, transmission and end-use demand sector. Five demand sectors, namely agriculture, industry, commercial, residential and transportation, are modelled and further disaggregated into 26 sub-sectors in the Global TIMES. The model determines the least-cost mix of technologies and fuels to meet the projected energy service demands for a given social economic development scenario. The model is calibrated based on 2010 historical data from a series of statistics and reports and the main modeling results for the year 2015 are also calibrated to available publications [31-35]. In this study, the Global TIMES model has been further improved by integrating an endogenous technology learning module to apply technology learning endogenously for low carbon electricity generation technologies. Figure 1 shows the region map of Global TIMES.

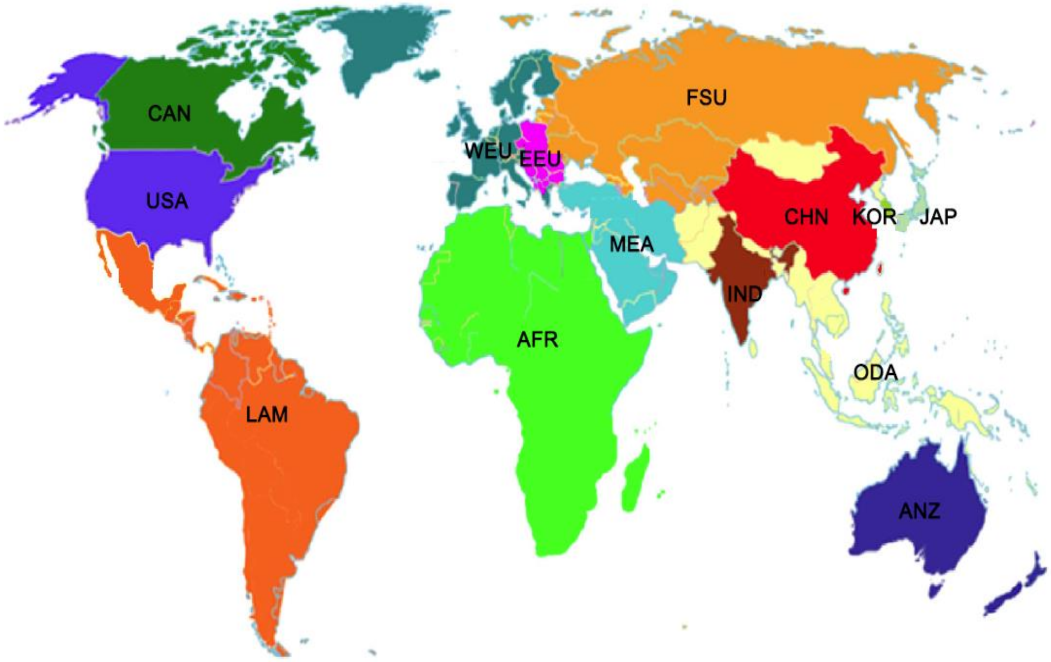

Figure 1: Regions in Global TIMES model

This paper focuses on the power sector which is becoming more and more important to low carbon society. In the model, we modelled more than 60 power generation technologies including existing and advanced low carbon technologies such as nuclear, hydro, onshore wind, offshore wind, solar photovoltaic (PV), concentrating solar power (CSP), biomass, CCS and etc.

2.2 Endogenous technology learning framework in Global TIMES

Technology learning reflects the fact that with the accumulation of certain factors (e.g. knowledge, experience, utilization, etc.), technology may see cost decline. Several patterns of technology learning are observed by researches: learning by doing, learning by researching, learning by using, etc.[36]. However, it is difficult to consider all these learning patterns in the Global TIMES model. Nevertheless, in order to assess the cost reduction of low-carbon technologies, we modelled the learning by doing mechanism by introducing a one-factor learning curve into Global TIMES. Learning by doing is a concept which allows the evaluation of reduction in capital cost when a technology's cumulative capacity increases. In Global TIMES, only the investment cost undergoes learning. The learning curve is expressed by an exponential regression:

$$C_t = C_0 \times (\frac{Q_t}{Q_0})^{\alpha} \quad (1)$$

where C_0 and Q_0 are the initial investment cost and initial capacity, C_t and Q_t are investment cost and cumulative installed capacity at time *t*, α is the elasticity of learning by doing. From Eq. (1) we can determine the progress ratio (PR) and learning rate (LR):

$$PR = 1 - LR = 2^{-\alpha} \quad (2)$$

The progress ratio represents the investment cost declines while the cumulative capacity doubles.

2.2.1 Multiregional learning

Some technologies have obvious regional characteristics [37]. The research, development, use and improvement processes of these technologies can results-in regional technology accumulation. However, such kind of technology accumulation is difficult to spread to other regions due to their obvious regional characteristics. For example, land management, irrigation, housing heating and cooking. In the learning curve-based technology development, the technology learning module described above (Section 2.2), the learning of a technology can only be gained through the deployment of the technology itself. Literature in technology learning shows that some technologies can be rapidly commercialized through a global technology accumulation, such as wind power, PV, steel making and some other technologies [37]. Thus, this paper models a global technology accumulation, assuming full spillover of knowledge and technologies across the regions modelled in the Global TIMES, using a multiregional learning approach to represent technology diffusion across boundaries. In order to model multiregional learning, we have created an additional region, called "Manufacturing", where the learning technologies are developed and made available to all the "real" regions in the model to use them. The manufacturing region consists only the set of learning technologies which undergoes ETL. In other "real" regions, the learning technologies are represented with all attributes except the investment cost. The following constraint is defined to ensure that learning in the Manufacturing Region can spread to all "real" regions:

$$VAR\_NCAP_M - \sum_{l=1}^{L} VAR\_NCAP_l = 0 \quad (3)$$

where VAR_NCAP_l is the newly installed capacity in region *l*, *M* represents the Manufacturing Region and *l*=1 to *L* represents each "real" region.

2.2.2 Multi-cluster learning

Another interesting variation of ETL literature is "multi-cluster learning", which is modelled in this study. Some technologies can rapidly diffuse and benefit other technologies which have common or similar core components. For example, IGCC, natural gas combined cycle and biomass gasification generation require one common component – the gas turbines. Through cluster learning, if we apply endogenous technology learning to gas turbines, the technology learning of gas turbines will benefit all these technologies. When we have more than one component that undergo ETL, then it is called a multi-cluster learning (Anandarajah et al, 2013).

Four types of CCS generation technologies, namely post-combustion coal CCS, oxyfuel combustion coal ccs, IGCC with CCS, and NGCC with CCS, are modeled through the multi-cluster learning approach in this study. This approach reflects that a cluster of technologies which share the same component – the "key component" – can benefit from each other's deployment and learn together. For example, air separation unit (ASU) plays the role as a key component. Oxy-fuel combustion with CCS and IGCC with CCS are technologies in the cluster in which ASU is used. Five components undergo ETL in the multi-cluster learning approach, and are linked to the generation technologies in which they are deployed in the model in an explicit manner (Figure 2). The phenomenon of multi-cluster learning is modelled in Global TIMES via the following modification of the formulation:

$$VAR\_NCAP_k - \sum_{i=1}^{I} VAR\_NCAP_i = 0 \quad (4)$$

where VAR_NCAP_i is the newly installed capacity of technology *i*, *k* represents the "key component" and *l*=1 to *L* represents technologies use component *k*. This ensures that learning on *k* spreads to all members of its cluster. Each of these component technologies is linked to power generation technologies that use them. For instance, a natural gas combined cycle uses a combined cycle and an anime CO_2 capture system. A post combustion CCS power plant, in contrast, uses an anime CO_2 capture system but no combined cycle; while an oxyfuel combustion power plant contains a gasifier. Components learn regardless of the technology they deploy. For example, cost reductions result from the deployment of ASU in IGCC also lead to cost reductions of ASU in oxy-fuel combustion. Table 1 shows the technologies undergo mulita-cluster learning in Global TIMES and the "key component" they use.

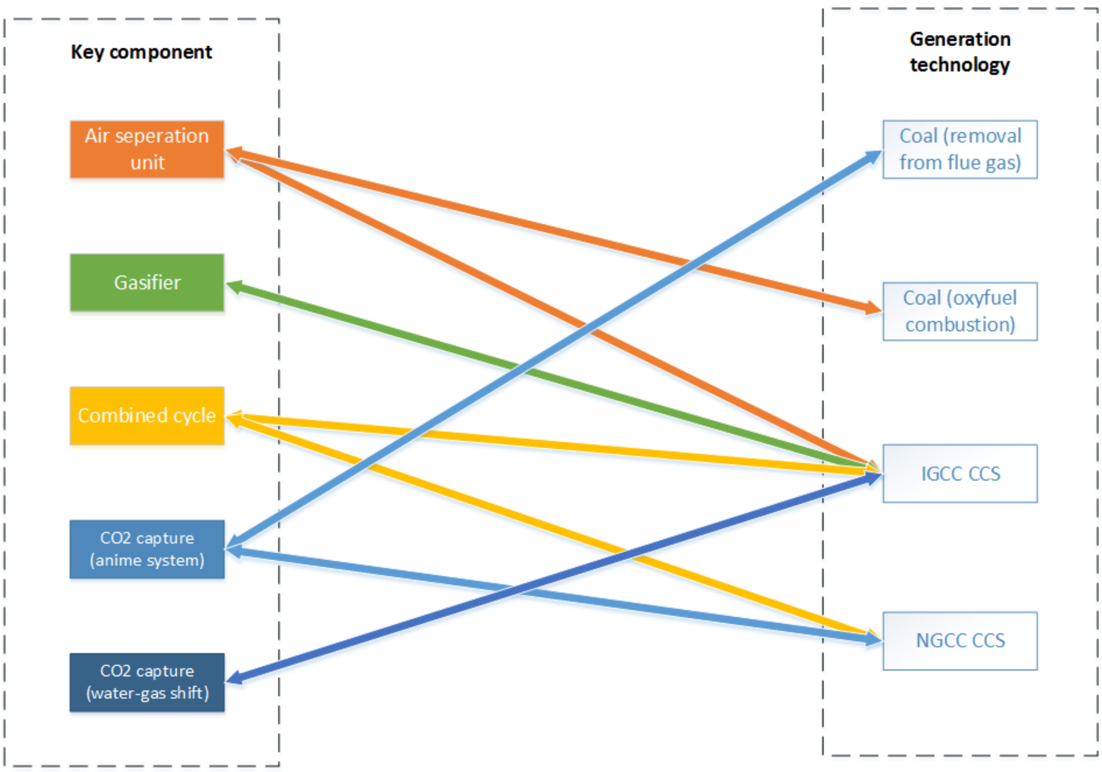

Figure 2: Multi-cluster learning framework in Global TIMES

Table 1: Technologies undergo multi-cluster learning and their key components

Technology type	Key component				
	Air	Gasifier	Combined	CO_2 Capture	CO_2 Capture

	Separation Unit		Cycle	(anime system)	(water-gas shift)
Post-combustion coal CCS	×	×	×	√	×
Oxyfuel combustion coal CCS	√	×	×	×	×
Integrated Gasification Combined Cycle with CCS	√	√	√	×	√
Natural Gas Combined Cycle with CCS	×	×	√	√	×

2.3 Data sources

This paper establishes a global energy technology database based on literature research, which provides the technical data for the energy system optimization model. Global TIMES contains more than 100 kinds of energy conversion and processing technology, covering the energy extraction, power generation and other processing and conversion technologies. The data for this study are mainly taken from the International Energy Agency (IEA) [39], the National Renewable Energy Laboratory (NREL) [40], the Energy Technology System Analysis Program (ETSAP) [41, 42], the National Pacific Northwest National Laboratory (PNNL) [43], the University College London (UCL) [43] and other research institutions. Table 2 presents the key parameters (progress ratio, initial cost and initial capacity) related to technology learning. These parameters are based on deployment level in 2010, which is the base year of the model. All costs are presented in 2005 US$. Progress ratios were collected from a series of literature review [45-52] .

Table 2 Data on key learning technologies and components [45-52]

	Initial cost ($/kW)	Initial capacity (GW)	Progress ratio
Onshore wind	1797	194.1	92%
Offshore wind	3310	2.9	91%
Solar photovoltaic	1978	36.3	82%
Concentrated solar power	4979	1.3	90%
Post-combustion coal CCS	5640	-	97%
Oxyfuel combustion coal CCS	6560	-	97%
Integrated Gasification Combined Cycle with CCS	6600	-	95%
Natural Gas Combined Cycle with CCS	3860	-	96%
Air Separation Unit	310	-	90%
Gasifier	562	-	91%
Combined Cycle	621	-	90%

CO_2 Capture (anime system)	318	-	90%
CO_2 Capture (water-gas shift)	234	-	97%

3. Scenarios

In order to explore the effect of technology progress and technology diffusion on the global climate target, three kinds of scenarios are designed: reference scenarios, long-term climate change mitigation scenarios and technology learning scenarios (Table 3).

The Reference Scenario (REF) serves as the basis for the analysis with no climate policy in it. The socio-economic data is taken from IIASA's SSP2 Scenario [14-17]. This scenario investigates the energy system development pathway without the consideration of climate goal. Technology costs are modelled under exogenous assumptions.

The Long-term Mitigation Scenario (LTM) is a greenhouse gases (GHGs) reduction scenario, in which a constraint of global cumulative carbon budget of 897 Gt CO_2 during 2015-2050 is applied, taken from literatures [1,54] for the Representation Concentration Pathways 2.6 (RCP2.6). No assumption on how the emission budget is distributed among regions in the model has been made. However, mitigation policies, in particular, NDCs (National Determined Contributions) for different countries/regions for the year 2025 or 2030 are considered in the model. Then, the Global TIEMS model will determine the optimal mitigation pathways and technology/fuel mix in the modeling period for different regions with global cost minimized to meet the cumulative carbon budget.

The technology learning scenarios contain three different scenarios. On the basis of Long-term Mitigation scenario, four types of power generation technologies – wind power, solar energy, coal CCS and natural gas CCS – were selected to simulate the effects of different technology learning approaches on the global energy system. In the ETL1 scenario, the standard approach of endogenous technology learning is used for the four types of technologies mentioned above, i.e. the technology investment decreases as the cumulative installed capacity of the technology in the region increases; The ETL2 scenario introduces a global diffusion equation for the four types of technologies, with a reduction in the cost of technology being affected by the global cumulative installed capacity; on the basis of the ETL2 scenario, the ETL3 considered multi-cluster learning mechanism for coal and natural gas CCS technologies, taking into account the coupling effects between them.

Table 3 Scenario definition

Scenario	Global cumulative CO_2 constraint	Technological progress assumptions			
		Wind	Solar	Coal CCS	Natural Gas CCS
REF	None	Exogenous assumptions			
LTM	897 Gt	Exogenous assumptions			
ETL1	897 Gt	Standard endogenous learning			
ETL2	897 Gt	Multiregional learning			
ETL3	897 Gt	Multiregional learning		Multiregional learning & multi-cluster learning	

4. Results and analysis

4.1 Transition of power sector structure

In order to achieve global long-term emission reduction targets, the energy system needs to change. The model results suggest that power generation sector is the most important energy conversion sector and the main sector of energy transformation. In 2050, the global electricity generation reach 43102 and 65768 TWh under REF and LTM scenarios, respectively. Moreover, as a high efficiency energy carrier, electricity increases its share under mitigation target in the end-use fuel portfolio. The share of electricity in the final energy consumption is 43.7% in 2050 under LTM scenario, much higher than the 22.7% in the REF scenario. Under the LTM scenario, traditional coal-, oil- and gas-fired power generation technologies will gradually be phased out, while renewable energy, nuclear power and CCS technology will gradually take the lead. Traditional coal power generation will peak in 2015, reaching the amount of 8876 TWh, and will decline gradually thereafter. In 2050, its capacity is of only about 10% of the 2010 level, accounting for about 1.4% of total generating capacity. The continuous decline in coal means that installed capacity and generations of nuclear, wind and solar increase significantly during the planning period. Under LTM, wind and solar capacity will reach 3768 and 5326 GW by 2050, respectively.

It can be seen from Figure 3 that, in ETL1 scenario, global electricity generation and capacity is comparable to LTM's level before 2030. After 2030, due to the increase in cumulative installed capacity of renewable power generation technologies, learning mechanism drives their cost decline and enhanced their expansion. In 2050, wind, solar, coal CCS and natural gas CCS power generation will increase by 2190, 526, 1095 and 657 TWh respectively compared with LTM scenario. The installed capacity of wind power and solar energy will increase rapidly from 2030 on, and the increment of wind power capacity will mainly appear in areas with cost advantages such as WEU and CHN. The increase of solar energy capacity mainly appears in IND, AFR, ODA and other regions with abundant solar energy resources. Coal CCS and natural gas CCS capacity start to grow in 2030, and will first appear in the developed countries and regions.

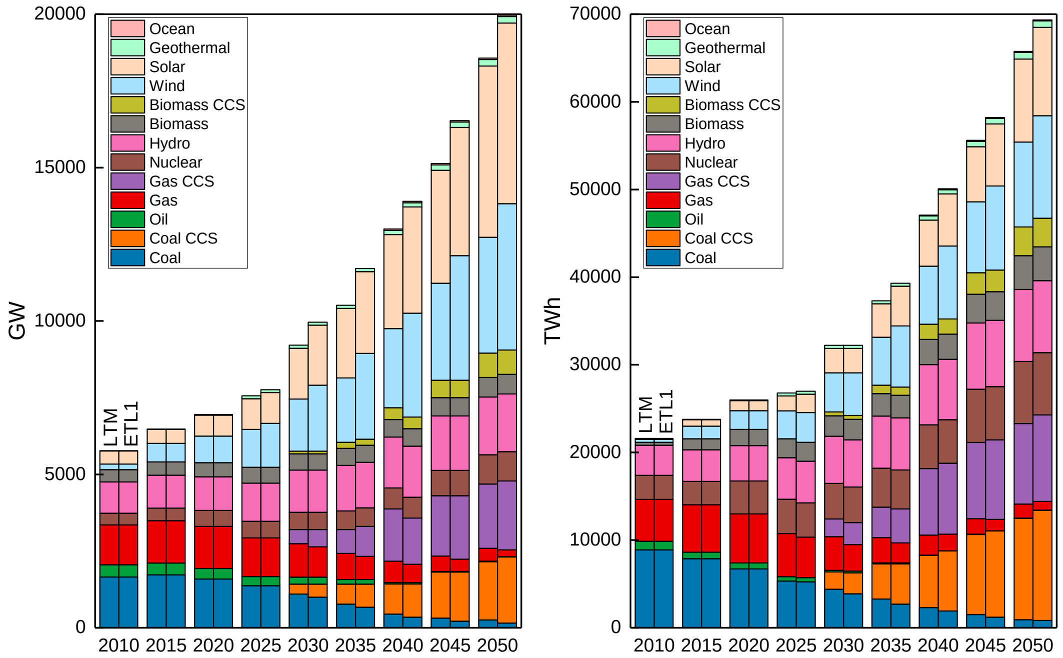

Figure 3: Global electricity capacity (left) and generation by technology (right) under LTM and ETL1

The four types of low-carbon power technologies (wind, solar, coal CCS and natural CCS) benefit from the global experience as the multiregional learning mechanism is introduced. Their investment cost will fall much faster in scenario ETL2 than in ETL1 as the global installed capacity increases. From global perspective, their installed capacity will be higher than the ETL1 scenario. But the development paths of different regions vary. At present, wind and solar power in Asian countries such as China and India are growing rapidly. It is the world's largest renewable energy power generation market. China alone accounted for 23% of global renewable energy generation by 2015[53]. In ETL1 scenario, since wind and PV have certain technology accumulation in these areas, they will become popularized in CHN and IND after 2030, and the installed capacity will grow rapidly. With the multiregional learning approach introduced by the ETL2 scenario, developed countries and regions such as WEU and the USA will also deploy more wind power and PV than the LTM scenario after 2030 (Figure 4), leading to lower generation costs of these technologies. This is because Global TIMES is to determine the optimization of global energy system but optimal for every region. Even if additional solar PV and wind may not be locally preferable strategies for WEU and USA, it is clearly optimal for the world because it enables faster diffusion in developing regions which are usually blessed with better resource potential and rely on technology spillovers from the developed countries. Unlike wind and solar PV, CCS technology is still in the R&D and demonstration stage, with a lower level of global technology accumulation and higher investment cost. In the context of the global technology diffusion under ETL2 scenario, the increase in installed capacities of both CCS technologies are not as much as wind and solar power. It implies that without the consideration of multi-cluster learning mechanism, the investment in currently preferable technologies (wind and solar) may lead to a lock-in in such technologies in the energy system.

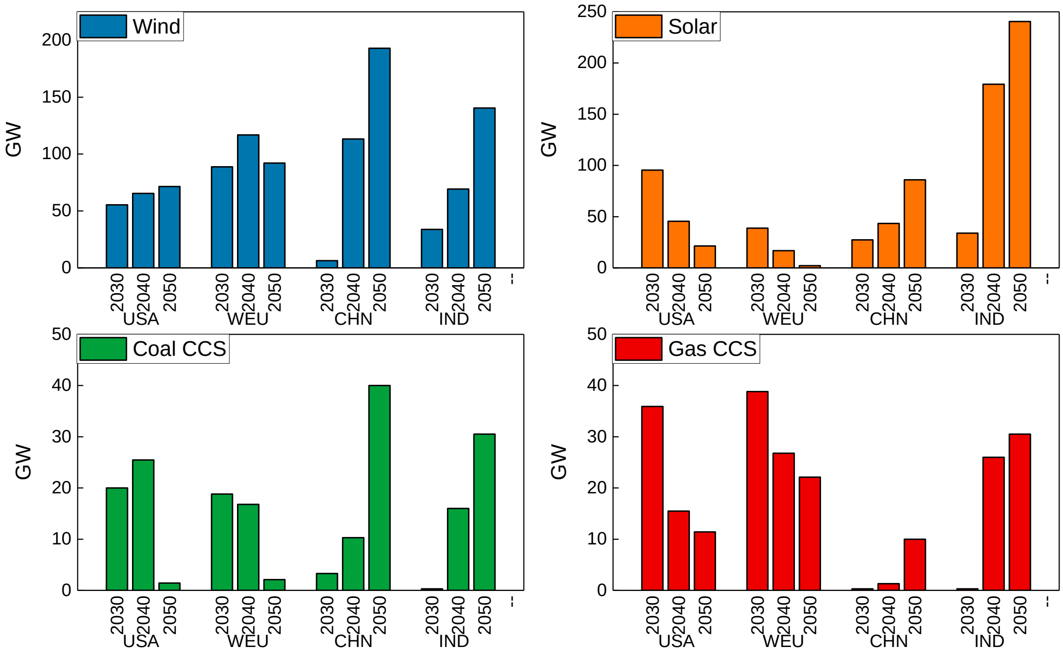

Figure 4: Increment of installed capacity under ETL2 compared with LTM

If experience gained from low-carbon technology can diffuse to other closely linked technologies, all associated technologies may become more cost-competitive. In the ETL3 scenario, the natural gas CCS technology will be first adopted in 2030 in WEU and USA (Figure 5). This is due to the relatively low cost of natural gas / shale gas resources in the USA and WEU, as well as the relatively lower R&D investment costs. Early deployment of natural gas CCS in these regions drives cost reduction in other associated technologies and in other regions of the world through the multi-clusters and multiregional learning mechanism. As a result, there are more installed capacity of gas-fired and coal-fired CCS technologies in each region. This also proves again that, for the developed countries, the deployment of new technologies may outperform local optima due to spillover benefits in other regions, which is the optimal option for the world.

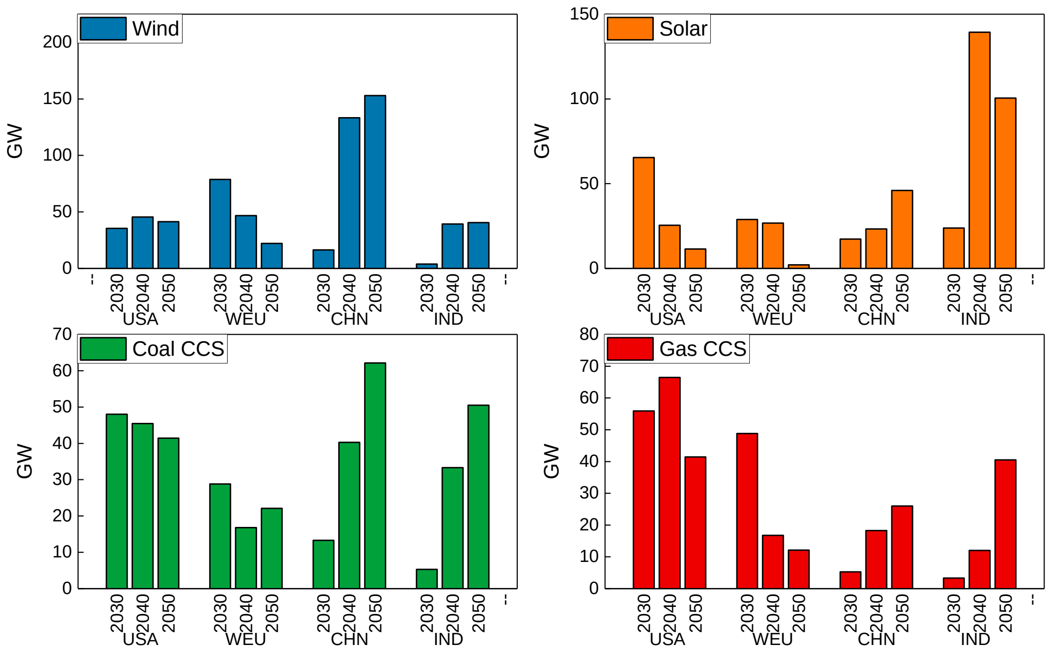

Figure 5: Increment of installed capacity under ETL3 compared with LTM

The "learning by doing" technology learning mechanism provides more cost-effective technology choices for the world to achieve long-term mitigation target. In the context of technology diffusion, this technology learning effect has public good characteristics. The promotion of low-carbon technologies in one country can increase the global technology knowledge stock, so that the cost in other regions and countries fall faster. Take CHN region for an example, driven by the learning curve, the levelized cost of electricity (LCOE) of wind, solar PV, IGCC CCS and NGCC CCS technologies in technology learning scenarios (ETL1, ETL2 and ETL3) are significantly lower than that of the LTM scenario's level. For example, under ETL1 scenario, the LCOE of onshore wind and solar PV is about 78% and 75% of the LTM level in 2050 (Figure 6). Under ETL2 scenario, the installed capacity of onshore wind and solar PV in CHN will not increase significantly before 2030. But thanks to the contribution of the developed countries to the global technology accumulation, the cost of onshore wind and solar photovoltaic will decline at a faster rate after 2030, reaching 64% and 61% of LTM's level by 2050. In ETL3 scenario, due to the multi-cluster learning mechanism among CCS technologies, the LCOE of CCS technologies in ETL3 scenario decline faster than that in LTM scenario. By 2050, the LCOE of IGCC CCS and NGCC CCS is 34.5% and 36.8% lower than LTM scenario. It implies that through multi-cluster technology learning, the two types of CCS technology can become more competitive than wind power and solar photovoltaic in the medium-long future. Taking into account the issue of renewable energy absorptive capability, CCS technologies are important to achieve low-carbon transition for global energy system.

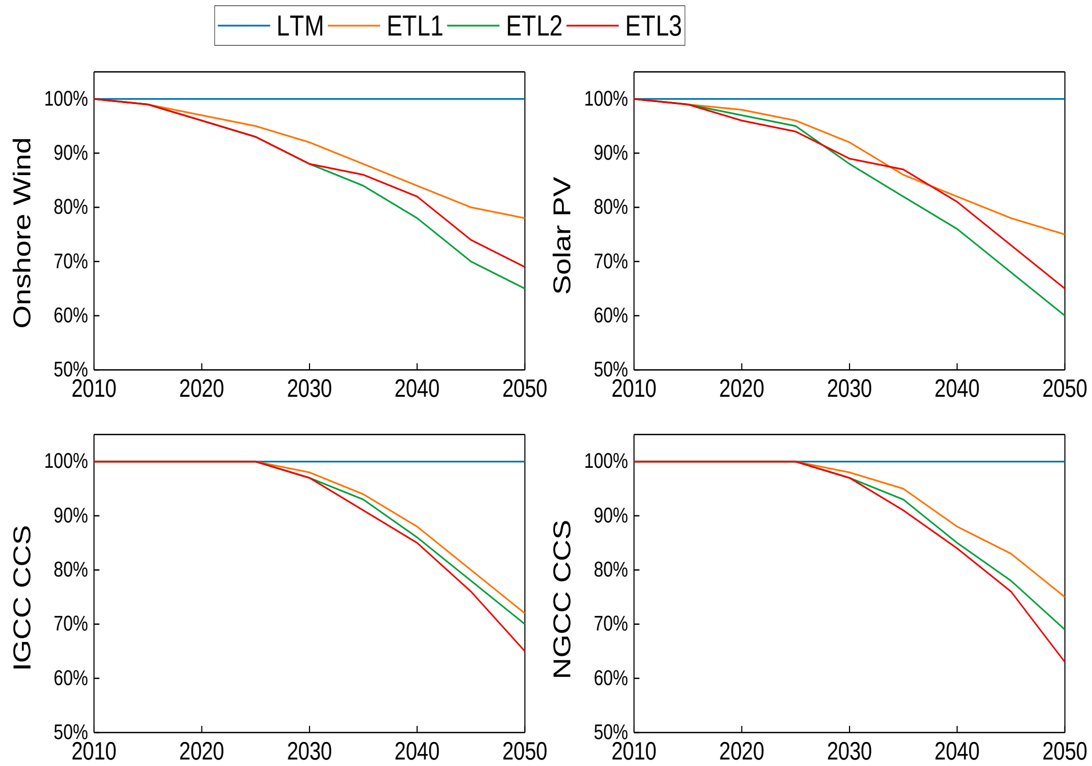

Figure 6: Change of LCOE of different technologies in CHN across scenarios

4.2 Impact on regional mitigation

In the Reference Scenario, global energy-related CO_2 emissions will increase year by year. By 2050, the global energy-related emissions will reach 1.73 times of 2010 level, with an annual growth rate of 1.39%. The accumulated CO_2 emission is 1455 Gt during 2015-2050. It will be difficult to achieve the target of controlling global warming at or below 2 °C of the pre-industrial level by the end of this century, which could have very serious consequences for the global ecology and the living environment. Therefore, in order to achieve global climate target, measures must be taken to control greenhouse gas emissions, especially those related to energy activities. To achieve long-term emission reduction targets, the cumulative global emissions between 2015 and 2050 need to fall by 41% under LTM scenario (the constraint of cumulative budget of 897 GtCO2 introduced) compared with REF. It requires immediate emission mitigation after 2015. In 2030 and 2050, global CO_2 emissions reduce by 17% and 51%, respectively, on the 2010 basis. China, India, Africa, Latin America, and other Asian countries need to peak in the year of 2015, 2030, 2025, 2015 and 2030 respectively and their peak levels are 9.6, 2.6, 1.2, 1.6 and 2.7 billion tons respectively, as shown in Figure 7. Given that these countries and regions are still in the process of industrialization and urbanization, their energy system should expand to support their future economic development. But the limited carbon budget does not allow these countries and regions to rely heavily on fossil energy, which are undoubtedly a huge challenge to these countries to solve their economic development problems.

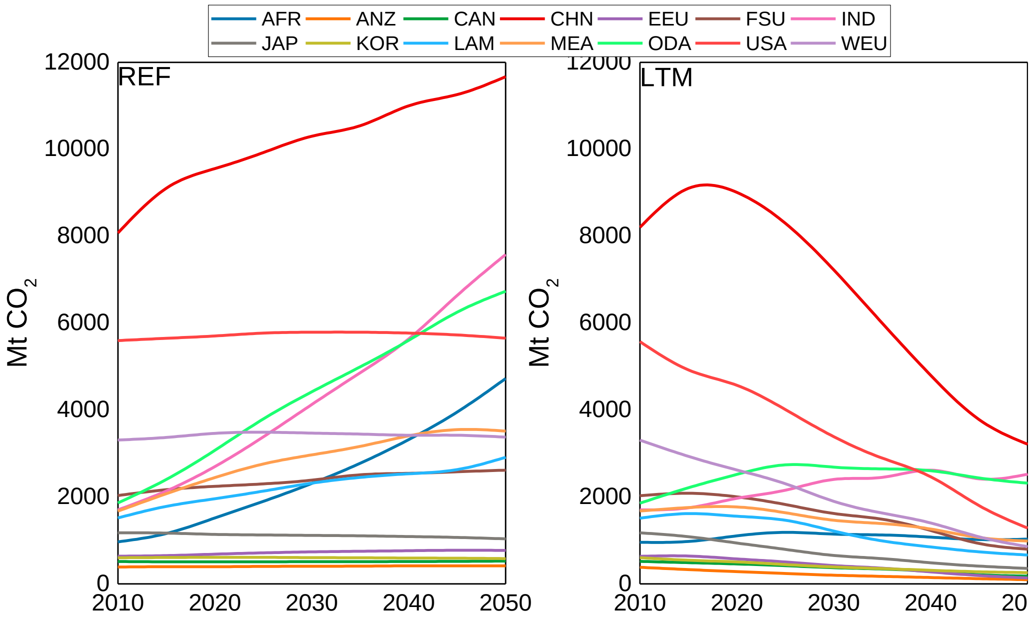

Figure 7: Regional emission pathway under REF (left) and LTM (right)

Regional emissions vary across the technology learning scenarios. In LTM scenario, the global emissions reductions between 2015 and 2050 will occur mainly in region CHN, USA, IND and WEU, accounting for 20.34%, 13.5%, 11.96% and 8.44% of the cumulative global emission reductions. These regions have several common characteristics: either their future energy consumption grow fast, so that they have great mitigation potential, such as CHN, IND, AFR, etc.; or they are blessed with large amount of renewable resources or technical advantages, such as the USA, WEU, JAP and so on. In ETL1 scenario, the low-carbon technologies in these regions are developing at a slightly faster rate than the rest of the world, and their mitigation contribution will increase. In ETL1, cumulative emissions reductions in CHN, IND, USA and WEU are 139.1, 83.0, 95.9 and 60.7 Gt, 1.4%, 2.4%, 4.2% and 5.3% higher than their cumulative mitigation amount under LTM scenario respectively. Although the cost of advanced low-carbon power generation technologies, such as wind power, solar photovoltaic and CCS, are still high in developing countries, the technology experience of these technologies in developed countries can be spread to developing countries and regions through multiregional learning mechanism under ETL2 and ETL3 scenarios. From a long-term perspective, the technology diffusion mechanism will allow developing countries and regions to have more cost-effective technology options to achieve long-term emission reduction targets, which will improve the capability and willingness of developing countries and regions to reduce CO_2 emissions. Taking the ETL3 scenario as an example, the cumulative reductions between 2015 and 2050 in CHN, IND and AFR are 143.2, 85.2 and 58.8 Gt, accounting for 20.53%, 12.22% and 8.42% of the global total respectively, which are 0.19, 0.26 and 0.21 percentage points higher than that of the LTM scenario. This is also a win-win result for developed countries. Because under a global carbon cap, the increase of cumulative reductions of developing countries means more emission space for developed countries. It illustrates the importance of multi-regional technology cooperation.

4.3 Impact on carbon abatement cost

Technological learning and technology diffusion mechanisms will ease the difficulty to achieve global and regional long-term emission mitigation targets as they can reduce technologies cost and increase the technology diffusion rate. The establishment of effective international technical cooperation mechanisms, as envisaged in the Paris Agreements, would effectively reduce long-term mitigation pressure.

First of all, technology diffusion can effectively reduce long-term abatement costs around the world. The development of energy system is path-dependent. Without international technology cooperation or diffusion, the global energy system may lock-in into traditional carbon-intensive technologies, resulting in higher abatement costs in the future. Technology diffusion can reduce the promotion cost of low-carbon technologies and enhanced the near-term greenhouse gas mitigation. In the context of a global emission budget, emission reductions have public goods characteristics. A country's near-term reduction activities not only increase its future emission space, but also affect other parts of the world, thereby reducing long-term abatement costs. Figure 8 shows the abatement cost for USA, WEU, CHN and IND in 2050 are 3.5%, 2.0%, 3.6% and 4.0% of GDP respectively in the LTM scenario. Due to the deployment of more new technologies, the abatement costs of USA and WEU under ETL2 and ETL3 scenarios in 2030 are higher than those under LTM scenario. However, due to the technology cost reduction by technology learning, abatement costs in all regions have different degrees of decline beyond 2030 compared with LTM scenario. Under ETL3 scenario, for example, the ratio of abatement cost to GDP in USA, WEU, CHN and IND will be 0.6, 0.2, 0.9 and 0.8 percentage points lower than those in LTM scenario in 2050.

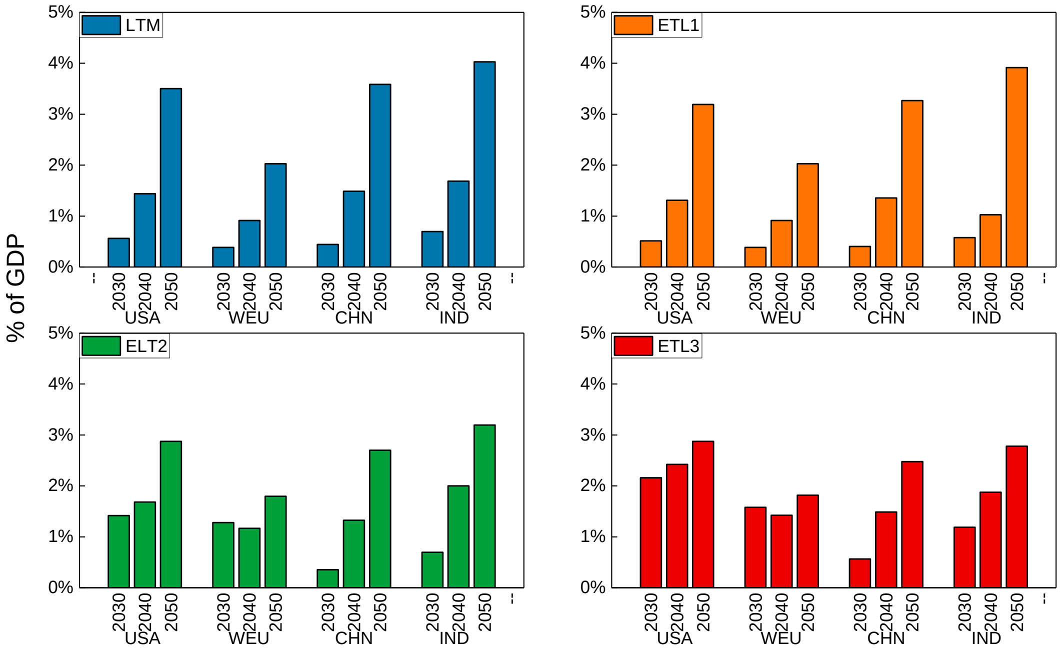

Figure 8: Ratio of the abatement cost to GDP in 2050

Secondly, technology diffusion can reduce the welfare loss caused by greenhouse gas mitigation. The implementation of a global CO_2 emission cap requires more investment in expensive low carbon technologies which will increase the energy system cost to meet the given energy services demands, or reduces energy service demand resulting to welfare loss. In LTM scenario, welfare loss is about 1.73% to GDP in 2050, as shown in Figure 9. Technology diffusion will result in an alleviation in the energy services demand reduction, due to two reasons. The first is the rapid development of low-carbon power technology makes the power sector contributes more to the total mitigation, which increases the long-term emission space for the end-use sectors, reducing the mitigation pressure on end-use sectors. The second is technology diffusion can reduce the cost of low-carbon power generation technology, thus reduce the overall electricity supply costs. This will meanwhile decrease the energy supply prices. The combined effect of these two causes will lead to a slight decrease in the energy service demand reduction of the end-use sectors, as well as in welfare losses. Under ETL1, ETL2 and ETL3 scenario, the ratio of global welfare loss to GDP in 2050 are 1.64%, 1.49% and 1.35%, respectively, which are 0.09, 0.24 and 0.38 percentage points lower than the value of LTM scenario in the same year.

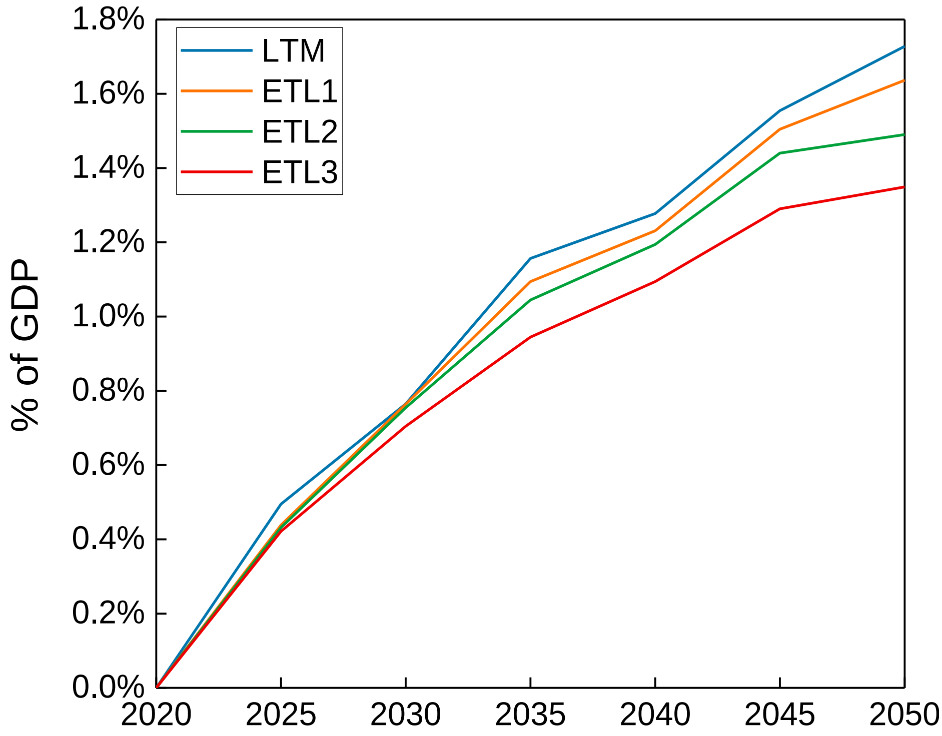

Figure 9: Ratio of welfare losses to GDP under different scenarios

Finally, technology diffusion can bring other benefits. On the one hand, the accelerating promotion of low-carbon technologies caused by technology diffusion is likely to promote the new energy industry and -economic growth. Hansen et al. (2003) suggested that the wind power promotion strategy in Denmark can raise the competitiveness of the Danish wind industry and also compensated for welfare losses owing to early deployment of wind energy [55]. As shown in Figure 10, the development of low-carbon technologies makes the global investment in power sector higher than LTM scenarios. In 2050, the total investment in ETL1, ETL2 and ETL3 scenario will be 0.82%, 0.84% and 0.86% of GDP respectively, which is 0.07, 0.09 and 0.11 percentage points higher than that of the LTM scenario. Most of the new investment is in wind power, solar photovoltaic, CCS and other low-carbon technologies, which will greatly promote the development of related upstream and downstream industries and domestic economic growth. On the other hand, the rapid promotion of low-carbon technologies can enhance the diversity of energy systems, reduce dependency on external fossil fuels, and thus enhance national energy security.

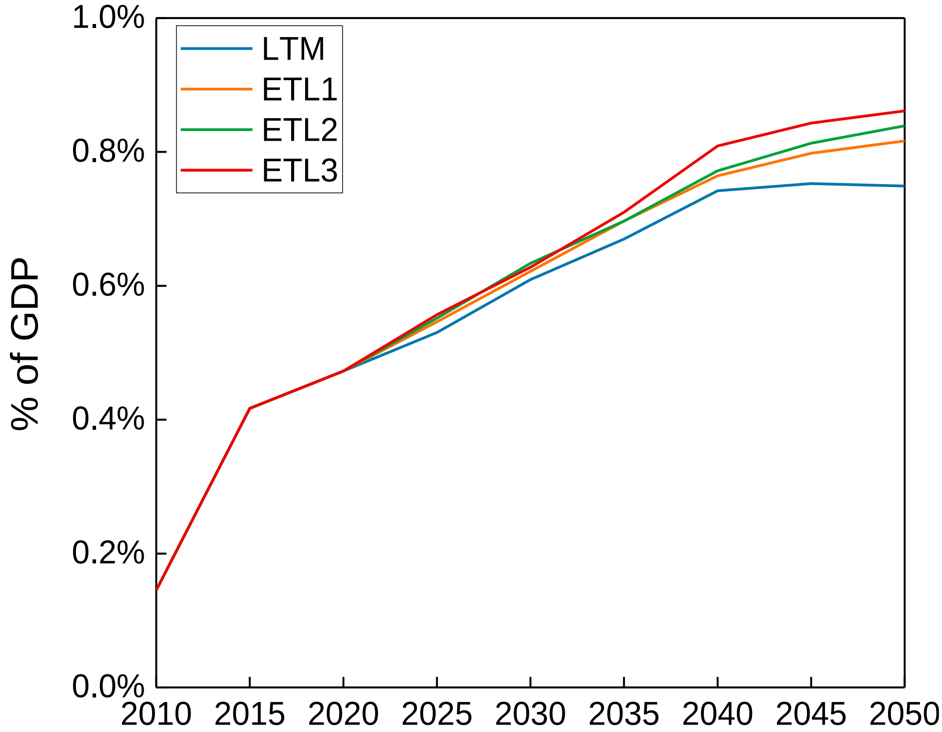

Figure 10 Ratio of investment cost of power sector to GDP across scenarios

5. Conclusion

This paper developed the electricity technology portfolio and estimated CO_2 emissions in different regions of the world during 2015 - 2050, by using a partial-equilibrium model, Global TIMES developed by Tsinghua University. We also assessed the impacts of technology learning and technology diffusion on low-carbon power generation technology, regional emission pathways and abatement costs through scenario analysis.

To control the global temperature rise below 2 °C or even 1.5 °C, energy-related CO_2 emissions will have to peak as soon as possible and then to achieve absolute great reduction before the first half of this century. Basically, all countries' emission space will be severely limited after 2015. Global energy systems need to undergo a profound low carbon transformation, especially in the power sector. Traditional coal-fired power plants need to be phased out meanwhile substantial increases in nuclear power, wind power and solar power and other low low-carbon power generation technologies are necessary. Under LTM, wind and solar PV will reach 3768 and 5326 GW by 2050 respectively.

Technology learning and technology diffusion have a positive effect on the global realization of long-term climate targets. The introduction of endogenous technology learning could increase the global installed capacity of wind power, solar PV, coal CCS and natural gas CCS by 970, 312, 221 and 150 GW respectively in 2050. In the context of global technology diffusion, the cost of low-carbon technologies will gradually decline with the global technology experience accumulation. From the perspective of global optimization, developed countries should take the lead in low-carbon technologies' R&D and investment. It would be beneficial for developed countries to promote transfer of advanced technologies to developing countries through technology cooperation to cope with global long-term mitigation target.

The establishment of an effective mechanism for international technology transfer and cooperation will improve the mitigation capability and willingness of developing countries and regions. The cumulative emission reductions of China, India and Africa under ETL3 scenario between 2015 and 2050 are expected to increase 5.81, 4.02 and 2.98 $GtCO_2$ respectively compared with LTM scenario. At the same time, technology diffusion can effectively reduce the long-term abatement costs around the world, reduce the welfare losses caused by emission reductions, and bring other benefits such as promoting development of new energy industries and enhancing regional energy security.

In short, technology diffusion through regional cooperation can reduce the global cost of carbon mitigation. The international community have realized the importance of technology cooperation and several technology-focused cooperation and mechanism have been established, e.g. Mission Innovation, South-South Cooperation, Energy and Climate Partnership of Americas, etc. In order to control the global temperature rise below 2 °C or even 1.5 °C, the international community need to further strengthen bilateral and multilateral cooperation on low carbon technology innovation, development and deployment.

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