A Discussion on Abatement Costs in an Integrated Assessment Model of Climate Change

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Abstract

In this study, we conducted a cost-benefit analysis with an Integrated Assessment Model of climate change. Firstly, we incorporated the effects of cost reduction of backstop technologies by RD&D investments into an abatement costs calculation. Secondly, we modeled the time lag between RD&D investments and the reduction of abatement costs brought by them. We call this the inertia regarding time lag, which previous studies did not address. The results show that RD&D investments have little impact on emission reductions in the near-term, but gradually have a significant impact on those in the long-term. Considering the inertia of learning-by-researching, the optimal RD&D investments path shifts lower than the case without inertia, but there is no significant difference in the optimal RD&D investments required in the first half of this century. In the case of imposing a temperature constraint, RD&D becomes much more important and the optimal RD&D investments path shifts significantly higher compared to the case of no temperature constraint. Although it is sometimes pointed out that technological innovation through RD&D investments means a postponement of abatement efforts, our results support the importance of near-term RD&D investments for further emission reduction in the future.

***Key words**:* Integrated Assessment Model, Abatement Cost, RD&D, Inertia

1. Introduction

1.1 Responses to climate change and integrated assessment model

As understanding the natural science of climate change makes progress[1)-3)], pressure grows on the world to respond to climate change. However, energy-related CO_2 emissions have increased almost persistently since 1990, albeit with a temporary decline amid a recession in 2009[4)]. In a recent bright sign, renewable energy has gradually grown cost competitive against fossil fuels. Nevertheless, actual greenhouse gas emissions have a wide gap with emissions required to achieve the goal of limiting global warming to well below 2°C compared to pre-industrial levels under the Paris Agreement[5)].

The world is required to cut GHG emissions to net zero at least by the end of this century to achieve the long-term goal under the Paris Agreement[6)], but present technologies cost too much to or cannot achieve decarbonization such as sectors that are difficult to electrify, including heat utilization in heavy industries and long-range transportation. The International Energy Agency's latest Energy Technology Perspectives[7)] pointed out that progress towards net-zero emissions will depend on faster innovation in electrification, hydrogen, bioenergy and CCUS (carbon capture, utilization and storage). It also indicated that some 40% of cumulative CO_2 emissions reductions (from a stated policies scenario) through 2070 in a sustainable development scenario will depend on technologies that are not commercially available today.

One reason why it is difficult to respond to climate change is that inertia works strongly in the global climate system and our social and economic systems. For instance, it is pointed out that the lifetime of several decades for energy system infrastructure brings about fossil fuel lock-in[8)]. Technological innovation takes much time. Research and development investments would take much time to bring about technology cost cuts and diffusion.

The abovementioned background leads us to think that the abatement of climate change (GHG emissions reductions) is important. Given that GHG emissions are linked closely to economic activities, however, a cost-benefit analysis considering the total balance between climate change and the economy is indispensable as a prerequisite. Integrated assessment models are available for such analysis, including DICE[9)], FUND[10)] and PAGE[11)].

These models that highly integrate relations between climate change and the economy are controversial because of their high sensitivity to parameter changes. There are numerous studies on discount rates[12)] and damages[13),14)]. Most of these studies estimate lower discount rates and higher damages and compare these estimates with traditional integrated assessment model estimation results, concluding that the abatement of climate change has become more urgent. Meanwhile, abatement costs that are as important as damages have been discussed less than discount rates or damages. As the abovementioned technological innovation (changes) and the inertia of social and energy systems are apparently required to be considered in regard to abatement costs, the following reviews earlier studies.

1.2 Learning by researching

The neoclassical theory of economic growth had given technological change as a total factor productivity growth rate exogenously, but P. Romer et al.[15] has created a model to internalize technological change. Some studies considered endogenous technology innovation for climate change model analyses. Modeling technological change is generally divided into learning by researching and learning by doing. The learning-by-doing modeling, though frequently used for bottom-up models, leaves the relationship between cumulative technology diffusion and cost falls in a black box, leading to an optimistic assumption that costs would decline even without investments to acquire new knowledge. It is also pointed out that a problem regarding statistical identification could cause overestimation of learning parameters[16]. As it is important to consider costs for bringing about technological change in a cost-benefit analysis, the following literature review focuses on the learning-by-researching modeling.

Some studies[17)-21] applied to learn by researching to cost-benefit analysis of climate change, using different modeling approaches to express the impacts of research, development and demonstration (RD&D) on technological change. Specifically, Goulder and Mathai (2000)[17] gave consideration to a decline in abatement costs, Nordhaus (2002)[18] to a decline in emission intensity, Popp (2004)[19] to a decline in energy intensity, and Popp (2006)[20] and Yin and Chang (2020)[21] to declines in energy intensity and backstop technology costs. They set model calibration criteria based on empirical research, present RD&D investments level and so on. These studies indicate that endogenous technological change would exert impacts on emission paths, however, that given opportunity costs for RD&D investments in energy technologies, the impacts would be limited.

WITCH[22] contributing to scenario analysis in the IPCC AR5 (5th assessment report by the Intergovernmental Panel on Climate Change) used a normal learning curve or a two-factor learning curve combining learning by researching with learning by doing to model specific technologies such as solar photovoltaics and batteries. WITCH is a multi-region model that considers spillover effects of knowledge from other countries when calculating knowledge stock.

In contrast to the abovementioned approaches using empirical knowledge (past data), there is an approach that combines expert elicitation about outlooks on individual technologies with technology-rich model analysis[23]. Studies under this approach used expert elicitation about specific technologies including solar PV power generation to estimate the relationship between RD&D investments and energy technology cost drops. The estimated relationship including uncertainties is put into a model handling specific technologies to analyze the impacts of RD&D investments in those technologies on GHG emission paths and emission reduction costs and consider optimum portfolios for RD&D investments in energy technologies. Such portfolios cover biomass power generation, biofuels, CCS, nuclear power generation, solar PV power generation and their combinations. GCAM[24], WITCH, MARKAL[25] and other models are used to express specific technologies. Some studies[26), 27] conducted cost-benefit analysis by using the GCAM model to express changes in a marginal abatement cost curve through cost drops for specific technologies with simple parameters and reflecting these changes in the abatement cost function in the DICE model.

Studies considering the impacts of learning by researching specific technologies apparently represent an important direction. Given that technologies subject to these studies are limited, however, they have difficulties in considering overall economic impacts that are significant for cost-benefit analysis.

1.3 Social and energy system inertia

Another challenge regarding abatement costs is to consider social and energy system inertia. In the DICE model, for instance, the abatement cost function (marginal abatement cost curve) is given as a prerequisite, indicating that abatement costs in a year depend on the CO_2 emission reduction rate in the year and are not affected by the previous year's rate. In an extreme case, abatement costs for a year would remain unchanged whether the emission reduction rate is raised from 0% or 90% to 100% in a period (five years). This assumption would be adequate if only energy-saving behaviors or fuel switching accompanied by no infrastructural renewal are assumed. However, it is not adequate for abatement means accompanied by the construction of infrastructure including long-life power generation equipment. This problem is naturally taken into account in bottom-up and other models giving consideration to the lifetime of the infrastructure. For these models, the marginal abatement cost curve is not a prerequisite but an estimation result changing depending on the emission path[28].

Grubb and Wieners (2020)[29] proposed a simple model to take social and energy system inertia into account regarding the abatement cost function in the DICE model, indicating that the consideration of inertia would lead the optimum emission reduction path to change from a rapid rise in the reduction rate as shown by the DICE model to a moderate change after the initial high rate.

1.4 Purpose of this study

As reviewed above, cost-benefit analysis studies using integrated assessment models have frequently considered discount rates and damages while failing to consider abatement costs, lacking balance.

Key points that should be considered regarding abatement costs include endogenous technological change resulting from learning by researching and social and economic system inertia. However, inertia in learning by RD&D investments has not fully been modeled.

Earlier studies modeled "stock inertia". Specifically, they introduced the concept of knowledge stock, indicating that knowledge stock growth brings about technological change (cost drops) (Equations (4) and (5)). RD&D investments represent flow bringing about knowledge stock growth and their contribution takes stock inertia into account.

However, in models for earlier studies, RD&D investments in a period contribute to knowledge stock growth in the next period, indicating no time lag beyond a time step. In reality, however, immature technologies naturally take much time to achieve cost cuts and diffusion after RD&D investments. Such "time lag inertia" should be modeled to assess the impacts of RD&D investments more adequately.

Given the above, this study aims to model the effects of learning by researching with time lag inertia taken into account in regard to abatement costs in the DICE integrated assessment model and to assess the impacts of the effects on cost-benefit analysis.

2. Methodology

2.1 DICE

The DICE model developed by W. Nordhaus incorporates climate change adaptation/damage costs and GHG emission reduction costs into the Ramsey-Cass-Koopmans model[30)-32)], a standard economic growth theory model, to conduct a cost-benefit analysis to integrally assess the balance between economic growth, and climate change adaptation/damage and abatement. Climate change adaptation/damage costs are expressed as the function of temperature rise, with a simple climate model incorporated to compute a temperature rise through GHG emissions.

In the DICE-2016R2 model as the latest DICE model, the function of abatement costs per emission is given as Equation (1) and the marginal emission reduction cost curve (Equation (1) was differentiated in regard to the reduction rate) as Equation (2). Abatement costs increase exponentially against the emission reduction rate of $\mu(t)$ in the relevant year ($\theta = 2.6$). $p_b(t)$ expresses backstop technology costs (marginal abatement costs at the reduction rate of 100%). The costs stood at US\$550/tCO_2 (in 2010 dollars) and would automatically fall at an annual rate of 0.5% (t in the equation indicates a five-year step, hereinafter the same). See literature[9)] for the entire picture of the DICE model.

$$\Lambda(t) = \frac{p_b(t)}{\theta}\mu(t)^{\theta} \tag{1}$$

$$MAC(t) = p_b(t)\mu(t)^{\theta-1} \tag{2}$$

In this equation:

$$p_b(t) = 550 \times (1 - 0.025)^{t-1} \tag{3}$$

2.2 Formulation of learning by researching

Here, we formulate learning by researching without considering time lag inertia. Based on earlier studies[17),18),20)], the reduction of backstop technology costs through learning by researching is expressed by Equations (4) to (6).

$$p_b(t) = 550/H(t) \tag{4}$$

$$H(t) = H(t-1) + aR(t-1)^b\, H(t-1)^{\varphi} \tag{5}$$

$$Q(t) = C(t) + I(t) + \kappa \cdot R(t) \tag{6}$$

Here, $H(t)$ stands for backstop technology knowledge stock and $R(t)$ for RD&D investments. Backstop technology costs do not decline automatically as time goes by, as shown in Equation (3), but they fall in line with growth in knowledge stock as an endogenous variable according to Equation (4). Knowledge stock is accumulated through contributions from RD&D investments and knowledge stock in the previous period according to Equation (5). Contributions from knowledge stock in the previous period indicate that knowledge accumulation from the past makes present knowledge accumulation easier. Equation (6) balances $Q(t)$ for output, $C(t)$ for consumption, $I(t)$ for capital investments and $R(t)$ for RD&D investments (each in trillions of 2010 US dollars), combining the original DICE equation with the third term of the right side.

In Equation (5), $0 < b$ and $\varphi < 1$ are assumed according to Popp (2006)[20)]. Then, parameters b and φ indicate that contributions from RD&D investments and knowledge stock in the previous period to present knowledge stock would decline in proportion to scale. As values around 0.5 are usually adopted for φ, we adopted the value of 0.54 by reference to Popp (2006)[20)]. We determined a and b by assuming that the automatic reduction of backstop technology costs in the original DICE model would come as RD&D investments remain at the current level. Specifically, we standardized knowledge stock for the reference year at 1 ($H(1) = 1$) and determined a at 0.0461 and b at 0.19 to make Equations (3) and (4) closer to each other as much as possible (to minimize the square sum of a $p_b(t)$ gap between 2015 and 2510) in case that low-carbon technology RD&D investments' share of GDP would remain unchanged from 0.022% in 2015. As for GDP, we used the results for the optimum solution in the original DICE model. The b value ranged from around 0.1 to 0.2 in calibration for earlier studies[18), 20)] indicating that our determination is consistent with the earlier studies.

We determined low-carbon technology RD&D investments' share of GDP at 0.022% for 2015 by multiplying the GDP share at 0.030%[calculated from 33)] for RD&D investments in low-carbon technologies (including energy efficiency, CCS, renewable energy, nuclear, hydrogen, fuel cell, other electricity and storage, and other cross-sectoral technologies) in OECD countries by the ratio of the GDP share at 2.31%[34)] for RD&D investments in areas including non-energy technologies in OECD countries to the global average GDP share at 1.70%[35)] for such investments (covering OECD and non-OECD countries (excluding some)).

The third term of Equation 6 represents opportunity costs for RD&D investments in backstop technologies. Generally, it is known that as RD&D investments generate the positive externality of knowledge spillovers beyond organization boundaries and induce underinvestment, the social return on such investments is at least two to four times as large as the private return[36)]. On the other hand, an increase in RD&D investments in some fields may cause a decrease in such investments in other fields (crowding-out). If $1 in RD&D investments in backstop technologies induces a $1 decline in those in other fields (crowding-out at 100%), with a return on the latter being $4, opportunity costs come to $4, meaning that κ stands at 4[18)]. Popp (2006)[20)] assumed crowding-out at 50% by reference to U.S. macro data. Meanwhile, Buonanno et al. (2003)[37)] formulated intensified RD&D investments contributing to both cutting emission intensity and raising productivity, assuming no crowding-out. As indicated above, no view has been established on κ assumptions. As this study focuses on changes that occur when time lag inertia is introduced for learning by researching, we assumed no crowding-out ($\kappa = 1$) but conducted a sensitivity analysis.

2.3 Introducing inertia for learning by researching

The formulation of learning by research based on earlier studies expressed stock inertia by introducing the concept of knowledge stock. This means that as knowledge stock rather than RD&D investments (flow) reduces backup technology costs, a large increase in RD&D investments in a period may have a limited impact on the reduction of backstop technology costs.

In Equation (5), RD&D investments in a period contribute to accumulating knowledge stock, or reducing technology costs, in the next period (one period covers five years here). In reality, however, some time lag may emerge between RD&D investments and the reduction of costs, particularly for technologies in the initial RD&D phase. There is also a time lag between the reduction of technology costs and the diffusion of relevant technologies, but this time lag has not been considered.

In this study, we expressed a series of inertia (time lag) impacts from RD&D investments in backstop technologies to the reduction of technology costs and the diffusion of technologies, as shown by Equation (7) against Equation (5) expressing traditional knowledge stock accumulation. In formulating the equation, we introduced parameter p (ranging from 0 to 1) expressing the strength of inertia against knowledge stock by reference to an earlier study[29)] that introduced inertia against the abatement cost function, enabling a sensitivity analysis on various p values.

$$\Delta H(t) = (1-p) \cdot h(t-1) + p \cdot \Delta H(t-1) \quad (7)$$

In this equation:

$$\Delta H(t) = H(t) - H(t-1) \quad (8)$$

$$h(t) = aR(t)^b \, H(t)^{\varphi} \quad (9)$$

The formulation allows knowledge stock in a period to depend on not only RD&D investments in the previous period but also on an increase in knowledge stock in the previous period. If p is 0, the equation returns to Equation (5). If p is 1, knowledge stock growth follows the past trend irrespective of RD&D investments in the previous period (a static state if $H(1)$ is equal to $H(2)$).

Here, knowledge stock growth stemming from RD&D investments in a period is accompanied by a time lag. Such investments' contributions to knowledge stock ($h\_lag(t+n)$) after the n period ($n \geqq 1$) are shown in Equation (10). Figure 1 plots $h\_lag(t+n)$ for $h(t)$ at 1 and p ranging from 0.1 to 0.9 (one period covers five years).

$$h\_lag(t+n) = \left\{(1-p)\sum_{\tau=0}^{n-1} p^{\tau}\right\} h(t) \tag{10}$$

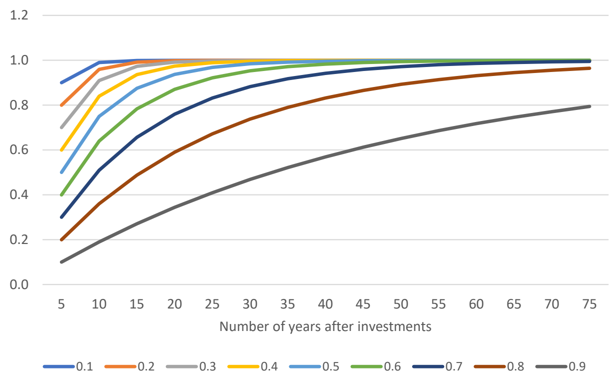

Figure 1 How RD&D investments bring about knowledge stock growth with a time lag
(Plotting parameter p ranging from 0.1 to 0.9)
Note: Potential growth is put at 1

According to Figure 1, 90% of potential knowledge stock growth through RD&D investments would come in five years if p is 0.1. If p is 0.9, however, 52% of such growth would come even in 35 years. In this study, we assumed a time lag from RD&D investments to the reduction of technology costs and the diffusion of technologies and put p at 0.5 for a case in which more than 90% of potential knowledge stock growth would come in 20 years after such investments. We also conducted a relevant sensitivity analysis.

2.4 Model development and solution

The original DICE model was developed as a nonlinear planning model on the GAMS model, allowing source code to be downloaded from the Nordhaus website. In this study, we replicated DICE-2016R2 as the latest version of the DICE model on a Python (Pyomo) model, replaced Equation (3) with Equation (4), added Equations (7) to (9) and modified Equation (6) (by adding the third term). We solved the model with Ipopt[38].

We combined three cases – absence of RD&D investments, presence of RD&D investments and absence of inertia (p = 0), and presence of RD&D investments and inertia (p = 0.5) – with the presence and absence of temperature constraints (global warming up to 2.5°C) to develop six cases for calculation (hereinafter, inertia refers to that through a time lag). It must be noted that as backstop technology costs are fixed at \$550/tCO_2 for comparative cases where RD&D investments are absent, our solutions differ from optimum solutions in the original DICE model.

3. Results and their consideration

Figure 2 indicates CO_2 emission estimation results. In cases where no temperature constraints are imposed, emissions in a case with consideration given to RD&D investments will be reduced from a case without consideration given to RD&D investments. Emissions will change little in the near future before the reduction accelerates from 2035. Without consideration given to RD&D investments, emissions will be reduced to zero in 2145. With consideration given to RD&D investments, however, emissions will be cut to zero in 2115. This is because accumulated knowledge stock will gradually reduce backstop technology costs (stock inertia). Not only RD&D investments in a year will reduce backstop technology costs in the year.

In a case with consideration given to time lag inertia from RD&D investments to the reduction of costs and the diffusion of technologies (knowledge stock growth through RD&D investments may not be brought about immediately, but 50% of such growth is here assumed to come in five years from investments and 94% in 20 years), the optimum emission path is slightly higher than in a case without consideration given to the inertia.

In a case where a 2.5°C limit on global warming is imposed, emissions will begin soon to rapidly decline and reach zero in 2040. Although the decline looks more rapid than a fall to net zero in 2050 for the goal of limiting global warming to 1.5°C, it must be noted that the DICE model subjects only industry-related CO_2 emissions to the reduction and leaves contributions from other GHG emissions. Under temperature constraints, differences between the cases are slight. However, a comparison between cases with and without RD&D investments indicates that the case with such investments sees lower future abatement costs and is optimal for cutting emissions more rapidly.

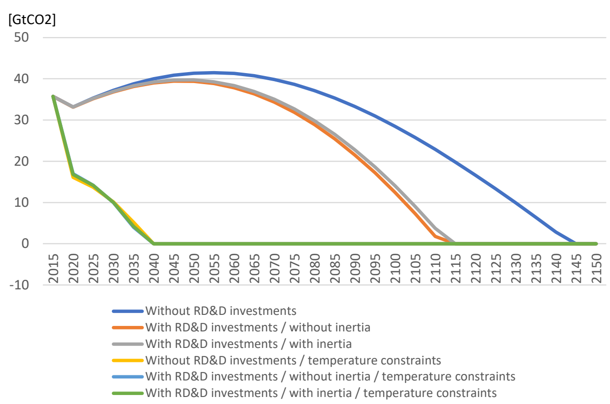

Figure 2 CO_2 emissions

Temperature rise is shown in Figure 3. In a case without temperature constraints or RD&D investments, global warming through 2150 will be 4.4℃. RD&D investments will cut global warming by 0.39℃ without inertia and by 0.36℃ with it. Under temperature constraints, there are few differences in global warming paths between the cases.

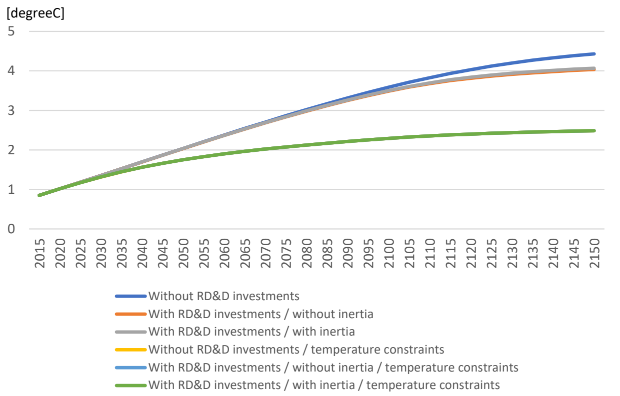

Figure 3 Temperature rise

Figure 4 shows RD&D investments. The baseline indicated by a dotted line shows an RD&D investment trend for a case where low-carbon technology RD&D investments' share of GDP is fixed at the present level (2015). In the calibration of parameters related to RD&D investments, we assumed that the annual cost reduction of 0.5% assumed in the DICE model would be achieved if RD&D investments are implemented according to the dotted line. Optimal RD&D investments start at a slightly lower level than in the baseline case and increase more rapidly.

RD&D investment levels and growth rates in a case with consideration given to inertia will be lower than in a case without such consideration. However, no major difference will arise in investment levels in the first half of this century. This means that even if there is some time lag from RD&D investments to the reduction of technology costs and the diffusion of technologies, the importance of RD&D investments in the first half of this century would remain unchanged.

In a case where temperature constraints are imposed, RD&D investment levels and growth rates will be far higher than in a case without such constraints until 2035 before investment levels remain almost unchanged. As for the effects of RD&D investments shown in Table 1, RD&D investments will cut abatement costs (before discounting) between 2015 and 2100 by 25.0% in a case without inertia and by 22.4% in a case with inertia. Therefore, the importance of RD&D investments in the first half of this century will dramatically increase in a case for seeking the early reduction of emissions. In a case where temperature constraints are imposed, RD&D investments in the near future will decline, if with consideration given to inertia, in contrast to a case without temperature constraints. In a case where early emission and abatement cost cuts are required under temperature constraints, a longer time lag before the emergence of RD&D investments' effects reduces the cost-effectiveness of investments, indicating the relatively greater impacts of inertia. Even with consideration given to inertia, however, optimal investment levels will remain far higher than in a case without temperature constraints.

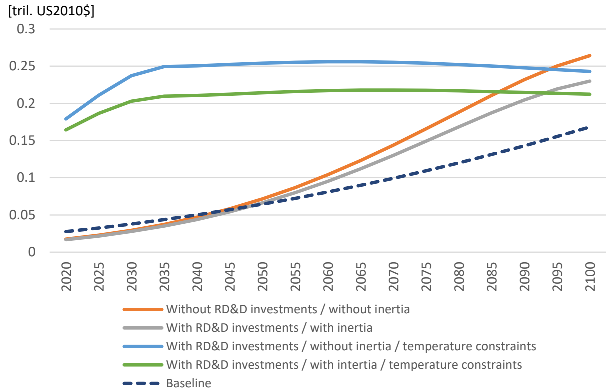

Figure 4 RD&D investments

Table 1 Abatement cost reduction through RD&D investments under temperature constraints (2015-2100, in comparison with a case without RD&D investments)

Case (under temperature constraints)	Reduction of abatement costs (before discounting)
With RD&D investments/without inertia	-25.0%
With RD&D investments/with inertia	-22.4%

4. Sensitivity analysis

We conducted a sensitivity analysis on the impacts of two highly uncertain parameters on RD&D investments. One is parameter p regarding time lag inertia of knowledge stock in Equation (7). The other is parameter κ regarding opportunity costs for RD&D investments in Equation (6). No temperature constraint is imposed on the following calculation.

Figure 5 shows parameter p sensitivity analysis results. As p rises, the optimal RD&D investment path gradually shifts downward. If p is up to 0.5 (50% of investments' contributions to knowledge stock will arise in five years from investments and

94% in 20 years), however, the optimal RD&D investment path would change little in the first half of this century.

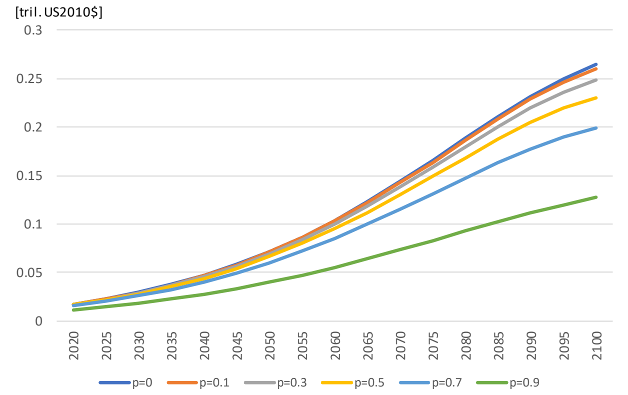

Figure 5 RD&D investments

(sensitivity analysis on parameter *p*)

Figure 6 shows parameter κ sensitivity analysis results ($p = 0.5$ for all cases). The degree of opportunity costs has great impacts on the optimal RD&D investment path. RD&D investments in 2050 in a case for assuming complete crowding-out (κ= 4) are 80% lower than in a case assuming no crowding-out. Given the presence of opportunity costs (the third term of Equation (6)), funds for RD&D investments in low-carbon technologies must be limited with consideration given to the entire economy. However, how much opportunity costs of RD&D investments would be is uncertain in the absence of sufficient knowledge, indicating the need for future relevant studies. Parameter κ has great impacts on an optimal RD&D investment level while exerting no impact on RD&D investment growth. For instance, RD&D investments in 2050 are some four times as large as in 2020 in all cases. This study aimed to assess the impacts of inertia in learning from researching on an optimal RD&D investment path and concluded that the optimal RD&D investment path in the first half of this century remains unchanged even in a case in which inertia is present. This conclusion does not change dramatically depending on parameter κ levels.

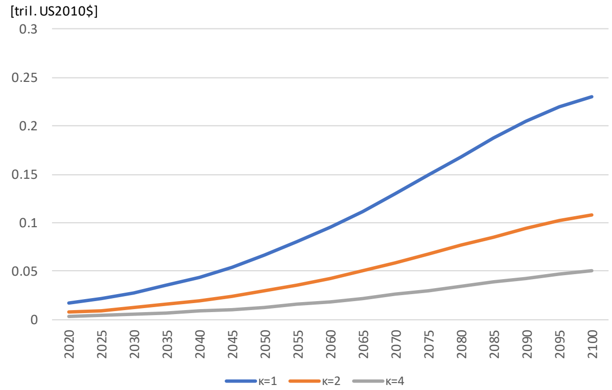

Figure 6 RD&D investments

(sensitivity analysis on parameter κ)

5. Conclusion

In this study, we conducted cost-analysis analysis after introducing learning by researching regarding abatement costs in the DICE integrated assessment model and reflecting a series of time lag inertia impacts from RD&D investments on the reduction of technology costs and the diffusion of technologies.

RD&D investments exert little impact on emission reductions over the short term but have great gradual impacts on emission reductions over the long term. In a case where time lag inertia is considered, RD&D levels and growth are lower than in a case where inertia is not considered. However, investment levels in these cases do not differ so much, indicating that RD&D investments in the near future would remain important. If temperature constraints are considered, however, RD&D investments in the first half of this century will become even more important.

It is pointed out that the promotion of technological innovation through RD&D investments to accelerate future emission reductions amounts to delaying global warming countermeasures. Given the results of this study, however, the importance of RD&D investments at present remains high even if a time lag before the emergence of the effects of investments is considered. At a time when the world seeks to achieve the long-term target under the Paris Agreement, the importance becomes even greater.

Considering uncertainties regarding the success of RD&D and the possibility that RD&D investments in low-carbon technologies could reduce those in other fields, we find that it is difficult to provide any firm conclusion on how much optimal investments would be. This point remains subject to future studies. In reality, however, sharp emission reductions exceeding 80% may apparently be impossible rather than costly at present. If the world seeks to achieve zero emissions finally, technological innovation and RD&D investments for such innovation would be indispensable irrespective of how emission paths would be.

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