A multi-model framework to assess the role of R&D towards a decarbonized energy system

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Abstract

Research and development (R&D) investments foster green innovation, which is key to decarbonize the energy system and attain long-term climate goals. In this paper, we link three integrated assessment models that possess a macroeconomic framework – WITCH, MERGE-ETL and GEM-E3 – with the bottom-up technology-rich energy system model TIAM-ECN, in order to quantitatively explore how investments in R&D can support deep decarbonization pathways. We take advantage of the endogenous technological learning feature of the first three models to derive R&D-induced capital cost reductions for strategic clusters of low-carbon technologies: solar energy, on- and offshore wind energy, carbon capture and storage, advanced fuels, and batteries for electric vehicles. We examine scenarios with different assumptions on CO_2 mitigation and R&D policy. These assumptions are harmonized among our four models, and capital cost reductions driven by R&D are exogenously incorporated in TIAM-ECN, which enables a detailed assessment of the required energy transition. Our results show that the stringency of climate change mitigation policy remains the key factor influencing the diffusion of low-carbon technologies, while R&D can support mitigation goals and influence the contribution of different types of technologies. If implemented effectively and without worldwide barriers to knowledge spill-overs, R&D facilitates the deployment of mature technologies such as solar, wind, and electric vehicles, and enables lower overall energy system costs.

Highlights

- With a multi-model framework we assess the effects of R&D on the energy transition.
- Mitigation targets influence decarbonization most, while R&D has a supporting role.
- Optimal R&D favours solar and wind energy over CCS technologies.
- Up to 1,000 bln $ can be saved in 2050 if free knowledge spill-overs exist.

1. Introduction

Keeping average global warming well below 2°C above pre-industrial levels as stated in the Paris Agreement (PA) is technically possible, but it requires unprecedented and consistent action (IPCC, 2018). Increase funding in research and development (R&D) into low-carbon energy technologies is part of it, as detailed explicitly or implicitly in the Nationally Determined Contributions (NDCs). These official pledges, submitted by signatory countries of the PA, reflect the current level of commitment towards achieving the global climate control goal (UNFCCC, 2015). However, the Working Group I contribution to IPCC's Sixth Assessment Report (IPCC, 2021) shows that, even under the strict implementation of the measures foreseen by the NDCs, global surface temperature is expected to increase at least until 2050 as a result of relentless high levels of greenhouse gas (GHG) emissions. The International Energy Agency's "Net Zero by 2050" report (IEA, 2021) also shows that current CO_2 mitigation pledges are not compatible with their initial aim: countries are lagging behind their mitigation efforts and urgent action is needed now to avoid global warming beyond 1.5°C in this century.

A key aspect of decarbonization pathways is the energy transition. In 2018, GHG emissions from energy corresponded to 76% of total emissions worldwide (Climate Watch, 2021). Hence, it is paramount that investment choices in the energy sector prioritize low carbon technologies. Some of these technologies are already mature enough to compete with conventional fossil fuel-based technologies, for instance, solar photovoltaics (PV) and onshore wind energy (Irena, 2020). Nevertheless, a diverse technology mix that will foster GHG mitigation at required levels also includes technologies at initial stages of development, i.e. at low technology readiness level (TRL), and currently available at relatively high costs. Offshore wind energy, carbon capture and storage (CCS) and advanced biofuels production are a few examples (IEA, 2020a; IEA, 2020b; IEA, 2020c).

Several studies (Bataille et al., 2016a; Grubb et al., 2014; Shayegh et al., 2017; Ockwel et al., 2015) indicate that incentives fostering innovation towards low carbon energy technologies are important instruments to be combined with GHG mitigation policies. A diverse policy mix that includes R&D investments is acknowledged as most effective to promote the deployment of abatement technologies (Stern and Valero, 2021; Zhu et al., 2021; Deleidi et al., 2021; Rogge et al., 2017). In literature, research on how technological change induced by R&D may accelerate decarbonization includes the use of integrated assessment models (IAMs) and energy system models, some of which are able to endogenously account for R&D-induced technology learning and diffusion. Most studies use a single model to explore R&D dynamics and its impacts on economy and environment or on the energy system: Bosetti et al. (2008) and De Cian et al. (2012) uses the WITCH model to focus on technology innovation and diffusion impacting GHG emissions and related policies, while Zhang et al. (2020) incorporate multi-level learning, which includes equipment trade and knowledge accumulation, in the REMIND model to assess technology diffusion. Leibowicz et al. (2016) focus specifically on the impacts of different endogenous technology diffusion formulations in MESSAGE model to inspect the implications for low-carbon technologies, while Fragkiadakis et al. (2020) look specifically at Europe and use the GEM-E3 model to analyse how public and private R&D can support the EU Green Deal.

IAMs can generate least-cost long-term scenarios for energy supply and consumption subject to multiple constraints on, among many others variables, CO_2 emissions, offering a sound basis to support the policy-making process for a low carbon society (IPCC, 2014; IPCC, 2018; IAMC, 2019). Although many IAMs rely on similar theoretical approaches to model R&D, such as one-factor and two-factor learning curves, they differ in many other aspects, such as regional and temporal scope, mathematical method, technology portfolio and sectoral representation (see for instance the different model descriptions available at IAMC Wiki; IAMC, 2021). These differences are likely to impact the resulting low carbon scenarios derived from these IAMs. To reduce the ensuing uncertainty in long-term decarbonization scenarios, it is customary to run multi-model exercises, where the same scenario assumptions are analysed with a set of different IAMs. Marcucci and Turton (2015) use this approach to assess induced technological change (ITC) under different levels of mitigation action. Several other multi-model studies that do not focus on R&D can be found in the literature (see e.g., Daioglou et al., 2020; Luderer et al., 2016; van der Zwaan et al., 2016; Rogelj et al., 2018; McCollum et al., 2018; Bosetti et al., 2015, Vrontisi et al., 2018).

In this paper, we investigate to which extent R&D investments support low carbon policies by combining a set of four global IAMs: WITCH, MERGE-ETL, GEM-E3 and TIAM-ECN. The first three IAMs endogenously account for R&D effects driving ITC in the energy and economy system, but adopt a simplified approach with respect to, for instance, the characterization of energy demand sectors, the definitions of temporal and regional resolution, and the representation of some secondary energy conversion chains. For that reason, their results with regard to technology diffusion in the energy system might neglect effects related to the interaction and integration of the different technologies and sectors, such as the integration costs of renewables and the CO_2 abatement potential of low-carbon and energy efficient options in the end-use sectors. Throughout this paper we refer to these models as IAMs with ITC. Complementarily, TIAM-ECN employs exogenous R&D-driven cost reduction trajectories, but provides a detailed representation of the global energy system, hence is suited to accurately assess the direct and indirect effects of R&D on the energy system transition.

We consider harmonized assumptions on learning and R&D parameters for a set of key technologies among the first three IAMs – WITCH, MERGE-ETL and GEM-E3, from which we derive capital cost reductions to be exogenously incorporated into TIAM-ECN. In addition, we adopt a harmonized approach regarding low carbon policies in all four models, allowing for a consistent set of low carbon scenarios. We then use TIAM-ECN to perform a detailed assessment of low-carbon technology diffusion at global level until 2050. By considering different R&D-induced cost reductions based on different R&D strategies and derived from different IAMs , we create a set of scenarios that allows us to quantify the effect that different R&D policies might have on the speed of low-carbon technology diffusion.

We explain our methodology in section 2, and we present the main results of our analysis in section 3. We finally discuss our findings and propose potential improvements in section 4.

2. Methodological Approach

In this section, we detail how we assess the role of R&D in supporting the expansion of low-carbon energy conversion technologies to tackle climate change mitigation. WITCH, MERGE-ETL and GEM-E3 are IAMs with a top-down representation of economy and endogenous calculation of R&D investments, whereas TIAM-ECN is a bottom-up technology-rich IAM with a focus on energy system aspects and with exogenous assumptions on R&D (see the supplementary information – SI - for more information). Our methodological approach includes soft-linking TIAM-ECN with the other three IAMs with respect to the evolution of technology capital costs. The three models with ITC generate different capital cost paths over time for different low-carbon technologies, subject to assumptions regarding R&D investment strategies. These cost paths are exogenously fed into in TIAM-ECN, which then creates scenario projections for the evolution of the global energy system. By considering costs deriving from different modelling frameworks, we reduce the uncertainty of our outcomes. Moreover, we assess energy transition pathways taking advantage of TIAM-ECN's technology richness combined with WITCH's MERGE-ETL's and GEM-E3's ITC features, allowing for a robust framework, from which policy recommendations can be derived. By employing a single bottom-up model (TIAM-ECN) to calculate the final energy mix in our scenarios, we ensure that the different R&D-induced cost reductions derived from the three IAMs with ITC are treated in a consistent manner. We focus on five key decarbonization technology clusters currently at different maturity levels: solar (photovoltaics - PV and concentrated solar power - CSP) and , wind (onshore and offshore), carbon capture and storage (CCS), advanced fuels and batteries for electric vehicles (EVs).

2.1. Modelling Framework

Our basic approach consists of harmonizing assumptions and input data related to R&D and climate change mitigation policies as much as possible, yet keeping each model's particularities and features. First, we harmonize scenario assumptions related to climate targets in all four models. Second, in order to isolate the effects of different representations of knowledge dynamics, models with ITC consider the same assumptions for the learning parameters: LBD and LBR rates, time from investment to cost reduction, knowledge depreciation rate, technology floor cost, initial knowledge stock. We refer the reader to the SI for more information on our methodology.

Once the learning parameters are harmonized among WITCH, MERGE-ETL and GEM-E3, these models generate a set of scenarios and the resulting capital cost reductions per technology cluster, period and scenario are incorporated in TIAM-ECN. Each model details the 5 groups of technologies differently, thus we have mapped the technologies from the three IAMs to the TIAM-ECN technology portfolio, incorporating cost reductions to the best matching processes in TIAM-ECN. Input data from 2005 to 2020 is taken from historical records in literature and is kept constant across scenarios. For more details on initial costs and technology disaggregation assumptions, we refer to the SI.

2.2. Scenario Framework

We consider a total of 21 scenarios generated by TIAM-ECN. These scenarios are differentiated along three variables: (i) climate policy, (ii) R&D policy and (iii) the IAM used to generate the capital cost reductions adopted by TIAM-ECN. We assess three different levels of climate policy:

- REF: this is the reference 'business-as-usual' scenario, reflecting current, and generally insufficient, efforts to reduce emissions. Deployment of low-carbon technologies, such as solar PV, in this scenario heavily depend on the corresponding cost assumptions.
- CB1460: We assume a global CO_2 emission budget of 1,460 $GtCO_2$ between 2011 and 2100, which is consistent with constraining global average temperature increase by 2100 to well below 2°C (IPCC, 2018). In addition, a carbon tax is exogenously imposed on methane (CH_4) and nitrous oxide (N_2O).
- CB710: We assume a global CO_2 emission budget of 710 $GtCO_2$ between 2011 and 2100, which is consistent with constraining global average temperature increase by 2100 to well below 1.5°C (IPCC, 2018). In addition, a carbon tax is exogenously imposed on CH_4 and N_2O.

Regarding R&D policy, WITCH and MERGE-ETL optimize their R&D investments while complying with the climate policy target. Thus, technology investment levels in REF correspond to an optimal level of investment in a baseline scenario aligned with SSP2 (Riahi et al., 2017), assuming that no extra effort is made in promoting low-carbon R&D. GEM-E3 incorporates the optimal level of investment from WITCH in each scenario, which is a key driver for capital cost evolution along with capital and labour. In the two climate scenarios we then consider three variants:

- OPT: R&D expenditure is freely optimized by the models with ITC so as to support achieving the climate targets set by the low carbon polices. These scenarios hold an "OPT" suffix.
- FIX: R&D strategy is fixed to REF levels despite the existence of low carbon policies. These scenarios hold a "FIX" suffix.
- OPS: This is a sensitivity case of OPT scenario, which was generated only by TIAM-ECN. In addition to optimal R&D expenditure from the three models with ITC, we assume perfect interregional knowledge spill-overs. These depend on the capacity of a region to absorb knowledge from abroad, which usually depends on the human capital stock (Fragkiadakis et al., 2019), as well as on intellectual property legislation and potential restrictions of knowledge diffusion. Here, we assume that regions can perfectly incorporate knowledge generated elsewhere and that there are no other types of constraints (such as patents, for instance) or cost-differentiations, leading to a global convergence of capital cost projections to the lowest level possible. These scenarios hold a "OPS" suffix.

For each set of R&D-induced cost reductions derived from the IAMs with ITC, TIAM-ECN generates one 'reference' (REF) scenario plus two 'carbon budget' (CB) scenarios with three variants regarding R&D assumptions (OPT, FIX and OPS), totalizing 21 scenarios. The first letter in each scenario (W, M or G) indicates the model inheritance of the scenario. Table 1 summarizes the set of TIAM-ECN scenarios, their names and their main features.

Table 1 – List of scenarios produced by TIAM-ECN and their corresponding characteristics.

Scenario:	CO_2 budget (Gton CO_2):	R&D Policy:	Exogenous capital cost reductions in TIAM-ECN generated by:
W_REF	0	Reference level	WITCH
W_CB1460_OPT	1,460	Optimal R&D pathway	WITCH
W_CB1460_FIX	1,460	Reference level	WITCH
W_CB1460_OPS	1,460	Optimal R&D pathway and Perfect Knowledge Spill-overs	WITCH
W_CB710_OPT	710	Optimal R&D pathway	WITCH
W_CB710_FIX	710	Reference level	WITCH
W_CB710_OPS	710	Optimal R&D pathway and Perfect Knowledge Spill-overs	WITCH
M_REF	0	Reference level	MERGE
M_CB1460_OPT	1,460	Optimal R&D pathway	MERGE
M_CB1460_FIX	1,460	Reference level	MERGE
M_CB1460_OPS	1,460	Optimal R&D pathway and Perfect Knowledge Spill-overs	MERGE
M_CB710_OPT	710	Optimal R&D pathway	MERGE
M_CB710_FIX	710	Reference level	MERGE
M_CB710_OPS	710	Optimal R&D pathway and Perfect Knowledge Spill-overs	MERGE
G_REF	0	Fixed to WITCH reference levels	GEM-E3
G_CB1460_OPT	1,460	Optimal R&D pathway	GEM-E3
G_CB1460_FIX	1,460	Reference level	GEM-E3
G_CB1460_OPS	1,460	Optimal R&D pathway and Perfect Knowledge Spill-overs	GEM-E3
G_CB710_OPT	710	Optimal R&D pathway	GEM-E3
G_CB710_FIX	710	Reference level	GEM-E3
G_CB710_OPS	710	Optimal R&D pathway and Perfect Knowledge Spill-overs	GEM-E3

3. Results

We divide the results in two sections: first, we show the capital cost projections generated by the three IAMs with ITC. Next, we present global results for all scenarios until 2050 derived from TIAM-ECN. We treat the perfect spill-over (OPS) scenarios separately, as variations of the OPT scenarios. We focus on the expansion of the 5 key technology clusters, and we discuss the impact of different R&D and climate policy set-ups on energy system costs.

3.1. Impact of R&D on Capital Costs

In Figure 1 we show capital cost reduction projections relative to 2020 per scenario and technology group as box plots. We present these results for the years 2030 and 2050, for the REF and CB710_OPT scenarios, i.e. respectively the most and least conservative scenarios with regard to R&D policy ambitions. The yellow box plots show results for fossil- and biomass-based CCS technologies (panels a to d), the blue box plots show results for variable renewable electricity (VRE), namely onshore and offshore wind (panels e and f) and solar PV and, in the case of WITCH, CSP (panels g and h). Red box plots show results for the remaining technology groups of advanced fuels (aggregating advanced routes for synthetic fuels and biofuels generation, such as Fischer-Tropsch, as well as hydrogen production from advanced technologies such as biomass gasification and electrolysis, panels i and j) and batteries for passenger and, in the case of WITCH, freight EVs (panels k and l). For the full set of results, including all time periods and scenarios and a detailed list of technologies per technology group, see the SI.

The size of the box plots in Figure 1 is determined by the number of energy conversion technologies representing each technology cluster, and the number of regions where these technologies are implemented in each model, which results in different ranges of capital cost reductions. Means, medians, first and third quartiles are depicted as x's, horizontal lines inside the boxes, lower limits and higher limits of the boxes, respectively. The whiskers below and above the boxplots indicate the lowest and highest quartiles of each group.

Results in Figure 1 show that capital costs may vary significantly depending on the model and technology group in both reported years despite the harmonization of knowledge-related parameters. While, in general, cost reductions are expected to be more pronounced in scenarios that optimize R&D policy (CB) than in REF, this pattern does not hold for some technology clusters for GEM-E3 and MERGE-ETL. This can be seen, for instance, in the fossil-based CCS results from MERGE-ETL (panels a and b) and the electric vehicles results from GEM-E3 (panels k and l). In the case of MERGE-ETL, this effect is due to R&D investments being allocated per technology component. Different components might benefit to a different extent from R&D-driven cost reductions, depending on the stringency of climate policies in each scenario. For CCS, for instance, R&D investments in the gasification component of coal power plants and in natural gas combined cycle turbines drive down capital costs of coal and natural gas power plants (panels a and b) in the REF scenario. On the other hand, R&D investments are shifted to the CO_2 capture component (CO_2 scrubbers) in CB scenarios, thus favouring capital cost reductions of biomass-based CCS technologies (panels c and d). In the case of GEM-E3, modest cost reductions in CB scenarios are caused by costs other than equipment, such as increased labour. This effect illustrates that macroeconomic implications of low carbon policies can in some cases offset the expected R&D-induced capital cost reductions related to equipment.

Capital costs of CCS technologies have different cost reduction profiles across models, with an average cost reduction no larger than 20% in the case of fossil-based CCS (see W_CB710_OPT scenario results in panels a and b of Figure 1) and a maximum of 40% average cost reduction of biomass-based CCS (see 2050 result for W_CB710_OPT scenario, panel d). Solar-based technologies display the largest cost reductions: mean values are around 70% in 2050 in both W_REF and W_CB710_OPT scenarios (panel f), and already between 50% and 60% in 2030 (see panel e). Similarly, wind energy technologies show a steeper cost reduction in scenarios derived from WITCH than from the other two models (panels g and h). Largest cost reductions, reflected by the first quartile and median observed at similar levels in W_CB710_OPT in 2050, reach almost 60%, reflecting the steep cost reductions foreseen for offshore wind technologies, and less than 40% in other models' results, which present more conservative and aggregated cost reductions.

Regarding advanced fuels, the most pronounced cost reductions are observed in CB710_OPT scenarios in 2050: median values in WITCH reach 60% and, in GEM-E3, 30% (panel i). Besides these outcomes, capital cost reductions are modest or absent, especially in 2030, indicating that these technologies might need a longer development time to benefit from R&D investments. Finally, panels k and l in Figure 1 show that electric vehicles are the least affected by R&D and climate policy packages, as they display the smallest cost reductions, with ranges in CB710_OPT scenarios that are similar or more modest than in REF. This indicates that factors other than combined R&D and stringent climate policies drive capital cost reductions for EVs. Moreover, no cost reductions for this technology group are observed for MERGE-ETL because this model does not include R&D for EV batteries.

3.2. Impact of R&D on the Energy System: Technology Diffusion and Costs

With the TIAM-ECN model, we assess the impact of the different capital cost paths on the development of the global energy system up to 2050. We present results for all scenarios in Table 1, but we treat the perfect spill-over scenarios (OPS) as a variation of the OPT scenarios, thus reporting OPS always in comparison to OPT for each technology cluster.

In Figure 2, we show TIAM-ECN projections for global final energy consumption (FEC) per energy carrier. Each of the three panels corresponds to results obtained with TIAM-ECN using capital cost reductions derived from WITCH (a), MERGE-ETL (b) and GEM-E3 (c). Each bar in the chart corresponds to a specific combination of scenario and time period. Figure 2 shows that the overall trends are similar across the three panels. Total FEC grows by about 40% between 2020 and 2050 in REF, while its growth in CB scenarios is less pronounced due to climate policies triggering the deployment of high-efficiency technologies. All CB scenarios have higher consumption of electricity, biomass and hydrogen hand-in-hand with lower fossil fuel consumption compared to the corresponding REF in 2050. TIAM-ECN's CB scenarios derived from WITCH (panel a) has the largest electrification level, which relates to the steeper capital cost reduction profiles derived from this model for CCS and VRE technologies, as shown in Figure 1. In comparison, TIAM -ECN scenarios with MERGE-ETL's and GEM-E3's costs (panels b and c, respectively) present a smaller increase in electricity consumption and a larger consumption of biomass and hydrogen. Moreover, by comparing results from OPT and FIX scenarios in Figure 2, one can note that the different R&D assumptions in these two group of scenarios do not lead to observable differences in the FEC composition until 2050. This indicates that the energy transition is more influenced by the stringency of climate policy than by different R&D frameworks.

Figure 3 shows TIAM-ECN projections for total installed capacity of power plants with CCS from fossil fuels (first row) and from biomass (second row) until 2050. Scenarios derived from MERGE-ETL incorporate cost reductions from CCS in advanced fuel technologies as well, however these are allocated in results for this specific technology group (see SI for an overview of CO_2 removal per technology group in each scenario). Each line represents the yearly total installed capacity in a specific scenario. Scenarios in which capital cost reductions are derived from WITCH, MERGE-ETL and GEM-E3 results are presented respectively in shades of blue (panels a and b), orange (c and d) and green (e and f) – this colour convention is consistently applied in all line-plots in this section. REF scenarios are plotted as solid lines with empty squares. Dark shaded lines with full diamonds and light shaded lines with full circles represent, respectively, CB710 and CB1460 scenarios. Dashed lines distinguish FIX from OPT scenarios. These results show that CCS technologies are significantly deployed at similar levels in all low-carbon scenarios, indicating that CO_2 mitigation policies play a key role in stimulating CCS deployment. On the other hand, consistent with Figure 2, there is no substantial difference between OPT and FIX scenarios, which suggests that R&D policy only influences CCS technology diffusion to a limited extent. Total capacity of power plants with fossil-based CCS in 2050 is higher in CB scenarios with costs from MERGE-ETL and GEM-E3 (panels c and e) than from WITCH (a), despite the modest capital cost reductions from the former models in comparison to the latter. Higher relative dependence on fossil fuels in the power sector (see SI for a detailed Figure on the evolution of the power sector) resulting from the more conservative capital cost reductions observed for competing technologies (such as solar and wind) in MERGE-ETL and GEM-E3 may justify this difference. Regarding biomass-based CCS, CB scenarios linked to WITCH present the highest capacity level in 2050, which is consistent with the largest capital cost reduction resulting from this model.

Once we add perfect spill-over assumptions to the optimal implementation of R&D policies, we observe a higher influence of R&D on CCS diffusion. Figure 4 shows the absolute difference, in GW, of OPS scenario results relative to OPT scenarios. No difference is observed for scenarios with costs from MERGE-ETL because it considers perfect regional overspill-overs by default, but remarkable differences can be observed in scenarios derived from WITCH and GEM-E3. In both W_CB1460_OPS and G_CB1460_OPS, power plants with fossil-based CCS have higher capacity than their OPT counterparts in 2040 and in 2050. However, installed capacity is lower in the more stringent G_CB710_OPS in all years, as well as in W_CB710_OPS in 2030. A similar trend is observed in results for biomass-based CCS, especially in scenarios derived from WITCH: installed capacity is lower relative to OPT scenarios under both carbon budgets. This downward trend might be explained, by the higher deployment of competing technologies under perfect spill-overs of knowledge, although CCS remains as a key technology for decarbonization due to the persistence of coal and gas in some regions.

Figure 5 depicts TIAM-ECN projections for installed capacity of variable renewable energy (VRE) technologies: solar PV and CSP (first row) and onshore and offshore wind (second row). Long-term impacts of R&D policies are limited for both technologies, since OPT and FIX scenarios are similar. In scenarios with capital costs derived from WITCH, a significantly higher amount of solar PV is deployed (panel a) compared to the corresponding counterparts with costs from MERGE-ETL and GEM-E3 (panels c and e, respectively). These results link directly with the higher electricity share in FEC shown in Figure 2 (panel a). Figure 5 also shows that solar is fairly deployed already in W_REF, indicating that the cost reduction pathway resulting from WITCH render this technology competitive even in absence of stringent climate policies. Low carbon and R&D policy schemes enable additional cost reductions (Figure 1), but do not substantially change the diffusion of solar (Figure 5). TIAM-ECN scenarios using capital cost reductions from MERGE-ETL (panel c) and GEM-E3 (panel e) show a much lower deployment of solar, which kicks-off after 2040 in CB scenarios. In fact, capital cost reductions resulting from these models are more conservative, as discussed in section 3.1, which is a consequence of R&D investments being limited to few components of a technology and of eventual offsets from macroeconomic effects.

Wind energy capacity increases substantially in all three REF scenarios, indicating that these technologies are cost-competitive even without low carbon policies. This is especially true for TIAM-ECN scenarios with capital costs from WITCH: capacity expands worldwide up to almost 8,000 GW (panel b). Results for CB scenarios with costs from WITCH are only up to a 1,000 GW higher than REF level in 2050, but results for 2030 indicate that low carbon policies accelerate diffusion, leading to around 2,000 GW more wind power capacity in the stringent policy scenario (W_CB710_OPT) relative to W_REF. Regarding TIAM-ECN scenarios with cost reductions from MERGE-ETL and GEM-E3 (panels d and f, respectively), a larger gap in capacity observed between CB and REF scenarios reflect the more conservative average capital cost reduction in REF derived from these models, as observed in Figure 1.

We observe that R&D policies in a perfect spill-over dynamics can significantly favour the expansion of VRE technologies (Figure 6). In scenarios with costs from WITCH and GEM-E3, installed capacity is higher in OPS than in OPT scenarios: G_CB710_OPS scenario, for example, shows an increase of 1,600 GW. In fact, the lowest capital costs observed for a region is a result from GEM-E3, which in OPS scenarios is spread globally, leading to a significant capacity expansion. In that context, solar and wind energy technologies seem to become more competitive under perfect spill-over assumptions, and they can even limit the expansion of CCS in the power sector.

Figure 7 shows TIAM-ECN results for FEC of electricity (first row), biofuels (second row) and hydrogen (third row) in scenarios with capital costs from WITCH (panels a, b and c), MERGE-ETL (d, e and f) and GEM-E3 (g, h and i). The higher level of electrification in WITCH-derived scenarios, which was observed in Figure 2, is also observed here. For each of the three models, electricity consumption levels are very similar among REF and CB scenarios, and only a slight increase is observed CB710 scenarios in 2050. This links with results shown in Figure 1 for technologies in both supply and end-use side (see, in special, G_CB710 results for CCS, VRE and EVs), in which, for instance, capital cost reductions for EVs in CB710 are similar or even smaller than in REF. This illustrates how cost increases incurred from mitigation policies might offset the effects of R&D investments on technology diffusion.

Biofuels consumption in final sectors declines over time in all cases (panels b, e and h), although CB scenarios present a less pronounced decrease due to the imposed carbon restrictions. This is an indirect effect of shifting biomass resources from final sectors to the power sector, which is a way to expand biomass-based CCS technologies in CB scenarios. Regarding hydrogen consumption in final sectors, it increases to over 30 EJ/yr by mid-century in all CB_710 scenarios (panels c, f, i). Consistent with previous results, the stringency of climate policy is the main differentiator among TIAM-ECN projections, while R&D strategy and choice of IAM with ITC model used to derive the cost assumptions have a smaller impact on the results. The slightly higher levels of hydrogen and biofuels consumption in projections based on MERGE-ETL may stem from the fact that this model has a very detailed set of technologies for advanced fuels production based on these two carriers, which is reflected in the capital cost reductions incorporated in TIAM-ECN.

When we add the assumption of perfect spill-overs to the OPT scenario, we can observe that electricity consumption is slightly favoured: CB1460_OPS and CB710_OPS scenarios inherited from both WITCH and GEM-E3 show a limited increase – inferior to 5% - in consumption of electricity relative to the corresponding OPT scenarios (Figure 8, panel a). This is an effect of the higher electricity production from VRE resulting from the perfect spill-over assumption of low solar and wind energy capital costs, which drives costs down. As consequence, consumption of biofuels and hydrogen is negatively affected, especially in CB710 scenarios in 2050, leading to less consumption in OPS than in OPT scenarios, as observed in panels b and c of Figure 8.

We also look at the impact of capital cost reductions driven by R&D and climate policy on energy systems costs. The energy system contains all energy conversion routes from resource to end-use and the corresponding energy extraction, conversion, transportation, and consumption costs. Hence, its costs include not only technology capital costs, but also fixed and variable operational and maintenance costs, trade costs, and commodity prices (when applicable). In Figure 9, we show the undiscounted annual energy system cost difference of CB scenarios relative to their corresponding REF in absolute terms (billion US dollars per year). The figure includes OPT, OPS and FIX scenarios. Scenarios derived from WITCH have the lowest additional cost, which is consistent with the fact that this model provides the most optimistic capital cost reduction ranges among the three IAMs with ITC. Aligned with what has been observed regarding technology diffusion, climate policies are the main driver of energy system cost additions, resulting in similar values in both OPT and FIX scenarios. Small negative values observed in 2030 and 2040 in CB1460 scenarios relate to lower costs from trade. Cost additions are clearly lowered in OPS scenarios, in which perfect spill-overs are possible. This is observed in both CB1460 and CB710 scenarios from WITCH and GEM-E3, and notably more prominent in the more stringent G_CB710_OPS scenario – around US$ 1,000 billion difference. The steep cost reductions derived from GEM-E3, especially in technologies that are currently already well consolidated, such as solar PV and wind energy, explain this result.

4. Discussion And Conclusions

In this study, we have used three IAMs with a macroeconomic framework and ITC – WITCH, MERGE-ETL and GEM-E3 – to quantify the impact of R&D investments combined with climate policy on the capital costs of five technology clusters: solar (PV and CSP), (on- and offshore) wind energy, CCS, advanced fuels, and batteries for EVs. Capital cost reductions resulting from these models were incorporated in the global bottom-up technology-rich energy system model TIAM-ECN in order to assess how they influence technology diffusion and energy system costs until mid-century. By soft-linking WITCH, MERGE-ETL and GEM-E3 with TIAM-ECN, we create a consistent framework to analyse how R&D can accelerate the energy transition. The use of three distinct modelling frameworks enables us to reduce the uncertainty of our outcomes and strengthen our conclusions.

Our results indicate that the stringency of climate change mitigation policy is the key factor influencing the diffusion of low-carbon technologies, while R&D supports mitigation goals and impacts the relative role of key technology groups. When free regional knowledge spill-overs are possible, this effect becomes stronger and the associated costs of the energy system are lowered. This outcome is in line with current literature that indicates that R&D policy should serve as a complement to CO_2 reduction policies and not as the main means to foster mitigation. This result also emphasizes the urgency to remove barriers to technology diffusion, so that countries around the world can profit from cost savings derived from R&D.

Results from the IAMs with ITC display large variations in projected capital cost reduction paths. WITCH projects steeper average capital cost reductions – especially for solar energy and CCS - than the other two IAMs with ITC. Outcomes from MERGE-ETL and GEM-E3 indicate that capital cost reductions might be, in some cases, more conservative under stringent climate policies than in the absence of them. These variations are caused by intrinsic differences in the models' setup. Some key aspects influencing results are, for example, the regional technology portfolios in each IAM, the way in which competition among different technologies is modelled, and the extent to which specific technologies can benefit from knowledge developed abroad. In addition, models differ on how they distribute R&D investments among technology components, and how they account for wider macroeconomic implications of stringent low carbon policies, such as labour costs. Our analysis shows that climate policies might generate offsets to the benefits from R&D, and that different model frameworks give different weights to the mechanisms that trigger these offsets. By highlighting these differences, our multi-model exercise provides novel insights to policymakers interested in designing effective policy packages that harmonize R&D efforts with climate mitigation policies under diverse macroeconomic contexts.

The results obtained with TIAM-ECN show that technology diffusion trends until 2050 are robust under the different capital cost reductions generated by the three IAMs with ITC. High shares of CCS and VRE are observed in all scenarios with stringent climate policies, independently of the specific capital cost reductions considered. As climate mitigation policies are the driving factor of low-carbon technology diffusion, results for OPT and FIX scenarios are similar with regard to FEC, although OPT scenarios display slightly accelerated capacity additions for some technologies, such as CCS.

The extent to which R&D-induced cost reductions affect technology diffusion is highly dependent on the level of spill-overs across regions. As illustrated by the OPS scenarios in our analysis, in a context of perfect regional learning spill-overs – i.e. allowing all regions to fully and equally benefit from technology cost reductions - we see a stronger correlation between R&D and technology diffusion. A change in the importance of some technology groups relative to others is clearly observed. In fact, results of our OPS scenarios show that the combination of highly stringent policies with R&D investments and perfect knowledge spill-overs favours VRE technologies, reducing the amount of deployed CCS capacity. This indicates that effective R&D speeds-up the expansion of already consolidated technologies, which explains the observation that additional energy system costs with respect to REF are in general lower in OPS scenarios than in the OPT and FIX ones. From a policy perspective, this result highlights the importance of (i) designing R&D policy packages that target technologies considered to be 'low-hanging fruit', which contribute cost-effectively to the energy transition, while (ii) at the same time also providing adequate support for technologies at lower TRL levels (e.g. CCS), which still play an essential role in decarbonizing the energy system under stringent climate policy regimes.

Our study has focussed mainly on key technologies contributing to decarbonization of energy supply options in the energy system. We acknowledge that R&D efforts focussing on key technologies in end-use sectors can play a crucial role in the energy transition by both reducing costs on the demand side and by reducing the energy demand itself due to the employment of energy efficient technologies. However, the model framework adopted in this study did not allow us to zoom in these technologies due to the lack of detailing of end-use sectors in IAMs with ICT. Further improvements related to the representation of end-use sectors in all four models and the scoping of our methodological approach are desirable and should be focus of further studies wishing to inspect the impacts of R&D on the low carbon energy transition under an integrated assessment perspective.

Declarations

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Ethical Approval, Consent to Participate, Consent to Publish

The study did not involve any human subjects and/or animals.

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Authors Contributions

LPPN - conceptualization, methodology, modelling (TIAM-ECN), writing; FdL - methodology, modelling (TIAM-ECN), writing; LAR - methodology, modelling (WITCH); LD - modelling (WITCH); ZV - methodology, modelling (GEM-E3); KF - modelling (GEM-E3); EP - methodology, modelling (MERGE-ETL); BvdZ - conceptualization, writing.

Data Availability Statement

The datasets generated during and/or analysed during the current study which were not included in the manuscript and in the SI are available from the corresponding author on reasonable request.

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Figures

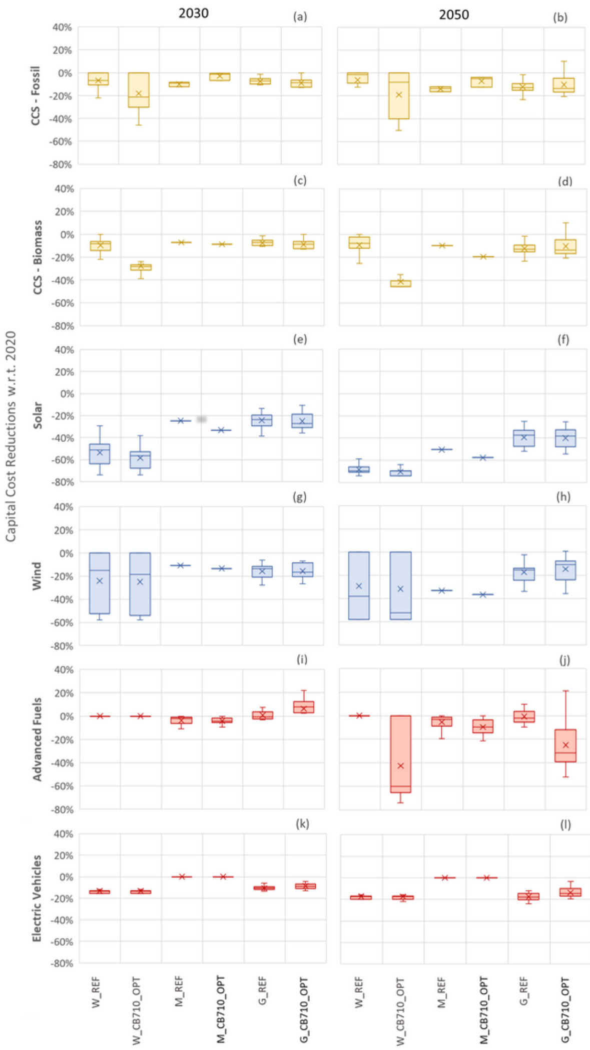

Figure 1

Capital cost reductions relative to 2020 for REF and CB710_OPT scenarios. Note: boxplots include costs of all available technologies and regions in each model. They show mean as 'x's and median as horizontal line inside the boxes.

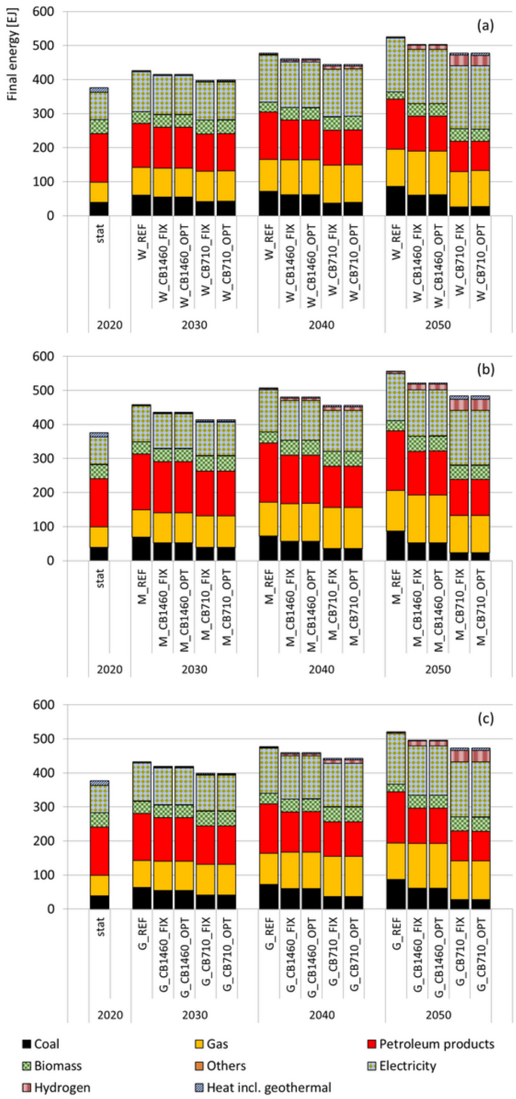

Figure 2

TIAM-ECN projections of Final Energy Consumption in Exajoules. R&D-driven technology investment cost reductions derived from WITCH (a), MERGE-ETL (b) and GEM-E3 (c).

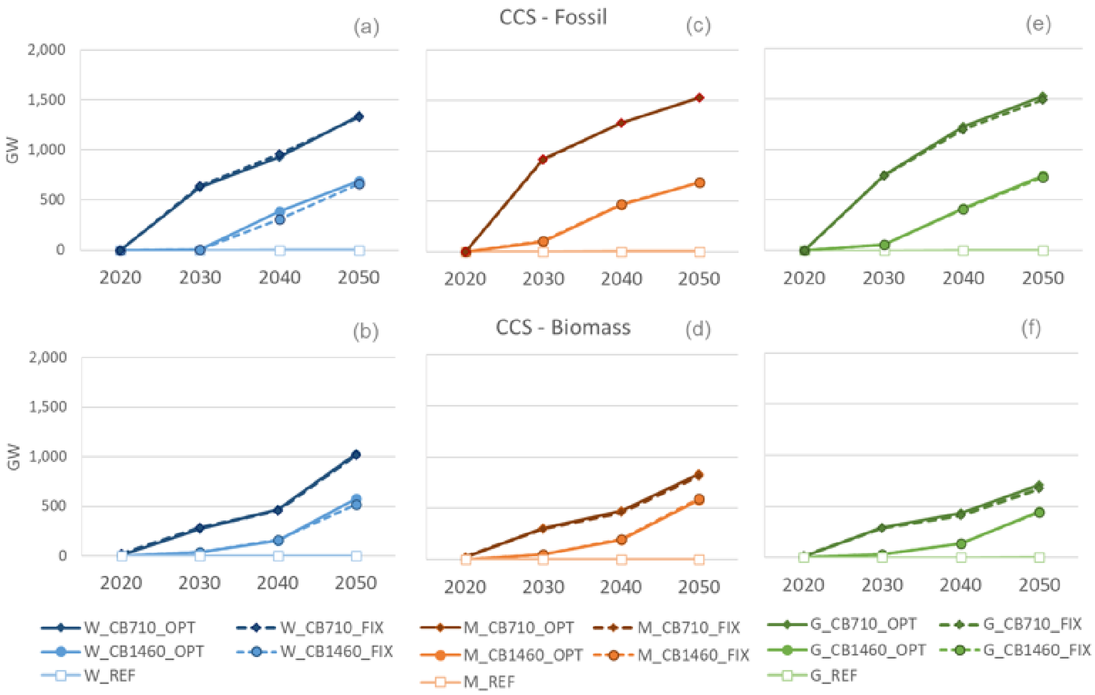

Figure 3

Total installed capacity of power plants with fossil-based (first row) and biomass-based (second row) CCS according to TIAM-ECN scenario projections. Underlying cost reductions for CCS are derived from WITCH (a and b), MERGE-ETL (c and d) and GEM-E3 (e and f).

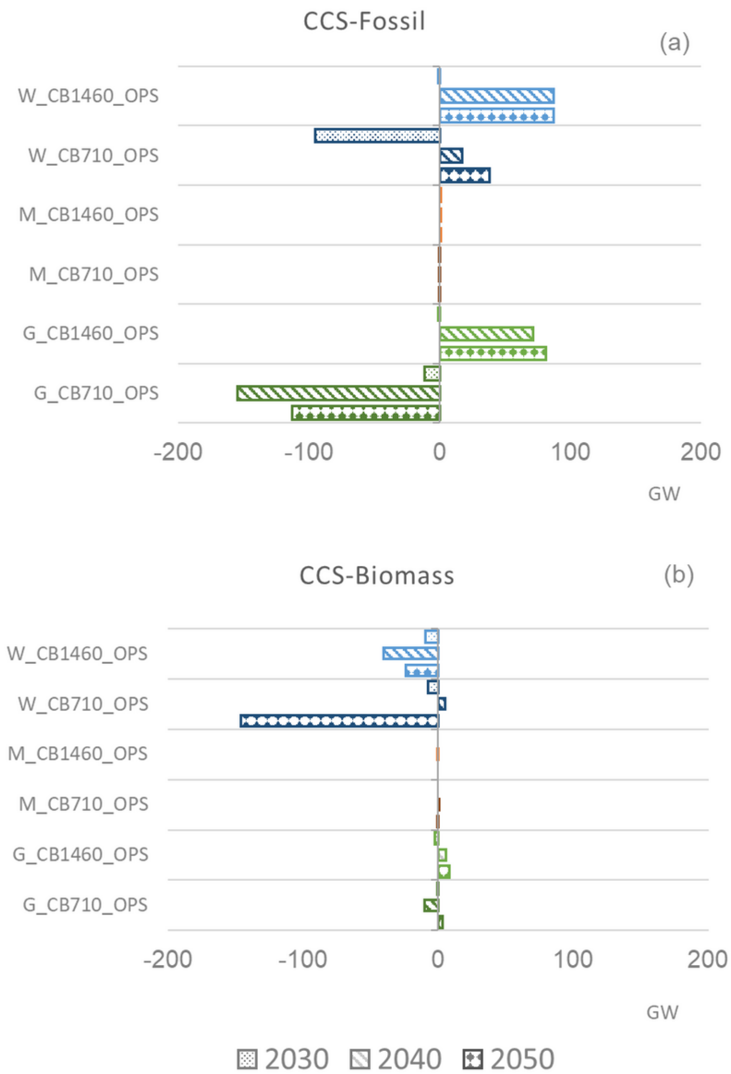

Figure 4

Perfect spill-over effect relative to OPT scenarios for CCS technologies reflected on the difference in total annual capacity.

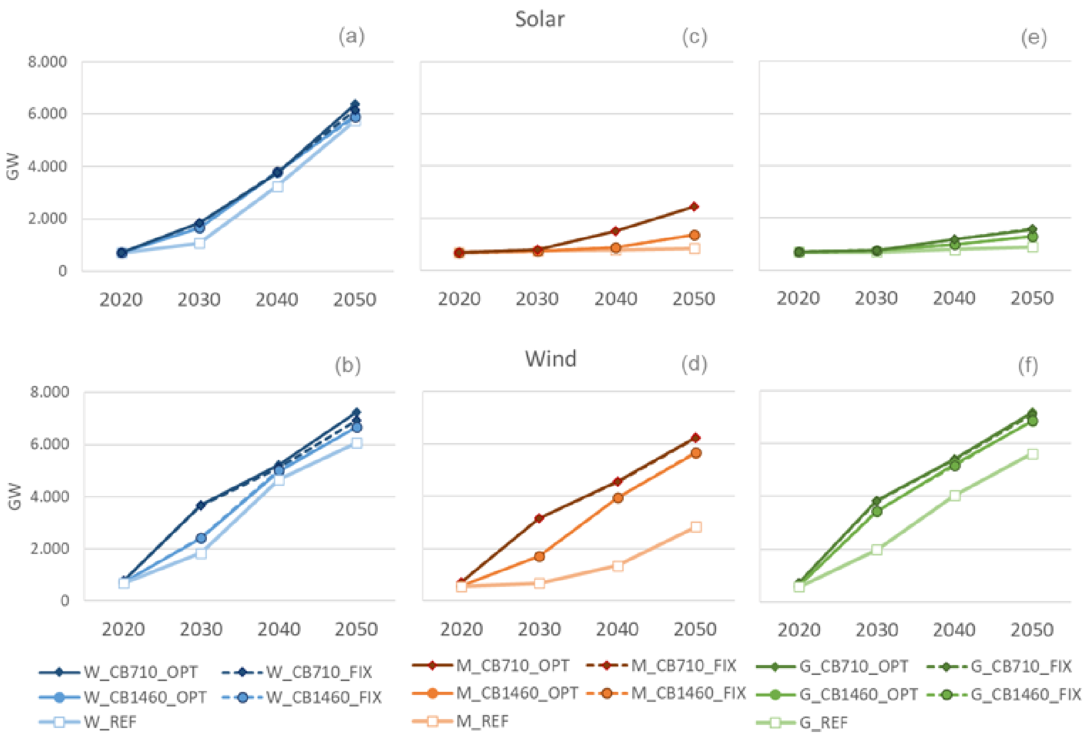

Figure 5

Installed power capacity of solar PV (first row) and wind (onshore and offshore, second row) in TIAM-ECN scenarios. Technology cost reductions derived from WITCH (a and b), MERGE-ETL (c and d) and GEM-E3 (e and f).

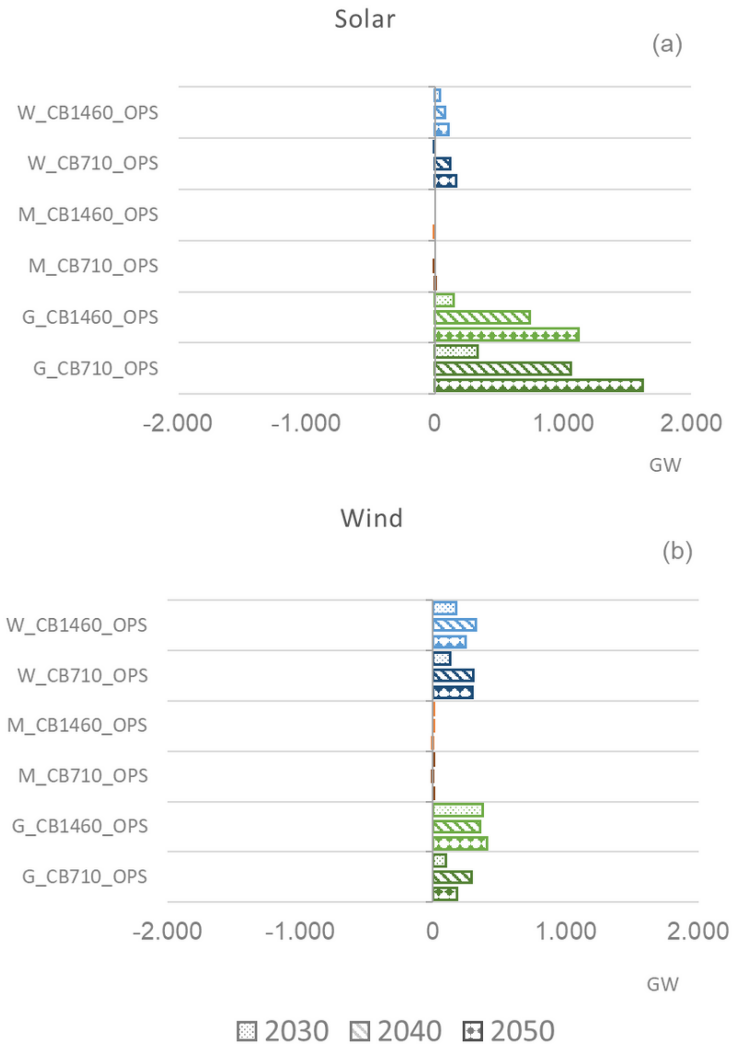

Figure 6

Perfect spill-over effect relative to OPT scenarios for solar and wind energy technologies reflected on the difference in total annual capacity.

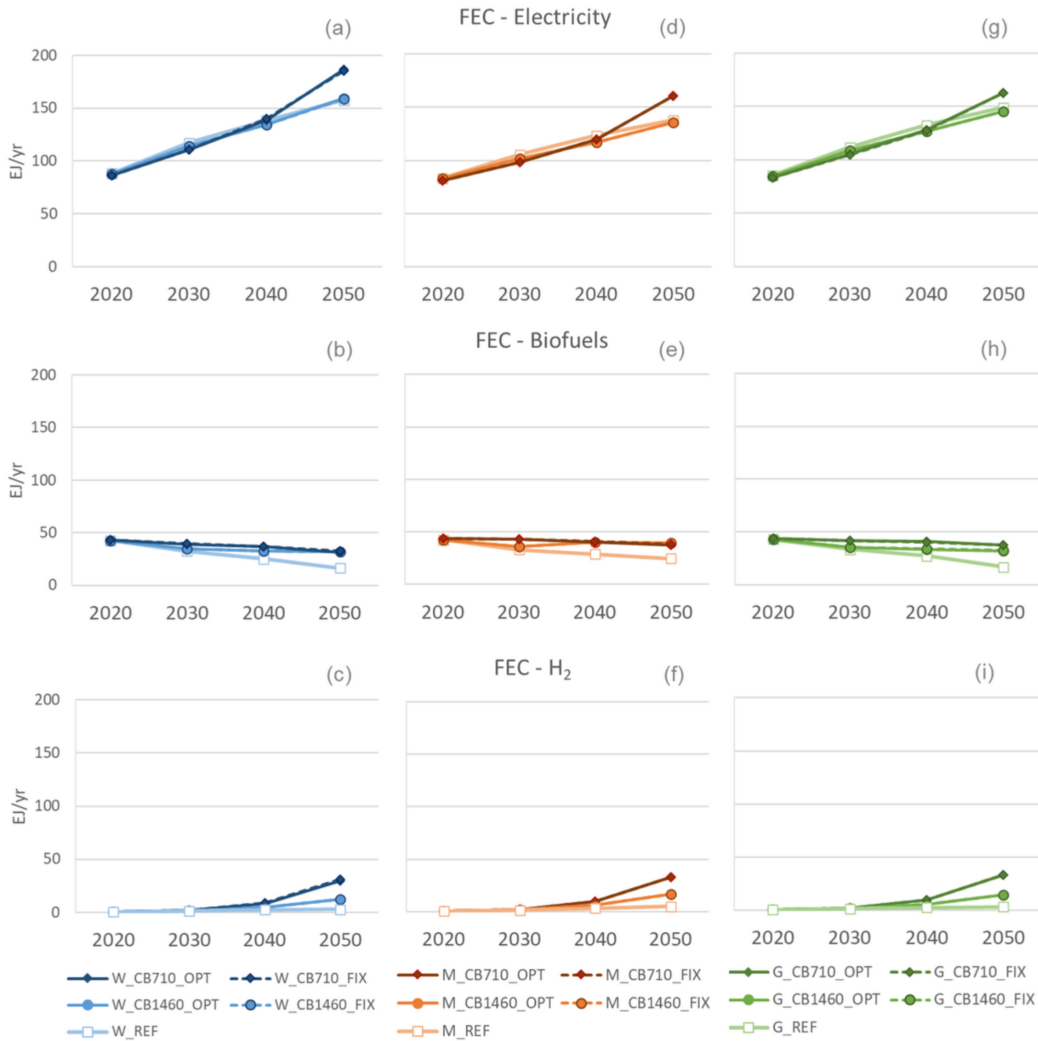

Figure 7

Final energy consumption of electricity (first row), biofuels (second row) and hydrogen (third row) in TIAM-ECN. Cost reductions derived from WITCH (a, b and c), MERGE-ETL (d, e and f) and GEM-E3 (g, h and i).

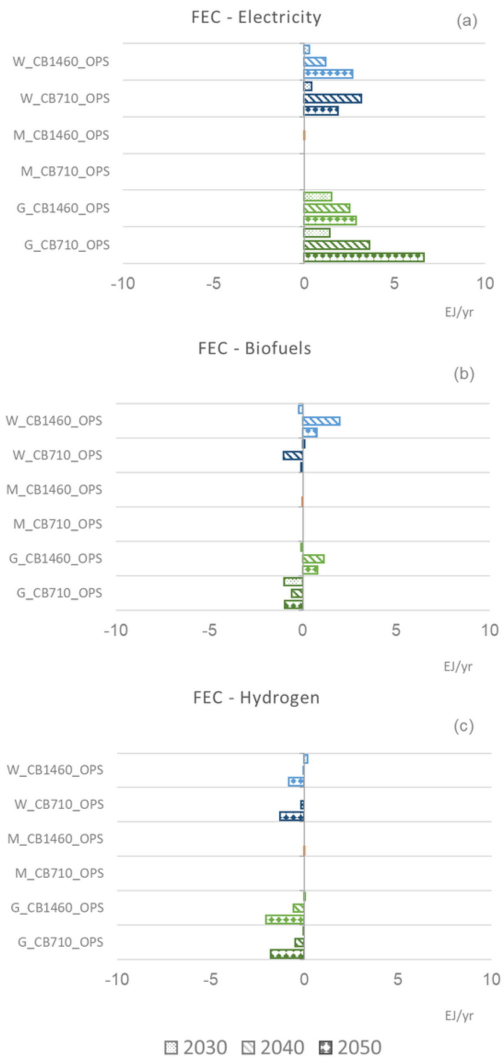

Figure 8

Perfect spill-over effect relative to OPT scenarios for electricity, biofuels and hydrogen final consumption reflected on the difference in annual final energy consumption.

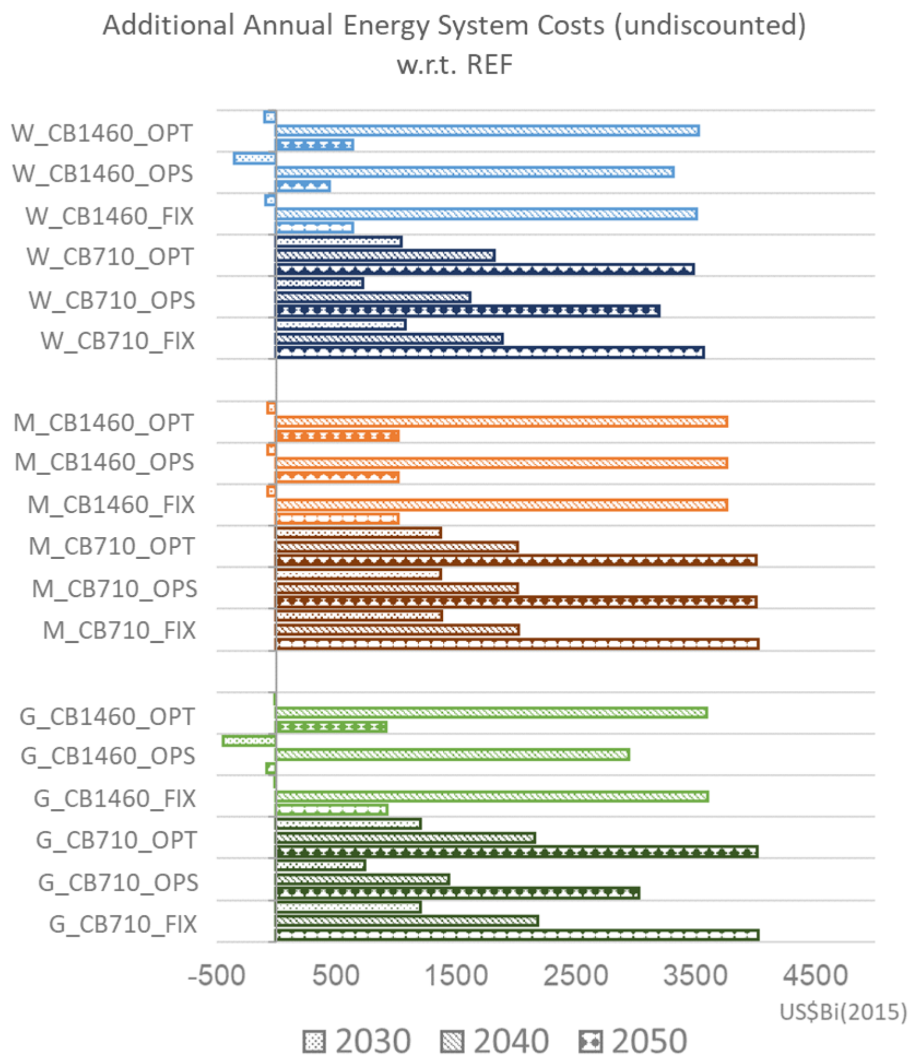

Figure 9

Additional annual undiscounted energy system costs relative to corresponding REF scenarios.

Supplementary Files

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- SupplementaryMaterial20220311blind.docx