Supplementary information
Climate policy accelerates structural changes in energy employment

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Contents

1 Employment factors and job estimates

1.1 Employment factors

1.1.1 Calculating employment factors

All EFs from Rutovitz et al., 2015 for OECD countries , are taken as values for the year 2020 in the current study but updated according to recent literature (Fragkos & Paroussos, 2018; IRENA, 2017a, 2017b). Following the methodology of Rutovitz et al., 2015, for countries without empirical data (mostly non-OECD), the EF is calculated by multiplying the OECD EF from Rutovitz et al., 2015 to a regional adjustment factor (section 1.1.2 below). Next, wherever possible, the resulting EFs have been replaced by country-specific values using mentioned in Rutovitz et al., 2015, recent studies (CEEW, 2019; Rutovitz et al., 2020; The Solar Foundation, 2020), or own calculations, e.g., coal EF (section 1.1.4 below). Lastly, some EFs are modified for specific countries/technologies by comparing the resulting jobs from the EF approach with bottom-up regional and global studies (Section SI 1.2.3) providing job estimates.

1.1.2 Calculating regional adjustment factors

For all those countries without an employment factor in 2020, a regional adjustment factor was used. This regional adjustment factor is the ratio of the labour productivity (excluding agriculture) for a country (lacking data) to the average OECD labour productivity (excl. agriculture).

The labour productivity (LP) is defined as the total output (GDP) per employed worker. The most updated and comprehensive data for the world on output, labour and labour productivity data is available from *The Conference Board Total Economy Database* (Conference Board, 2020). Labour productivity from this database, however, cannot directly be used to calculate the adjustment factor because developing countries often contain a disproportionally large number of people in agriculture, i.e., the labour productivity in agriculture is often much lower than other sectors (Rutovitz et al., 2015). So that this effect doesn't bias the results (which would result in higher regional adjustment factors and higher employment factors), agricultural GDP and people employed in agriculture (World Bank, 2019) were subtracted from the total GDP and total people employed respectively, to obtain a new labour productivity excluding agriculture. Since employment in agriculture for energy use (either as electricity, biogas, biofuels, or heating) is a small percentage of the total employment in agriculture in developing countries, the adjustment factor was not changed for biomass-based supply technologies. The relative LP is calculated by dividing the country-specific LP to OECD average LP. Finally, the regional adjustment factor is inverse of the relative LP. The employment factor of a non-OECD country (lacking data) is then the product of employment factor (OECD) and the regional multiplier. Note that the regional multiplier remains the same for all activities and technologies.

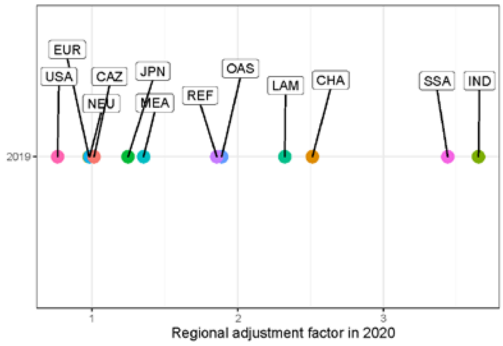

Figure S1 Aggregated regional adjustment factor (weighing on GDP) factor in 2020 based on (inverse of) labour productivity (excluding agriculture and relative to OECD in 2019). Note that this figure already aggregates the regional multipliers for various countries into REMIND regions.

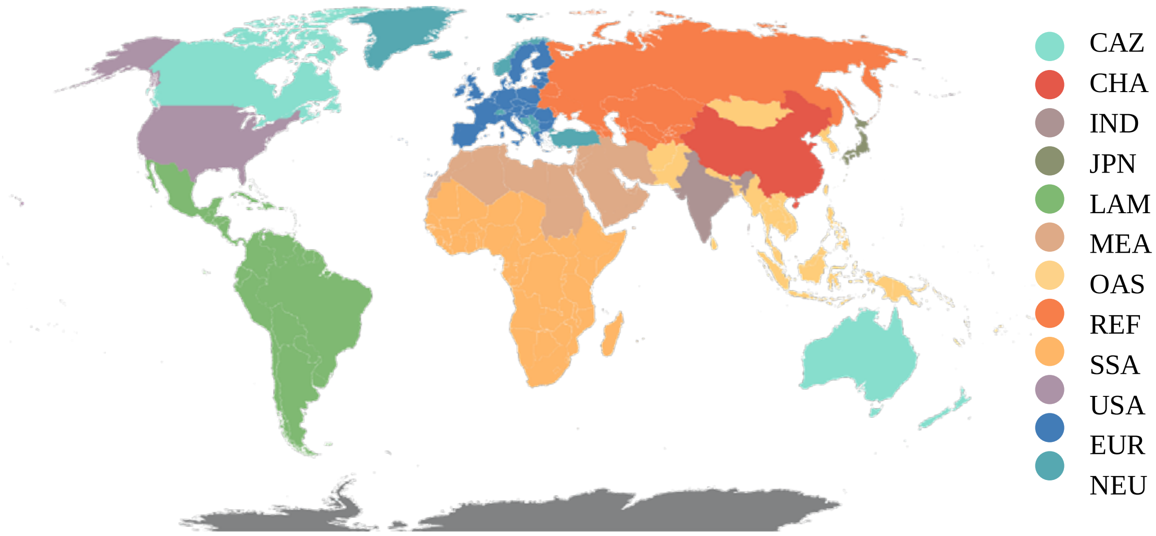

Figure S2 REMIND regions

1.1.3 Aggregating employment factors

The last step to obtain regional employment factors is to aggregate country-level results, obtained from 1.1.2 into (REMIND) regions (see Figure S2). For all technologies and activities, except fuel supply, the weighing was based on the 2019 electricity generation for that technology (data from BP 2020). For e.g., for the region EUR, employment factors for countries with higher absolute total solar power generation would be weighed more and viz-versa. For fuel supply (excluding Biomass), the weighing is based on production of that fuel (in EJ, data from BP 2020). For Biomass fuel supply, weighing is based on the employment in agriculture (Conference Board, 2020; World Bank, 2019). The results for the 12 REMIND regions are given in Figure S2 for different technologies and activities.

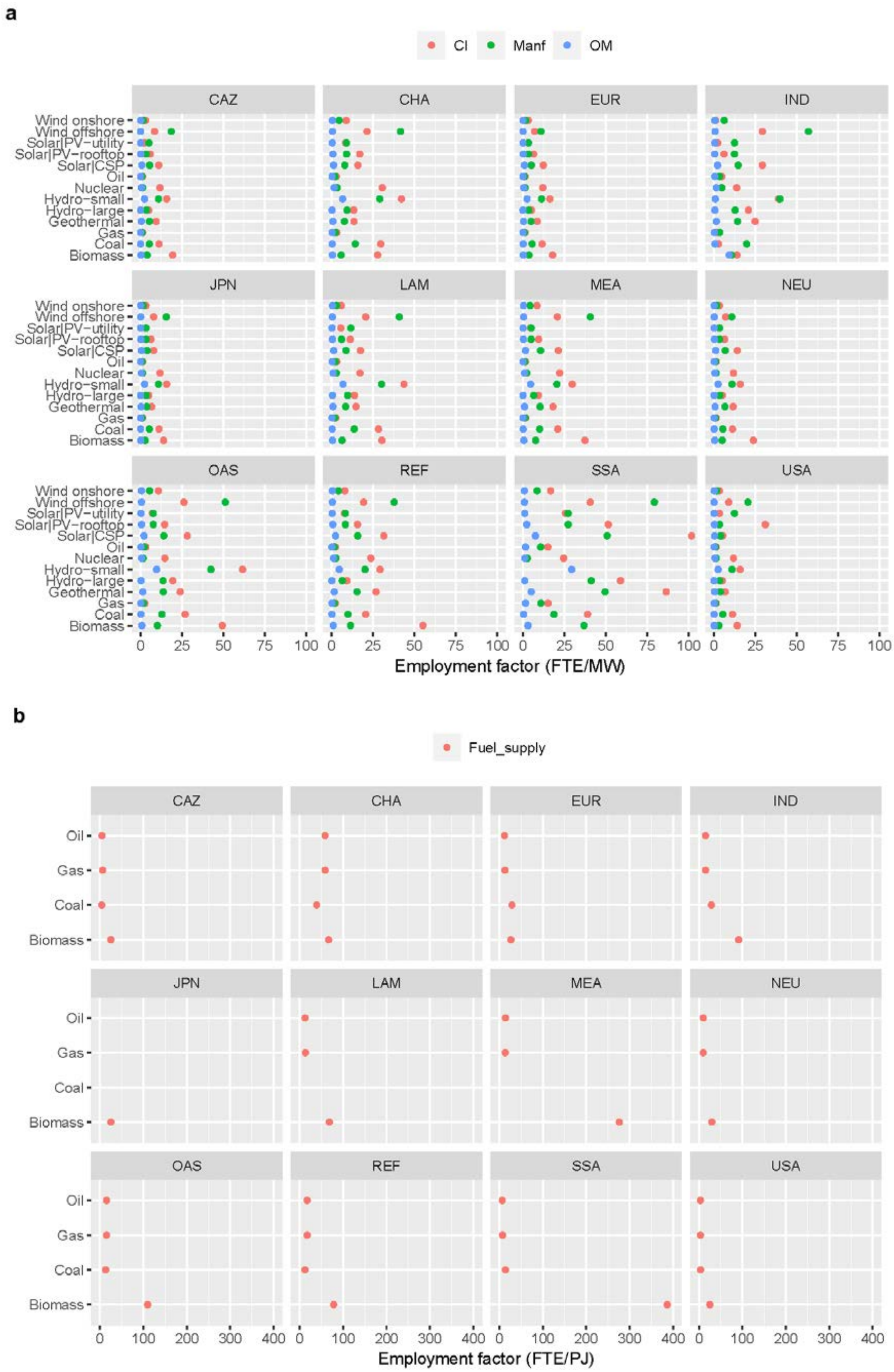

Figure S3 Employment factor by REMIND regions and technology, for (a) activity (only C & I, Manf, and O & M), (b) fuel supply for 2020.

1.1.4 Employment factors for coal fuel supply – historical and projections

Employment factors for coal fuel supply (Jobs/PJ) were calculated by using the employment in the sector (sources mentioned in Table 1) and the total production of coal (BP, 2020). The latest available EF was assumed to be the EF for 2020, e.g., if employment data for a country was available only until 2017, the EF in 2017 was assumed to be the same for year 2020. The countries covered produced 93% of the world coal (in EJ) in 2019 (BP, 2020). The values from 2020-2030 were extrapolated based on historical trends, while the EF further until 2050 were based long-term declining trends in the sector (see Table 1 for exact numbers, Figure S4).

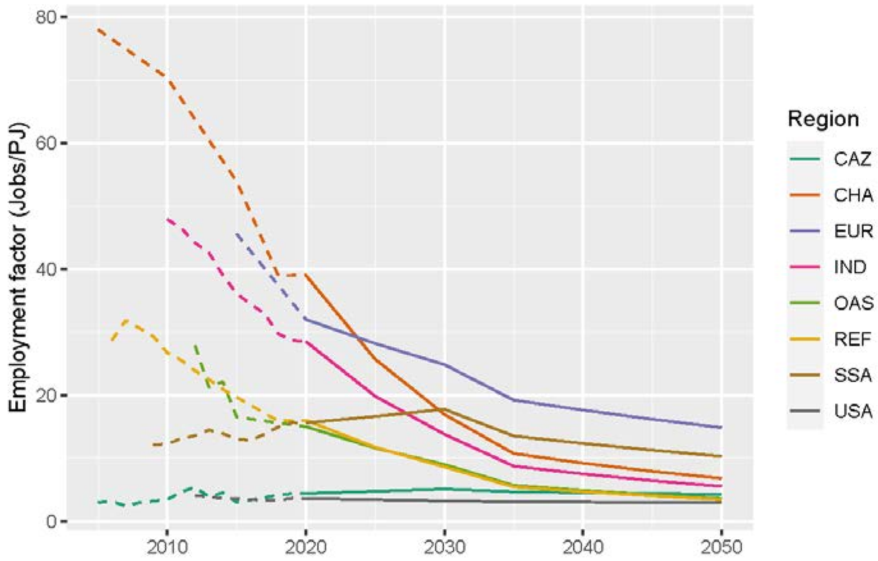

Figure S4 Historical (dashed) and estimated (solid) projections of employment factors (Jobs/PJ) for coal fuel supply for REMIND regions.

Country/Region	Share in production in 2019 (%)[1]	2020 Employment factor (Jobs/PJ) [2]	Annual change (%) 2020-2030	Annual change (%) 2030-2050	Employment source
EU	3	32[3]	-2.5	-1.5	(ILO, 2020)

[1] Data from BP, 2020

[2] Employment factors for 2020 are assumed to be the same as the data for the latest available year. E.g., for India this is 2019, China 2018 etc.

[3] Weighted average of major coal producing countries in EU

Indonesia	9	15	-7	-3	(ILO, 2020)
Russia	5.5	16	-6	-3	(Kalacheva & Savon, 2014)
South Africa	3.6	15.6	-2	-1.5	(Minerals Council South Africa, 2020)
Australia	7.8	4.4	1.5	-0.2	(Australian Industry and Skills Committee, 2017)
United States of America	8.5	3.6	-1.3	-0.3	(U.S. Bureau of Labor Statistics, 2020a)
China	47.6	39	-8	-3	(He et al., 2020)[4]
India	7.6	28.5	-7	-3	(Coal India Limited, 2019)[5]

Table S1 2020 Employment factors for coal fuel supply including projections for various countries/regions. These countries were then aggregated into REMIND regions to produce Figure S3.

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1.2 Comparison of job-estimates

Due to the different methods and boundaries (for e.g., between direct and indirect jobs) of measuring jobs, there is no 1:1 comparison between jobs estimates from the literature (both peer-reviewed and grey) and this study. However, comparisons (when the main assumptions are clear) can still be useful to get an indication if the numbers from this study make sense and assess the relative confidence of estimates for different technologies/regions. Figure S4 and S5 shows the comparison of comparison of global and regional jobs from REMIND in 2020 using the employment factor approach and other sources. Data behind the figures is available on https://gitlab.pik-potsdam.de/amalik/energy-employment.

1.2.1 Calculating jobs from employment factors

The schematic depicting the calculation of energy supply jobs for a particular year is shown in Figure 1 of the main paper. Due to the temporal nature of C & I (construction and installation) and manufacturing jobs, some studies (Rutovitz et al., 2020) divide the resulting job numbers for these activities with the average construction period to get the jobs in that year. This approach, however, has not been followed in this paper and has important implications for bottom-up comparisons. Jobs

[4] The data includes employment in both coal power plants and coal fuel supply. It was assumed that 94% of total jobs were in coal fuel supply, rest in coal power plants,

[5] CIL report only includes employees of CIL, which produces 80% of India's coal (Coal India Limited, 2019). Thus, EFs here are only for CIL.

for technologies with especially long construction durations like hydro and nuclear might be over-estimated because employment anticipated from under-construction capacity in the coming years is already calculated in 2020

1.2.2 Scope of jobs in studies

IRENA publishes "The Annual Review of Renewable energy jobs" since 2013. The data includes global direct and indirect jobs for the RE sector. Direct jobs are defined as *"employment that is generated directly by core activities without considering the intermediate inputs necessary to manufacture renewable energy equipment or construct and operate facilities. These directly involved industries are also called renewable energy industries (sectors)"* and indirect jobs as "*employment in upstream industries that supply and support the core activities of renewable energy deployment. Usually, these workers do not consider themselves as working in renewables; they produce steel, plastics or other materials, or they provide financial and other services"* (IRENA, 2014).

The "State of the Renewable Energy" annual reports prepared by EuObserver also measures both direct and indirect employment for EU countries. Direct employment is defined as "*those in renewable equipment manufacturing, renewable plant construction, engineering and management, operation and maintenance, biomass supply and exploitation"*, whereas indirect employment as *"employment in secondary activities, such as transport and other services"* (EuObserver, 2018).

IEA job estimates used in (IEA, 2020) also calculate global direct and indirect jobs in energy supply. Direct jobs are "*those that are created to deliver a final good or project*" and indirect jobs as *"supply chain jobs created to provide inputs to a final project or product"*. Unlike the previous two reports, data from this report has been extracted from the text.

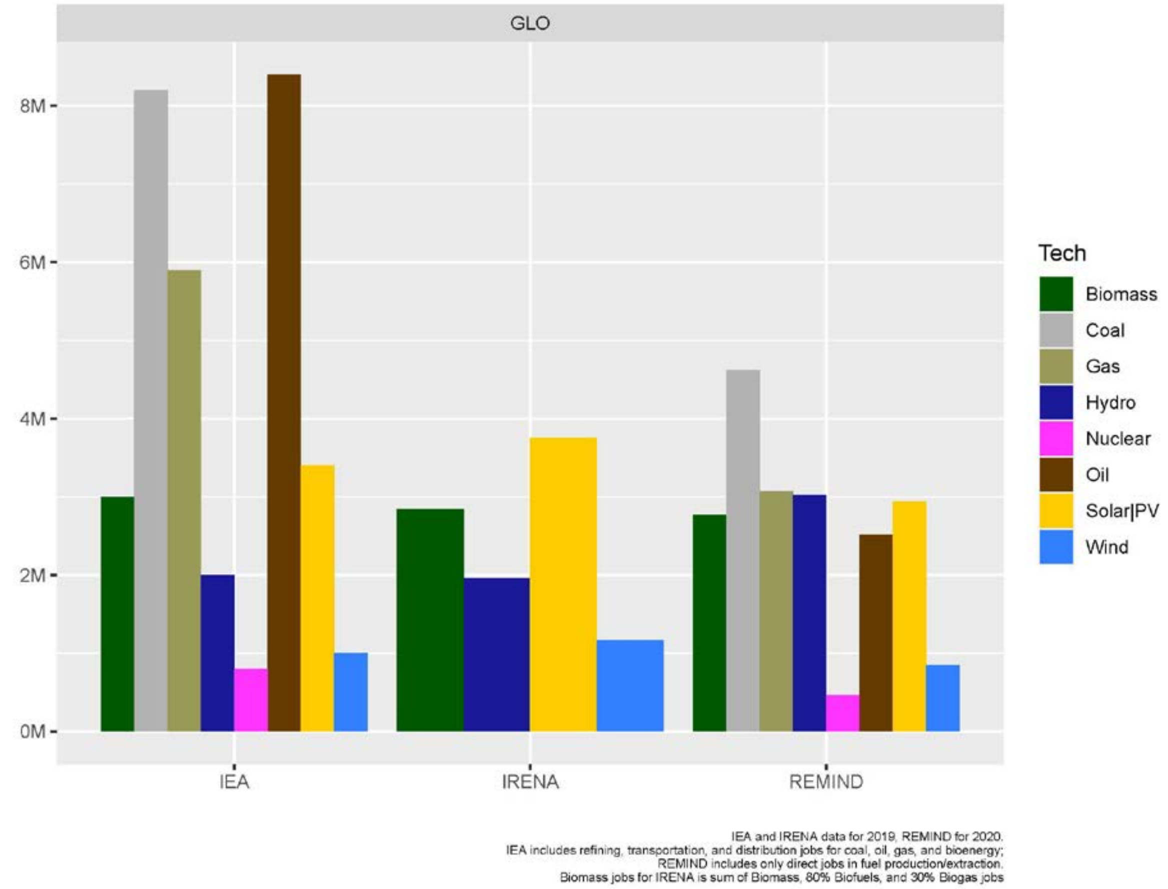


Figure S5 Comparison of global job estimates in different energy supply technologies from various sources, including REMIND. Values for IEA have been extracted from (IEA, 2020)

1.2.3 Comparison of global job estimates

Because of the wider scope of jobs for both IEA and IRENA (direct and indirect) compared to REMIND, jobs in the former can be assumed to be as an upper bound for REMIND jobs. Figure S4 shows the comparison between the three. Coal, oil, and gas (fuel supply) jobs in IEA include jobs in production, transportation, and distribution, whereas REMIND (fuel supply) jobs only include resource extraction, hence the large difference between the two. IRENA divides bioenergy jobs into solid biomass, biofuels and biogas jobs; with biofuels also including jobs in refining. Since the current methodology does not include refining jobs or biogas, only the jobs in biomass fuel supply (planting and harvesting) have been considered from IRENA for the comparison. This was done by assuming 80% of the jobs in biofuels, where most jobs are still in fuel supply (IRENA, 2020a), but only 30% in biogas, where most jobs are presumably in C & I, Manufacturing, and O & M (operation and maintenance) of biogas plants. Considering this, REMIND numbers stay at or below values from IRENA and IEA.

1.2.4 Comparison of regional jobs estimates

For comparison at a regional level, the 12 REMIND regions were divided into 3 countries (USA, IND, CHN) and 2 regions (EUR and Rest of World – RoW) and additional sources were added, where available.

Figure S5 shows one problem of using uniform relative labour productivity as a proxy for employment factor. Despite excluding agriculture to calculate the relative labour productivity, India and Rest of the World (Figure S5b and Figure S5c), still have higher employment for biomass in REMIND compared to IRENA. On the other hand, jobs for China (Figure S5e) is at or below the numbers from IRENA.

The job estimates from REMIND for other technologies and regions are at or below the estimates from REMIND and/or other data sources, except hydropower for which a comparison is difficult because the current methodology compresses jobs spread over subsequent years into one year (already mentioned in Section 1.2.1)

Note that this comparison is a work in progress and other data sources will be added as and when made available.

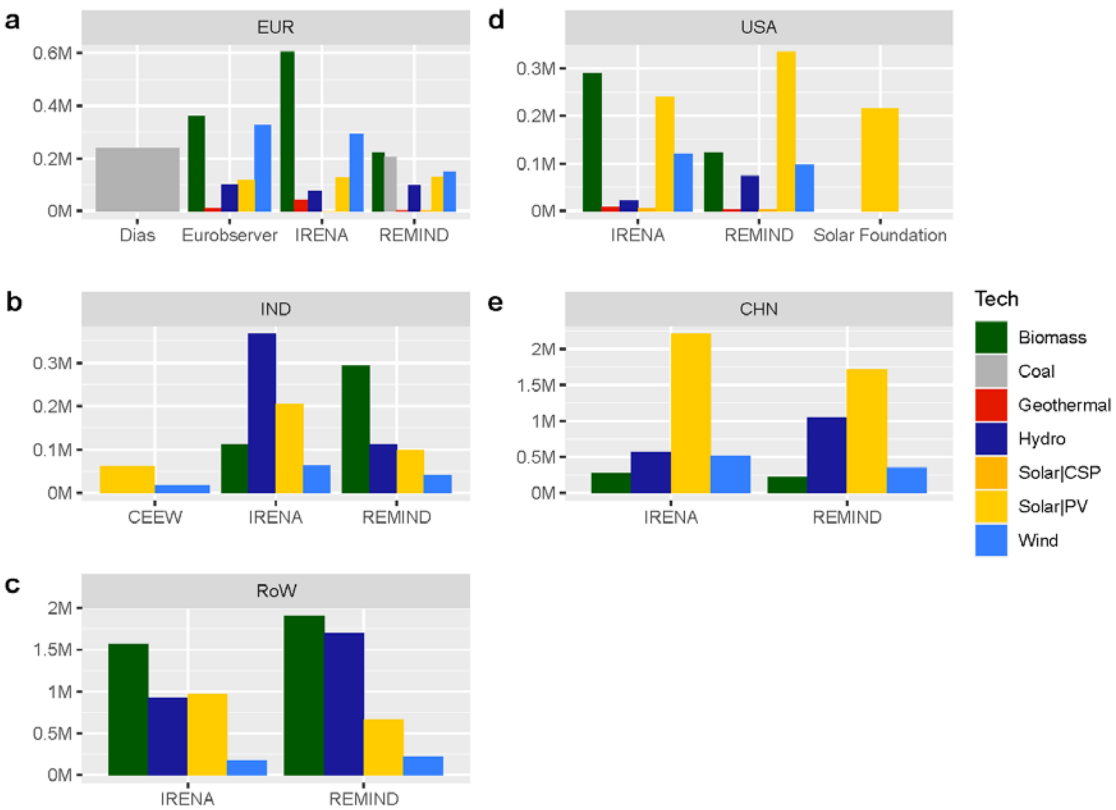


Figure S6 Comparison of job estimates for various technologies and Countries/Regions (a-e) between REMIND and other sources. Data from Dias et al. is from 2015 (only direct jobs in coal fuel supply and electricity), Euobserver data from 2018 (direct and indirect jobs), IRENA for 2018-2019 (direct and indirect jobs), Solar foundation for 2019 (only direct jobs incl.), CEEW for 2018 (direct jobs), REMIND for 2020 (direct jobs).

2 Evolution of employment factors

Starting from the employment factors in 2020 (section 1.1), employment factors evolve based on certain assumptions. Rutovitz, Dominish, and Downes 2015 assume that employment factors evolve based on i) the capital costs of technologies, and ii) for non-OECD countries, the regional adjustment factor evolves with (inverse of the) GDP per capita (relative to OECD). This study uses the same approach with one main difference - the regional adjustment factors evolve with (inverse of) GDP per capita for all regions, and not relative to OECD.

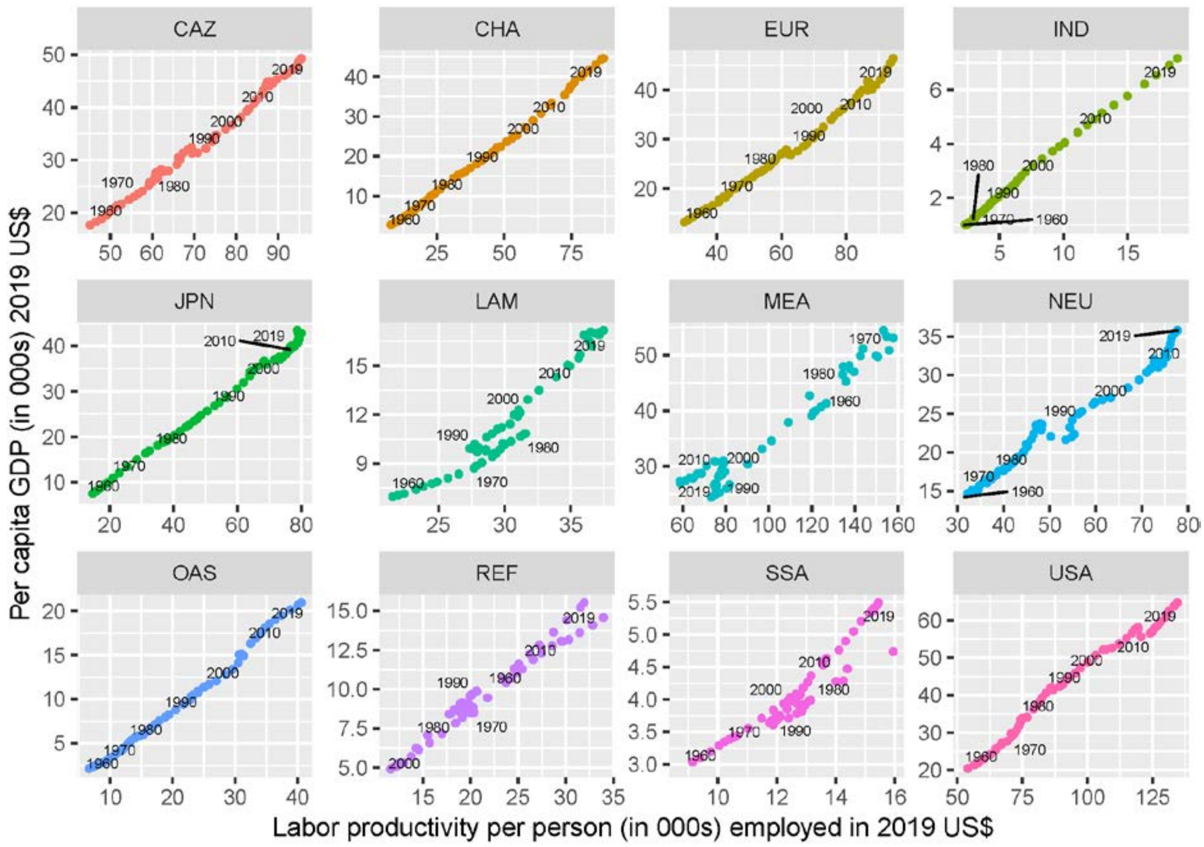


Figure S7 Per-capita GDP (in 000s US $ 2019) vs. Labour productivity per person employed (in 000s US$ 2019). The data for around 130 countries was available from The Conference Board Total Economy Database, July 2020. These countries were grouped into (REMIND) regions and their values averaged.

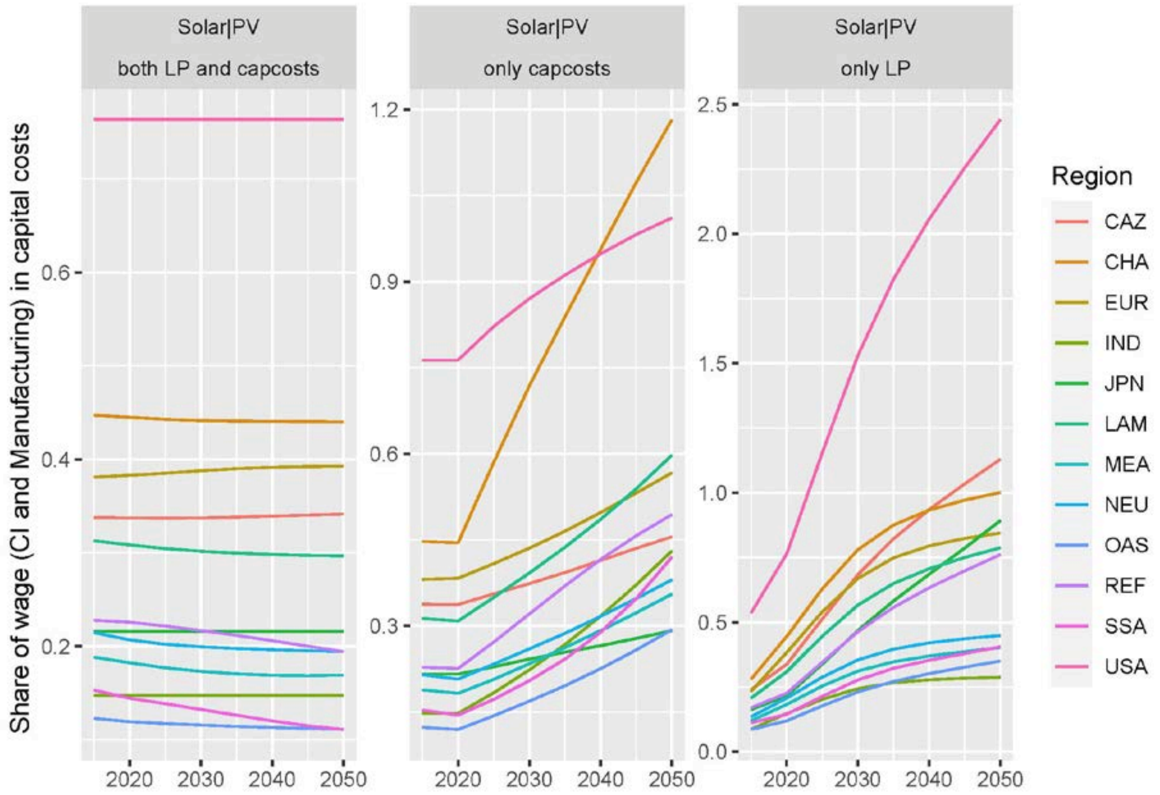


Figure S8 Share of wage in capital costs (considering employment factors in both C & I and Manufacturing) for different EF scenarios, for a 1.5C Policy case for Solar PV. The annual per capita wage for each employee in a region is assumed to be the GDP per capita of that region. Capital costs for Solar PV are taken from REMIND.

2.1 Choosing the main EF scenario

Based on the assumptions that the EF depends on the labour productivity (LP) and capital costs, we create three EF-scenarios. Merits and demerits of each are mentioned below and a table summarising them is available as Table S2.

1. EF scenario "Only LP" (labour productivity) represents the case where the employment factors (for all technologies and activities) evolve depending on the (inverse of) GDP per capita. The GDP per capita is linearly correlated to the labour productivity (when expressed in $ output per worker) (see Figure S7). Thus, as countries get richer, not only does labour gets more skilled but the factor of production shifts from labour to capital leading to an increase in labour productivity. Higher GDP growth rates for non-OECD countries also lead to a faster reduction in employment factors for these countries. The problem with this approach is twofold, i) it applies a uniform rule across all technologies and activities, failing to include their different nature and stage of maturity, and ii) it underestimates the rate of EF decrease for key technologies (like solar PV), Figure S8 illustrates this

point - assuming that EF decreases only with improvements in labour productivity, the share of labour costs in total capital costs becomes close to or greater than 1[6], leading to an impossible result.

2. EF scenario “only capital costs” represents the scenario where the EFs evolve only with the capital costs of a technology. In REMIND, regionally differentiated capital costs converge in 2050 (see SI section 2.2). A few technologies, namely solar PV, wind, and solar CSP also include learning, i.e., the capital costs decrease depending on the cumulative capacity. Capital costs evolution of technologies are applied to the C & I, Manufacturing and O & M stages while fuel supply employment factors (except for coal) do not change. The main advantage of this approach is that unlike #1, it treats technologies differently and only changes EF for activities not involving fuel supply. The main disadvantages of this approach are – i) that capital costs for some technologies (in certain regions) increase in the future (Figure S8b) implying an increase in Jobs per MW. This is likely improbable given that increasing wages and mechanization leads to lesser people employed in an activity, ii) it provides no method to fuels involving production/fuel supply.

3. Both LP and capcosts – Under this scenario, EFs evolve with both the capital costs and labour productivity, resulting in a faster decline in EF for key technologies like solar PV and wind This makes sense - under the assumption of decreasing capital costs and increasing wages, employment factors need to decrease faster than the rate at which capital costs decrease. The combination of the two can be thought of as a union between forces influencing employment factors inside and outside the industry. While capital costs evolution considers developments within the industry, developments outside the energy supply industry but which affect still its production, e.g., artificial intelligence, are considered through the labour productivity term.

A summary table (Table S2) is shown below.

EF scenario	**Description**	**Pros**	**Cons**
Only LP	EF evolution depends upon Improvements in labour	Provides a way to account for EF decrease for both fuel supply and non-fuel supply activities	• Doesn’t differentiate between technology or activity • For some rapidly evolving technologies, the share of

[6] The average wage was assumed to be the GDP per capita (except for USA, where it was taken as 0.9 times the GDP per capita (U.S. Bureau of Labor Statistics, 2020b)) and capital costs data was from REMIND.

	productivity only		wage in total capital costs might become close to or more than 1 (see SI).
Only capcosts	EF evolution depends upon decline factors based on capital costs	Treats technologies differently	• Provides a way to account for EF development only for non-fuel supply activities (i.e., those with a capital costs) • Capital costs for some region/technology combination might increase in the future, thus implying increasing employment factors.
Both LP and capcosts	Both improvements in LP and decrease in capital costs	• Accounts for fuel supply activities. • Accounts for region/technologies with increasing capital costs.	• Might exaggerate the EF decline in certain technologies

Table S2 Showing the pros and cons of the different EF scenarios

2.2 Sensitivity analysis of EF-scenarios

The main paper only considers results using the main EF-scenario. Results from other EF-scenarios (as mentioned in Table S2) are shown in Figures S9 to S12.

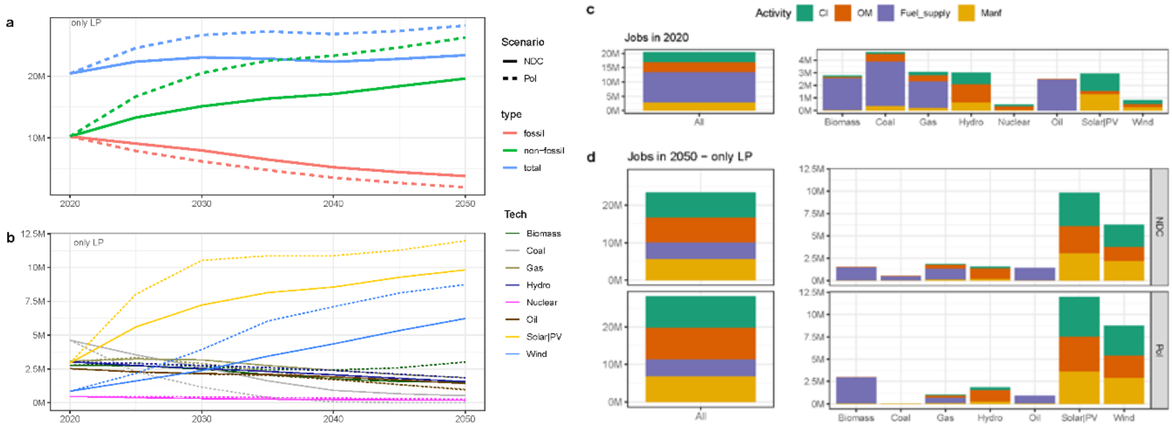


Figure S9 Total jobs by type – fossil and non-fossil for the EF-scenario (only LP) for weak (NDC) and strong (1.5C) policy scenarios

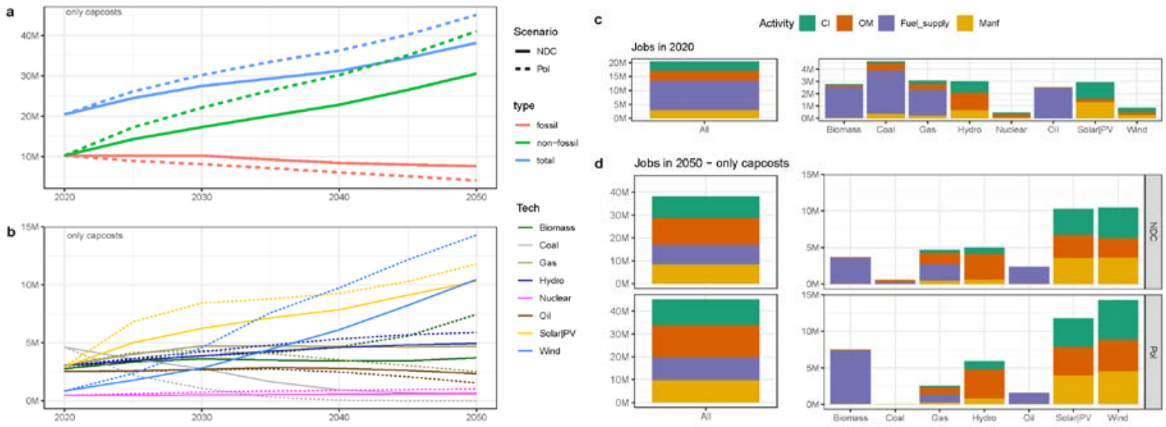


Figure S10 Total jobs by type – fossil and non-fossil for the EF-scenario (only capcosts) for weak (NDC) and strong (1.5C) policy scenarios

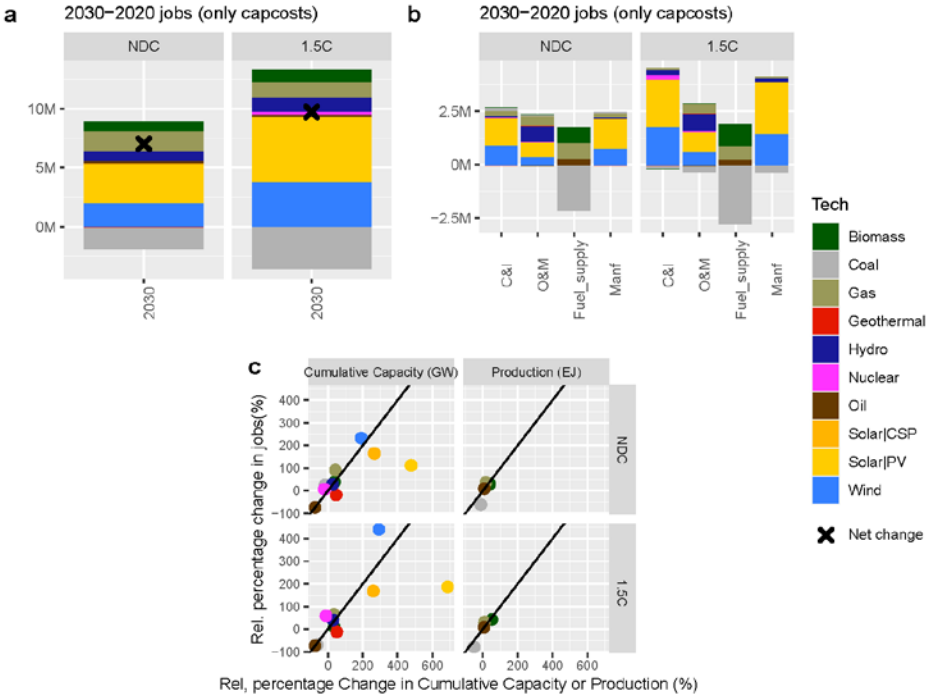


Figure S11 (a) Difference in Global jobs (2030-2020) for different technologies (with cross denoting the net gain/loss) and (b) activities and (c) relative percentage change in jobs vs. relative percentage change in capacity/production (in 2030 relative to 2020), for EF scenario – only LP

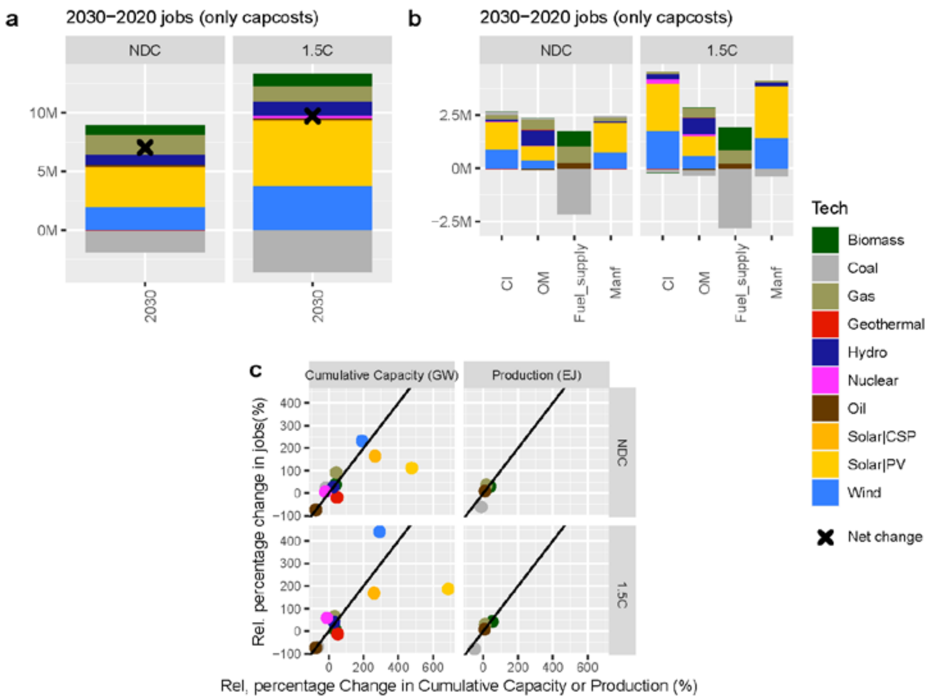


Figure S12 (a) Difference in Global jobs (2030-2020) for different technologies (with cross denoting the net gain/loss) and (b) activities and (c) relative percentage change in jobs vs. relative percentage change in capacity/production (in 2030 relative to 2020), for EF scenario only capcosts

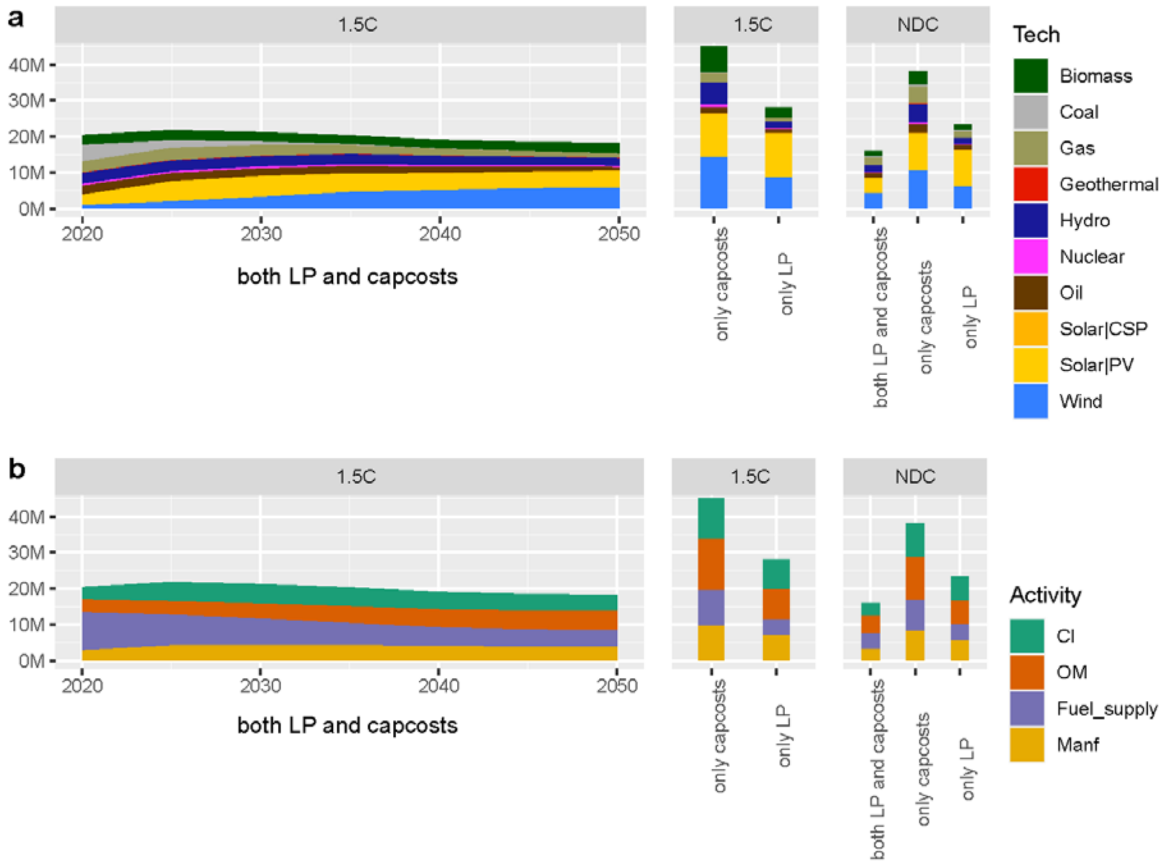


Figure S13 Area plots for total jobs by EF-scenario and scenarios by technology and activity, in 2050

2.3 Capital costs

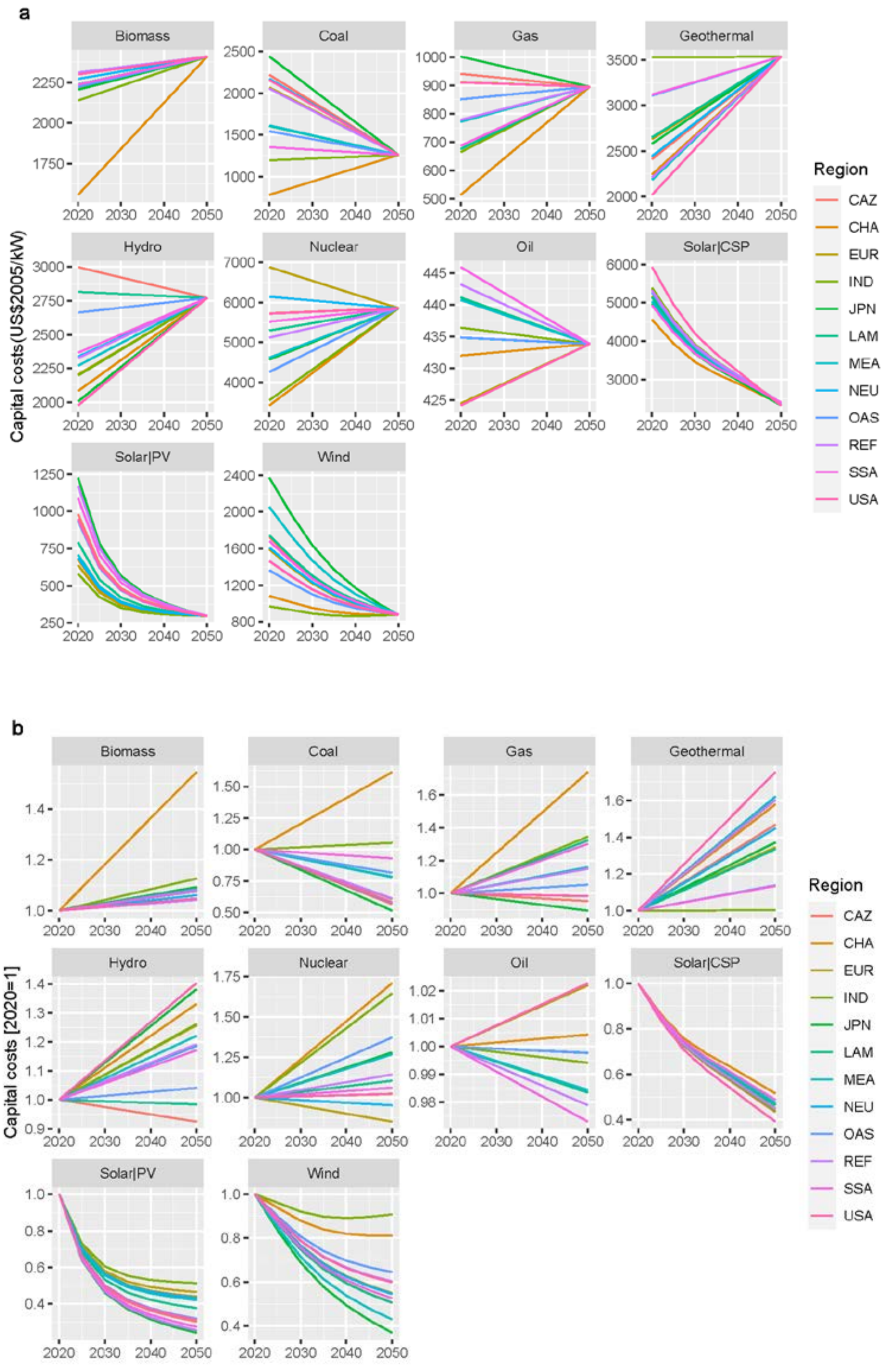


Figure S14 Regionally aggregated capital costs (a) absolute and (b) relative for various technologies from REMIND.

2.4 GDP per capita

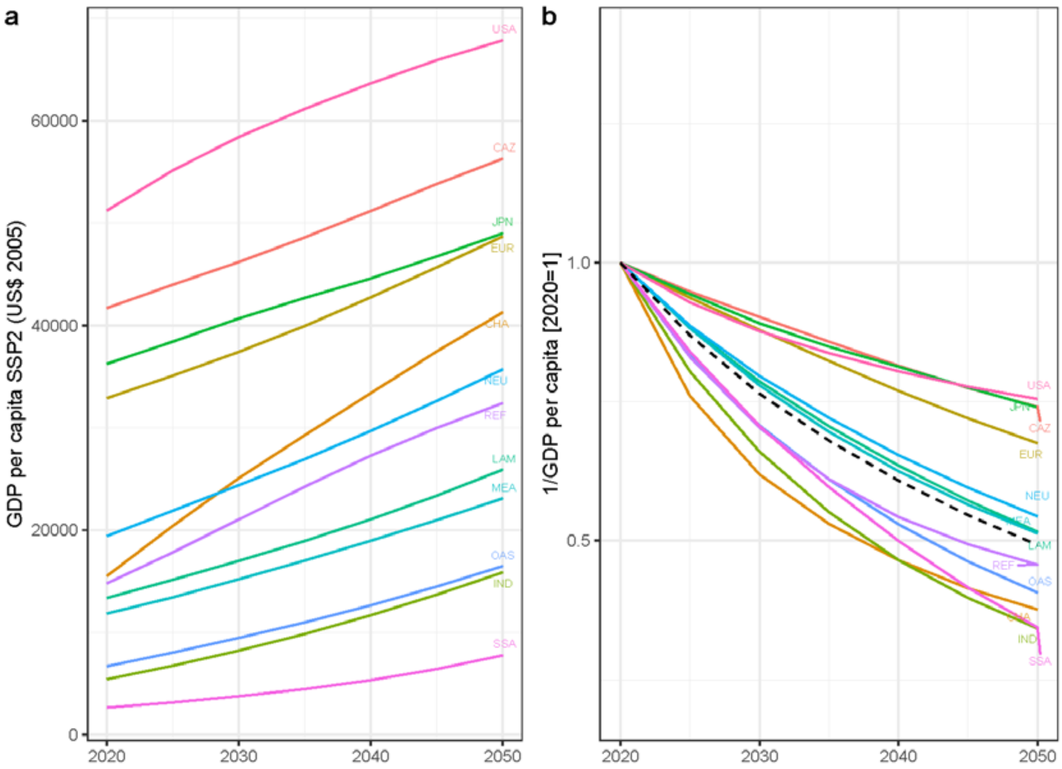
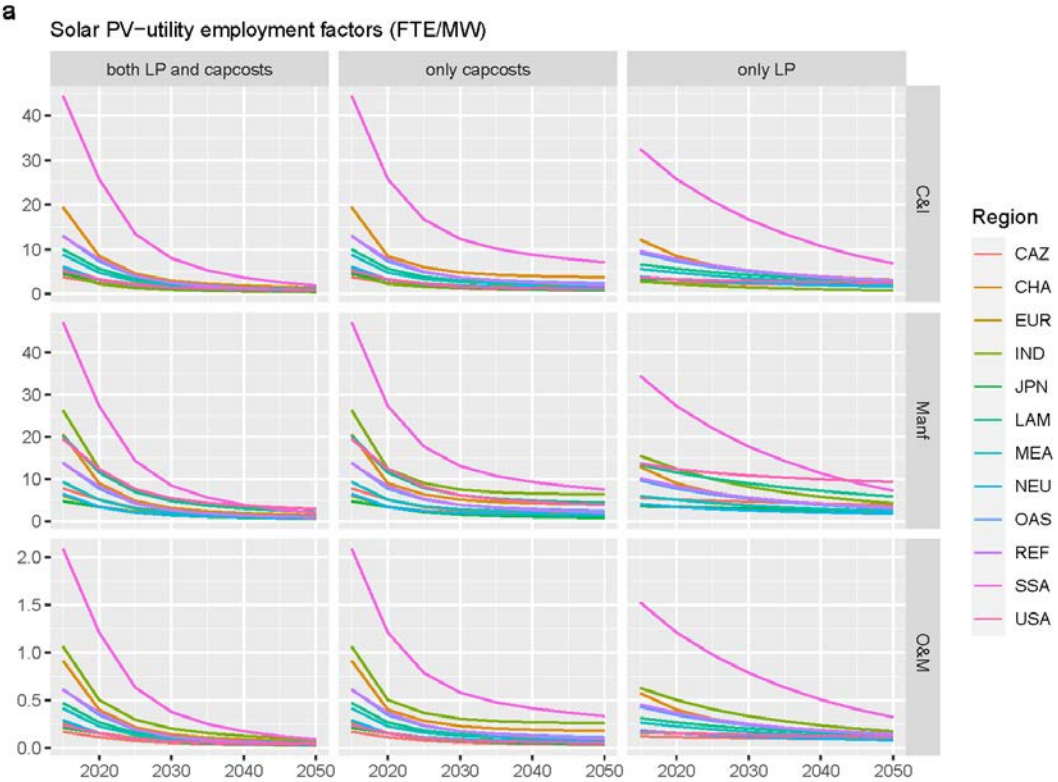


Figure S15 Absolute (a) and inverse of (b) GDP per capita (relative to 2020) for REMIND regions (SSP2). The black dashed line in b represents the average of all regions.

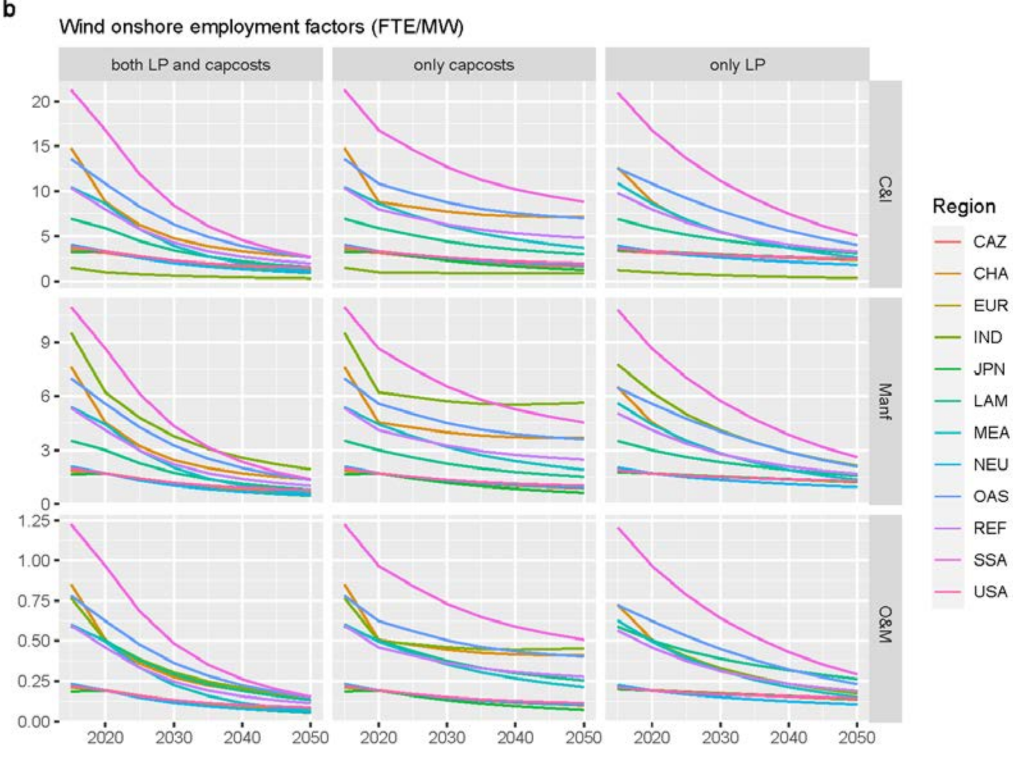
2.5 Evolution of employment factors for key technologies

a



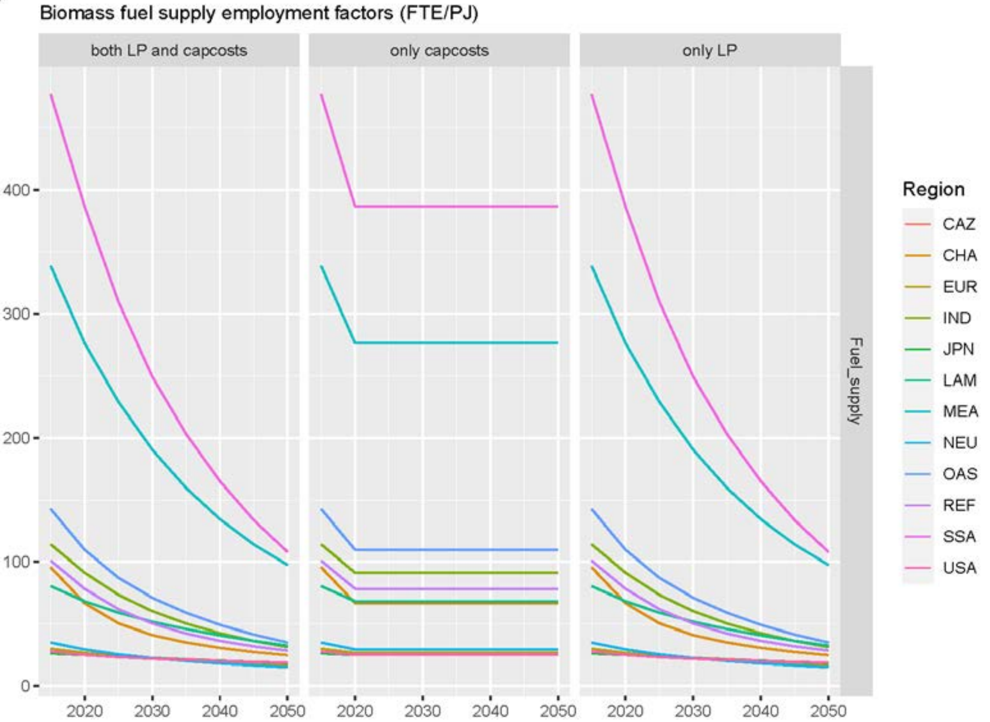
Solar PV−utility employment factors (FTE/MW)
both LP and capcosts
only capcosts
only LP
C&I
Manf
O&M
Region
CAZ
CHA
EUR
IND
JPN
LAM
MEA
NEU
OAS
REF
SSA
USA

b



Wind onshore employment factors (FTE/MW)
both LP and capcosts
only capcosts
only LP
C&I
Manf
O&M
Region
CAZ
CHA
EUR
IND
JPN
LAM
MEA
NEU
OAS
REF
SSA
USA

c



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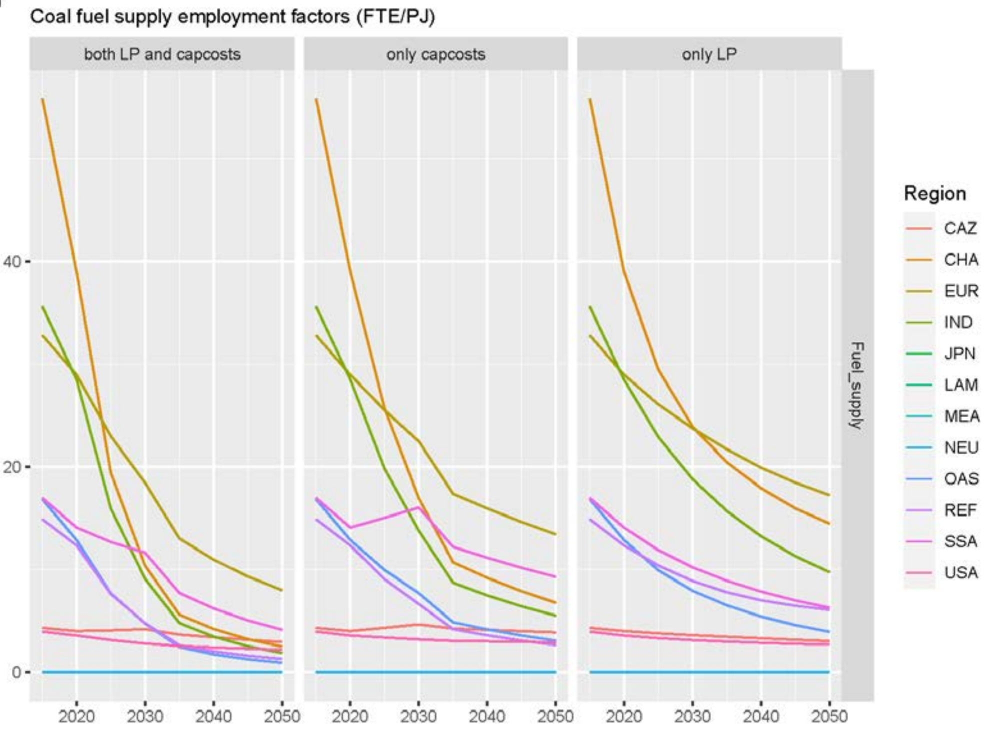

Figure S16 Employment factors for a) Solar PV-utility, b) Wind onshore, c) Biomass Fuel Supply, and d) Coal Fuel supply, classified by EF scenario and activity.

3 Capacity and Generation from REMIND

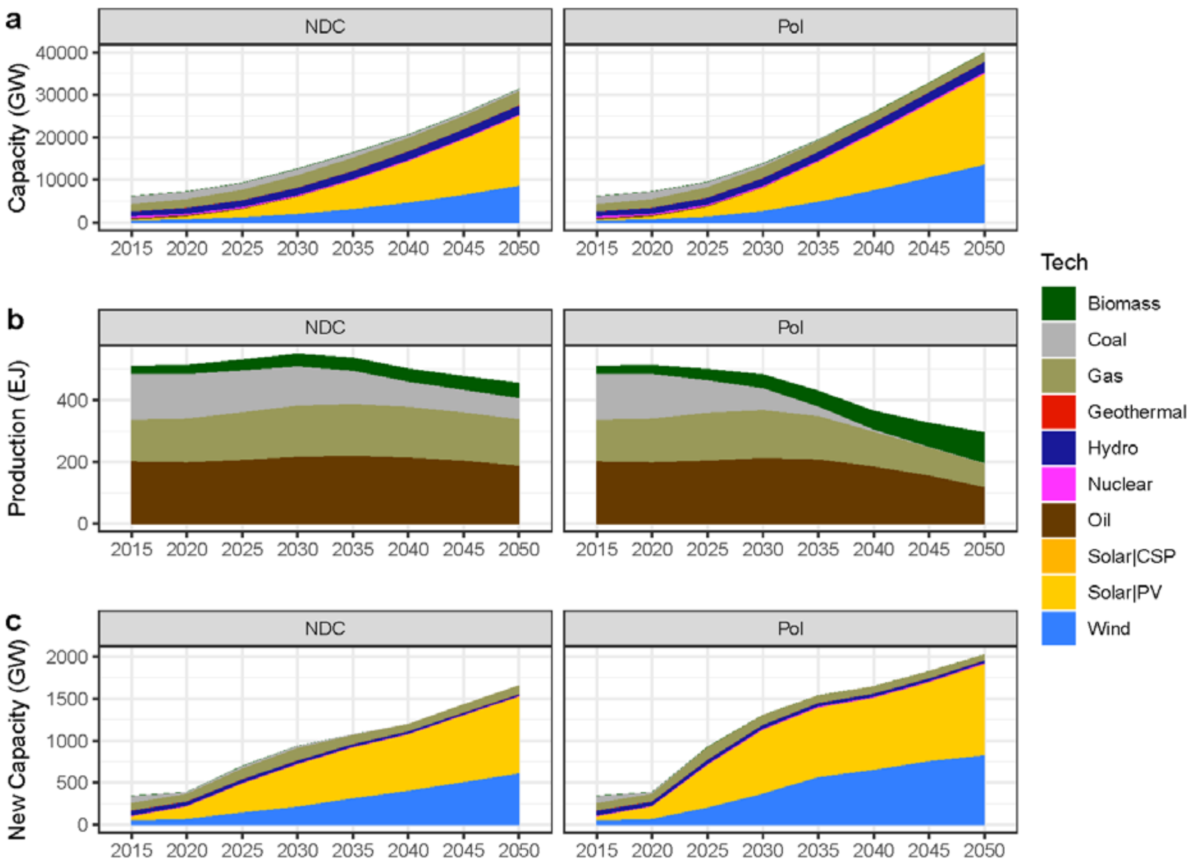

Figure S17 (a) Total cumulative capacity (GW), (b) Production (EJ), and (c) New or added capacity from REMIND until 2050 for the two scenarios - NDC and Pol (1.5C).

4 Miscellaneous

4.1 Share of sub-technologies

Sub-technologies refer to minor forms of a main technology which are not considered in REMIND. These include solar-pv rooftop, small hydro, and wind offshore. REMIND numbers are assumed to be the sum of both the major and minor form, i.e., for e.g., solar pv_{REMIND} = solar pv-utility + solar-pv rooftop. Thus, to break these down, shares of the respective forms are required. The shares in 2020 are assumed to be from the latest data from IEA 2019 and IRENA 2020b.

The assumption of how the shares evolve in shown in Figure S18 for the 12 REMIND regions. It is assumed that for all countries, solar rooftop PV accounts for 30% of total solar PV installations in 2030 (shares change linearly), except for Indian and Japan where a share of 40% is assumed to account for the unavailability of large tracts of land needed for large solar farms. For all countries, the shares do not change after 2030.

For wind offshore, top 20 countries with the longest coastline[7] get 30% share in 2050. For countries without a shoreline/landlocked[8], there is no wind offshore. For all other countries, a 10% share in 2050 is assumed. The aggregated regional shares are given in Figure S14.

For small hydropower, the share is assumed not to change over time.

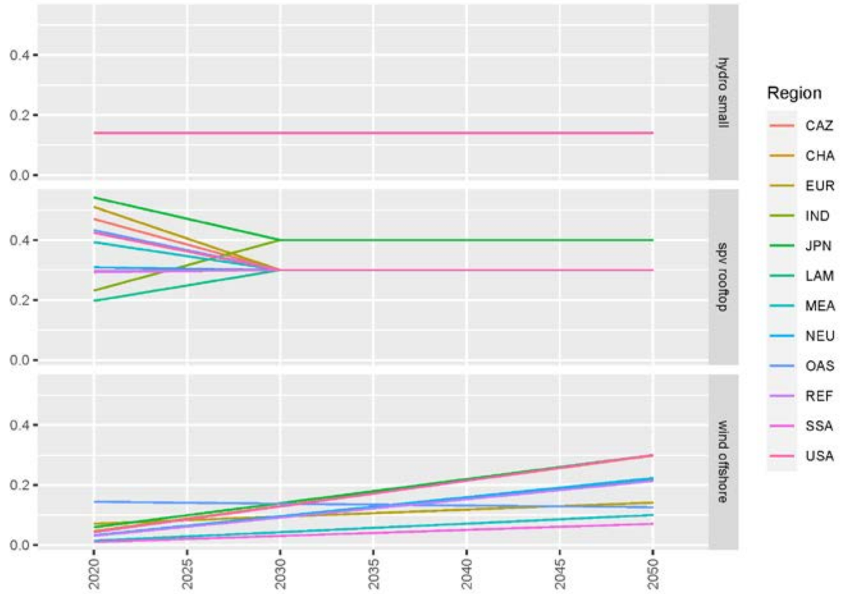

Figure S18 Historical and projected share of "sub-technologies" assumed in the study. The data for 2020 is (actually) from 2018. Shares are calculated by dividing the total "sub-technology" capacity to the total technology capacity. Total solar, wind, and hydro capacity from IRENA (2020). Distributed spv, wind offshore and small hydro capacity from (IEA Renewables 2019), and IRENA 2020 respectively.

4.2 Share of activity in total jobs

[7] These are Canada, Norway, Indonesia, Greenland, Russia, Philippines, Japan, Australia, United States of America , Antarctica , New Zealand , China , Greece , United Kingdom , Mexico , Italy , Brazil , Denmark , Turkey , India. Data from https://www.citypopulation.de/en/world/bymap/Coastlines.html

[8] These are Monaco , Afghanistan , Andorra , Armenia , Austria , Azerbaijan , Belarus , Bhutan , Bolivia , Botswana , Burkina Faso , Burundi , Central African Republic , Chad , Czech Republic , Eswatini , Ethiopia , Hungary , Kazakhstan , Kyrgyzstan , Laos , Lesotho , Liechtenstein , Luxembourg , Malawi , Mali , Moldova , Mongolia , Nepal , Niger , North Macedonia , Paraguay , Rwanda , San Marino , Serbia , Slovakia , South Sudan , Switzerland , Tajikistan , Turkmenistan , Uganda , Uzbekistan , Zambia , Zimbabwe

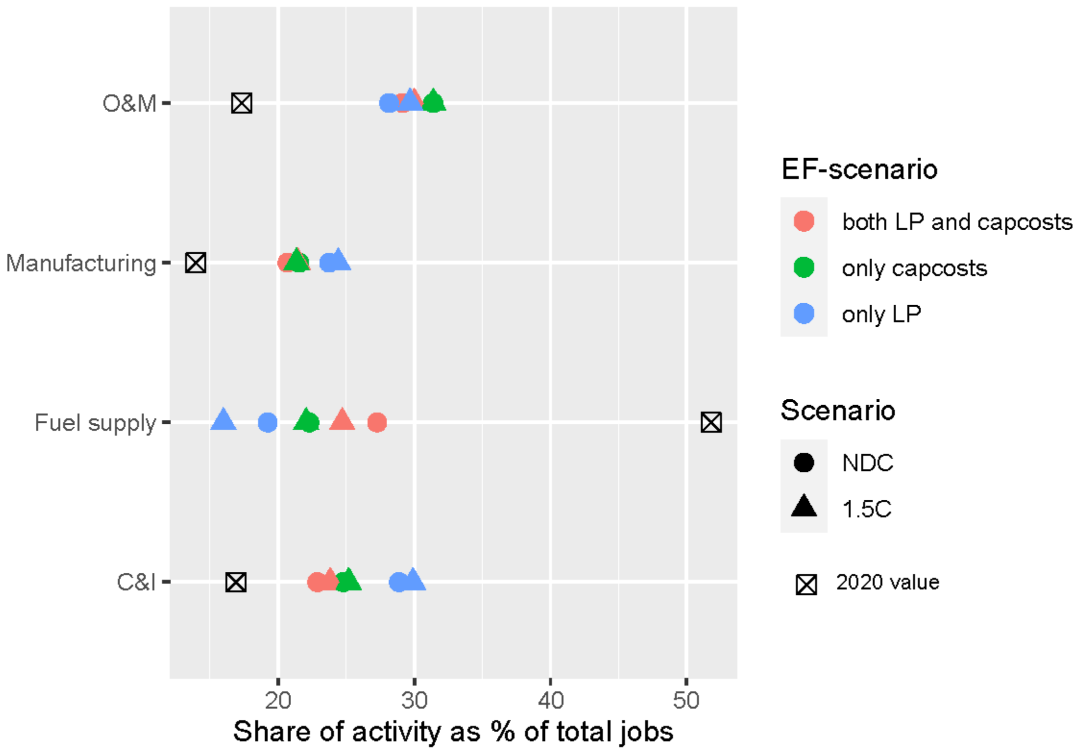

Figure S19 Share of activity in percent of total jobs, comparison between 2020 (boxed cross) and 2050

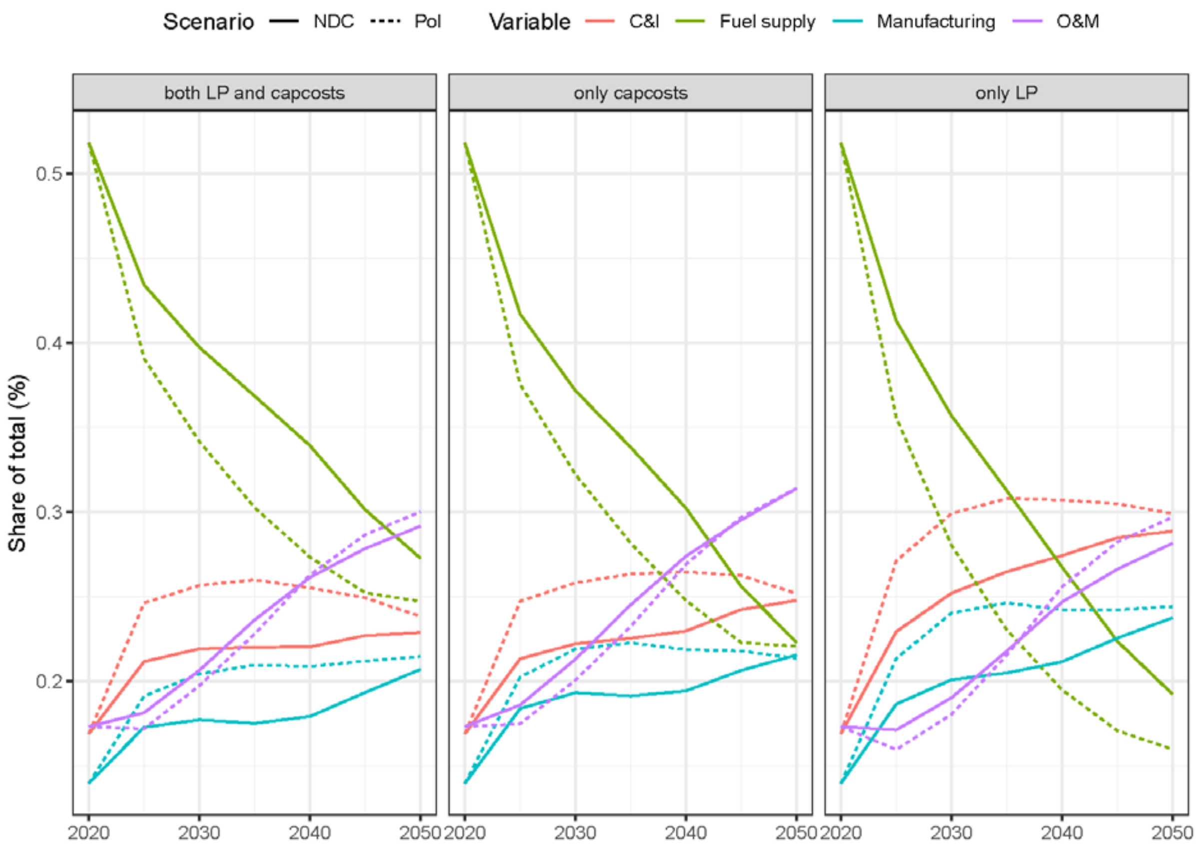

Figure S20 Share of activity in total jobs for different scenarios and EF-scenarios

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