Supplementary S1: List of symbols

Paths:

NAT: Denotes any variable calculated with the National driven path method (based on country-level data and extrapolations, mainly used for near-term results).

IAMatt: Denotes any variable calculated with the IAMatt path method, based on regional IAMs data (serving as an attractor for long-term results).

Output: Consolidated path (output of the downscaling tool) calculated as a linear combination of NAT and IAMatt paths, depending on the time of convergence *tc*. Denotes any variable calculated as a linear combination of the NAT and IAMatt paths (methods).

Convergence Parameters:

ϕ: Time dependent Weights, based on a time of convergence *tc*

γ: Variable utilized to calculate ϕ weights, normally coincides with time ($\gamma = t$).

Sets:

t: Time

t0: Base year

tc: Time of convergence (depending on variables and the scenario to be downscaled)

c: Country

R: Regional from Integrated Assessment Models (unless specified otherwise)

s: Sector (e.g. Industry), where capital S means the total (sum across sectors)

e: Energy Carrier (e.g. Electricity), where capital E means the total (sum across energy carriers)

f Fuel (e.g. “Coal”), where capital F means the total (sum across all fuels)

$f_{w/CCS}$: Fuel with CCS (Carbon Capture Sequestration and Storage), if applicable. Example Coal with CCS

$f_{wo/CCS}$: Fuel without CCS. Example Coal without CCS

i: Criteria for downscaling the electricity sector in the NAT path

Log-Log model parameters:

EI: Energy Intensities, defined as the specific variable under consideration (e.g. Final Energy), divided by its respective MAIN sector

MAIN: the denominator of the energy intensity EI (depending on the specific variable under consideration). Please see table 2 for a full list.

α: Intercept of the linearized log-log model

β: Slope of the linearized log-log model

Logistic model parameters

L: Carrying capacity (upper bound of the logistic curve)

X: GDP per capita

X_0: The GDP per capita value associated with the inflection point of the curve

k: Steepness (logistic growth rate) of the curve

Socioeconomic variables:

GDP: Gross Domestic Product in PPP (Purchasing Power Parity)

POP: Population

Energy Variables:

EN: Generic energy variables (including all the Final, Secondary, Primary energy variables), for any path (IAMatt or NAT)

FEN: Final Energy variables, for any path

SEN: Secondary Energy variables, for any path

PEN: Primary Energy variables, for any path

Structure Adjustments:

$\widehat{FEN}$: Final energy variables, after introducing consistency at the sectorial level (so that the sum of all sub-sectors matches the total in each country)

$\widehat{SEN}$: Secondary energy variables, after introducing consistency at the sectorial level (so that the sum of all sub-sectors matches the total in each country)

Secondary Energy variables - specific for the NAT path

SENnat: “Secondary Energy” variables, calculated with the “NAT path” method

ELnat: “Secondary Energy|Electricity” variables, calculated with the “NAT path” method

ELInat: “Secondary Energy|Electricity” variables, calculated with the “NAT path” method, using specific set of criteria “i”

histratio: Country level data divided by the regional data, using historical data at the base year t0

GOV: Projected governance indicators based on Andrijevic et al 2020

GW: Projected installed capacities of fossil fuels based on remaining technical lifetime, calculated from the PLATTS database

MC: Projected electricity generation from renewables, based on supply cost curves, calculations based on Gernaat et al 2021

Emissions variables:

$\widehat{CO2EN}$: Energy related CO2 emissions, calculated as the emissions factors multiplied by the energy mix (before harmonization to match regional IAMs results)

$CO2EN$: Energy related CO2 emissions, after harmonization with regional IAMs results

ICO2: Industrial Processes emissions

σ: Standard deviation of direct land use emissions by country c, for the 2010-2020 time period, using the average of 3 Bookkeeping Models for the “LULUCF” net category (Grassi et al 2021).

LU: Land Use results, calculated as the sum of direct land use emissions (LUD) and indirect land use emissions (LUI)

LUD: Direct land use emissions by country c (R indicates regional results from IAMs)

LUI: Indirect land use emissions by country c.

NOTE the “R” index indicates regional results from the IMAGE/LPJmL model (Grassi et al. 2021), and not from IAMs (because IAMs normally do not provide results for indirect land use emissions).

$non\widehat{CO2}$: Downscaled non-CO2 emissions by country c, before harmonization

$nonCO2$: Downscaled non-CO2 emissions by country c, after regional harmonization with IAMs results

Gbau: Projected non-CO2 emissions by country c from the GAINS model.

NOTE: the “R” index denotes is the sum of country level results within the region) in the BAU scenario

Gstab: Projected non-CO2 emissions by country c from the GAINS model.

NOTE: the “R” index denotes is the sum of country level results within the region in the maximum abatement potential (stabilization) scenario

GHG Greenhouse Gas Emissions (Kyoto Gases)

BECCS Carbon Sequestration from Biomass with CCS (Carbon Capture and Storage)

EF Emission factors

Country-level emissions targets:

GHG:* Emission targets

GAP: Emissions Gap

ENGAP Energy gap (emissions gap divided by average emission factor)

avemifactor Average emissions factor of fossil fuels

Sensitivity analysis:

IAMatt:* Alternative IAMatt path

Γ: A generic variable used to calculate time-dependent weights ϕ

Integral Minimization (see supplementary information):

ω: A time-dependent weight, representing the relative size of each country within the region

h: Final energy variable at the country level. This value is utilized to calculate the relative weight of each country within the region, in the integral minimization approach.

o: Harmonized final energy using an integral minimization approach

δ: Cumulative difference between the harmonized (h) and the output (o) in the integral minimization approach

Convergence based on the quality of historical data (see supplementary information):

Maxtc: Time of convergence based on the quality of historical data (see supplementary information)

ρ: Weights based on the timing of convergence “maxtc”

Supplementary S2: Final Energy

S2.1 Final Energy from Hydrogen

To downscale “Final Energy|Hydrogen” (*e=H2*) we use a different approach compared to the one described in section 2.1. Since hydrogen is a relatively new technology there is lack of historical data. Therefore, it is not possible to estimate a relationship between hydrogen and income per capita based on historical data.

Indirect electrification with hydrogen can complement direct electrification for the sectors in which direct electrification is hard to achieve (Ueckerdt et al., 2021)). Therefore, we assume that hydrogen will be used by end-use sectors at a rate proportional to the use of electricity. To do so, we calculate a regional benchmark defined as hydrogen divided by electricity demand (from IAMs), for both NAT and IAMatt paths. The hydrogen results ($FEN_{t,c,e=H2}$) will be different across the two paths, as electricity demand ($FEN_{t,c,e=EL}$) is different.

$$FEN_{t,c,e=H2} = \frac{FEN_{t,R,e=H2}}{FEN_{t,R,e=EL}} FEN_{t,c,e=EL} \tag{S1}$$

S2.2: Final Energy from Heat

For the IAMatt path, we downscale “Final Energy|Heat” (e=H) by using the same approach described for hydrogen, as shown in the equation below:

$$FEN_{t,c,e=H} = \frac{FEN_{t,R,e=H}}{FEN_{t,R,e=EL}} FEN_{t,c,e=EL} \tag{S2}$$

For the NAT path, we use the base-year historical data (*t=t0*) to allocate heat at the country level, as shown in the equation below:

$$\widehat{FEN_{t,c,e=H}} = \frac{FEN_{t=t_0,c,e=H}}{FEN_{t=t_0,c,e=EL}} FEN_{t,c,e=EL} \tag{S3}$$

These preliminary results are denoted by a "wide hat" to indicate that they are not yet aligned with regional IAMs results. Then, we standardise these results so that the sum across countries is equal to one, and then scale them by the regional IAMs data ($FEN_{t,R,e=H}$), as shown in the equation below:

$$FEN_{t,c,e=H} = \frac{\widehat{FEN_{t,c,e=H}}}{\sum_c \widehat{FEN_{t,c,e=H}}} FEN_{t,R,e=H} \tag{S4}$$

S2.3: An integral minimization approach to align the sum across countries with regional IAMs results

A simple way to harmonize the results is to scale up or down the results using a proportional method, as we do for the "IAMatt" path. For example, if the sum of country-level results is 10% higher than the regional data, all countries can be shifted upwards by the same percentage.

In the "NAT" path we downscale final energy results by considering historical trends in relation to GDP per capita. In this context using a proportional method, will break consistency with historical trends in all countries. Therefore, in this section we present a method to harmonize the results with regional IAMs data, while minimizing the discrepancy between the "unharmonized" (in line with historical trends) and harmonized projections (in line with regional IAMs results). We refer to this approach as "integral minimization" as the aim is to minimize the integral between the harmonized and unharmonized energy intensity projections, over GDP per capita. A simple way to achieve this goal is to distinguish countries based on their size, so that the big countries will make the most of the adjustments required to match regional IAMs results. In this manner, the small countries will preserve their own trajectories without deviating too much from historical trends.

To illustrate the methodology, we consider a single IAM region encompassing fours countries. These countries are divided into two groups (big and small):

- Small countries: country1, country 2,
- Big countries: country2 and country3

The first country is the smallest in the region and has a strong historical trend relationship (e.g. a high- R-squared and a long historical time series). The last country is the biggest country in the region. In the table below, we assume that the regional IAMs data is equal to 11, whereas the sum of current (unharmonized) results across countries is equal to 10:

Countries	c (country index)	u (unharmonized)	h (harmonized)	*ω (weights)*	δ	o (output)
Country1	1	1	1.1	0.1	0	1
Country2	2	2	2.2	0.22	0.1	2.02
Country3	3	3	3.3	0.43	0.28	3.12

Country4	4	4	4.4	1	0.46	4.86
Sum		10	11			11

Table S1: Regional harmonization for a region comprising 4 countries, with γ=100%.

As a first step, we apply a simple (proportional) harmonization as shown in column "h". This column can be calculated by multiplying all countries by 11/10=1.1. This proportional harmonization serves as a reference. Next, we develop an alternative method that considers the robustness of historical trends into the harmonization process. This alternative method should allow small countries with strong historical trends (e.g. characterized by high R-squared and long-time series) to follow these patterns. The main rational for this is that small countries do not significantly affect the regional balance, as their contribution is minor compared to the entire region. In contrast, larger countries should bear most of the adjustments, as they have the greatest impact on the regional data. To achieve this goal, we calculate a weight (ω) representing the relative size of each country within the region, as defined in the equation below:

$$\omega_{t,c} = \frac{h_{c,t}}{\sum_c h_{c,t} - \sum_c^{c-1} \mathrm{h}_{c,t}} \tag{S5}$$

The weight ω increases as we move from smaller to bigger countries and approaches 1 for the last country in the region. The same formula can be simplified as follows:

$$\omega_{t,c} = \frac{h_{c,t}}{\sum_c^{c-1} \mathrm{h}_{c,t}} \tag{S6}$$

At this point, each country follows a linear combination of harmonized (h) and unharmonized (u) results, by using (γ) as a weighting factor, along with a residual amount (δ) multiplied by the weights (ω):

$$o_{t,c} = \gamma\, u_{c,t} + (1-\gamma)\, h_{c,t} + \omega\, \delta_{c,t} \tag{S7}$$

The residual amount (δ) represents the cumulative difference between the harmonized (h) and the output (o) of all preceding countries.

$$\delta_{t,c} \quad = \quad \sum_{c}^{c-1} h_{t,c} - \mathrm{o}_{c,t} \tag{S8}$$

This means that if $\gamma = 0$, each country will follow a simple harmonization approach (column "o" will coincide with column "h") and "δ" remains zero throughout. However, for any $\gamma \neq 0$, each country will deviate from the "reference" harmonization, creating a residual (δ) that is absorbed by the remaining larger countries.

As a result, the sequence of countries affects the final outcomes. For instance, if we swap country 3 and 4 (and keep δ=100%), the results will change as follows:

Countries	**c (country index)**	**u (unharmonized)**	**h (harmonized)**	***ω (weights)***	**δ**	**o (output)**
Country1	1.00	1.00	1.10	0.10	0.00	1.00
Country2	2.00	2.00	2.20	0.22	0.10	2.02
Country4	4.00	4.00	4.40	0.57	0.28	4.16
Country3	3.00	3.00	3.30	1.00	0.52	3.82
Sum		10	11			

Table S2: Regional harmonization, with γ=100% and a difference sequence of countries (country1, country2, country4, country3).

At this stage, we calculate the energy intensities associated with the output (o) and the unharmonized (u) results. We then identify an optimal list of larger countries by minimizing the absolute difference between the energy intensities linked to "u" and "o", measured over GDP per capita. This difference, calculated as an integral over GDP per capita, is weighted using the R-squared value from the historical regression. In this way, countries with stronger historical trends have a greater influence on the objective function being minimized.

Another "lever" that can be used to minimize the integral is the γ parameter. The graph below shows how varying γ impact the results across countries:

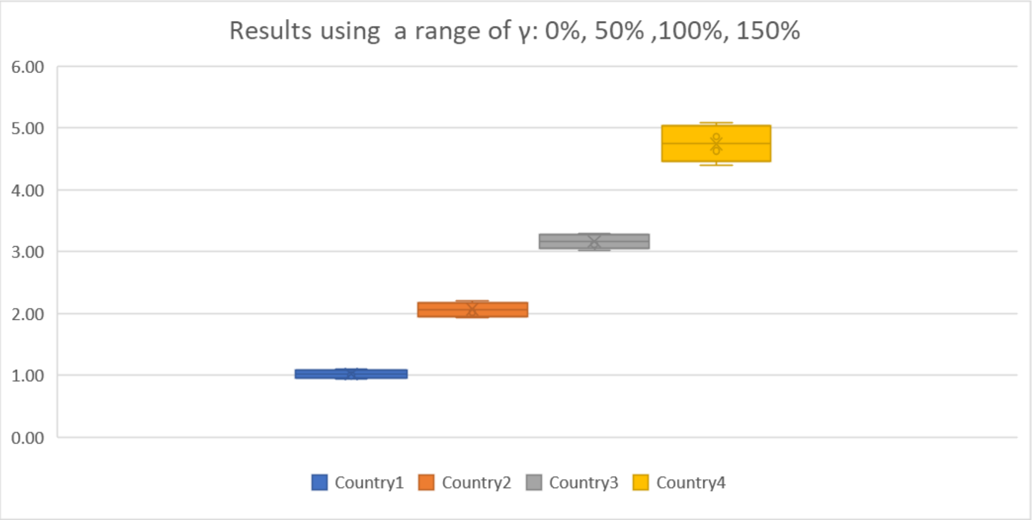


Figure S1: Results associated with a range of γ values across countries.

Therefore, we find the optimal γ value that minimizes the objective function (sum of integral values across all countries), as illustrated in the graph below:

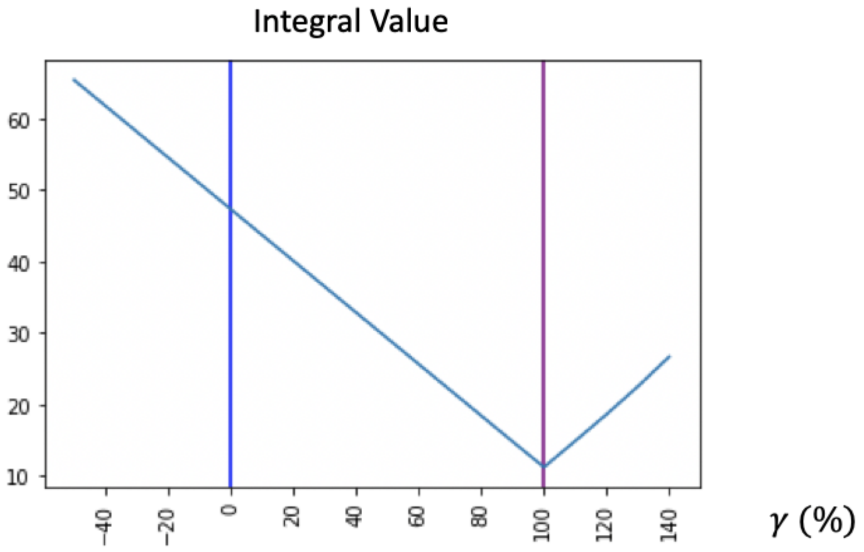


Figure S2: Integral value associated with the correction rate value γ. The purple line represents the optimal γ associated to the lowest integral value, whereas the blue line represents a simple harmonization approach ($\gamma = 0$) and its (higher) integral value.

S2.4: Final energy – Convergence based on the quality of historical data

In order to provide realistic results at the country-level, historical data should be interpreted and combined with regional IAMs results. For example, historical data show that the energy intensity usually increases in the very early stages of industrializations and then declines as GDP per capita increases (this pattern is known as "the hill of energy intensities" (GEA, 2012)). As a result, if we run a linearized log-log regression using the entire historical time series (including when the energy intensity is increasing), we might find a relatively weak relationship. At the same time, our estimates might incorporate dynamics that characterize early development stages, and therefore may not represent well expected future developments. To avoid this problem, the algorithm should be able to select the most appropriate starting date of the time series (for example by eliminating data before the "hill" in the energy intensity). This can be achieved by selecting the optimal "starting point" of the historical time series that will span until the most recent data. In the DSCAL algorithm, this selection process is done by maximizing the r-squared of the regression, multiplied by the number of observations available in the "selected" historical data. This means that the number of historical observations can be reduced by half only if the r squared of the regression will (at least) double. In other words, the algorithm tries to find a relationship that is as long and as stable as possible.

However, it is also important to evaluate historical data in the context of IAMs results. IAMs scenarios or SSPs storylines usually envisage increasing GDP per capita over time, whereas historical data show that in 16 countries GDP per capita has declined during the period 1980-2010 (including for example Saudi Arabia, Brunei, Haiti, Venezuela, Zimbabwe etc.).
In such cases, relying solely on historical trends may lead to artifacts, as future income per capita growth could differ significantly from past developments. To address this issue, we introduce an additional data point for countries with declining GDP per capita. This data point, refer to the future energy intensity expected in 2100, based on the IAMatt path.
By doing so, we combine the historical data information (until the most recent available year) with the energy intensity results (based on regional IAMatt path) in 2100. This process aims to reconcile historical (NAT) trends to the long-term (IAMatt) path when historical data deviates from expected patterns.
In a similar manner, we introduce some degree of convergence when the quality of historical trend is poor. For instance, some countries have relatively short historical time series, while others have experienced significant structural breaks, such as the Former Soviet Union countries in the 1990s. In such cases, reliable historical estimates are hard to obtain. To overcome these problems, we assume that the degree of convergence is tied to the robustness of the historical data. We assume a slower convergence "max_tc" for historical estimates with a relatively high number of observations and high r-squared, as shows in the graph below:

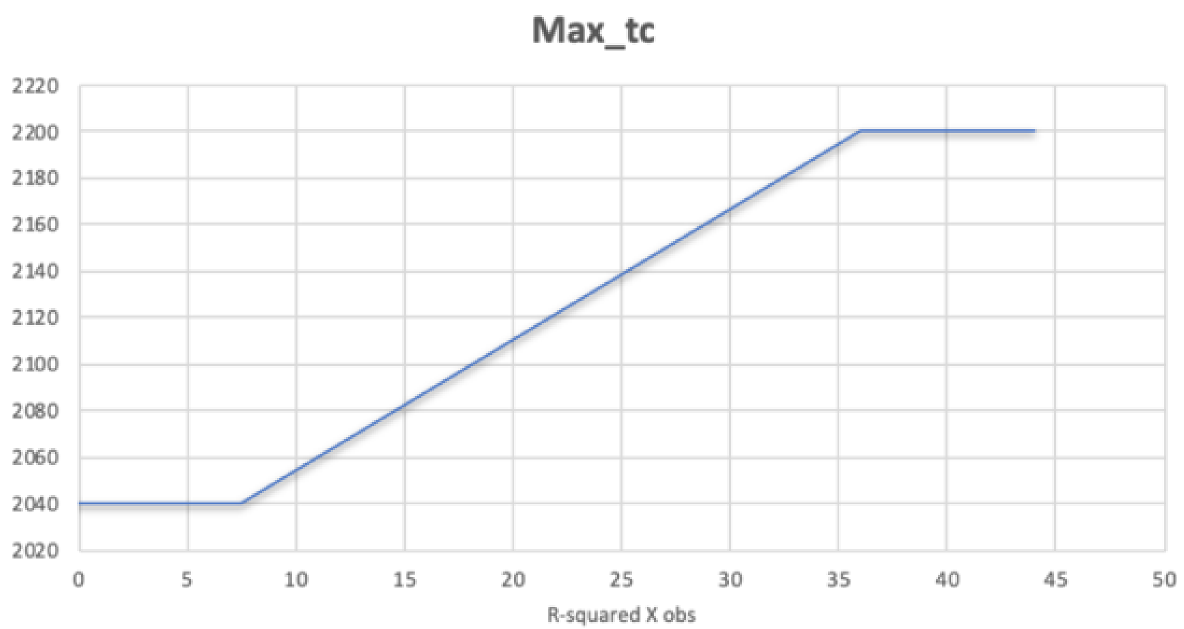


Figure S3: Timing of convergence ("Maxtc") as a function of the R-squared multiplied by the number of observations. We assume a convergence in 2040 if r-squared lower or equal than 7.5 (e.g., 25 observations with an r-squared of 0.3) and linearly increases up to 2200 (e.g., 36 observations with and an r-squared equal to 1).

Moreover, the quality of historical data can be also evaluated by comparing the slope of the NAT path (based on historical trends) to that of the "IAMatt" path (based on future IAMs scenarios). If the slopes have opposite signs, it suggests that historical trends deviate significantly from the developments anticipated in future scenarios. Should this happen, we assume a faster convergence to the IAMatt path, with "maxtc" equal to 2040. Otherwise, we apply a time of convergence "maxtc" as shown in the table above.

Finally, we compute the weights based on "maxtc" and the slope of the historical trend regression, using the equation below.

$$\rho_{t,c} = \left(\frac{t - maxtc}{tb - maxtc}\right)^{max(1,\beta_c)} \tag{S9}$$

The β in the equation above refers to the slope of historical trends. A negative slope leads to a linear function as shown in figure S4. A slope greater than 1 means that weights will decline at a faster rate, hence leading to a faster convergence to the IAMatt. This prevents unreasonably high growth rates in the energy intensities.

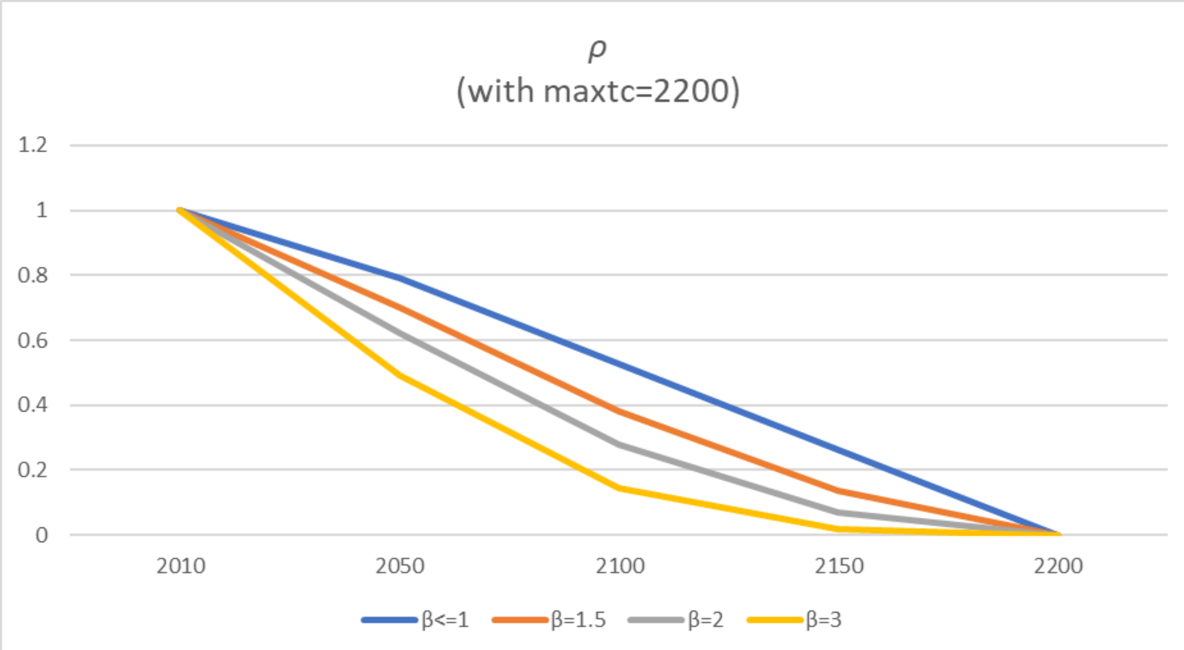


Figure S4: Weights over time as according to different β, assuming *maxtc=2200*.

Finally, we recalculate the "NAT" path using ρ as weights:

$$NAT_{t,c} = (1 - \rho_{t,c})\, IAMatt_{t,c}\, \rho_{t,c}\, NAT_{t,c} \tag{S10}$$

Supplementary S3: Sensitivity analysis

S3.1Parametrization index of final energy variables

This section shows the parametrization index of the sensitivity analysis of final energy data.

The table shows the index of the parallel coordinate graph (Figure 5.1, panel b) when varying the Functional form (FUNC):

Table S3 Index of parallel coordinate graph of figure 5.1, panel b

INDEX	FUNC	TC
0	log-log	2150
1	s-curve	2150

The table shows the index of the parallel coordinate graph (Figure 5.2, panel b) when varying the Functional form (FUNC) and the time of convergence (TC):

Table S4 Index of parallel coordinate graph of figure 5.2, panel b

INDEX	FUNC	TC
0	log-log	2100
1	log-log	2150
2	log-log	2200
3	s-curve	2100
4	s-curve	2150
5	s-curve	2200

The table shows the index of the parallel coordinate graph (Figure 5.3, panel b) when varying the Functional form (FUNC), the time of convergence (TC) as well as alternative "IAMatt" paths, with the three associated dimensions:

- Time of convergence (TC*)
- The variable used (VARIABLE), either GDP (per capita) or time
- And whether a linear or log-scale is employed (SCALE)

When the default IAMatt is used, all these three dimensions are reported as "default":

Table S5 Index of parallel coordinate graph of figure 5.3, panel b

INDEX	FUNC	TC	TC*	VARIABLE	Scale
0	log-log	2100	2050	GDP	linear
1	log-log	2100	2100	GDP	linear
2	log-log	2100	2050	GDP	log-scale

3	log-log	2100	2100	GDP	log-scale
4	log-log	2100	2050	time	log-scale
5	log-log	2100	2100	time	log-scale
6	log-log	2100	2050	time	linear
7	log-log	2100	2100	time	linear
8	log-log	2100	default	default	default
9	log-log	2150	2050	GDP	linear
10	log-log	2150	2100	GDP	linear
11	log-log	2150	2050	GDP	log-scale
12	log-log	2150	2100	GDP	log-scale
13	log-log	2150	2050	time	log-scale
14	log-log	2150	2100	time	log-scale
15	log-log	2150	2050	time	linear
16	log-log	2150	2100	time	linear
17	log-log	2150	default	default	default
18	log-log	2200	2050	GDP	linear
19	log-log	2200	2100	GDP	linear
20	log-log	2200	2050	GDP	log-scale
21	log-log	2200	2100	GDP	log-scale
22	log-log	2200	2050	time	log-scale
23	log-log	2200	2100	time	log-scale
24	log-log	2200	2050	time	linear
25	log-log	2200	2100	time	linear
26	log-log	2200	default	default	default
27	s-curve	2100	2050	GDP	linear
28	s-curve	2100	2100	GDP	linear
29	s-curve	2100	2050	GDP	log-scale
30	s-curve	2100	2100	GDP	log-scale
31	s-curve	2100	2050	time	log-scale
32	s-curve	2100	2100	time	log-scale
33	s-curve	2100	2050	time	linear
34	s-curve	2100	2100	time	linear
35	s-curve	2100	default	default	default
36	s-curve	2150	2050	GDP	linear
37	s-curve	2150	2100	GDP	linear
38	s-curve	2150	2050	GDP	log-scale
39	s-curve	2150	2100	GDP	log-scale

40	s-curve	2150	2050	time	log-scale
41	s-curve	2150	2100	time	log-scale
42	s-curve	2150	2050	time	linear
43	s-curve	2150	2100	time	linear
44	s-curve	2150	default	default	default
45	s-curve	2200	2050	GDP	linear
46	s-curve	2200	2100	GDP	linear
47	s-curve	2200	2050	GDP	log-scale
48	s-curve	2200	2100	GDP	log-scale
49	s-curve	2200	2050	time	log-scale
50	s-curve	2200	2100	time	log-scale
51	s-curve	2200	2050	time	linear
52	s-curve	2200	2100	time	linear
53	s-curve	2200	default	default	default

S3.2: Sensitivity analysis – Electricity

This section shows the sensitivity analysis in the "composite" path for fuels with small uncertainty range (oil, nuclear, hydro, biomass and geothermal):

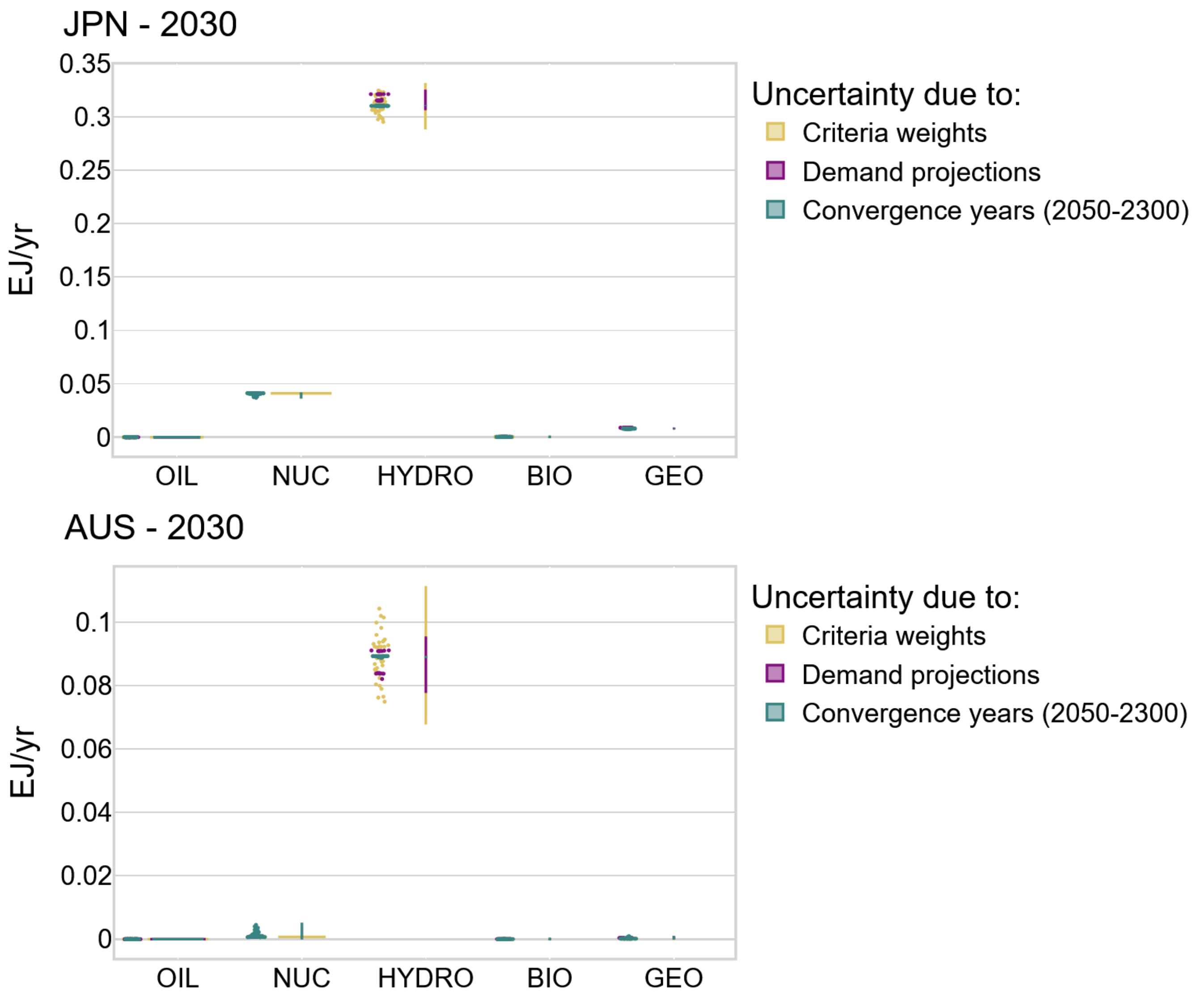


Figure S5 Uncertainty range in the electricity mix in Australia (AUS) and Japan (JPN) in 2030, downscaled from the MESSAGE current policy scenario, under the "composite" path. The graph shows the uncertainty arising from different components including: i) criteria "weights" (n=37), ii) "demand" projections (n=18), iii) "convergence" (n=51).

The graphs below show how the different criteria weights affect the downscaling of secondary energy electricity results, in the Pacific OECD region of MESSAGE. The graphs show results for each fuel in 2030 in a current policy scenario, under the "NAT" and "COMPOSITE" paths. Please note that in each downscaling run, the sum of weights (x axis in the graph) across all criteria (e.g. in the case of solar: cots curve, base year share, and governance criteria) always adds up to one.

The different criteria are:

- historical data: "DF_BASE_YEAR_SHARE"
- stranded assets: "DF_GW_ALL_FUELS"
- governance "DF_GOV"
- supply cost curves: "DF_COST_CRITERIA"

The default criteria used in the NGFS 2023 project are outlined in table 5.

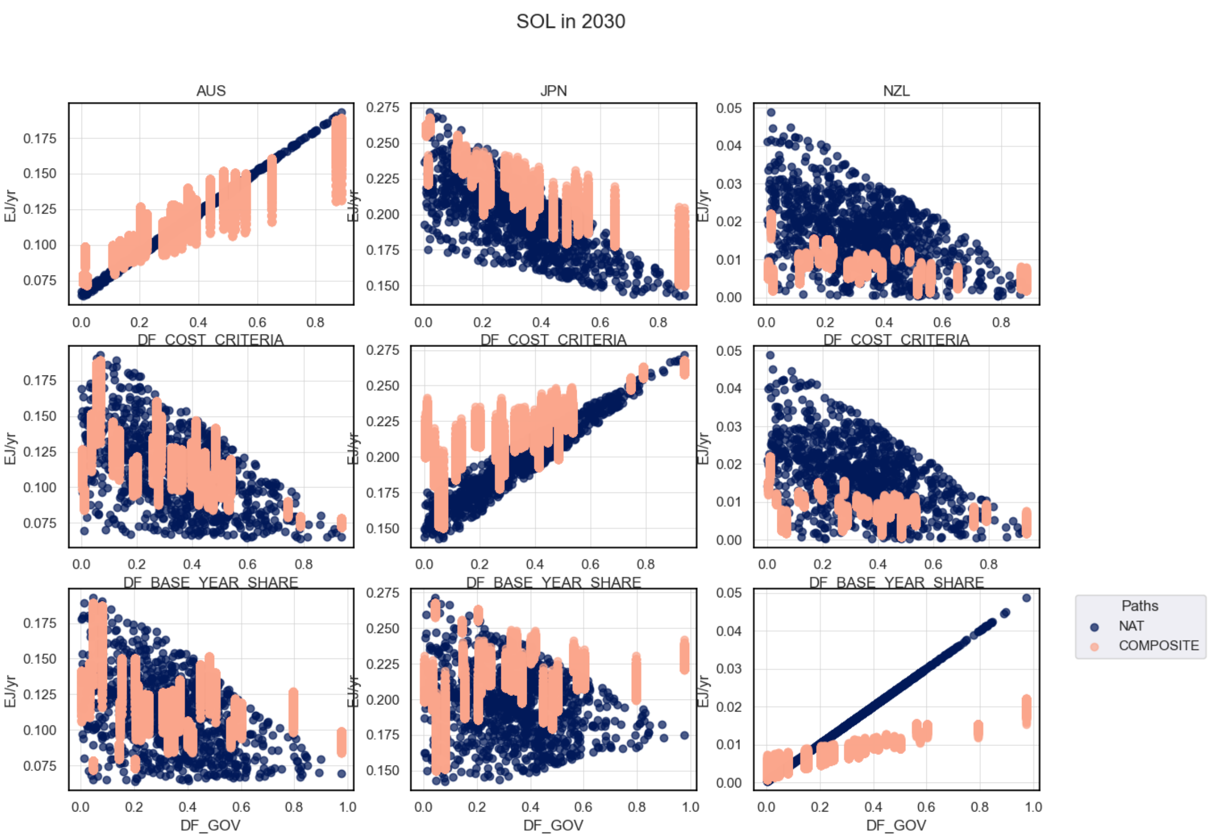
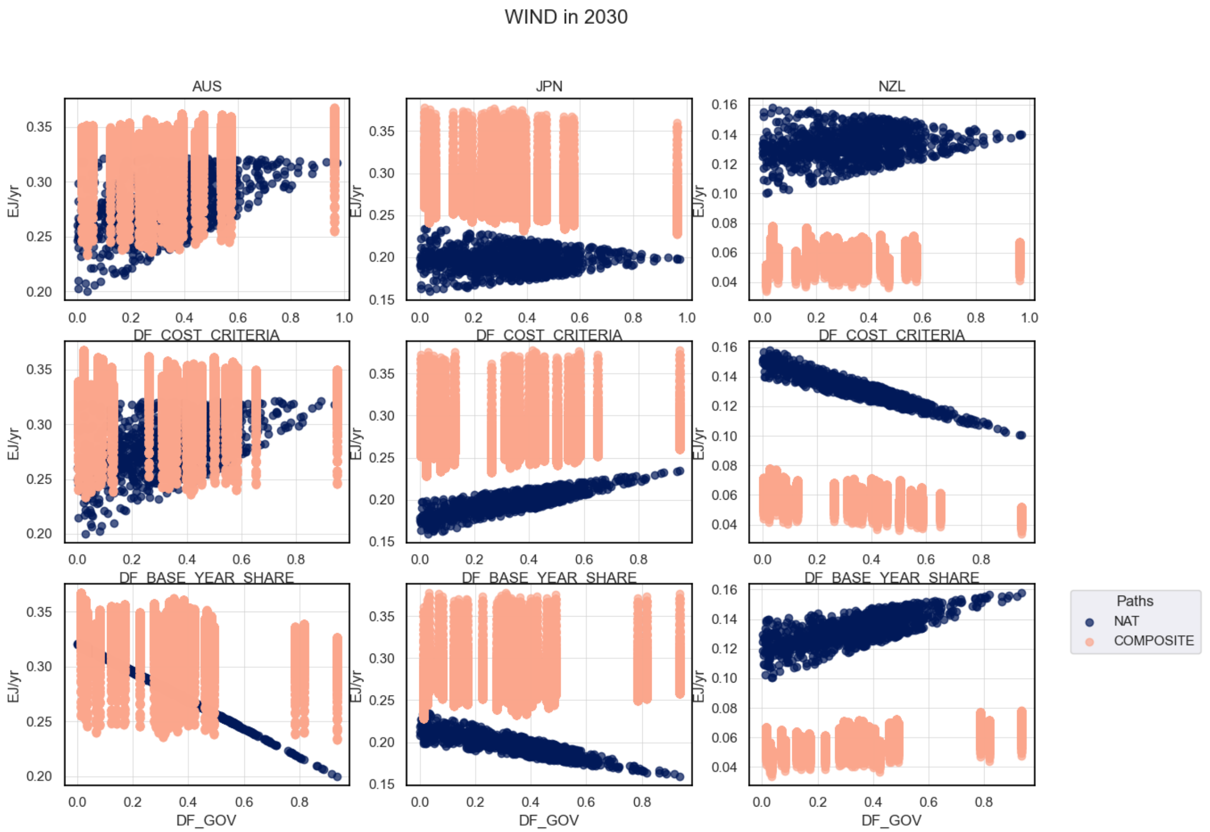


Figure S6– Electricity generation from solar



235 **Figure S7– Electricity generation from wind**

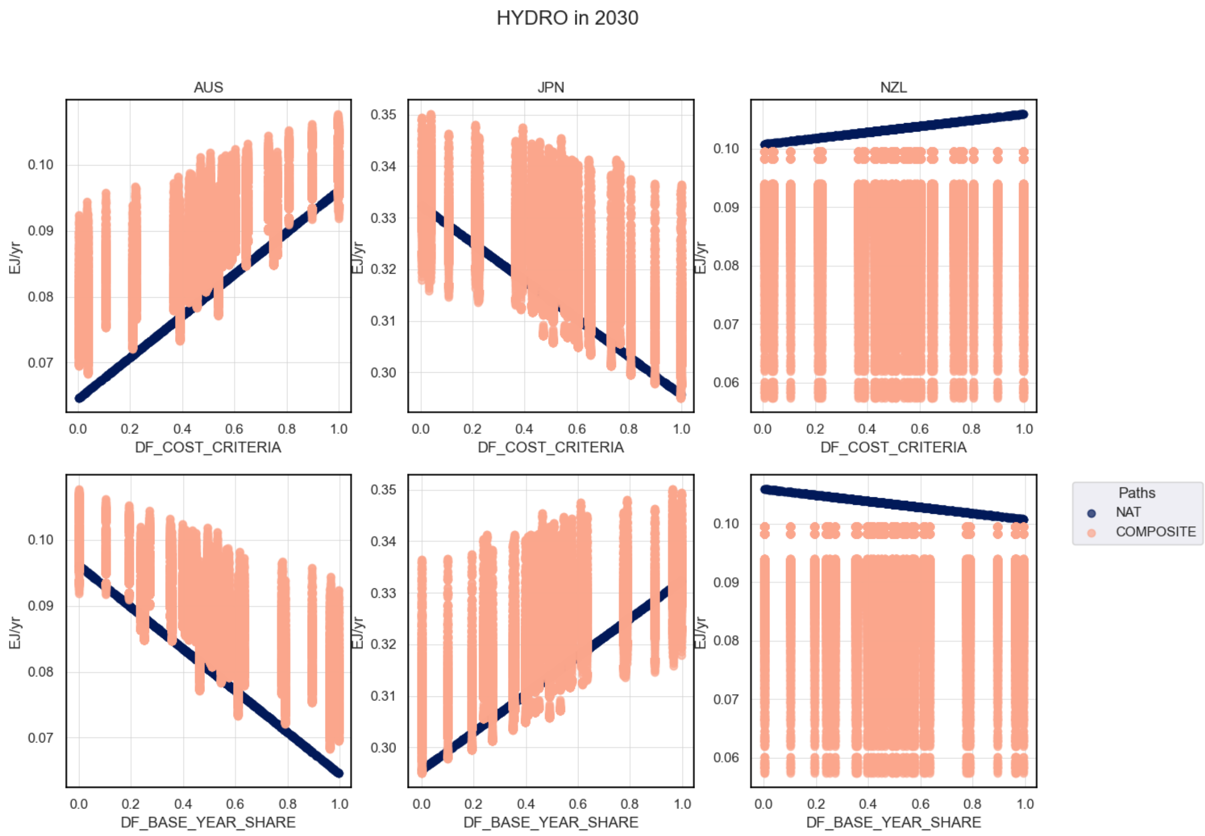
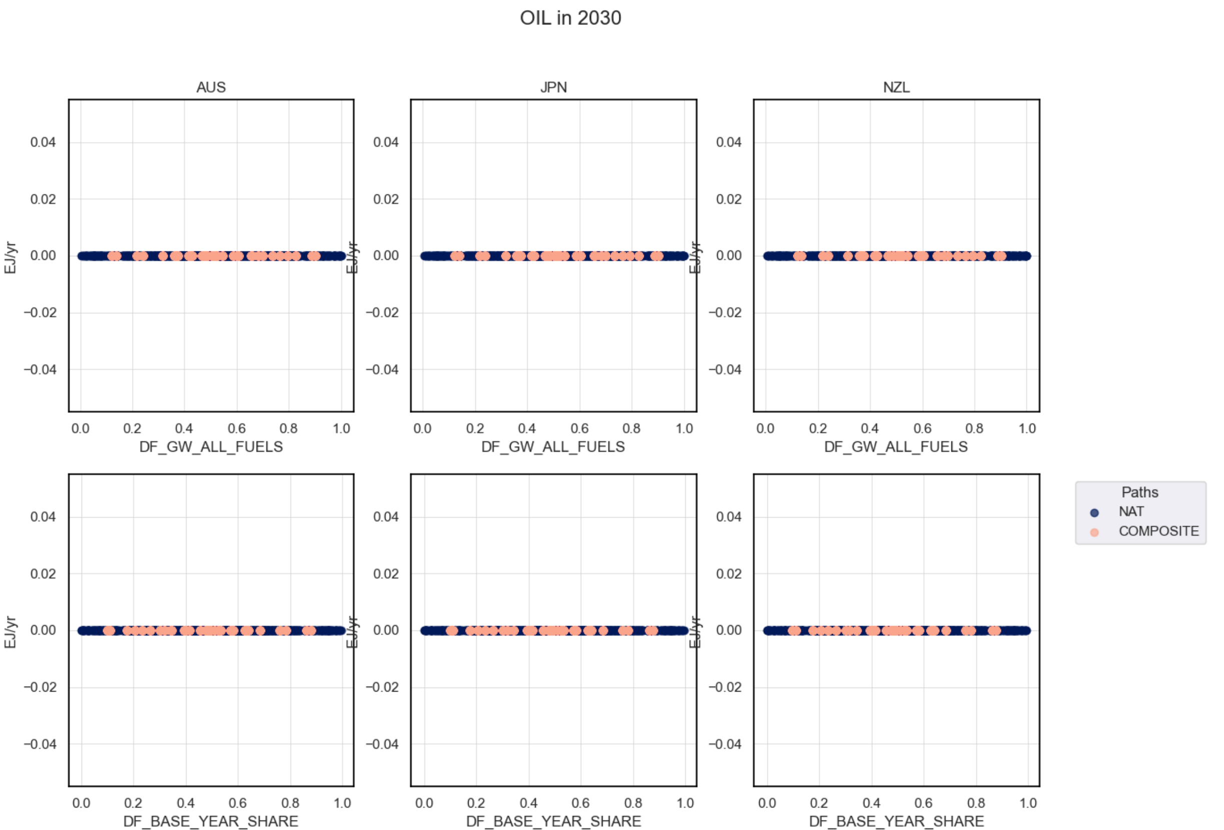


Figure S8– Electricity generation from hydro



240 **Figure S9– Electricity generation from oil**

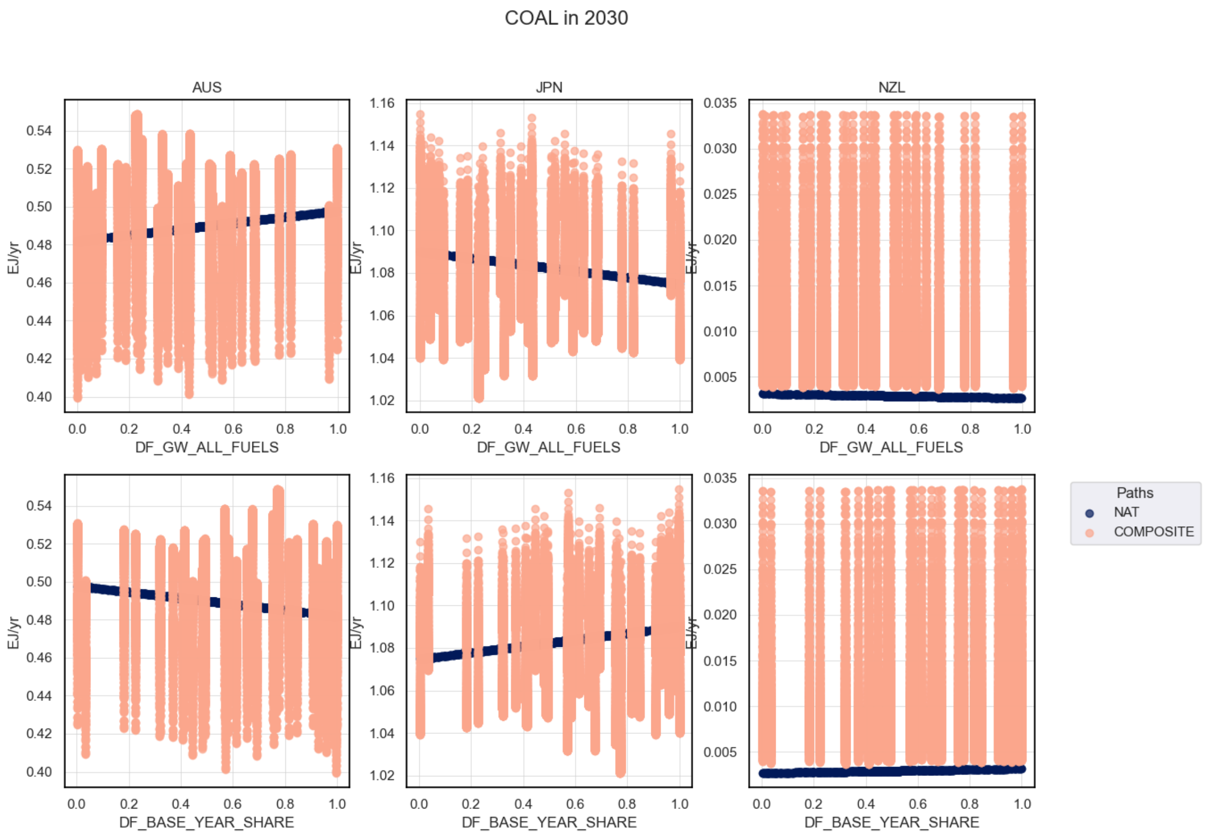
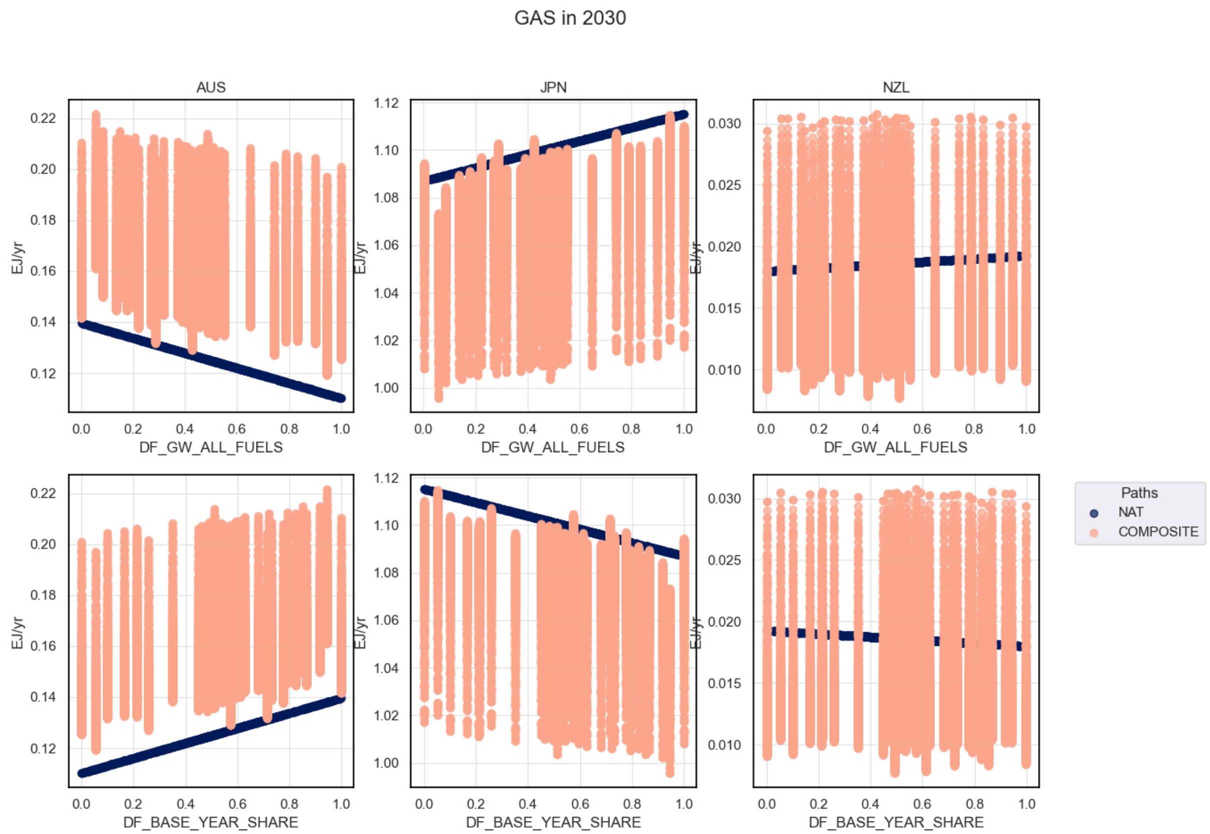


Figure S10– Electricity generation from coal



245 **Figure S11– Electricity generation from gas**

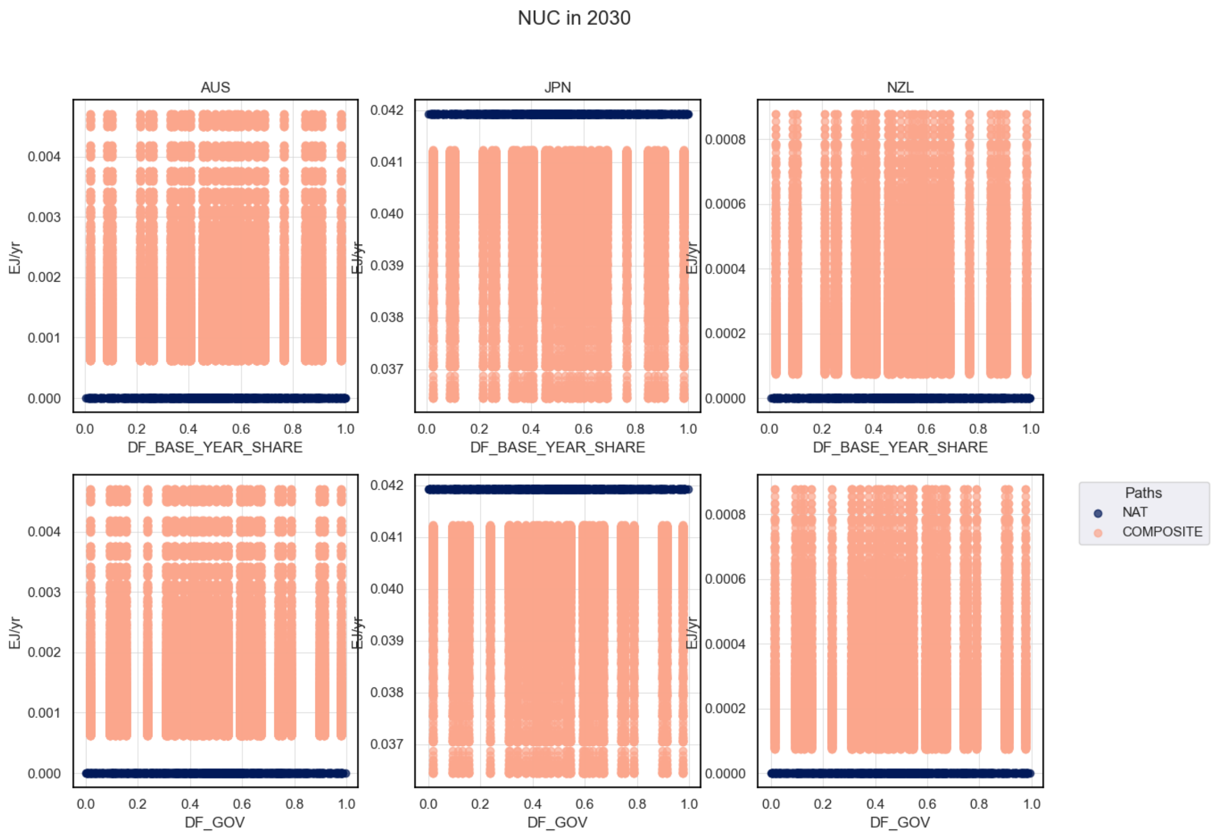


Figure S12– Electricity generation from nuclear

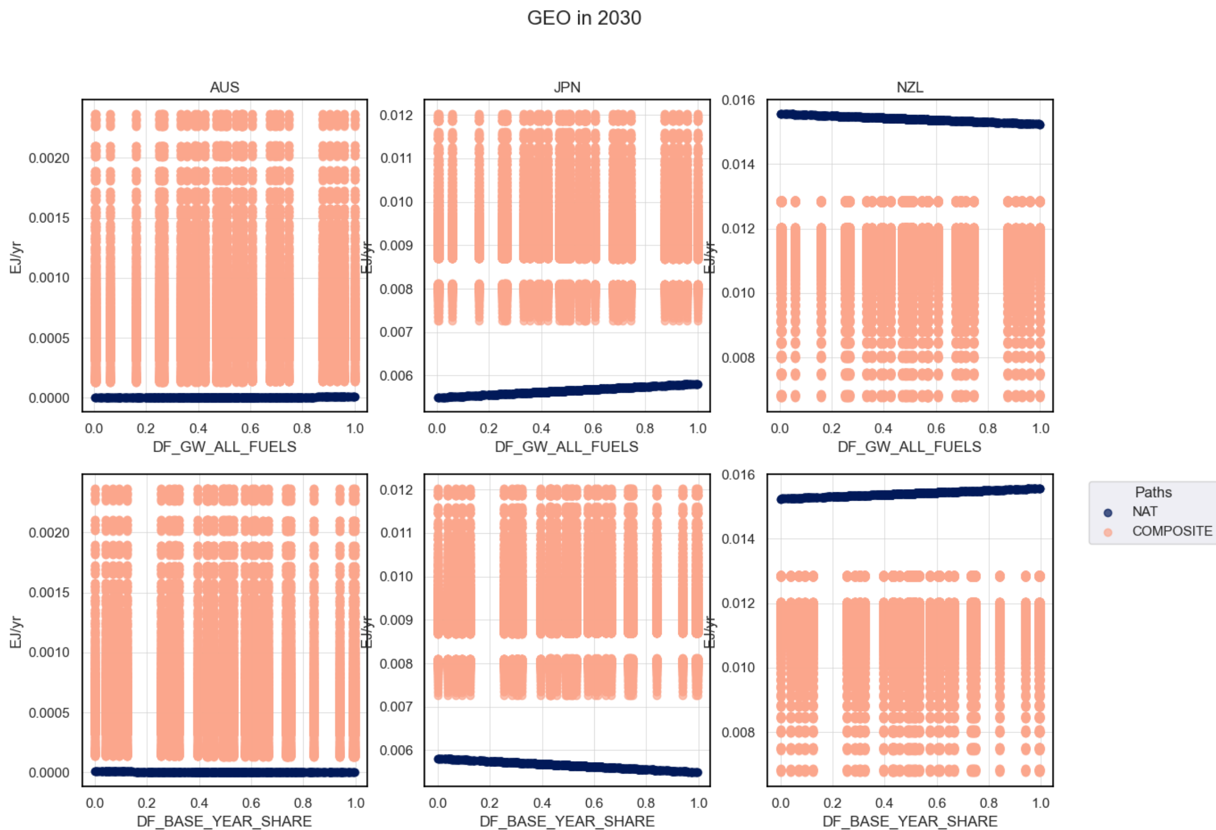
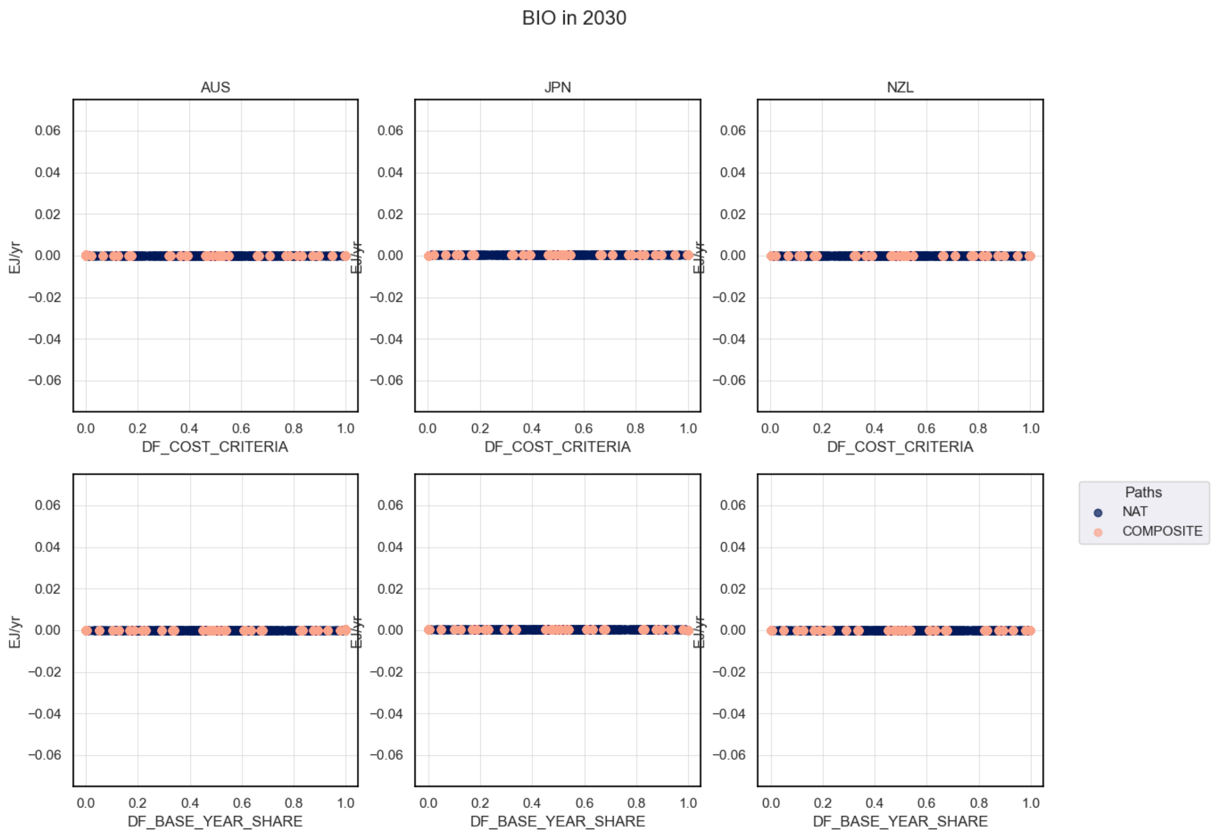


Figure S13– Electricity generation from geothermal energy



250
Figure S14– Electricity generation from biomass