Energy Transformation Cost for the Japanese Mid-century Strategy: Energy System Feedback Effects in an Economic Model

Abstract

Energy systems and economic models are typically employed independently in analyses of climate change mitigation policy. The costs of climate change mitigation policy are one of the main concerns regarding CO_2 emissions reduction actions. An economic model is a useful tool to assess the economic implications of policy interventions. However, such models are known to project higher costs than energy system models. Here, we show the extent to which policy costs can be lower than those from conventional economic models by integrating an energy system model's outputs into an economic model, using Japan's mid-century climate mitigation target as an example. The GDP losses estimated with the integrated model were significantly lower than those in the conventional economic model by more than 100% in 2050. Industry and service sector energy consumption are the main factors causing these differences. Our findings suggest that this type of integrated approach would be highly beneficial for setting national mid-century climate policies.

Main text

Climate change mitigation is one of the greatest societal challenges facing most countries, particularly developed countries, as reduction of energy-related CO_2 emissions is key to reducing greenhouse gas (GHG) emissions. In 2015, more than 190 counties reached the Paris Agreement[1] and each country submitted their own National Determined Contribution (NDC) for near-term targets. Along with those targets, countries were also asked to engage in long-term planning, known as a mid-term century strategy[2,3] in some countries. Under the long-term global goal declared in the Paris Agreement of keeping the global mean temperature increase at less than 2°C over the pre-industrial level (hereafter, 2°C goal), the net CO_2 emissions in this mid-century plan must be close to neutral according to numerous scenario studies carried out using Integrated Assessment Models (IAMs)[4].

Macroeconomic costs or additional investment costs for climate change mitigation represent one of the greatest concerns related to the shift toward low-carbon societies[5]. The Intergovernmental Panel on Climate Change (IPCC) fifth assessment report summarises climate mitigation costs, and GDP or consumption losses in 2050 are around 2–5%[4]. There are multiple possible ways to interpret these numbers. It may be too expensive to pay directly for climate change prevention that delays GDP growth for a couple of years. Others may think this cost is low enough for the benefit of avoiding widespread climate change impacts and irreversible risks associated with catastrophic events. To address macroeconomic mitigation costs, IAMs normally represent GHG emissions reduction costs either through an energy system model or an economic model, often termed bottom-up and top-down models, respectively. The Global Change Assessment Model (GCAM)[6], Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE)-MACRO[7], and Targets IMage Energy Regional simulation model (TIMER)[8] are well-known global energy system models, and national models have also applied similar approaches[9, 10]. Examples of the latter models are EPPA[11] and Asian-Pacific Integrated Model/ Computable General Equilibrium (AIM/CGE)[12], which are based on multi-sectoral computable general equilibrium (CGE) models.

Traditionally, CGE models tend to project policy costs that are higher than those of energy system models[13] (see also Supplementary Information). One possible reason for this tendency is that parameters in CGE models are calibrated against a historical period in which it is difficult to decouple economic growth and energy consumption (or CO_2 emissions). Some argue that aggregated energy system representation is disadvantageous to understanding drastic energy system changes and their macro-economic implications. Thus, incorporating energy system model information into CGE models may lead to results of lower macro-economic costs than previously reported.

Integrating CGE and energy system model information offers a great advantage in representing the feedbacks inherent across economic and energy systems. To this end, several model integration attempts have been made[14, 15, 16], whereas investigators such as Tuladhar et al.[17], Arndt et al.[18], and Bohringer et al.[19, 20] incorporated disaggregated information on power sectors. Drastic energy transformation requires large-scale variable renewable energy penetration. In IAMs, they are represented in some way[21, 22] and their representations are adequate to provide regional- and global-scale energy analyses. The key issue of the variability in renewable energy is strongly dependent on national- and local-scale grid systems, availability of solar and wind power, battery technology, and other power energy sources that can be used to balance the demand and supply. Recently, numerous modelling studies have addressed these issues[23, 24, 25] and integration of a power dispatch model with an energy system model has been attempted[26]. However, no estimates have been made of the macroeconomic implications of consistently dealing with energy systems and the stability of further power generation.

Here, we describe the macroeconomic implications of climate mitigation policy using an integrated modelling framework wherein an energy system model, AIM/Enduse [Japan] (called AIM/Enduse hereafter), and a power dispatch model, AIM/POWER, are inter-linked with the multi-sector economic model AIM/CGE. This modelling framework allows us to assess the macroeconomic impacts of climate change mitigation policies with concrete specification of detailed energy technologies, ensuring a stable power supply with consideration of long-term (daily) and short-term (less than hourly) power fluctuations. Consequently, we identify the magnitude of the differences in macroeconomic costs for climate change mitigation using values derived from this newly integrated model and the conventional economic model approach, and determine which sector's representation is an influential factor.

The principle of this methodology is based on the concept that energy simulation from the energy system model is more reliable than that from the economic model, as the energy supply and demand are technologically represented in detail in the energy system model. Similarly, the power dispatch model's power supply technological representation is more reliable than that of the energy system model. We overcome the disadvantages of these models by exchanging information and iterating it among models. The model integration procedure is illustrated in Figure 1. We begin with the AIM/Enduse run, which provides energy system information to AIM/CGE and AIM/POWER. Then, these two models of energy projections and their outcomes are further fed into AIM/Enduse. Finally, we confirm whether the models reach sufficient convergence for our purposes (see Supplementary Information for more detailed discussion about reaching convergence). See the Methods section for a list of indicators exchanged among models and representations of the indicators in conventional CGE model approaches. Note that for CGE results, we compared the stand-alone CGE model ("CGE results 1" in Figure 1) with the integrated model ("CGE results 3") as a reference.

We applied this framework to Japan as a case study. The Japanese government has declared a long-term greenhouse gas (GHG) emissions reduction target of 80% by 2050 as the nation's long-term goal in the Plan for Global Warming Countermeasures adopted in 2016[27]. The issue of mitigation cost is particularly crucial in Japan, as this plan stresses simultaneous achievement of the long-term climate goal and economic growth, which is one of the main elements criticised by opponents of radical CO_2 emissions reduction[28]. In addition, as mitigation costs in Japan estimated in previous studies vary significantly across the IAM[29], application of this framework would be beneficial for Japan's climate policies. We analysed scenarios without and with climate mitigation policy, which are referred to as the baseline and mitigation scenarios, respectively, in this paper.

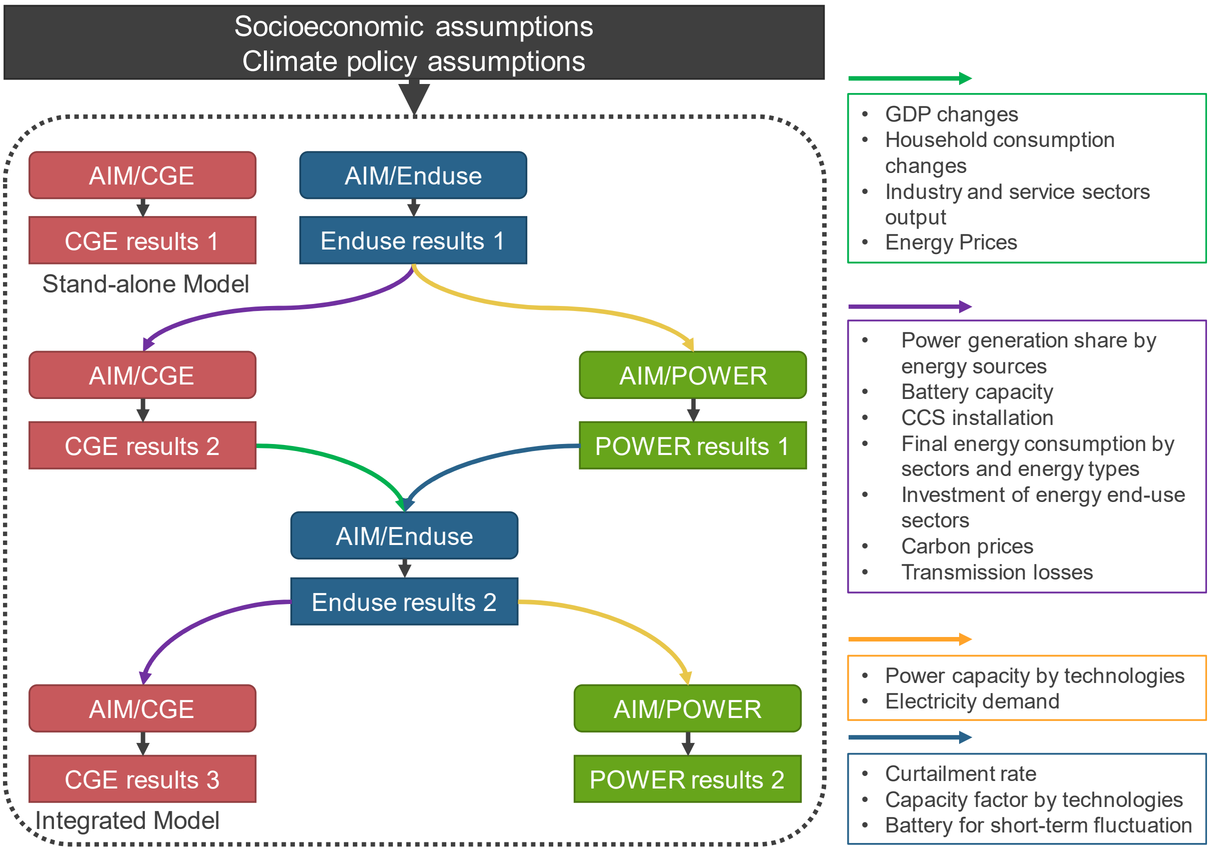

Figure 1. Model integration strategy.

Energy system in Japan's mid-term century strategy

An 80% reduction of GHG emissions requires substantial changes in the energy system compared to the current system or the baseline scenario (Figure 2**a**). As a result of Japan's unique socioeconomic circumstances, with a decreasing population and modest economic growth (Supplementary Figure S1), the overall energy system shows little change in the future under the baseline scenario. The main differences relative to the base year in baseline 2050 modelling is the share of nuclear energy, which reflects the current societal attitude toward nuclear power that limits new construction (Figure 2**b**). Regarding CO_2 emissions, the baseline level is stable or may even decline over time (Figure 2**d**). Meanwhile, the mitigation scenario exhibits large-scale renewable energy penetration, energy demand reduction, compositional changes characterised by the use of more carbon-neutral energy sources, and strong electrification (Figure 2**f**).

This power system, which relies heavily on variable renewable energy, requires measures to stabilise the power supply system and demand responses. Curtailment in onshore wind increases, particularly after 2020 when variable renewables start to expand (Figure 3**a**). Furthermore, when coal-fired power is completely phased out around 2040, offshore wind also exhibits a curtailment increase. The battery requirements for short-term fluctuations also increase sharply after 2020, whereas the capacity factor of thermal power plants declines (Figure 3**b,c**). We also show the daily electricity supply and demand profiles for selected days in 2050 (Figure 3**d**).

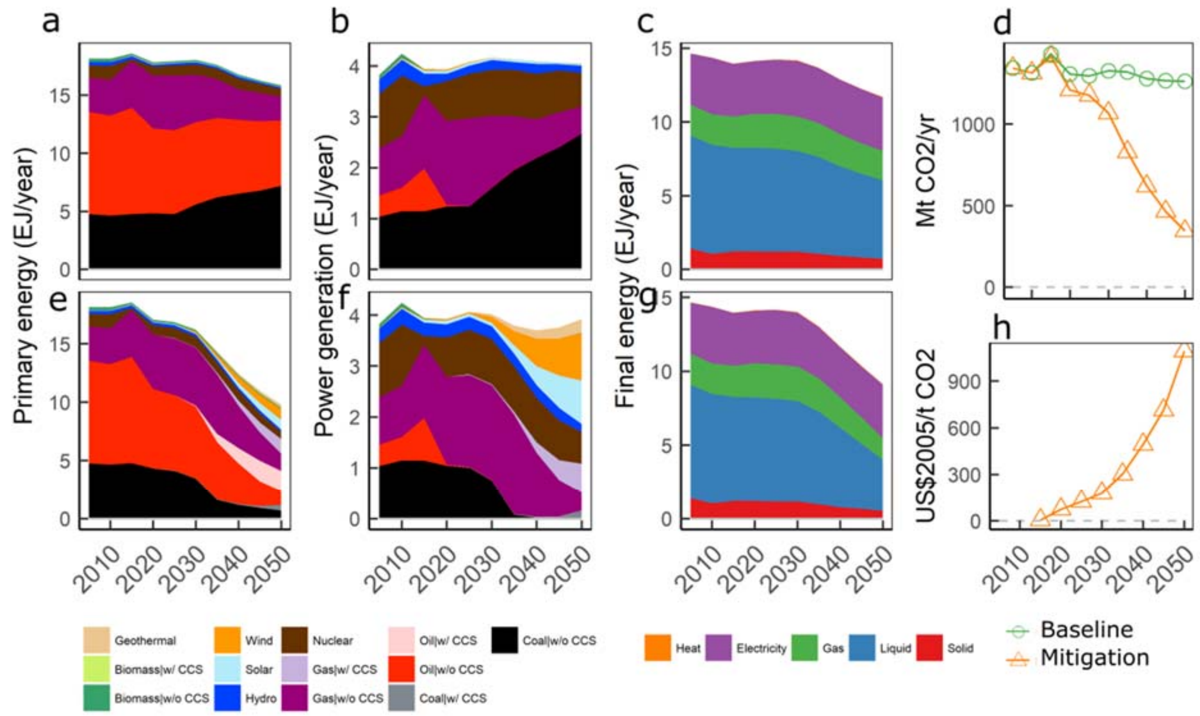

*Figure 2. Primary energy source (panels **a** and **e**), power generation (panels **b** and **f**), final energy demand (panels **c** and **g**), CO_2 emissions (panel **d**), and carbon price (panel **h**) projections. Panels **a**, **b**, and **c** show the baseline scenario, whereas panels **e**, **f**, and **g** show mitigation scenarios.*

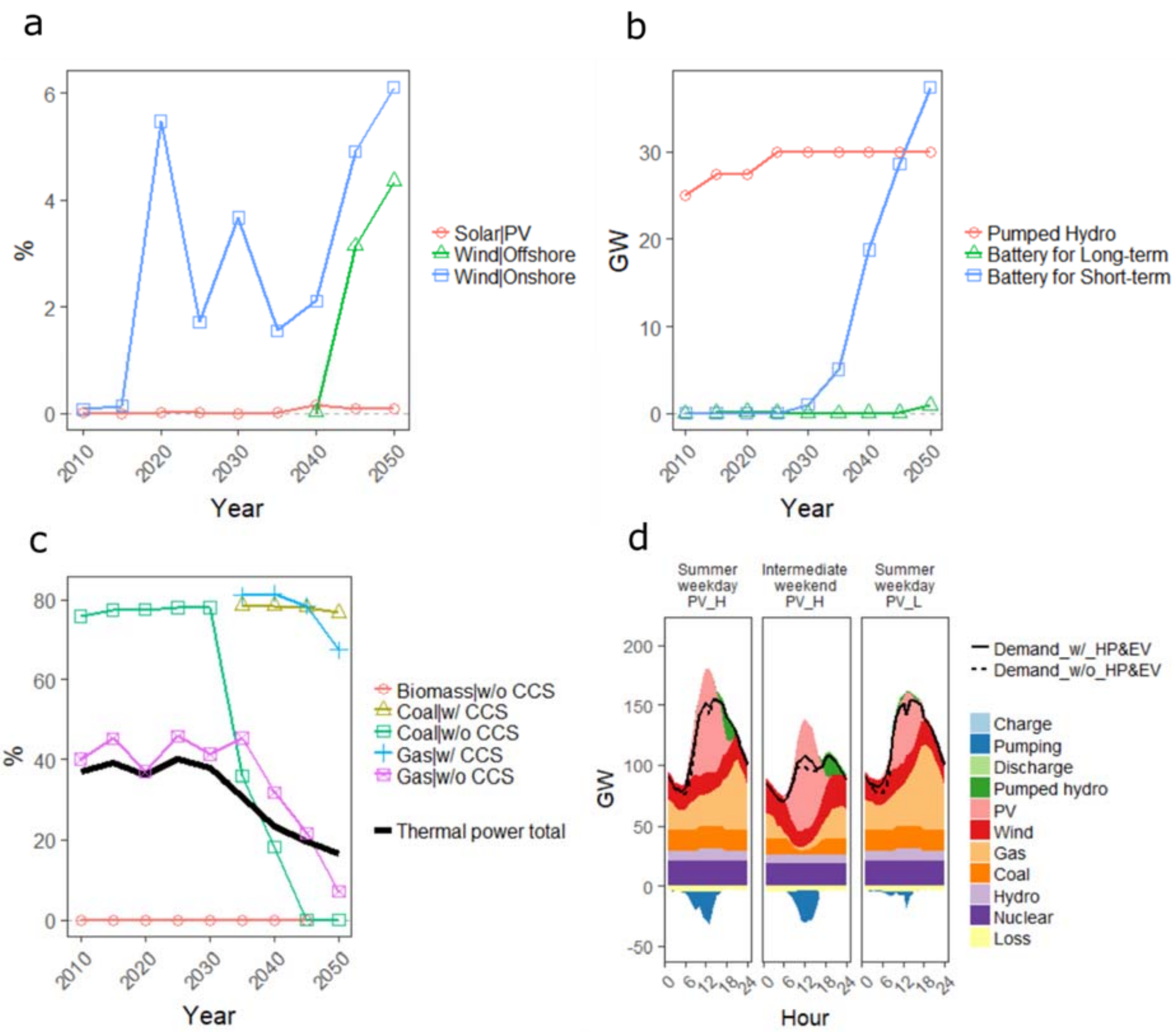

Figure 3. Power system reactions to large-scale renewable energy penetration. ***a*** *is the curtailment rate,* ***b*** *is the installed capacity of technologies to stabilise fluctuations in the electricity supply,* ***c*** *is the capacity factor of thermal power, and* ***d*** *illustrates the profiles of electricity demand and supply on selected three typical days (PV_H and PV_L indicate sunny and cloudy days, respectively).*

Mitigation costs

Mitigation costs, as measured by GDP loss rates, increase over time as emissions reductions become deeper, as illustrated in Figure 4**a**. The CGE stand-alone results reach more than 2.5% after 2030, whereas the integrated model is lower, around 1.2% in 2050 (Figure 4**a**). The additional energy system costs in the AIM/Enduse stand-alone are plotted in the same figure, and are notably similar to the integrated model results (blue lines in Figure 4**a**). The mitigation costs under such deep emissions reductions are usually not as low as this study's estimates from the CGE stand-alone model[4]. Once the energy system model's results are reflected in the economic models, it may follow that integrated models will be able to estimate similar mitigation costs to those from energy system models.

We further implemented sensitivity scenarios with varying technological availability, which may lead to non-linear energy system responses, to investigate the robustness of our findings. For this purpose, we selected two technological variation scenarios wherein more power stability measures are needed; namely, options with no nuclear and no carbon capture and storage (CCS). These results can be interpreted as a simple uncertainty analysis, but they have more meaningful policy implications because the perception of nuclear power in Japan has changed drastically since the Fukushima accident, and there is limited geologically appropriate space for CCS on Japanese territory. Figure 4**b** illustrates the relationship of mitigation costs in the CGE stand-alone and integrated models for this sensitivity analysis. Here, we again see systematic overestimates in the stand-alone model. Comparison of this integrated model's GDP losses and additional energy system costs derived from AIM/Enduse shows a similar trend to that in Figure 4**c**. The energy and emissions overview are provided in the Supplementary Information (Figure S2 and Figure S3).

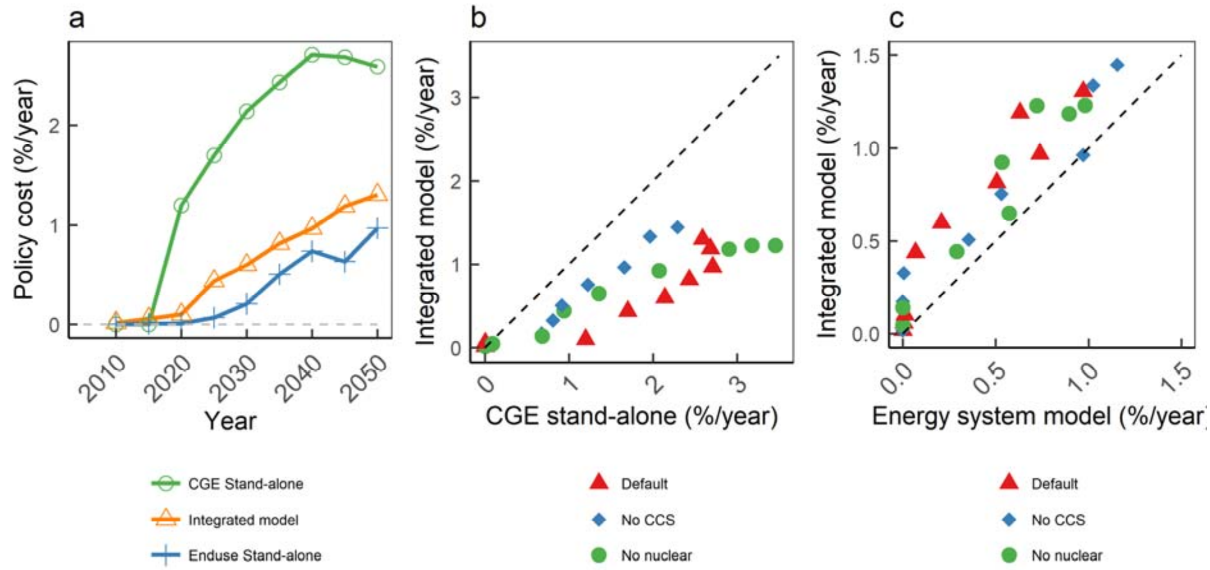

Figure 4. Climate change mitigation cost. ***a*** *Time-series mitigation cost AIM/CGE results are represented as GDP loss rates relative to baseline scenarios. AIM/Enduse results are expressed as additional energy system costs of GDP relative to baseline scenarios.* ***b*** *and* ***c*** *show 5-year mitigation costs with varying technological availability;* ***b*** *illustrates the relationship of GDP losses in the CGE stand-alone and integrated models, and* ***c*** *shows GDP losses in the CGE stand-alone model and additional energy system costs in AIM/Enduse. The energy system model results shown here correspond to Enduse_results1 in Figure 1.*

Sectoral contributions to changes in mitigation costs

To investigate the extent to which the energy system model's output information for each sector contributes to mitigation cost differences compared to the stand-alone CGE, we ran diagnostic scenarios with and without incorporating energy system information by sector (see Methods for more details). Then, we regressed all scenario results, estimating dummy variables for each sector. The energy system model's integration for industry and service sectors can mitigate the GDP loss rates by 0.40% and 0.50%, respectively (Table 1). The residential sector's incorporation of energy information can also decrease GDP loss rates, although the magnitude of this change is smaller than those for the industry and service sectors (0.18%). Energy supply sector incorporation had a 0.40% impact on GDP loss due to consideration of curtailment and battery installation from power dispatch model results. The transport sector's effect is ambiguous, and its *t*-value is too small to reject the null hypothesis.

To verify the robustness of these findings, we tested another regression model that assumes year is a fixed effect (independent dummy variables). The results show similar trends, such as the industry and service sectors having large contributions with sufficient statistical significance, whereas the transport and residential sectors' contributions are low or their *t*-values are too small for statistical confidence of a non-zero effect (Table S4).

*Table 1. Regression results of diagnostic scenarios. Significance is represented as ***, <0.001; **, < 0.01; and *, < 0.05.*

	Estimate	Std. Error	*t*-value	$\Pr(>\lvert t\rvert)$	
(Intercept)	0.918	0.057	16.111	< 2e-16	***
2030	0.150	0.060	2.516	0.0128	*
2035	0.451	0.060	7.578	1.75E-12	***
2040	0.725	0.060	12.182	< 2e-16	***
2045	0.900	0.060	15.121	< 2e-16	***
2050	1.029	0.060	17.286	< 2e-16	***
Energy Supply	0.398	0.034	11.570	< 2e-16	***
Industry	-0.404	0.034	-11.753	< 2e-16	***
Service	-0.501	0.034	-14.587	< 2e-16	***
Transport	0.036	0.034	1.033	0.3028	
Residential	-0.182	0.034	-5.288	3.54E-07	***

Decomposition of mitigation costs

To determine which sectors contribute to GDP losses, the value added by each sector, as estimated by the economic model, is decomposed into three factors of 1) output changes, 2) value-added productivity (output per value-added), and 3) residuals. Moreover, we compared the outputs of stand-alone CGE and integrated model runs. The AIM/CGE stand-alone model shows remarkable value-added decreases in the industry (IND) and service sectors (SER) in 2030, whereas the integrated model does not. These trends remained consistent for the year 2050, with the CGE stand-alone model showing large changes in the service sector. This result is consistent with those described in the previous section, wherein the industry and service sector's energy system information, i.e. the representation of production functions in those sectors, are critical factors for differentiating overall GDP losses between the two models. The output decrease in the service sector is the largest element reducing GDP in the CGE stand-alone model. This result may be driven by changes in household expenditures for services, which were around 3.4% and 0.0% in the CGE stand-alone and integrated models, respectively, in 2050. These differences may be due to changes in total income.

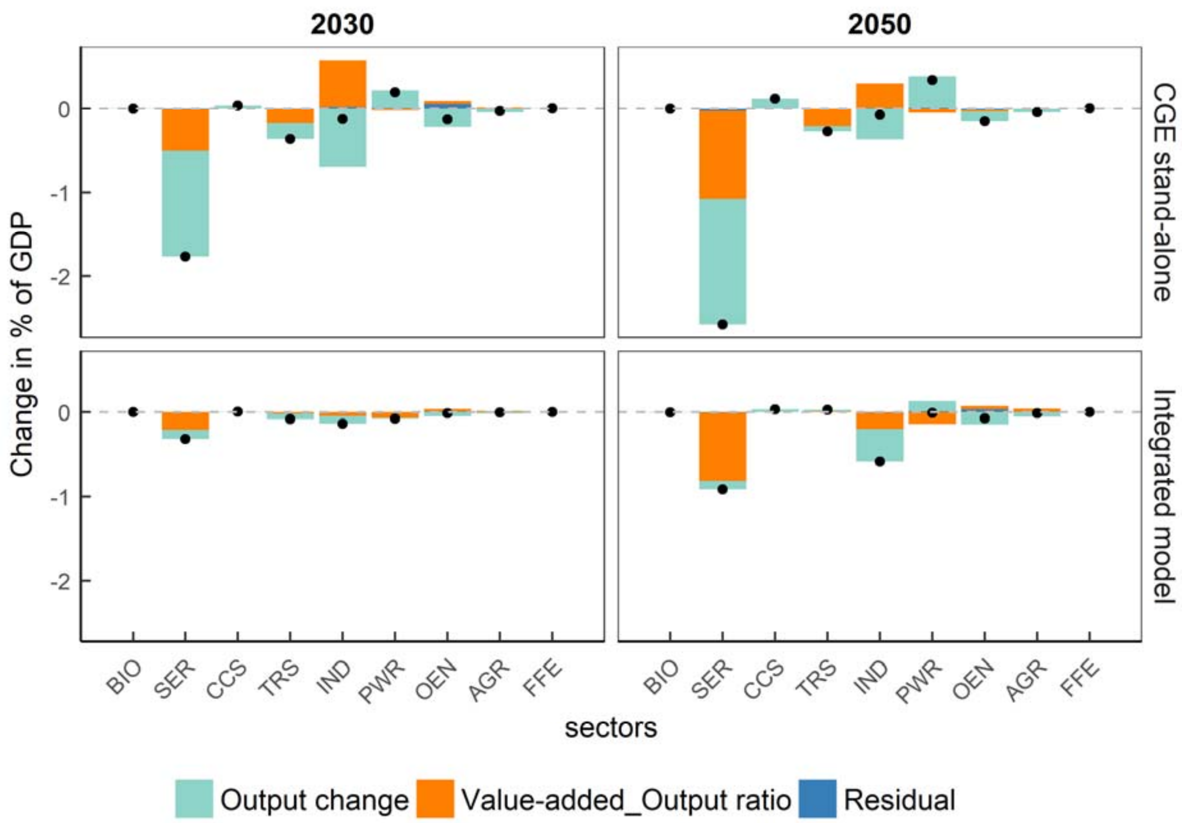

Figure 5. Decomposition analysis of GDP changes across sectors. Value-added changes relative to baseline scenarios are expressed as percentages of GDP. Legend entries "Output change", "Value-added_output ratio", and "Residual" refer to output changes, value-added productivity changes, and residuals, respectively. The top and bottom panels show CGE-stand alone and integrated model results, respectively. Sectors are BIO: Bioenergy industry, SER: service sector, CCS: CCS industries, TRS: Transportation, IND: manufacturing and construction, PWR: power, OEN: other energy supply, AGR: agriculture, and FFE: fossil fuel extraction.

Discussion and conclusions

We attempted to address the problem of whether decarbonising the energy system is considerably harmful to macroeconomic growth. Ultimately, we found that this will not occur if energy system information is appropriately reflected in the economic model. The critical determinants of mitigation costs that changed when integrating energy system information into an economic framework in the newly developed integrated model were identified as the industry and service sectors' energy consumption and production functions. Moreover, the short-term and long-term power stability associated with large-scale variable renewable penetration is ensured through incorporation of a power-dispatch model into the modelling framework. These findings may change the general perception of climate change mitigation costs in terms of macroeconomic losses and provide important policy insights.

Overall, as long as an energy system model is more reliable than the CGE model in terms of energy-related variables, the energy representation in the conventional CGE should be replaced by the energy system model outputs. The contributions of the industry and service sectors to GDP loss mitigation are caused by the production function form and its parameters. Basically, for most conventional CGE models, the substitution elasticity of energy and value-added in these sectors use values referenced from the literature[30]. This representation has two possible disadvantages. First, historical price-induced energy and capital substitutability data are based on past events and limited to developed countries. Future technological availability, which is represented by the energy system model in this study, may change drastically. Second, the elasticity parameter is normally assumed to be uniform, but it should differ among sectors, and probably regions (this study uses the global model's uniform value for the stand-alone model).

To represent the production functions, an alternative approach to CES-type methods already exists in the econometric method [31]. In contrast to this approach, our method relies on realistic representation of technological availability. Therefore, we can identify explicit technological changes that are consistent with the general equilibrium framework. Note that this process implicitly assumes that currently non-existent technologies are excluded, whereas the conventional approach using possible substitution could implicitly assume an infinite possibility to decrease energy consumption in response to energy price signals.

GDP loss differences associated with the household sector's representation in the conventional and integrated models were small, but this result may suggest the disadvantages of measuring the mitigation cost as GDP loss. Household expenditure is a major component of GDP in the expenditure accounting system, and increases in household expenditure directly boost GDP. Hence, purchasing relatively expensive energy devices such as electric vehicles and heat pumps will not directly decrease GDP, but rather may offset the negative impacts of climate change mitigation costs. Notably, this GDP increase is attributed to the additional expenditure, which may not contribute to an increase in actual welfare. This finding may show one of the limitations of accounting for climate mitigation costs using this type of model.

An energy system model simply represents the reduction potential of energy-consuming devices, but numerous other possibilities exist to change the energy service itself. Artificial intelligence may maintain energy devices more efficiently, or transport demand could be reduced. Material consumption can also change through sharing of goods and services. From that perspective, the mitigation potential and associated cost may be underestimated. Meanwhile, these societal changes could have indirect effects in the opposite direction in terms of energy consumption, as information technology would require additional electricity. The monetary savings realised by decreasing energy usage could be spent on other things, and if it were spent on energy-intensive activities (e.g. tourism using air travel), energy consumption and emissions could increase.

The energy system model's representation of technological diffusion is based on linear programming with some constraints. Thus, this model may be interpreted as the extreme case where a single technology is selected at some point under certain price conditions, such as only electric vehicles being sold in a private car market. Meanwhile, the CES or logit formulations that are typically used in economic models allow multiple possibilities, implicitly assuming heterogeneity in goods and consumers, whose real behaviour should be represented by a utility function that accounts for non-monetary value[32]. This notation is important when interpreting household results derived from integrated model results, where some models may select economically unrealistic technologies without full consideration of their practicality. However, according to our results, industrial activities have more influence over mitigation cost and our conclusions would hold true if we included such heterogeneity.

As reported in the results section, some variables show discrepancies between the two models in the base year. Although we think that this discrepancy does not affect our main conclusion, a more consistent understanding of this type of modelling framework is needed. This understanding may be accomplished by calibrating both models, but such calibration will require substantial additional efforts to fully harmonise the base year data. Although this calibration is not expected to change our conclusions, it is a worthwhile endeavour for future research.

Methods

Here, we developed an integrated modelling framework that incorporates energy system, power-dispatch, and CGE models, as illustrated in Figure 1. Each model's output is exchanged with the others. We executed the model for two iterations. Because the discrepancy improvements were sufficiently small, we stopped the calculation after the second iteration. The calculation begins with an AIM/Enduse run and then uses AIM/CGE and AIM/POWER. AIM/Enduse is run again, considering the AIM/CGE and AIM/POWER outputs. We conducted scenario-based simulations through 2050. The energy system and related CO_2 emissions are the scope of this study, as Japanese GHG emissions are associated with these factors.

AIM/CGE model

The CGE model used in this study is a recursive dynamic general equilibrium model that covers all regions of the world and is widely used in climate mitigation and impact studies[33, 34, 35, 36, 37]. The main inputs for the model are socioeconomic assumptions of the drivers of GHG emissions such as population, gross domestic product (GDP), energy technology, and dietary preferences. The production and consumption of all goods and GHG emissions are the main outputs based on price equilibrium.

One characteristic of industrial classification is that energy sectors, including power sectors, are disaggregated in detail, because energy systems and their technological descriptions are crucial for the purposes of this study. Moreover, to appropriately assess bioenergy and land-use competition, agricultural sectors are highly disaggregated[38]. Details of the model structure and its mathematical formulas were provided by Fujimori, Masui [39].

Production sectors are assumed to maximise profits under multi-nested constant elasticity substitution (CES) functions at each input price. Energy transformation sectors input energy and are value-added based on a fixed coefficient, whereas energy end-use sectors have elasticities between energy and the value-added amount. These sectors are treated in this manner to account for energy conversion efficiency in the energy transformation sectors. Power generation from several energy sources is combined using a logit function[40], although a CES function is often used in other CGE models. We chose this method to represent energy balance because the CES function does not guarantee a material balance[41]. As discussed by Fujimori, Hasegawa [38], a material balance violation in the CES would not be critical if the share was similar to the calibrated information. In this study, climate mitigation changes the power generation mix when compared to that of the base year, and therefore is a key treatment. The variable renewable energy cost assumption is shown in SI section 2. Household expenditures on each commodity are described with a linear expenditure system (LES) function. The savings ratio is endogenously determined to balance savings and investment, and capital formation for each item is determined using a fixed coefficient. The Armington assumption, which assumes imperfect substitutability between domestically produced and traded goods[42], is used for trade, and the current account is assumed to be balanced.

To construct energy supply cost curves, we implemented multiple sources of information. Solar and wind supply curves are from a study considering urban distance[43]. Biomass data is from a land-use allocation model[44].

AIM/Enduse model

The energy system model used in this study is a recursive dynamic partial equilibrium model based on detailed descriptions of energy technologies in the end use and supply sectors. In this study, we used the multi-region version of AIM/Enduse [Japan][45], which divides Japan into 10 regions (see Figure S4) based on the power grid system. Mitigation options are selected based on linear programming to minimise total energy system costs that include investments for mitigation options and energy costs subject to exogenous parameters such as cost and efficiency of technology, energy prices, energy service demands and emission constraints. Detailed information on the model structure and parameter settings are provided in Kainuma et al. (2003)[46].

The power sector is modelled in detail, considering the balances of electricity supply and demand in 3-h steps to assess the impacts of variable renewable energies (VREs). This sector also includes measures to integrate VREs into the grid, such as electricity storage, demand response (DR) using battery-powered electric vehicles and heat pump devices, and interconnections.

In energy-demanding sectors, wide mitigation options are included, such as energy-efficient devices and fuel switching in the industrial, building, and transportation sectors. The industrial sector also includes innovative technologies such as carbon capture and storage (CCS). However, the AIM/Enduse stand-alone model does not account for some mitigation options that contribute to reduction in service demands.

AIM/POWER model

The power-dispatch model used in this study is a recursive dynamic partial equilibrium model focused on generation planning for the power sector. This model can simulate hourly or annual electricity generation, generation capacity, plant locations, and multiple flexible resources, and includes interregional transmission, dispatchable power, storage, and demand responses. These variables were selected based on linear programming while minimising the total system costs, including capital costs, operation and maintenance costs, and fuel costs under several constraints, including satisfying electricity demand, CO_2 emissions reduction targets, or both. In this study, we used a version of the model that classifies Japan into 10 regions (see Figure S4). Detailed information about this model can be found in Shiraki et al. (2015)[47].

AIM/POWER can explicitly simulate the hourly demand-supply balance of electricity, with consideration of daily variations in photovoltaic output caused by weather conditions as well as seasonal and weekday/weekend variations in demand. In addition, the demand-supply balance of electricity within an hour is modelled using the fluctuations and flexible range of each generator. Although generators and flexible resources are modelled in detail, electricity demands are provided exogenously. Thus, the power-dispatch stand-alone model does not account for the electrification trend and increased capacity of demand in response to technologies.

Information from AIM/Enduse provided to AIM/CGE

The following information is given to AIM/CGE from AIM/Enduse outputs.

1) Power generation share by energy source
2) Battery capacity for stabilising fluctuations of the power supply
3) CCS installation
4) Change ratio of final energy consumption by sector and energy type
5) Investment in energy end-use sectors
6) Carbon prices
7) Transmission losses

Final energy consumption is input into four sectors (industry, transport, service and residential). We exogenously populate these sectors, while autonomous energy efficiency improvement (AEEI) parameters are endogenised. This treatment maintains the same number of equations and variables as in the conventional CGE approach. To integrate household energy consumption and its energy device purchase activities, we divided the modelling of household expenditure into four categories, such as car-use activities and other energy consumption activities, as illustrated in the supplementary information (Figure S5). Because the absolute value of energy consumption is not fully harmonised between these two models, we compare the change ratios of energy consumption with 2010 levels, which is the base year of the AIM/Enduse model, for final energy consumption determination. If the corresponding energy consumption was zero or very low in 2010 (less than 1 ktoe), the change ratio can lead to unrealistic projections; therefore, we use absolute values. The investment in energy end-use sectors is input as an incremental capital cost compared to the baseline case, implicitly assuming that the baseline investment cost is inherent in the CES substitution. Moreover, the capital input coefficients are fixed at baseline levels so that additional energy investment is represented by AIM/Enduse information rather than CES substitution elasticity in the mitigation scenarios. Power generation is divided into shares from various energy sources because the absolute amount of power generation is determined by the demand side, and transmission losses are also considered. Battery capacity is input as an absolute amount.

Information from AIM/CGE provided to AIM/Enduse

AIM/Enduse uses the following information generated by AIM/CGE:

1) GDP changes
2) Household consumption changes
3) Industry and service sector outputs
4) Energy price changes

Economic information from AIM/CGE is input into AIM/Enduse as changes in energy service demand for each sector. Transport demand is associated with GDP projection in AIM/Enduse and we proportionally change the transport demand based on changes in GDP. The industry service demand is altered by the outputs. Energy service demand in the household and industrial sectors could have low or high elasticities to relevant economic activity variables, such as household consumption and outputs of service sectors, but remains an uncertain factor. Based on Swedish econometric analysis[48], we tentatively applied an elasticity value of 1.0.

Information from AIM/Enduse provided to AIM/POWER

AIM/POWER's role is to present the feasibility of power dispatch given an electricity demand and installed power capacity. Thus, AIM/Enduse provides the following items to AIM/POWER:

1) Electricity demand
2) Power generation installed capacity
3) Demand response technological availability, such as heat-pump water heaters and electric vehicles

Information from AIM/POWER provided to AIM/Enduse

AIM/POWER provides more realism in terms of technologies to stabilise short-term fluctuations in the power system than the other two models used in this study. Moreover, the power system would respond to large-scale renewable energy installation by changing the capacity factor for conventional power generation systems (e.g. coal-fired power). In summary, the following AIM/POWER information is given to AIM/Enduse:

1) Battery capacity needed to stabilise short-term electricity fluctuations
2) Curtailment ratio
3) Capacity factors

Scenario assumptions

There are two basic assumptions for future scenarios, namely, baseline and mitigation, which are carried out with and without carbon pricing to reduce GHG emissions by 80% in 2050. Basic assumptions on technological conditions, such as nuclear scenarios and CCS capacities, are taken from previous studies[49]. In the results section, we describe how the mitigation cost differs from that in the stand-alone AIM/CGE run to identify each sector's contribution to the changing mitigation costs.

Analytical method for the diagnostic scenario runs

To investigate the extent to which AIM/Enduse output information for each sector contributes to mitigation cost adjustment compared to the conventional CGE approach, we ran diagnostic scenarios with and without incorporation of AIM/Enduse data by sector, as noted in the supplementary information (Table S3). Ultimately, we conducted 32 scenarios with various combinations of AIM/Enduse information for energy supply, industry, service, transport, and residential sectors taken into account or excluded. Then, we regressed the factors, as shown below.

$$GDPLOSS_s = \sum_{(s,j)\in SJ} a_j X_j + e_s$$

where $GDPLOSS_s$ is the GDP loss rate (% change) for scenario s, a_j is a dummy parameter representing a set of years and sectors that incorporates AIM/Enduse information (energy supply, industry, service, residential and transport), X_j is the estimated variable, and e_s is an error term.

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