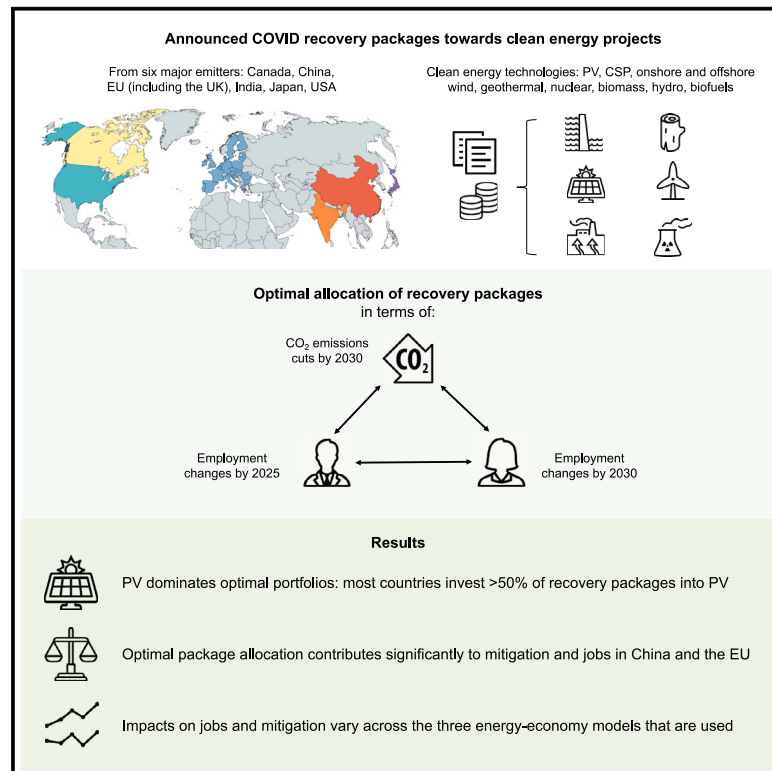# One Earth

COVID-19 recovery packages can benefit climate targets and clean energy jobs, but scale of impacts and optimal investment portfolios differ among major economies

Graphical abstract

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In brief

Several countries announced post-pandemic green recovery packages to stimulate green growth. However, how to manage the investments to optimize green job growth and CO_2 emissions reduction remains unclear. Here, we incorporate investment portfolio analysis into three different energy-economy models to examine the climate-employment co-benefits of green recovery packages in six major emitting regions. Results of the three models all indicate that a dominance of funding towards solar power can lead to reductions in both CO_2 emissions and unemployment, most notably in the EU and China.

Highlights

- Analysis of emissions and employment impact of six regions' COVID-19 recovery plans

- Solar photovoltaics funding dominance maximizes emissions cuts and employment gains

- Green recovery packages can have notable impacts in the EU and China

- Size of outcomes is highly dependent on the specific energy-economy model used

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Article

COVID-19 recovery packages can benefit climate targets and clean energy jobs, but scale of impacts and optimal investment portfolios differ among major economies

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SCIENCE FOR SOCIETY A low-carbon transition is urgently needed to meet the 1.5C Paris climate targets. The coronavirus disease 2019 (COVID-19) pandemic, however, has imposed widespread economic burdens, including declines in investments and employment, which have hindered the development of many sectors, including clean energy. There is an opportunity to combine post-pandemic recovery packages with green growth aspirations, but the extent to which investments can be managed in a way that achieves both employment growth and greenhouse gas emissions reductions, given varying socioeconomic conditions, remains unclear. We attempt to resolve this issue by evaluating different investment strategies across six major emitters (Canada, China, the European Union (EU), India, Japan, and the US) using three energy-economic computational models. Our estimates suggest that green recovery plans should allocate at least 50% of funds to solar power production to obtain both CO_2 emissions reductions and employment gains. This is particularly the case in the EU and China.

SUMMARY

To meet the Paris temperature targets and recover from the effects of the pandemic, many countries have launched economic recovery plans, including specific elements to promote clean energy technologies and green jobs. However, how to successfully manage investment portfolios of green recovery packages to optimize both climate mitigation and employment benefits remains unclear. Here, we use three energy-economic models, combined with a portfolio analysis approach, to find optimal low-carbon technology subsidy combinations in six major emitting regions: Canada, China, the European Union (EU), India, Japan, and the United States (US). We find that, although numerical estimates differ given different model structures, results consistently show that a >50% investment in solar photovoltaics is more likely to enable CO_2 emissions reduction and green jobs, particularly in the EU and China. Our study illustrates the importance of strategically managing investment portfolios in recovery packages to enable optimal outcomes and foster a post-pandemic green economy.

INTRODUCTION

The pandemic has posed significant challenges to human societies, beyond public health: following drastic policy responses to curb virus spread, economic activities forcefully paused. This, in turn, resulted in an impending economic recession with multiple socioeconomic implications,[1] including for the labor market. Indicatively about 1.8 million jobs had been lost in the

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EU between September 2019 and September 2020,[2] while early estimates in the US foresaw a loss of about 20 million jobs,[3] with expectations for a lagging employment recovery.[4] Narrowing down to the energy sector, coronavirus disease 2019 (COVID-19) resulted not only in short-term delays in deployment but also in permanent job losses due to project cancellations along the global energy supply chain.[5] Notably, renewable energy projects have been affected worldwide with considerable employment implications, resulting from, for example, solar photovoltaics (PV) and wind turbine material supply-chain disruptions from China, and renewable energy technology suppliers placing staff on furlough.[6,7] It has been estimated that almost 600,000 clean energy jobs were lost in the United States over the course of 2020, more than twice the total clean energy jobs gained in the preceding three years.[8] Voices in science and policy alike have advocated for a green stimulus focusing on clean energy technologies, to align economic recovery with climate mitigation efforts, and hopes were high that the recovery from the pandemic could become a turning point in public support to fight the climate crisis in the early stage of the pandemic.[9,10] Despite a relatively small chunk of global recovery spending being channeled toward clean-energy-related projects,[11] there remains a wide range of possible clean technology portfolios that could benefit from this stimulus, while helping drive the low-carbon transition and boosting energy-sector job creation.[12]

In literature, there are positive indications that a transition from fossils to renewables typically creates net jobs,[13] after accounting for workforce redistribution among sectors.[14–16] Recent work has showcased large employment gains from a complete shift to a fully renewable power sector,[17] even more so for combined efforts in heat, transport, and desalination,[18] while broader Paris-compliant mitigation pathways show similar findings for energy-sector employment.[19] However, evidence on COVID-19 and associated recovery efforts is still scarce. In this respect, macroeconomic and integrated assessment models (IAMs) have been used to assess the pandemic's impacts on CO_2 emissions[20] and macroeconomic indicators,[21] as well as its medium- to long-term implications for the energy transition[22] and the goals of the Paris Agreement.[23] Regarding the estimation on the potential outcomes of post-pandemic green recovery, modeling efforts have shed light on the gap between pledged recovery packages and the Paris-compliant investment needs,[24] as well as the impacts of possible green ways forward.[25,26] However, of these studies, only one considered employment implications[26] from a macroeconometric perspective and, like similar macroeconomic modeling studies,[27–31] provided only aggregated economy-wide insights. There is evidence from the Global Financial Crisis of 2008–2009 that renewable energy stimulus has a higher jobs impact than other stimulus measures.[9] However, it is important to consider specific regional dynamics in the context of specific stimulus measures. In this context, the extent to which green investments as part of the recovery stimulus can contribute to both climate mitigation and specifically energy-sector employment gains remains understudied, with no specific IAM-based analyses to our knowledge.

Here we contribute to this debate by studying the optimal allocation of announced recovery packages toward clean energy projects in six major emitters (Canada, China, EU, India, Japan, and the United States, together covering the majority of announced

green recovery funds globally) in terms of further CO_2 emissions cuts and employment gains against a pre-pandemic current-policy baseline.[32] To improve the accuracy and robustness of the estimates, our adopted method overcomes three methodological challenges. First, acknowledging IAM analyses are highly dependent on the model used and the underlying economic-engineering approach,[33,34] we employ a diverse ensemble of three well-established IAMs (GCAM-PR, TIAM-Grantham, GEMINI-E3) to understand how each modeling approach affects outcomes. Second, building on recent efforts,[35,36] we link these IAMs with employment factor databases that provide the necessary granularity for targeted technology interventions,[37] to address criticisms on model representation of energy-economy feedbacks[38] and employment considerations.[39] Third, since IAMs typically only optimize costs in respect to emissions constraints, we integrate the models with portfolio analysis,[40] to economically integrate and simultaneously optimize emissions cuts with near- and long-term employment gains. Our results indicate that the optimal allocation, i.e., best investment portfolios as derived from integrating IAMs with a portfolio analysis framework, of COVID-19 recovery packages over power-sector technologies in China and the EU have the potential to significantly contribute to their respective 2030 mitigation targets, while also employing a significant share of pandemic-related unemployed population until 2030, compared with where the two regions would be headed given their current policy efforts and absent any recovery finance spending. For China, this means that optimal allocation of the available recovery funds in a portfolio of clean energy supply technologies can cut up to two times the CO_2 emissions gap of the country's 2030 nationally determined contribution (NDC) target of reducing the carbon intensity of its economy by at least 65% relative to 2005, while in the same period covering 4%–22% of the jobs lost due to COVID-19. For the EU, and depending on the three models' emissions trajectories, optimal recovery spending could help approach the "Fit for 55" CO_2 emissions target (i.e., reduce CO_2 emissions by at least 55% by 2030, against 1990 levels) by 7%–48%, while mitigating the pandemic-related job losses by up to around 9% by the end of the decade. Packages in the United States and India are measured to contribute significantly less, with contributions in the range of 0%–3%. The expected impact of packages in Canada lies in between, while results for Japan are inconclusive due to stronger model variation. Obtained optimal portfolios suggest that, when optimally allocating recovery funds between emission reduction and employment creation objectives, most countries would invest over 50% of their energy-focused green recovery packages in financing PV, over 10% in onshore wind, while investments in other clean energy technologies strongly depend on the country, preferred objective, and model applied. Overall, our results suggest that the recovery response to the COVID-19 pandemic can provide a strong green stimulus in which economic recovery is aligned with improved mitigation efforts.

RESULTS

Method summary

Financial support for clean energy technologies may have an impact on greenhouse gas (GHG) emissions and energy-sector jobs through several channels. Due to the nature of clean energy
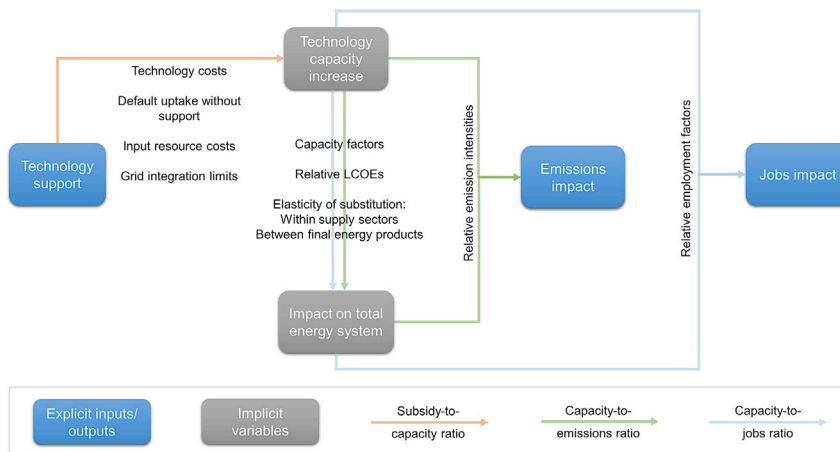
Figure 1. Schematic overview of how technology support may affect emissions and employment

Two main mechanisms are considered here. First, supporting a specific technology through subsidies can lead to a capacity increase for this technology, which can subsequently affect emissions and jobs, based on the relative emissions and employment factors of the technology. Second, increasing the capacity of a technology can potentially substitute capacity from another technology on the total energy system, leading to more changes in emissions and jobs. For instance, additional renewable energy capacity can substitute capacity from emissions-intensive technologies. The potential for substitutions is based on the capacity factors of all technologies in the system as well as their relative levelised costs of energy (LCOEs) and the elasticity of substitution.

technologies, which are usually more labor-intensive[19,41] and, by definition, less carbon-intensive compared with their conventional alternatives, the net impact of such support tends to simultaneously create additional energy-sector jobs and avoid GHG emissions. However, this does not make financial support for clean energy technologies by definition a cost-efficient policy instrument, nor may all clean energy technologies be equally worth financing.

The effectiveness of financial support is strongly technology and region dependent, due to a mix of factors, such as the cost-effectiveness of each technology, the impact on the overall energy mix, and the relative differences in emission and employment factors of the supported technology and the replaced alternatives. Furthermore, the region-specific context is a crucial factor. A classic example of inefficient financing is to provide support for new investments that would have occurred also in the absence of such support.[42] Since a regulator cannot discriminate between financing those investments that are additional and those that are not, large sums of finance could flow as a windfall gain to investors that were anyway going to invest in a certain technology. There may also be other physical limits that constrain the effectiveness of additional financial support, such as the intermittency of renewable technologies or the availability of bioenergy resources. In such cases, excess capacity driven by financial support may be left idle or its production curtailed.[43] Combining the two previous examples, there may also be a temporal inefficiency; e.g., if short-term financial support pushes a technology's capacity toward integration limits that would have been reached anyway at a later stage. In such a case, financial support in one period would only have short-term effects as they reduce investment opportunities in the next period.

Due to all these factors that affect the CO_2 emissions and employment impacts of financial support (Figure 1), IAMs with detailed energy system representation are useful tools to find an optimal technology portfolio for planned financial support programs. We approach this task by applying increasing subsidy rates individually for nine clean technologies on top of region-specific (pre-pandemic) energy and climate policies,[32] and measure the marginal effectiveness in reducing emissions and increasing employment using three IAMs that differ significantly in their solution mechanisms and temporal dynamics (e.g., perfect versus myopic foresight). We then apply a robust portfolio

analysis for each region-model combination to find a Pareto-optimal set (i.e., a set of points where no improvements are possible in one metric without affecting at least one other metric) of technology portfolios, optimizing over emissions reduction and employment creation within a pre-announced green COVID-19 recovery budget for each region.[40] The obtained Pareto frontiers (the sets of all Pareto-efficient solutions) aim to identify trade-offs between the cumulative amount of CO_2 emissions abated, the number of job-years created over this entire decade (2021–2030) (hereafter "full-decade employment"), and the number of short-term job-years (up to 2025) (hereafter "short-term employment") created. The first two objectives can be considered as overarching objectives that policymakers may have when deciding on financial support packages. The latter objective has been chosen for its relevance to the need for recovery from the COVID-19 crisis and the typical goal of policymakers to seek immediate returns on their spendings. See experimental procedures for all details on the applied IAMs and recovery packages, and the detailed methodology.

Potential impacts of COVID-19 recovery packages

With a few exceptions, nearly all portfolios simultaneously abate CO_2 emissions and have a positive net impact on both long-term and short-term employment (Figure 2), confirming the positive synergy between employment and clean energy transition found in the literature.[13–15,17,19] However, for most Pareto frontiers, we find a relative trade-off between emissions abatement and full-decade employment creation, depending on the technologies financed. In three cases (Japan and EU with TIAM-Grantham, and India with GCAM-PR), there is a subset of portfolios reducing employment. In most analyses with trade-offs, we find that short-term employment is closely linked to full-decade employment, meaning that the technologies providing net employment gains until 2030 also create most short-term jobs. However, in three cases (China, EU, and Japan with GCAM-PR), short-term employment is at odds with full-decade employment, and, in fact, more short-term jobs are created in portfolios maximizing emissions abatement. An aggregated representation of cross-model ranges per region is provided in Figure S1, further highlighting the diverse trade-offs among the three objectives observed in each region as well as showcasing the different model outcomes.
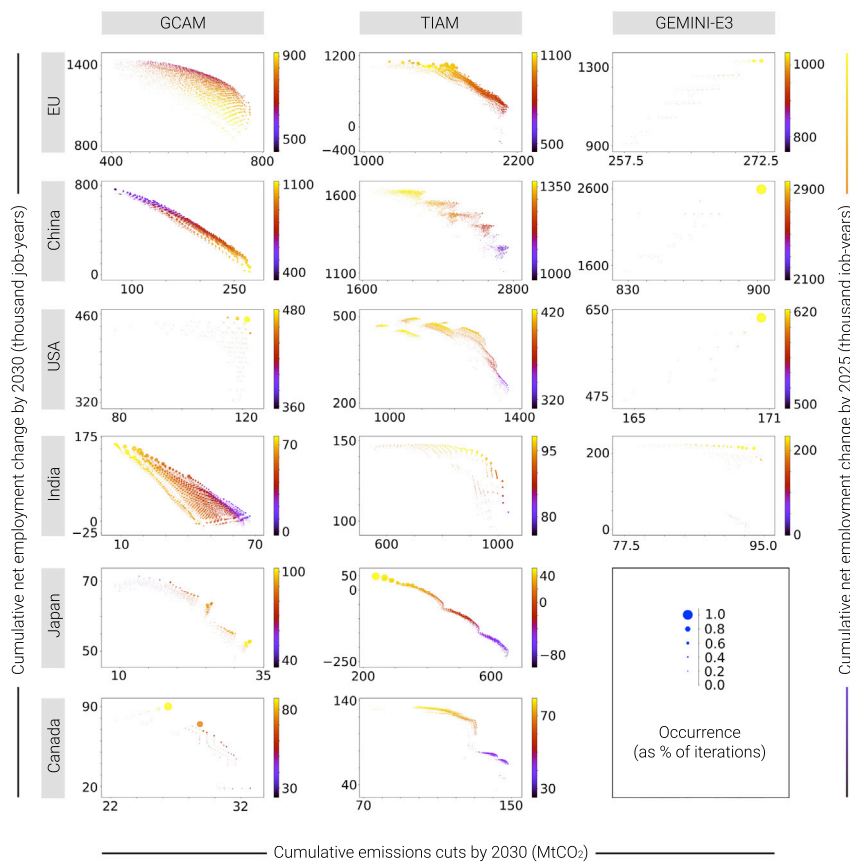
Figure 2. Scatterplots including all Pareto-optimal scenarios in each combination of models and countries, based on three objectives

The x axis represents cumulative emissions cuts by 2030, y axis cumulative net employment change by 2030, and color axis cumulative net employment change by 2025. Dot sizes represent robustness of each portfolio in the Monte Carlo simulation (with 1 indicating a robustness of 100% following the robustness definition in the experimental procedures). Results show that all six regions can achieve further emissions cuts while creating energy-sector jobs in the short and long term, by pursuing a green recovery from COVID-19. Relative trade-offs exist between CO_2 emissions abatement and job creation, as well as in some cases between short-term and long-term employment gains. The full results with all portfolios and objective contributions can be found in https://doi.org/10.5281/zenodo.6998390 labeled Data S5–D20.

jectives. Overall, we find that solar PV, which has become highly cost-competitive over the past decade and still relatively labor intensive in the construction phase, is the preferred clean energy technology for financial support in most analyses and across regions, while onshore wind also takes up a relevant share of most recovery packages. The other technologies, especially those with low penetration levels under the current policies baseline, play an important role in some model-region-objective niches, with technology preferences tending to differ significantly when optimizing one objective or another (Figure 3). For example, results from GCAM-PR indicate a considerable role (>20% of the recovery budget) for offshore wind and biofuels in maximizing full-decade employment in the EU, and for nuclear energy in the EU, China, India, and Japan. Results from TIAM-Grantham give an important role to geothermal energy in reducing emissions in Japan and the United States, to concentrated solar power (CSP) in India and to biomass in Canada, in line with potentials suggested in the literature.[47–49] Hydroelectricity (TIAM-Grantham) and biomass (GEMINI-E3) play an important role in maximizing energy jobs in India in the longer run (for potentials see Chaurasiya et al.[50] Hiloidhari et al.[51]). This highlights the value of modeling these recovery packages on top of pre-modeled, region-specific baselines and employing a diverse set of models and policy interactions to identify which technology support is more cost-effective in each region.

Role of model diversity

Despite soft harmonization of techno-economic assumptions and applied pre-pandemic energy and climate policies,[52] outcomes from the three employed models differ substantially: the average outcome differences of the same subsidy package are up to 10-fold for emissions (China, United States) and 6-fold for employment (China), while there are also pronounced differences in the optimal technology portfolios (Table 1). There are

Taking an average of all portfolios weighted by their robustness level (i.e., the likelihood that a portfolio is found on the Pareto frontier, see experimental procedures) for each of the analyses (Table 1) gives an impression of the overall impact and technology mix of each country-model combination. While the inter-model uncertainty is too big to provide precise answers, overall tendencies can be identified. Emissions impacts of COVID-19 recovery packages in the EU, China and Canada are likely to have a non-negligible contribution (>4%) to closing the emissions gap between pre-pandemic policy packages and renewed NDC targets, the latter being compatible with a ~2°C future.[44,45] The relatively small green recovery packages in the United States and India are likely insufficient, while inter-model uncertainty is too strong for Japan to draw conclusions. In terms of employment, the recovery packages in the EU and China would put a relevant share of the new pandemic-driven unemployed back to work by an increase in energy-sector employment, predominantly in the short term. Employment gains are less profound for the United States, India and Canada, while the USA and India experienced the highest absolute decrease in employment among the countries analyzed in this study.[4,46] For Japan, inter-model differences are too big to draw a conclusion.

Investment portfolios for optimized outcomes

A key policy question from this study is how to distribute recovery funds over different clean technologies to achieve certain ob-

Table 1. Average outcomes and technology portfolios per country-model combination

Region (green recovery budget)	Model	Outcome on each objective (absolute terms)[a]			Objectives relative to targets			Technology portfolio mix[a] (% of subsidy budget)								
		Accumulated CO_2 abatement (million tons CO_2)	Energy-sector jobs 2021–2030 (thousand job-years)	Energy-sector jobs 2021–2025 (thousand job-years)	Emissions reductions relative to NDC target gap[b] (% of gap)	New energy-sector jobs relative to jobs lost in COVID-19 crisis[c] (% 2021–2030)	New energy-sector jobs relative to jobs lost in COVID-19 crisis[c] (% 2021–2025)	PV	CSP	Onshore wind (%)	Offshore wind (%)	Geothermal (%)	Nuclear (%)	Biomass (%)	Hydro (%)	Biofuels (%)
EU (96 b$)	GCAM	645	1,238	804	29.50	9.20	11.94	0.00	0.00	53.40	12.80	0.00	15.30	0.00	NA	18.60
	TIAM	1,839	677	948	48.30	5.03	14.08	78.80	4.20	7.20	2.30	0.00	0.20	5.70	1.50	NA
	GEMINI-E3	269	1,249	977	6.70	9.28	14.51	74.8[d]		16.3[e]		NA	NA	8.90	NA	NA
China (60 b$)	GCAM	197	403	780	5.40	3.82	14.78	46.70	0.00	19.40	0.90	0.30	31.70	0.80	NA	0.20
	TIAM	2,257	1,490	1,262	210.40	14.13	23.93	54.40	1.80	23.80	2.10	2.20	0.00	14.60	1.10	NA
	GEMINI-E3	872	2,280	2,712	NA	21.62	51.43	94.6[d]		2.1[e]		NA	NA	3.20	NA	NA
United States (26 b$)	GCAM	116	424	445	1.30	1.53	3.21	88.00	0.00	5.90	1.80	0.10	0.40	0.50	NA	3.20
	TIAM	1164	438	405	12.20	1.58	2.91	68.70	0.50	16.50	2.60	7.80	0.00	0.50	3.40	NA
	GEMINI-E3	169	590	591	1.80	2.12	4.26	91.6[d]		0[e]		NA	NA	8.40	NA	NA
India (9 b$)	GCAM	43	56	47	1.20	0.19	0.33	30.10	0.00	30.00	1.70	0.20	33.30	0.10	NA	4.60
	TIAM	877	138	95	NA	0.48	0.66	74.00	2.20	7.00	0.00	0.00	0.00	1.10	15.40	NA
	GEMINI-E3	90	201	207	2.90	0.69	1.43	78.3[d]		6.9[e]		NA	NA	14.70	NA	NA
Japan (6 b$)	GCAM	25	61	82	1.50	2.20	6.10	75.50	0.00	6.90	0.40	0.40	14.10	0.80	NA	1.90
	TIAM	503	−96	−19	36.60	−3.60	−1.40	57.20	0.00	4.50	2.30	23.20	6.50	3.60	2.70	NA
Canada (3 b$)	GCAM	29	62	63	4.00	1.60	3.20	58.90	0.00	40.00	0.30	0.10	0.00	0.60	NA	0.00
	TIAM	120	112	65	9.80	2.80	3.30	28.60	0.00	11.90	8.60	0.00	11.80	32.80	6.30	NA

NA, not applicable.

[a]Numbers are weighted averages of all portfolios (e.g., dots) in Figure 2. The weight of each portfolio is defined by the robustness level.

[b]This column first calculates the difference in cumulative 2021–2030 emissions of each region on model in the current policies baseline[29] with emissions in the latest 2030 NDC submissions, and then divides the recovery package abatement by this emissions gap. Assumed NDC targets (applied to CO_2 only) are −55% w.r.t. 1990 in the EU, −65% emissions intensity w.r.t. 2005 in China, −51% w.r.t. 2005 in the United States, −45% emissions intensity w.r.t. 2005 in India, −46% w.r.t. 2013 in Japan, and −42.5% w.r.t. 2005 in Canada. NA results appear for model-region combinations where the current policy baseline already achieves the latest NDC target.

[c]For these columns, first the number of new unemployed in 2021 relative to 2019 is calculated by multiplying the unemployment rate by total labor force[4,43]; we focus on unemployment in 2021 instead of 2020 to filter out large temporal unemployment driven by hard lockdowns during 2020). Then it divides the amount of recovery package job-years in the energy sector by 10 (2021–2030) and 5 (2021–2025) and divides it by the total amount of new unemployed.

[d]For the GEMINI-E3 model, the subsidy budget for solar PV and CSP is combined.

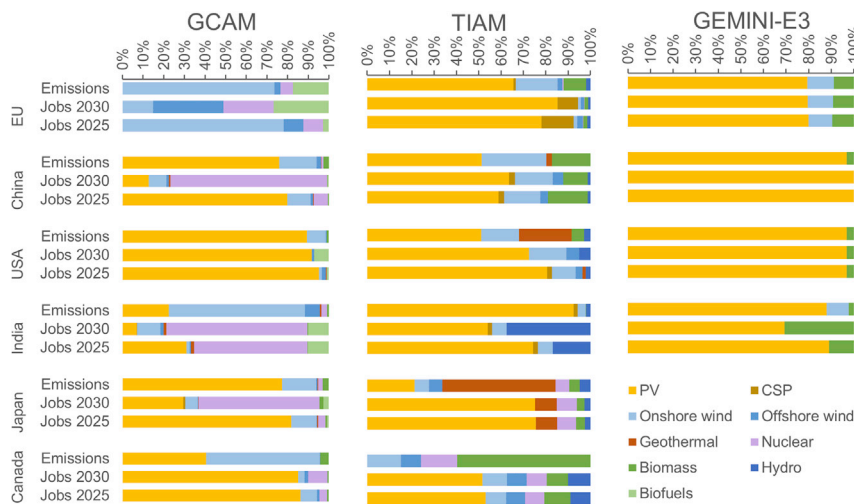[e]For the GEMINI-E3 model, the subsidy budget for onshore and offshore wind is combined.

Figure 3. Technology mix of portfolios maximizing each objective per model-country combination

For each objective independently, we isolated the top 5% of portfolios that maximize that objective. We then used the robustness of each portfolio as a weight and calculated the weighted average of their investment mixes (in the top 5%), to create an ideal portfolio that represents the best-performing solution for each distinct objective.

many model-specific factors that affect the effectiveness of technology finance, and which are hidden in a "black box" between the presented inputs (budgets) and outputs (emissions, jobs). By disentangling this causality into three ratios (Figure 1) for each model-country-technology combination, the influence of model behavior on outcomes is exposed.

The first ratio measures how much additional capacity (in nominal value) is installed for each dollar in support, which can be seen as a support "amplifier" (Figure S2 in SI-1). For nearly all technologies and countries, GCAM-PR and TIAM-Grantham see decreasing returns for each additional dollar of support. This is because the logit technology choice mechanism in GCAM-PR[53] causes gradually decreasing returns, with the first dollar of support for a certain technology stimulating more capacity deployment than subsequent support to the same technology. In comparison, the technology-rich, winner-takes-all optimization mechanism in TIAM-Grantham implies that the cheapest technology can dominate all new deployment. This mechanism amplifies the returns to scale curve as, once the subsidy achieves cost-competitiveness for a specific low-carbon technology, then this results in a large degree of deployment (much more than GCAM-PR), with further subsidies having less additional impact. This effect explains why, in TIAM-Grantham, more technologies receive at least some minimal support, as the first dollars of support in each technology are relatively more effective. In contrast, the relatively flat curves observed for GCAM-PR cause those technologies that are not too competitive—due to either or a mix of technology costs, climatic conditions, and/or market saturation (e.g., solar PV in the EU)—not to receive any support at all. The results for GEMINI-E3, in comparison, show increasing returns to scale for support in some technologies (PV in the EU, China, and the United State, biomass in China and the United States). As the model tries to reach equilibrium over time, the benefits of temporary financial support in one period will be largely reverted in subsequent periods, inducing an implicit penalty toward earlier support. Meanwhile, the model intents to optimize the timing of financial support over time. With higher budgets dedicated to a specific technology, a relatively higher share of that budget is going to allocated at the later support years (com-

ing online post 2025). Spreading out financial support over time increases the cumulative technology uptake until 2030 with more support for those technologies. These increasing returns to scale explain why GEMINI-E3 finds it is optimal to invest nearly all the budget in one (best-performing) technology (Figure 3), avoiding trade-offs between different objectives when selecting technology portfolios (Figure 2)."

The other two ratios measure the emissions and employment impact of each additional unit of technology capacity (Figures S3 and S4 in SI-1, respectively). As such, they summarize the energy system interactions caused by an additional unit of clean energy capacity in each model, and the combined set of emissions and employment factors of the energy system response. These ratios tend to be technology and country specific and, in contrast to the support-to-capacity ratio, can be both positive and negative. For instance, a new support-driven wind park that is competing with both clean and fossil energy alternatives may replace more labor-intensive alternatives and may increase the demand for energy as a whole through a rebound effect induced by lower electricity prices. Figure S3 (in SI-1) shows much stronger emissions reductions per unit of support-driven capacity unit for TIAM-Grantham, which can be explained by the energy system impact of the additional capacity: additional capacity affects mainly the dispatch of other existing capacity in the model, which means that renewables with nearly zero marginal costs reduce the running hours of predominantly thermal power plants fueled by coal and gas. In contrast, GCAM-PR and GEMINI-E3 have constant capacity factors for each technology throughout the model simulations. This means new support-driven capacity of one renewable technology either substitutes capacity additions for all other technologies (including renewables) or increases capacity additions for all other technologies (including fossil fuel technologies) if the financial support substantially drives down energy prices (the latter occurs in GCAM-PR only). In jobs, differences are less pronounced, and the major reason why GEMINI-E3 stands out is the dominance of PV in the portfolios, which is among the most labor-intensive technologies per unit of support (see Figure S4 in SI-1).

Another important difference among the models is that TIAM-Grantham applies inter-temporal optimization with perfect foresight toward future modeling periods, whereas GCAM-PR and GEMINI-E3 are recursive-dynamic models, which means that each modeling period solves independently without knowledge on future costs and policies. Given that the modeled recovery packages affect two modeling periods (2025 and 2030, the latter

due to construction times; see Scenario protocol in Experimental procedures), this limited foresight may cause somewhat unexpected model behavior driven by temporal dynamics, such as the increasing returns to scale in GEMINI-E3 explained earlier in this section, as well as trade-offs between short- and long-term employment in GCAM-PR: in the case of technologies that are already very competitive—often due to a combination of low technology costs, good conditions, and pre-existing policies supporting their deployment (onshore wind in the EU, solar PV in China and Japan)—additional financial support from recovery packages has such a large impact on capacity that it significantly drives down the electricity price, affecting the whole energy system. However, in the next period, less of that competitive technology will be supported by the recovery packages. This causes the electricity price to rebound, negatively affecting employment in the entire sector due to overcapacity, and hence creating a trade-off between short-term and long-term employment.

Despite potential real-world temporal uncertainties for investors regarding announced recovery packages, overall, the perfect foresight principle in TIAM-Grantham is likely more adequate for modeling the impact of pre-announced financial support packages over time.[54] Apart from the inter-temporal optimization function, the electricity dispatch model with flexible capacity factors in TIAM-Grantham also reflects better how supported intermittent technologies compete with existing technologies in the market. However, the winner-takes-all mechanism for technology choice, which causes very high technology uptake with minor financial support, can be deemed less realistic in a real-world setting, and the more gradual technology substitution in GCAM-PR and GEMINI-E3 reflects the support-driven uptake of low-carbon technologies better from a real-world perspective. These heterogeneous strengths and weaknesses of each model highlight the importance of diverse model ensembles, like the one employed here, in shedding light on various effects of policy and providing a robust assessment within a spectrum of uncertainty inherent in model theory and dynamics.[55]

DISCUSSION

This study examines how to distribute the publicly announced green COVID-19 recovery packages in six large economies to optimize emissions abatement and employment creation and demonstrates the progress that such packages can help make toward each of the objectives. While for some economies (EU and China) such packages provide good progress toward either or both objectives under our assumptions, for other economies (the United States, India, Japan, and Canada) the potential impact is less profound.

In terms of emissions, progress in emissions abatement falls short of 2°C-compatible pathways, contradicting effective green recovery IAM scenarios published before the extent of green recovery packages was announced.[10,26,56] However, the main reason for that is the green share in total recovery funds being much smaller than assumed in those studies; at the same time, our analysis only focused on the power and biofuel sectors. Another important difference between this study and earlier IAM studies is that we projected the impact of recovery funds on top of an existing current policy trajectory. In contrast, earlier studies

defined the investment gap by looking at differences in low-carbon investments between pre-existing reference and Paris-compliant scenarios, without taking interactions between existing policies and public incentives into account.[10,57] Our results, and especially the large differences obtained across the three models applied in this analysis, imply that focusing on required low-carbon investments is an oversimplified technique of measuring whether packages are in line with mitigation goals, due to the large uncertainty in the extent to which green investments could achieve emission cuts.[58] We show and clarify how structural differences in the way different models operate (e.g., economic theories, foundations, principles), and, in turn, the interacting effect of existing emission reduction policies, can yield vast differences in the measured impact of green investments on mitigated emissions. Since none of the models can be objectively classified as better or worse for these types of analyses, model diversity should be seen as an important prerequisite to capturing the entire solution space of a specified research question, while a lack of such diversity may give a false sense of precision.

In terms of employment, the structure of the impact in most countries is more focused on short-term employment gains relative to other studies (e.g., Pollitt et al.[26]), while the absolute impact is hard to compare due to strong differences in assumed recovery package sizes. A caveat in the employed modeling approach is the use of employment factors to estimate net energy-sector jobs, following various recent literature,[17–19] an approach potentially disregarding wage dynamics and longer-run impacts, assuming perfect labor mobility across different sectors and skillsets without considering additional investment in retraining or reskilling and change in job multiplier in the long run due to change in labor productivity[59] and automation.[60] Also, renewables-driven net job gains in the energy sector can be offset by job losses in other sectors if gross domestic product (GDP) is negatively affected.[61] Logically, in a full-employment economy model that does not consider voluntary and involuntary unemployment, net job gains in one sector need to be drawn from other sectors, but full employment is not a very realistic assumption for both developed as well as developing countries. Nevertheless, we opted to use employment factors as we analyze economic recovery packages, of which the explicit purpose is to create employment in a non-full-employment market. Besides, not all three models can obtain labor market results, rendering employment factors the most straightforward way to harmonize the job creation estimate across all modeling results. A final caveat is on the choice of the objective function. We focused on quantitative employment numbers, while not taking into account qualitative employment aspects such as wages. Given that the pledged recovery funds are driven by the economic downturn as a result of the COVID-19 pandemic, we assumed that employment quantities are more relevant than quality to policymakers in the light of economic crisis recovery, but we do fully acknowledge that policy-maker objectives are heterogeneous and might differ from the ones we have used.

This study suggests that, when optimally allocating recovery funds between emission reduction and employment creation objectives, most countries would invest over 50% of their energy-focused green recovery packages in financing PV, over 10% in onshore wind, while investments in other clean energy

technologies strongly depend on the country, preferred objective, and model applied. However, a mix of supply problems and quickly recovered demand (in part due to post-COVID stimulus measures) has caused a strong increase in prices for many materials over the course of 2021,[62,63] affecting costs of PV and wind projects throughout the world by 16%–70% and 10%–25%, respectively.[64] This inflationary impact of recovery policies is not taken into account in this analysis and the lack of material and supply-chain representation is a weakness in many IAMs that are used in these types of analyses.[65]

Overall, this study shows that green economic stimulus, if strategically spent, has the potential to both achieve emission reductions and increase employment, in line with recent publications on this topic[18,19] as well as empirical evidence in the EU.[13] Of the 16 region-model combinations in this study, only one (Japan with TIAM-Grantham) suggested that most optimal green portfolios imply a decrease in employment. Nevertheless, the outputs also show that, despite the double benefits of green recovery packages, many countries have not managed to pursue significant green recovery packages, despite the astronomical size of total economic recovery spendings announced during the COVID-19 pandemic.[10] Since an important requisite for green stimulus packages to have a beneficial rather than an inflationary impact is that the economy is in an economic downturn with relatively high unemployment, political preparedness to rapidly pursue well-balanced green stimulus packages in times of economic crisis is crucial, utilizing such crises to achieve the green transformations required for reducing emissions.[66] For example, the relatively high impact of the EU's recovery packages compared with those of, e.g., the United States may hint at relatively high political preparedness in the EU to put the energy transition as a high priority when designing policy to combat recession and unemployment. Our results also show that the optimal technological breakdown of recovery packages differ significantly by country and, critically, by objective. Different technologies should be prioritized depending on whether the main focus of the policy is on emission reductions or employment goals. While employment creation is often high on the political agenda in crisis times, it is important for policymakers to carefully weigh the importance and impact of both objectives (as well as other ones not considered in this study) and ensure that the impact of recovery packages is beneficial for both objectives rather than inflationary. The use of modeling tools that are well calibrated for the focus region can be instrumental in weighting out the most robust response to future crises.[67]

EXPERIMENTAL PROCEDURES

Resource availability
Lead contact
Further information and requests for resources and materials should be directed to and will be fulfilled by the lead contact, Dirk-Jan van de Ven (dj.vandeven@bc3research.org).

Materials availability
This study did not generate new unique reagents.

Data and code availability
All data presented in this paper are available in this paper's supplemental information has and have been deposited and are publicly available at Zenodo: https://doi.org/10.5281/zenodo.6998390. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

Model ensemble
GCAM-PR and TIAM-Grantham are partial equilibrium models that achieve equilibrium between supply and demand for energy in each sector represented, accounting for changes in energy prices that result from changes in fuels and technologies used to satisfy energy service demands in these sectors. GCAM-PR operates on a recursive-dynamic cost-optimization basis, which means that it solves for the least-cost energy system in a given period, before moving to the next time period and performing the same exercise. TIAM-Grantham, on the other hand, operates on a perfect-foresight welfare cost-optimization basis, whereby all consequences of technology deployments, fuel extraction, and energy price changes over the entire time horizon are considered when minimizing the cost of the energy system, so as to provide energy service demands within specified emissions constraints.

GEMINI-E3 is a computable general equilibrium (CGE) model with a more detailed, multiple-sector representation of the economy that considers how the impacts of specific policies spread across economic sectors and regions and how they affect environmental parameters. The model's operation is similar to that of GCAM-PR and TIAM-Grantham but differs in that market equilibrium is assumed to take place simultaneously in each market/region. It features richer representation of the economy, which, however, requires calibration to data on national and international socio-accounting information, as well as input in the form of a series of elasticities of substitution.

An overview of the three models with their study-relevant features and technology coverage is displayed in Table 2. More information on the three models, including a detailed summary and their economic rationale, is provided in Notes S1–S3, as well as in the I2AM PARIS platform (https://www.i2am-paris.eu).

Scenario protocol
Before running the numerous subsidy scenarios for different technologies, a baseline was defined with which each subsidy scenario is compared to quantify the impact of subsidies. This baseline scenario ought to represent where the region is headed given its climate policies in place, before COVID-19 recovery packages were announced. Hence, the current policies scenario was selected from Sognnaes et al.,[32] which for the EU is further detailed in Nikas et al.,[68] from which each model used its own trajectory, with an important amendment for the purposes of this study: to avoid the competition between existing current policies and the new technology subsidies (e.g., in the form of subsidies lowering the costs of achieving current policies), which could potentially alter the trajectories defined by policies already in place, the complete set of current policies was fixed, so that the newly modeled energy policies can come on top of what is already achieved with current policies. Fixing these current policies depended on each model. For example, based on the outcomes of the current-policies scenario, the implicit subsidy (e.g., the feed-in tariff required to achieve a certain renewable energy systems (RES) share) or tax (e.g., the EU Emissions Trading System [ETS] price) may be read in, and applied as, fixed subsidies and taxes in a new baseline, so that the outcome is precisely equal to the current-policies scenario, but such implicit subsidies (e.g., feed-in tariffs) and taxes (e.g., EU ETS) would be no more dependent on changes in the costs of energy technologies until 2030. These amendments would only be necessary for the policies applied in the regions of this study (Canada, China, EU, India, Japan, and the United States). Canada and Japan were not modeled in GEMINI-E3 since these countries were not independently represented in the model.

On top of these current policies, subsidy scenarios are run individually for each technology and model region. First, a "max-subsidy" level is determined, in which the full budget of each country is spent on a given technology, and subsequently 50 runs are performed with gradual levels of subsidization (2%, 4% ..., 100% of the max-subsidy value) for that technology only. On several occasions, the 100% run may not spend the entire budget; e.g., if a certain technology is not taken up sufficiently even if it were fully subsidized (due to, for example, high non-capital costs). If a certain technology contained more sub-technologies (e.g., utility-scale PV and rooftop PV), as was the case in GCAM-PR and TIAM-Grantham, the subsidy levels were calculated using the sub-technology with the lowest costs, and the same absolute subsidy value was then applied to all sub-technologies.

Considering the construction time of different technologies, we also acknowledge that there should realistically be a delay from the point projects

Table 2. Model key characteristics

Model	Model type	Temporal solution dynamic	Technology choice mechanism	Technology dispatch	Technology representation[b]								
					Solar PV	Solar CSP	Onshore wind	Offshore wind	Geo thermal	Nuclear	Biomass	Hydro power	Bio fuels
TIAM-Grantham	partial equilibrium	inter-temporal optimization	winner takes it all	flexible capacity factors	✔	✔	✔	✔	✔	✔	✔	✔	
GCAM-PR	partial equilibrium	recursive dynamic	logit choice	constant capacity factors	✔	✔	✔	✔	✔	✔	✔		✔
GEMINI-E3	computable general equilibrium	recursive dynamic	nested CES[a] function	constant capacity factors	✔[c]	✔[c]	✔[d]	✔[d]			✔		

[a]CES, constant elasticity of substitution.
[b]Non-represented technologies may imply that the technology supply is fully or partially pre-determined and not subject to market dynamics, hence irrelevant in the current study design. Solar
and wind technologies in GEMINI-E3 are represented under single technologies with (weighted) average costs.
[c]Represented as solar energy technology combining PV and CSP.
[d]Represented as wind power combining onshore and offshore wind.

are given a green light until they are connected to the grid. This implies that, even if all subsidies are to be spent in the 2021–2025 period, they may not enter the energy mix until the next period (2026–2030). Based on this construction delay, Table 3 shows for each technology the approximate pre-calculated shares of the subsidized output that would come online in either the 2021–2025 period or the 2026–2030 period (due to construction delay).

Budget selection

For the EU, the Recovery and Resilience Facility (RRF) is the largest component of the NextGenerationEU program, the bloc's landmark recovery instrument. The RRF is intended to provide up to EUR 312.5 billion and EUR 360 billion in grants and loans, respectively. Considering (1) the EUR 75 billion of the RRF's green pillar, which is expected to be channeled into clean energy projects on the selected technologies, excluding related infrastructure investments (e.g., storage),[69] and adding to that (2) EUR 5 billion from the UK fiscal plan,[70] a maximum budget of EUR 80 billion (USD 96 billion) was selected.

China announced a significant recovery package of around USD 740 billion, around USD 200 billion of which is in the form of quotas for special bonds issued by local governments for infrastructure. Currently, the lack of central government guidelines on the types of projects that should be prioritized for investment may lead to the budget flowing toward conventional energy projects.[71] Here, we assumed that about 30% of this budget for infrastructure can be used for projects related to the technologies of interest to our study (i.e., a level of ambition similar to the EU's) and assessed what would be the best allocation if a budget of USD 60 billion was used for green investments.

In the United States, of the three fiscal plans for recovery, only the second package accommodates a dedicated budget (USD 26 billion) for investments related to the technologies analyzed here,[72] and this is the budget used in this research. This, however, does not include recent pledges by the Biden Administration, which are still under formulation and are thus omitted from the analysis.

In India, of the nearly USD 400 billion package announced, only USD 9 billion is allocated toward energy.[73] Although most of this is expected to head to the coal sector, we used this budget to carry out a what-if analysis, exploring how to optimally allocate it to support green energy.

Finally, from the packages announced in the context of their economic recovery from COVID-19, Canada and Japan have pledged that USD 17.6 billion[74] and USD 19.2 billion[75] will be dedicated to support the green transition, as part of their broader roadmaps to net-zero. In the case of Japan, and considering the vague nature of the pledges, an amount of USD 6 billion was used, following a similar level of ambition as with the EU (and a similar assumption as with the budget for China; around 30% of the announced package toward the technologies of interest for this study). For Canada, drawing from the Healthy Environment and a Healthy Economy plan,[76] which is part

of the total announced budget, and which implicitly ties funds oriented toward green projects in the short term with the COVID-19 recovery, an amount of USD 3 billion was selected based on the share allocated for low-carbon power generation.

Employment factors

The level of employment is presented as a net-difference compared with the current policy scenario, as net employment is deemed more constructive in terms of job variations brought about by a transition.[33]

The two partial equilibrium IAMs used in this study (GCAM-PR and TIAM-Grantham) lack internal processes to account for employment, while the GEMINI-E3 CGE model only provides aggregated results due to limited granularity in terms of sectoral and fuel representation.[36] For this reason, we use employment factors to estimate the job impact of each subsidy level for the selected technologies, on top of the baseline trajectory projecting where the region is headed given its current climate policies.

To assess employment in each scenario, the contribution of each fuel to the energy mix is considered. Total employment of the energy sector is estimated based on the aggregation of employment factors in construction, manufacturing (driven by power-sector capacity additions), operation and maintenance (driven by total power-sector capacity), extraction (driven by fossil fuel, uranium, and bioenergy production), and refinery (driven by refined liquids production).

For each fuel, job category, and country, datasets labeled Data S1–S4, which can be found at https://doi.org/10.5281/zenodo.6998390, include the employment factors used to calculate the final employment level. These were collected from, or based on, the literature as follows:

- For RES technologies and biofuels, employment factors were drawn from Rutovitz et al.,[41] a comprehensive database commonly employed in relevant modeling analyses (e.g., Fragkos and Paroussos,[35] Ram et al.[17]).
- For fossil fuels, the values were drawn from Pai et al.,[19] building on Rutovitz et al.[41] but including regional disaggregation of fossil fuel factors.
- Although the time horizon of the analysis is limited to 2030, causing the impact of changes in the factors to be small, to account for the impact of technological learning curves on employment, employment factors are assumed to decline proportionally with cost projections for each technology.[17] Technology costs (e.g., CAPEX, OPEX) are harmonized across the three models following the harmonization protocol established in Giarola et al.[52]

Since each of the country analyses in this study is independent, employment factors for manufacturing and extraction have been corrected for the share of domestic supply. For simplicity, we ignored re-exports of goods, as well as the

Table 3. Technologies to be included in subsidy runs, if covered by model, and timing of projects coming online if all subsidies were spent in projects, for which construction starts in 2021–2025

Technology	Sector	Share (%) of projects coming online in		Subsidization in models:
		2021–2025	2026–2030	
Biomass	electricity generation	60	40	GCAM, TIAM, GEMINI-E3
Hydro	electricity generation	0	100	TIAM
Nuclear	electricity generation	0	100	GCAM, TIAM
Solar PV	electricity generation	80	20	GCAM, TIAM, GEMINI-E3
Solar CSP	electricity generation	60	40	GCAM, TIAM
Geothermal	electricity generation	60	40	GCAM, TIAM
Wind onshore	electricity generation	60	40	GCAM, TIAM, GEMINI-E3
Wind offshore	electricity generation	20	80	GCAM, TIAM
Biofuels	refining capacity	60	40	GCAM

geographical distribution of specific components for each technology. Therefore, employment factors are multiplied by the relative share of domestic supply in domestic demand for the last year, in which real-world data could be found (2018 or 2019), and cannot exceed one. In other words, if a country is a net exporter of manufactured supplies or fuels, all additional manufacturing or extraction jobs are assumed to occur in the country itself; while, if a country imported, e.g., 50% of domestic demand in 2018, only half of the newly created manufacturing or extraction jobs would occur in the country itself. These multipliers to correct for international trade of fuels and manufacturing products can be found at https://doi.org/10.5281/zenodo.6998390, labeled Data S1–S4.

Portfolio analysis

IAM results feed into a multi-objective optimization model, with a view to maximizing the returns of the assumed green part of COVID-19 recovery fiscal programs, expected to be allocated toward the 10 technologies considered (Table 2), in terms of new employment created in the energy sector and of further CO_2 emissions cuts. Contrary to performing a standalone cost-optimal analysis based on the modeling outputs, this integration of the IAMs with a portfolio analysis model allows us to consider additional objectives (e.g., employment), which are typically outside the capabilities and cost-optimization solution scope of IAMs (including this study's modeling ensemble).

We define three different objective functions. The first objective revolves around further reducing CO_2 emissions; we use 2030 as a time horizon for this objective, considering that 2030 is a milestone year in NDCs. The second objective lies in creating new energy-sector jobs; assuming policymakers seek to maximize immediate returns on recovery funds spent in the next 5 years, we use 2025 as a time horizon for this objective. However, aside from differences across the six regions given their domestic resources and manufacturing capacity, different projects imply different allocations of new jobs along the project pipelines; a key question, therefore, is whether new jobs created in the near term (2025) by subsidies in the considered technologies can be sustained in the longer run. As a result, we also define a third objective, which is maximizing new employment gains by the end of the decade. In the optimization problem, the input of the three objectives is considered as a net difference between each scenario (subsidization on one technology) and the baseline. Based on the modeling results, each subsidy level on each technology independently corresponds to a specific impact across the three objectives, formulating the payoff tables to facilitate the functional relationship that links the objectives with the amount of subsidy spent.

In summary, the portfolio analysis process seeks to optimize emissions cuts by 2030, employment gains by 2025, and employment gains by 2030 simultaneously. This can be summarized in Equations (1) and (2):

$$max \; [E_{2021-2030}(MtCO_2), \; J_{2021-2025}(job\;years), J_{2021-2030}(job\;years)]$$
(Equation 1)

$$subject\;to\; \sum_i x_i < Region\;Budget\;(USD)$$
(Equation 2)

where:

- $E_{2021-2030}$: cumulative CO_2 emission reductions from 2021 to 2030
- $J_{2021-2025}$: cumulative job-years in the period 2021–2025
- $J_{2021-2030}$: cumulative job-years in the period 2021–2030
- Region Budget: the available budget of each region
- x_i: the decision variable of the optimization problem, representing the amount of subsidy spent on technology i (i is based on the technology subsidization capabilities of each model; see Table 2).

The optimization process is based on an open-source (Python) implementation of the AUGMECON-R algorithm,[77] which is based on the ε-constraint family of optimization methods, with the addition of a lexicographic optimization approach (nested objectives) in the augmented (AUGMECON) versions. Our algorithm is further improved to optimally allocate the objective functions within the nested loops of the algorithm toward capturing all solutions, thereby considerably reducing execution time. Following this approach, the algorithm is not required to weigh the objectives (e.g., weighting method), thereby avoiding the need to scale the objectives and consequently bypassing a common criticism that scaling can have a strong influence on the results.[78] As such, because of the lexicographic solution mechanism, any identified trade-off among different objectives derives directly from the payoff tables and the solution and is not an arbitrary choice made by the modeler (i.e., via scaling). The goal of the employed optimization algorithm is to identify all non-dominated solutions (investment mixes across technologies); these comprise the solutions, for which there exist no alternative solution performing better across all objectives (i.e., solutions, for which the performance along no objective can be improved without reducing the efficiency along the other objectives). These solutions are termed Pareto-optimal solutions; it should be noted that Pareto optimality is always problem specific.

Finally, to increase confidence in the resulting optimal technological subsidization portfolios, we assume that the outputs of IAMs (CO_2 emissions cuts as well as both near-term and long-term employment gains per subsidy level of each technology for each region) feature uncertainty. We employ 100 Monte Carlo simulations for each portfolio optimization problem, carried out in a ±5% range following a normal distribution (with a mean value the model results and a ±5% SD), in an approach similar to Forouli et al.[40] Considering the complexity of the optimization problems (three objectives, numerous subsidy levels, across three models and six countries), it was computationally exhaustive to increase the number of iterations, without providing considerable improvements on the accuracy of the results. In particular, the number of iterations was set to 100 after gradually reducing the number of iterations from an initial level of 1,000 and observing whether it produced significant differences with the 1,000-iteration-run. Until the level of 100 iterations, differences were found to be negligible, hence we continued with this number to optimize between outcome robustness and computing time.

We define robustness as the number of times a subsidization portfolio is found optimal (i.e., as part of the Pareto frontier) among the 100 Monte Carlo simulations. In other words, if a specific budget allocation is found optimal in n simulations (based on the Pareto optimality previously discussed), then the

robustness of this portfolio is *n*%. Following this definition, higher robustness indicates that a portfolio is non-dominated (or Pareto-optimal) across a larger number of iterations. In the figures, robustness is reflected in the size of each point (portfolio): the larger the point of a portfolio, the higher its robustness (see legend in Figures). The robustness level of each portfolio is used as a weight to aggregate all portfolios into one representative portfolio (e.g., Table 1) for each case (model-country combination). This way, from the entire Pareto frontiers (which entail thousands of different portfolios), these weighted-average portfolios can provide quick insights into the direction policymakers need to take, as well as an anticipated average performance across all objectives. Contrary to employing an average of the portfolios, using a weighted average based on the robustness of each portfolio ensures that outliers (i.e., portfolios appearing in a very small number of iterations and therefore less representative of optimality) play a smaller role in this process.

AUTHOR CONTRIBUTIONS

D.V., A.N., A.G., K.K., S.M., and A.F. collectively designed the study and conceptualized the methodological framework. D.V., G.C., A.C., M.G., S.G., S.M., S.P., and M.V. performed the energy-economic model runs. A.N., K.K., A.F., and T.K. performed the portfolio analysis on these model outcomes. D.V., A.N., S.M., T.K., and G.X. were responsible for the design of the figures in the manuscript. All authors collectively edited drafts and were responsible for the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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