

Exploring pathways of solar PV learning in Integrated Assessment Models

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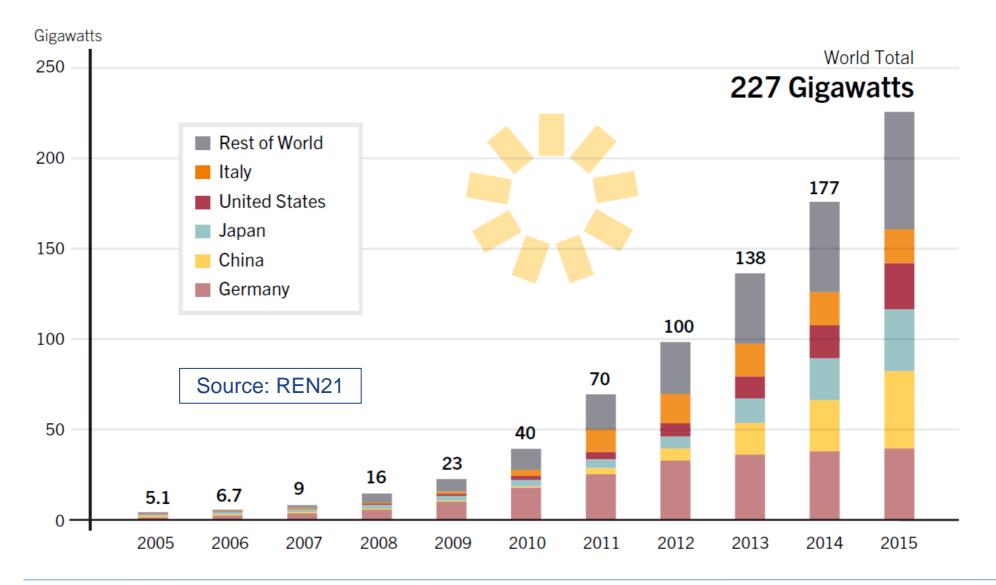
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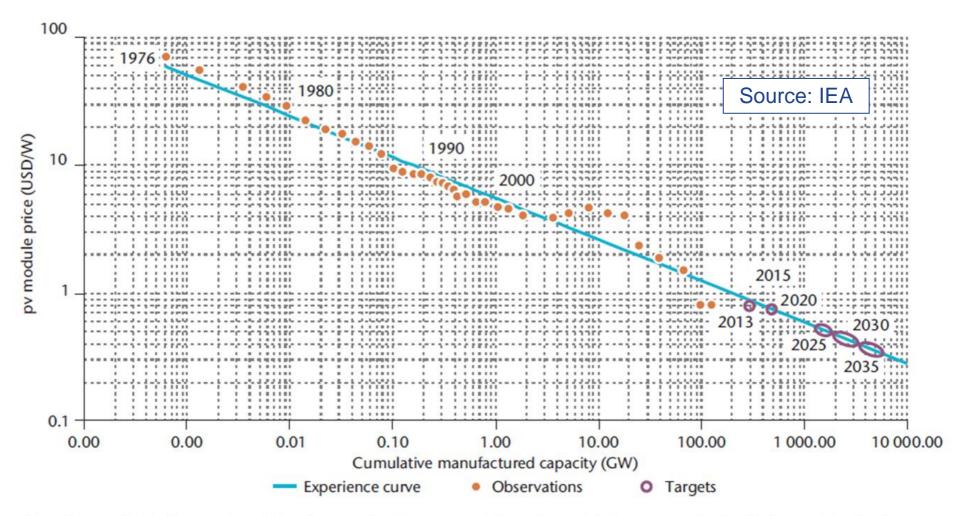


Motivation and Scope I – PV global capacity





Motivation and Scope II – PV module price



Notes: Orange dots indicate past module prices; purple dots are expectations. The oval dots correspond to the deployment starting in 2025, comparing the 2DS (left end of oval) and 2DS hi-Ren (right end).



Motivation and Scope III – Objectives and models

Objectives

- From a policy-relevancy perspective, explore different scenarios related to the possible future cost patterns of the solar PV technology
- From a modeling perspective, assess the responsiveness of models to changes in the cost data input

Participating models (\rightarrow Follow-up of the ADVANCE project on system integration modeling)



REMIND • Intertemporal optimal-growth general equilibrium models • WITCH

In this presentation Preliminary analysis of the first submission results



Protocol

	Scenario Name	Policy	Learning Rate	Floor Cost
1	ADV4-PV-BASE-LR-ref-FC-ref	Baseline	Ref	Ref
2	ADV4-PV-MIT-LR-ref-FC-ref	Mitigation	Ref	Ref
3	ADV4-PV-MIT-LR-50p-FC-ref	Mitigation	+50%	Ref
4	ADV4-PV-MIT-LR-25p-FC-ref	Mitigation	+25%	Ref
5	ADV4-PV-MIT-LR-25m-FC-ref	Mitigation	-25%	Ref
6	ADV4-PV-MIT-LR-50m-FC-ref	Mitigation	-50%	Ref
7	ADV4-PV-MIT-LR-ref-FC-0	Mitigation	Ref	0
8	ADV4-PV-MIT-LR-50p-FC-0	Mitigation	+50%	0
9	ADV4-PV-MIT-LR-25p-FC-0	Mitigation	+25%	0
10	ADV4-PV-MIT-LR-25m-FC-0	Mitigation	-25%	0
11	ADV4-PV-MIT-LR-50m-FC-0	Mitigation	-50%	0

Mitigation \rightarrow ctax | cumulative 1000 GtCO₂ in 2011-2100 in the Ref-Ref scenario \rightarrow 2°C



Learning-by-Doing and Floor Cost

Investment cost (Learning-by-Doing):

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

Floor cost: hard bound

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

Floor cost: soft bound

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

- CC_t = capital cost at time t
- CC₁ = initial capital cost
- K_t = global cumulative capacity at time t
- K₁ = global initial capacity
- b = a measure of the strength of the learning effect
- FC = floor cost

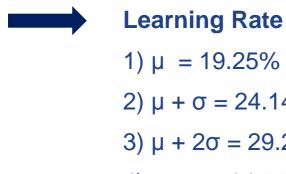


Reference

Witajewski-Baltvilks, J., Verdolini, E., and Tavoni, M. (2015). Bending the learning curve, Energy Economics, Vol. 52, pp. S86-S99

LR = Learning Rate = cost decrease deriving from doubling the installed capacity = -1 + 2^b

Empirical estimate \rightarrow b = $\mu \pm \sigma$ = -0.254 ± 0.058



2) $\mu + \sigma = 24.14\%$ (+25.4% wrt μ)

3) μ + 2 σ = 29.24% (+51.9% wrt μ)

4) μ - σ = 14.55% (-24.4% wrt μ)

5) $\mu - 2\sigma = 10.04\%$ (-47.8% wrt μ)

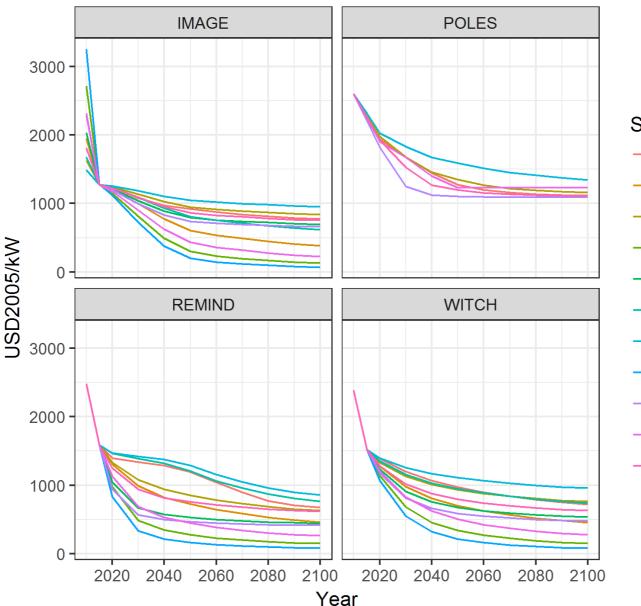
Thus the $\pm 25\%$ and $\pm 50\%$ sensitivity cases



Modeling assumptions (stocktaking)

	IMAGE	POLES	WITCH	REMIND		
Cost calculation	Endogenous					
Type of endogenous modeling	One-factor learning curve (LbD)					
Regional differentiation	No, only one global cost					
Type of floor cost	"Soft bound" (asymptotic floor cost)					
Plant depreciation	Linear	Linear	Exponential	Concave		
Depreciation rate	0.1	0.04	0.044	-		
Lifetime [years]	25	25	25	30		
2005 investment cost [USD2005/kW]	6580	4650	4650	4900		
Learning rate	18%	15%	17%	20%		
Floor cost [USD2005/kW]	600	500	400	370		





Solar PV investment cost over time - World - All scenarios

SCENARIO

- ADV4-PV-MIT-LR-25m-FC-ref
- ADV4-PV-MIT-LR-25p-FC-0
- ----- ADV4-PV-MIT-LR-25p-FC-ref

- ----- ADV4-PV-MIT-LR-50p-FC-0

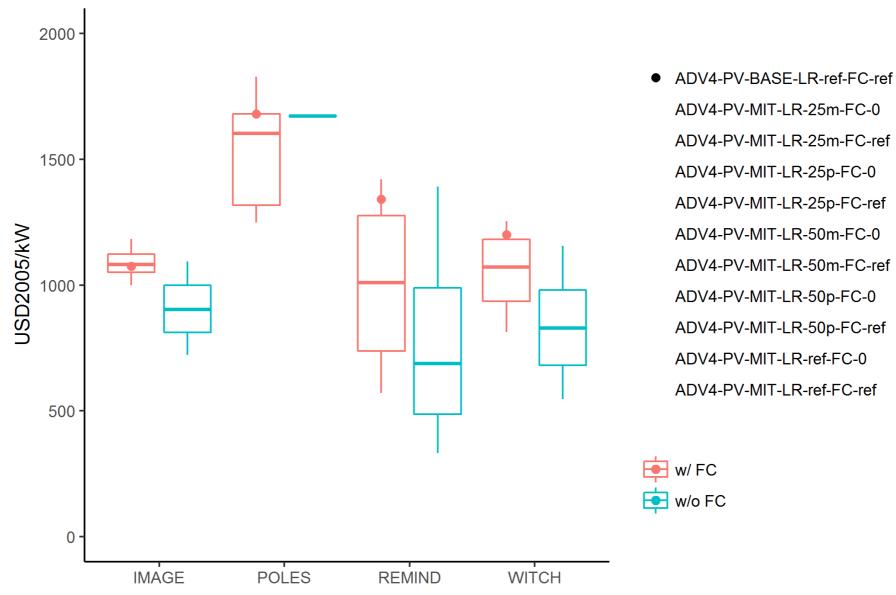
- ADV4-PV-MIT-LR-ref-FC-ref



PV investment costs – Comments

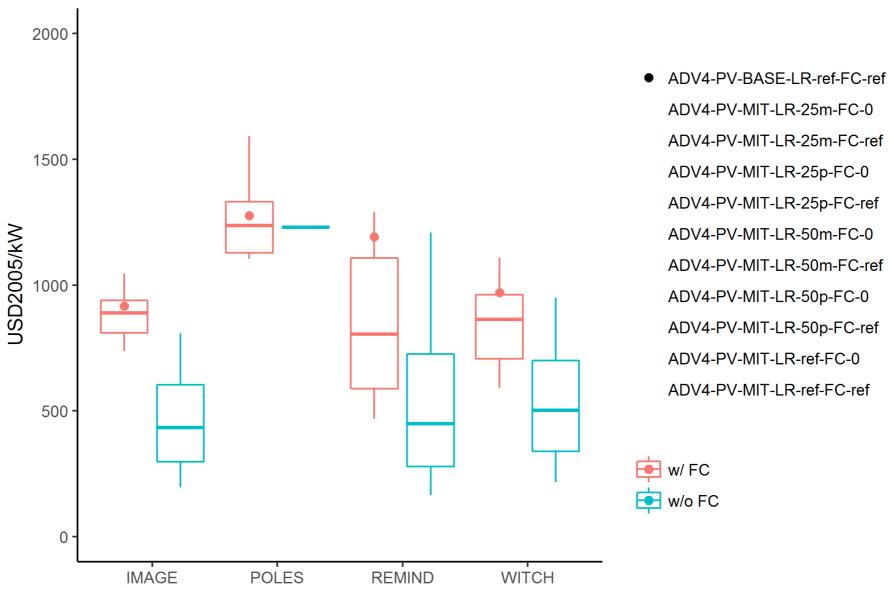
- A problematic behavior is found in POLES, as all scenarios without floor cost i) report the very same cost pattern, which cannot be, and ii) do have a hard floor cost → implementation issues.
- Graphs show that the PV cost evolution across scenarios in IMAGE, REMIND, and WITCH is coherent: all models span a range of about 80-1000 USD/kW in 2100.





Solar PV investment cost with and without floor cost - World - 2030

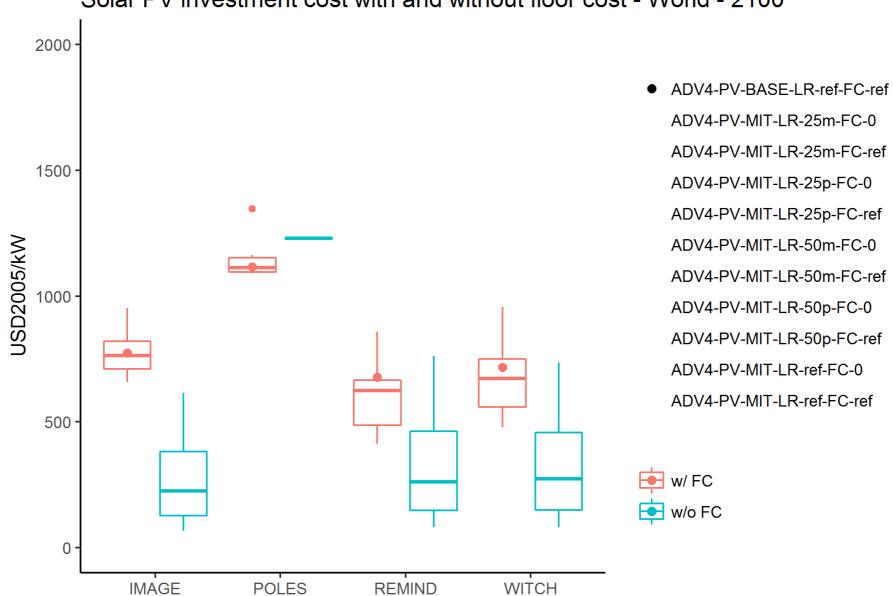




Solar PV investment cost with and without floor cost - World - 2050

ADV4-PV-MIT-LR-50m-FC-0 ADV4-PV-MIT-LR-50m-FC-ref ADV4-PV-MIT-LR-50p-FC-0 ADV4-PV-MIT-LR-50p-FC-ref ADV4-PV-MIT-LR-ref-FC-0 ADV4-PV-MIT-LR-ref-FC-ref





Solar PV investment cost with and without floor cost - World - 2100

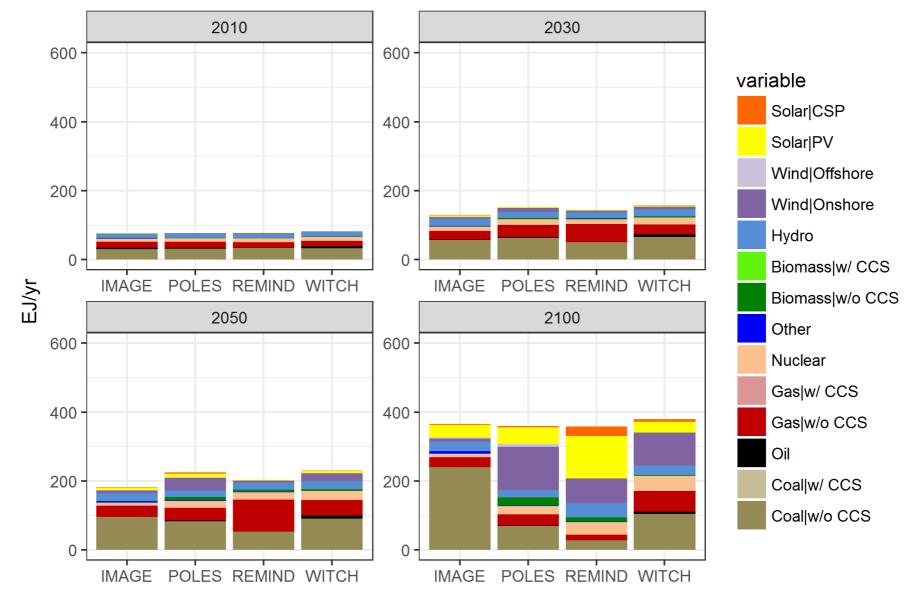


PV investment costs (box plot) – Comments

- This graph allows analyzing the cost "width" across scenarios, distinguishing between the cases with and without floor cost.
- The dot represents the baseline case; the box plots refer to the mitigation cases: the line extremes are the ±50% cases, the rectangle edges are the ±25% cases, while the "median" is the reference case.
- The graph highlights the cost issues in POLES.
- Apart from POLES, the distribution is most compact in IMAGE, then comes WITCH and finally REMIND.
- As already noted, the latter three models are substantially in line with each other.

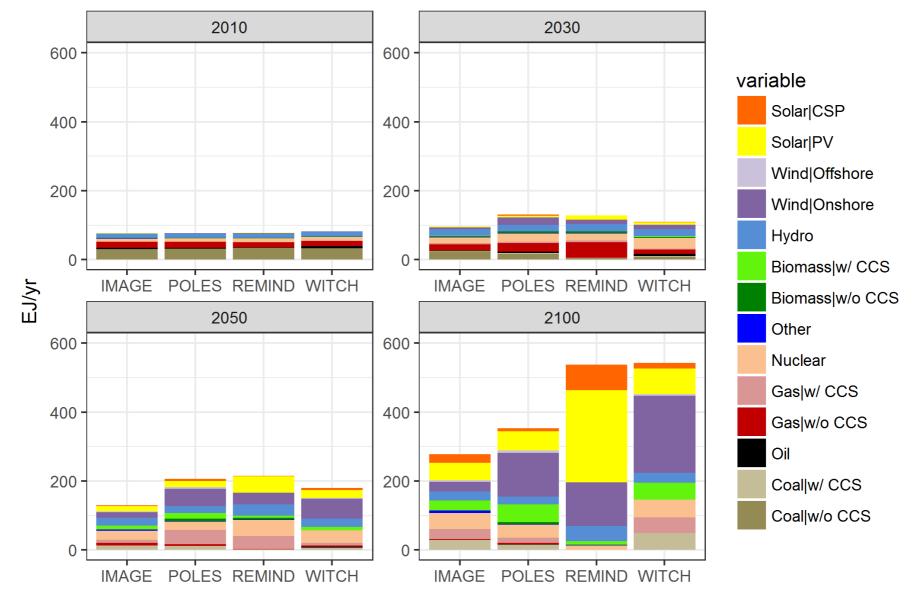


Electricity mix in selected years - Baseline scenario - World (Same scale)





Electricity mix in selected years - Reference scenario - World (Same scale)

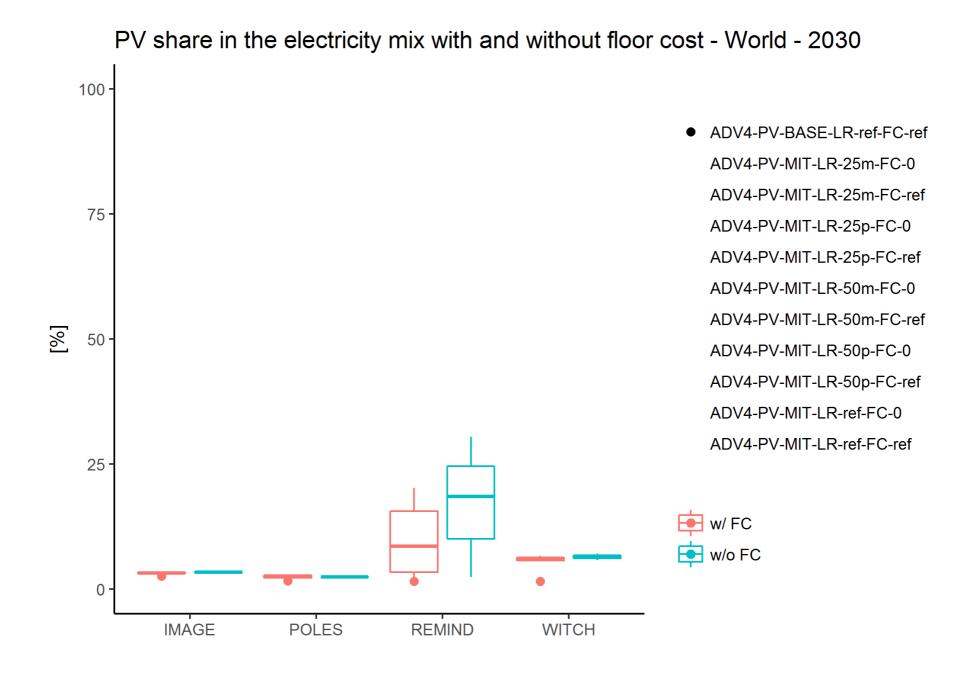




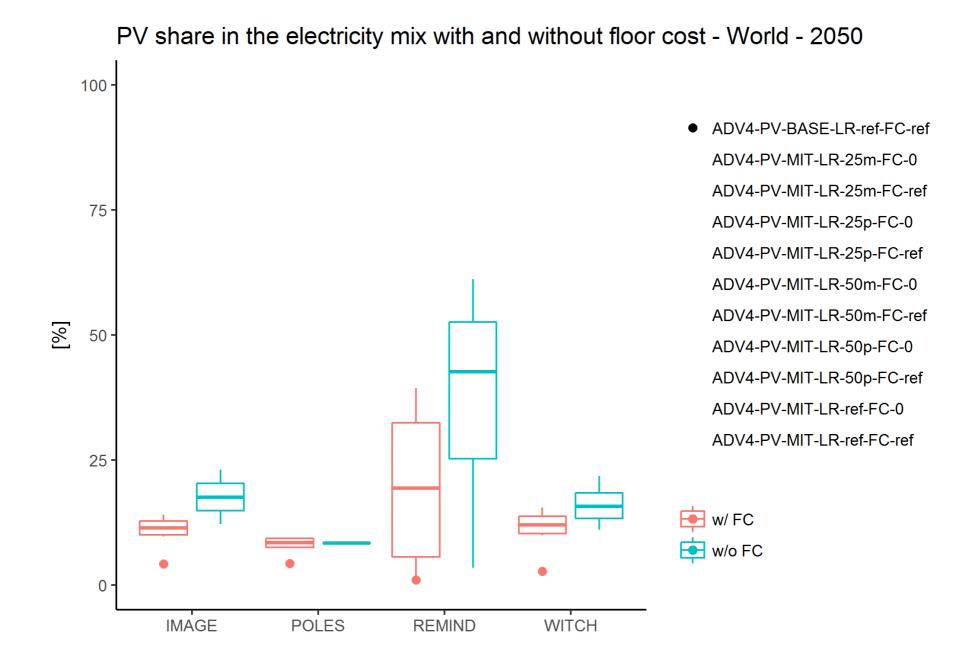
Electricity mix (Base. and Ref. scenarios) – Comments

- Compared to the baseline scenario, in the reference scenario the total electricity generation decreases in IMAGE, remains substantially constant in POLES, while it increases in REMIND and WITCH → energy efficiency vs. electrification
- Despite the cost evolution similarities, PV penetration in REMIND is way higher than in the other models, which are mutually similar.

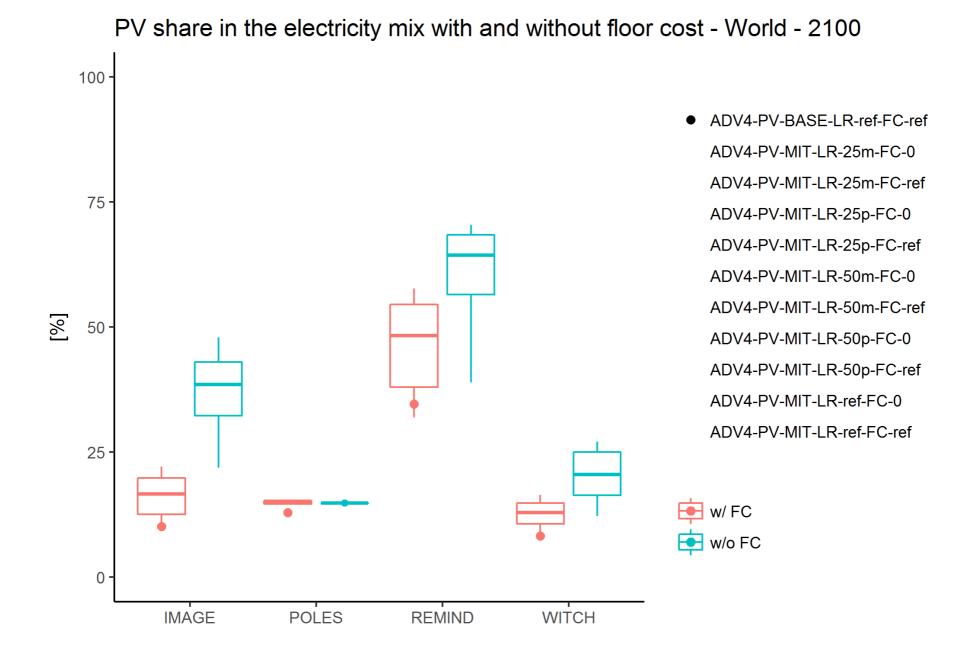












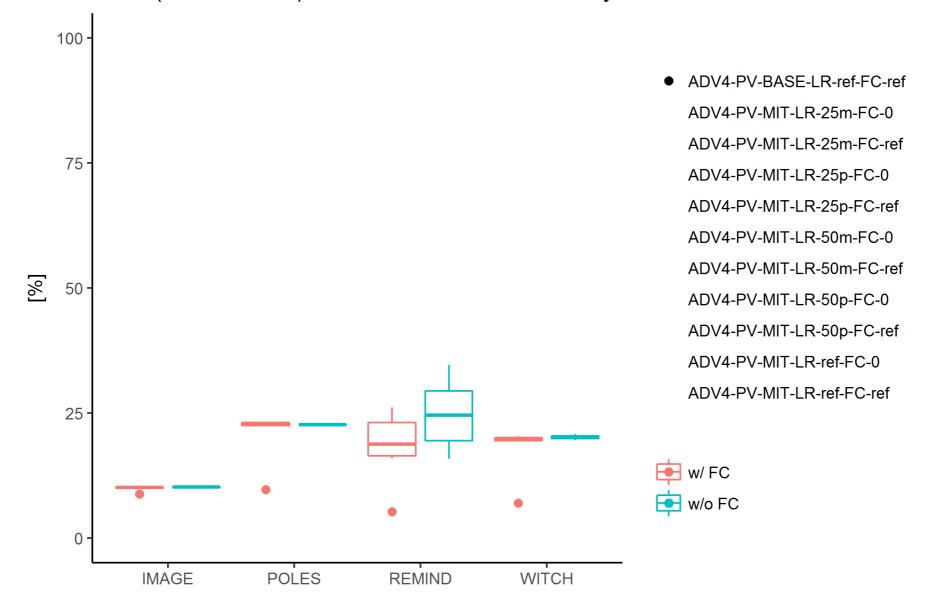


PV share – Comments

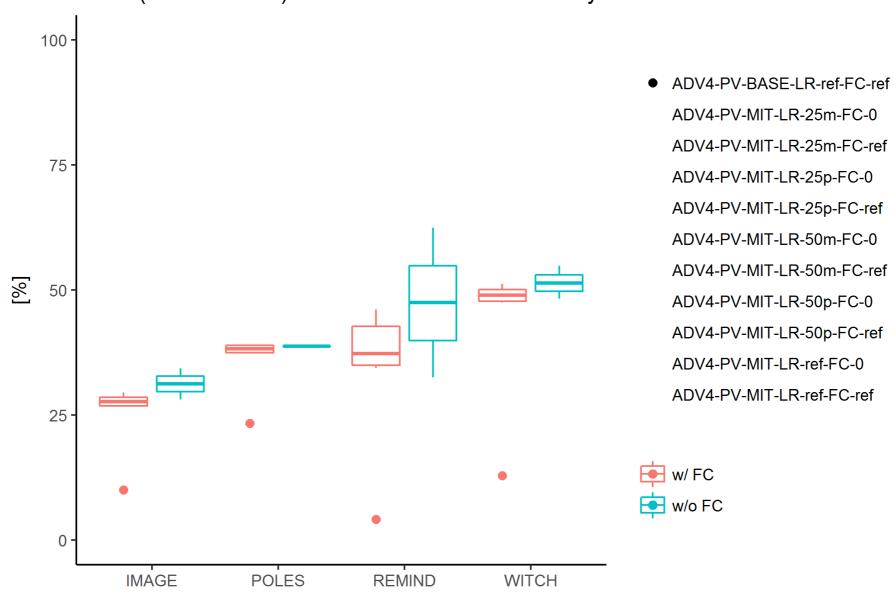
- PV penetration is obviously higher without floor cost, except for POLES.
- As said, REMIND shows the highest PV share across models. Then we have IMAGE, WITCH, and finally POLES.
- The same "model rank" applies to sensitivity as well: REMIND shows the largest one (especially in 2050, while this diminishes in 2100), followed by IMAGE, WITCH, and finally POLES.
- In particular, REMIND shows sensitivity to the learning rate already in 2030, while all the other models show differences in penetration in 2050 and 2100 only.
- POLES is basically insensitive to the different learning rates.
- **IMAGE** shows the highest sensitivity to the removal of the floor cost.



Solar (PV and CSP) + wind share in the electricity mix - World - 2030

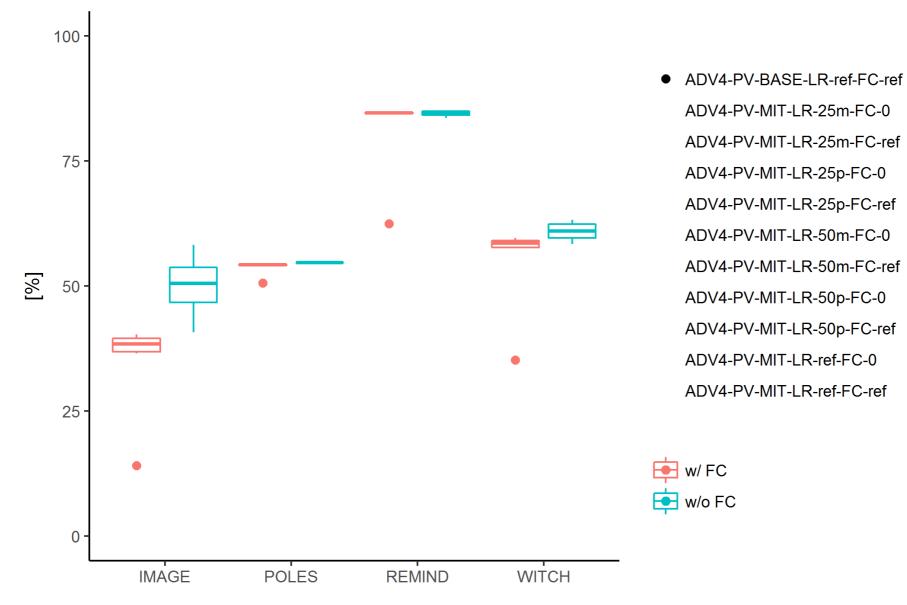






Solar (PV and CSP) + wind share in the electricity mix - World - 2050





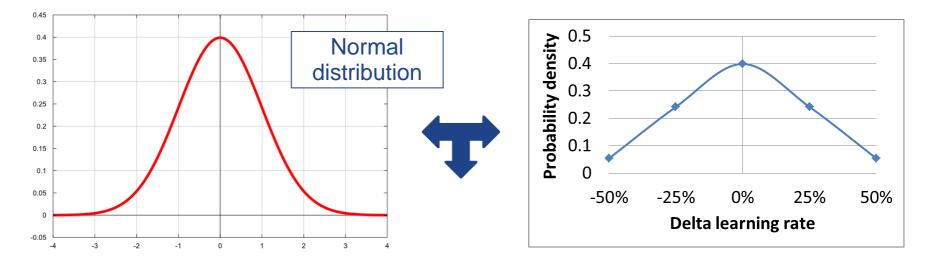
Solar (PV and CSP) + wind share in the electricity mix - World - 2100

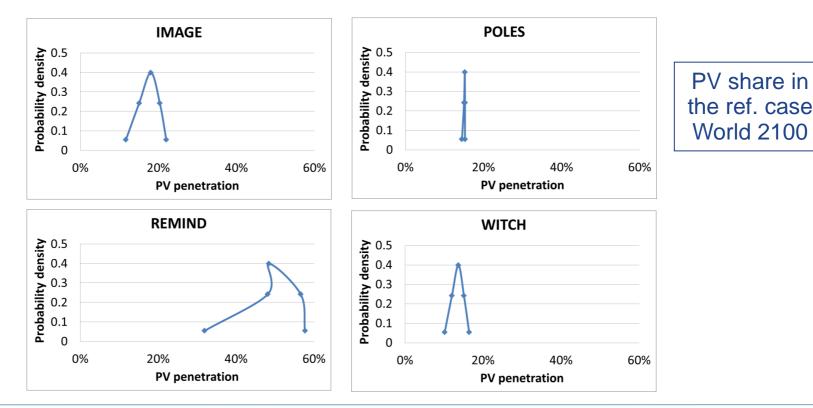


PV + CSP + wind share – Comments

- If we sum solar PV, CSP and wind, the sensitivity markedly reduces in all models, except partly for IMAGE.
- A similar behavior (though less "extreme") would be found if we considered wind only.
- This means that the higher/lower PV penetration associated to the different learning rates primarily occurs to the detriment/benefit of wind and CSP.
- This is particularly clear in WITCH, which basically shows no sensitivity (similarly to POLES, but the latter did not show sensitivity in the PV penetration alone either).
- In particular, REMIND seems to have reached a "Variable Renewable Energy threshold" around 80-85% in 2100.
- The same substantially applies to POLES (~ 55%) and WITCH (~ 60%).





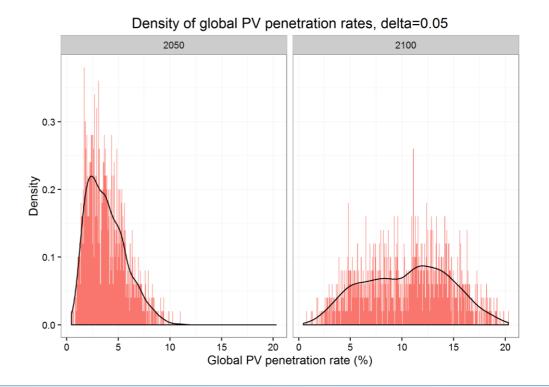




Statistical analysis

- The previous slide is a draft of what I would like to develop after the next submission.
- The objective is to derive statistical information in order to obtain the "real" penetration, weighting the different PV shares on the probability density of the corresponding learning rate (basing on the assumption that the learning rate profile replicates a normal function).

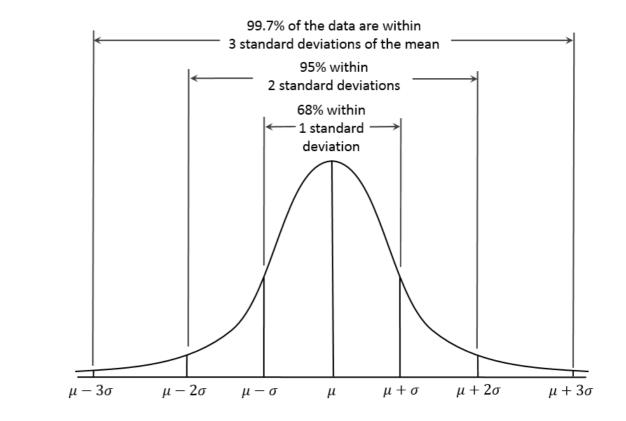
 The easiest solution would be to carry out a weighted average; a more sophisticated solution would be to derive a statistical distribution like in the example aside (although with much fewer samples).





Additional scenarios

 In the light of what discussed in the previous slide, it will be worth to add the μ ± 3σ (thus ± 75%) scenarios, both with and without floor cost, in order to have a more complete statistical picture.



• For the sake of completeness (for instance, in order to have complete charts in box plots), the ADV4-PV-BASE-LR-ref-FC-0 scenario, i.e. a **baseline with no floor cost**, will be added as well.





THANK YOU FOR YOUR ATTENTION

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