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Future prospects of renewables, CCS, and nuclear in the European Union and beyond

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Future prospects of renewables, CCS, and nuclear in the European Union and beyond

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1. The Project

1.1 Preface

The MERCURY project – "Modeling the European power sector evolution: low-carbon generation technologies (renewables, CCS, nuclear), the electric infrastructure and their role in the EU leadership in climate policy" is a H2020-MSCA Marie Skłodowska-Curie 2015 Global Fellowship carried out by the Fellow Samuel Carrara.

The Beneficiary is Fondazione Eni Enrico Mattei (FEEM), Milan, Italy. The outgoing host is the Renewable & Appropriate Energy Laboratory (RAEL) of the University of California, Berkeley (UC Berkeley). The project Supervisor at FEEM was Prof. Massimo Tavoni until July 2018 and Prof. Manfred Hafner afterwards, while the Supervisor at UC Berkeley is Prof. Daniel M. Kammen.

The project lasted two years. It started on January 16, 2017 and it finished on January 15, 2019. The first year was dedicated to the outgoing phase at UC Berkeley, while the second year was dedicated to the return phase at FEEM.

1.2 Proposal Abstract

The reduction of greenhouse gas emissions is a vital target for the coming decades. From a technology perspective, power generation is the largest responsible for CO_2 emissions, therefore great mitigation efforts will be required in this area. From a policy perspective, it is common opinion that the European Union is and will remain leader in implementing clean policies.

Basing on these considerations, the power sector and the European Union will be the two key actors of this project. The main tool adopted in this work will be WITCH, the Integrated Assessment Model (IAM) developed at Fondazione Eni Enrico Mattei (FEEM).

The description of the power generation sector in WITCH is quite detailed, but needs to be integrated, especially as far as the electric infrastructure downstream the power generation system is concerned. In the first half of the project, developed at the outgoing host, the modeling of the electric sector will thus be completed and refined. In particular, four main aspects need to be assessed: i) system integration (i.e. the issues related to the non-negligible penetration of intermittent renewables in the grid), ii) electricity storage, iii) electrical grid, and iv) electricity trade.

In the second half of the project, developed at the return host, the improved WITCH model will be employed in scenario assessment calculations.

Firstly, the prospects in Europe of renewables, Carbon Capture and Storage (CCS) and nuclear will be analyzed. In particular, attention will be focused not so much on the pure technology aspects, but rather on policy issues such as the role of incentives in renewable diffusion, the slow CCS deployment, or the effects of the nuclear reactors ageing, or of their phase-out.

Secondly, the focus will move on assessing the role of these technologies (and the consequent evolution of the electric infrastructure) according to different mitigation scenarios, and in particular considering different levels of global participation in EU-led climate mitigation.

2. Introduction – Scope of Deliverable 2.1

Deliverable 2.1 refers to the last but one paragraph of the proposal abstract reported in Section 1.2, i.e. to Work Package 2, aimed at investigating of the prospects for the main low-carbon power technologies in Europe (renewables, CCS, and nuclear) as emerging from the present policy context.

The original title of the deliverable as conceived in the proposal was “Technology prospects: EU policy scenario”. The final title is more specific, but essentially the main focus does not change, even if the new title highlights an extension of the geographical scope: results are not presented for the European Union only, but also at a global level, essentially for the sake of comparison.

The first part of the activity focuses on renewables. Indeed there has been a slight deviation from the original plan here.

Before the beginning of the MERCURY project, in fact, the Fellow started working as coordinator of a multi-model exercise focused on learning in Integrated Assessment Models in the context of the FP7 ADVANCE project[1]. In IAMs, the cost evolution of renewable technologies is normally modeled through a learning curve, which describes the capital cost reductions deriving from dedicated R&D investments and/or from the experience gained through capacity deployment (only the latter applies to this exercise). The key parameter is the learning factor, which translates investments and capacity deployment into the actual cost reduction. The objective of the exercise is to explore different cost pathways associated to different learning rates, analyzing how

[1] http://www.fp7-advance.eu/

they influence the solar PV penetration in the electricity mix and the re-arrangement of the electricity mix itself (primarily, the impact on the other renewables).

This activity – which involves four IAMs, including WITCH of course – could not be completed within the end of ADVANCE. As one can see, the topic perfectly suits WP2 of MERCURY, and precisely the part concerning renewables, therefore the Fellow decided to absorb this activity in the relevant part of WP2.

The other two activities, instead, completely adhere to the project proposal.

CCS has widely been recognized as one of the main low-carbon solutions for the next decades, but its actual commercial maturity is yet to come. MERCURY investigates the impact of the delayed deployment of this technology from a climate, energy, and economic perspective.

Similarly, nuclear is a power technology which could play a fundamental role in future climate change mitigation, but its actual prospects are awkward in many parts of the world, especially Europe, and more in general the OECD countries. In this area, in fact, many countries revised their development plans after the incident at the Fukushima power plant in 2011. At the same time, reactors have been ageing and a considerable number are approaching the end of their operational lifetime, therefore huge investments would be needed just to maintain the same generation level. In this perspective, this task aims at exploring the real prospects of nuclear, also trying to understand the economic and policy implications of neglecting this technology in addressing climate change.

A paper has been produced for each of these three topics. The present deliverable is essentially the collection of these three papers, attached in the next pages. The relevant titles are:

- Exploring pathways of solar PV learning-by-doing in Integrated Assessment Models
- The techno-economic effects of the delayed deployment of CCS technologies on climate change mitigation
- Reactor ageing and phase-out policies: global and European prospects for nuclear power generation

Exploring pathways of solar PV learning-by-doing in Integrated Assessment Models

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Abstract

The capital cost of solar photovoltaics (PV) has constantly decreased over the past decades, and market competitiveness is not far now. The literature agrees in predicting further cost decrease in the future, even if uncertainty remains on the actual path. Most importantly, it is unclear how reducing costs will translate in actual PV penetration in the energy system in the long term. Integrated Assessment Models (IAMs) generate low carbon transition scenarios, but typically assume exogenous learning and have not explored future ranges of PV cost decline systematically. Here, we report from a multi-model comparison involving four IAMs with a twofold objective: i) explore different PV capital cost pathways deriving from different assumptions on endogenous learning-by-doing, and ii) assess the impacts that these low cost pathways have on the penetration of PV and Variable Renewable Energies (VREs) in the electricity mix.

Results show that PV penetration in the electricity mix in the long-run (average over the period 2050-2100) can range between 10-72% depending on the scenario, but that it is not very sensitive to capital cost, and responds asymmetrically to learning rates. Sensitivity of PV penetration to capital cost reduction is averagely 0.4 across scenarios. This highlights the importance of non-capital cost factors, most importantly system integration, and the competition from alternative low carbon sources, including Carbon Capture and Storage (CCS). The diffusion of PV crowds out other variable renewable energy such as wind and concentrated solar power, resulting in lowered sensitivity of the penetration of VREs to PV costs. These results point to the need to further evaluate how different low carbon alternatives interact when exploring low carbon pathways.

Introduction

In 2015, the Paris Agreement marked the path for climate change mitigation in the coming decades (Schellnhuber et al., 2016). Reaching ambitious mitigation goals compatible with the long-term target of 2°C requires an electrification of the energy sector and a parallel decarbonization of the electricity sector (Creutzing et al. , 2017, Capros et al., 2012, and Wei et al., 2013). In this perspective, the importance of solar photovoltaics (PV) as a power technology has rapidly grown in the last years, reaching 400 GW of global installed capacity in 2017 (SolarPower, 2018), and according to virtually all studies it will play a major role in the future energy scenario (Kriegler et al., 2014). One of the most important factors influencing PV penetration in the electricity mix is its investment cost. This cost constantly decreased in the past and this trend is expected to continue in the next decades (IEA, 2014 and Pietzcker et al., 2014). However, substantial uncertainty still remains on the actual future cost evolution and on the consequent impacts on PV penetration (Nelson et al., 2012 and Mileva et al., 2013). Indeed, models have regularly underestimated the speed of cost decrease of solar PV (Luderer et al., 2017) and, more in general, its share in energy projections (Creutzing et al. , 2017).

Integrated Assessment Models (IAMs) are widely used tools to explore future mitigation pathways and capture in a coherent tool the different dimensions of climate change mitigation, involving energy, economy, and the environment. In the past years, a consortium of European research teams participated in the ADVANCE project (http://www.fp7-advance.eu/), aimed at developing new modeling solutions for power sector dynamics, with a particular focus on the challenges of integrating solar and wind technologies in the electricity system (Pietzcker et al., 2017). The multi-model exercise conducted in that context highlighted once again the paramount role that Variable Renewable Energies (VREs, i.e. wind and solar), and especially solar PV, will play in future power systems (Luderer et al., 2017).

The ADVANCE exercise carried out a sensitivity analysis on the most relevant parameters affecting VRE diffusion (e.g. capital costs, resource availability), but did not perform any extensive analysis of the cost patterns related to the technology learning process. Therefore the ADVANCE teams whose models have an endogenous description of the capital cost evolution of power technologies decided to follow up the exercise exploring the impacts of the different cost patterns on PV penetration in the electricity mix and on other relevant variables. The main objective of this work is to explore different scenarios related to the possible future endogenous cost patterns of the solar PV technology and the relevant impacts on the electricity mix. To our knowledge, this is the first multi-model exercise exploring endogenous cost pathways, whereas the several cost sensitivity analyses present in the literature, as well as the IPCC reports, have always had an exogenous approach. Such an exercise also allows assessing the responsiveness of models to changes in the cost data input. A review on the PV capital cost trends over the last decades, and in particular on the learning rates which describe this trend, is also proposed.

Learning curves and learning rates

Integrated Assessment Models do not investigate the actual socio-technical dynamics that leads to cost reductions. Rather, they try to identify simplified empirical correlations which are adopted to project future patterns.The investment cost evolution for renewable power technologies in IAMs is often modeled through an endogenous learning process, mainly described according to two schemes, which can be applied singularly or jointly: learning-by-doing (LBD) and learning-by-researching (LBR). LBD relates the cost decrease to the experience gained with deployment, while LBR describes the cost decrease as a consequence of dedicated R&D investment. The vast majority of IAMs implement a one-factor learning curve according to the LBD framework, see equation (1):

$$CC_t = CC_1 \left(\frac{K_t}{K_1}\right)^{-b} \qquad (1)$$

where the ratio between the capital cost at time t (CC_t) and the initial one (CC_1) depends on the ratio between the cumulative capacity at time t (K_t) and the initial one (K_1) to the negative power of a parameter (b), which measures the strength of the learning effect. It relates to the learning rate, LR, which measures the rate at which unit costs decrease for each doubling of the cumulative capacity, through the following relationship: LR = $1\text{-}2^{-b}$. Thus, a 20% learning rate means that technology costs fall by 20% when the cumulative installed capacity doubles compared to the initial level.

Models normally include a floor cost (FC) to set a minimum price below which investment costs cannot fall. The floor cost can either be applied as a hard bound or a soft bound. In the first case, no changes are applied to the LBD formula and the cost is fixed to the floor cost once the threshold has been reached, see equation (2):

$$CC_t = max\left\{FC, CC_1 \left(\frac{K_t}{K_1}\right)^{-b}\right\} \qquad (2)$$

In the second case, the floor cost identifies the “incompressible” portion of the initial cost which cannot undergo learning (asymptotic formulation), see equation (3):

$$CC_t = FC + (CC_1 - FC) \cdot \left(\frac{K_t}{K_1}\right)^{-b} \qquad (3)$$

In this configuration, the same learning rate generates a lower cost decrease with respect to the hard bound formula.

IAMs rely on empirical evidence for the calibration of learning rate parameters. Several reviews have been carried out of the existing empirical literature on historical learning rates for power generation technologies, both in terms of LBD and in terms of LBR. Focusing on solar PV, Table SM-1 in the Supplementary Material summarizes the estimates reported in the reviews carried out in the last decade (Rubin et al., 2015, Baker et al. 2013, de La Tour et al. 2013, Junginger et al. 2008, Kahouli-Brahmi 2008, Neij 2008) along with some new econometric analyses (Witajewski-Baltvilks et al. 2015, Lee 2012).

LBD estimates a cluster around 20% of cost reduction for each doubling in the cumulative installed capacity, with a range from 9 to 47%. The broad range in estimates is due to the temporal and geographical characteristics of the data set used in the estimation, the empirical specification, and the extent to which endogeneity issues are addressed (Soderholm and Sundqvist 2007, Nordhaus 2009, Witajewski-Baltvilks et al. 2015). Witajewski-Baltvilks et al. (2015) show how LBD rates can vary when statistical uncertainty is considered and when some of the variables that are generally omitted from experience curves, such as policies and energy prices, are included.

As discussed in Sagar and van der Zwaan (2006), it is not clear how learning rates should be extrapolated when moving into the future. Soderholm and Sundqvist (2007) find that learning rate estimates over more recent periods are larger than those calculated on the full sample because of the market power that characterizes the initial diffusion of the technology, whereas the increased competition that emerged during the diffusion stage led to a faster decline in technology costs. However, bias could also go in the other direction because of diminishing returns and the difficulty of further reducing costs beyond certain levels. Additionally, what has not been fully explored is how different learning rates interact with floor cost used by some models to determine technology penetration. This is one point addressed in this work, especially considering that no estimate refers to the soft bound formulation.

Only a few estimates are available in the literature for future periods. IEA (2014) and Neij (2008) provide an estimate for LBD rates up to 2035 and 2050 respectively, whereas Verdolini et al. (2018) present a review on recent expert elicitation exercises about future cost reduction stemming from different levels of R&D expenditures, see Table SM-3. While LBR estimates tend to be lower than the few estimates reported in the empirical literature, LBD rates are not very different from the ones estimated from historical data.

Involved models and scenario design

Four IAMs agreed to take part in this exercise: IMAGE, POLES, REMIND, and WITCH, see Table 1 and Methods. Monetary values reported in Table 1 and in the rest of the paper are expressed in USD2015. All participating models implement the learning-by-doing modeling scheme, and in particular the soft-bound modeling scheme for the floor cost, with clear benefits in the exercise coherence.

	IMAGE	**POLES**	**REMIND**	**WITCH**
Model type	Partial equilibrium model	Partial equilibrium model	General equilibrium model	General equilibrium model
Solution method	Recursive dynamic simulation	Recursive dynamic simulation	Intertemporal optimization with perfect foresight	Intertemporal optimization with perfect foresight
Temporal horizon	2100	2100	2100	2100
PV cost calculation	Endogenous	Endogenous	Endogenous	Endogenous
Type of endogenous modeling	One-factor learning curve (LbD)	One-factor learning curve (LbD)	One-factor learning curve (LbD)	One-factor learning curve (LbD)
Regional differentiation	Yes, with (limited) spillover effects on learning	No, only one global cost	No, only one global cost	No, only one global cost
Type of floor cost	“Soft bound” (asymptotic floor cost)	“Soft bound” (asymptotic floor cost)	“Soft bound” (asymptotic floor cost)	“Soft bound” (asymptotic floor cost)

Plant depreciation	Linear	Linear	Concave	Exponential
Depreciation rate	0.1	0.04	-	0.044
Lifetime [years]	25	25	30	25
Investment cost in 2015 [$/kW]	1576	1924	1916	1879
Learning rate	20%	15%	20%	20%
Floor cost [$/kW]	433	619	458	495
References	de Boer and Van Vuuren, 2017	Després et al., 2017	Ueckerdt et al., 2017	Emmerling et al., 2016 and Carrara and Marangoni, 2017

Table 1 – Main features of the models participating in the exercise.

The exercise consists in a sensitivity analysis on the two main learning parameters: the learning rate and the floor cost. In particular, a matrix of fourteen main cost scenarios is considered: seven learning rate cases (reference and ±25%, ±50%, and ±75% with respect to reference) combined with two floor cost cases (with and without floor cost).

The choice of the learning rate cases derives from an empirical estimate on the PV learning rate carried out in the context of the ADVANCE project (Witajewski-Baltvilks et al., 2015) which identifies i) 19% as the mean of the relevant normal distribution, and ii) the relative variations of ±25%, ±50%, and ±75% as the ±σ, ±2σ, and ±3σ values, respectively. The reference learning rate is meant to be the default one of the single model. No harmonization efforts have been made across models, considering their calibration needs which might lead to different choices within a reasonable range. Indeed, all models implement a learning rate of 20%, with the exception of POLES (15%).

The no floor cost case, especially if coupled with high learning rates, might well lead to an extreme condition where the PV investment cost approaches zero. This is obviously a hardly policy-relevant scenario, but it is useful to conduct diagnostic runs to check the behavior of models in such a configuration and compare their outcome (Kriegler et al., 2015).

These scenarios are explored in a standard mitigation policy, where a carbon tax is applied in order to achieve a long-term target of limiting the temperature increase in 2100 with respect to the pre-industrial levels below 2°C with a likely chance, in line with the Paris targets. In detail, the tax starts in 2020 and is calibrated so as to reach a global cumulative amount of CO_2 emissions equal to 1000 Gt in the period 2011-2100 in the reference scenario. The same tax is then applied to all the other mitigation scenarios. No further sensitivity analysis is conducted on the policy dimension, since this aspect is not within the scope of this work (in any case it has been thoroughly addressed in many other research works). A baseline case (no policy) is added for benchmarking purposes, considering the two scenarios with and without floor cost. The total is thus sixteen scenarios, detailed in Table SM-4.

Results

The set of explored learning rates produces a wide range of capital cost patterns throughout the century, see Figure 1 (IMAGE reports the global average cost weighted on PV capacity in the different regions). This range practically covers all the possible cost futures. All models show a robust behavior with this respect. In the baseline case, costs span a range of 1057-1316 $/kW in 2050 and 571-1027 $/kW in 2100. In the reference mitigation case, the range is 665-1156 $/kW in 2050 and 495-981 $/kW in 2100. In the most pessimistic scenario (MIT-LR-75m-FC-ref) the range is 1467-1726 $/kW in 2050 and 1348-1512 $/kW in 2100, while in the most optimistic scenario (MIT-LR-75p-FC-0) the range is 53-273 $/kW in 2050 and 21-73 $/kW in 2100. The pessimistic scenario considers the hypothesis of essentially no cost decrease over the century (the average cost decrease is only 20% across models), while the lower bound reached in the optimistic scenario essentially corresponds to a null cost. Both configurations are unrealistic, but as already noted it can be interesting to stress models in these extreme conditions.

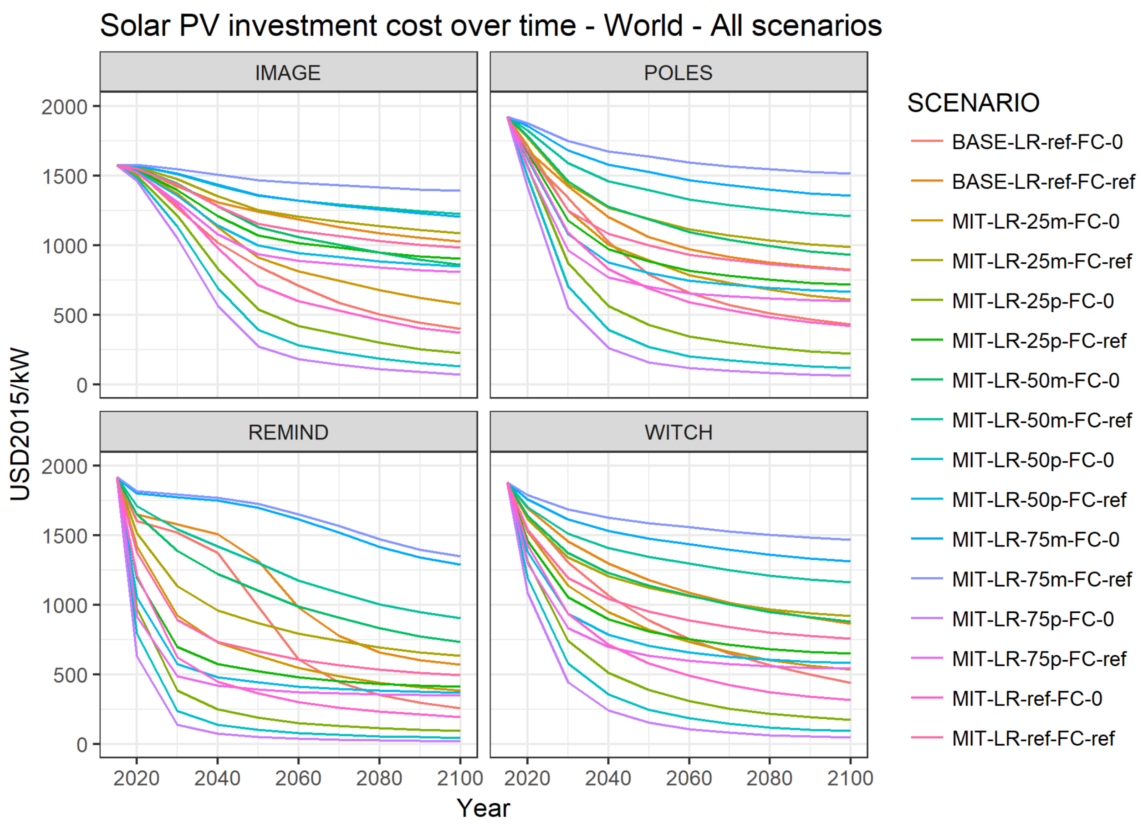

Figure 1 – Global solar PV investment cost over time. Scenario names are defined as follows: policy (BASE = baseline or MIT = mitigation), learning rate (ref = reference learning rate, 25m = ref-25%, 50m = ref-50%, 75m = ref-75%, 25p = ref+25%, 50p = ref+50%, 75p = ref+75%), floor cost (ref = reference floor cost, 0 = no floor cost).

As predictable, the different cost pathways lead to very different PV penetration levels in the corresponding scenarios. The interesting insight, however, is that comparable cost patterns lead to marked differences across models. Figure 2 provides a more detailed overview of the average PV penetration over the period 2050-2100 in the sixteen scenarios, dividing between the two cases with and without floor cost. Average results in the 2050-2100 period are shown in order to discuss long-term trends without focusing on any specific year. In general, scenarios without the floor cost show higher penetration than scenarios where the reference floor cost is applied, as in the latter case the learning effect operates on a limited portion of the initial cost and thus the cost decrease is faster. It is interesting to note that REMIND, which shows the highest PV penetration levels, also shows the highest sensitivity to learning rates. In particular, the average PV penetration in 2050-2100 in the reference mitigation scenarios is 53% with floor cost and 67% without floor cost, respectively. The range comprised between the LR-75m and LR-75p scenarios is 13-62% with floor cost and 14-72% without floor cost (baseline scenarios are excluded from this account as they are reported only as benchmarks). On the opposite side, not only is POLES the model generating the lowest PV penetration levels, but it is also characterized by the lowest elasticity, especially in the scenarios with floor cost. More in detail, PV penetration in the reference mitigation scenarios is 17% with floor cost (with a range of 14-18%) and 20% without floor cost (with a range of 14-29%), respectively. IMAGE and WITCH show intermediate and very similar results. In IMAGE, the average PV share is 16% in the reference mitigation scenario with floor cost (range: 10-19%) and 27% without floor cost (range: 12-39%), while for WITCH the corresponding results are 19% (range: 12-24%) and 26% (range: 13-35%), respectively.

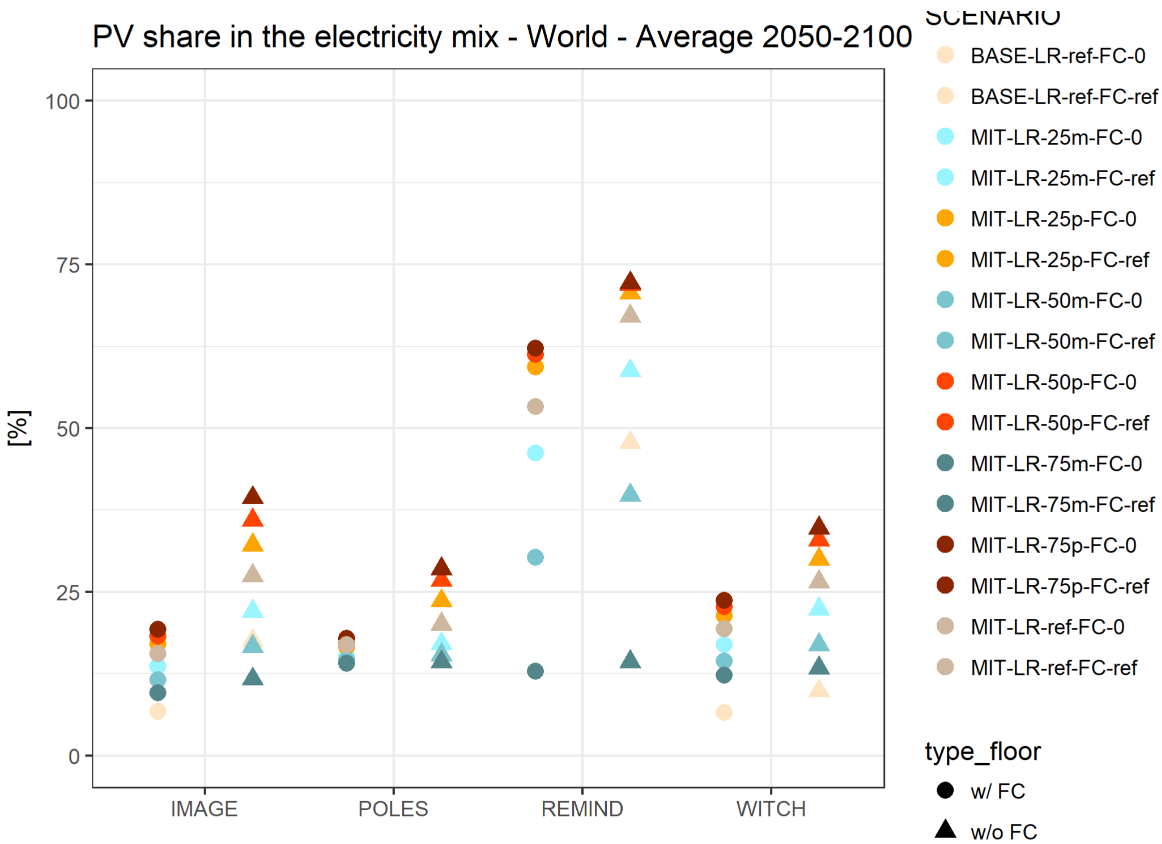

Figure 2 – Global solar PV share in the electricity mix (average 2050-2100).

Three main insights can be drawn from these results. First, despite the huge differences in the explored cost patterns, most models show a relatively modest sensitivity in terms of PV penetration. The most evident case is given by POLES in the scenarios with floor cost: PV penetration is practically insensitive to capital cost changes and remains restricted to a four-percentage point range. In this perspective, only REMIND is a clear outlier, showing a huge sensitivity to capital costs. Second, even in the extreme cases where PV can be installed practically for free, penetration does not reach particularly high levels, and in all models except REMIND it remains well below 50%. Third, in all models and in both floor cost configurations, PV penetrations show an asymmetric behavior, tending to collapse towards a sort of upper bound: this means that models show higher sensitivity to lower learning rates than to higher learning rates. This fact is highlighted in Figures SM-1 and SM-2 in the Supplementary Material, which explicitly show the relative variation of PV penetration in the different learning rate scenarios centered on the reference case, with and without floor cost, respectively.

Figure 3 provides a full overview of the PV penetration as a function of the relative cost reduction with respect to 2015, in order to quantify the sensitivity of PV penetration to capital cost reductions.

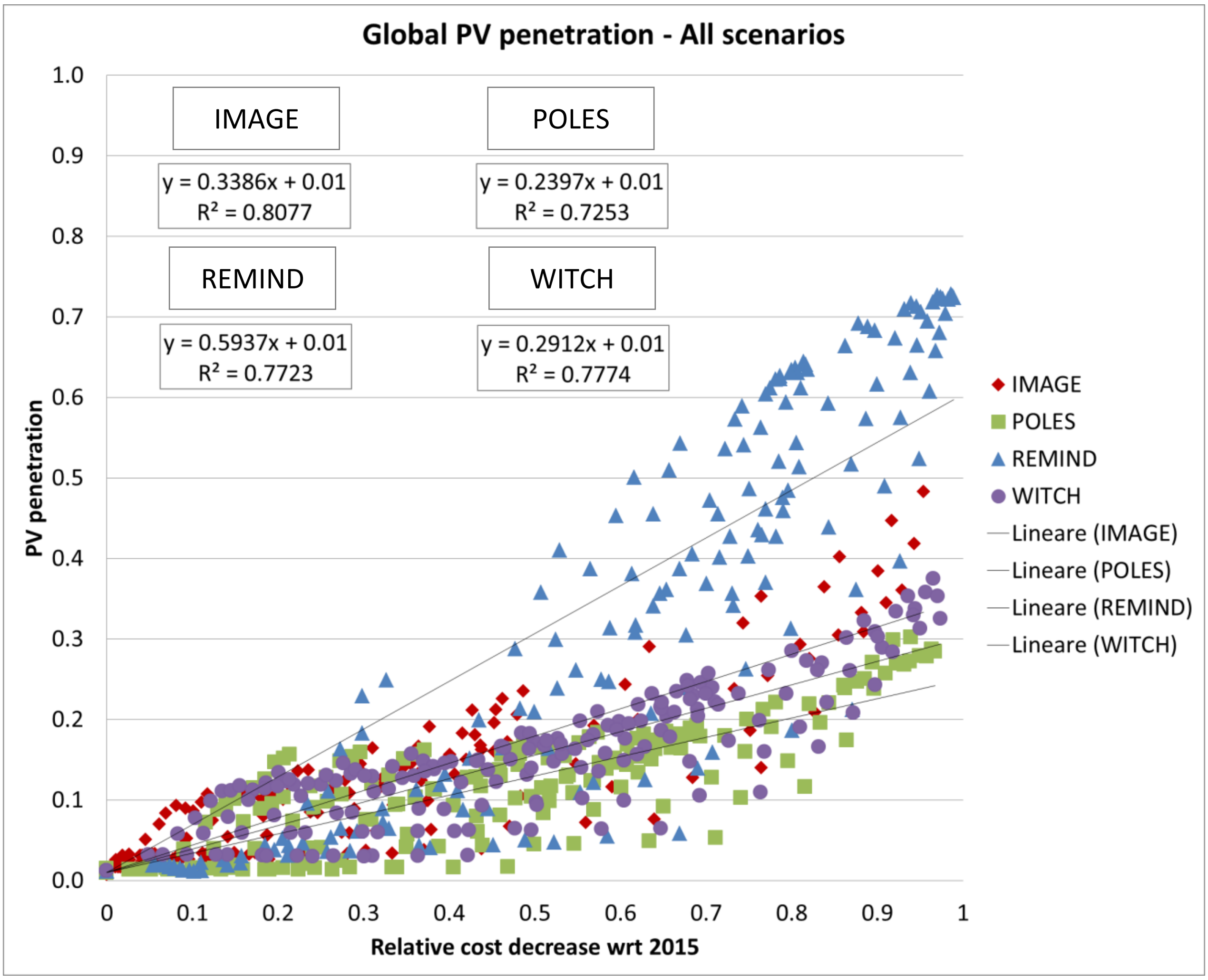

Figure 3 – Global PV penetration: sensitivity to cost reduction (each point corresponds to one specific year, independently of the scenario to which it belongs). The interpolating line starts from 0.01 on the y-axis as this is the global PV penetration in 2015.

REMIND shows the highest sensitivity, being equal to 0.59 (every percentage point of cost decrease implies an increase of 0.59% in PV penetration). The other three models show a similar sensitivity: IMAGE 0.34, POLES 0.24, WITCH 0.29. The overall average is 0.40. Results are indeed quite different between the two halves of the century, as shown in Figures SM-5 and SM-6. In the period 2015-2050, the average sensitivity is 0.31 (IMAGE 0.20, POLES 0.19, REMIND 0.46, WITCH 0.24), while in the period 2050-2100 the average sensitivity is 0.46 (IMAGE 0.39, POLES 0.28, REMIND 0.72, WITCH 0.33).

Models clearly show that with cost collapsing to zero (i.e. to a relative cost reduction equal to 1), PV penetration is well far from 100%. Rather, a general accumulation towards a sort of boundary is found (with the partial exception of IMAGE). This highlights the importance of non-capital cost factors, especially system integration, and the competition with other low-carbon technologies in achieving mitigation targets. In this perspective, however, it is important to note that the exercise is not focused on discussing the feasibility or the implications of a fully-solar or fully-renewable electricity mix (see for instance the debate in Jacobson et al., 2015 and Clack et al., 2017). It considers solar PV given its historical and projected cost evolution, but the framework could be applied to any similar technology.

How are the different PV penetration levels reflected on the overall penetration of Variable Renewable Energies? Figure 4 reports the average VRE penetration in 2050-2100 in the explored scenarios, replicating the graph regarding PV penetration of Figure 2. It is noted that in this work, VREs comprise wind and both solar technologies, i.e. PV and CSP (Concentrated Solar Power), coherently with Pietzcker et al., 2017.

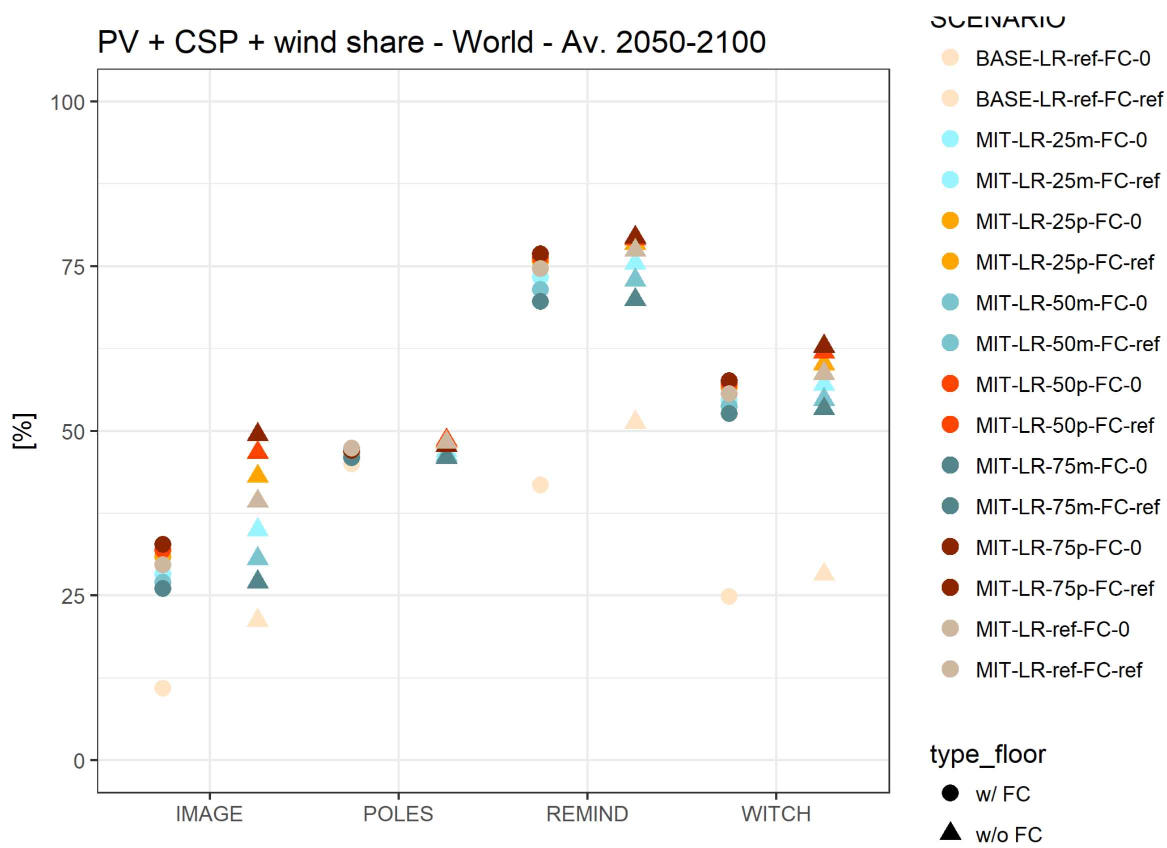

Figure 4 – Global VRE share in the electricity mix (average 2050-2100).

With the partial exception of IMAGE, VRE penetration appears practically insensitive to the different PV capital cost paths. This is observed both in terms of reduced distance between scenarios within each of the two floor cost configurations and across the two floor cost configurations. Essentially, the higher/lower PV penetration associated to the different capital cost patterns occurs to the detriment/benefit of wind and CSP. In other words, wind and CSP almost completely compensate the variations related to PV. This result is particularly remarkable in REMIND, which is characterized by a very strong sensitivity as far as the mere PV share was concerned. If the floor cost is applied, this model shows a VRE penetration of 75% (range: 70-77%), while penetration is equal to 77% (range: 70-79%) if no floor cost is considered. A similar sensitivity range characterizes WITCH: VRE penetration in the reference case is 56% (range: 53-58%) with floor cost, while it is 59% (range: 53-63%). POLES shows practically no sensitivity: VRE penetration is clustered in the range 46-47% with floor cost and in the range 46-48% without floor cost. As said, IMAGE is the only model showing a significant residual sensitivity: in the scenarios with floor cost, indeed VRE penetration does not vary markedly, being 30% in the reference case and showing a range of 26-33%. Scenarios without floor cost have a higher dispersion, instead: the result in the reference case is 39%, while the range is 27-49%.

This limited variability is clearly reflected in the relative variation of VRE penetration in the different learning rate scenarios centered on the reference case which is shown in Figures SM-12 and SM-13.

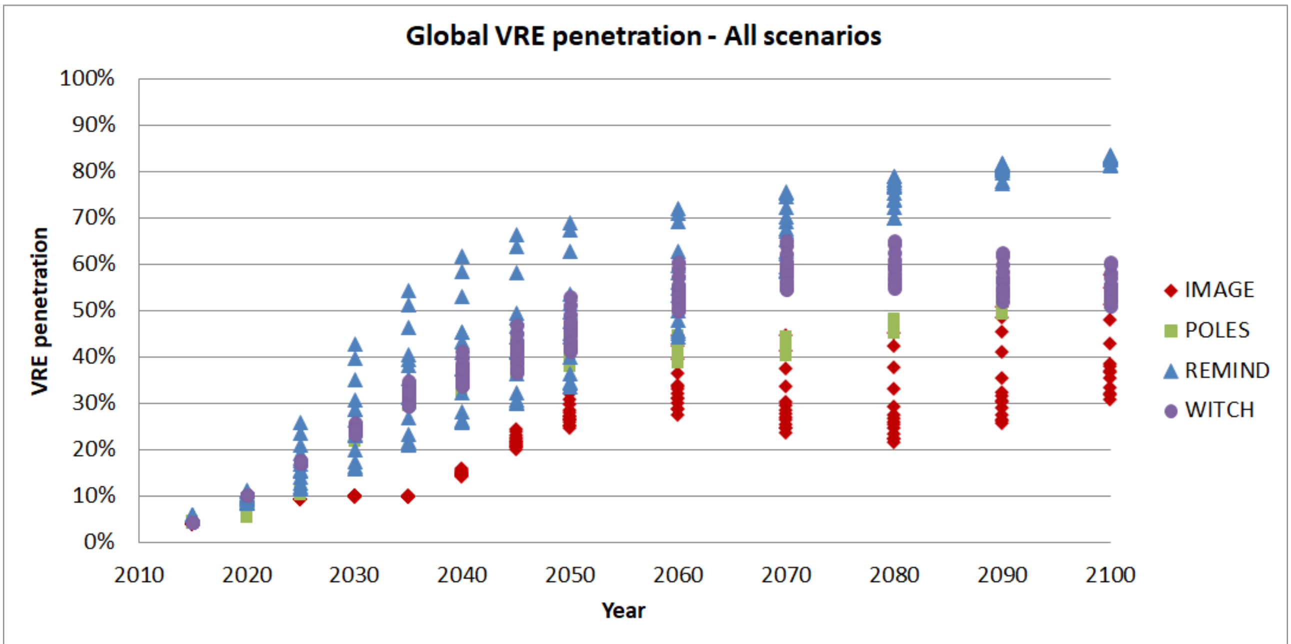

Figure 5 – Global VRE penetration.

It is interesting to note that here a clear collapse towards a sort of upper boundary is observed in REMIND only, see Figure 5. In fact in this model the VRE penetration monotonously grows over time and the broad variability found in the first half of the century progressively disappears as VRE penetration converges to about 83%. This result is in line with Luderer et al. (2017), which describes the main set of scenarios carried out in the ADVANCE exercise mentioned at the beginning of this paper. That multi-model exercise explored, among others, a scenario where the Levelized Cost Of Electricity (LCOE) of VREs was aligned with the lowest among traditional technologies (typically coal), showing that VRE penetration even in this generous case would not exceed 70-80% on average across models on average in the period 2050-2100. This result highlighted that the integration challenges, i.e. the issues related to the non-negligible penetration of variable power sources in the electricity grid, are of paramount importance and, in general, have an impact which is comparable to direct technology costs. POLES too shows a monotonous behavior and a sort of convergence towards an asymptotic value, even if this value is around 50%, well below the “integration threshold” found in Luderer et al., 2017. As a consequence, the limited variability has to be explained with “internal” modeling reasons. This also applies to WITCH, which does not show any clear boundary level: the evolution of VRE penetration freely follows its path, with a mutual “exchange” of the PV, CSP, and wind contributions depending on the PV cost pattern. The limited sensitivity shown by WITCH can be explained with the Constant Elasticity of Substitution (CES) framework that characterizes this model. In a CES structure, inputs are combined in a production function with a level of substitutability defined by the relevant elasticity (in this case, inputs are the energy generation contributions from the different technologies). Lower-than-infinite elasticities imply that the inputs are not linearly combined, i.e. they cannot be considered completely substitutable. This framework is adopted in order to implicitly model what in reality is experienced as preference for heterogeneity: with a fully-linear, unconstrained framework, the energy system would be dominated by the cheapest technology, whereas in reality the market is characterized by a plurality of choices, driven by a wealth of social, political, and technological aspects which cannot fully be translated into simple economic constraints. Carrara and Marangoni (2017) discuss the benefits of choosing an intermediate elasticity in the node combining the VRE and non-VRE inputs in WITCH. Still, the CES structure is such that variations in one input (in our case, different levels of PV generation derived from variable capital costs) have a primary impact on the closest CES nodes (hence, wind and CSP) and only secondarily on the other technologies. Finally, in IMAGE the sensitivity increases over time instead of diminishing. In this case, neither a real barrier due to the integration challenges nor specific internal constraints seem to be present, allowing higher flexibility in response to the different PV cost inputs.

It is finally interesting to analyze how the different PV and VRE penetration levels impact on the overall electricity mix (Figure 6).

In the baseline scenario with floor cost, models project quite a similar global electricity demand averaged over the period 2050-2100, comprised between 290 EJ/yr (IMAGE) and 343 EJ/yr (WITCH). To put these numbers in perspective, this means about a threefold to fourfold increase from the 87 EJ/yr registered in 2015 (IEA, 2107). The no policy scenario results in a dominance of fossil-based plants in IMAGE: coal and gas production sum up to 74% of the whole generation, while VREs are limited to 11%. On the other hand, POLES and REMIND envisage a strong decarbonization even in the absence of mitigation policies: VREs account for 45% and 42% of the electricity mix, respectively, even if with a prevalence of wind in POLES (27%-18%), while solar – almost completely PV – prevails in REMIND (33%-9%). WITCH shows an intermediate result: 25% of VRE penetration, with prevalence of wind (17%-8%).

Several research works have highlighted that the mitigation of greenhouse gas emissions can have opposite effects on the electricity demand: if energy efficiency measures prevail, demand is likely to decrease with respect to the baseline projections, whereas if a strong electrification of the energy sector coupled with a decarbonization of the electricity sector prevails (especially based on renewables), demand is likely to increase. The models involved in this exercise show quite a diverse behavior: focusing on the reference mitigation case with floor cost (MIT-LR-ref-FC-ref), IMAGE shows the first trend (the average 2050-2100 global electricity demand decreases to 224 EJ/yr), REMIND shows the second trend (demand rises up to 423 EJ/yr), while the two effects tend to compensate in POLES (310 EJ/yr) and WITCH (357 EJ/yr). Unsurprisingly, the electricity mix is dominated by VREs in REMIND (75%), while “centralized” technologies, i.e. Carbon Capture and Storage (CCS), nuclear, and hydro have the lion’s share in IMAGE

(67%), with VREs accounting for 30% only. Intermediate results are found in POLES and WITCH, where VREs account for 47% and 56% of the electricity mix, respectively (interestingly, in POLES it is about the same level found in the baseline scenario).

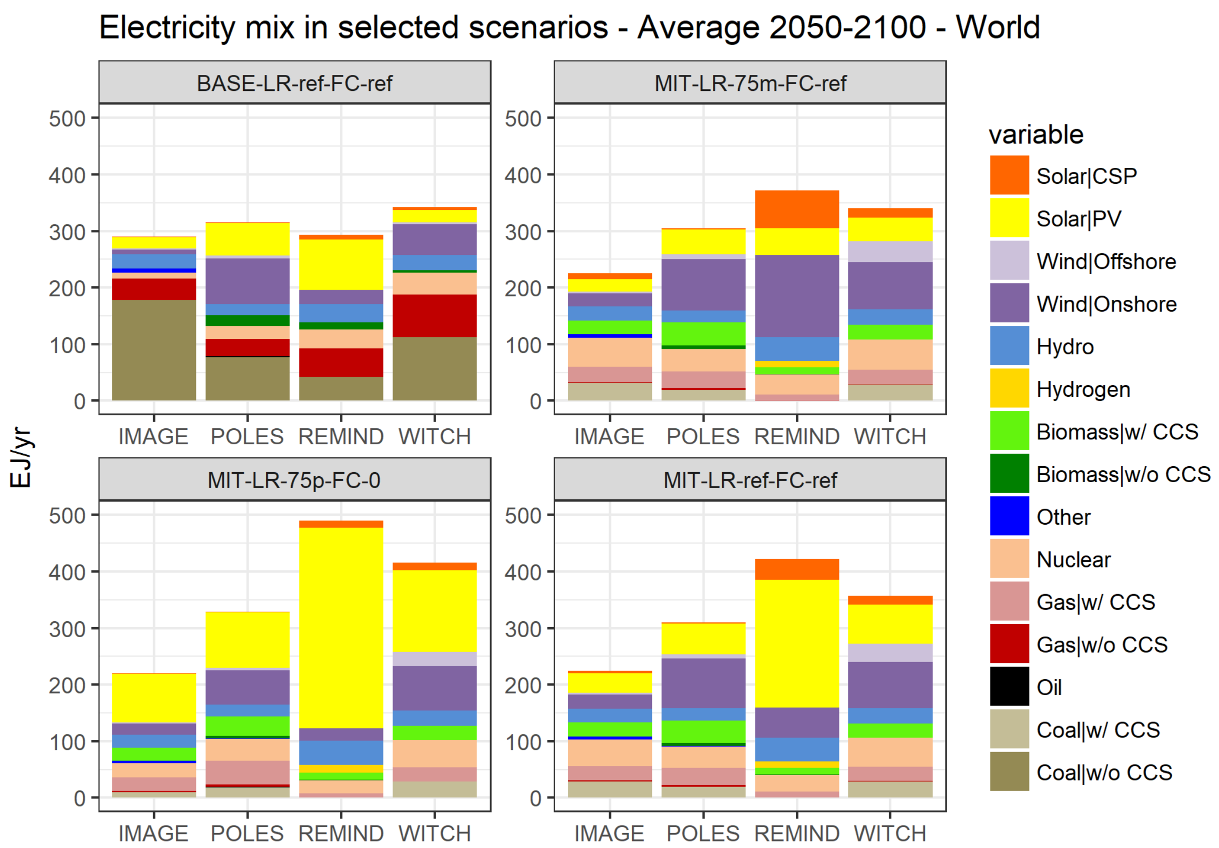

Figure 6 – Electricity mix in selected scenarios (BASE-LR-ref-FC-ref, MIT-LR-ref-FC-ref, MIT-LR-75m-FC-ref, MIT-LR-75p-FC-0).

Conclusions and discussion

This paper describes a multi-model exercise aimed at exploring different endogenous learning routes applied to solar PV and their impacts on PV penetration in the electricity mix. The exercise involves four Integrated Assessment Models which describe the cost evolution of solar PV according to a learning-by-doing framework with floor cost. Scenarios are explored on a standard mitigation policy compatible with the Paris targets and cover a wide variety of cost patterns compatible with any reasonable cost futures.

Global PV penetration in the long run (in particular, averaging over the 2050-2100 period) spans a range of 10-72%, with a marked growth with respect to the current 1% in all scenarios and models. Despite the marked variation of costs and the variability observed across models, all models tend to show a limited sensitivity to PV penetration in their specific results. Sensitivity of PV penetration to capital cost reduction is averagely 0.4 across scenarios, being lower in the first half of the century (0.31) than in the second half (0.46). Sensitivity is not symmetric with respect to increasing or decreasing learning rates, being markedly higher for the latter. Indeed, all models tend to show a sort of "threshold" on which PV penetration tends to collapse even in the most favorable scenarios. This highlights the role of non-capital cost factors, especially system integration, and the competition with alternative low carbon sources, including Carbon Capture and Storage. In this regard, it is reminded that it is not within the scope of this work to discuss the feasibility or the implications of reaching a fully-solar or fully-renewable electricity portfolio. Sensitivity to PV capital cost even diminishes when all variable renewable energies (i.e. wind and solar CSP in addition to PV) are focused. This means that, according to the models participating in this exercise, competition of solar PV takes place primarily with wind and CSP, and the higher/lower penetration related to lower/higher capital costs mainly occurs to the detriment/benefit of these technologies. This is partly explained with modeling reasons (e.g. the role of the Constant Elasticity of Substitution framework in the WITCH model), but also suggests the need for further research concerning the competition within variable renewable energies, and between them and the other power technologies, which indeed is not within the scope of this work.

Acknowledgments

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Exploring pathways of solar PV learning-by-doing in Integrated Assessment Models – Supplementary Material

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Learning-by-doing in solar PV: evidence from the existing literature

Soderholm and Sundqvist (2007) show that explicitly accounting for economies of scales reduces learning-by-doing (LBD) rates, suggesting that if this driver is not modelled, LBD rates are upward biased. Soderholm and Sundqvist (2007) show that including a time trend so as to capture any underlying change in trend other than R&D knowledge stock or installed capacity absorbs all variation otherwise captured by the R&D stock, whereas LBD rates are quite stable, especially when endogeneity issues are taken into account.

Most IAMs use an approach based on endogenous technological change modelled through a one-factor learning curve (LBD) as described in equations (1) and (2). This is the case for E3MG, IMACLIM, IMAGE-TIMER, REMIND and WITCH. A few models (MERGE-ETL, POLES – but not in the version adopted in this work) use a two-factor learning curve for endogenous technological change, considering both the effects of learning-by-doing and learning-by-researching, whereas some other models (e.g. MESSAGE and GCAM) use an exogenous technical change by defining different investment costs for future periods (which vary according to reference/policy scenarios). Table SM-2 summarizes the learning rates and the floor costs used by the IAMs with endogenous technological change. Since models rely on empirical literature, it is not surprising that the range of LBD rates in terms of minimum, maximum and mean values is similar to the range emerging from the empirical literature in Table SM-1.

Source	# Factors	Rate	LR (%)			Timeframe	Method
			min	**max**	**mean**		
Baker et al. (2013)	1	LBD	17	35	20	na	Review
Junginger et al. (2008)	1	LBD	10	47	22	1957-2006	Review
Kahouli-Brahmi (2008)	1	LBD	18	35	23	1959-1998	Review
La Tour et al. (2013)	1	LBD	10	30	21	1965-2005	Review
Lee, conference proceeding (2012)	2	LBR	9	15	11	2001-2010	Regression analysis
Lee, conference proceeding (2012)	2	LBD	10	10	10	2001-2010	Regression analysis
Neij (2008)	1	LBD	10	47	20	1976-2001	Review
Rubin et al. (2015)	1	LBD	10	47	23	1959-2011	Review
Rubin et al. (2015)	2	LBR	10	14	12	1971-2001	Review
Rubin et al. (2015)	2	LBD	14	32	18	1971-2000	Review
Witajewski-Baltvilks et al. 2015, Mod 1	1	LBD	9	33	20	1990-2012	Regression analysis
Witajewski-Baltvilks et al. 2015, Mod 2	1	LBD	10	46	27	1990-2012	Regression analysis

Witajewski-Baltvilks et al. 2015, Mod 3	1	LBD	10	29	19	1990-2012	Regression analysis
Witajewski-Baltvilks et al. 2015, OLS	1	LBD	10	14	12	1990-2012	Regression analysis

Table SM-1: Learning rate estimates based on the empirical evidence.

Source	**# Factors**	**Type**	**LR (%)**			**Timeframe**	**Floor cost**
			min	**max**	**mean**		**(2015$/kW)**
E3MG (Edenhofer et al. 2010)	1	LBD	na	na	30	Constant	1546
IMACLIM (Bibas et al. 2012)							
central station PV	1	LBD	15	25	na	Constant	1215
rooftop PV	1	LBD	15	25	na	Constant	2121
IMAGE-TIMER (Baker et al. 2013)	1	LBD	na	na	35	2000	0
	1	LBD	na	na	9	2100	0
MERGE-ETL (Magné et al. 2010)	2	LBD	na	na	10	Constant	0
	2	LBR	na	na	10	Constant	0
POLES (Criqui et al. 2015)	2	LBD	na	na	20	2010	1361
	2	LBR	na	na	45	2010	1361
REMIND (Luderer et al. 2015)	1	LBD	na	na	20	Constant	619
WITCH (Emmerling et al., 2016)	1	LBD	na	na	16.5	Constant	619

Table SM-2: Learning rates and floor costs in IAMs. Miminum, maximum, and mean values for LR result from the survey of existing models with endogenous technological change. "Constant" means that the LR is constant over time, whereas in the other cases LR is varying over time and values for 2000/2010/2100 are provided.

Source	# Factors	Rate	R&D	LR (%)			Timeframe	Method
			Level	min	max	mean		
Bosetti et al. (2016) CMU	1	LBR	High	-1	13	6	Future: 2030	Expert elicitation
Bosetti et al. (2016) FEEM	1	LBR	High	4	12	7	Future: 2030	Expert elicitation
Bosetti et al. (2016) Harvard	1	LBR	High	-3	11	3	Future: 2030	Expert elicitation
Bosetti et al. (2016) CMU	1	LBR	Low	-2	13	5	Future: 2030	Expert elicitation
Bosetti et al. (2016) FEEM	1	LBR	Low	1	10	6	Future: 2030	Expert elicitation
Bosetti et al. (2016) Harvard	1	LBR	Low	-2	8	2	Future: 2030	Expert elicitation
Bosetti et al. (2016) UMass	1	LBR	Low	-1	7	4	Future: 2030	Expert elicitation
Bosetti et al. (2016) FEEM	1	LBR	Mid	2	11	6	Future: 2030	Expert elicitation
Bosetti et al. (2016) Harvard	1	LBR	Mid	-1	10	3	Future: 2030	Expert elicitation
Bosetti et al. (2016) UMass	1	LBR	Mid	-1	7	5	Future: 2030	Expert elicitation
Neij (2008)	1	LBD	-	15	25	20	Future: 2050	Expert elicitation / Extrapolation from historical values
OECD/IEA (2014)	1	LBD	-	20	20	20	Future: 2035	Extrapolation from historical values

Table SM-3: Learning rate estimates based on expert elicitation.

Scenario matrix

	Scenario Name	Policy	Learning Rate	Floor Cost
1	BASE-LR-ref-FC-ref	Baseline	Ref	Ref
2	BASE-LR-ref-FC-0	Baseline	Ref	0
3	MIT-LR-75p-FC-ref	Mitigation	+75%	Ref
4	MIT-LR-50p-FC-ref	Mitigation	+50%	Ref
5	MIT-LR-25p-FC-ref	Mitigation	+25%	Ref
6	MIT-LR-ref-FC-ref	Mitigation	Ref	Ref
7	MIT-LR-25m-FC-ref	Mitigation	-25%	Ref
8	MIT-LR-50m-FC-ref	Mitigation	-50%	Ref
9	MIT-LR-75m-FC-ref	Mitigation	-75%	Ref
10	MIT-LR-75p-FC-0	Mitigation	+75%	0
11	MIT-LR-50p-FC-0	Mitigation	+50%	0
12	MIT-LR-25p-FC-0	Mitigation	+25%	0
13	MIT-LR-ref-FC-0	Mitigation	Ref	0
14	MIT-LR-25m-FC-0	Mitigation	-25%	0
15	MIT-LR-50m-FC-0	Mitigation	-50%	0
16	MIT-LR-75m-FC-0	Mitigation	-75%	0

Table SM-4 – Scenario set.

Sensitivity of PV penetration

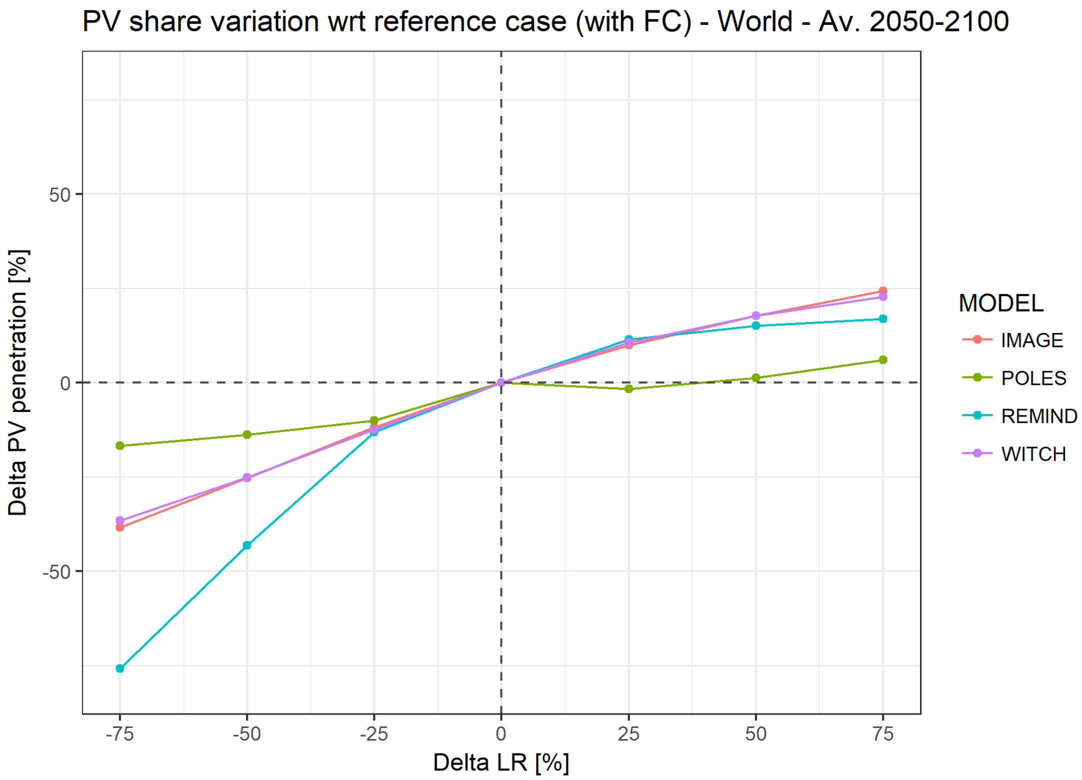

Figure SM-1 – PV share relative variation with respect to the reference case (scenarios with floor cost).

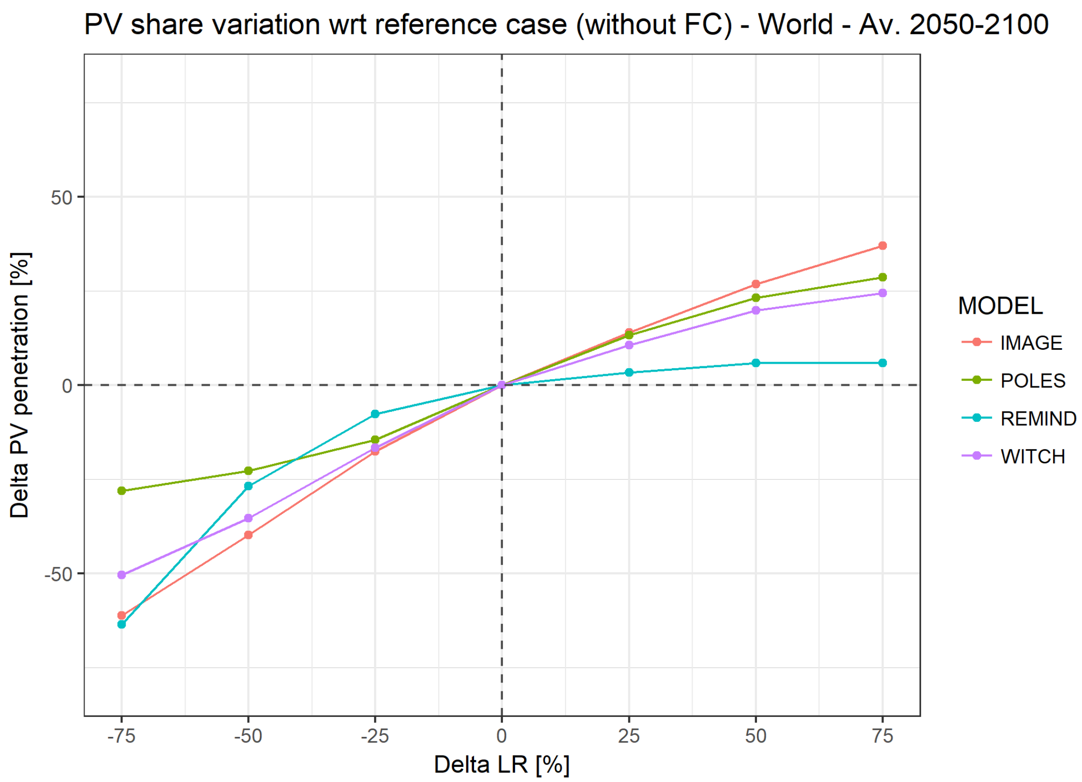

Figure SM-2 – PV share relative variation with respect to the reference case (scenarios without floor cost).

Sensitivity of PV penetration to capital cost reduction

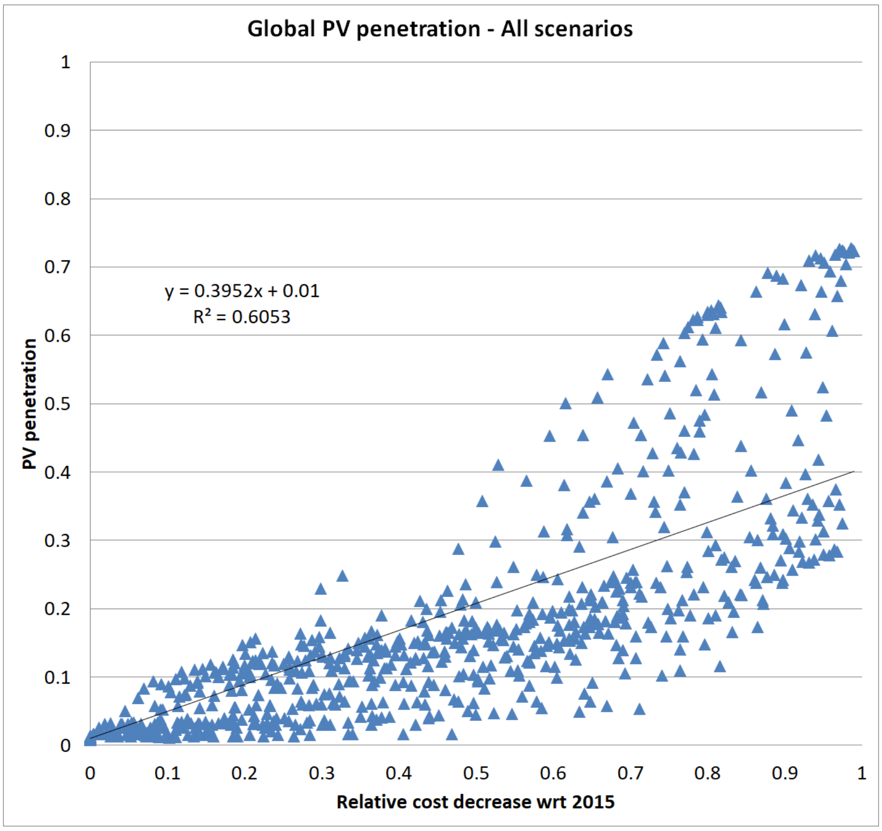

Figure SM-3 – Global PV penetration: sensitivity to cost reduction (all models).

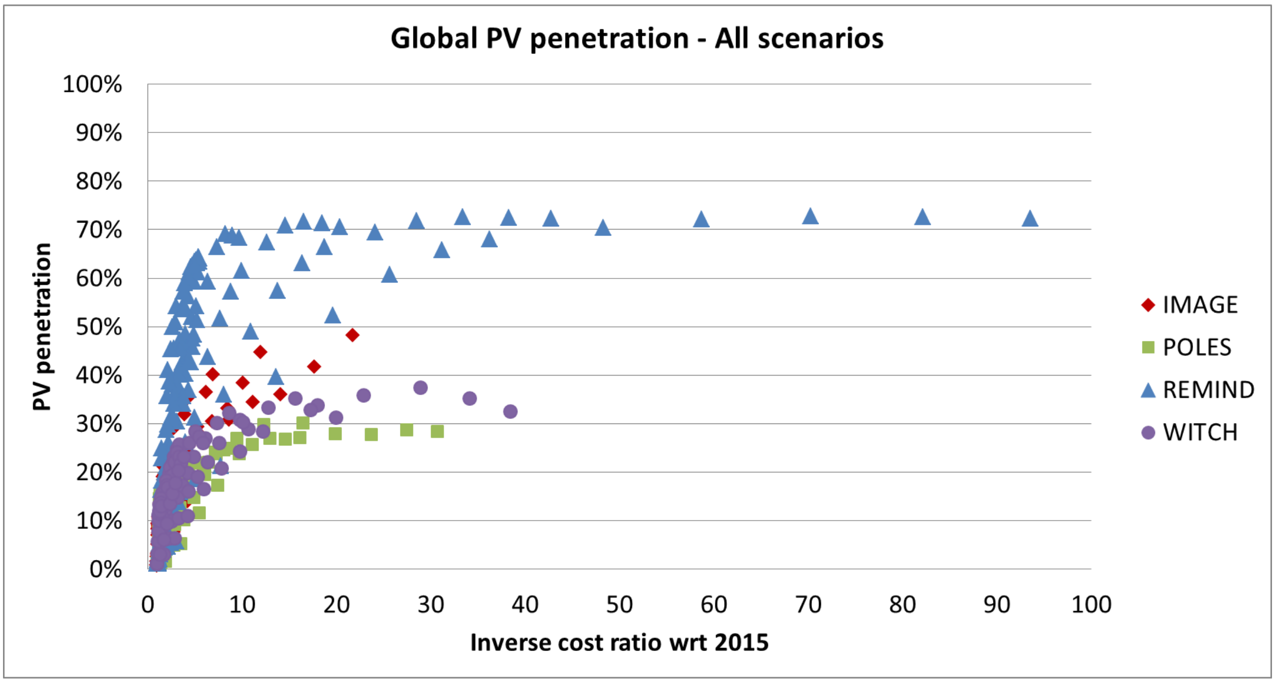

Figure SM-4 – Global PV penetration: sensitivity to cost reduction (each point corresponds to one specific year, independently of the scenario to which it belongs). Cost reductions are expressed as the ratio between the capital cost in 2015 and the capital cost in the relevant year.

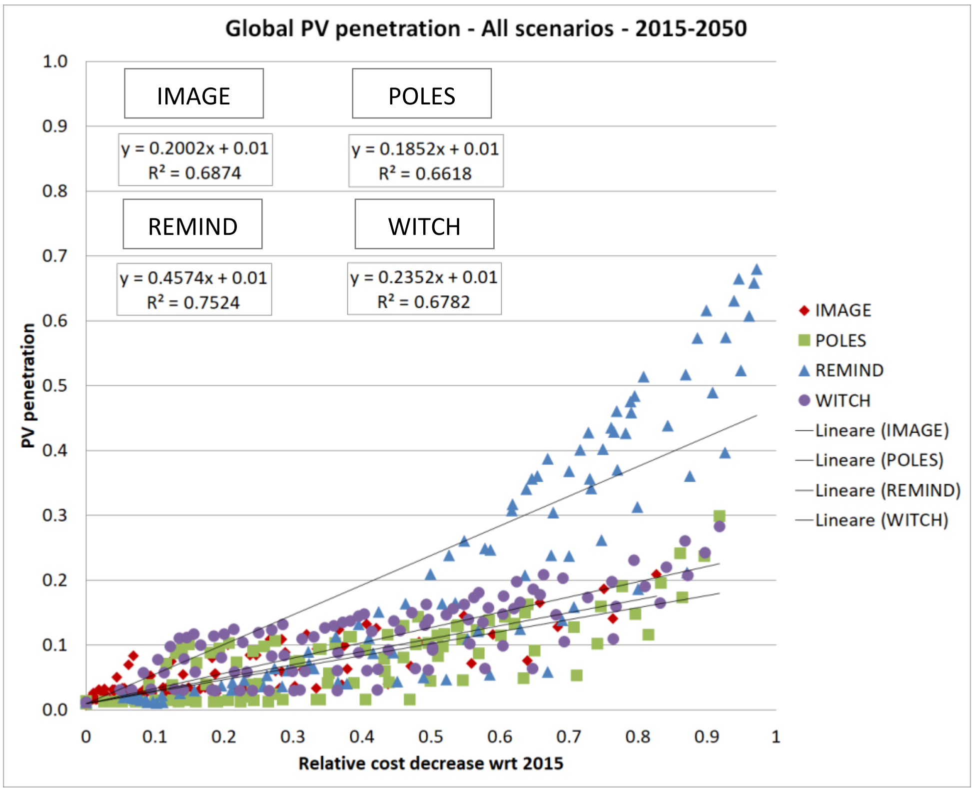

Figure SM-5 – Global PV penetration: sensitivity to cost reduction (2015-2050).

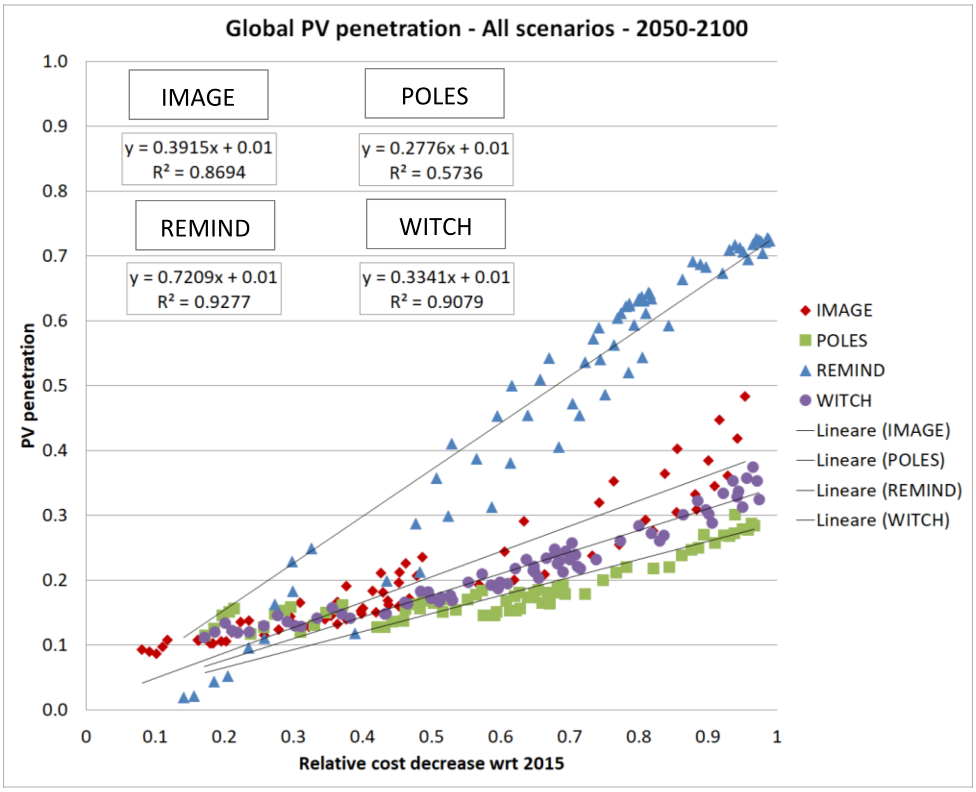

Figure SM-6 – Global PV penetration: sensitivity to cost reduction (2050-2100).

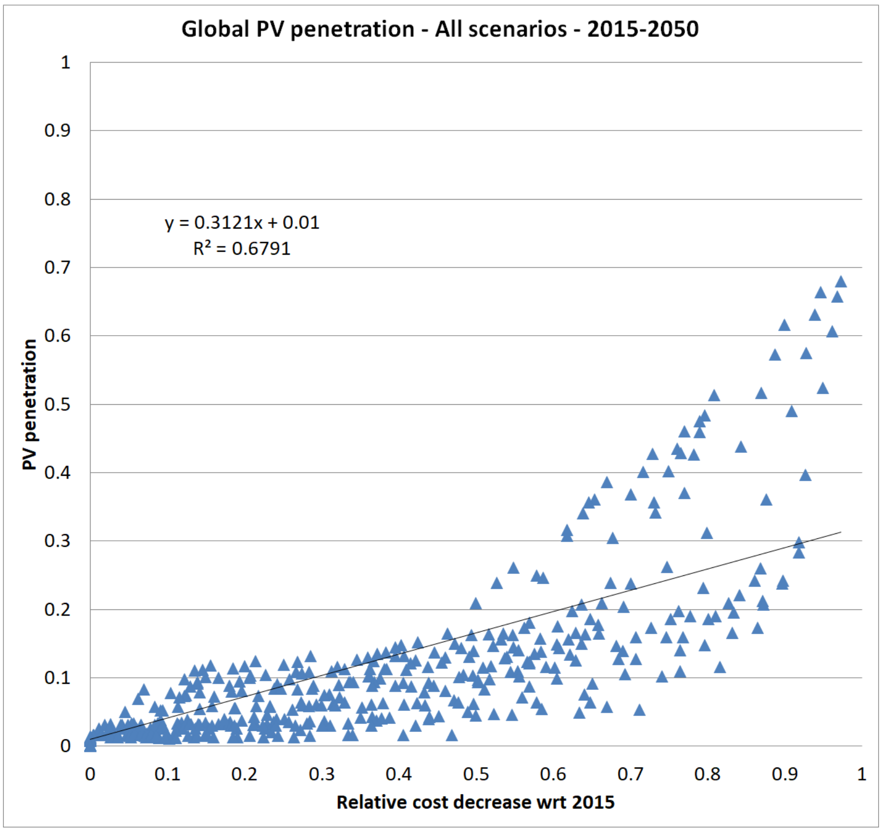

Figure SM-7 – Global PV penetration: sensitivity to cost reduction (2015-2050, all models).

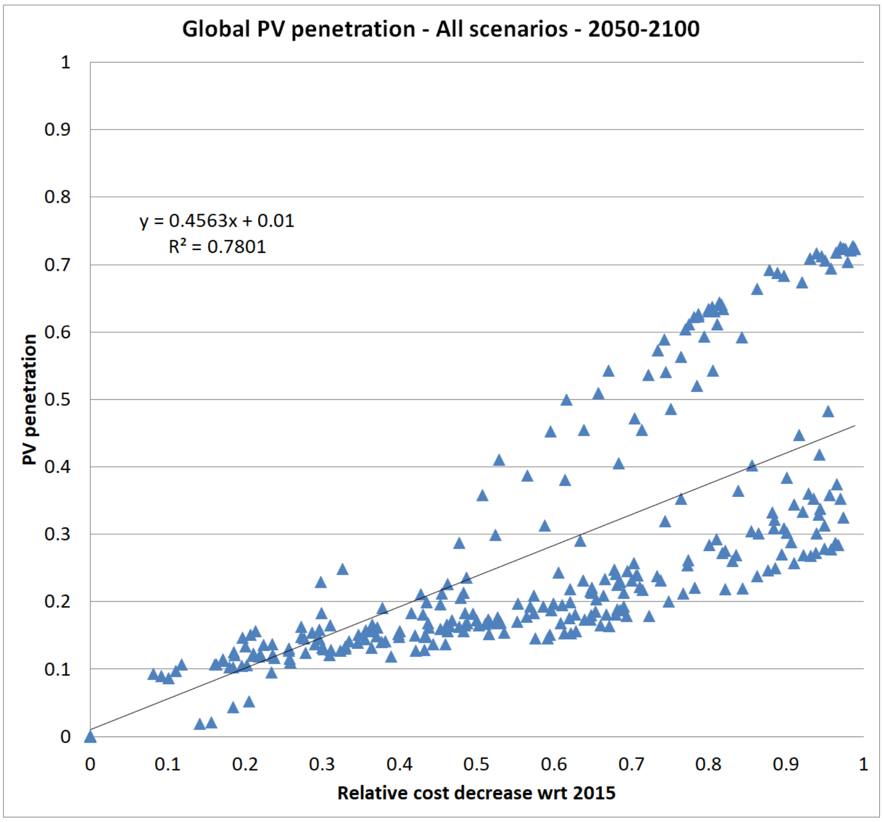

Figure SM-8 – Global PV penetration: sensitivity to cost reduction (2050-2100, all models).

“Statistical” PV penetration

As discussed in the main text, Witajewski-Baltvilks et al. (2015) provide an empirical estimate of the PV learning rate, not only in terms of mean value (19%) but in terms of statistical normal distribution, where the relative variations of ±25%, ±50%, and ±75% correspond to the ±σ, ±2σ, and ±3σ values, respectively. These values allow deriving the statistically average PV penetration shares, weighting the shares associated to the different learning rates on the relevant values of the normal distribution, schematized in Figure SM-9. The weights of the normal distribution corresponding to the median and the ±σ, ±2σ, and ±3σ levels are 0.3989, 0.2420, 0.0540, and 0.0044, respectively.

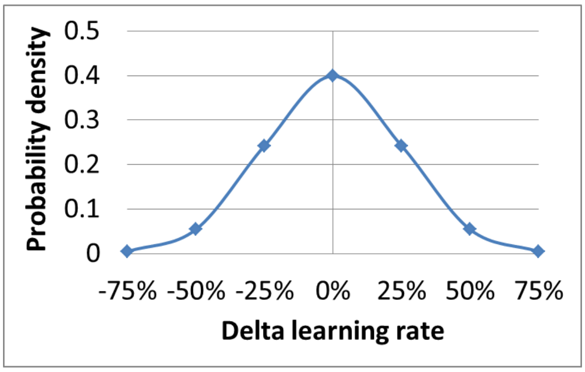

Figure SM-9 – Normal probability density function.

Figures SM-10 and SM-11 show the comparison between the average PV penetration in 2050-2100 in the reference mitigation scenario and the penetration rate obtained with the statistical average, for both configurations with and without floor cost, respectively. As noted in Figure 2 in the main text, models show higher sensitivity to low learning rates, therefore the statistical average penetration rate is lower than the reference one, apart from POLES in the scenarios without floor cost. Indeed, differences are not particularly broad, with the partial exception of REMIND (see Table SM-4).

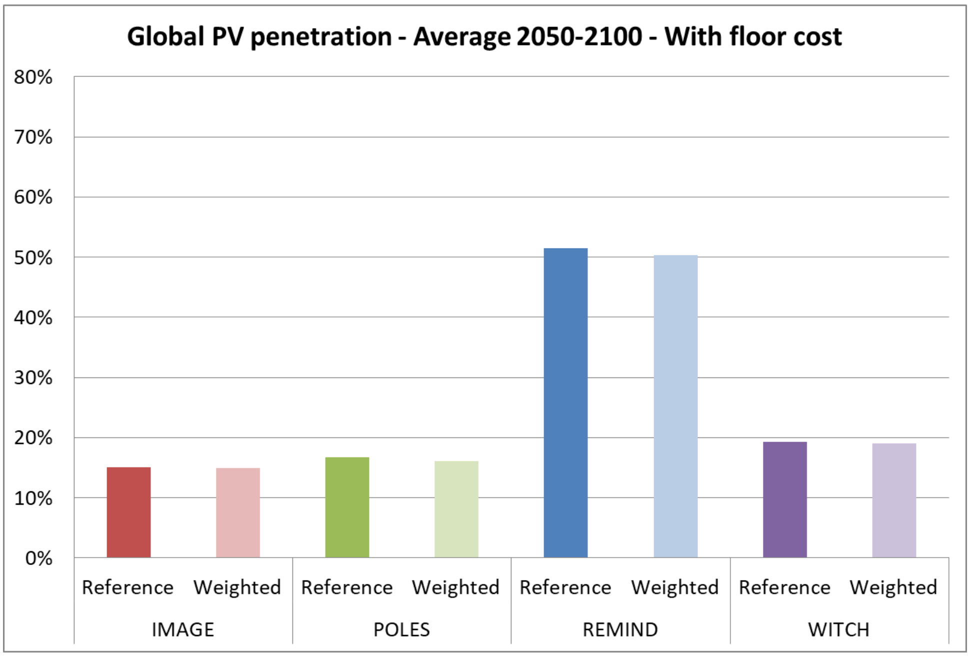

Figure SM-10 – Global PV penetration, average 2050-2100, with floor cost.

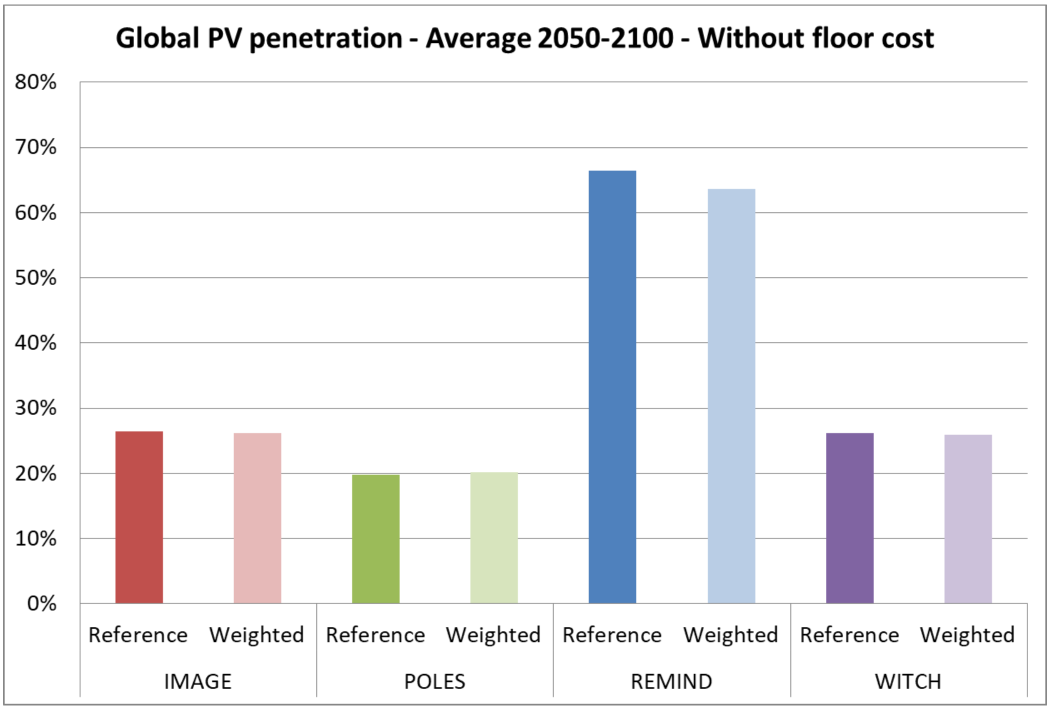

Figure SM-11 – Global PV penetration, average 2050-2100, without floor cost.

	With floor cost		**Without floor cost**	
	Reference	**Weighted**	**Reference**	**Weighted**
IMAGE	15.12%	14.99%	26.40%	26.15%
POLES	16.75%	16.14%	19.82%	20.12%
REMIND	51.50%	50.33%	66.36%	63.59%
WITCH	19.25%	19.06%	26.21%	25.91%

Table SM-4 – Global PV penetration, average 2050-2100.

Sensitivity of VRE penetration

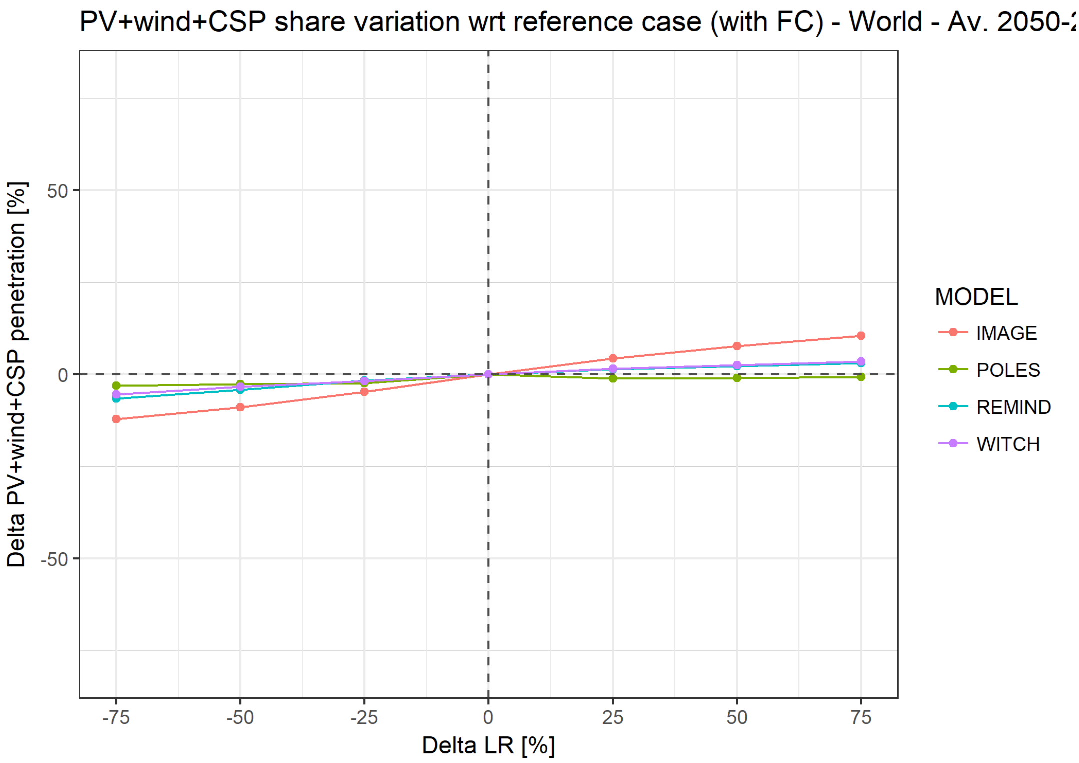

Figure SM-12 – VRE share relative variation with respect to the reference case (scenarios with floor cost).

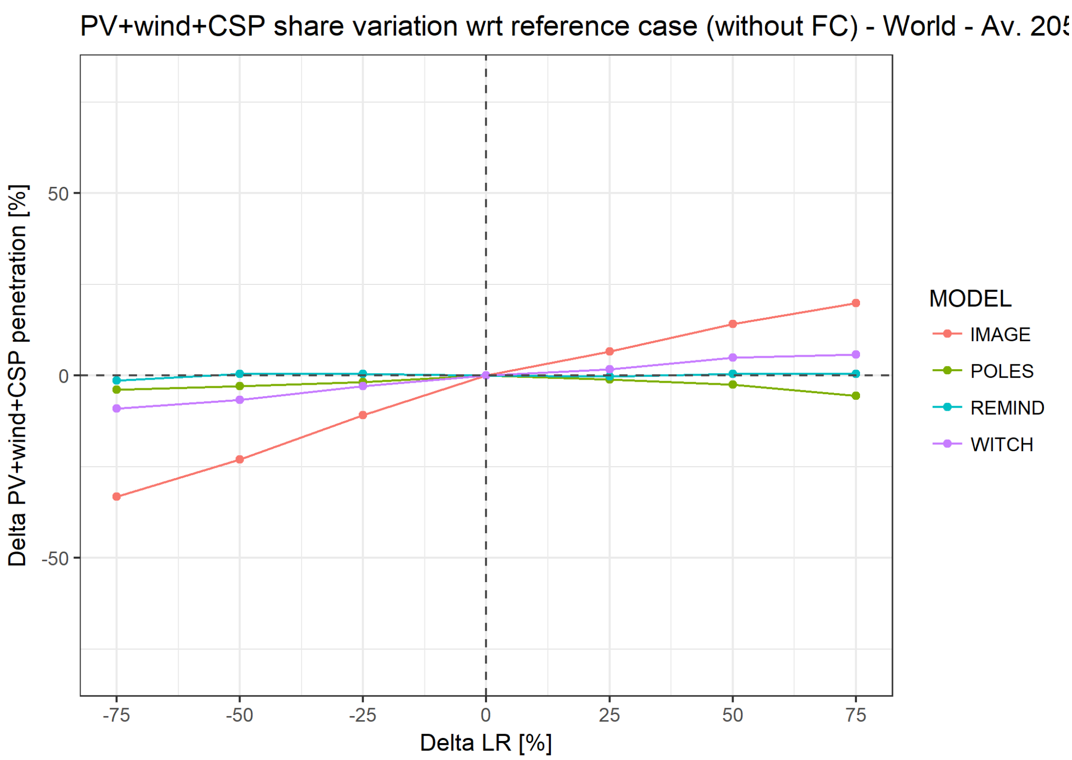

Figure SM-13 – VRE share relative variation with respect to the reference case (scenarios without floor cost).

VRE penetration: scatter plots

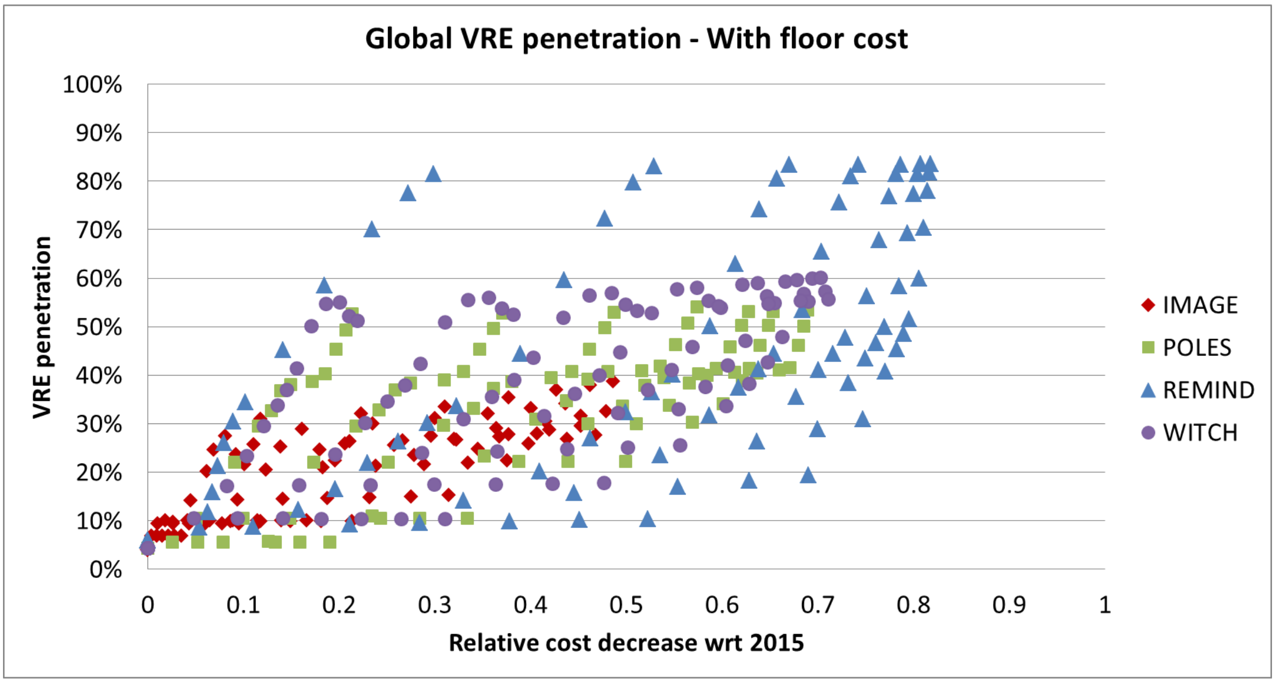

Figure SM-14 – Global VRE penetration, with floor cost.

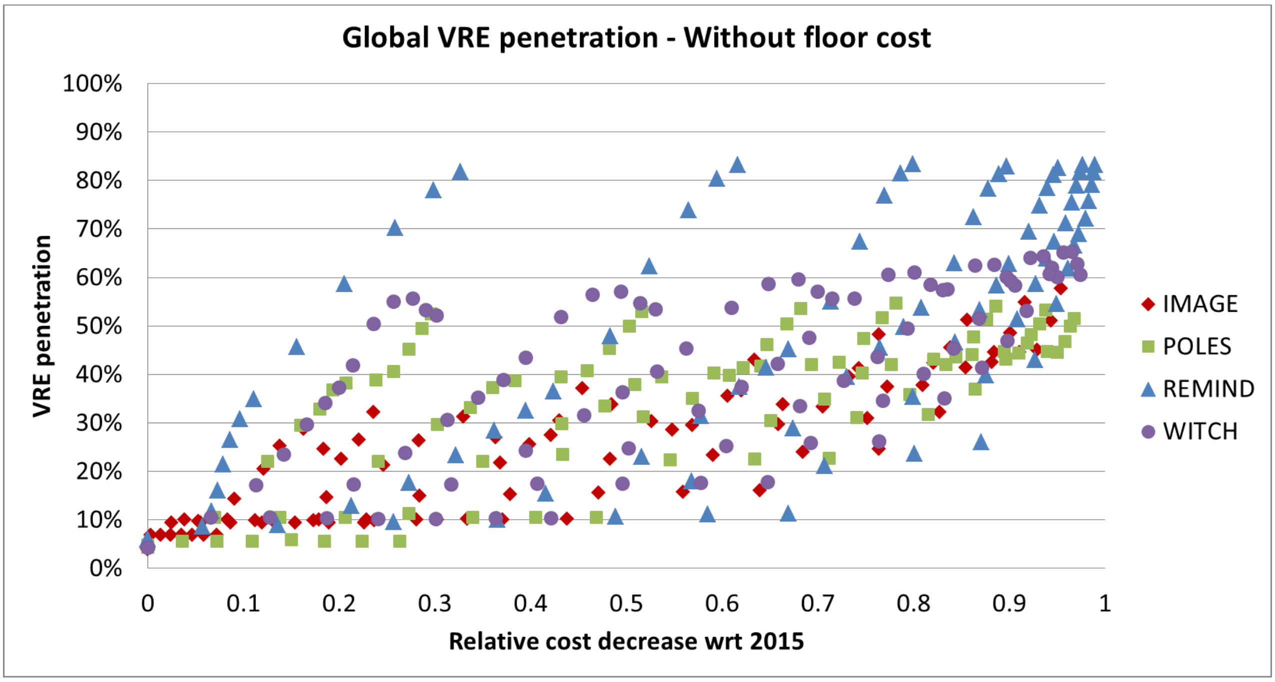

Figure SM-15 – Global VRE penetration, without floor cost.

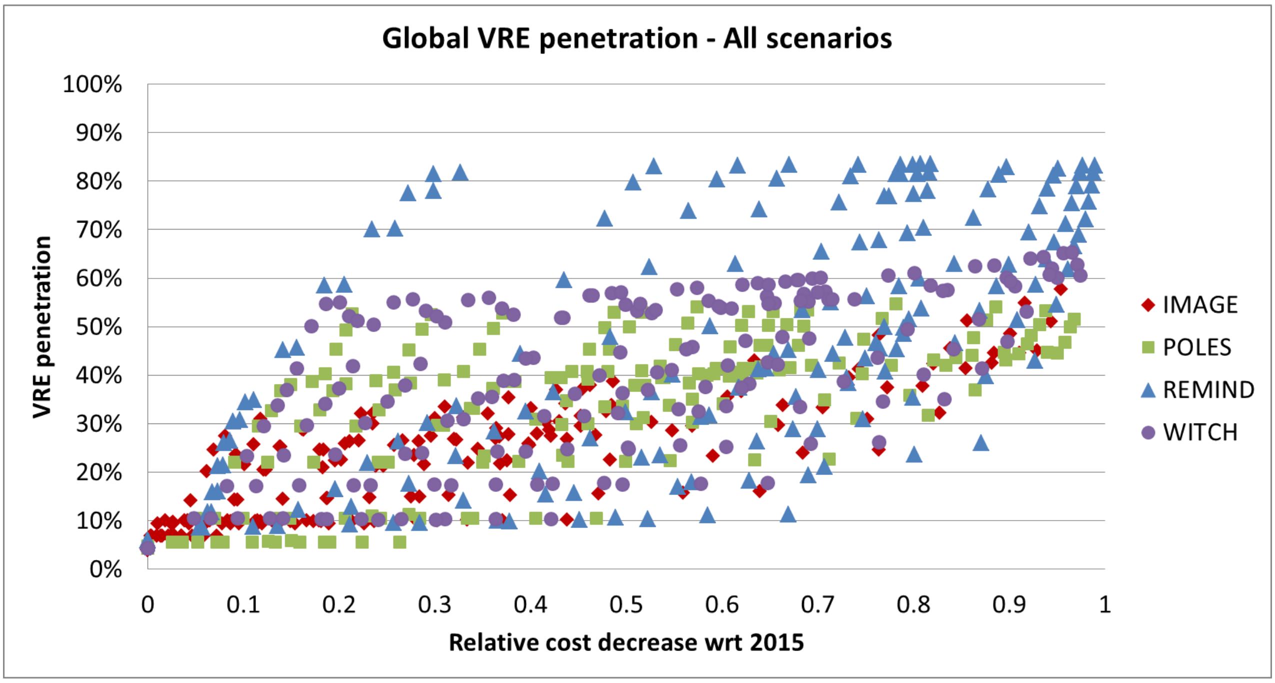

Figure SM-16 – Global VRE penetration, all scenarios.

Electricity mix

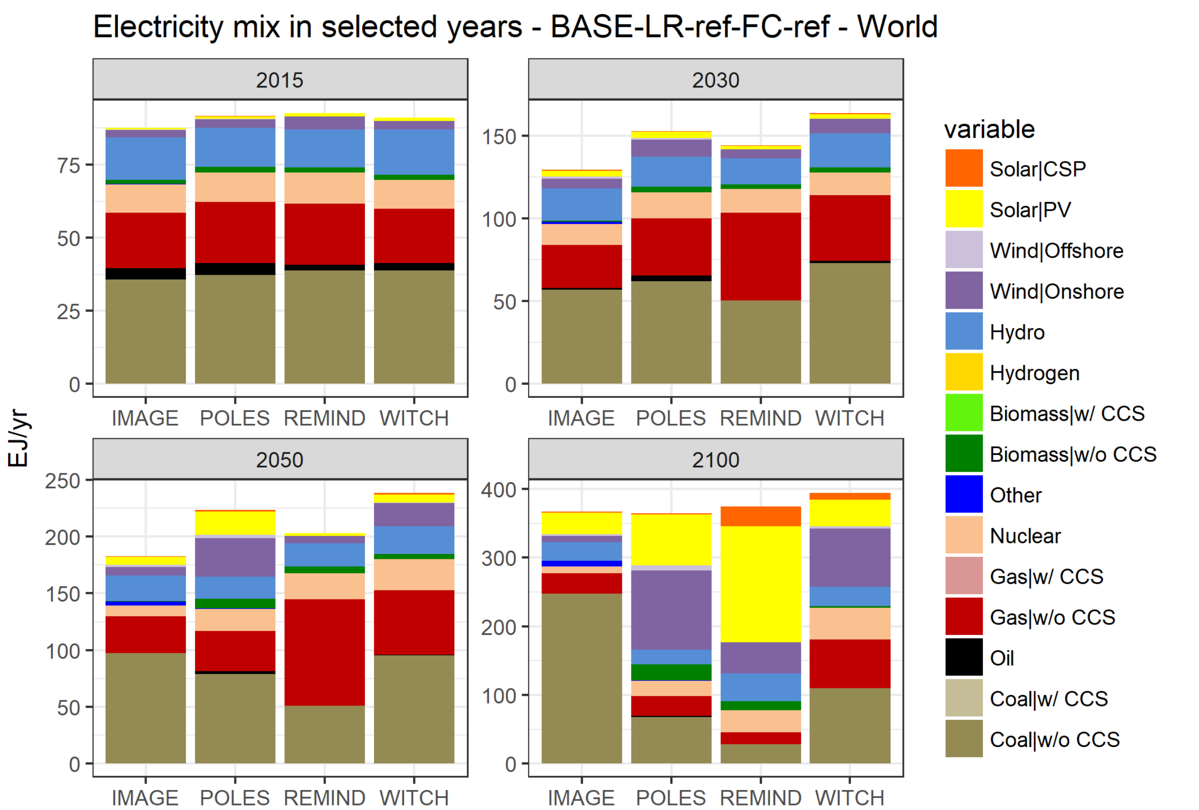

Figure SM-17 – Global electricity mix in selected years (Baseline scenario).

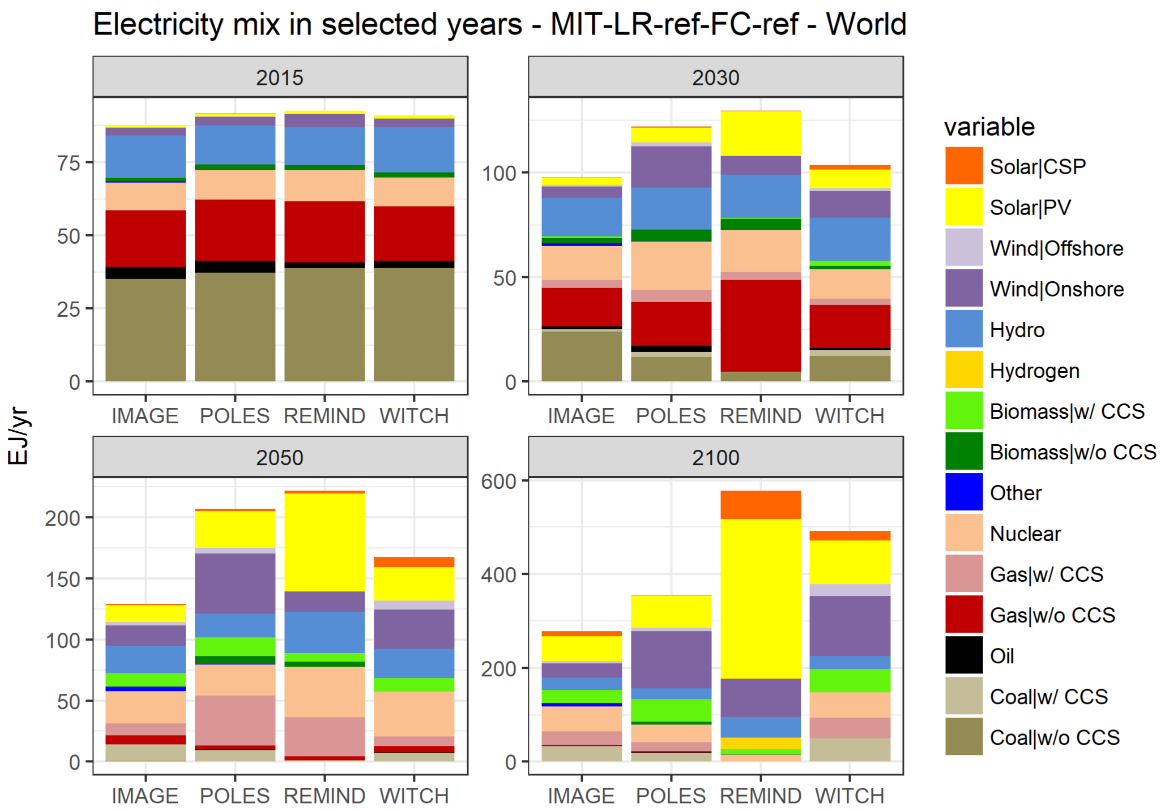

Figure SM-18 – Global electricity mix in selected years (Reference scenario).

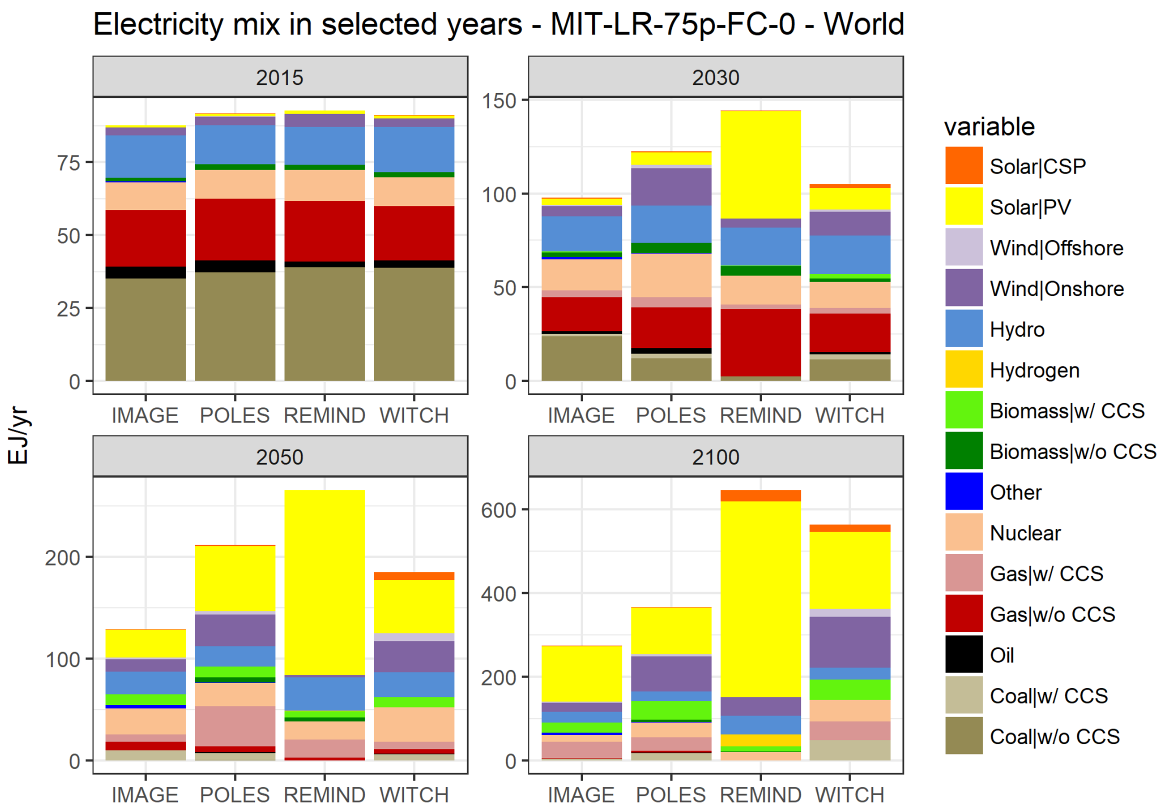

Figure SM-19 – Global electricity mix in selected years (Optimistic scenario).

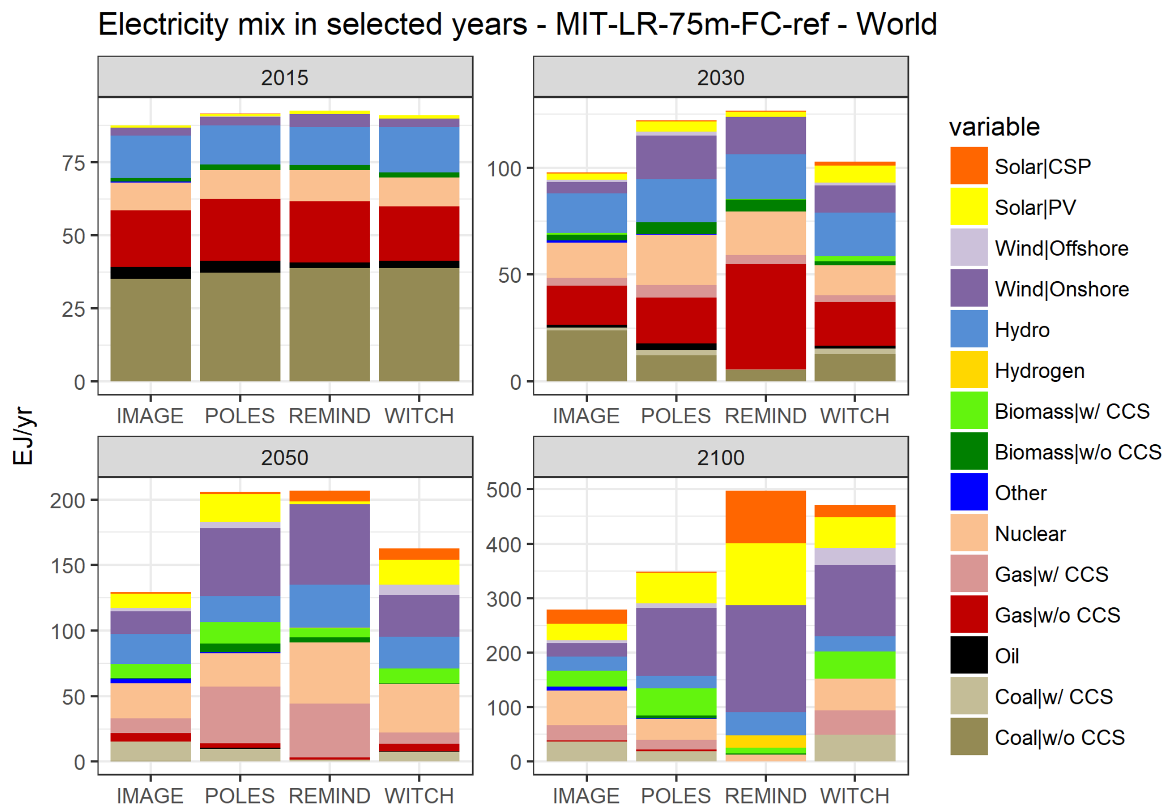

Figure SM-20 – Global electricity mix in selected years (Pessimistic scenario).

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The techno-economic effects of the delayed deployment of CCS technologies on climate change mitigation

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Abstract

Meeting the targets of climate change mitigation set by the Paris Agreement entails a huge transformation of the energy sector, as low- or no-carbon technologies are predicted to gradually substitute traditional, fossil-based technologies. In this perspective, the vast majority of energy scenarios project a fundamental role of Carbon Capture & Storage (CCS). However, uncertainty remains on the actual techno-economic feasibility of this technology: despite the considerable investment over the recent past, commercial maturity is yet to come.

The main aim of this work is to evaluate the impacts of a progressively delayed deployment of CCS plants from a climate, energy, and economic perspective, focusing in particular on the power sector. This is done with the Integrated Assessment Model WITCH, exploring a wide set of long-term scenarios over mitigation targets ranging from 1.5°C to 4°C in terms of temperature increase with respect to the pre-industrial levels.

The analysis shows that CCS will be a key mitigation option at a global level for carbon mitigation, achieving about 30% of the electricity mix in 2100 (with a homogeneous distribution across coal, gas, and biomass) if its deployment is unconstrained. If CCS deployment is delayed or forbidden, penetration cannot reach the optimal unconstrained level, resulting in a mix rearrangement, with a strong increase in renewables and, to a lesser extent, nuclear. The mitigation targets can be met, but policy costs are 35% to 72% higher without the implementation of CCS than in the corresponding unconstrained scenarios. In Europe, CCS is not projected to be a considerable mitigation option, therefore the sensitivity analysis over the mitigation targets and the CCS deployment years does not highlight meaningful technical and economic changes.

Keywords: carbon capture and storage, power generation, climate change mitigation, Integrated Assessment Models

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1. Introduction

Climate change mitigation is acknowledged as one of the major challenges that the mankind will have to face in the 21st century (IPCC, 2014). With the Paris Agreement, reached in 2015 during the Conference of Parties 21 (COP21), almost all countries of the world have committed to pursuing the ambitious target of limiting to 2°C the global temperature increase in 2100 with respect to the pre-industrial levels, making all the possible efforts to stay as close to 1.5°C as possible, in order to further limit detrimental climate impacts (Schellnhuber et al., 2016). However, these targets are very difficult to be reached, as they entail huge technological and economical fundamental transformations, as well as an internationally coordinated action.

Carbon Capture & Storage (CCS) has widely been recognized as one of the main technological solutions to decarbonize the energy sector and virtually all research studies project a considerable role in future mitigation pathways (Krey et al., 2014 and Koelbl et al., 2014), especially if the target is to stay below 2°C (Rogelj et al., 2015). This technology consists in capturing the carbon dioxide generated in plants fed with fossil fuels or biomass and storing it in proper underground deposits or marine aquifers (IEA, 2013). Its main advantage is the possibility to achieve a (theoretically) zero carbon energy generation adopting fossil fuels plants, i.e. without massively reconsidering the current generation paradigm that still dominates the energy sector (IEA, 2017). Indeed, even negative emissions can be achieved if CCS plants are fed with biomass which is replaced at a pace equal to consumption: in this case, the carbon neutrality related to the use of biomass (net of the emissions associated to the whole life cycle concerning harvesting, transport etc.) is complemented by the CO_2 removal in the CCS plant. An additional advantage is related to the dispatchability of these plants, which is a fundamental aspect in a future energy scenario where non-dispatchable renewables (primarily wind and solar) will likely reach significant shares in the electricity mix. CCS availability would also entail economic savings in pursuing mitigation targets (Davidson et al., 2017).

However, large-scale CCS deployment is yet to come. Safety concerning the stability of storage sites, public acceptance, high technology costs, incomplete or unclear regulatory framework, the absence of business models, and a general uncertainty on the socio-economic impacts are major obstacles that still hinder the take-off of this technology (Creutzig et al., 2013 and Muratori et al., 2016). As a result, so far, very few and small scale plants have been installed worldwide (GCCSI, 2017).

In this context, the main objective of this work is to investigate the role that CCS could play in carbon mitigation and in particular assess the techno-economic impacts that a progressively delayed deployment of this technology can have both in terms of re-arrangement of the energy mix and in terms of policy costs. In other words, how urgent is it to start installing CCS plants for the feasibility of more and more stringent climate targets?

This work focuses on the electricity sector, which is described in detail in the model adopted in this work, the Integrated Assessment Model (IAM) WITCH.

The paper is structured as follows. Section 2 describes the WITCH model, and especially how CCS technologies are modeled therein. Section 3 reports the scenario design. Section 4 reports and extensively discusses the most relevant results of the analysis. Finally, Section 5 concludes.

2. Methodology

2.1 The WITCH model

The tool adopted in this research is the World Induced Technical Change Hybrid (WITCH) model. WITCH is a dynamic optimization Integrated Assessment Model (IAM) designed to investigate the socio-economic impacts of climate change over the 21st century (Bosetti et al., 2006 and Emmerling et al., 2016). It combines a top-down, simplified representation of the global economy with a bottom-up, detailed description of the energy sector, nested in a Constant Elasticity of Substitution (CES) structure (Figure 1). The model is defined on a global scale: countries are grouped into thirteen aggregated regions, which strategically interact according to a non-cooperative Nash game. The thirteen economic regions are USA (United States), WEURO (Western EU and EFTA countries), EEURO (Eastern EU countries), KOSAU (South Korea, South Africa and Australia), CAJAZ (Canada, Japan and New Zealand), TE (Transition Economies, namely Russia and Former Soviet Union states and non-EU Eastern European countries), MENA (Middle East and North Africa), SSA (Sub-Saharan Africa except South Africa), SASIA (South Asian countries except India), EASIA (South-East Asian countries), CHINA (People's Democratic Republic of China and Taiwan), LACA (Latin America and Central America) and INDIA (India).[1] As the model acronym suggests, technological change is endogenously modeled in WITCH, and it regards energy efficiency and the capital cost of specific clean technologies.

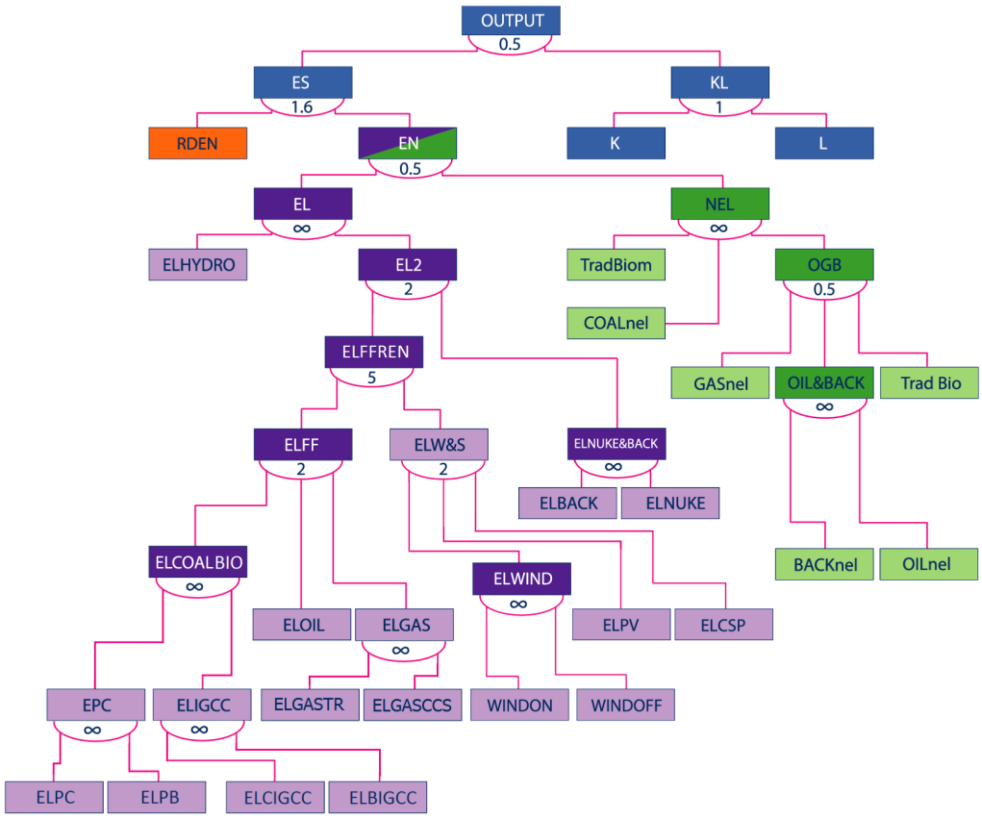

Figure 1 – The CES structure in WITCH.

[1] The aggregated results for Europe derive from the combination of WEURO and EEURO.

The CES structure reported in Figure 1 shows how the top-down aggregated economic model is linked with the disaggregated energy sector. In particular, energy services (ES) and the aggregated capital and labor node (KL) are combined to produce the final economic output of the model. Energy services are provided by the combination of the capital of energy R&D (RDEN), which is a proxy of energy efficiency, and the actual energy generation (EN). This node models the fact that the same energy services can be obtained through a lower level of energy input if there is higher energy efficiency. The EN node is divided between the electric (EL) and non-electric sector (NEL), with a progressive disaggregation down to the single technologies. The electric sector has a higher detail, while the non-electric sector mostly reports nodes which collect consumption from all the non-electric usages of one specific energy source, except for the road passenger and road freight transport sectors, which are the only demand sectors being explicitly modeled[2] (see Bosetti and Longden, 2013, and Carrara and Longden, 2017).

Focusing on the electric sector, the hydroelectric technology is found first (ELHYDRO), which is essentially exogenous in the model. The other technologies converge to the EL2 node, which is divided between two further nodes: EFLFFREN, i.e. the combination of fossils and renewables, and ELNUKE&BACK, i.e. the combination of nuclear and backstop. The fossil node (ELFF) has three group of technologies: i) coal&biomass (ELCOALBIO), further divided into pulverized coal without CCS (ELPC), pulverized biomass without CCS (ELPB), integrated gasification coal with CCS (ELCIGCC), and integrated gasification biomass with CCS (ELBIGCC); ii) oil, only without CCS (ELOIL); iii) gas (ELGAS), with and without CCS (ELGASTR and ELGASCCS, respectively). Variable renewable energies (ELW&S) have i) wind (ELWIND), further divided between onshore (WINDON) and offshore (WINDOFF); ii) solar PV (ELPV); iii) solar CSP (ELCSP). Nuclear and backstop feature traditional fission nuclear (ELNUKE) and a backstop technology (ELBACK). The latter models a hypothetical future technology which generates electricity with no fuel costs and no carbon emissions, although characterized by high capital costs. It can be interpreted as an advanced nuclear technology, for instance nuclear fusion or advanced fast breeder fission reactors. However, this technology is not considered in the scenarios explored in this work. Concerning the non-electric sector, the first distinction is between traditional biomass (TradBiom), coal (COALnel) and the aggregated node formed by oil, gas, and modern biomass (OGB), which precisely features gas (GASnel), traditional biofuels (Trad Bio), and the combination (OIL&BACK) between oil (OILnel) and a non-electric backstop technology, i.e. advanced biofuels (BACKnel).

The CES structure tries to capture from a modeling point of view the preference for heterogeneity that is experienced in the real world, where the choice of investing in energy technologies does not normally depend on economic considerations only. The numbers reported in the CES scheme under the specific nodes indicate the relevant elasticity of substitution. As suggested by the name, this value quantifies the level of substitutability between the sub-nodes that converge in the specific node. Zero elasticity means that the production factors are not substitutable and thus they are summed in fixed shares. Infinite elasticity means that the production factors are completely interchangeable and thus the competition between the two occurs on an economic basis only. Intermediate elasticities result in an intermediate behavior. More details concerning the CES structure can be found in Carrara and Marangoni, 2017.

[2] These sectors are not shown in the CES scheme.

2.2 CCS modeling

WITCH models four CCS technologies, three in the electricity sector and one in the non-electric sector. The three electric technologies have been listed in the previous section and feature coal, gas, and biomass (the latter often indicated with BECCS). For all of them, the CCS technology directly competes with the relevant non-CCS technology, to which it is related through an infinite elasticity. The non-electric technology is applied to non-electric coal, even if it does not directly appear in the CES structure and it is not considered in this work[3].

CCS modeling occurs on two levels, one regarding the power technologies and the other regarding the capture and storage costs.

Concerning the power plants, Table 1 summarizes the main modeling assumptions for the three categories of CCS power plants.[4] It should be noted that no further technological differentiation is considered in this work within each fuel category (e.g. oxy-fuel combustion, post-process capture or other specific technological solutions). Concerning the data not reported in the table, O&M costs across regions are averagely 45 $/kW for gas and 75 $/kW for coal and biomass, respectively[5]. Efficiency of coal plants starts at 39% in 2015, linearly increases up to 43% in 2050, and then remains constant in the second part of the century. This is assumed to replicate the progress of the efficiency of non-CCS plants subtracting a 7%-efficiency loss related to the capture and storage process. Efficiency in biomass plants follows the same rationale, with a 10%-shift downwards. Efficiency in gas plants is regionally differentiated in 2015 (values are comprised between 39% and 51%), with a common convergence to 55% in 2050, which is held constant afterwards.

	COAL CCS	**GAS CCS**	**BECCS**
Investment cost [$/kW]	3925	1856	5162
Lifetime [years]	40	25	25
Capacity factor	85%	70%	80%

Table 1 – Modeling assumptions for the CCS power plants.

CO_2 sequestration, transport, and storage are modeled via regional supply cost curves, which depend on site availability. The unit cost curve $C_{CCS}(t,n)$ has a convex shape and is shown in Equation 1 (t and n refer to time step and region, respectively):

[3] For the sake of coherence, the working hypotheses in terms of CCS deployment which will be described in Section 3 have been applied to the non-electric sector too. However, this work focuses on the power sector, therefore no further details are provided on the non-electric side.
[4] If not differently specified, values are held constant across regions and over the century.
[5] Only fixed O&M costs are considered. Costs are expressed in USD2015.

$$C_{CCS}(t,n) = a_{CCS}(n) \cdot \exp(\alpha_{CCS}(n) \cdot M_{CCS}(t,n)^{\beta_{CCS}(n)}) \quad (1)$$

where M_{CCS}(t,n) is the cumulated amount of CO_2 captured over the years (the capture rate is fixed to 90% for all the three power technologies), while a, α, β are parameters calibrated on the storage capacities in the different regions as derived from IPCC, 2005, which estimates a global capacity between 1678 and 11100 $GtCO_2$. The total CCS cost is finally computed by multiplying the unit cost C_{CCS} by the amount of fuel burnt in the relevant power plants.

Global prices of fossil fuels are endogenously calculated in WITCH, while it is coupled with the Global Biosphere Management Model (GLOBIOM, see Havlík et al., 2014) to model land use. GLOBIOM provides biomass supply cost curves to WITCH for different economic and mitigation trajectories. This allows assessing woody biomass availability and cost.

3. Scenario design

The analysis considers a set of 25 scenarios where five climate targets are combined with five temporal options related to CCS deployment. The five climate targets refer to the temperature increase in 2100 with respect to the pre-industrial levels and are equal to 3.5°C, 3°C, 2.5°C, 2°C, and 1.5°C (the two latter are the most relevant in the Paris Agreement perspective[6]). The five temporal options refer to the starting year when investing in CCS is allowed. These years are 2020, 2040, 2060, and 2080, which are in addition to the case where CCS is not installed at all. As investment take time to materialize, this framework implies that the first deployment year in the first four cases is 2025, 2045, 2065, and 2085, respectively. Somehow, the no CCS case which would correspond to fixing the starting year of investment in 2100, i.e. the first deployment year in 2105, after the temporal horizon of WITCH.

A complementary baseline or Business-as-Usual (BAU) scenario has also been run, where no carbon policy is applied. De facto this leads to no CCS deployment by construction: in fact, in the absence of a carbon signal, there is no reason to invest in a carbon-removal technology which is by definition more expensive than the corresponding non-CCS plants. The baseline scenario leads to a temperature increase in 2100 of about 4°C (4.08°C, precisely), which explains why the explored climate mitigation targets start at 3.5°C.

Table 2 summarizes the different options within the climate target and investment dimensions. In particular, the table provides the acronyms for the CCS deployment year which will be used in the graphs shown in Section 4 ("i" stands for investment). The scenario names are generated combining the target and the CCS year, e.g. 3.5C_i20 or3C_i40.[7]

Climate target	BAU, 3.5°C, 3°C, 2.5°C, 2°C, 1.5°C
CCS first investment year	2020 (i20), 2040 (i40), 2060 (i60), 2080 (i80), no CCS investment (ioff)

Table 2 – Scenario dimensions.

[6] The goal of the Paris Agreement is to "keep a global temperature rise this century well below 2 degrees Celsius above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius" (UNFCCC, 2015).

[7] This naming scheme does not apply to the Business-as-Usual scenario, which is simply called "Baseline".

Figure 2 shows the temperature increase over the century in the 26 scenarios converging to the six climate targets described above. It can be noted that, whereas all scenarios from 2°C upwards converge uniformly towards the relevant target, the 1.5°C scenarios show a broader pattern. These scenarios, in fact, are at the frontier of technical feasibility in WITCH, and with a delayed deployment of CCS the convergence can take place slightly above 1.5°C (from exactly 1.5°C in the i20 case to 1.6°C in the ioff case). Indeed, the deviation is limited and it does not prevent from fully accepting these scenarios in the analysis.

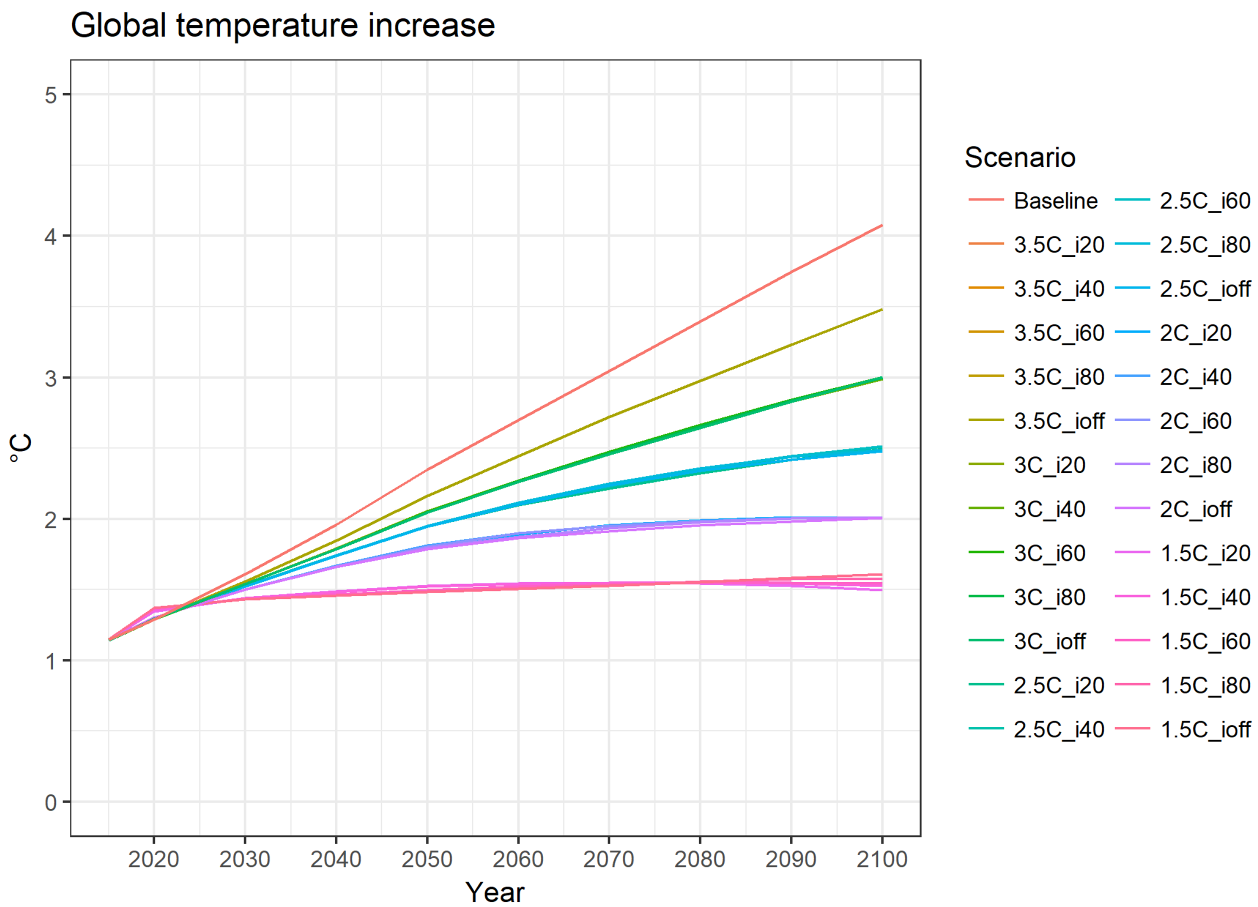

Figure 2 – Global temperature increase with respect to the pre-industrial levels.

The climate targets are reached via the application of a carbon tax on greenhouse gas (GHG) emissions. The tax starts in 2020 and grows exponentially in order to yield the desired temperature increase. As will be shown in the next section, the delayed or forbidden deployment of CCS plants causes by definition an increase in the mitigation costs, as it hinders a technology option which would be otherwise used. This implies an increase in the carbon tax if the same climate target is to be reached. Operatively, a common starting value has been fixed for the different climate targets (referring to the database of similar optimized scenarios) and then the growth rate has been recursively adjusted in order to reach the relevant temperature. No details are provided on the actual values implemented, as the economic focus will be put on the overall policy cost (shown in Section 4) rather than on the specific carbon tax values, which are not within the interests of this work.

Figure 3 shows the resulting GHG emission patterns in the different scenarios. Kyoto gases are considered, i.e. carbon dioxide, methane, nitrous oxide, and fluorinated gases. [8]

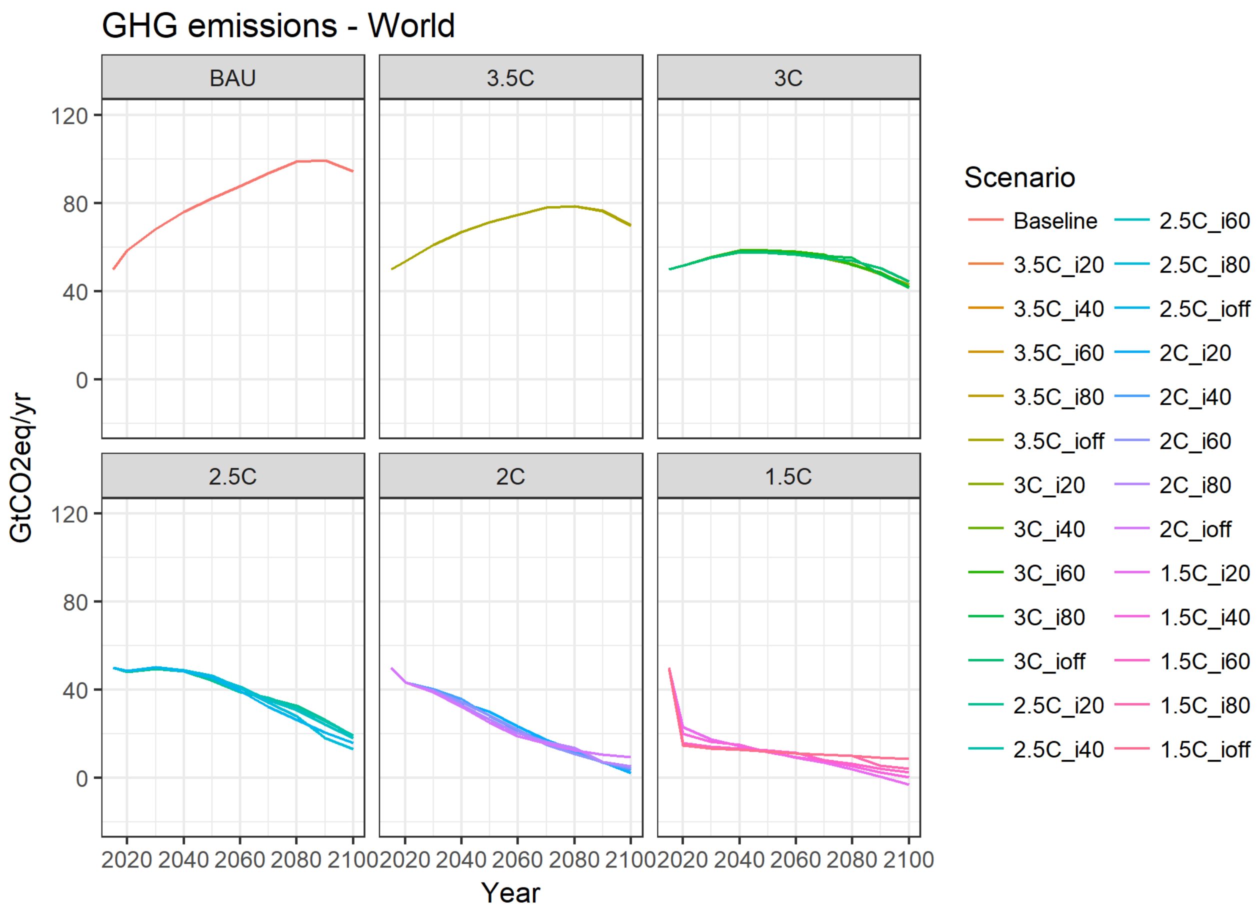

Figure 3 – Global GHG emissions.

In 2015 global GHG emissions accounted for 50 $GtCO_2eq$. In the baseline scenario GHG emissions grow up to about 100 $GtCO_2eq$ in 2080/2090, with a slight decrease towards the end of the century (94 $GtCO_2eq$ in 2100). The same pattern is found in the 3.5°C scenarios, where emissions peak at 78 $GtCO_2eq$ in 2070/2080 and then decrease to 70 $GtCO_2eq$ in 2100. The 3°C target entails that emissions remain substantially constant all over the century, with a peak at 58 $GtCO_2eq$ in 2040 and a smooth decrease down to around 42 $GtCO_2eq$ in 2100. The 2.5°C target, instead, implies a constant emission decrease to about 15-20 $GtCO_2eq$ starting in 2030/2040 after a few decades of relative constancy. The 2°C target requires an immediate and constant decrease, achieving a total net emission amount of few thousands of $GtCO_2eq$ in 2100. Finally, the 1.5°C target would entail a sudden and dramatic cut of emissions by two or three times in the very first years, with a constant decrease down to zero or even net negative emissions in 2100. As will be discussed in the next section, the extraordinary fall in emissions after 2015 makes this set of scenarios practically infeasible in this design. However, it is not within the scope of this work to discuss about the

[8] The impact of non-CO_2 gases is assessed via the Global Warning Potential technique. According to this scheme, each GHG is associated to a coefficient which quantifies its relative greenhouse power with respect to carbon dioxide. According to the last IPCC report (IPCC, 2014) the 100-year GWP is 28 for methane and 265 for nitrous oxide, while fluorinated gases have a GWP in the order of hundreds to thousands.

feasibility of this emission pattern and the policy that would make it possible. Here the focus is on understanding what role can be played by CCS in achieving these long-term targets and its technical and economic impacts with a multi-decadal perspective.

4. Results

It is interesting to start by observing how CCS deployment evolves at a global level in the scenario set, see Figure 4. In general, the progressively more and more ambitious emission targets imply a progressively more and more substantial rearrangement of the energy sector, and in particular of the power sector that is focused in this work. In particular, the role of low-carbon or no-carbon power technologies, among which CCS power plants, progressively grows, until they dominate the sector in the more stringent scenarios.

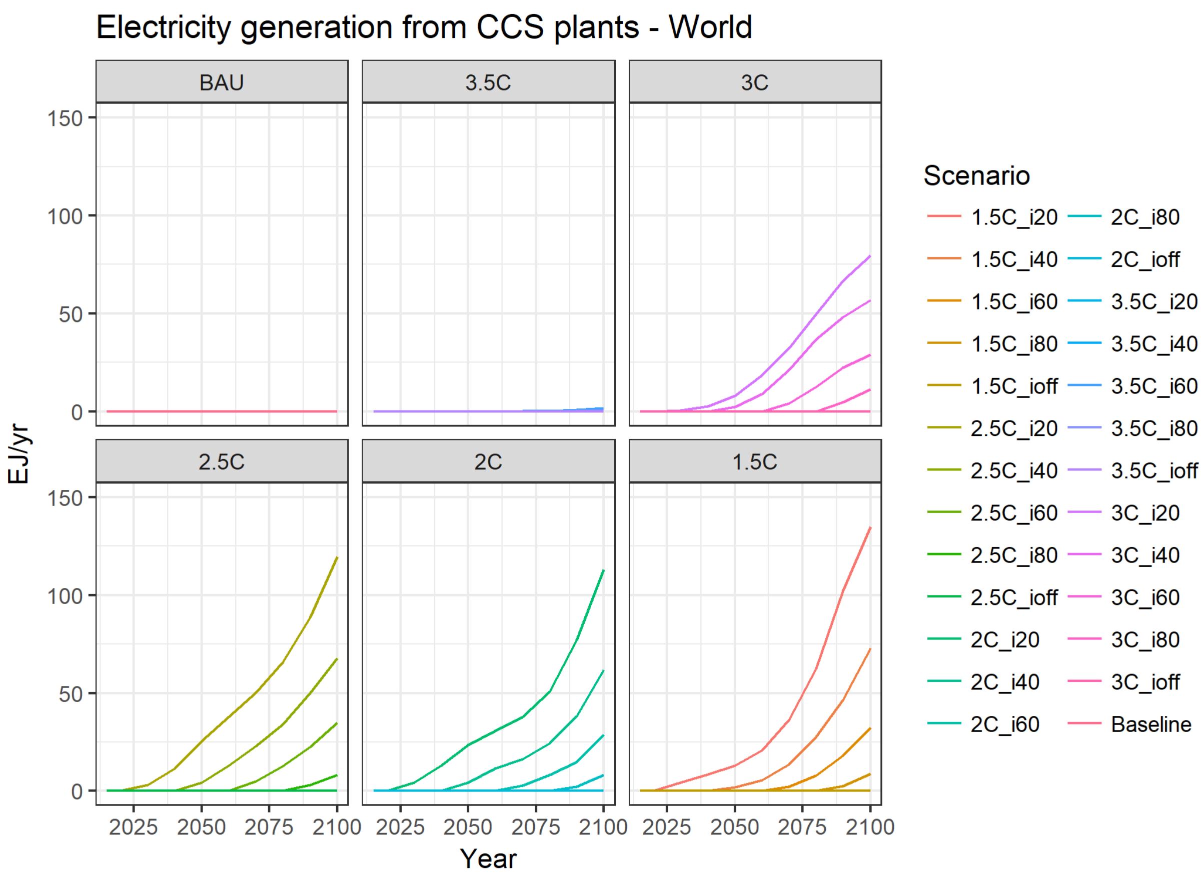

Figure 4 – Global CCS generation.

In the baseline case, no CCS deployment is observed. This is quite a trivial result: if there is no carbon signal, there is no need to install a group of low-carbon technologies which are by far more expensive than the corresponding non-CCS ones. The carbon signal is too low in the 3.5°C scenarios as well, except for a negligible deployment in the last years of the century. From the 3°C downwards, instead, CCS is regularly installed. Figure 4 clearly shows that the delayed trigger to CCS deployment does have a considerable effect: in all cases, as soon as CCS installation is permitted, it actually starts, with a constant growth over the following decades. It is interesting to note that under no cases can CCS capacity reach the level that is achieved if it can be deployed 20 years in advance. This is mostly due to the constraints affecting the capacity that can physically be installed over a five-year period, but it also highlights that CCS is an option that is fully exploited in the unconstrained scenarios, if available. It can also be noted that the CCS generation has a similar pattern across the scenario set, especially from 2.5°C to 1.5°C: in 2100, CCS generation reaches 113-134 EJ/yr in the i20 scenarios, 61-72 EJ/yr in the i40 scenarios, 29-35 EJ/yr in the i60 scenarios, and 8-10 EJ/yr in the i80 scenarios, respectively (by definition, it is zero in the ioff scenarios). Figure 5 provides a detail on the CCS generation in 2100.

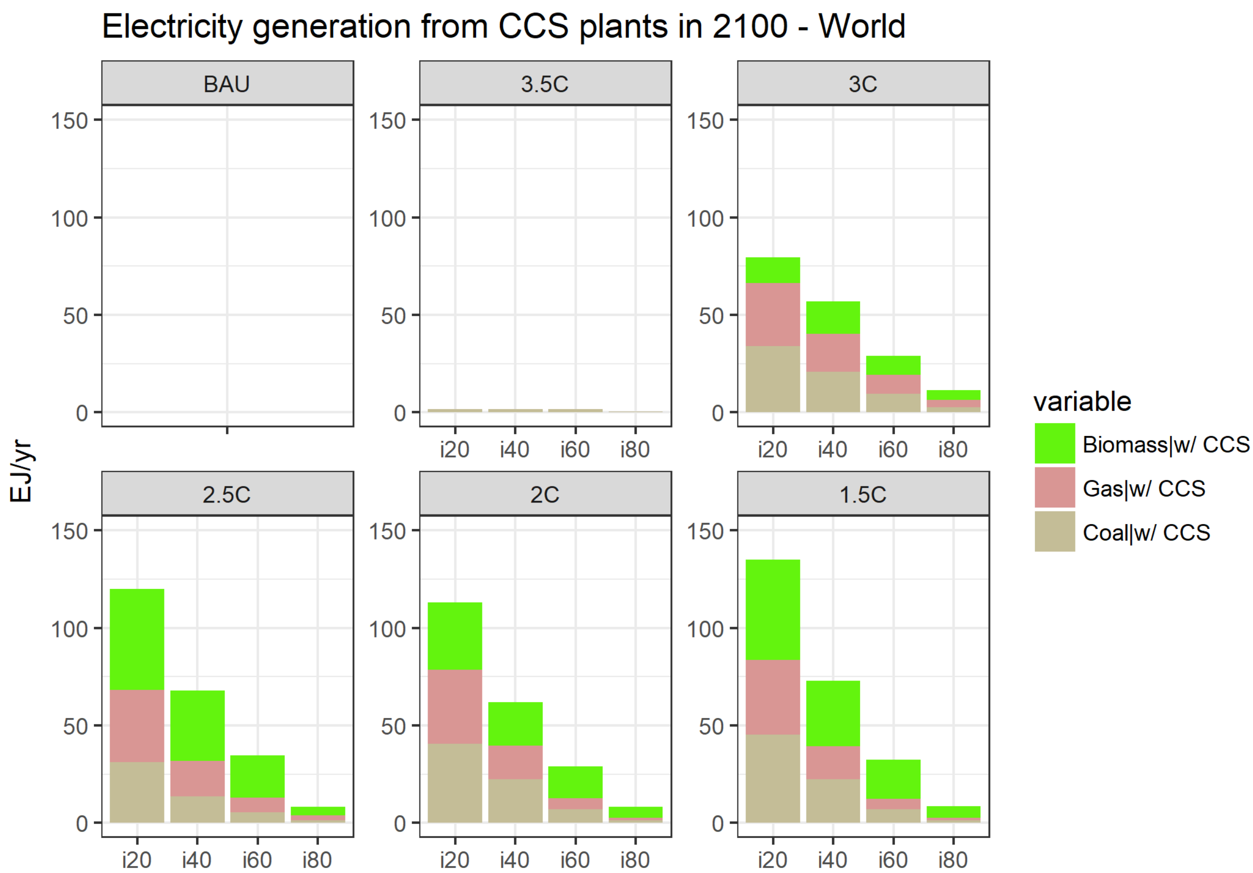

Figure 5 – Global CCS generation in 2100 by source.

The graph, in addition to underlying that a late CCS deployment leads to a lower CCS generation, also shows that the three CCS power technologies (coal, gas, and biomass) provide quite a homogeneous contribution, even if late deployment seems to favor the BECCS technologies. The ioff scenarios are not shown here for the reasons explained above.

What are the impacts on the overall electricity generation amount and mix? Electricity generation is shown in Figure 6.

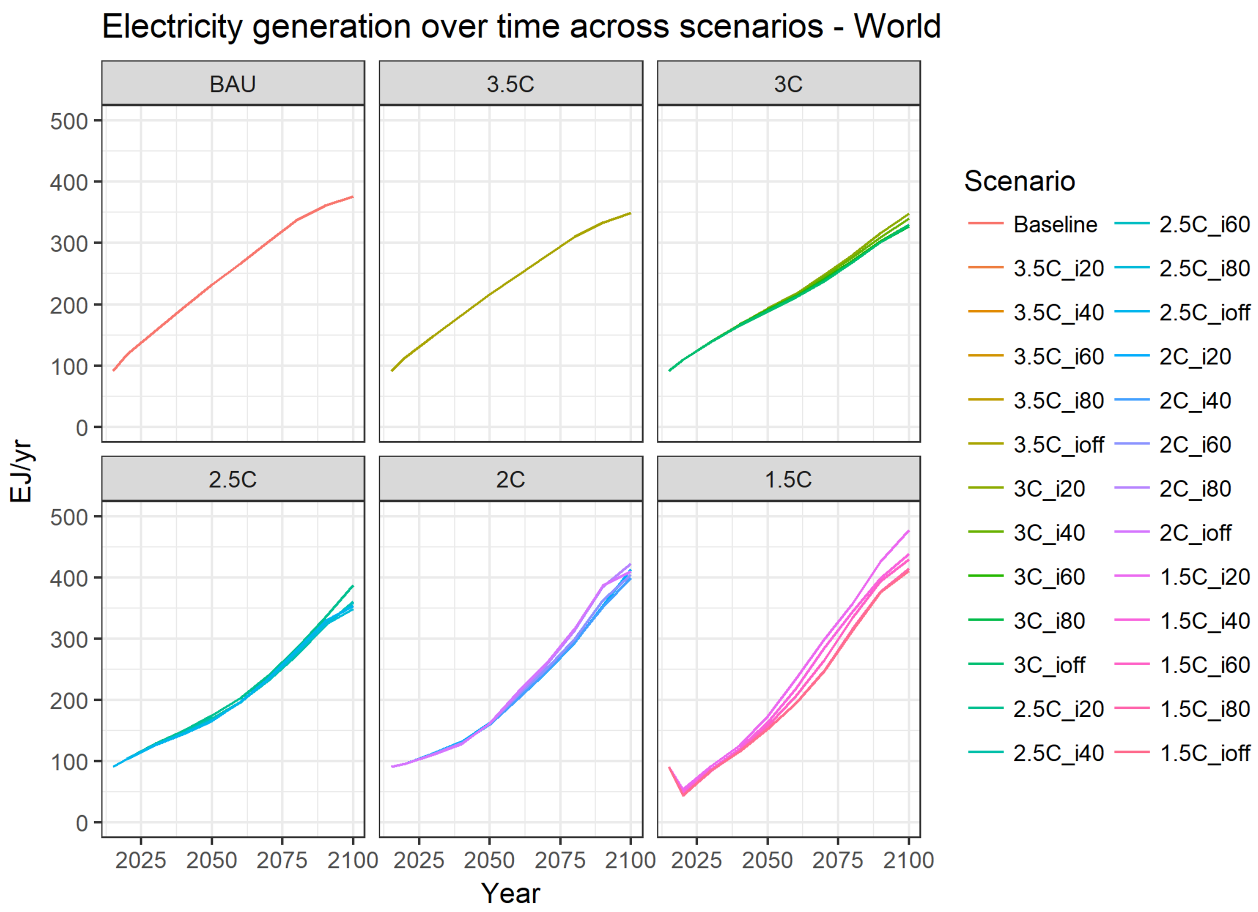

Figure 6 – Global curtailed energy conversion.

Electricity generation starts from 90 EJ/yr in 2015 and progressively grows over time in all scenarios (with the partial exception of the 1.5°C scenarios, which show a dramatic (and unlikely) decrease in the electricity generation associated to the emission pattern discussed in the previous section: it is not possible to massively rearrange the power sector in such a short period to meet with the mitigation requirement, therefore the only solution is to cut the overall generation. In the BAU scenarios, the final value in 2100 is 376 EJ/yr. As a progressively increasing carbon tax is applied, the demand growth slightly slows down, at least until the 2.5°C scenarios: the 2°C scenarios show an opposite behavior, with a convergence in 2100 at around 400 EJ/yr, and even more so in the 1.5°C scenarios, which achieve the 450 EJ/yr area.

These results highlight the two possible and contrasting patterns to achieve carbon mitigation. On the one hand, emissions can be reduced simply by reducing demand. On the other hand, emissions can be reduced by shifting energy demand from highly emitting to low emitting fuels or carriers. As the power sector shows more viable routes for decarbonization than other sectors, mitigation futures can arguably entail an electrification of the energy sector with a parallel decarbonization of the power sector. In the milder scenarios the first tendency prevails, while in the more stringent scenarios the opposite occurs.

Figure 7 shows the CCS relative penetration in the electricity mix as resulting from the previous two figures: it can be noted that in the absence of deployment constraints, i.e. if investment is allowed from 2020, CCS technologies can reach about 30% in the electricity mix in 2100.

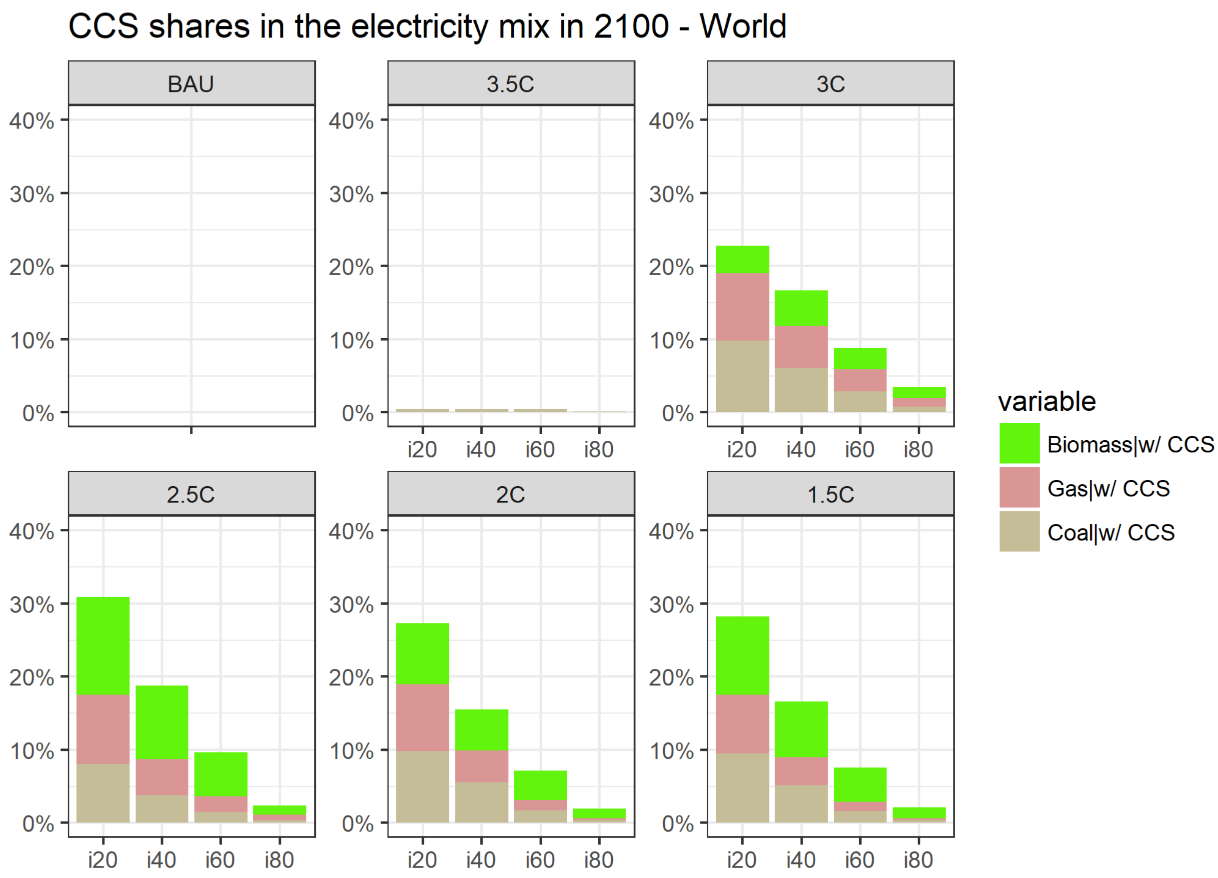

Figure 7 – Global CCS relative penetration in the electricity mix in 2100 by source.

Figures 8 and 9 provide a more general view on the overall electricity mix in 2100. The former shows the absolute generation, while the latter focuses on the relative shares.

In the baseline scenario, fossil fuels (without CCS) dominate the electricity mix, accounting for 50% of the total (coal 30%, gas 18%, and oil 2%). Nuclear accounts for 12% (substantially the same level as today), hydro 7%, while variables renewables (wind and solar) account for 30%, approximately two thirds from wind and one third from solar. The 3.5°C scenarios are characterized by a very similar electricity mix, simply with a 10%-shift from fossils to wind and solar.

More impacts can be seen in the 3°C scenarios, i.e. where CCS technologies appear in a non-negligible amount. As already noted, the delayed deployment of CCS implies lower and lower shares for this technology in 2100. Its contribution is mostly compensated by renewables, nuclear, and also gas without CCS, which is still a viable technology for this mild climate target. This no longer happens in the more stringent climate targets. Figure 7 has already shown that in all these cases, CCS accounts for about 30% of the electricity mix in 2100 if its deployment is allowed starting from 2020. If CCS is constrained, there is no room for non-CCS technologies (apart from a negligible gas contribution in the 2.5°C scenarios) and the electricity mix tends to “converge” to a solution dominated by renewables (with about 35% wind onshore, 10% wind offshore, 30% solar PV, and 5% solar CSP, i.e. 80% in total), with a complementary contribution of nuclear (12%) and hydro (8%).

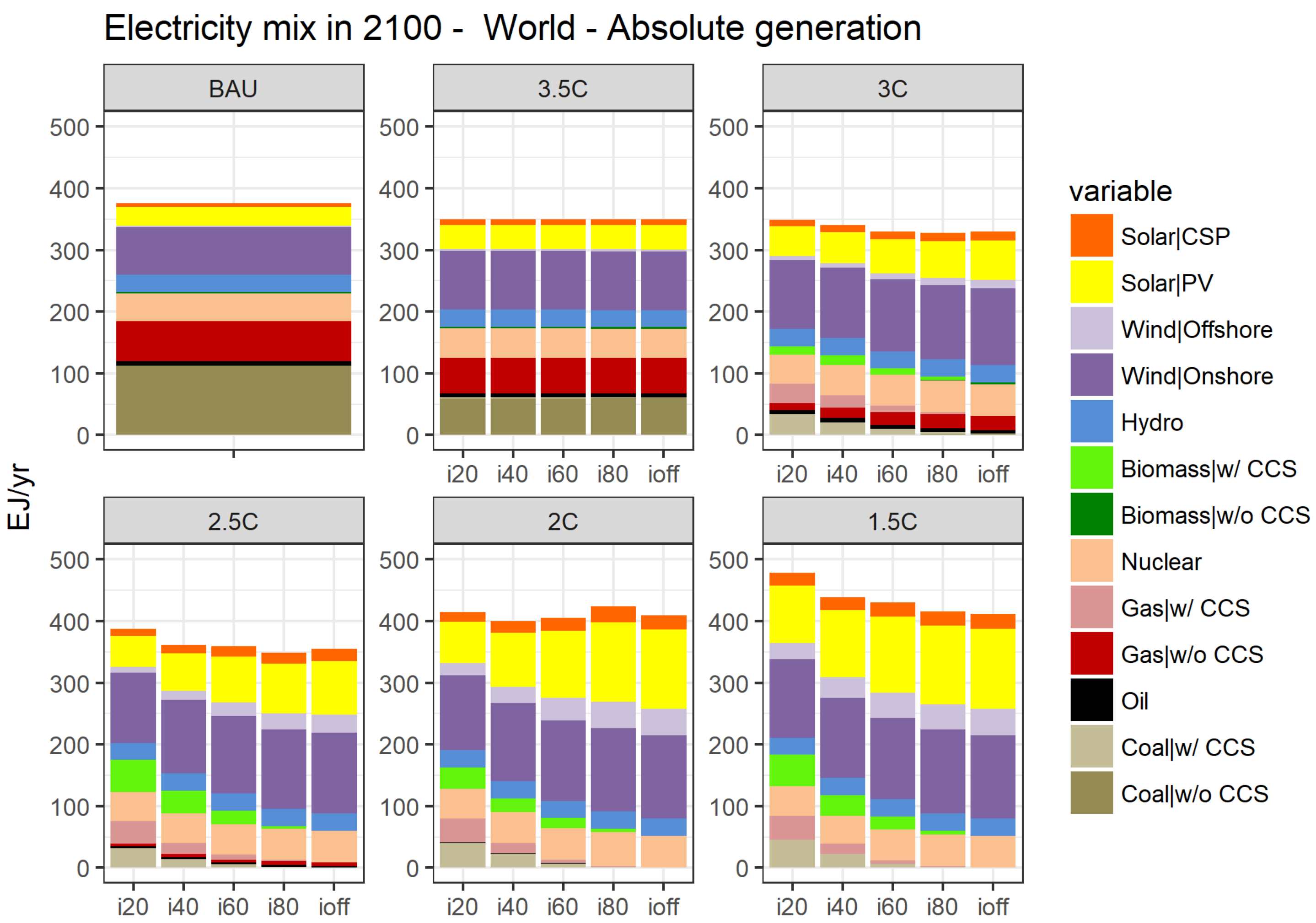

Figure 8 – Global electricity mix in 2100: absolute generation.

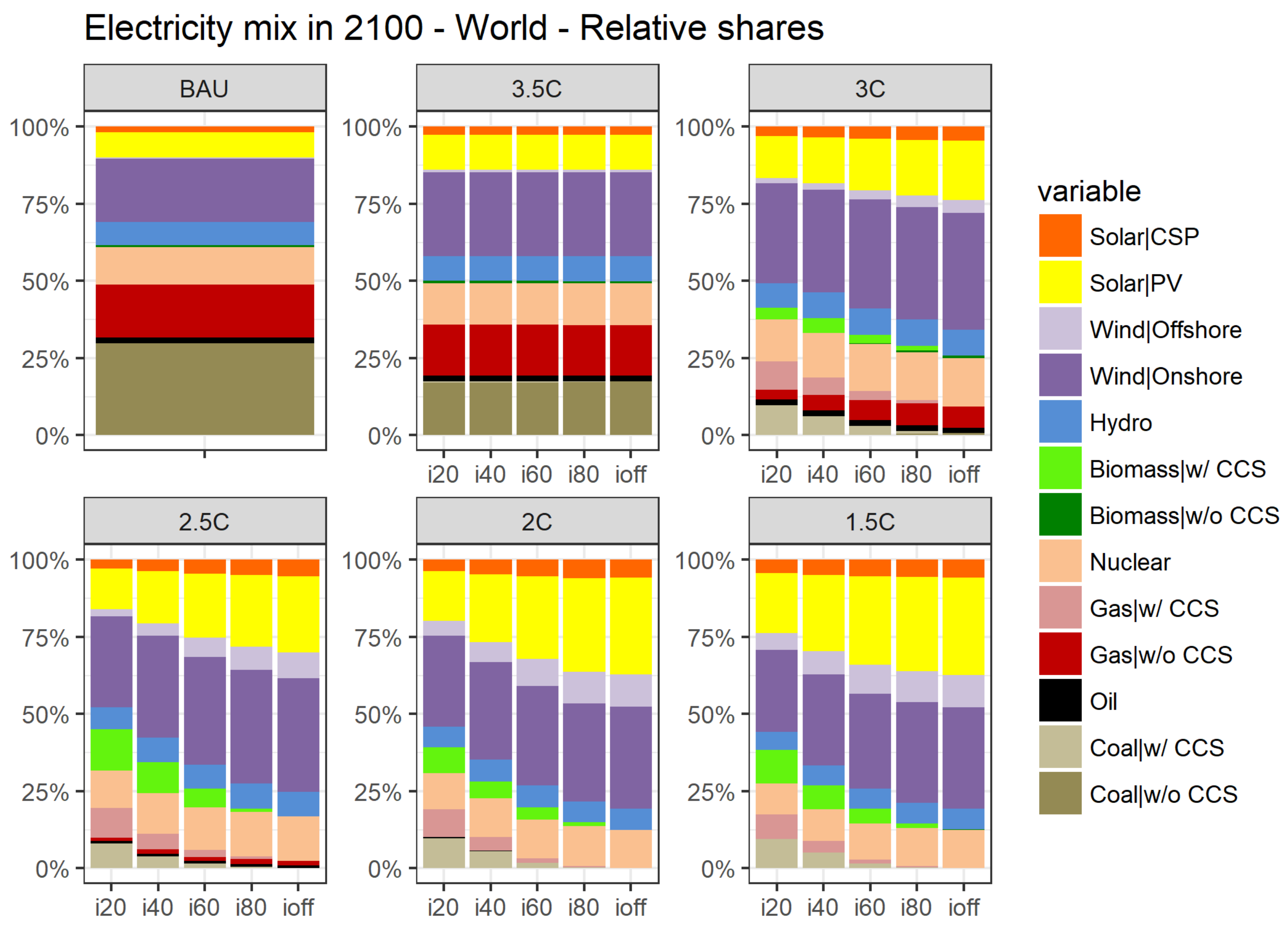

Figure 9 – Global electricity mix in 2100: relative shares.

Concerning the latter result, it should be noted that such a huge penetration of renewables would imply a profound re-structuring of the electricity system. From a modeling point of view, it is not easy to cope with the system integration issues in IAMs, as the low temporal and spatial scales which characterize these aspects are in contrast with the need of providing long-term projections over an horizon of decades, considering aggregated annual quantities and focusing on large regions. However, it is not within the scope of this paper to discuss these topics: here it is sufficient to underline that the model considers huge investment in storage capacity and grid expansion to comply with this renewable deployment. The reader is referred to Carrara and Marangoni, 2017 for further details on the WITCH model and to Pietzcker et al., 2017 for an overview of IAMs.

In order to have a more dynamic view of the electricity mix without focusing on 2100 only, Figures from 10 to 13 show the evolution of the electricity mix over time in selected years (2025, 2050, 2075, and 2100) for the two boundary groups of CCS deployment options, i.e. i20 (thus, the unconstrained CCS scenarios) and ioff (thus, the no CCS scenarios), for all the climate targets. BAU results are always reported for benchmarking purposes. In particular, Figures 10 (i20) and 12 (ioff) report the absolute generations, while Figures 11 (i20) and 13 (ioff) report the relative shares.

These figures help visualize how coal, and then gas, are progressively phased-out in the mitigation scenarios. This happens smoothly over the decades in the milder mitigation scenarios, quite strongly after 2025 in the more stringent scenarios. Naturally, the phase-out is more urgent for coal than for gas, as the former is characterized by specific emissions which are about twice as those of the latter. In the i20 scenarios, fossil phase-out is compensated by the progressive CCS penetration, in addition to the massive deployment of renewables.

Furthermore, Figures 8 and 9 highlighted that biomass without CCS is barely present in the electricity mix in 2100. Indeed, Figures 10 to 13 show that this technological solution does have a non-negligible penetration in the first decades, but in the long run it is phased out, underlining that biomass is appealing only if coupled with CCS technologies in order to allow negative emissions.

Finally, it has already been noted that the 1.5°C scenarios would imply a huge cut in the electric generation immediately after 2015 in order to meet with the carbon mitigation requirements. Indeed, this implies an immediate retirement of most (i20) or all (ioff) of fossil plants. As a result, the 2025 electricity mixes are (almost) completely characterized by a carbon free generation deriving from hydro, nuclear, and variable renewables. It has already been discussed that this scenario is really extreme, but it is interesting to explore these barely-feasible conditions for comparison purposes.

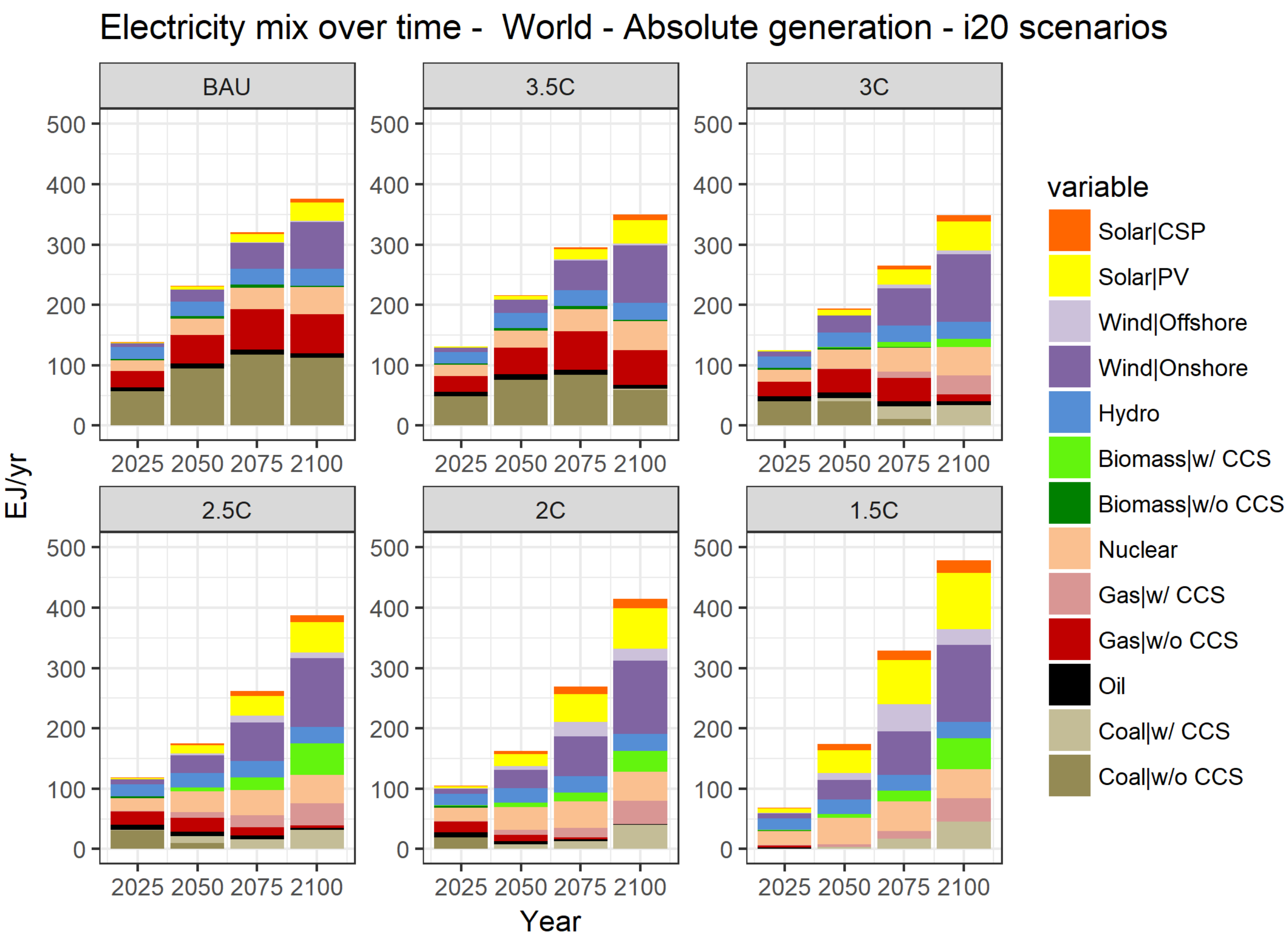

Figure 10 – Global electricity mix over time in the i20 scenarios (unconstrained CCS): absolute generation.

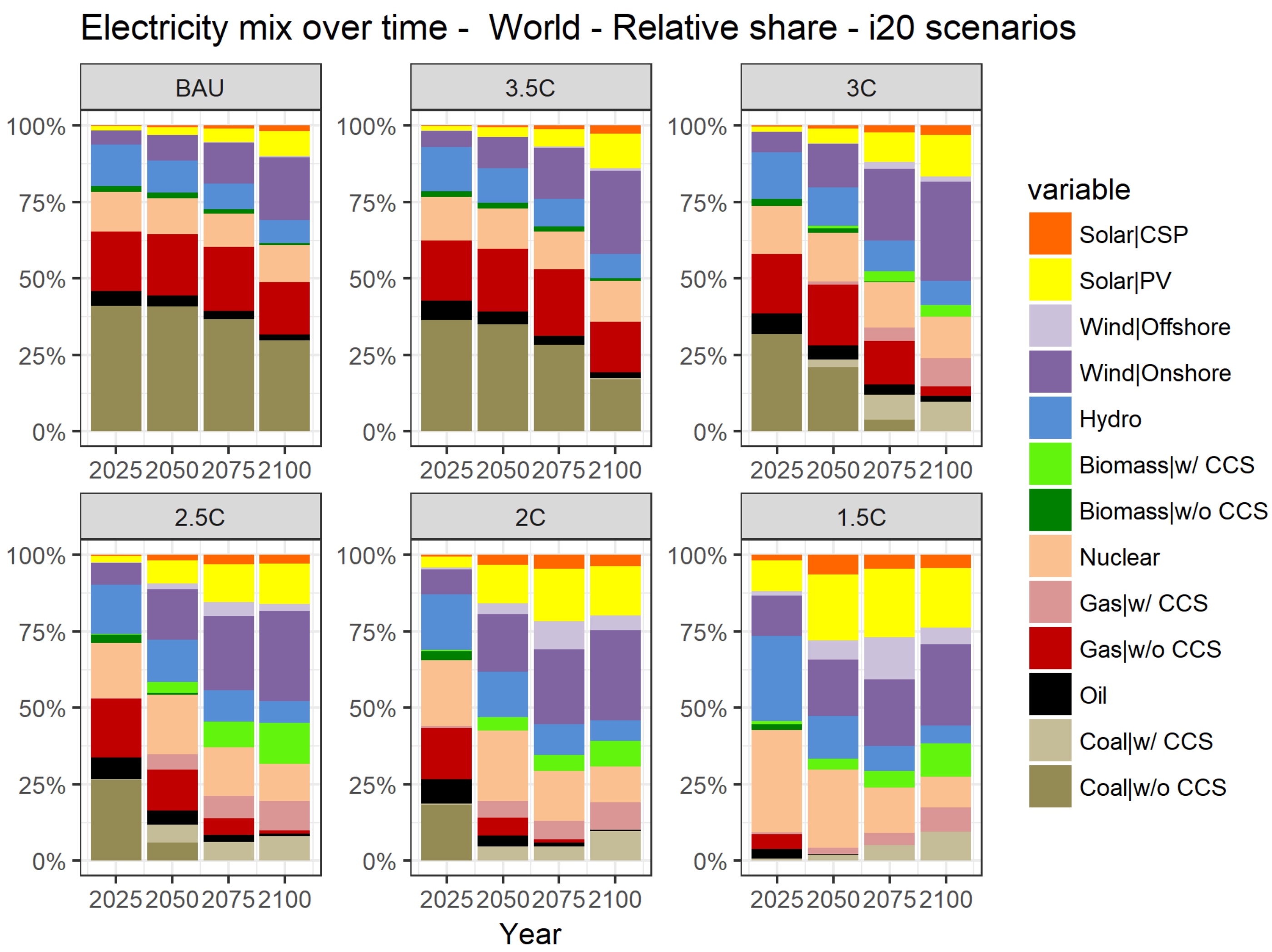

Figure 11 – Global electricity mix over time in the i20 scenarios (unconstrained CCS): relative shares.

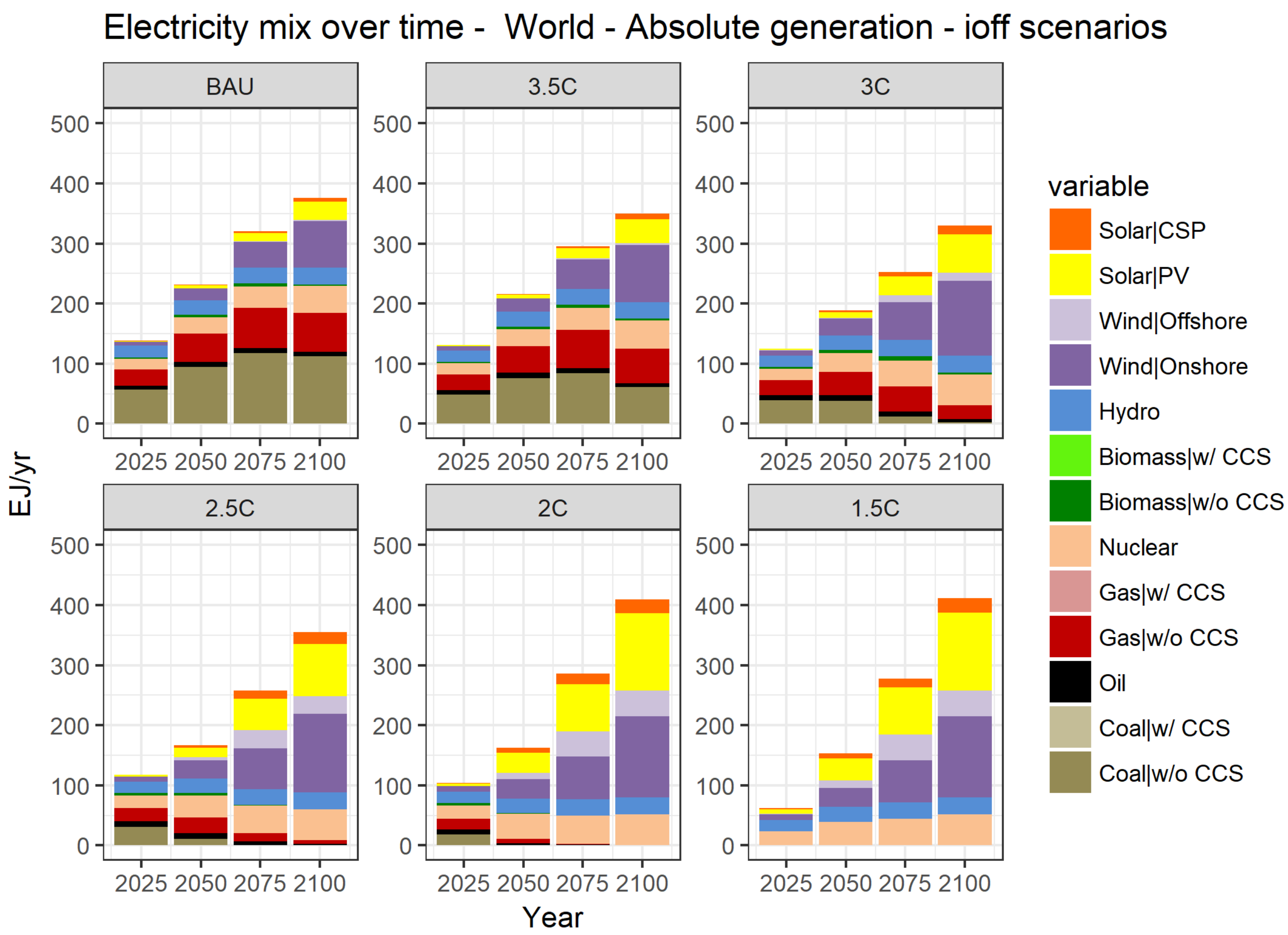

Figure 12 – Global electricity mix over time in the ioff scenarios (no CCS): absolute generation.

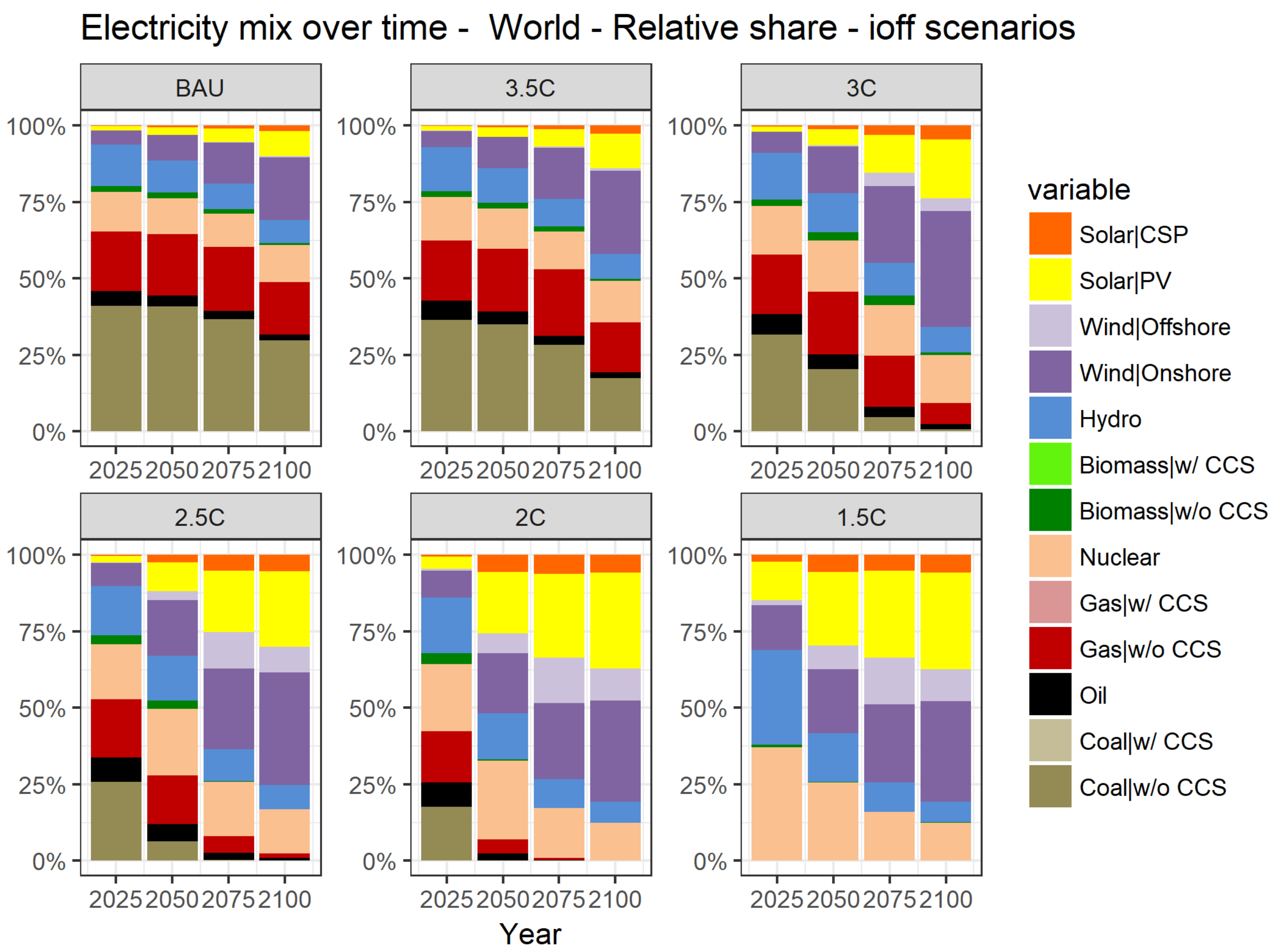

Figure 13 – Global electricity mix over time in the ioff scenarios (no CCS): relative shares.

Figure 14 shows the policy costs in the different scenarios. Policy costs are evaluated as the cumulated GDP loss over the century with respect to the cumulated GDP in the baseline case, considering a discount factor of 2.5%. Values are shown on the same scale, in order to facilitate a comparison of the orders of magnitude across the different scenarios.

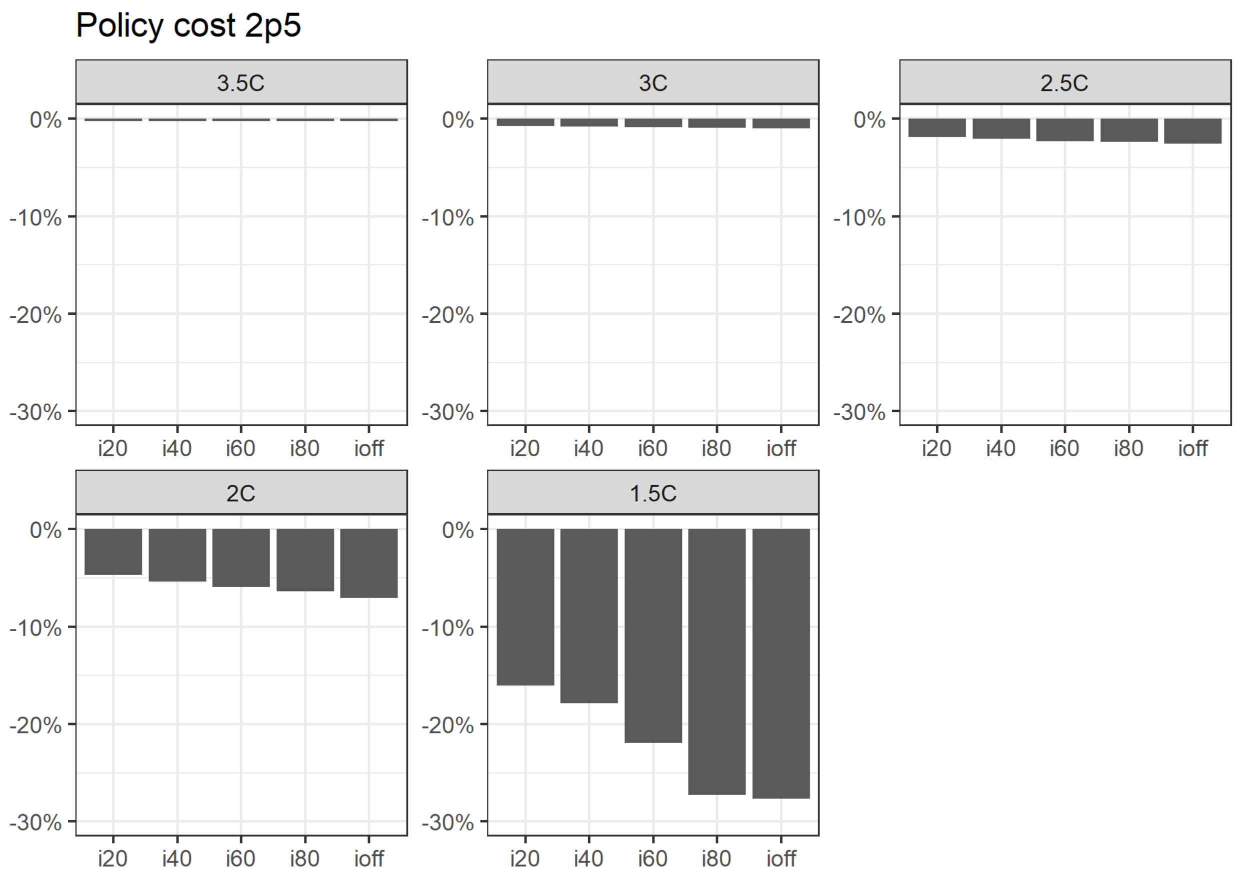

Figure 14 – Policy costs.

Policy costs in the 3.5°C scenarios are negligible, around 0.2%: after all, the stringency of the target is very mild, so the required changes to the economic and energy systems are almost null. As discussed in the previous pages, CCS is not deployed in these scenarios, so results are not differentiated per CCS deployment year within this target. A moderate difference emerges in the 3°C scenarios, where policy costs are around 0.7-1%. In particular the ioff scenario has a policy cost which is 35% higher than the i20. In the 2.5°C scenarios, policy costs range between 1.9% and 2.7%, with the no CCS case costing 38% more than the unconstrained CCS scenarios. If reaching 2.5°C entails relatively moderate costs, achieving the Paris-compatible 2°C target implies much higher expenses. If CCS can be deployed with no constraints, the aggregated GDP loss is 4.7%. This values increases with a progressively delayed CCS deployment, up to 7.1% in the no CCS case, 51% more than the former. Finally, the profound revolution which is required to achieve the 1.5°C target has inevitable enormous effects on the policy costs. With a fully unconstrained technology portfolio the policy cost is about 16.1%, while it rises up to 27.6% in the corresponding ioff case, i.e. 72% more than the unconstrained case. Therefore, not only is the delayed deployment of CCS impacting on the policy cost, but this impact increases in relative terms with the policy stringency.

Finally, a brief focus on the European prospects is reported. Indeed, Europe does not have a considerable storage potential, additionally it is characterized by a huge renewable potential and technology maturity. These two factors imply that CCS will not be a main mitigation option in this region according to the WITCH scenarios.

Figure 15 reports the CCS shares in the electricity mix in 2100 in the explored scenarios. As noted in Figure 7 discussing the global results, CCS does not penetrate the market in the BAU and the 3.5°C scenarios. Some CCS generation appears in the 3°C scenarios, with a good distribution across the three considered technologies. Differently from the global results, however, there is no variability as a function of the CCS deployment year: CCS penetration is around 2-3% independently of when CCS installation is allowed. This insensitivity to the installation year is found in the more stringent policy scenarios as well, where, furthermore, CCS penetration i) does not increase significantly with mitigation stringency, and ii) is almost completely deriving from biomass.

The negligible role played by CCS in the European electricity mix is evident in Figure 16, which shows the whole electricity mix in the explored scenarios. Already in the BAU case, renewables dominate the long-term mix, achieving some 70% (about 40% wind and 20% solar, mostly PV, and 10% hydro), which is added to about 20% of nuclear. Coal and gas sum up to 10% only. Naturally the fossil contribution decreases in the 3.5°C and disappears in the more stringent scenarios, only partially substituted by CCS, as noted, whereas the remaining technologies essentially maintain their very same shares across all scenarios.

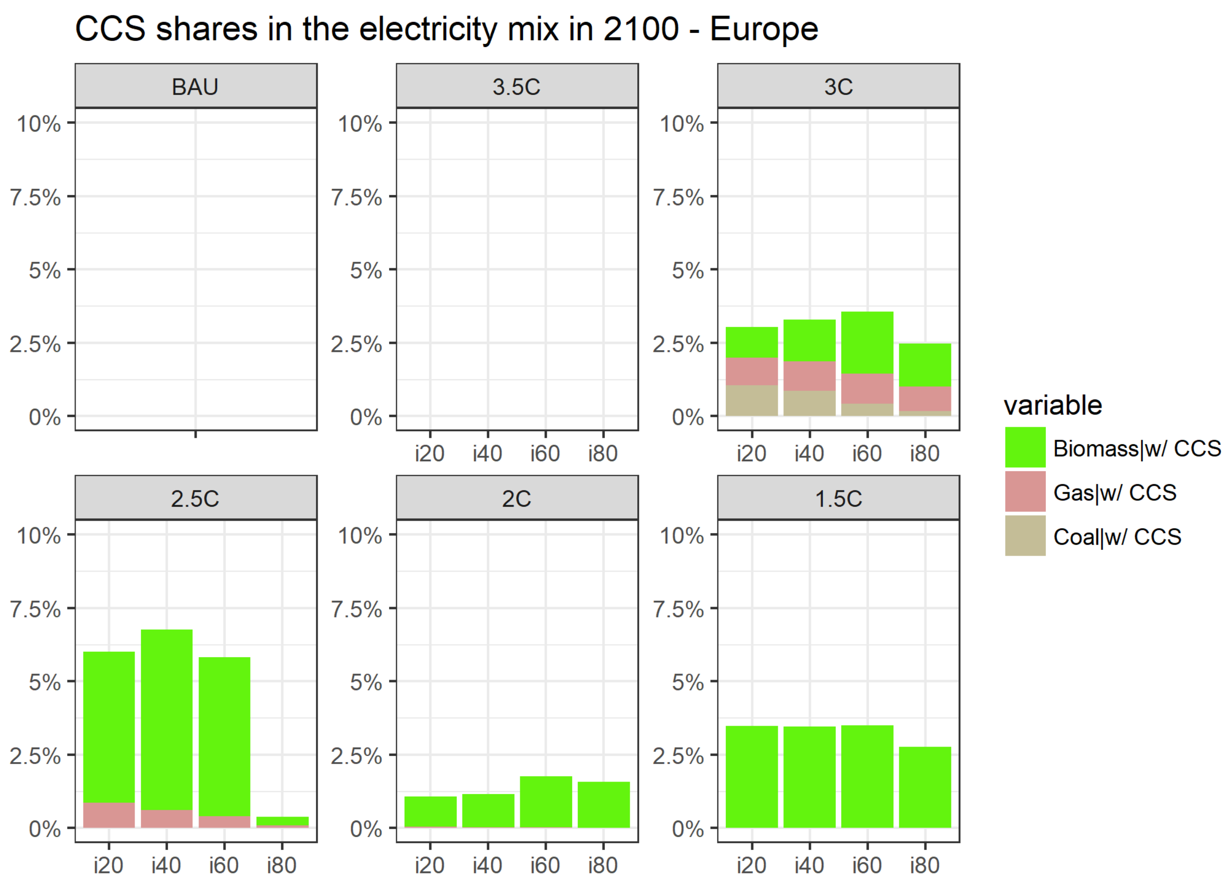

Figure 15 – European CCS relative penetration in the electricity mix in 2100 by source.

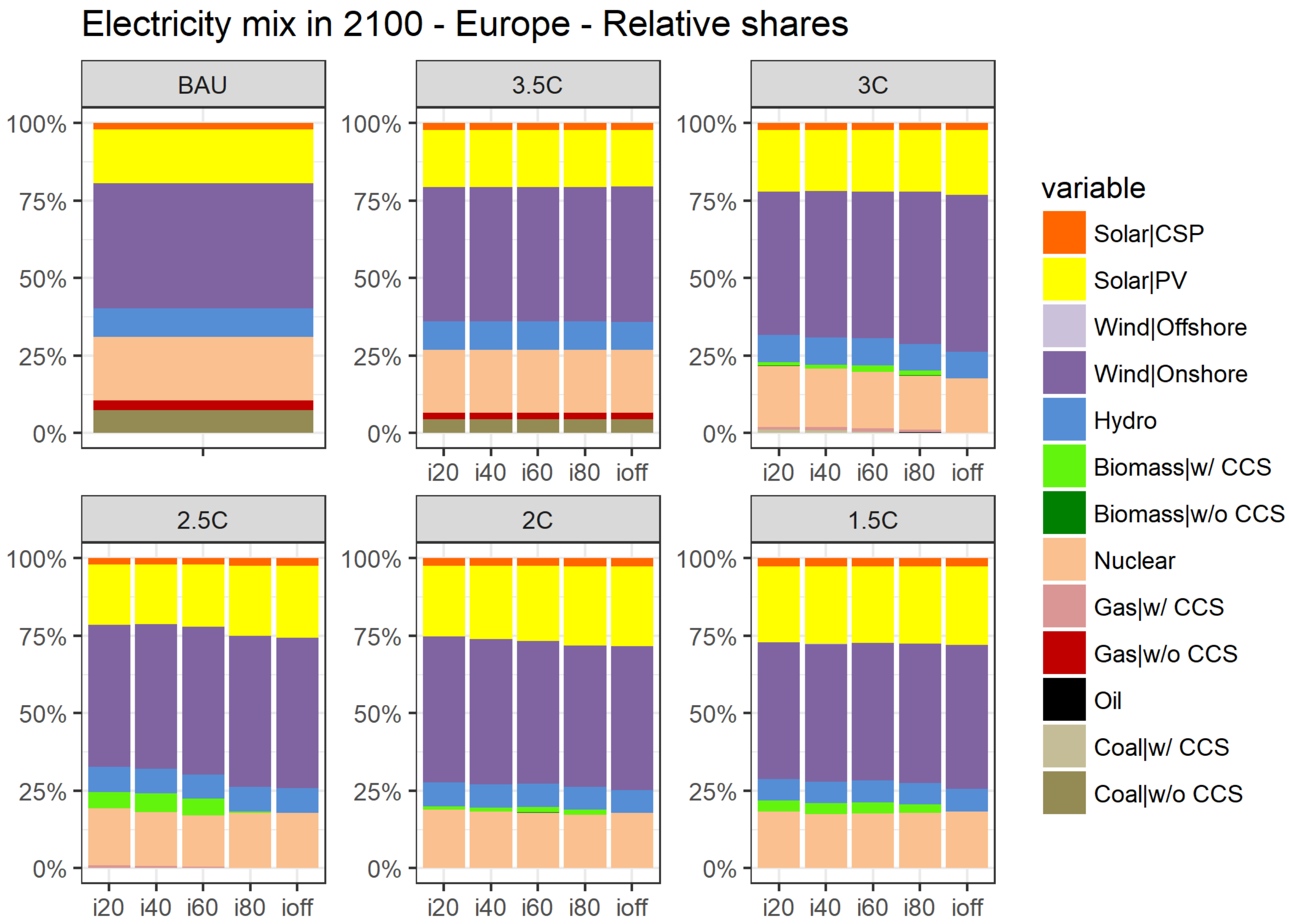

Figure 16 – European electricity mix in 2100: relative shares

5. Conclusions

CCS is considered one of the key technologies in the perspective of climate change mitigation. Its main advantage consists in eliminating carbon dioxide emissions without shifting away from the fossil-based paradigm which still characterizes the power sector. However, in reality many issues still hinder its diffusion, such as safety concerns about storage sites, public acceptance, high technology costs, and the absence of a common regulatory framework and of business models.

The main aim of this work is to explore the techno-economic consequences that a delayed deployment of CCS can have on the electricity mix and on the economic system as a whole. Five deployment options have been considered with reference to the starting year from which CCS installation is allowed: 2020 (i.e. the unconstrained scenario, as global CCS capacity is practically negligible as of today), 2040, 2060, and 2080, in addition to the no CCS scenario. These five scenarios have been explored over a wide set of policy targets, ranging from the no policy or Business-as-Usual, which leads to 4°C as a temperature increase in 2100 with respect to the pre-industrial levels, to 1.5°C.

Scenarios confirm the consolidated result in the literature that CCS is likely to play a major role in the decarbonization of the electricity sector at a global level, as it is installed in all scenarios with a policy target equal to 3°C or less. In all these cases, as soon as the investment in CCS is allowed, this option is immediately activated by the optimization model. Due to expansion constraints, the delayed installation prevents CCS from reaching the optimal level which would be achieved in the unconstrained scenarios.

This implies a progressively lower penetration in the electricity mix as the deployment is delayed: global CCS penetration is around 25-30% in 2100 in all scenarios from 1.5°C to 3°C, gradually decreasing to zero as the deployment is delayed or not allowed. The contribution from coal, gas, and biomass is quite well balanced. The impact on the overall electricity demand is such that it diminishes with the progressively delayed CCS deployment. This decrease is indeed quite little if mitigation is limited to 2°C (the difference is lower than 5% in 2100 from the no CCS to the unconstrained CCS scenario), while it is more marked in the 1.5°C scenarios, where the difference in 2100 between the two extreme investment cases (i.e. i20 and ioff) is around 15%. The absence of CCS is mostly compensated by renewables (notably wind and solar), with also a partial increase in nuclear.

Removing (partially or totally) CCS from the optimal electricity mix has inevitable effects on the overall economic performance. The analysis on the changes in policy costs has shown that, within the specific policy targets, the no CCS scenario is characterized by a cumulative GDP loss which is averagely 50% higher than the corresponding unconstrained CCS scenarios, thus proving the strong economic impact of the delayed CCS deployment.

Special attention has also been put on Europe. Indeed, this region is characterized by low availability of storage sites for CCS and by high renewable potential and technology maturity. This results in a very low CCS penetration in all scenarios: even in unconstrained conditions and in the most stringent scenarios, CCS never exceeds 5% in the electricity mix in 2100. The obstacles to CCS penetration are thus much more relevant on a global level as a whole than specifically on a European level.

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Reactor ageing and phase-out policies: global and European prospects for nuclear power generation

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Abstract

Nuclear is considered as a valuable option for the decarbonization of the power generation, as it is a no-carbon, yet commercially consolidated technology. However, its real prospects are uncertain: if some countries, especially in the non-OECD area, have been extensively investing in nuclear, many OECD countries, which host the vast majority of operational reactors worldwide, feature old fleets which will not be replaced, as phase-out policies are being implemented.

Research scenarios often consider polarized conditions based on either a global unconstrained nuclear development or a generalized phase-out. The main aim of this work is instead to explore the techno-economic implications of policy-relevant scenarios, designed on the actual nuclear prospects in the world regions, i.e. mainly differentiating policy constraints between the OECD and the non-OECD regions.

The analysis, conducted via the Integrated Assessment Model WITCH, shows that nuclear generation constantly grows over the century, even if in general the nuclear share in the electricity mix does not significantly change over time, both at a global and at a European level (apart from a temporary increase in the first part of the century). Over time, and especially if constraints are applied to nuclear deployment, the nuclear contribution is compensated by renewables (mainly wind and solar PV) and, to a lower extent, by CCS (only marginally in the EU).

The policy costs related to the nuclear phase-out are not particularly high (0.4% additional global GDP loss with respect to the unconstrained policy scenario), as they are almost completely compensated by innovation and technology benefits in renewables and energy efficiency. Phase-out policies applied only to the OECD regions do not entail any additional policy costs, while non-OECD regions marginally benefit from lower uranium prices. A sudden shutdown of nuclear reactors in the OECD regions results in a doubling of these losses and gains.

Keywords: nuclear, power generation, climate change mitigation, Integrated Assessment Models

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1. Introduction

Meeting with increasing energy demand via low-carbon solutions is a major goal for the 21st century in order to avoid detrimental effects on climate (IPCC, 2014). In 2015, almost all world countries signed the Paris Agreement committing to limiting to 2°C the global temperature increase in 2100 with respect to the pre-industrial levels and to pursuing efforts to reach 1.5°C, in order to further contain potential negative impacts (Schellnhuber et al., 2016). Clearly, these targets are very ambitious, since they entail profound technological and economical efforts as well as political coordination among countries.

Nuclear is widely recognized as one of the main technologies which will play an important role in decarbonizing the power sector (Krey et al., 2014 and Koelbl et al., 2014). Its main advantage is the possibility to couple technological maturity (nuclear has commercially been exploited since the 50s of the 20th century) with virtually no carbon dioxide emissions and without the dispatchability issues that affect variables renewable energies such as wind and solar.[1]

Nuclear power was characterized by a huge development especially in 70s and 80s. The accidents in Three Miles Island, USA (1979) and, above all, in Chernobyl, Former Soviet Union (1986) determined a substantial fall in the investments, mostly due to the safety concerns that were raised by those events. A general renaissance took place during the first decade of the 21st century, but the accident at the Fukushima-Daiichi, Japan (2011) revived public concerns about safety, which ultimately resulted in a reconsideration of the nuclear expansion policies in many countries of the world (Wittneben, 2012). Concerns about nuclear proliferation, waste management that is still an open issue, the shortage of qualified workforce in the reactor construction and high or uncertain costs (at least in some areas of the world) are the other main points representing an obstacle to nuclear diffusion (Ahearne, 2011). The long construction time (8-10 years) and operational life of plants (40+ years) make the uncertainty concerning electricity demand and public acceptance particularly relevant in discouraging investments (Cardin et al., 2017).

These factors jeopardize the future prospects of nuclear energy. As will be discussed in Section 3, in general two opposite tendencies are found worldwide, which roughly distinguish OECD and non-OECD countries. In OECD countries (with the main exception of the Republic of Korea), on the one hand many nuclear reactors are approaching the end of their operational life and on the other hand political, social, and economic constraints hinder the construction of new plants. Therefore, even in presence of massive investments to extend the operational lifetime of reactors (from about 40 to about 60 years), the prospects in these countries are controversial. Instead, in non-OECD countries, and especially China, India, and Russia, nuclear is characterized by high momentum and ambitious expansion plans are in place for the next decades.

In this context, the main objective of this work is to investigate the actual prospects of nuclear and their consequent impacts on the electricity mix and the policy costs, taking into consideration real-world aspects such as the policies implemented by countries and the ageing of reactors. This allows exploring more credible and meaningful scenarios, whereas assessment exercises often consider “digital” options only, i.e. either a global unconstrained nuclear expansion or global phase-out (Rogner and Riahi, 2013 and Hof et al., 2019). The exercise is carried out with the Integrated Assessment Model (IAM) WITCH.

[1] It is true, though, that the functioning and huge dimensions of reactors (averagely around 1000 MW, up to 1600 MW in the latest models) result in a general inflexibility, so that a plant normally operates at full rate 7-8000 hours per year with limited load variations. These aspects could be addressed by developing smaller plants, the so-called Small Modular Reactors (SMRs), whose commercial maturity, however, is yet to come (Budnitz et al., 2018).

The paper is structured as follows. Section 2 describes the WITCH model, and especially how nuclear is modeled therein. Section 3 discusses more in detail the nuclear global scenario and the policy context, and in particular the policies implemented or planned by world countries. Section 4 describes the scenario design which has been defined according to the policy landscape described in the previous section. Section 5 presents the main results of the analysis. Section 6 finally concludes.

2. Methodology

2.1 The WITCH model[2]

The tool adopted in this research is the World Induced Technical Change Hybrid (WITCH) model. WITCH is a dynamic optimization Integrated Assessment Model designed to investigate the socio-economic impacts of climate change over the 21st century (Bosetti et al., 2006 and Emmerling et al., 2016). It combines a top-down, simplified representation of the global economy with a bottom-up, detailed description of the energy sector, nested in a Constant Elasticity of Substitution (CES) structure (Figure 1). The model is defined on a global scale: countries are grouped into thirteen aggregated regions, which strategically interact according to a non-cooperative Nash game. The thirteen economic regions are USA (United States), OLDEURO (Western EU and EFTA countries[3]), NEWEURO (Eastern EU countries), KOSAU (South Korea, South Africa, and Australia), CAJAZ (Canada, Japan, and New Zealand), TE (Transition Economies, namely Russia and Former Soviet Union states, and the non-EU Eastern European countries), MENA (Middle East and North Africa), SSA (Sub-Saharan Africa except South Africa), SASIA (South Asian countries except India), EASIA (South-East Asian countries), CHINA (People's Democratic Republic of China and Taiwan), LACA (Latin America and Central America) and INDIA (India).[4] As the model acronym suggests, technological change is endogenously modeled in WITCH, and it regards energy efficiency and the capital cost of specific clean technologies. Global prices of fossil fuels are endogenously calculated, while the model is coupled with the Global Biosphere Management Model, GLOBIOM (Havlík et al., 2014) to describe land use. GLOBIOM provides biomass supply cost curves to WITCH for different economic and mitigation trajectories. This allows assessing woody biomass availability and cost.

The CES structure reported in Figure 1 shows how the top-down aggregated economic model is linked with the disaggregated energy sector. In particular, energy services (ES) and the aggregated capital and labor node (KL) are combined to produce the final economic output of the model. Energy services are provided by the combination of the capital of energy R&D (RDEN), which is a proxy of energy efficiency, and the actual energy generation (EN). This node models the fact that the same energy services can be obtained through a lower level of energy input if there is higher energy efficiency. The EN node is divided between the electric (EL) and non-electric sector (NEL), with a progressive disaggregation down to the single technologies. The electric sector has a higher detail, while the non-electric sector mostly reports nodes which collect consumption from all the non-electric usages of one specific energy source, except for the road passenger and road freight transport sectors, which are the only demand sectors being explicitly modeled[5] (see Bosetti and Longden, 2013, and Carrara and Longden, 2017).

[2] For the sake of simplicity, this section has almost entirely been taken from the CCS paper.
[3] EFTA (European Free Trade Association) features Iceland, Liechtenstein, Norway, and Switzerland.
[4] The aggregated results for Europe derive from the combination of OLDEURO and NEWEURO.
[5] These sectors are not shown in the CES scheme.

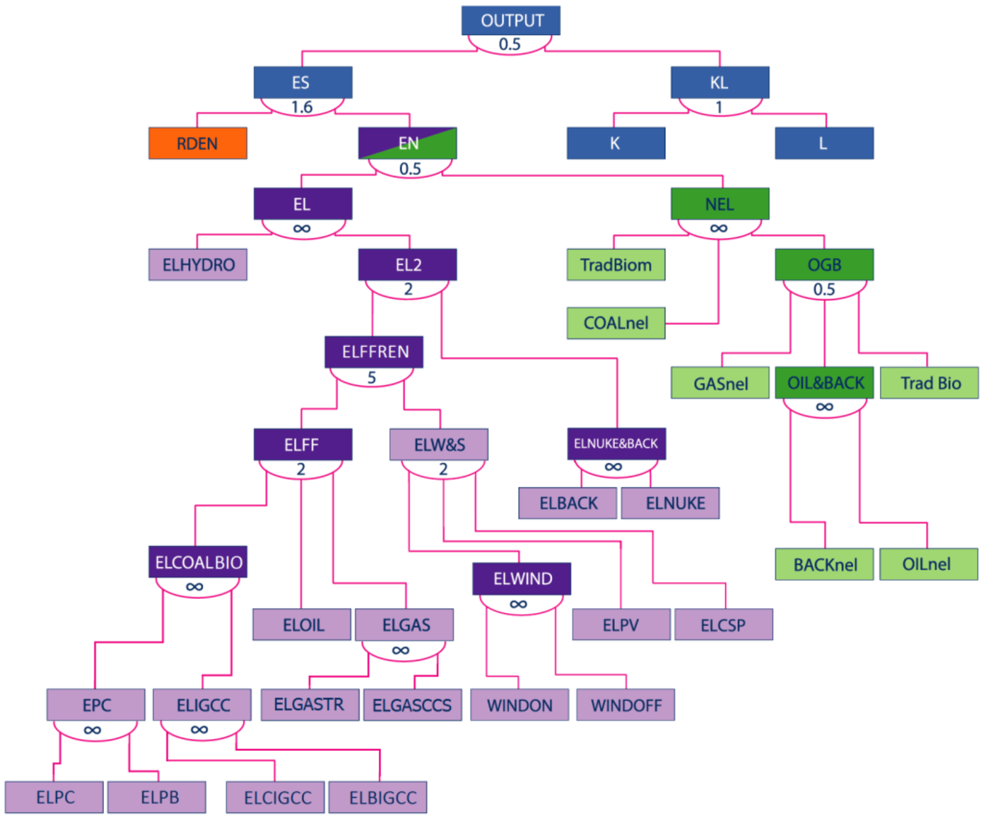

Figure 1 – The CES structure in WITCH.

Focusing on the electric sector, the hydroelectric technology is found first (ELHYDRO), which is essentially exogenous in the model. The other technologies converge to the EL2 node, which is divided between two further nodes: EFLFFREN, i.e. the combination of fossils and renewables, and ELNUKE&BACK, i.e. the combination of nuclear and backstop. The fossil node (ELFF) has three group of technologies: i) coal&biomass (ELCOALBIO), further divided into pulverized coal without CCS (ELPC), pulverized biomass without CCS (ELPB), integrated gasification coal with CCS (ELCIGCC), and integrated gasification biomass with CCS (ELBIGCC); ii) oil, only without CCS (ELOIL); iii) gas (ELGAS), with and without CCS (ELGASTR and ELGASCCS, respectively). Variable renewable energies (ELW&S) have i) wind (ELWIND), further divided between onshore (WINDON) and offshore (WINDOFF); ii) solar PV (ELPV); iii) solar CSP (ELCSP). Nuclear and backstop feature traditional fission nuclear (ELNUKE) and a backstop technology (ELBACK). The latter models a hypothetical future technology which generates electricity with no fuel costs and no carbon emissions, although characterized by high capital costs. It can be interpreted as an advanced nuclear technology, for instance nuclear fusion or advanced fast breeder fission reactors. However, this technology is not considered in the scenarios explored in this work. Concerning the non-electric sector, the first distinction is between traditional biomass (TradBiom), coal (COALnel) and the aggregated node formed by oil, gas, and modern biomass (OGB), which precisely features gas (GASnel), traditional biofuels (Trad Bio), and the combination (OIL&BACK) between oil (OILnel) and a non-electric backstop technology, i.e. advanced biofuels (BACKnel).

The CES structure tries to capture from a modeling point of view the preference for heterogeneity that is experienced in the real world, where the choice of investing in energy technologies does not normally depend on economic considerations only. The numbers reported in the CES scheme under the specific nodes indicate the relevant elasticity of substitution. As suggested by the name, this value quantifies the level of substitutability between the sub-nodes that converge to the specific node. Zero elasticity means that the production factors are not substitutable and thus they are summed in fixed shares. Infinite elasticity means that the production factors are completely interchangeable and thus the competition between the two occurs on an economic basis only. Intermediate elasticities result in an intermediate behavior. More details concerning the CES structure can be found in Carrara and Marangoni, 2017.

2.2 Nuclear modeling

The investment cost for new nuclear plants is 4709 $/kW[6]. The same cost is applied to all world regions, even if in reality some differences may be found. Future model improvement will differentiate costs across regions. O&M costs do vary across regions, instead. Only fixed O&M costs are explicitly considered, which are comprised between 160 $/kW and 220 $/kW, while no variable O&M are accounted for. However, waste management and storage costs are explicitly considered: they start at 0.1 c$/kWh in 2015 and increase slightly more than linearly with the relative increase in nuclear generation (MIT, 2003), which is a direct proxy of waste production. Uranium ore is considered sufficiently abundant to meet the increasing nuclear demand over the century, and in particular reserves are considered sufficiently large at prices below 350 $/kg, i.e. the level at which reprocessing spent fuel and fast breeder reactors become competitive, which would prevent any further rise in the uranium price (Bunn, 2005). The process of conversion, enrichment, and fuel fabrication of the uranium ore is also taken into account, and the relevant cost is fixed to 300 $/kg (MIT, 2003). The efficiency of nuclear power plants is 35%, the capacity factor is 85%, while the standard lifetime is 40 years (Tavoni and van der Zwaan, 2011).

3. Nuclear global landscape

As of November 30, 2018, there are 454 operational reactors in 31 countries worldwide, with an equivalent net capacity of 400 GW, while 54 reactors are under construction in 18 countries (4 of which not included in the previous 31), with an equivalent net capacity of 55 GW (IAEA, 2018).[7,8] Additional 26 countries have decided or have been considering to invest in nuclear, even if no reactors are practically under construction yet (Budnitz et al., 2018). Figure 2 shows the global situation in terms of operational and under construction rectors, also specifying the age of the former, grouping countries according to the WITCH regions. In the following, a brief description of the current status and the implemented policies is provided for each region.

The **USA** have 98 operational reactors, i.e. the highest number worldwide. The American fleet is also the oldest, as the average reactor age is around 38 years, i.e. close to the reference operational life of 40 years. On the other hand, only two reactors are under construction, expected to come online in 2021 and 2022 respectively (Gattie et al., 2018). This means that the US are going to face severe ageing issues in the coming decades. Indeed, as mentioned in the Introduction, the operational lifetime of a nuclear reactor can normally be extended from 40 to 60 years, if dedicated upgrade and revamping works are carried out

[6] Costs are expressed in USD2015.
[7] These figures indicate that the average capacity for each reactor is about 1 GW. This will implicitly be assumed in the following: capacity will explicitly be specified only if different from this reference value.
[8] Henceforth, the reference IAEA, 2018 will implicitly be assumed for all statistical data if not differently specified.

(Perrier, 2018). This strategy is extensively applied in the US (Volk et al., 2019), and most reactors have already obtained the relevant authorization (Davis, 2012). Still, in the absence of investment in new reactors, the retirement of the existing ones will begin around 2030 and will result in a complete phase out in some 20 years (Gattie et al., 2018).

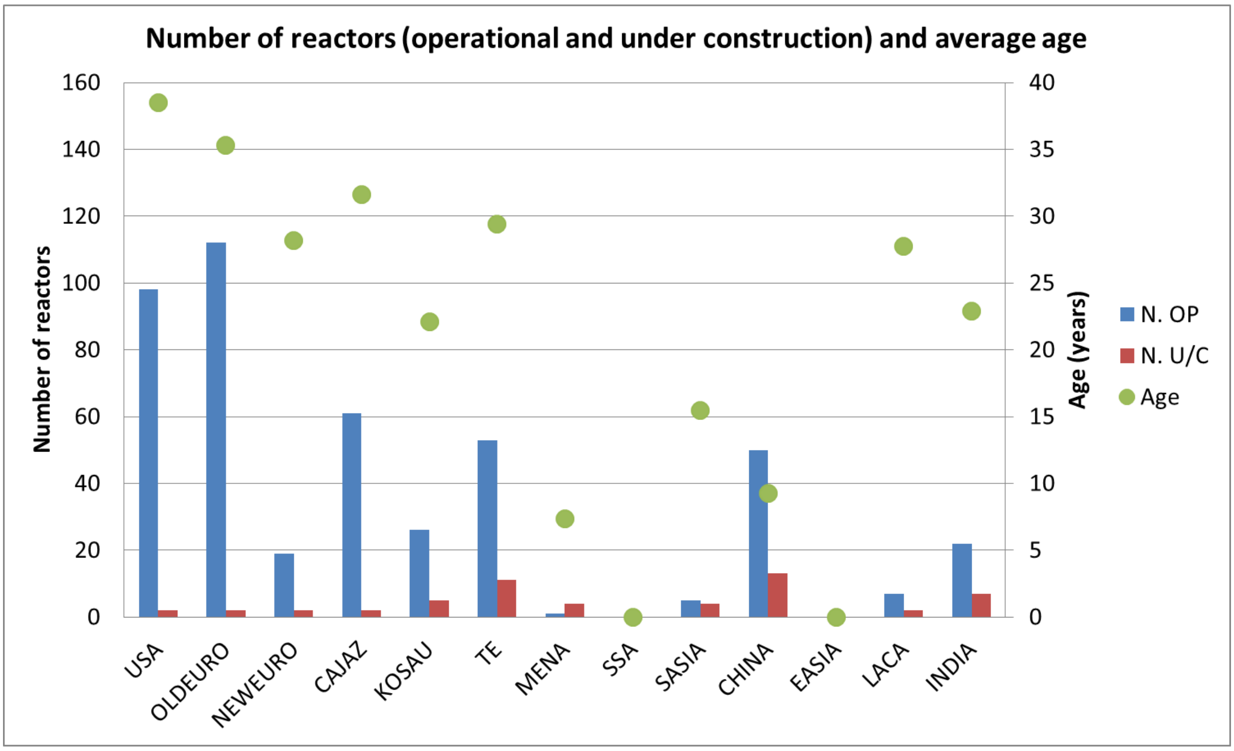

Figure 2 – Regional distribution of nuclear reactors and their age.

Similar conditions occur in the **OLDEURO** region, i.e. in Western Europe. Here the operational reactors are 112 with an average age of 35 years, whereas only two reactors are under construction, specifically in France (Flamanville) and Finland (Olkiluoto). Construction works for additional two reactors will shortly be started in the United Kingdom (Hinkley Point). All these four plants are EPR (European Pressurized Reactors) of 1.6 GW of net capacity each. With its 58 reactors, France is the country which relies most on nuclear: this technology accounted for about 71% of the total national electricity generation in 2017. The plan would be to decrease this share to 50% in 2025, but this target is unlikely to be met (Volk et al., 2019). Most likely, life extension programs will be implemented. In 2010, Germany had 17 operational reactors and approved a policy allowing the extension of the reactors operational lifetime by averagely 12 years. The Fukushima accident in 2011 determined a radical change: the oldest 8 reactors were immediately shut down, while the remaining 9 will be closed within 2022, well before their planned operational end (Rogner, 2013). Most of the other countries have been implementing similar yet milder phase-out policies, as early retirement is not normally considered and life extensions are often planned or applied. These countries are Sweden (8 reactors), Belgium (7), Spain (7), Switzerland (5), and the Netherlands (1), which will all phase out within the next twenty years. The same applies to Finland apart from the plant under construction in Olkiluoto (its four operational plants are already about 40 years old). The United Kingdom plans to phase out its 15 plants (accounting for 9 GW) within 2030, but, apart essentially from France, it is the only country in the region considering nuclear as the main carbon mitigation technology, so that 16 GW of new installations are planned in the next years (Volk et a., 2019). All in all, a strong capacity reduction is easily forecastable in this region in the near future.

A similar situation is found in **NEWEURO**, i.e. Eastern Europe, which features 19 operational reactors, with an average age of almost 30 years, and two reactors under construction (in Slovakia). Lithuania, Bulgaria and Slovakia had partly to shut down their old plants as one of the conditions to be admitted to the EU (Volk et a., 2019). The remaining plants will progressively be phased out in the next decades.

The **CAJAZ** region includes the country that obviously has most been affected by the Fukushima accident, i.e. Japan. Nowadays, 42 of the 54 existing plants in 2011 are still considered operational (while two are under construction), even if only 5 have generated electricity in 2017, whereas the remaining 37 are still waiting for decisions on their future (Volk et al., 2019). However, the Japanese government still aims at achieving a nuclear share in the electricity mix of 20-22% in 2030 (WNA, 2018a), i.e. slightly below the pre-Fukushima levels, as the share was equal to 26% in 2010 (IEA, 2012). Canada essentially replicates the conditions of the other Western countries: old reactors, no new constructions ongoing, and investment in extending the operational life.[9]

The **KOSAU** region is quite peculiar within the OECD regions. The core country here is the Republic of Korea. This country has 24 relatively recent reactors (the average age is 21 years) and it has strongly been investing in nuclear: 5 reactors are under construction and plans are to continue along this path in the next decades, which makes the Republic of Korea the only Western country strongly investing in nuclear without major issues. South Africa has two operational reactors which are 33 and 34 years old, respectively. Plans to build new capacity within 2030 have been suspended, therefore only life extension interventions may reasonably be considered in this country for the near future (WNA, 2018b).

Transition Economies (**TE**) face similar problems as Western countries in terms of ageing of nuclear reactors, as most reactors were built during the Cold War in the 70s and 80s and are currently undergoing works for life extension (Volk et al., 2019). However, considerable investments in new capacity are in place, especially in Russia (6 reactors are under construction), but also in Ukraine (2), Belarus (2), and Turkey (1), which allows forecasting optimistic futures for nuclear in this region.

Middle East and North Africa (**MENA**) is a “young” nuclear region. The first plant was inaugurated in the Islamic Republic of Iran in 2011, while 4 reactors are under construction in the United Arab Emirates, with works expected to progressively end in the very next years. No other countries have implemented or planned investments, however.

Sub-Saharan Africa except South Africa (**SSA**) and South-East Asian countries (**EASIA**) do not have any operational nor under construction reactors.[10]

South Asian countries (**SASIA**) have considerably been investing in nuclear. Pakistan has a very recent fleet, as 3 of its 5 reactors were inaugurated in the last decade, and two additional reactors are under construction. Two reactors are also under construction in Bangladesh.

The same applies to the main other South Asian country, that is an independent region in WITCH, i.e. **INDIA**. 22 operational reactors with an average age of 23 years and 7 reactors under construction highlight bright prospects for nuclear in this country.

[9] Nuclear power plants are not present in New Zealand, and no different plans are in place. The same will apply to Australia in the KOSAU region.
[10] For an overview on the nuclear debate in the EASIA countries, see Putra, 2017.

A similar and even more positive scenario is found in **CHINA**: its 46 reactors have an average age of 7 years and 11 plants are under construction. Similarly to India, huge development can be predicted for the next decades, as nuclear is considered an excellent technology to cope with the enormous growth in energy demand while also meeting with the climate mitigation requirements. For this region, it should be noted that Taiwan is a nuclear country: here prospects are less bright, as the four operational reactors are approaching the age of 40 and the construction of two reactors has recently been suspended.[11] It is clear, however, that the dimensions of this country are not such as to affect the overall evaluation of the CHINA region.

Finally, Latin and Central America (**LACA**) features three countries with nuclear power plants, i.e. Argentina, Brazil, and Mexico. There are 7 operational reactors in the region, with quite a high average age (28 years). Two reactors are under construction, and plans (especially in Argentina, see WNA, 2018c) are to continue investing in this technology. Hence, the nuclear share in this region is not very high, but it is expected to at least maintain its levels in the coming future.

To conclude, this overview has described in detail the general distinction between the OECD and non-OECD regions (with the exception of the Republic of Korea)[12] that had been anticipated in the Introduction: optimistic nuclear prospects can be expected for most non-OECD countries that have nuclear power, and especially Russia, India, and China, while more complicated futures can be estimated for OECD countries.

4. Scenario design

The nuclear landscape described in the previous section is the main reference for the definition of the scenarios explored in this exercise. Indeed, the coherent picture which characterizes the OECD and the non-OECD countries allows considering a limited set of scenarios, which are five in total.

First of all, a baseline or Business-as-Usual (BAU) scenario has been run as a benchmark. No mitigation policies nor other technological constraints are considered in this scenario.

The other four scenarios are explored in a mitigation policy compatible with the Paris targets. In particular, a uniform carbon tax is applied in all regions starting from 2020 so as to reach a global cumulative amount of CO_2 emissions equal to 1000 Gt in the period 2011-2100. This would limit the temperature increase in 2100 with respect to the pre-industrial levels below 2°C with a likely chance (IPCC, 2014). In particular, this corresponds to a temperature increase of 1.8°C in WITCH, whereas the baseline scenario leads to a temperature increase of about 4°C. In terms of annual global CO_2 emissions, the policy scenarios entail a constant decrease from 36 Gt/yr in 2015 down to -8 Gt/yr in 2100[13], while the no policy scenario has CO_2 emissions constantly growing to about 75 Gt/yr until around 2080, then remaining substantially constant until the end of the century.[14]

One scenario (CTAX) is run without any other constraints, and in particular nuclear energy is freely optimized by the model in all regions. On the opposite, one scenario (CTAX_global_phase-out) considers a

[11] These two reactors formally still appear as under construction in IAEA, 2018, however.

[12] The exception of the Republic of Korea among the OECD countries will implicitly be assumed henceforth with no further specification. OECD regions in this work will thus be USA, OLDEURO, NEWEURO, and CAJAZ.

[13] Negative emissions can be reached via biomass CCS and afforestation in WITCH.

[14] The overall greenhouse gas emissions (GHG) start at 50 $GtCO_2eq$/yr and increase to 93 $GtCO_2eq$/yr in 2100 in the baseline scenario, while they decrease to -3 $GtCO_2eq$/yr in the policy scenarios.

nuclear phase-out in all regions of the world, considering a life extension to 60 years for all reactors.[15] A more realistic scenario (CTAX_OECD_phase-out) applies the phase-out policy to the OECD countries only, i.e. to the USA, OLDEURO, NEWEURO, and CAJAZ regions, while no constraints are applied to non-OECD regions. The last scenario (CTAX_OECD_switch-off) considers a more extreme situation where nuclear is immediately and completely abandoned in the OECD regions starting from 2020.

5. Results

Figure 3 shows the global evolution of the electricity generation from nuclear in the different scenarios. It can immediately be noted that nuclear generation grows in all scenarios in the long run (it starts at 10 EJ/yr in 2015), with the obvious exception of the CTAX_global_phase-out scenario, where by definition nuclear generation tends to zero over time. The unconstrained CTAX scenario implies a higher generation than the baseline scenario, as the policy stringency would further trigger higher investments in low-carbon technologies. However, the model considers nuclear as a worthwhile technology even in the absence of carbon signal, therefore the BAU scenario too is characterized by a robust growth.

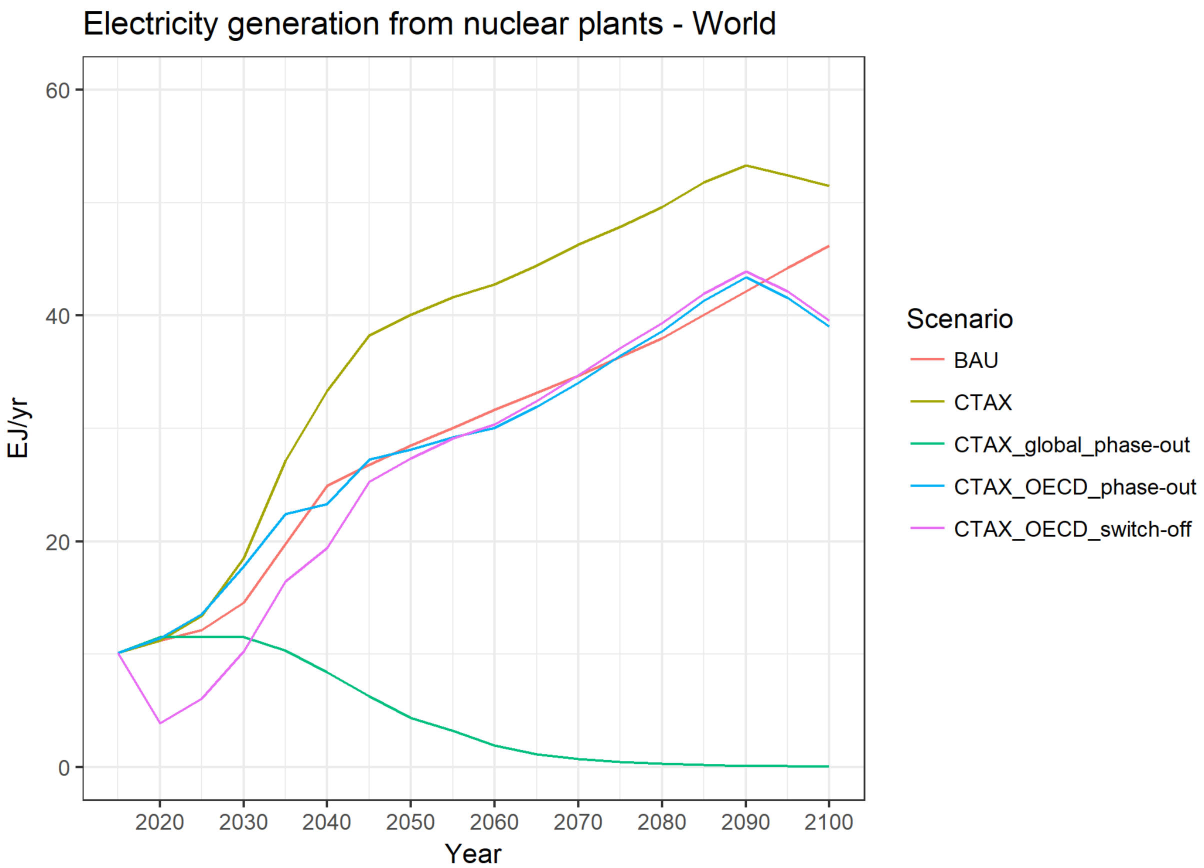

Figure 3 – Global nuclear generation.

[15] Section 3 discussed that this will be the case in most countries of the world. In Germany, all nuclear reactors will be shut down in 2022, but this roughly compensates with the intentions by the United Kingdom to keep investing in nuclear. Therefore the 60-year extension hypothesis can be considered acceptable in the OLDEURO region as well.

The constraints on nuclear growth in the OECD countries are such that nuclear generation is significantly lower in the CTAX_OECD_phase-out and the CTAX_OECD_switch-off scenarios than in the unconstrained CTAX scenario, essentially replicating the BAU results. In the CTAX_OECD_switch-off, in particular, nuclear generation starts to grow immediately after the 2020 shock, implying that the growth in the non-OECD countries more than compensates the generation end in the OECD countries. Indeed, the lower uranium demand in the OECD countries related to these scenarios implies lower fuel prices for non-OECD countries. This boosts nuclear generation considerably higher than in the CTAX scenario, see Figure 4.

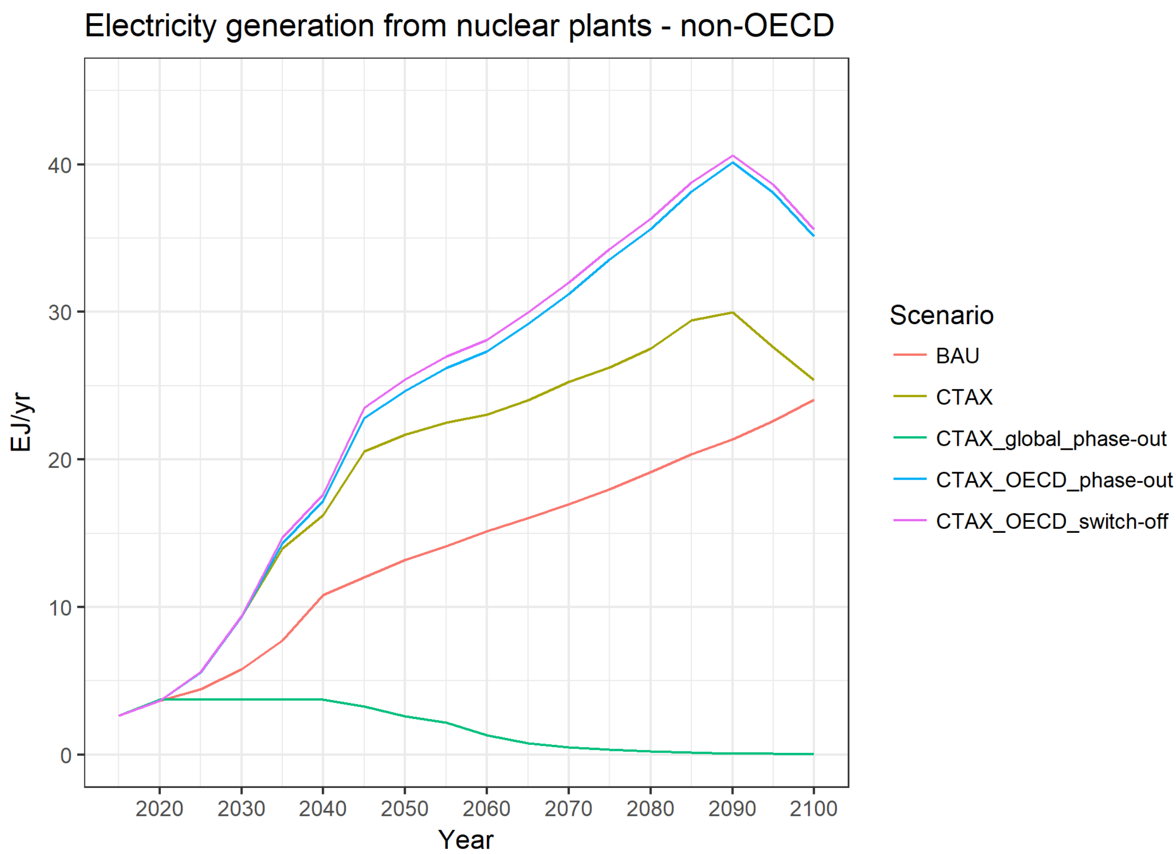

Figure 4 – Nuclear generation in non-OECD regions.

The global electricity demand does not markedly change among the four policy scenarios, even if there is a considerable difference between them and the BAU scenario, see Figure 5. This graph also indirectly highlights an important aspect of decarbonization. In general decarbonization can be achieved via two main strategies. The first one is to reduce emissions simply by reducing energy demand. This is the most straightforward strategy, as it does not entail a profound reconfiguration of the energy sector, and is what happens in the policy scenarios in the short term: here the electricity demand grows very mildly, compared to a more consistent growth in the BAU scenario. However, whereas the increase in the BAU scenario is fairly regular over the century, in the policy scenarios the electricity demand starts growing very fast after about 2040 and it overcomes the BAU levels around 2070/2080. This happens because the second decarbonization strategy is now deployed, which consists in increasing the share of electricity in the overall secondary energy demand with a parallel decarbonization of the electricity sector (which in general guarantees the easiest decarbonization routes).

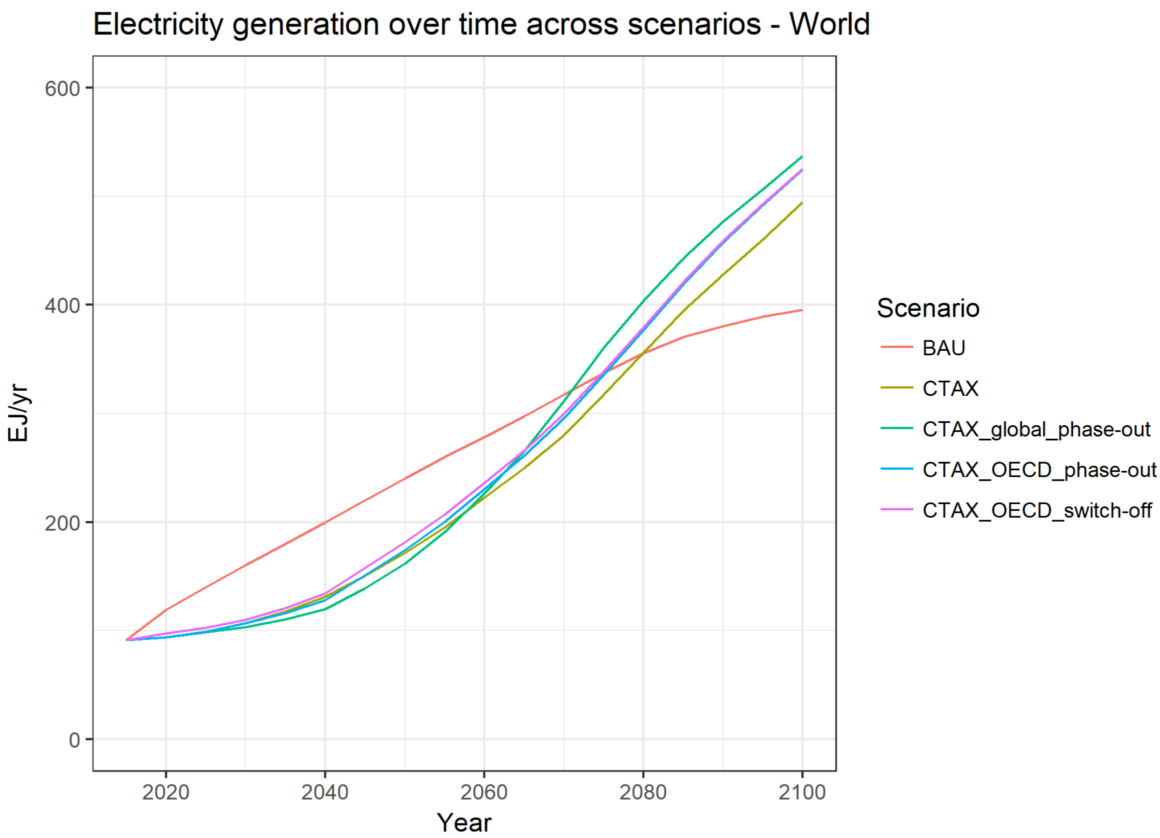

Figure 5 – Global electricity demand across scenarios.

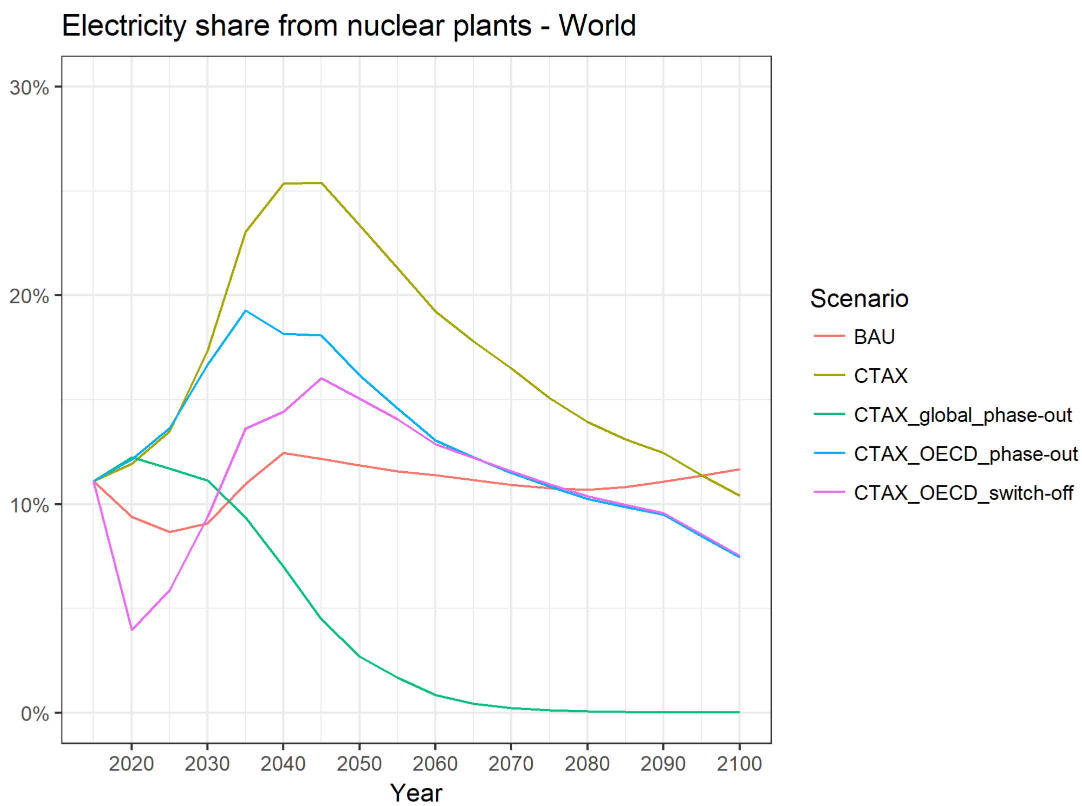

Figure 6 – Global nuclear share across scenarios.

The evolution of the nuclear share in the electricity generation mix (Figure 6) naturally derives from the combination of Figure 3 and Figure 5. The 2015 level of 11% is more or less constant over the century in the BAU scenario, as the nuclear growth is substantially in line with the overall electricity demand growth (around 2% per year). The CTAX_global_phase-out is obviously characterized by a constant decrease to zero, while all the other policy scenarios show a marked increase until about 2040 (to a maximum level which is progressively lower as the stringency of the constraints on nuclear increases, i.e. 25% in the CTAX scenario, 19% in the CTAX_OECD_phase-out scenario, 16% in the CTAX_OECD_switch-off scenario), which is followed by a decrease down to the initial levels towards the end of the century.

This happens because of the tremendous growth of renewables, notably wind and solar PV, which progressively gain market shares and become dominant in the second part of the century. This fact is clearly visible in Figure 7 and Figure 8, which show the evolution of the electricity mix at a global level in four selected years (2025, 2050, 2075, and 2100): the former shows the absolute generation, while the latter shows the relative shares.

First of all, both figures highlight that the carbon tax applied in the policy cases is such that the electricity sector is already fully decarbonized by 2050, when only a residual share of gas without CCS still appears in the electricity mix. This obviously does not apply to the BAU scenario, where fossils do not suffer from any constraints and they still maintain almost half of the generation portfolio in 2100, despite a growth in renewables which progressively become attractive even in the absence of the carbon tax.

The behavior of electricity demand has already been discussed above: in 2025 and 2050 this is higher in the BAU scenario than in the policy ones, in 2075 the levels are similar, while in 2100 the policy scenarios show a much higher demand. Here it is interesting to note an additional point: it has been said that the overall demand is similar across the policy scenarios, but a more precise observation would highlight that it grows with respect to the unconstrained CTAX scenario if constraints (phase-out or switch-off) are applied to the OECD countries, and even more if phase-out regards all regions. This happens because the constraints on nuclear imply higher investments in the other low-carbon technologies. Since WITCH features an endogenous technological modeling of the investment cost for renewables – in particular, wind onshore, wind offshore, solar PV, and solar CSP, while this does not apply to hydro and CCS – this implies considerable innovation benefits for wind and solar technologies, that are thus able to reach higher generation levels, which more than compensates the reduction or the absence of nuclear generation. As a result, the aggregated penetration of solar and wind technologies reaches 35% of the electricity mix in 2100 in the BAU scenario, 54% in the CTAX scenario, 59% in the CTAX_OECD_phase-out as well as the CTAX_OECD_switch-off scenarios, and 67% in the CTAX_global_phase-out scenario.

The sever impact that such a considerable penetration of variable renewable energies would have on the energy system is a topical and well-known issue. The stability of electrical grid requires that demand and supply be constantly in balance and this is not trivial if generation comes from plants fueled with a variable energy source. Abstracting from the technical aspects, it is not easy to model this issue in Integrated Assessment Models: these phenomena take place on very small spatial and temporal scales, whereas IAMs generate scenarios which span an horizon of decades, providing average annual quantities and considering large, aggregated regions. It is not within the scope of this paper to thoroughly discuss such an aspect. To this purpose, the reader is referred to Carrara and Marangoni, 2017 for further details on the WITCH model and to Pietzcker et al., 2017 for an overview of IAMs. However, one effect, i.e. the deployment of huge storage capacity to sustain the renewable expansion, can be easily highlighted: see Figure 9 which shows the power capacity evolution in the same selected years as Figure 7 and Figure 8.

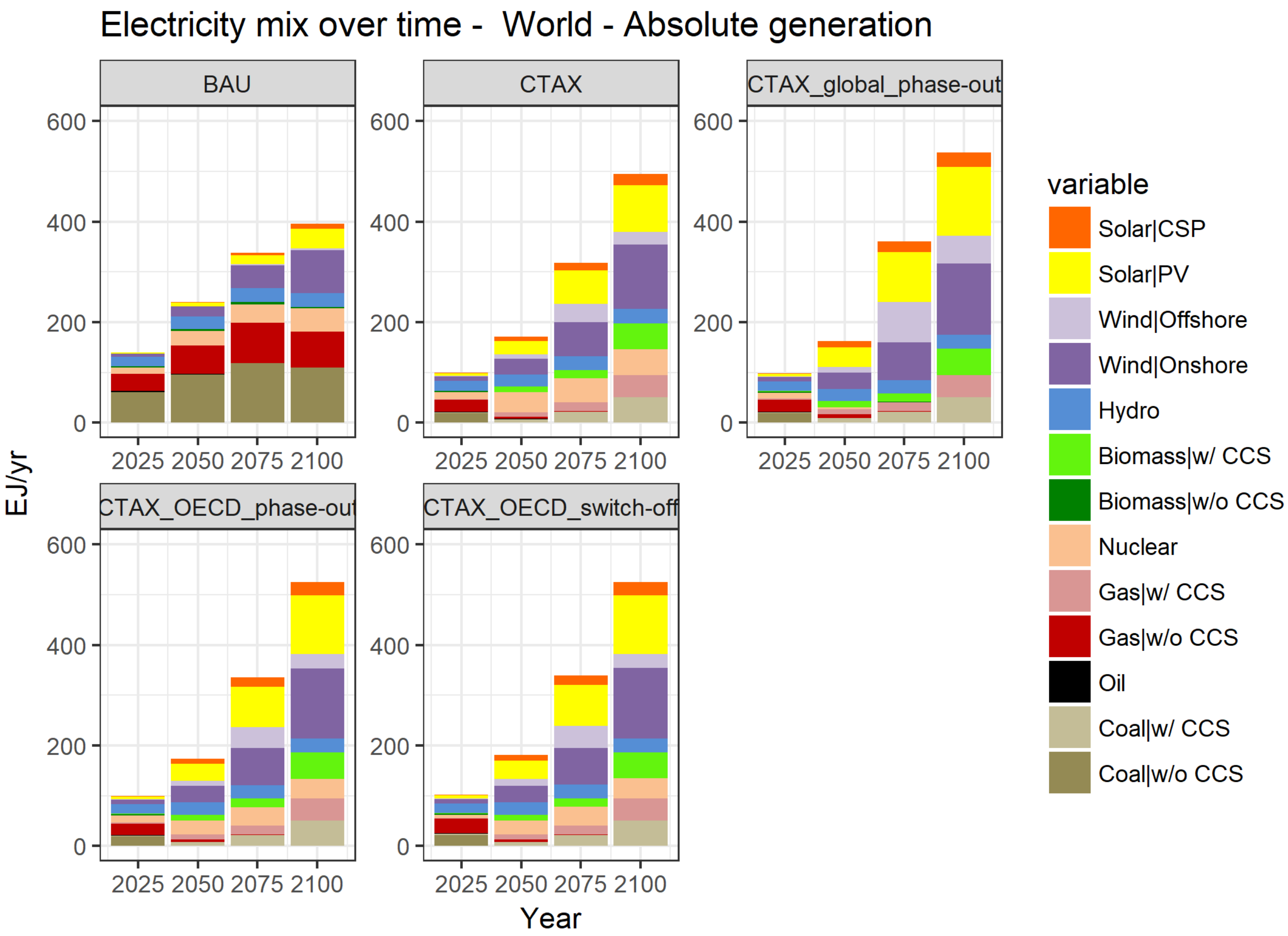

Figure 7 – Global electricity mix over time: absolute generation.

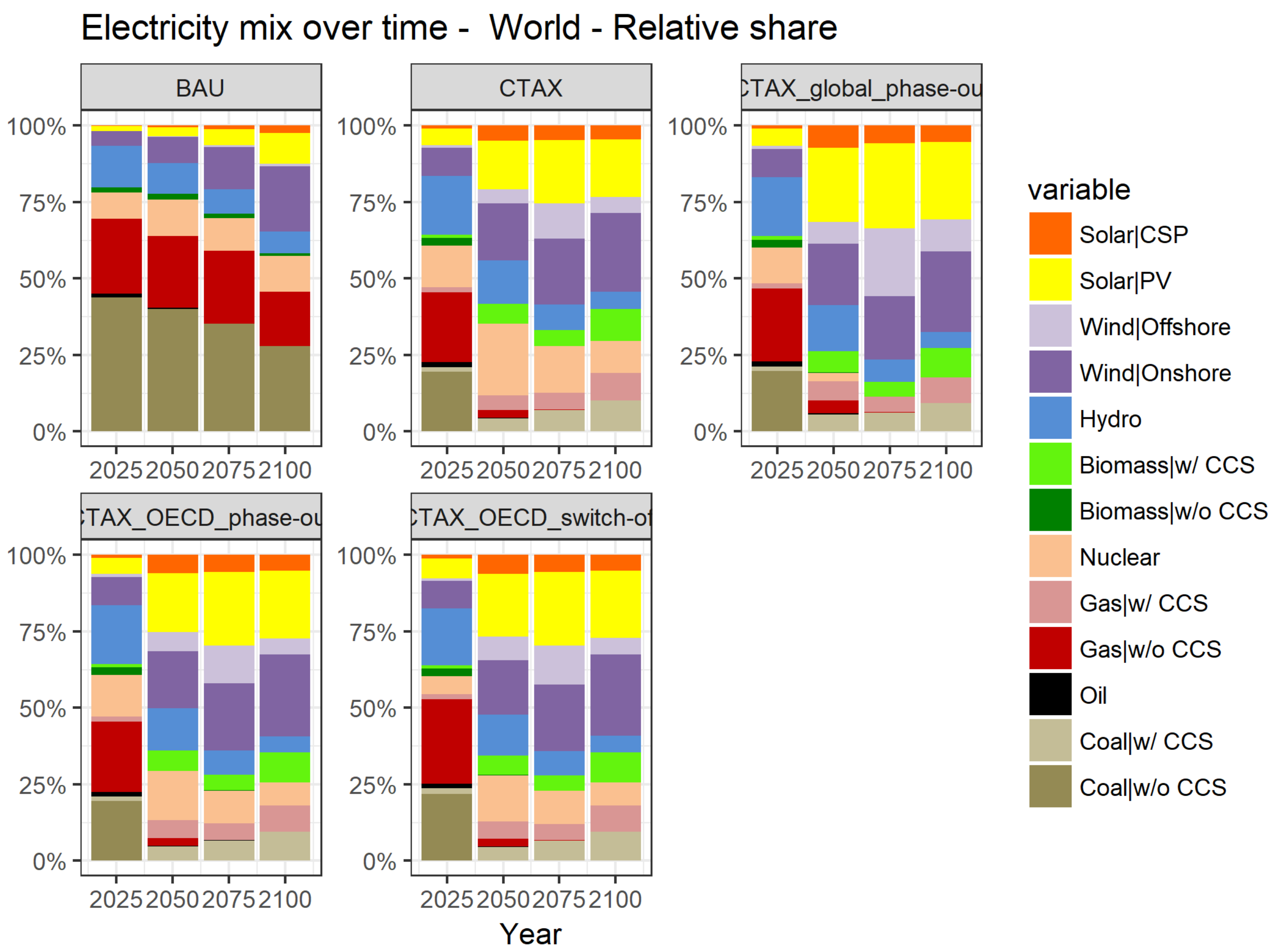

Figure 8 – Global electricity mix over time: relative generation shares.

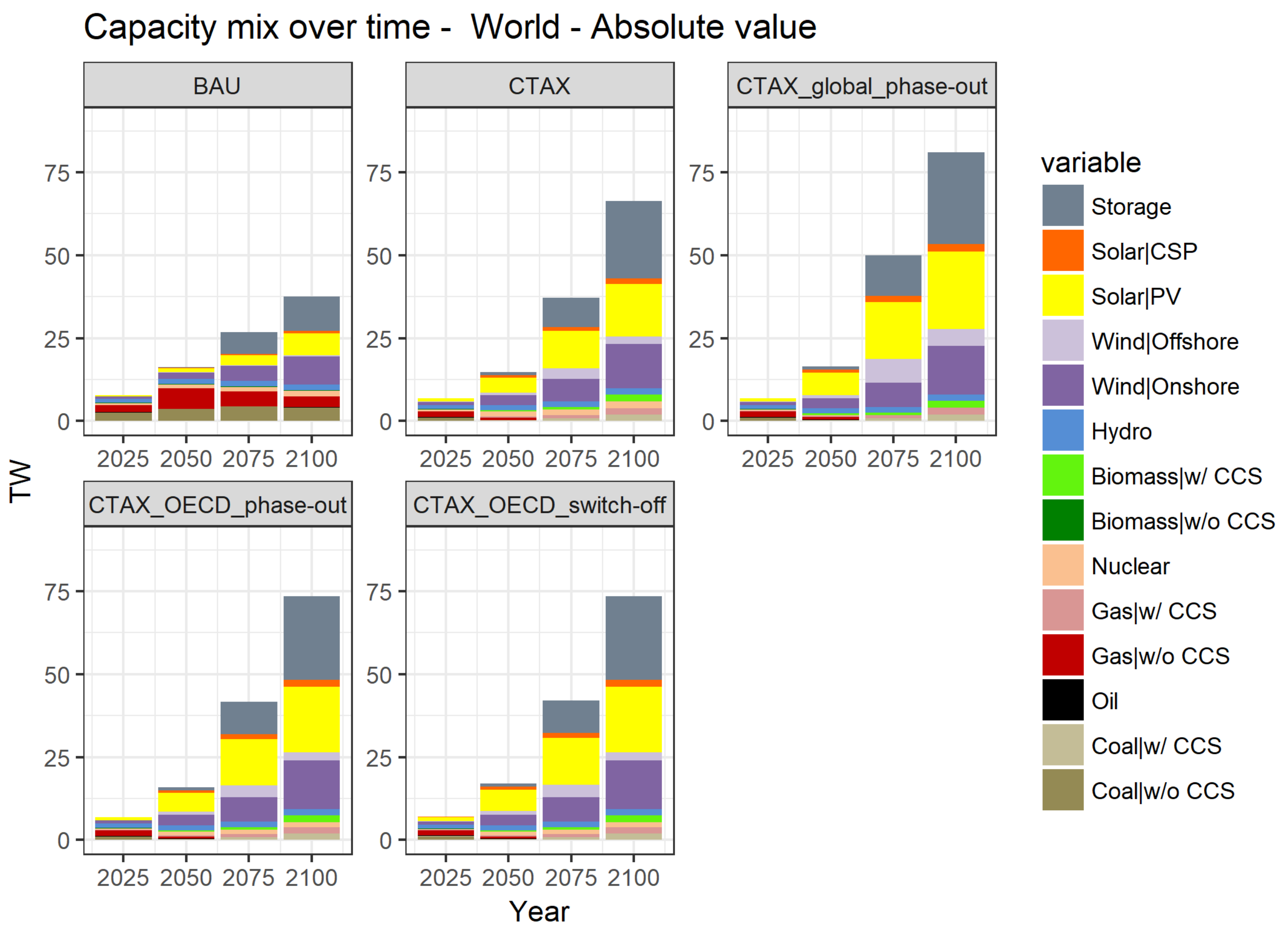

Figure 9 – Global electricity mix over time: capacity.

It can be noted that, whereas considerable storage capacity is required in the second half of the century (in addition to a similar growth in the electric infrastructure, not shown here), this is not necessary in the first half, when the moderate renewable growth can be "absorbed" by the remaining generation fleet which provides sufficient flexibility.

Moving the attention on the regional results, Figure 10 shows the evolution of the nuclear share in the unconstrained CTAX scenario in the thirteen WITCH regions (as well as at global level for comparison purposes).

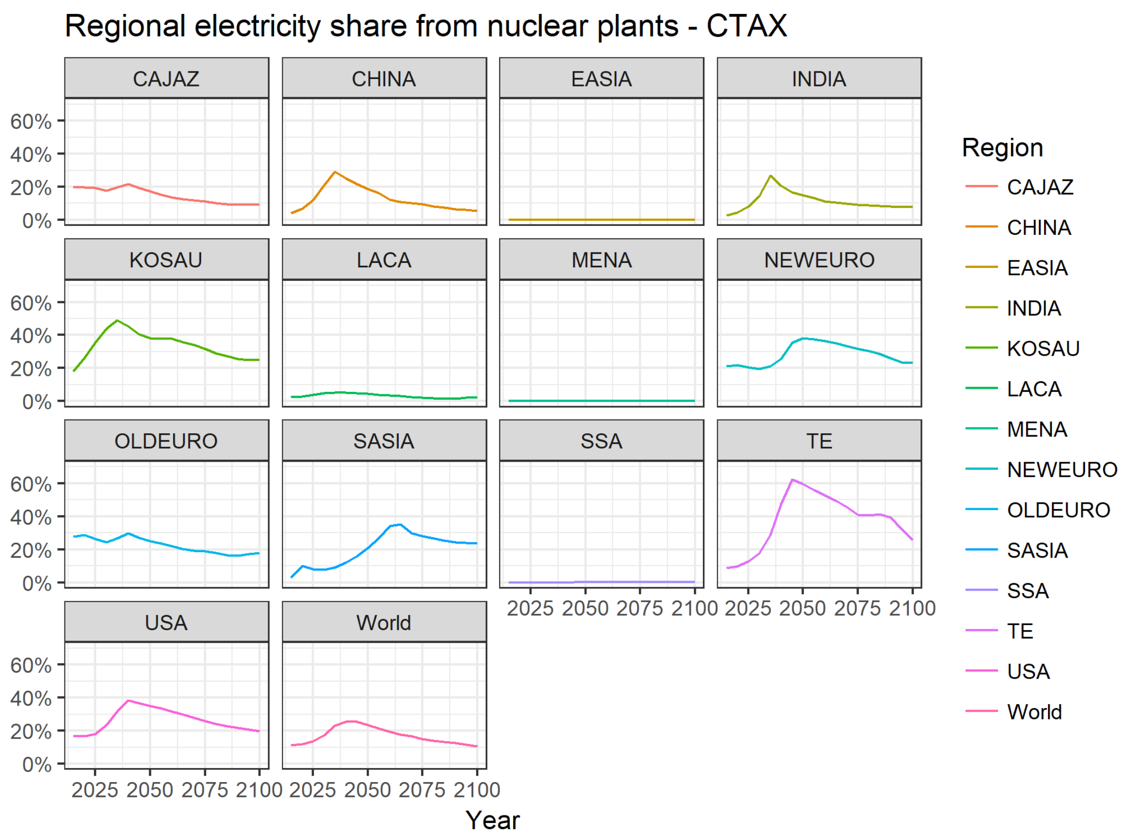

Figure 10 – Regional nuclear share in the CTAX scenario.

The graph shows that, for most regions, the optimization model provides results in line with the actual policy landscape and prospects. Nuclear generation remains zero or close to zero in the regions which today have neither reactors nor investments plans, i.e. EASIA and SSA, and in the regions which do have a small nuclear share but do not have any particular expansion plans, i.e. LACA and MENA. The nuclear share instead grows in the regions which have ambitious expansion plans: CHINA, INDIA, KOSAU, SASIA, and TE, at least until mid-century. After that date, as already discussed, nuclear does not stop growing in absolute terms, but it does so slower than renewables, which gain more and more market shares, so that the relative nuclear shares decreases. On the other hand, the nuclear share immediately starts decreasing in those regions which are characterized by critical nuclear prospects, such as CAJAZ and OLDEURO, where decarbonization is mostly carried out via renewables and, for the former, CCS. The only two regions not fully in line with the actual policy landscape are NEWEURO and USA, which show a marked growth despite the present conditions which do not suggest such an evolution for the next decades.

Remaining at a regional level, it is interesting to focus on the European results. Europe is naturally given by the combination of OLDEURO and NEWEURO, where the former substantially accounts for 90% of the total in terms of economic and social weight between the two.

First of all, Figure 11 shows the evolution of the nuclear share in Europe. The main aim is naturally to compare the BAU and the CTAX scenarios, which essentially have the same progress, with a substantial constancy of the nuclear share over time. The CTAX_global_phase-out, CTAX_OECD_phase-out, and CTAX_OECD_switch-off scenarios, in fact, show a trivial behavior. In the latter, nuclear generation immediately falls to zero in 2020, while in the two phase-out scenarios (which are equivalent for Europe), the share gradually decreases to zero over the next decades.

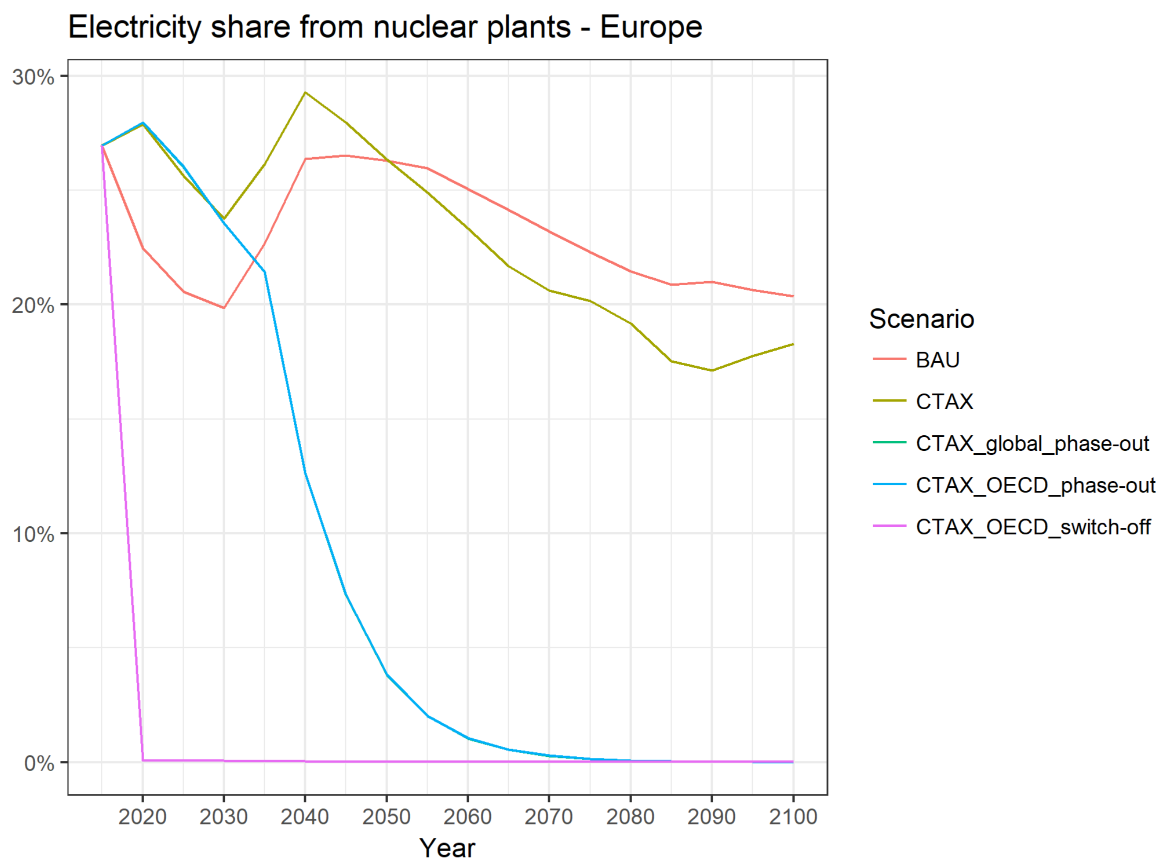

Figure 11 – European nuclear share across scenarios.

Figures 12, 13, and 14 show the generation (in absolute and relative values) and the capacity mixes in the four selected years for the five scenarios. Two major differences emerge from the global results. First, the renewable penetration is considerable already in the BAU scenario, where fossils have a marginal role even in the absence of a climate policy. Therefore it is not surprising that these technologies dominate (with nuclear) the power landscape in the mitigation scenarios. Second – and related to the first – the CCS penetration is negligible: this is due to the low availability of storage sites and, again, to the high potential and technology maturity that renewables have in this region. The enormous penetration of solar and wind is such that a corresponding amount of storage capacity is needed to ensure grid stability, as clearly shown in Figure 14.

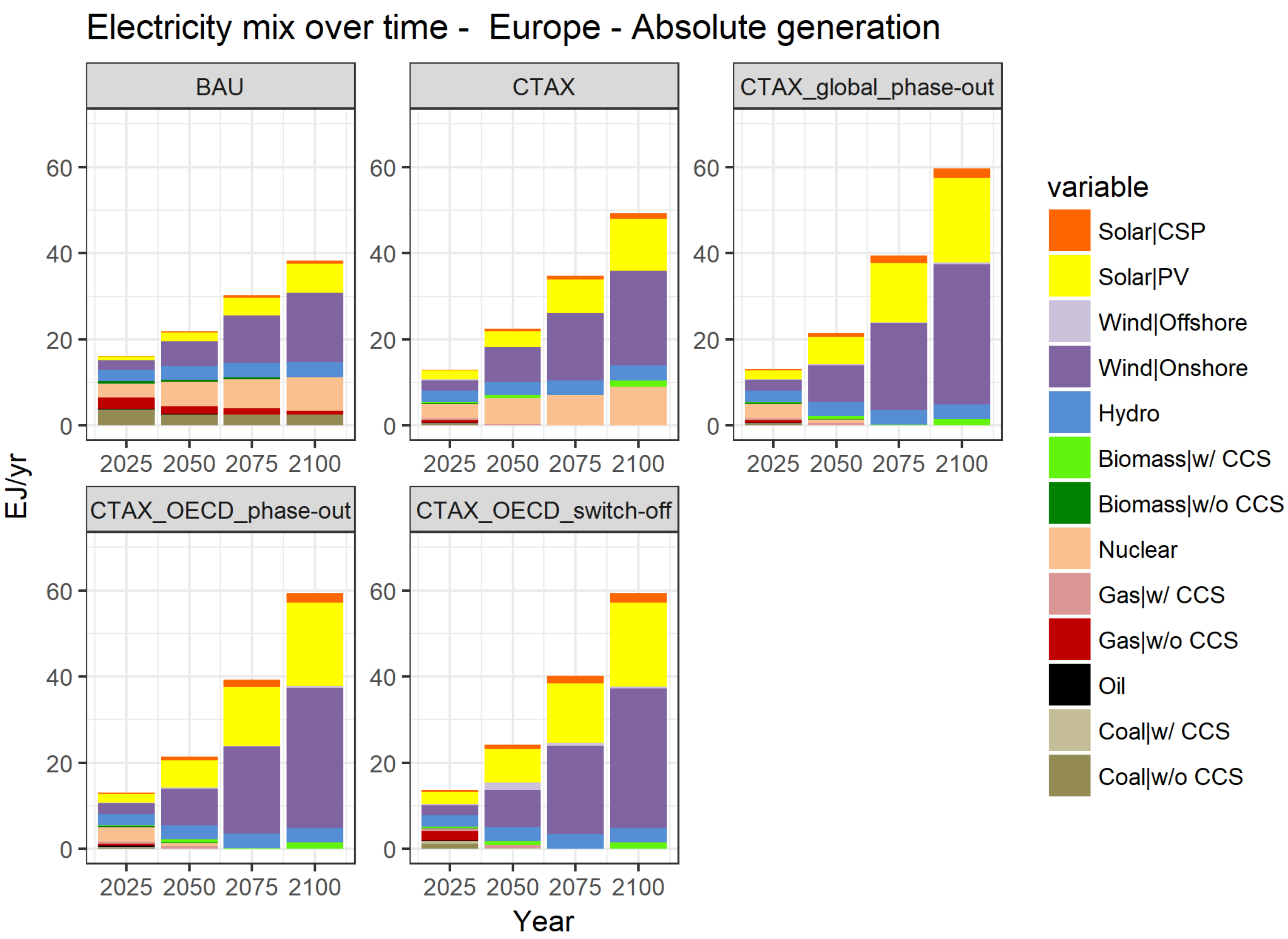

Figure 12 – European electricity mix over time: absolute generation.

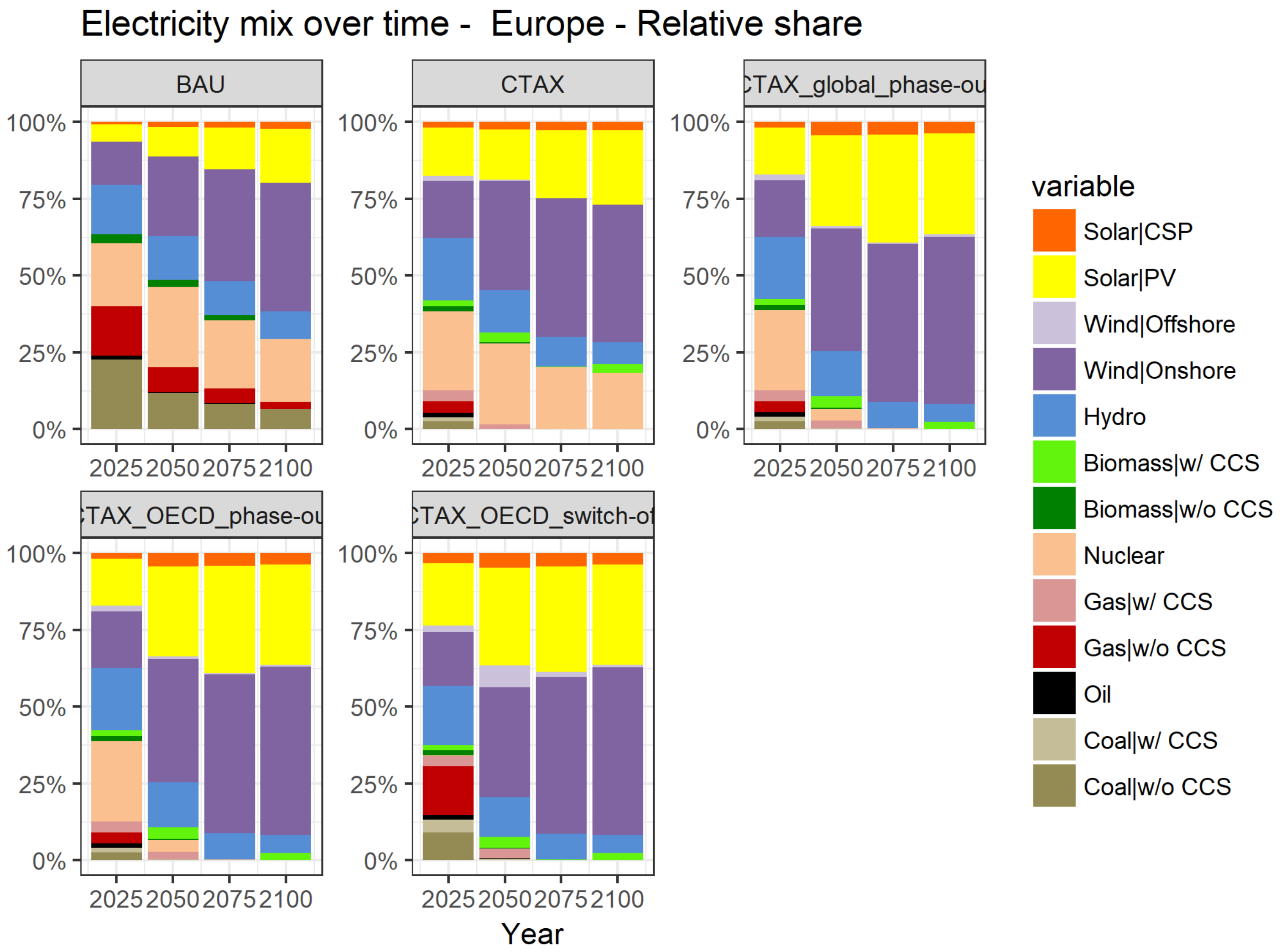

Figure 13 – European electricity mix over time: relative generation shares.

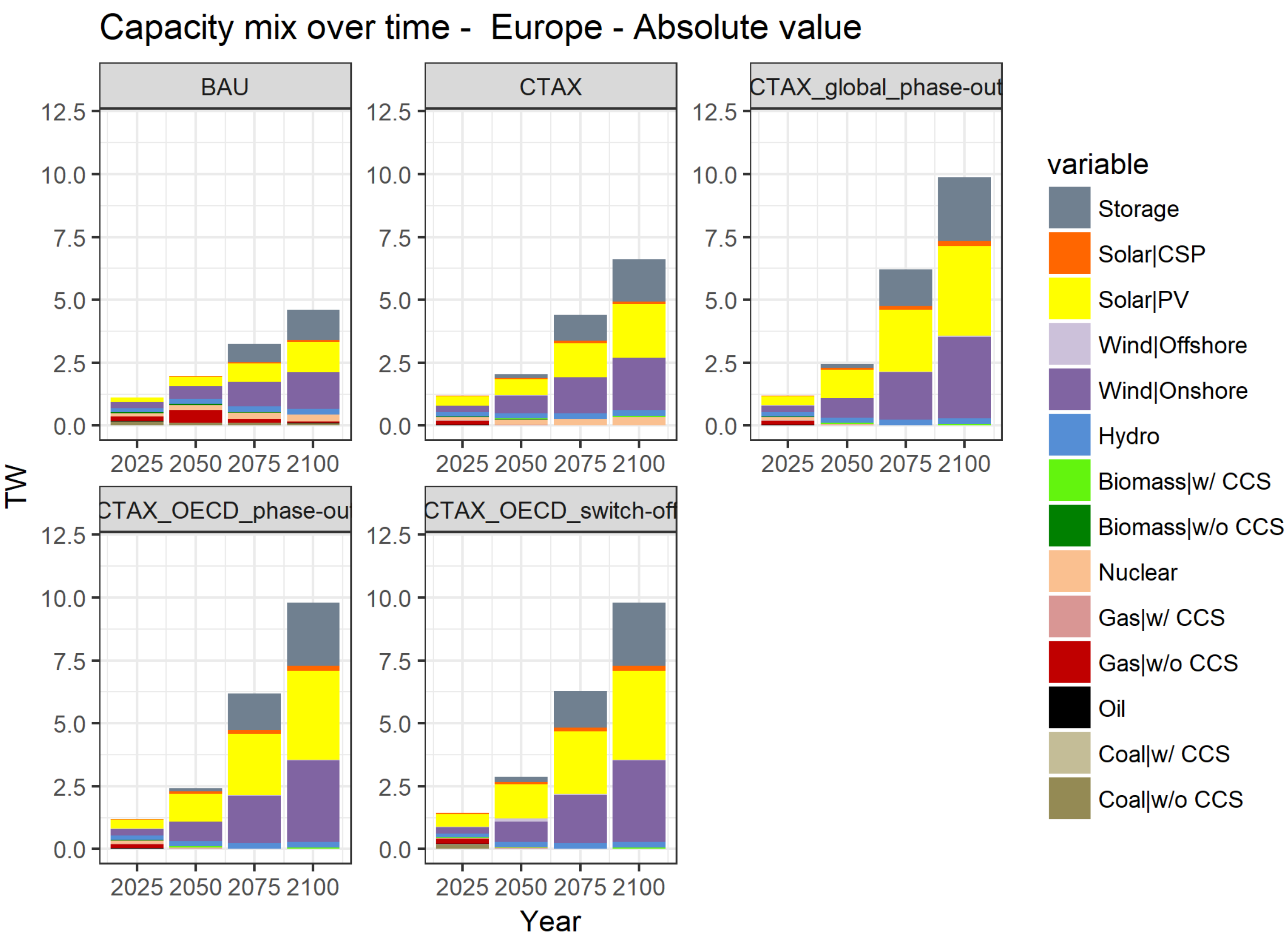

Figure 14 – European electricity mix over time: capacity.

It is finally interesting to assess the economic impacts of the different scenarios, and in particular the policy costs. These costs are evaluated as the cumulated GDP loss over the century with respect to the cumulated GDP of the baseline case, considering a yearly discount factor of 2.5%. First of all, Figure 15 shows the policy costs in the different regions in the unconstrained CTAX scenario, which is the benchmark of the mitigation scenarios portfolio.

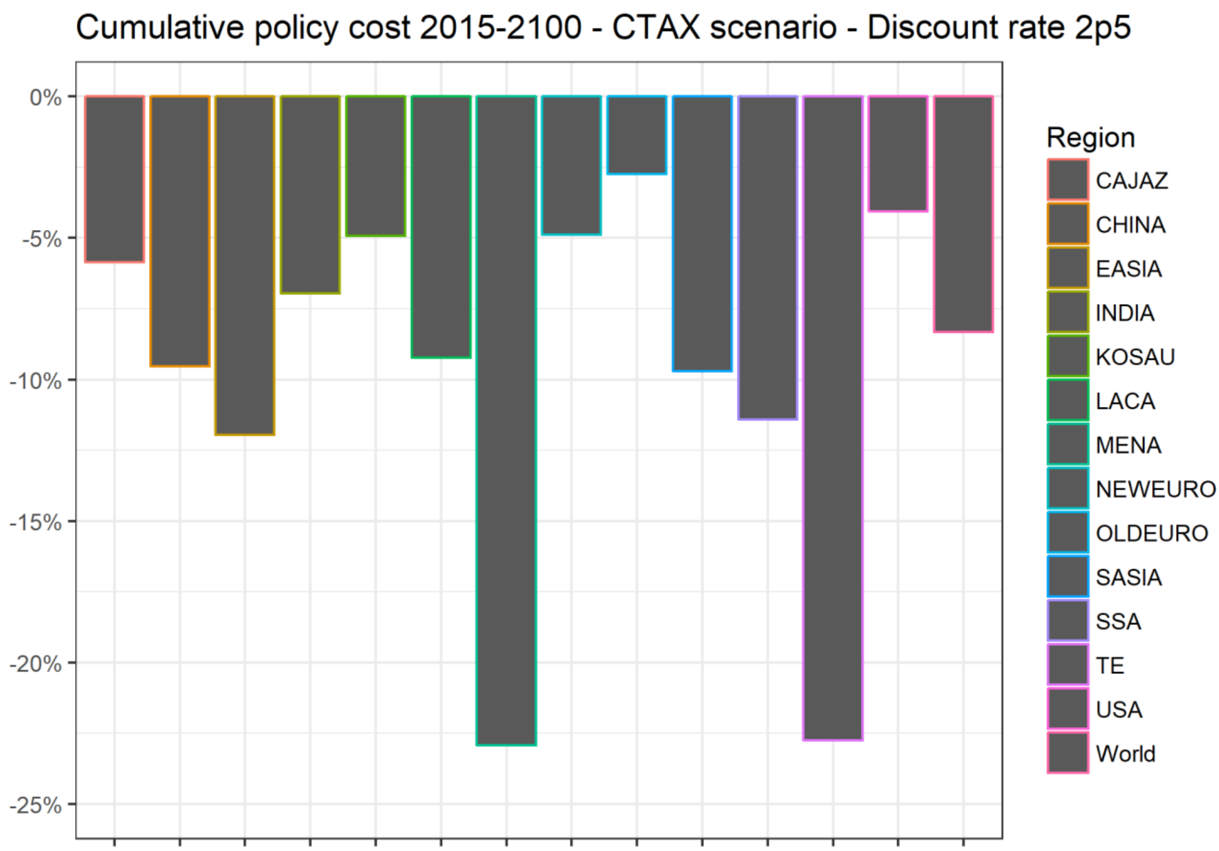

Figure 15 – Regional policy costs in the CTAX scenario.

The average global GDP loss is 8.3%. However, marked differences are found across regions. MENA and TE are the two regions which by far are affected most by the mitigation policies: the GDP loss amounts to about 23% here. This result is unsurprising, as these are the two main exporters of fossil fuels: the implementation of the carbon tax results in a global drop of fossil consumption and so happens to the economic performance of these regions, which is added to the lower domestic consumption that the policy allows. On the other end, OLDEURO is the region which is affected least by the mitigation policy: GDP loss is less than 3% here. Also in this case no major surprise can arise: the previous figures have shown that in this region a considerable decarbonization already takes place in the BAU scenario, i.e. the economic optimization per se leads to a low-carbon portfolio without the implementation of a carbon policy, which simply expands this tendency.

Focusing on the economic impacts of the nuclear phase-out or switch-off policies, a previous paper (De Cian et al., 2011) explored this aspect highlighting a point that has already been mentioned in the previous pages: the innovation benefits regarding the technologies which undergo learning (signally wind and solar), as well as the overall efficiency of the energy sector, result in lower costs (investment costs for renewables and for the energy sector in general) which essentially compensate the phase-out costs. But what happens at regional level? And what are the impacts of differentiated policies? Figure 16 shows the policy costs in the remaining three mitigation scenarios, highlighting the difference with respect to the unconstrained CTAX scenario in percentage points. This is done in order to abstract from the effects of the mitigation policy, and focus on the pure effects of the nuclear policy.

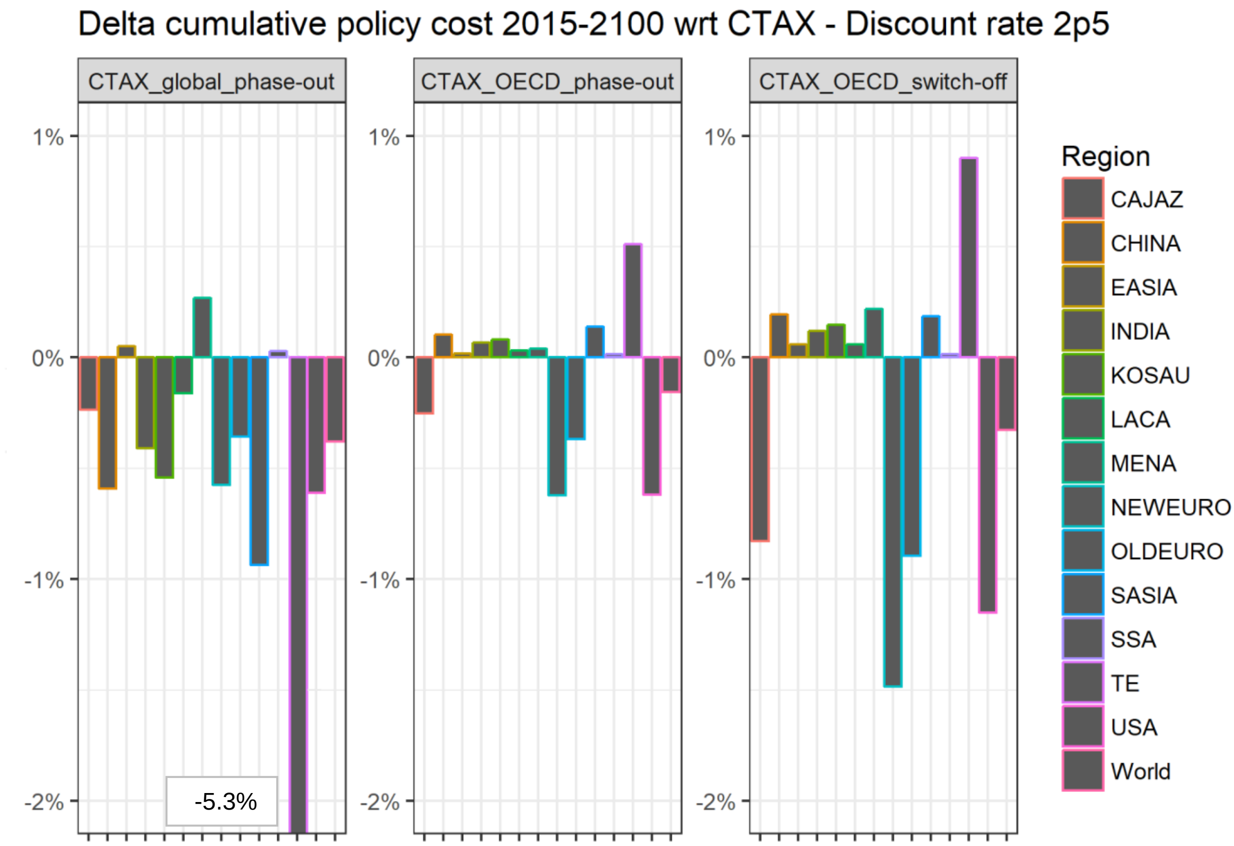

Figure 16 – Regional policy costs in the mitigation scenarios: difference with respect to the CTAX scenario.

The TE result immediately emerges in the CTAX_global_phase-out scenario: the additional GDP loss is 5.3%, markedly more than any other region in all the considered scenarios. Considering that the GDP loss in the CTAX scenario is already equal to 23%, this means an overall loss of 28%. The reason must be found in Figure 10: TE is the region that would invest more in nuclear, and the innovation benefits related to renewables are completely insufficient to compensate the absence of a technology that, in the unconstrained CTAX scenario, would almost reach 60% of the generation share towards mid-century. All the other regions are not extraordinarily affected by the global phase-out (the additional losses are within 1%). The specific results, however, depend on the nuclear penetration that would be achieved in the unconstrained scenario, therefore it is not surprising that SASIA, CHINA, INDIA, and NEWEURO show the highest additional losses and that the three regions where nuclear would not be deployed anyway, i.e. EASIA, MENA, and SSA, even gain (although quite marginally) from the global phase-out. MENA, in particular, can benefit from the slightly higher gas demand, to be used in CCS plants. The global additional GDP loss is less than 0.4%, again highlighting the almost total compensation of the policy cost via the innovation benefits. To put this number in perspective, an equivalent scenario with a constraint applied to CCS instead of nuclear would entail a 5%-growth in the policy cost (Carrara, this issue), which is even more remarkable considering the lower average share over the century that CCS would achieve in the unconstrained policy scenarios with respect to nuclear.

If the phase-out is limited to the OECD regions (CTAX_OECD_phase-out), a clear polarization is found. The OECD regions show the economic loss of renouncing nuclear, even if being the only regions which phase out does not cause any additional costs with respect to the global phase-out scenario (i.e. the additional GDP loss in the OECD regions is practically the same in the central and in the left-hand graphs). The non-OECD regions show very marginal benefits (apart from TE, for the reasons described above), essentially related to the lower costs of uranium deriving from the OECD phase-out.

Finally, the CTAX_OECD_switch-off shows the same qualitative behavior as the CTAX_OECD_phase-out scenario, even if results are quantitatively more marked, given the higher stringency of the technological constraint. The OECD regions show an additional GDP loss which is averagely around 1%, while the relative gain in the non-OECD regions is averagely 0.2% (almost 1% in TE), i.e. losses and gains approximately double.

6. Conclusions

Nuclear is expected to be one of the key technologies in the future power landscape, especially if mitigation policies are implemented. Its main advantage consists in generating electricity with a consolidated and well-known technology without emitting carbon dioxide. However, many issues, and especially public acceptance, hinder its deployment in many areas of the world. This is added to concerns about nuclear proliferation and waste management, the shortage of qualified workforce in the reactor construction and high or uncertain costs.

The nuclear landscape is very polarized between OECD and non-OECD countries. The former feature the most numerous fleets, but most reactors are approaching the end of their operational life and governmental policies are in most cases against further nuclear development and only consider dedicated investments for the lifetime extension of existing reactors. The latter instead, apart from some regions which do not feature and do not intend to invest in nuclear, show higher momentum and more ambitious expansion plans, especially China, India, and Russia.

This work has explored the techno-economic implications of policy-relevant nuclear scenarios, designed on the actual prospects for this technology in the world regions, i.e. mainly differentiating policy constraints between OECD and non-OECD regions.

Results show that global nuclear generation is expected to grow in all unconstrained scenarios (BAU and CTAX), with a higher growth in the policy case, as in this scenario nuclear partly compensates the retirement of fossil plants. If constraints (phase-out and switch-off) are applied to nuclear in the OECD regions, nuclear growth is more moderate, and is in line with the BAU scenario. Naturally, in the CTAX_global_phase-out, nuclear generation globally tends to zero over few decades. The considerable growth in terms of generation does not correspond to an analogous marked growth in terms of share in the electricity mix, as the overall electricity demand grows accordingly. Indeed, in the policy scenarios the share does significantly increase in the first decades, but then it approximately returns to the 2015 levels, in correspondence of the huge expansion of renewables (notably wind and solar PV) which prevail on nuclear and CCS in the mitigation portfolio. The huge expansion of variable renewable energies entails the deployment of a substantial storage capacity, which is needed to ensure grid stability.

The electricity landscape is not very different in Europe. However, this region is characterized by low availability of CO_2 storage sites and by high renewable potential and technology maturity, which hinder the penetration of CCS technologies. Therefore, power generation is dominated by wind and solar without major alternatives.

The implementation of a mitigation policy has well-known negative economic effects (the cumulated global GDP loss over the century is about 8% with respect to the baseline scenario), especially in the fossil exporting countries (23% GDP loss in MENA and TE), as the need for decarbonization implies a strong reduction in fossil consumption. The additional policy costs related to the nuclear constraints, however, are not substantial, as most regions have an additional GDP loss of less than 0.5% (0.4% at a global level): this happens because the phase-out costs are almost completely compensated by the innovation benefits in the renewable and the overall energy efficiency areas stimulated by the nuclear phase-out itself. TE shows an additional 5%-loss, being the region that would have the highest nuclear penetration in the unconstrained scenarios. If constraints are applied to the OECD regions only, no additional losses are found here with respect to the global phase-out scenario, while the non-OECD regions slightly benefit from the lower uranium costs. The CTAX_OECD_switch-off scenario simply exacerbates these results: the average additional GDP loss in the OECD regions and the average GDP gain in the non-OECD regions approximately double.

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