PARIS
REINFORCE

21/10/2022

D4.6 Second portfolio analysis of technological and policy mixes

WP4 – Robustification & Socio-Technical Analysis Toolbox

Version: 1.00

www.paris-reinforce.eu

Disclaimer

Copyright Message

Grant Agreement Number	820846		Acronym	Paris Reinforce
Full Title	Delivering on the Paris Agreement: A demand-driven, integrated assessment modelling approach			
Topic	LC-CLA-01-2018			
Funding scheme	Horizon 2020, RIA – Research and Innovation Action			
Start Date	June 2019	Duration	42 Months	
Project URL	https://www.paris-reinforce.eu/			
EU Project Officer	Frederik Accoe			
Project Coordinator	National Technical University of Athens – NTUA			
Deliverable	D4.6 Second portfolio analysis of technological and policy mixes			
Work Package	WP4			
Date of Delivery	Contractual	31/10/2022	Actual	21/10/2022
Nature	Report	Dissemination Level	Public	
Lead Beneficiary	National Technical University of Athens (NTUA)			
Responsible Author	Alexandros Nikas	Email	anikas@epu.ntua.gr	
	NTUA	Phone	+30 210 772 3612	
Contributors	Anastasios Karamaneas, Haris Doukas (NTUA); Dirk-Jan Van de Ven (BC3); Alessandro Chiodi (E4SMA); Sigit Perdana, Marc Vielle (EPFL); Ajay Gambhir, Sara Giarola, Alexandre C. Köberle (Imperial); Georgios Xexakis (HOLISTIC)			
Reviewer(s):	Shivika Mittal (Imperial); Maurizio Gargiulo (E4SMA)			
Keywords	COVID-19 recovery; clean energy technology; green jobs; energy sector employment; portfolio analysis, multi-objective programming; uncertainty analysis; integrated assessment models; AUGMECON-Py			

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

EC Summary Requirements

1. Changes with respect to the DoA

No changes with respect to the work described in the DoA.

2. Dissemination and uptake

With several countries announcing post-pandemic green recovery packages to stimulate green growth, this deliverable serves as a policy guideline on how to manage the investments to optimise CO_2 emissions reduction and green job growth, as well as contribute to the understanding of the dynamics of clean technology subsidy support on employment gains and emissions reductions Considering that, different energy-economy models show different outcomes on the employment gain and emission reduction synergies and trade-offs, this deliverable inform the modelling community on the impact of model diversity in capturing the full extend of the solution space. Finally, the open-source AUGMECON-Py software, is made publicly available as a contribution to the operational research community to be used in future studies.

3. Short summary of results (<250 words)

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. Here, we first introduce, AUGMECON-Py a portfolio analysis software building on the AUGMECON-R algorithm, with the capacity to address the computationally intensive aim of the study. We then 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, although exact mixes differ given different model-structures, and can have significant impact both in terms CO_2 emissions reductions and employment gains. This is particularly the case in the EU and China. Finally, we delve in the EU case to highlight a potential for around 400-770 MtCO2 emissions reduction by 2030, as well as about 550-915 and 850-1,450 thousand job-years created by 2025 and 2030 respectively, on top of the policies currently in place, but with clear trade-offs among the three objectives.

4. Evidence of accomplishment

This report, the three peer-reviewed publications (in SoftwareX, One Earth, Energy Policy), the European Commission's Policy Publication, "Climate Action in the Post-COVID-19 World" for COP26, and the presentation of the case study results in the "Fourteenth IAMC Annual Meeting 2021" conference (29 November – 3 December 2021).

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Preface

PARIS REINFORCE will develop a novel, demand-driven, IAM-oriented assessment framework for effectively supporting the design and assessment of climate policies in the European Union as well as in other major emitters and selected less emitting countries, in respect to the Paris Agreement. By engaging policymakers and scientists/modellers, PARIS REINFORCE will create the open-access and transparent data exchange platform I^{2}AM PARIS, in order to support the effective implementation of Nationally Determined Contributions, the preparation of future action pledges, the development of 2050 decarbonisation strategies, and the reinforcement of the 2023 Global Stocktake. Finally, PARIS REINFORCE will introduce innovative integrative processes, in which IAMs are further coupled with well-established methodological frameworks, in order to improve the robustness of modelling outcomes against different types of uncertainties.

NTUA - National Technical University of Athens	GR	
BC3 - Basque Centre for Climate Change	ES	
Bruegel - Bruegel AISBL	BE	
Cambridge - University of Cambridge	UK	
CICERO - Cicero Senter Klimaforskning Stiftelse	NO	
CMCC - Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	IT	
E4SMA - Energy, Engineering, Economic and Environment Systems Modelling Analysis	IT	
EPFL - École polytechnique fédérale de Lausanne	CH	
Fraunhofer ISI - Fraunhofer Institute for Systems and Innovation Research	DE	
Grantham - Imperial College of Science Technology and Medicine - Grantham Institute	UK	
HOLISTIC - Holistic P.C.	GR	
IEECP - Institute for European Energy and Climate Policy Stichting	NL	
SEURECO - Société Européenne d'Economie SARL	FR	
CDS/UnB - Centre for Sustainable Development of the University of Brasilia	BR	
CUP - China University of Petroleum-Beijing	CN	
IEF-RAS - Institute of Economic Forecasting – Russian Academy of Sciences	RU	
IGES - Institute for Global Environmental Strategies	JP	
TERI - The Energy and Resources Institute	IN	

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Executive Summary

The purpose of this deliverable is to perform robustness and uncertainty analyses of modelling results employing the multi-objective optimisation and uncertainty analysis framework developed in D4.2, to provide optimal portfolios of policies/technologies that perform well independently of any scenario's realisation and synthesise robust policy recommendations.

In Section 1, we first develop and present the open source AUGMECON-Py software, expanding the AUGMECON-R algorithm, to handle the computational complexity of the integrated assessment modelling-multi-ojbective framework presented in D4.2. Therefore, AUGMECON-Py is a Python framework for solving large and complex multi-objective linear programming problems under uncertainty, optimally and robustly capturing all solutions. On the core of the AUGMECON-Py software lies the integration of a well-established optimisation algorithm (AUGMECON) with Monte Carlo analysis that helps maximise robustness against stochastic uncertainty, thereby avoiding the complexity of numerous cascading methods and code scripts. Using an object-oriented language, AUGMECON-Py overcomes limitations of its predecessors regarding memory requirements, and further extends the solution algorithm to ensure no efficient solution is left outside the solution grid. The framework is easily accessible, offering effortless data pre- and post-processing, management, and visualisation of results.

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. In Section 2, we use three energy-economic models, combined with the portfolio analysis approach AUGMECON-R and the respective AUGMECON-Py software presented in Section 2, 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.

Based on the potential ability of the EU COVID-recovery package to contribute to their respective 2030 mitigation targets, while also employing a significant share of pandemic-related unemployed population until 2030, in Section 3 we perform a deep dive in the EU green recovery space. In particular, to tackle the negative socioeconomic implications of the COVID-19 pandemic, the EU introduced the Recovery and Resilience Facility, a financial instrument to help Member States recover, on the basis that minimum 37% of the recovery funds flow towards the green transition. Section 4 contributes to the emerging modelling literature on assessing COVID-19 vis-à-vis decarbonisation efforts, with a particular focus on employment, by optimally allocating the green part of the EU recovery stimulus in selected low-carbon technologies and quantifying the trade-offs between resulting emissions reductions and employment gains in the energy sector. In a similar approach with the global analysis, we integrate GCAM and AUGMECON-Py, by significantly expanding the analysed recovery space, aiming to identify robust portfolio mixes and expand on the findings presented in D4.2. We find that it is possible to allocate recovery packages to align mitigation goals with both short- and long-term energy-sector employment, although over-emphasising the longer-term sustainability of new energy-sector jobs may be costlier and more vulnerable to uncertainties compared to prioritising environmental and near-term employment gains. Robust portfolios with balanced performance across objectives consistently feature small shares of offshore wind and nuclear investments, while the largest chunks are dominated by onshore wind and biofuels, two technologies with opposite impacts on near- and long-term employment gains.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Contents

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Table of Figures

Table of Tables

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

1 AUGMECON-Py: A Python framework for multi-objective linear optimisation under uncertainty

This section has been published in SoftwareX:

- Forouli, A., Pagonis, A., Nikas, A., Koasidis, K., Xexakis, G., Koutsellis, T., Petkidis, C, & Doukas., H. (2022). AUGMECON-Py: A Python framework for multi-objective linear optimisation under uncertainty, *SoftwareX, 20*, 101220.

1.1 Motivation and significance

The analysis performed in D4.2 related to the optimal allocation of renewable energy subsidies from the COVID-19 recovery packages to maximise both emissions and employment impacts, has proven the usefulness of accompanying conventional modelling studies with multi-objective methods that incorporate uncertainty analysis. However, the progress in terms of the recovery both in the EU and globally, the updated information related to the fiscal packages, as well as the high uncertainty regarding where the money will flow to, create the need to enhance the recovery space analysed, by elaborating on the recovery package selection, the employment factors, and even the models used to better reflect uncertainty. It is evident that such elaborations require high computational needs and a software that will incorporate, exploit and even expand the AUGMECON-R algorithm presented in D4.2 to enable a deep dive in the recovery space.

For these reasons, in this section, we present AUGMECON-Py, a Python framework for solving multi-objective linear programming problems under uncertainty. The AUGMECON-Py solution framework is based on the principles of the robust augmented ε-constraint method (AUGMECON-R) (Nikas et al., 2022) for finding exact solutions of linear programming problems of multiple objective functions. The AUGMECON-R algorithm, as well as its predecessors (AUGMECON2 (Mavrotas, 2009)) and AUGMECON (Mavrotas and Florios, 2013)) are widely used in literature and practice for the timely optimisation of complex systems that feature multiple evaluation criteria, constraints of different nature, and numerous decision variables. The fields of application of the AUGMECON algorithms include inter alia supply chain management (Torabi et al., 2013; Bootaki et al., 2014; Bootaki et al., 2016; Canales-Bustos et al., 2017; Musavi and Bozorgi-Amir, 2017; Rayat et al., 2017; Vieira et al., 2017; Savzar et al., 2018; Ehrenstein et al., 2019; Qiu et al., 2019; Shekarian et al., 2019; Xin et al., 2019; Gavranis and Kozanidis, 2017; Bal and Satoglu, 2018; Attia et al., 2019; Habibi et al., 2019; Resat and Unsal, 2019; Roshan et al., 2019; Saedinia et al., 2019; Vafaeenezhad et al., 2019; Mohammed and Duffuaa, 2020), energy and climate action (Forouli et al., 2019a; Forouli et al., 2019b; Van de Ven et al., 2019), energy planning (Hombach and Walther, 2015; Tartibu et al., 2015; Arancibia et al., 2016; Cambero and Sowlati, 2016; Cambero et al., 2016; Mohammadkhani et al., 2018; Rabbani et al., 2018; Sedighizadeh et al., 2018; Razm et al., 2019), waste management (Mavrotas et al., 2013; Mavrotas et al., 2015b; Inghels et al., 2016), investment portfolio analysis (Xidonas et al., 2011; Khalili-Damghani et al., 2012), transportation (Inghels et al., 2016; Xidonas et al., 2011), project selection (Khalili-Damghani et al., 2012; Mavrotas et al., 2015a), and network optimisation and planning (Schaeffer and Cruz-Reyes. 2016; Florios and Mavrotas, 2014; Oke and Siddiqui, 2015; Mousazedeh et al., 2018; Rahimi et al., 2019). AUGMECON-R, which is the most recent member of the AUGMECON family of methods, allows for easy and timely solution of very demanding (in terms of time and processing requirements) problems of numerous objective functions.

However, as the authors in (Nikas et al., 2022) present, there is a set of limitations in the current implementation of the AUGMECON-R algorithm. These are linked to both the employed optimisation algorithm and the use of the General Algebraic Modelling System (GAMS) for algorithm development and solution. The need to overcome these limitations has motivated the development of the AUGMECON-Py framework. First, the implementation of

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

the AUGMECON-R algorithm in an object-oriented language, such as Python, satisfies the need for dynamic memory allocation, which is critical for AUGMECON-R considering the—potentially unavailable—memory space required. Previous attempts at implementing augmented ε-constraint methods in Python (Wouter and Paterakis, 2021) are further enhanced, as far as the employed optimisation algorithm is concerned, with AUGMECON-Py additionally ordering the objective functions by value range in the external loops to ensure that no efficient solution is left outside the solution grid. Second, solving multi-objective optimisation problems typically entails the assessment of results against perturbations to input data (stochastic uncertainty) such as in the form of a Monte Carlo analysis. This, however, has hitherto been outside the scope and capabilities of the AUGMECON family of methods. AUGMECON-Py, thus, provides a conveniently compact tool, combining multi-objective optimisation analysis with uncertainty and robustness analysis, thereby avoiding the complexity of numerous cascading methods and code scripts.

Considering the above, the AUGMECON-Py framework implements an improved version of the AUGMECON-R algorithm in Python and extends it to a complete tool for multi-objective optimisation under uncertainty, with which the user can undemandingly interact to handle the inputs and represent/visualise the outputs of the problem. For user interaction, preparation of the input files is required for the definition of the optimisation problem parameters and constraints, as well as for the selection of a set of options necessary to parameterise the uncertainty analysis exercise and to visually represent results. For convenience, the set of code options that may be selected by the user are all incorporated within a dedicated script (file: user_options.py).

AUGMECON-Py is used in the following sections to perform portfolio analysis for the optimal allocation of COVID-19 recovery packages towards clean energy infrastructure in multiple countries, as well as a deep dive in the EU recovery context (Van de Ven et al. 2022; Koasidis et al., 2022).

1.2 Software description

1.2.1 Software architecture

The software architecture (Figure 1) is based on the three basic pillars of the desired functionality: the input and processing of data and the model creation (file: reader.py); the implementation of the extended version of the AUGMECON-R multi-objective optimisation algorithm (file: augmecon.py); and the solution of the optimisation model, either individually or iteratively. The latter additionally features Monte Carlo simulations in order to assess the robustness of the solutions, followed by the collection and presentation of solutions/results (file: utils.py).

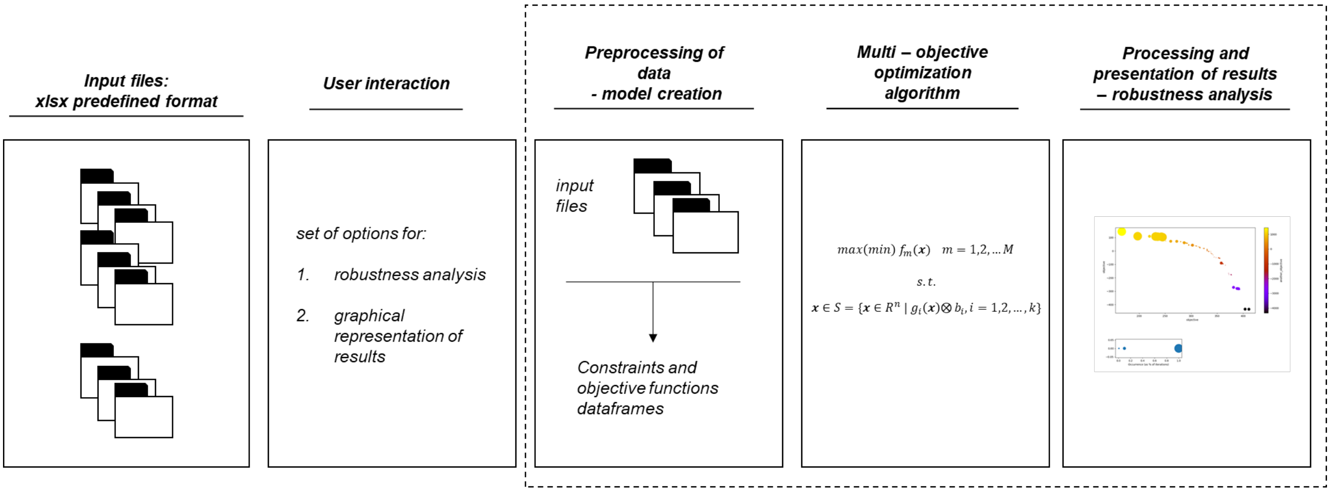


Figure 1: AUGMECON-Py architecture

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

1.2.2 Software functionalities

1.2.2.1 Pre-processing of data – model creation

The input data necessary to create the optimisation problem are provided by the user in xlsx spreadsheets in a predefined format, one for each constraint and one for each criterion/objective function.

In the sheets corresponding to the problem constraints, the upper left cell value represents the right-hand side of the constraint, and the rest of the sheet consists of a table showing the coefficients of the decision variables participating in the constraint. Decision variables corresponding to the same line in the table are considered mutually exclusive and subject to additional constraints, ensuring their mutual exclusion. The same rules apply for the spreadsheets corresponding to the objective functions, with the difference here being that the upper left cell of the latter is left empty. For an example of the input data sheets see Section 1.3.

The implementation proceeds by reading and validating the format of the spreadsheets, using the Python pandas library. In case of an error due to incorrect input, the program points to the exact file, line and type of the error. Next, the optimisation model is created, by adding the corresponding objective functions as well as the related constraints and coefficients. At this stage also lies the novelty of the present implementation, concerning the optimal execution of the optimisation algorithm, by ordering the objective functions by value range in the external loops to ensure that no efficient solution is left outside the solution grid. This is achieved via the following procedure: the data is read in a random order, and the payoff table and objective function ranges are calculated; the functions with the largest ranges are identified and the data is reordered, towards placing the objective functions with the larger ranges in the outer loops, and then read again. Then, the optimisation model is created using the Python pyomo library and, finally, the generated model running the optimisation is solved using the class named "MoipAugmeconR".

1.2.2.2 Construction of the multi-objective optimisation algorithm

The optimisation solution algorithm is implemented within the "MoipAugmeconR" class and consists of a set of sub-classes, each corresponding to a step of the optimisation process:

- Step 1: Creation of the payoff table (class: self.create_payoff_table) using lexicographic optimisation.
- Step 2: Conversion of the model corresponding to the optimisation problem to a model suitable for implementing AUGMECON-R (class: self.build_augmecon_problem).
- Step 3: Application of the solution process (class self.run_augmecon_r); the solution process is implemented by navigating on a step-by-step basis through the $\mathrm{N_2} \times \mathrm{N_3} \times \ldots \times \mathrm{N_p}$ grid, where $\mathrm{N_i}$ is the integer range of the objective function $\mathrm{f_i}$.
- Step 4: Getting Pareto optimal solutions, clearing duplicates, and building the exact Pareto front of the problem (class: self.display_pareto)

1.2.2.3 Processing and presentation of results – robustness analysis

As output, the software produces information on the optimal solutions in dedicated spreadsheets. In addition, the software provides the functionality of building the Pareto front for problems of N objective functions (here we indicatively provide the code for three objective functions), while enabling the assessment and representation of the robustness of the solutions, by repeatedly solving the optimisation problem considering % changes to the input parameters of the model.

As far as the interpretation of information within the output spreadsheets is concerned, each line of the sheet is

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

linked to an optimal solution and indicates the value of each objective function for the respective solution point, as well as each of the activated decision variables and its contribution to each objective function and constraint of the problem. When robustness analysis is applied, information on both the frequency of occurrence of the generated solutions, compared to the number of iterations of the uncertainty simulation, and the frequency of activation of each of the decision variables is also included within the spreadsheets. For graphical representation, the third dimension is represented by a respective colour scale, while the robustness of solutions is depicted through the size of the circle that represents each optimal solution.

1.3 Illustrative examples

In this section an illustrative example is discussed, aiming to showcase the main functions of the AUGMECON-Py framework while solving a multi-objective optimisation problem under uncertainty. The exact code for running the presented example can be found at the AUGMECON-Py repository. Here, a problem of selecting among the optimal combinations of several technology options under different subsidy levels is presented. This numerical example draws from data and the problem statement presented in [49] and aims to highlight the applicability and added value of AUGMECON-Py in a problem which is highly relevant for the selection of low-carbon technology investments. In particular, 100 mutually exclusive subsidy level options of eight technologies (decision variables) are examined. The example considers three objective functions related to sustainability and socioeconomic factors: 1) created jobs in the long term, 2) emissions reductions, and 3) created jobs in the short term. Each of the objective functions ($k, k = 1,2,3$) can be written as $maximise\ Z_k = \sum_{i=1}^{8}\sum_{j=1}^{100} Objective_k(i,j) * B(i,j)$, where $Objective_k(i,j)$ is the performance of the i_{th} technology under subsidisation j in achieving the goals set by objective function k. The binary variables Bi, j represent the selection of subsidisation j for technology i. The problem also consists of one constraint, with its right-hand side value being 26000 (upper left cell), representing the total available budget. Mathematically, this can be written as $\sum_{i=1}^{8}\sum_{j=1}^{100} Subsidy\ (i,j) * B(i,j) \leq 26000$.

The coefficients of the decision variables in the constraint and objective functions are inserted through xlsx worksheets as in Figure 2.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	26000	SubsidyLevel_1	SubsidyLevel_2	SubsidyLevel_3	SubsidyLevel_4	SubsidyLevel_5	SubsidyLevel_6	SubsidyLevel_7	SubsidyLevel_8	SubsidyLevel_9	SubsidyLevel_10	SubsidyLevel_11	SubsidyLevel_12	SubsidyLevel_13
2	Technology1	1964	2152	2340	2528	2716	2904	3092	3280	3468	3656	3844	4031	4230
3	Technology2	1528	1673	1818	1963	2108	2252	2397	2542	2687	2832	2977	3122	3273
4	Technology3	1679	1844	2010	2175	2341	2507	2672	2838	3003	3169	3334	3500	3679
5	Technology4	617	688	759	830	901	972	1042	1113	1184	1255	1326	1397	1487
6	Technology5	1464	1614	1764	1913	2063	2213	2363	2513	2663	2813	2963	3113	3282
7	Technology6	1708	1879	2050	2220	2391	2562	2733	2903	3074	3245	3416	3586	3774
8	Technology7	1433	1581	1728	1876	2024	2172	2319	2467	2615	2763	2911	3058	3226
9	Technology8	756	950	1144	1338	1532	1725	1919	2113	2307	2500	2694	2888	3082

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1		SubsidyLevel_1	SubsidyLevel_2	SubsidyLevel_3	SubsidyLevel_4	SubsidyLevel_5	SubsidyLevel_6	SubsidyLevel_7	SubsidyLevel_8	SubsidyLevel_9	SubsidyLevel_10	SubsidyLevel_11	SubsidyLevel_12	SubsidyLevel_13	SubsidyLevel_14
2	Technology1	39251	42965	46680	50394	54108	57822	61537	65251	68965	72679	76394	80108	83979	87850
3	Technology2	2151	2352	2552	2753	2954	3155	3355	3556	3757	3958	4158	4359	4565	4771
4	Technology3	11060	12138	13216	14294	15372	16449	17527	18605	19683	20761	21839	22917	24072	25227
5	Technology4	1137	1285	1432	1580	1727	1875	2022	2170	2317	2464	2612	2759	2963	3167
6	Technology5	2805	3103	3401	3699	3998	4296	4594	4893	5191	5489	5788	6086	6432	6778
7	Technology6	3810	4220	4630	5040	5450	5860	6270	6680	7090	7500	7910	8320	8798	9277
8	Technology7	-437	-436	-435	-434	-433	-432	-432	-431	-430	-429	-428	-427	-377	-326
9	Technology8	2701	3675	4648	5622	6595	7569	8542	9516	10490	11463	12437	13410	14384	15357

Figure 2: Illustrative example using the typical input worksheet for constraint (top) and objective function (bottom) decision variables coefficients

The user selects a set of options regarding the output files, the Monte Carlo simulations, and the graphical representation of results. Following the order representation shown in Figure 3, these options refer to:

- Output options: the name of the file; the value applied to the arbitrary coefficients of the payoff table's lowest values (in case of an unknown true nadir point); and the option to extract the graphical output and results analysis in xlsx file.
- Monte Carlo simulation options: the option to select the number of iterations as well as the standard deviation of the selected probability distribution. Here a normal distribution and its mean value are

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

selected.

- Graphical results: the name and scale of the axes, the graph title; the graph colour; for the case of Monte Carlo simulations, the option to select whether to present only the initial (i.e., without uncertainty) Pareto optimal solutions or all solutions (with colour opacity for those not included in the initial Pareto front), as well as whether to present those solutions above a certain level of robustness. In case all solutions are plotted (i.e., including those appearing in a Monte Carlo iteration but not in the original problem), the resulting figure should not be interpreted as a Pareto frontier, but rather as an aggregation of all independent Pareto frontiers across the iterations, when mapped on top of one another.

```
from utils import *

input_files = [
    'sample_input', ]

for file in input_files:
    opts = Options(
        filename=file,
        save_graph_output=True,
        save_excel_output=True,
        mc_iterations=5,  # > 1 for monte carlo
        mc_std_deviation_percentage=[.05, .05, .05, .05, .05, .05, .05, .05, .05, .05, .05, .05, .05, .05, .05, .05, ],
        #  .2 corresponds to std deviation equal to 20% of the mean value. only valid for iterations > 1.
        #  percentage is set by decision variable. order of decision variables same as order of lines in excel sheet
        name_graph_axes=['1st objective', '2nd objective', '3rd objective'],
        #  order of names is linked to the order of objectives in the input sheet.
        #  First name goes to 1st objective etc
        scale_graph_axes=[1, 1, 1],
        #  order of scales is linked to the order of objectives in the input sheet.
        #  First scale goes to 1st objective etc
        graph_title=f'{file}',
        graph_color='blue',
        nadir_undercut=.7,
        plot_all_output_solutions=False,
        #  for monte carlo iterations. 'False' plots only initial problem's solutions.
        #  'True' also prints the rest with opacity
        plot_cutoff=0.00,
        #  0.00 to 1.00: threshold for a solution's robustness, so that the solution appears in the plot.
    )
    run_iterations(opts)
```

Figure 3: Code example for the selection of user options

- Output worksheet, with information on the objective functions' values (columns B, C, D) within each optimal solution (column A), as well as on the participation of the decision variables in the constraints (columns F, G) and problem objectives (columns H – K) - in both absolute value (columns F, H, J) and percentage of total value (columns G, I, K)—see Figure 4.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

	A	B	C	D	E	F	G	H	I	J	K
1		second_objective	third_objective	first_objective		subsidies_constraint_abs	subsidies_constraint_%	second_objective_abs	second_objective_%	third_objective_abs	third_objective_%
2	solution 1	498400	432684	2986	Technology1-SubsidyLevel_87	21707	83	388151	78	412459	95
3	solution 2	498329	463739	2290	Technology1-SubsidyLevel_95	24074	93	426782	86	455197	98
4	solution 3	496765	467206	2130	Technology1-SubsidyLevel_96	24375	94	431668	87	460611	99
5	solution 4	451213	482264	12158	Technology1-SubsidyLevel_100	25577	98	451213	100	482264	100
6	solution 6	498233	455834	2459	Technology1-SubsidyLevel_93	23473	90	417010	84	444371	97
7	solution 8	496668	459300	2298	Technology1-SubsidyLevel_94	23773	91	421896	85	449784	98
8	solution 11	498135	447928	2626	Technology1-SubsidyLevel_91	22872	88	407237	82	433544	97
9	solution 13	496572	451394	2467	Technology1-SubsidyLevel_92	23172	89	412124	83	438957	97
10	solution 16	498039	440023	2795	Technology1-SubsidyLevel_89	22270	86	397465	80	422718	96
11	solution 17	496474	443488	2635	Technology1-SubsidyLevel_90	22571	87	402351	81	428131	97
12	solution 20	496607	435866	2815	Technology1-SubsidyLevel_88	21989	85	392808	79	417588	96
13	solution 23	496968	428529	3006	Technology1-SubsidyLevel_86	21425	82	383494	77	407330	95
14	solution 25	495535	424372	3026	Technology1-SubsidyLevel_85	21143	81	378836	76	402200	95
15	solution 27	494605	420388	3041	Technology1-SubsidyLevel_84	20862	80	374179	76	397071	94
16	solution 29	493674	416403	3055	Technology1-SubsidyLevel_83	20580	79	369522	75	391941	94
17	solution 31	492743	412418	3070	Technology1-SubsidyLevel_82	20298	78	364865	74	386812	94
18	solution 33	491813	408434	3084	Technology1-SubsidyLevel_81	20016	77	360208	73	381683	93
19	solution 35	490882	404449	3098	Technology1-SubsidyLevel_80	19735	76	355551	72	376553	93
20	solution 37	489951	400464	3112	Technology1-SubsidyLevel_79	19453	75	350894	72	371424	93
21	solution 39	489021	396480	3127	Technology1-SubsidyLevel_78	19171	74	346237	71	366295	92
22	solution 41	488297	392773	3148	Technology1-SubsidyLevel_77	18907	73	341787	70	361444	92
23	solution 43	487573	389067	3170	Technology1-SubsidyLevel_76	18643	72	337336	69	356593	92
24	solution 45	486849	385362	3192	Technology1-SubsidyLevel_75	18378	71	332886	68	351743	91
25	solution 47	478056	358274	3198	Technology1-SubsidyLevel_68	16529	64	301735	63	317788	89
26	solution 49	477333	354568	3219	Technology1-SubsidyLevel_67	16264	63	297285	62	312937	88
27	solution 52	448524	478135	12167	Technology1-SubsidyLevel_99	25277	97	446327	100	476850	100

Figure 4: Indicative output worksheet on the values of the objective functions and participation of decision variables

- In case of a Monte Carlo simulation, the generated worksheet presents information on both the frequency of occurrence of the generated solutions (sheet on the left) and the frequency of activation of each of the decision variables (sheet on the right)—see Figure 5. For example, information on the sheet on the left can be interpreted as follows: the first Pareto optimal solution appears 4 times across the Monte Carlo iterations (column A) and the selected decision variables corresponding to the examined optimal solution are "technology 1 on subsidy 99 – T1S99" and "technology 4 on subsidy 2 – T4S2" (column B). The optimal solution is part of the original problem (i.e., without uncertainty) (column C) and the values of the objective functions of the optimal solutions are shown in columns D – F. As 5 Monte Carlo iterations are conducted here, the examined optimal solution is deemed robust, appearing as optimal in 4 out of 5 runs (80%). For the decision variables of the examined optimal solution, the sheet on the left shows that "T1S99" appeared in five, and "T4S2" in nine, among the entire set of optimal solutions. Here, the most optimal and robust technology subsidisation option is technology 1 – subsidy level 88.

	A	B	C	D	E	F
1	Times of Occurrence	active variables	In Initial Problem	second_objective	third_objective	first_objective
2	4	Technology1-SubsidyLevel_99, Technology4-SubsidyLevel_2	1	448524	478135	12167
3	3	Technology1-SubsidyLevel_98, Technology4-SubsidyLevel_6	0	444676	473312	12079
4	3	Technology1-SubsidyLevel_100	1	451213	482264	12158
5	3	Technology1-SubsidyLevel_88, Technology3-SubsidyLevel_13	0	405217	441660	12073
6	3	Technology1-SubsidyLevel_88, Technology3-SubsidyLevel_14	0	405797	442815	12150
7	3	Technology1-SubsidyLevel_97, Technology8-SubsidyLevel_3	0	495202	470672	1970
8	3	Technology1-SubsidyLevel_91, Technology8-SubsidyLevel_13	1	498135	447928	2626
9	3	Technology1-SubsidyLevel_88, Technology8-SubsidyLevel_17	1	496607	435866	2815
10	3	Technology1-SubsidyLevel_88, Technology3-SubsidyLevel_11, Technology4-SubsidyLevel_1	0	406023	440564	12061
11	3	Technology1-SubsidyLevel_97, Technology4-SubsidyLevel_10	0	440828	468488	11992
12	2	Technology1-SubsidyLevel_98, Technology8-SubsidyLevel_2	0	496863	475112	1961
13	2	Technology1-SubsidyLevel_96, Technology4-SubsidyLevel_14	0	437190	463778	11907
14	2	Technology1-SubsidyLevel_92, Technology3-SubsidyLevel_4, Technology4-SubsidyLevel_1	0	421478	454388	12114
15	2	Technology1-SubsidyLevel_95, Technology8-SubsidyLevel_6	0	495104	462766	2138
	2	Technology1-SubsidyLevel_88, Technology3-SubsidyLevel_10,	0	405990	439781	12016

	A	B
1	Times of Occurrence	Tech
2	50	Technology1-SubsidyLevel_88
3	22	Technology1-SubsidyLevel_92
4	14	Technology1-SubsidyLevel_96
5	13	Technology1-SubsidyLevel_89
6	13	Technology1-SubsidyLevel_83
7	12	Technology3-SubsidyLevel_1
8	10	Technology1-SubsidyLevel_90
9	9	Technology1-SubsidyLevel_98
10	9	Technology4-SubsidyLevel_2
11	9	Technology4-SubsidyLevel_6
12	9	Technology4-SubsidyLevel_5
13	9	Technology4-SubsidyLevel_1
14	9	Technology1-SubsidyLevel_97
15	9	Technology8-SubsidyLevel_13
16	8	Technology3-SubsidyLevel_2
17	8	Technology8-SubsidyLevel_6
18	8	Technology3-SubsidyLevel_4
19	8	Technology1-SubsidyLevel_78
20	7	Technology8-SubsidyLevel_17
21	7	Technology4-SubsidyLevel_3
22	6	Technology4-SubsidyLevel_8
23	6	Technology3-SubsidyLevel_6
24	6	Technology3-SubsidyLevel_10
25	6	Technology3-SubsidyLevel_5
26	5	Technology8-SubsidyLevel_3
27	5	Technology1-SubsidyLevel_99

Figure 5: Indicative output worksheets in case of Monte Carlo simulations

- Graphical results present the Pareto front of the exact optimal solutions and can incorporate robustness information—see Figure 6. Each of the solutions (points) in the graph represent an optimal solution, which

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

consists of a set of decision variables (technology options under different subsidy levels). The active decision variables in each solution are presented in column B (Figure 5). Each solution has a specific contribution in each of the objective functions of the problem, which are the values of axes x, y and the colour scale (exact values are shown in columns D-F, Figure 5). The size of the dot in each solution is relevant to the robustness of the optimal solution. The calculation of the robustness is based on the information shown in column A (Figure 5) and its value is included in the graph's legend (Figure 6).

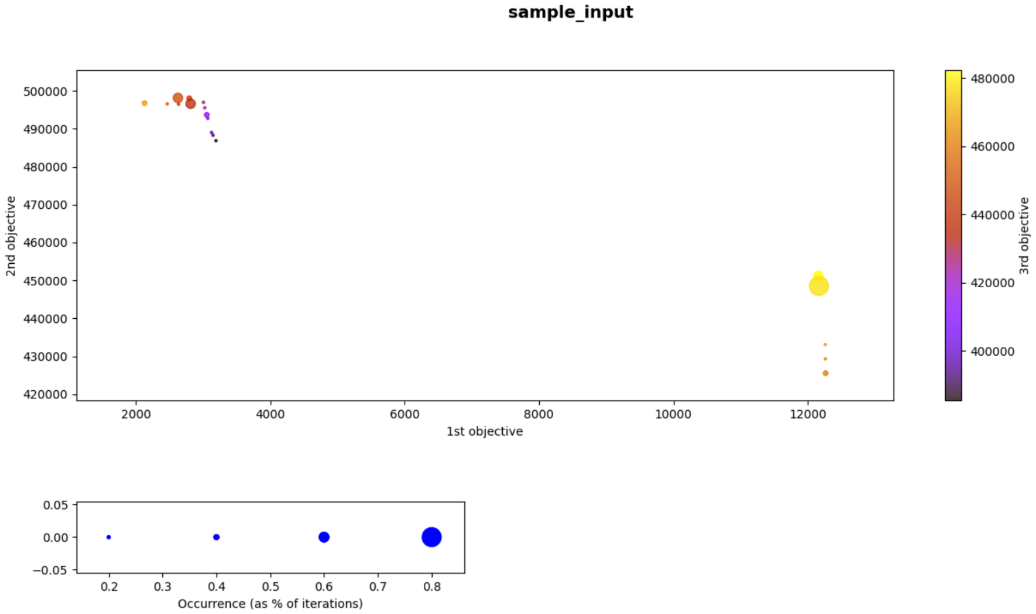


Figure 6: Indicative graphical output with robustness information

1.4 Impact

The novelty of the presented AUGMECON-Py software lies in the integration of a powerful optimisation algorithm with a stochastic uncertainty analysis methodology to maximise robustness, by iteratively solving the optimisation problem without any further requirements for cascading the original optimisation model with different methods or tools (e.g., (Fourouli et al., 2019a; Van de Ven et al., 2019)). This feature of the AUGMECON-Py framework can help answer challenging research questions, where evaluation under uncertain inputs is required. Examples of works, where assessment of the robustness of solutions generated by the AUGMECON optimisation algorithm is needed, *inter alia* include (Fourouli et al., 2019a; Forouli et al., 2019b; Van de Ven et al., 2019; Forouli et al., 2020). Also, the model's capacity to solve integer problems fast allows for the transformation of any non-integer problem to an integer one, expanding the algorithm's field of application to non-integer multi-objective problems. Compared to previous model versions, the new Python implementation allows to more easily specify, parameterise, run, and evaluate the outcomes of the optimisation (whether assessed against stochastic uncertainty or not), by making use of the variety of libraries offered in Python for data pre- and post-processing and visualising results. Easy model use and flexibility of parameterisation render advanced programming or optimisation knowledge/expertise unnecessary, contributing to further expansion and exploitation of the model.

To showcase its value, the new optimisation algorithm is employed for indicative problems presented and discussed by Nikas et al. (2022), and its performance is compared against the performance of the AUGMECON-R algorithm, which is implemented in GAMS. Both algorithms are run using an Intel® Core™ i7 – 1065G7 CPU @1.30 GHz, 1498 MHz processor and a 12GB RAM memory, to solve the problems. Running the model requires a license for an MIP solver—here, Gurobi 9.1.1 is used (academic license). The selected problems for evaluation include a

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

'4kp40 uncorrelated', a '4kp50 binary', a '5kp40', and a '6kp50' problem, which stand for/correspond to selected knapsack problems of four, four, five, and six objective functions (and constraints) and of 40, 50, 40, and 50 decision variables, respectively. In all problems, the actual nadir points are considered known *a priori*. Uncorrelated problems assume no correlation between elements of the objective function coefficient matrix and those of the constraint coefficient matrix. Details on the problems' structure and coefficients can be found in Nikas et al. (2022).

Table 1 summarises the performance differences between AUGMECON-R and AUGMECON-Py for all problems.

Table 1: Performance comparison between AUGMECON-R (R) and AUGMECON-Py (Py) with the true nadir points

	4kp40 uncorrelated		4kp50 binary		5kp40		6kp50 binary	
	R	Py	R	Py	R	Py	R	Py
CPU Time	39 min 38sec	14 min 23 sec	25 sec	2 sec	158 sec	35 sec	19 min 01 sec	4 min 32 sec
Models solved	10855	11094	176	169	618	621	6269	5797
Infeasibilities	359	359	28	28	114	114	863	863
Duplicate solutions	7324	7562	102	95	378	381	4563	4091
Dominated solutions	0	0	0	0	0	0	0	0
Solutions in the Pareto front	3172	3172	46	46	126	126	843	843

These findings indicate that AUGMECON-Py has the capacity to timely solve time-intensive, complex problems, ensuring accuracy and robustness of results and securing that no solution is missed. Solution times are dependent on the solvers' performance, as well as on the details/specifications of the problem. Nevertheless, from Table 1 it is evident that the presented implementation in Python is about three times faster for the 4kp40 uncorrelated problem and more than ten times faster for the 4kp40 binary problem. For the 5kp40 and 6kp50 problems AUGMECON-Py is more than four times faster for both problems. These differences are particularly important when the robustness of the optimisation results needs to be assessed, where—due to the large number of variables and repetitive Monte Carlo iterations—the increased time requirements discourage the user from analysing the results and render solving in the previous GAMS implementation of the method practically impossible.

1.5 Conclusions

This work presents the implementation of AUGMECON-Py, a complete tool for multi-objective optimisation under uncertainty. Within this framework, large and complex optimisation problems can be solved accurately, securing that no solution is missed and allowing to assess the robustness of solutions. AUGMECON-Py is based on the AUGMECON-R algorithm, a robust augmented ε-constraint method for solving multi-objective linear programming problems: AUGMECON-Py ports this algorithm in Python and extends its functionalities/benefits. Within the heart of the AUGMECON-Py framework lies the implementation of an uncertainty analysis methodology, which is embedded as additional feature to the optimisation process. From a user interaction perspective and compared to AUGMECON-R implemented in GAMS, the Python implementation offers a diversity of additional libraries, and better opportunities for data pre- and post-processing as well as management and visualisation of results. This way, the user can run the model under different scenarios by flexibly altering the model's input data and choose between different data output formats to analyse the results. AUGMECON-Py has already been used successfully to support low-carbon investment decisions (van de Ven et al., 2022) and can be further used in fields where stochastic uncertainty is significant. Future implementations of the algorithm can focus on implementing parallelisation methods (i.e., multiprocessing, multithreading) to further increase the solving speed of the algorithm while retaining the current levels of software usability. In addition, the creation of a

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

graphical user interface must be considered, to further facilitate the interaction with the users and allow them to easily define preferences regarding the creation of the output files, the execution of MC simulations, and the graphical representation of results.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

2 Different shades of green: how COVID-19 green recovery packages benefit climate targets and green job growth among major economies

This section has been published in One Earth:

- van de Ven, D. J., Nikas, A., Koasidis, K., Forouli, A., Cassetti, G., Chiodi, A., ... & Gambhir, A. (2022). COVID-19 recovery packages can benefit climate targets and clean energy jobs, but scale of impacts and optimal investment portfolios differ among major economies. *One Earth, 5*(9), 1042-1054.

2.1 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 (Nicola et al., 2020), including for the labour market. Indicatively about 1.8 million jobs had been lost in the EU between September 2019 and September 2020 (Eurostat, 2020b), while early estimates in the US foresaw a loss of about 20 million jobs (Coibion et al., 2020), with expectations for a lagging employment recovery (IMF, 2021). Narrowing down to the energy sector, 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 (IEA, 2020). Notably, renewable energy projects have been impacted worldwide with considerable employment implications, resulting from for example solar PV and wind turbine material supply chain disruptions from China, renewable energy technology suppliers placing staff on furlough (IRENA, 2020b; Sovacool et al., 2020). It has been estimated that almost 600,000 clean energy jobs were lost in the USA over the course of 2020, more than twice the total clean energy jobs gained in the preceding three years (Chen et al., 2022). 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 (Hepburn et al., 2020; Andrijevic et al., 2020). Despite a relatively small chunk of global recovery spending being channelled towards clean energy-related projects (IEA, 2021b), 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 (Jaeger et al., 2021).

In literature, there are positive indications that a transition from fossils to renewables typically creates net jobs (Markandya et al., 2016), after accounting for workforce redistribution among sectors (Stoll and Mehling, 2020; Wang et al., 2020; Ju et al., 2022). Recent work has showcased large employment gains from a complete shift to a fully-renewable power sector (Ram et al., 2020), even more so for combined efforts in heat, transport, and desalination (Ram et al., 2022), while broader Paris-compliant mitigation pathways show similar findings for energy-sector employment (Pai et al., 2021). 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 (Shan et al., 2021) and macroeconomic indicators (Lahcen et al., 2020), as well as its medium-to-long-term implications for the energy transition (Kikstra et al., 2021) and the goals of the Paris Agreement (Keramidas et al., 2021). Regarding the estimation on the potential outcomes of post-pandemic green recovery, modelling efforts have shed light on the gap between pledged recovery packages and the Paris-compliant investment needs (Rochedo et al., 2021), as well as the impacts of possible green ways forward (Dafnomilis et al., 2022; Pollitt et al., 2021). However, of these studies, only one considered employment implications (Pollitt et al., 2021) from a macroeconometric perspective and, like similar macroeconomic modelling

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

studies, (Spijker et al., 2020; Fujimori et al., 2020; Fragkos et al., 2018; Distelkamp and Meyer, 2019; D'Alessandro et al., 2020) provided only aggregated economy-wide insights. There is evidence from the Global Financial Crisis of 2008-9 that renewable energy stimulus has a higher jobs impact than other stimulus measures (Hepburn et al., 2020). But 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.

Building, on the EU analysis presented in D4.2, here we contribute to this debate by studying the optimal allocation of announced recovery packages towards clean energy projects in six major emitters (Canada, China, EU, India, Japan, and the USA, 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 (Sognnaes et al., 2021). To further improve the accuracy and robustness of the estimates compared to D4.2, our adopted method overcomes three methodological associated challenges. First, acknowledging IAM analyses are highly dependent on the model used and the underlying economic-engineering approach (García-García et al., 2020; Zerrahn, 2017), we employ a diverse ensemble of three well-established IAMs (GCAM-PR, TIAM-Grantham, GEMINI-E3) to understand how each modelling approach affects outcomes. Second, building on recent efforts (Fragkos and Paroussos, 2018; Malik et al., 2021), we link these IAMs with the most up to date employment factor databases that provide the necessary granularity for targeted technology interventions (Patrizio et al., 2018), to address criticisms on model representation of energy–economy feedbacks (Keppo et al., 2021) and employment considerations (Ciarli and Savona, 2019). Third, since IAMs typically only optimise costs in respect to emissions constraints, we integrate the models with portfolio analysis (Forouli et al., 2020), to economically integrate and simultaneously optimise emissions cuts with both near- and long-term employment gains (expanding on the single employment objective in D4.2), considering that the purpose of the recovery package is to be spent as quickly as possible. 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 to 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 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 USA 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.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

2.2 Results

2.2.1 Method summary

Financial support for clean energy technologies may have an impact on GHG emissions and energy-sector jobs through several channels. Due to the nature of clean energy technologies, which are usually more labour-intensive (Pai et al., 2021; Rutovitz et al., 2015) and by definition less carbon-intensive in comparison to 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 (Wirl, 2000). 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 (Xia et al., 2020). Combining the two previous examples, there may also be a temporal inefficiency—e.g., if short-term financial support pushes a technology´s capacity towards 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 7), 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 9 clean technologies on top of region-specific (pre-pandemic) energy and climate policies (Sognnaer et al., 2021), 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 vs 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, optimising over emissions reduction and employment creation within a pre-announced green COVID-19 recovery budget for each region (Forouli et al., 2020). 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.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

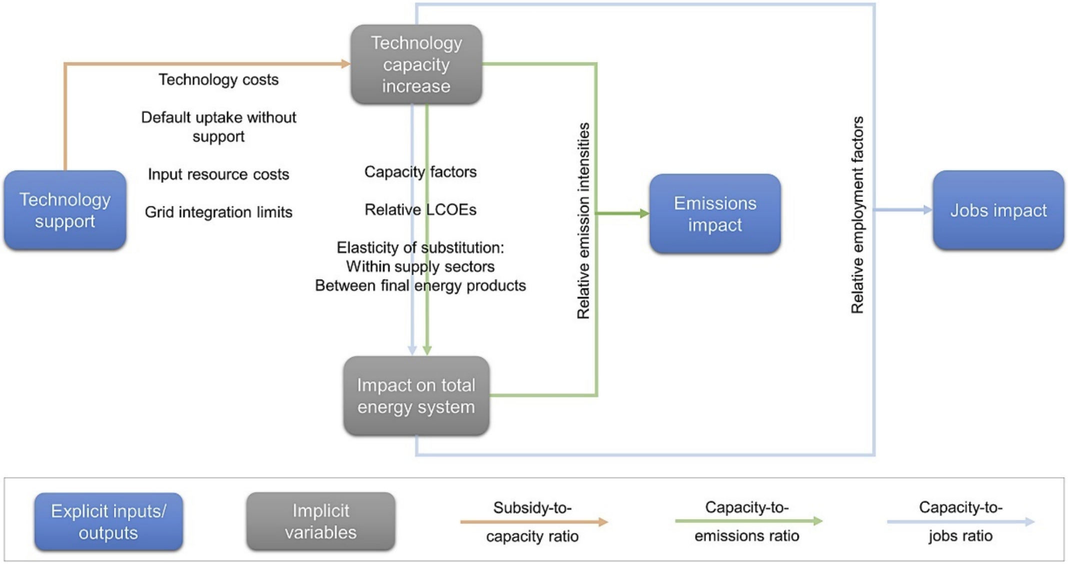


Figure 7: Schematic overview of how technology support may affect emissions and employment

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 impact 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 LCOEs and the elasticity of substitution.

2.2.2 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 8), confirming the positive synergy between employment and clean energy transition found in the literature (Markandya et al., 2016; Stoll and Mehling, 2020; Wang et al., 2020; Ram et al., 2020; Pai et al., 2021). 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 maximising 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.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

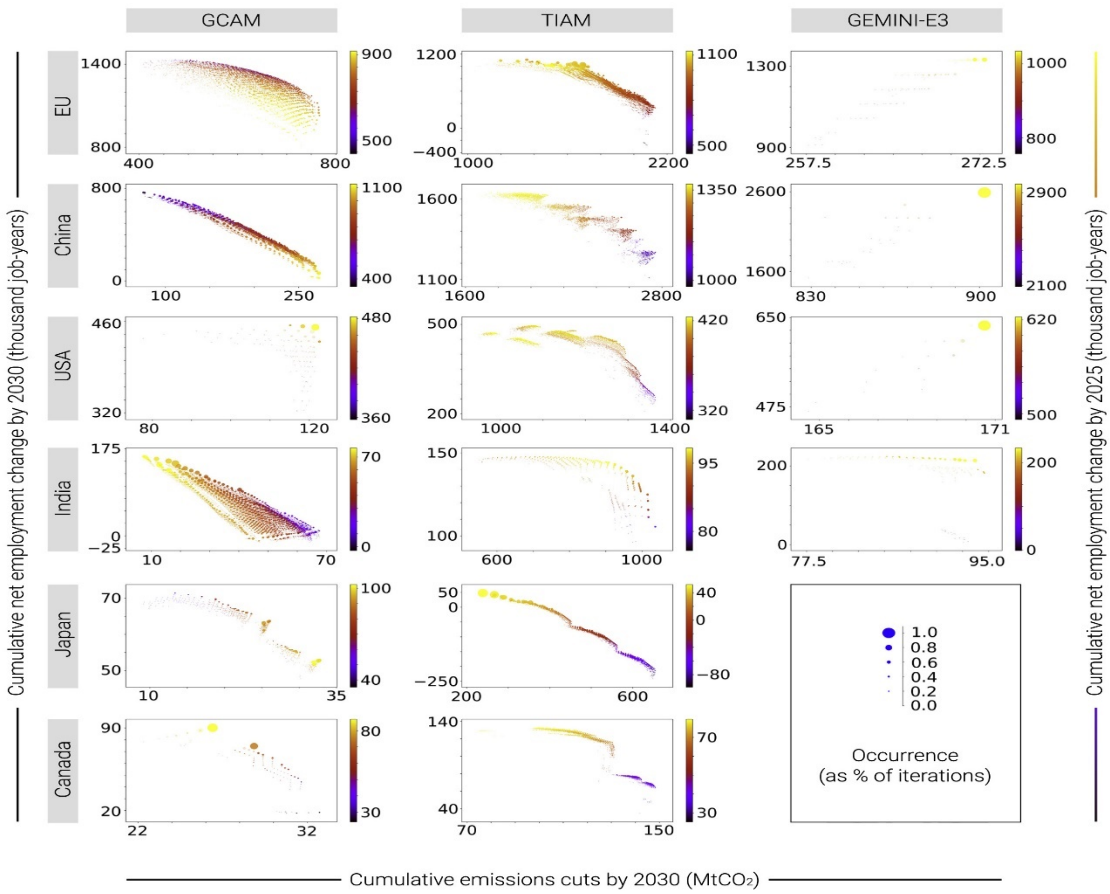


Figure 8: Scatterplots including all Pareto-optimal scenarios in each combination of models and countries, based on three objectives

The x-axis represents cumulative emissions cuts by 2030, y-axis cumulative net employment change by 2030, and colour 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 CO2 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 labelled Data S5-D20.

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 2) 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 ~2ºC future (IEA, 2021a; Climate Action Tracker, 2021). The relatively small green recovery packages in the USA 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 USA, India and Canada, while in fact the USA and India experienced the highest absolute decrease in employment among the countries analysed in this study (IMF, 2021 ;Vyas, 2022). For Japan, inter-model differences are too big to draw a conclusion.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Table 2: Average outcomes and technology portfolios per country-model combination

		Outcome on each objective (absolute terms) [a]			Objectives relative to targets			Technology portfolio mix [a] % of subsidy budget								
Region (green recovery budget)	*Model*	*Accumulated CO_2 abatement (Mn 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*	*Geo-thermal*	*Nuclear*	*Biomass*	*Hydro*	*Bio-fuels*
EU	**GCAM**	645	1238	804	29.50%	9.20%	11.94%	0.00%	0.00%	53.40%	12.80%	0.00%	15.30%	0.00%	*NA*	18.60%
(96 b$)	**TIAM**	1839	677	948	48.30%	5.03%	14.08%	78.80%	4.20%	7.20%	2.30%	0.00%	0.20%	5.70%	1.50%	*NA*
	GEMINI-E3	269	1249	977	6.70%	9.28%	14.51%	74.8%		16.3% [e]		*NA*	*NA*	8.90%	*NA*	*NA*
China	**GCAM**	197	403	780	5.40%	3.82%	14.78%	46.70%	0.00%	19.40%	0.90%	0.30%	31.70%	0.80%	*NA*	0.20%
(60 b$)	**TIAM**	2257	1490	1262	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	2280	2712	*NA*	21.62%	51.43%	94.6% [d]		2.1% [e]		*NA*	*NA*	3.20%	*NA*	*NA*
USA	**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%
(26 b$)	**TIAM**	1164	438	405	12.20%	1.58%	2.91%	68.70%	0.50%	16.50%	2.60%	7.80%	0.00%	0.50%	3.40%	*NA*
	GEMINI-E3	169	590	591	1.80%	2.12%	4.26%	91.6% [d]		0% [e]		*NA*	*NA*	8.40%	*NA*	*NA*
India	**GCAM**	43	56	47	1.20%	0.19%	0.33%	30.10%	0.00%	30.00%	1.70%	0.20%	33.30%	0.10%	*NA*	4.60%
(9 b$)	**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	**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%
(6 b$)	**TIAM**	503	-96	-19	36.60%	-3.60%	-1.40%	57.20%	0.00%	4.50%	2.30%	23.20%	6.50%	3.60%	2.70%	*NA*
Canada	**GCAM**	29	62	63	4.00%	1.60%	3.20%	58.90%	0.00%	40.00%	0.30%	0.10%	0.00%	0.60%	*NA*	0.00%
(3 b$)	**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*

[a] Numbers are weighted averages of all portfolios (e.g., dots) in Figure 8. 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 USA, -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 labour 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 divide 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.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

2.2.3 Investment portfolios for optimised outcomes

A key policy question from this study is on how to distribute recovery funds over different clean technologies to achieve certain objectives. Overall, we find that solar PV, which has become highly cost-competitive over the past decade and still relatively labour-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 optimising one objective or another (Figure 9). For example, results from GCAM-PR indicate a considerable role (>20% of the recovery budget) for offshore wind and biofuels in maximising 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 USA, to CSP in India and to biomass in Canada, in line with potentials suggested in the literature (Hymans, 2021; Duggal et al., 2022; Purohit et al., 2013). Hydroelectricity (TIAM-Grantham) and biomass (GEMINI-E3) play an important role in maximising energy jobs in India in the longer run (for potentials see (Chaurasiya et al., 2013; Hiloidhari et al., 2019)). This highlights the value of modelling these recovery packages on top of pre-modelled, 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.

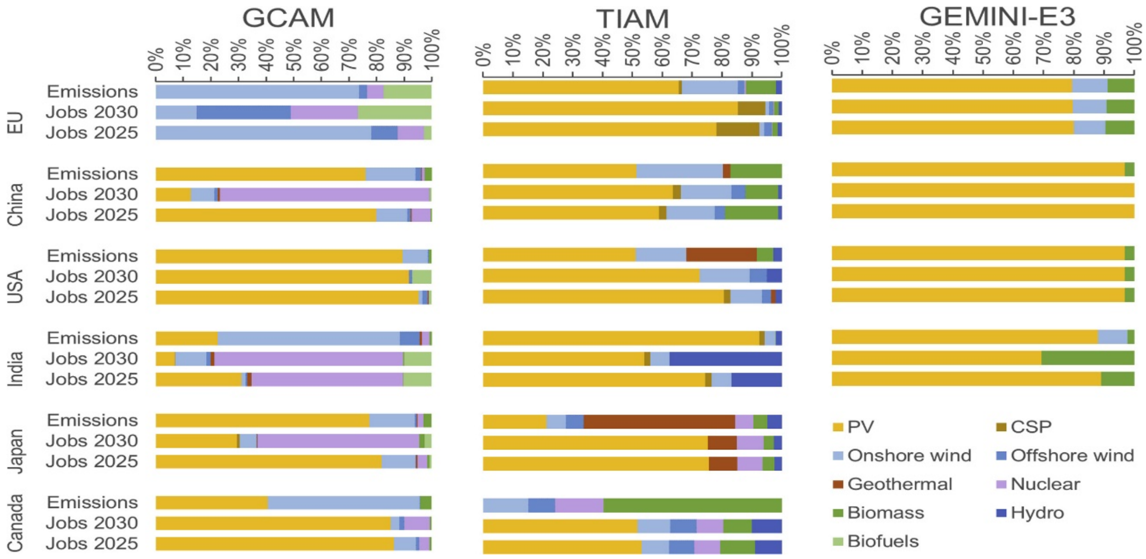


Figure 9: Technology mix of portfolios maximizing each objective per model-country combination

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.

2.2.4 Role of model diversity

Despite soft harmonisation of techno-economic assumptions and applied pre-pandemic energy and climate policies (Giarola et al., 2021), outcomes from the three employed models differ substantially: the average outcome differences of the same subsidy package are up to ten-fold for emissions (China, USA) and six-fold for employment (China), while there are also pronounced differences in the optimal technology portfolios (Table 2). There are 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 7) for each model-country-technology combination, the influence of model behaviour on outcomes

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

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 A2.2 in Appendix 2). 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 (Clarke and Edmonds, 1993) 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 optimisation 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 USA, biomass in China and the USA). 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 towards earlier support. Meanwhile, the model intents to optimise 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 (coming 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 9), avoiding trade-offs between different objectives when selecting technology portfolios (Figure 8)."

The other two ratios measure the emissions and employment impact of each additional unit of technology capacity (Figure A2.3 and A2.4 in Appendix, respectively). As such, they summarise 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 labour-intensive alternatives and may increase the demand for energy as a whole through a rebound effect induced by lower electricity prices. Figure A2.3 (in Appendix 2) 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 fuelled 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 labour-intensive technologies per unit of support (see Figure A2.4 in Appendix 2).

Another important difference among the models is that TIAM-Grantham applies inter-temporal optimisation with perfect foresight towards future modelling periods, whereas GCAM-PR and GEMINI-E3 are recursive-dynamic

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

models, which means that each modelling period solves independently without knowledge on future costs and policies. Given that the modelled recovery packages affect two modelling periods (2025 and 2030, the latter due to construction times; see Table 4), this limited foresight may cause somewhat unexpected model behaviour 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 modelling the impact of pre-announced financial support packages over time (Heuberger et al., 2018). Apart from the inter-temporal optimisation 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 heterogenous 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 (Guivarch et al., 2022).

2.3 Discussion

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

In terms of emissions, progress in emissions abatement falls short of 2ºC-compatible pathways, contradicting effective green recovery IAM scenarios published before the extent of green recovery packages was announced (Andrijevic et al., 2020; Pollitt et al., 2021; Forster et al., 2021). 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 (Andrijevic et al., 2020; Bertram et al., 2021). 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 (Tanaka et al., 2022). We show and clarify how structural differences in the way different models operate (economic theories, foundations, principles, etc.), and in turn the interacting effect of existing emission reduction policies, can yield vast differences

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

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. (2021)), while the absolute impact is hard to compare due to strong differences in assumed recovery package sizes. A caveat in the employed modelling approach is the use of employment factors to estimate net energy sector jobs, following various recent literature (Ram et al., 2020; Ram et al., 2022; Pai et al., 2021), an approach potentially disregarding wage dynamics and longer run impacts, assuming perfect labour 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 labour productivity (IRENA, 2020a) and automation (Josten and Lordan, 2022). Also, renewables-driven net job gains in the energy sector can be offset by job losses in other sectors if GDP is negatively effected (Fragkos and Fragkiadakis, 2022). Logically, in a full-employment economy model that doesn't consider voluntary and involuntary unemployment, net job gains in one sector need to be drawn from other sectors, but full employment is not very realistic assumption for both developed as well as developing countries. Nevertheless, we opted to use employment factors as we analyse economic recovery packages, of which their explicit purpose is to create employment in a non-full-employment market. Besides, not all three models can obtain labour market results, rendering employment factors the most straightforward way to harmonise the job creation estimate across all modelling 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 policy-makers in the light of economic crisis recovery, but we do fully acknowledge that policy-maker objectives are heterogenous 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 (European Parliament, 2021; CRS, 2021), affecting costs of PV and wind projects throughout the world by 16-70% and 10-25%, respectively (IEA, 2021c). 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 (Nikas et al., 2022c).

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 (Ram et al., 2022; Pai et al., 2021) as well as empirical evidence in the EU (Makrandya et al., 2016). 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 (Andrijevic et al., 2020). Since an important requisite for green stimulus packages to have a beneficiary 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, utilising such crises to achieve the green transformations required for reducing emissions (Cazcarro et al., 2022). For example, the relatively high

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

impact of the EU´s recovery packages compared to those of, e.g., the USA 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 prioritised 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 beneficiary for both objectives rather than inflationary. The use of modelling tools that are well-calibrated for the focus region, can be instrumental in weighting out the most robust response to future crises (Peng et al., 2021).

2.4 Methods

2.4.1 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-optimisation 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-optimisation basis, whereby all consequences of technology deployments, fuel extraction, and energy price changes over the entire time horizon are considered when minimising 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 3. More information on the three models, including a detailed summary and their economic rationale, is provided in the I^{2}AM PARIS platform (https://www.i2am-paris.eu).

Table 3: 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	Geothermal	Nuclear	Biomass	Hydropower	Biofuels
TIAM-Grantham	Partial equilibrium	Inter-temporal optimisation	Winner-takes-it-all	Flexible capacity factors	✓	✓	✓	✓	✓	✓	✓	✓	
GCAM-PR	Partial equilibrium	Recursive dynamic	Logit choice	Constant capacity factors	✓	✓	✓	✓	✓	✓	✓		✓

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

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*

2.4.2 Scenario Protocol

Before running the numerous subsidy scenarios for different technologies, a baseline was defined to 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. (2021), which for the EU is further detailed in Nikas et al. (2021a), 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 modelled 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 RES share) or tax (e.g., the EU 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 USA). Canada and Japan were not modelled 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 subsidisation (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 subsidised (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 are given 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 4 shows for each technology the approximate pre-calculated shares of the subsidised output that would come online in either the 2021-2025 period or the 2026-2030 period (due to construction delay).

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Table 4: 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***		***Subsidisation 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

2.4.3 Budget selection

For the EU, the Recovery and Resilience Facility (RRF) is the largest component of the NextGenerationEU programme, 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 (i) the EUR 75 billion of the RRF's green pillar, which is expected to be channelled into clean energy projects on the selected technologies, excluding related infrastructure investments (e.g., storage) (EY, 2020), and adding to that (ii) EUR 5 billion from the UK fiscal plan (HM Government, 2020), 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 prioritised for investment may lead to the budget flowing towards conventional energy projects (Gosene and Jotzo, 2020). 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 analysed here (The New York Times, 2020), 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 are allocated towards energy (Observer Research Foundation, 2021). 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 (Government of Canada, 2021) and USD 19.2 billion (IISD, 2020) 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 towards the technologies of interest for this study). For Canada, drawing from the "Healthy Environment and a Healthy Economy" plan (Environment and Climate Change Canada, 2021) which is part of the total announced budget, and which implicitly ties funds oriented towards green projects in the short term with the

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

COVID-19 recovery, an amount of USD 3 billion was selected based on the share allocated for low-carbon power generation.

2.4.4 Employment factors

The level of employment is presented as a net-difference compared to the current policy scenario, as net employment is deemed more constructive in terms of job variations brought about by a transition (García-García et al., 2020).

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 (Malik et al., 2021). 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 labelled Data S1-S4 that can be found in https://doi.org/10.5281/zenodo.6998390, includes 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. (2015), a comprehensive database commonly employed in relevant modelling analyses (e.g., (Fragkos and Paroussos, 2018; Ram et al., 2020)).

For fossil fuels, the values were drawn from Pai et al. (2021), building on Rutovitz et al.(2015) but including regional disaggregation of fossil fuel factors.

Although the time horizon of the analysis is limited to 2030, rendering 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 (Ram et al., 2020). Technology costs (e.g., CAPEX, OPEX) are harmonised across the three models following the harmonisation protocol established in Giarola et al (2021).

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 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 in https://doi.org/10.5281/zenodo.6998390, labelled Data S1-S4.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

2.4.5 Portfolio analysis

IAM results feed into a multi-objective optimisation model, with a view to maximising the returns of the assumed 'green' part of COVID-19 recovery fiscal programs, expected to be allocated towards the ten technologies considered (Table 3), 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 modelling outputs, this integration of the IAMs with a portfolio analysis model allows to consider additional objectives (e.g., employment), which are typically outside the capabilities and cost-optimisation solution scope of IAMs (including this study's modelling 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 maximise immediate returns on recovery funds spent in the next five 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 maximising new employment gains by the end of the decade. In the optimisation problem, the input of the three objectives is considered as a net-difference between each scenario (subsidisation on one technology) and the baseline. Based on the modelling 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 optimise emissions cuts by 2030, employment gains by 2025, and employment gains by 2030 simultaneously. This can be summarised in equations (1) and (2):

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

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

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 optimisation problem, representing the amount of subsidy spent on technology i (i is based on the technology subsidisation capabilities of each model; see Table 3).

The optimisation process is based on an open-source (Python) implementation of the AUGMECON-R algorithm (Nikas et al., 2022a), which is based on the ε-constraint family of optimisation methods, with the addition of a lexicographic optimisation 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 towards 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 (Mavrotas, 2009). As such, because of the lexicographic solution mechanism, any identified trade-off among different

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

objectives derives directly from the payoff tables and the solution and is not an arbitrary choice made by the modeller (i.e., via scaling). The goal of the employed optimisation 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 as Pareto-optimal solutions; it should be noted that Pareto optimality is always problem-specific.

Finally, to increase confidence in the resulting optimal technological subsidisation 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 optimisation problem, carried out in a ±5% range following a normal distribution (with a mean value the model results and a ±5% standard deviation), in an approach similar to Forouli et al. (2020). Considering the complexity of the optimisation 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 iterations and observing whether it produced significant differences with the 1,000-iteration-run. Until the level of 100 iterations, differences were found negligible, hence we continued with this number to optimise between outcome robustness and computing time.

We define 'robustness' as the number of times a subsidisation 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 2) 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.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

3 Towards a green recovery in the EU: Aligning further emissions reductions with short- and long-term energy-sector employment gains

This section has been published in Energy Policy:

- Koasidis, K., Nikas, A., van de Ven, D. J., Xexakis, G., Forouli, A., Shivika, M., Gambhir, A., Koutsellis, T., & Doukas, H. (2022). Towards a green recovery in the EU: Aligning further emissions reductions with short- and long-term energy-sector employment gains. *Energy Policy*, in press.

Key results and policy recommendations presented in this chapter, form the basis of the PARIS REINFORCE contribution to the COP26 European Commission's Policy Publication, "Climate Action in the Post-COVID-19 World":

- Nikas, A., van de Ven, D. J., Koasidis, K., Forouli, A., Shivika, M., Gambhir, A., & Doukas, H. (2022). Investigating Optimal Allocations for Green Recovery Funds. In *Climate Action in the Post-COVID-19 World*. European Commission

3.1 Introduction

As discussed in Section 2, the EU has mobilised financial resources to assist Member States' economic recovery as part of the NextGenerationEU programme, and specifically the Recovery and Resilience Facility (RRF). Through these instruments, the EU aims to provide additional financial support to Member States and fund recovery-oriented investments in the near term (European Commission, 2020a). To jointly address the socio-economic impacts of the health and climate crises, Member States' national recovery and resilience plans should allocate at least 37% in support of a green transition and include investments towards tackling climate change. Among the overarching objectives of the recovery and resilience plans is to support the sectoral integration of 40% of the 500GW of renewable energy that is aimed to be installed by 2030, as part of the EU's path to net-zero (European Commission, 2020b), which will help the EU realise its updated pledges as part of the EU Green Deal.

The aim of the fiscal package as a whole is the recovery of a flourishing and healthy economic system from a broad perspective, with the goal to improve performance on economy-wide indicators such as GDP, imports, and exports. However, considering that the COVID-19 pandemic had a major negative impact on labour markets around the world, a key goal of this recovery package lies in job creation. The labour market in the European Union (EU) has taken a considerable blow. From a low point of 6.4% in March 2020, harmonised (seasonally adjusted) unemployment saw a rise to 7.8% in August 2020 (Eurostat, 2022), which corresponds to an equivalent of 2.5 million jobs lost within a period of five months. Although employment rates appear to return to pre-pandemic levels as of late 2021, the labour market is far from a full recovery, which is expected to lag behind any 'return to normal' (IMF, 2021). First, this sharp increase in unemployment disrupted a seven-year period of an almost steady decrease, a trend that might have continued in the absence of COVID-19. Second, the nature of employment itself has changed as a result of the pandemic, including remote/hybrid working, reduced working hours, and employment income losses of around 5% in 2020 (Eurostat, 2020a). Third, permanent job losses from COVID-19, such as those in the energy sector due to project cancellations and/or supply chain-related delays (IRENA, 2020b), will further accelerate the shift of workforce and capital among sectors and the reallocation of EU jobs, with the latter expected to be around 1.2% by 2050 before the pandemic (Clays et al., 2019; Fragkos and Paroussos, 2018). This leads to the establishment of new norms in the labour market, and especially in the energy sector, where such changes come on top of the expected shifts from decarbonisation efforts such as, for example,

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

the potential loss of 160,000 jobs in the coal sector (Alves Dias et al., 2018), unless attention is paid to reskilling. As such, it is evident that even the part of the recovery package that is focused on the green transition and the financing of renewable energy projects should expand its focus on environmental targets and incorporate additional dimensions such as employment implications, especially on the largely affected power generation and fuel sectors, to be in line with the broader goals of the recovery.

This is especially the case as, not unlike climate change itself, COVID-19 can be viewed as a disruptive force (Kivimaa et al., 2021) in the broader landscape of the energy system, tending to destabilise organisational structures. However, opportunities for change also emerge from these crises, providing the choice for different pathways to be followed as the energy system evolves in the light of these disruptions (Geels and Schot, 2007). However, the sustainability of these pathways is not ensured. In the absence of committed sustainable policy reaction, windows of opportunity can trigger lock-ins and carbon-dependent trajectories, which are more difficult to destabilise in the long run (Nikas et al., 2022b). Therefore, guiding policymaking throughout the three intertwined crises (health, economic, and climate) towards a sustainable pathway emerges as a major, complex challenge. To provide policymakers with useful insights, climate- and energy-economic models—including integrated assessment models (IAMs)—have been typically employed to address topics around the pandemic and employment. Table 5 summarises key recent research on these topics. However, it is evident that only a handful of studies consider these two dimensions simultaneously and, of those, most lack the regional disaggregation (i.e., they are global studies), and/or a decomposition of employment (i.e., they offer aggregated employment results), and/or typically only calculate the impact of specific policies on employment, instead of optimising for employment on top of climate goals. This leaves a gap in the literature of studies aiming to inform EU policymakers on the optimal impact that the green part of the recovery package can have on emissions and other energy system outcomes, while considering employment implications.

Table 5: Recent literature on climate economy modelling exercises related to COVID-19 and/or employment

Study	Model	Region	Inclusion of COVID-19	Inclusion of employment	Method for including employment
(Pai et al., 2021)	WITCH	Global	N/A	Energy-sector employment	Employment factors
(Malik et al., 2021)	REMIND	Global	N/A	Energy-sector employment	Employment factors
(Malik and Bertram, 2022)	REMIND	India	N/A	Energy-sector employment	Employment factors
(Shan et al., 2021)	Adaptive regional input–output (ARIO)	Global	Impacts of COVID-19 and fiscal stimuli on global emissions	N/A	N/A
(Lahcen et al., 2020)	CGE	Belgium	Macroeconomic impact of the COVID-19 crisis	N/A	N/A
(Kikstra et al., 2021)	MESSAGE-GLOBIOM	Global	Impact of post-pandemic recovery to the medium- and long-term energy transition	N/A	N/A

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

(Keramidas et al., 2021)	PIRAMID framework	Global	Pathways considering the immediate effects of the pandemic	Only as input	IMF and ILO projections (assuming no long-term impact from COVID)
(Rochedo et al., 2021)	COFFEE-TEA, PROMETHEUS	Global	Gap between pledged recovery packages and actual investment needs of the Paris Agreement	N/A	N/A
(Dafnomilis et al., 2020)	E3ME, GEM-E3-FIT, IMAGE	Global	Scenarios exploring the long-term impact of the COVID-19 crisis	Aggregated global employment	Macro-economic model projections
(Pollitt et al., 2021)	E3ME	Global	Macroeconomic impacts of COVID-19	Aggregated global employment	Macro-econometric model projections
(Ju et al., 2022)	AIM/Enduse, TIMES-Japan, Input-Output model	Japan	N/A	Domestic electricity-related employment (disaggregated only per activity)	Introducing coefficients from the I/O to the partial equilibrium models
(Fragkos et al., 2021)	GEM-E3-FIT	EU	N/A	Involuntary unemployment and income by skill	Internal model calculations based on the GTAP database
(Fragkos and Fragkiadakis, 2022)	GEM-E3-FIT	Global	Short-term impacts of COVID-19 on GDP	Global disaggregation based on activity and skills	Internal model calculations based on the GTAP database
(Joshi and Mukhopadhyay, 2022)	E3-India	India	N/A	Regional employment and aggregated per sector	Internal model calculations
(Spijker et al., 2020)	E3ME	Netherlands	N/A	Economy-wide employment	Internal model calculations
(Fujimori et al., 2020)	AIM (combined with multiple components)	Asia	N/A	Unemployment rate	Internal calculations of the AIM/Hub component (demographic trend-driven)
(D'Alessandro et al., 2020)	EUROGREEN	France	N/A	Economy-wide employment	Internal model calculations

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

(Tamba et al., 2022)	PRIMES-TRIMOVE, JRC-GEM-E3	EU	Only the assumption that COVID-19 will not affect EV sales	Sectoral (transport) employment	Based on JRC-GEM-E3 calculations
(Zhang et al., 2022)	SWITCH-China, Job Impact Model for China Power System (JIMC)	China	Reference scenario based on the coal-based COVID response	Energy-sector employment	Employment factors based on the JIMC model
(den Elzen et al., 2022)	IMAGE, GLOBIOM, GEM-E3-FIT	Global	Economic projections based on the the implications of the COVID-19 pandemic	Aggregated global employment	Based on GEM-E3-FIT calculation s
(van de Ven et al., 2022)	GCAM, TIAM, GEMINI	Global (USA, EU, China, India, Japan, Canada)	COVID-19 recovery packages	Energy-sector employment	Employment factors

To address this gap, the main goal and novelty of this research is to identify and inform EU policymakers on the optimal allocation of the green part of the RRF towards subsidies for low-carbon technologies to maximise the emissions reductions achieved by broader energy system changes, while also maximising the impact these changes can have on energy-sector employment. Acknowledging the EU-level policy challenges in terms of tackling the socioeconomic consequences of the pandemic, and in response to the region's climate mitigation efforts (inter alia reflected in the European Green Deal), this study aims to answer two principal research questions:

- Towards which low-carbon technologies should EU green recovery package funds be allocated to robustly maximise emissions cuts and employment gains?
- What are the dynamics and trade-offs among the potentials for emissions reductions as well as near- and long-term employment opportunities in the EU, driven by RRF spending in clean energy technology subsidies?

To answer these questions, we employ the Global Change Analysis Model (GCAM) (Calvin et al., 2019), coupled with the AUGMECON-R multi-objective portfolio optimisation model (Nikas et al., 2022a) and a Monte-Carlo-based stochastic uncertainty analysis framework (Forouli et al., 2020). Doing so allows us to investigate different technology subsidisation portfolios while accounting for the underlying uncertainty that is associated with the employment and emissions performance of the subsidisation of each technology.

The large EU recovery package has brought up significant divergence based on the model, in terms of how the budget is spent. This is particularly evident in Figure 9, where according to GCAM, the EU has to diverge from the common global trend appeared to heavily invest in the EU. On top of that, clear trade-offs between short- and long-term employment planning have appeared, increasing the need to revisit the EU analysis of D4.2 following the most updated protocol and budget selection, to enhance the provision of policy recommendations. As such, we enhance the resolution of the recovery scenario space as well as highlight the trade-offs among the optimisation goals and the robustness of optimal investment mixes against parametric uncertainties, allowing to perform a deep-dive into the EU with targeted policy implications.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

3.2 Methond and Tools

To address the two research questions, we use a multi-level integrated modelling framework. First, considering that Member States have the flexibility to define the structure of their national recovery and resilience plans, we assess what part of the RRF package can realistically be channelled into clean energy projects in the EU as a whole. GCAM is then used to calculate the energy-system impacts of different subsidy levels for each of the considered clean energy technologies. We translate these energy-system impacts into implications for emissions as well as jobs across the entire energy sector, using established employment factor databases. Next, we use AUGMECON-R to carry out a portfolio analysis of the technological subsidies considering multiple employment and emissions criteria. We, finally, run a Monte Carlo simulation, assuming the implicit uncertainty of the calculated emissions and employment impacts to evaluate the optimal investment portfolios based on their robustness to the employed uncertainty perturbations. The overall process is presented in Figure 10, while the details of the methodology are elaborated in the next sub-sections.

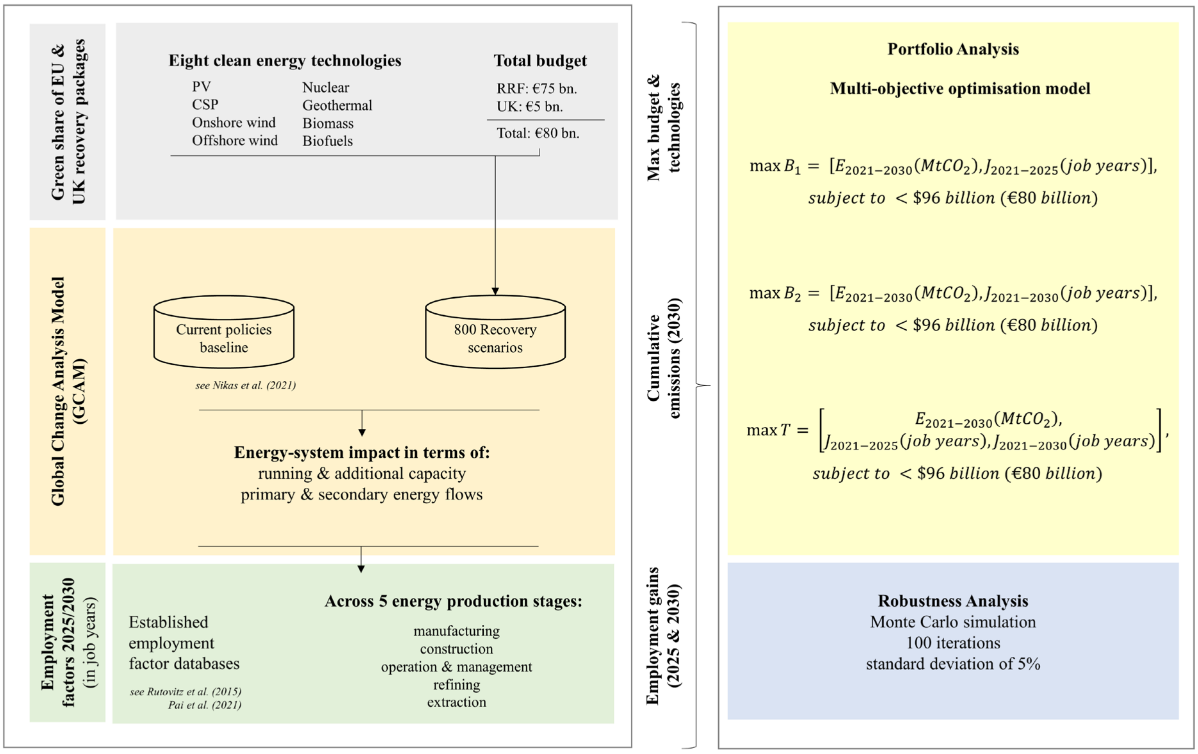


Figure 10: Methodological approach

3.2.1 EU green recovery package: budget and technology selection

The NextGenerationEU is a financial instrument aiming to raise €750 billion from the capital market to establish the RRF temporary recovery instrument (€672.5 billion), a centrepiece mechanism to tackle the negative socioeconomic impact of the pandemic (European Commission, 2020a). Among the eligibility criteria, the European Commission (EC) expect national plans to allocate at least 37% and 20% of the requested funding towards green and digital investments and reforms, respectively, with emphasis on contributing to the flagship initiatives identified by the 2021 Annual Sustainable Growth (European Commission, 2021). Specifically for the green transition, these initiatives should be aligned with the updated target of the European Green Deal of 55% emissions reduction by 2030 (Jäger-Waldau et al., 2020). This entails that the green investments of the RRF should be used to develop 40% of the additional 500GW of renewables required by 2030, install 6 GW of electrolyser capacity, produce and transport 1 million tonnes of renewable hydrogen across the EU, double the renovation

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

rate, and build one of the three million charging points and half of the 1,000 hydrogen stations needed by 2030. Updated information on the implementation of RRF enable us to perform a more accurate estimation of the available budget and therefore a more targeted anaysis compared to the preliminary range assumed in D4.2.

Based on these priorities and guidelines, about €250 billion can be expected to be used in support of investments in renewables and broader clean energy projects, energy efficiency in the built environment, and sustainable transportation. Estimates based on expected and/or announced projects indicate that around €75 billion will flow towards eight clean energy technologies, including utility-scale photovoltaics (PV), concentrated solar power (CSP), onshore and offshore wind, nuclear, geothermal, biomass, and biofuels, excluding related infrastructure investments (EY, 2020). This indications hint that the respective share of the funds is subject to competition among these eight technologies, contrary to other pillars of the RRF, in which the allocation is more straightforward (i.e., grid infrastructure). This raises the challenge of identifying how to best allocate the available budget with a view to maximising the environmental and socioeconomic benefits. GCAM lacks a separate, disaggregated representation of the United Kingdom (UK), as most integrated assessment models typically used to support key international scientific assessments and high-level national and international climate policymaking; we therefore also account for approximately €5 billion from the UK fiscal plan towards similar investments (HM Government, 2020), bringing the total of our selected budget to €80 billion for the eight low-carbon technologies.

3.2.2 Baseline and Recovery Scenarios

Climate-economy models and IAMs have largely been used to address topics regarding COVID-19 (e.g., Shan et al., 2021; Kikstra et al., 2021; Lahcen et al., 2020; Pollitt et al., 2021), as presented in Table 5. Here, we use GCAM, a "recursive dynamic" cost-optimisation integrated assessment model, to assess the impact of the subsidies to these eight technologies on the energy system. To assess the contribution of the recovery scenarios, a pre-pandemic baseline was configured based on the "where is the EU headed" scenario logic (Nikas et al., 2021a), which quantified the impact of current policies in the EU until 2030. These policies include the pre-pandemic targets (i.e., 43% emissions reductions in EU ETS sectors, 32% renewables in the energy sectors, 3.5% advanced biofuels in the fuel mix by 2030, -32.5% energy consumption by 2030; details on how these policies are modelled in the current policies can be found in Nikas et al. (2021a) and Sognnaes et al. (2021)) before the increased ambition of the European Green Deal and the "Fit for 55" package update. The recovery package should additively contribute to the implementation of these newly established goals.

We calculate 100 scenarios on top of this current policy baseline and for each of the eight technologies individually (800 scenarios in total), gradually increasing the subsidy with each step until reaching the highest subsidy amount possible—i.e., the lowest among maximum technology costs (depending on capital and non-capital costs) and the available budget of €80 billion (corresponding to 96 billion USD in 2020, which is the monetary value used internally in GCAM). Apart from emissions, the impact of each subsidy on running capacity, additional capacity, and primary and secondary energy for 12 technology/fuels (biofuels, biomass, coal, CSP, natural gas, geothermal, nuclear, onshore and offshore wind, oil, PV, and rooftop-mounted photovoltaics) was extracted from GCAM for each scenario, enabling the calculation of employment implications (see Section 3.2.3).

The results for the recovery scenarios were reported as a net difference from the baseline. This approach is found preferable when analysing job variation, as it enables understanding employment shifts compared to the baseline across all technologies instead of gross employment. The approach also accounts for the replacement of jobs from conventional sources (García-García et al., 2020), which is a grave concern for many communities that heavily rely on the fossil fuel industry (Baran et al., 2020).

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

3.2.3 Employment factors

Modelling the labour market is usually a daunting process since, in a full-employment job market, jobs added in one area just slash jobs in other areas and/or raise wages. As presented in Table 5, there are usually two approaches in including employment implications in climate-economy models: (a) models with internal representation of labour markets, which however tend to provide aggregated employment results, and (b) employment factors, which usually do not capture broader trends in the markets and labour shifts and mobility. Contrary to models based on input-output tables (Distelkamp and Meyer, 2019; D'Alessandro et al., 2020), computable general equilibrium (CGE) models (Fujimori et al., 2020; Fragkos et al., 2018) or macroeconometric models (Spijker et al., 2020), GCAM does not represent the labour market internally; therefore, to address this gap, the use of external databases of employment factors is required (Fragkos and Paroussos, 2018; Malik et al., 2021). Since the main goal of this study is to calculate optimal packages of specific low-carbon technology subsidies based on their energy-system impacts, and on top of that include employment implications to consider socioeconomic goals of the recovery, the route of GCAM with employment factors is selected for two reasons. First, as a technology-rich model with detailed energy and climate-system representation, GCAM is ideal for simulating the substitution of high- for low-carbon technologies, in response to their relative costs and changes thereof driven by subsidies, before calculating the associated emissions cuts and other energy-system implications. Second, albeit imperfect (that is despite their wide use in the literature to project job market outcomes of low-carbon futures—see, e.g., Table 5), the use of employment factors offers a more disaggregated level of employment estimates across different sectors and mainly technologies of key interest for our study.

Since recovery scenarios are calculated on top of current policies and the subsidies are applied after 2021, net employment in 2020 is assumed to be zero. For 2025 (the first time-step of GCAM runs), employment for each of the 12 technologies was calculated for 5 different processes/stages of energy production: (i) extraction and/or (ii) refining (fossil fuels, biomass, and biofuels), as well as (iii) operation and management, (iv) construction, and (v) manufacturing (all but biofuels), using the factors presented in Table 6. To harmonise employment calculations across the different stages, we calculated employment gains in job-years. Employment factors for the power sector were drawn from Rutovitz et al. (2015), a well-established and widely used database in the literature (Malik et al, 2021). Exceptionally, factors for fossil fuels and biofuels were extracted from Pai et al. (2021), which was based on Rutovitz et al. (2015) but introduced a more detailed spatial representation of these fuels. Manufacturing and extraction factors were adapted based on the EU's domestic capacity to locally create the jobs required for the additional installed capacity of each technology; for example, manufacturing materials for PV panels in the EU depend on imports, implying that a share of the jobs created for each new installed capacity of solar PV should be counted elsewhere (such as China, which dominates the supply chain). These import factors were calculated based on the relative share of domestic supply in domestic demand (IEA, 2019; World Nuclear Association, 2019), assuming this share will not markedly change in the near-term, i.e., until 2025, when recovery funds are allocated.

Table 6: Employment factors in 2025

Employment factors 2025							
Technology	Manufacturing	Construction	Operation & Management	Refining	Extraction	Manufacturing import factor	Extraction import factor
	Job-years per GW installed			*Job-years per PJ processed*		*Share of demand from import (2018 values) (%)*	
Biofuels	-	-	-	7.3	-	-	-

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Biomass	2690	12800	1500	-	29..9	-	5.2
Coal	5400	11200	140	-	26.9	-	52.4
CSP	3627	7255	405	-	-	-	-
Gas	930	1300	140	-	8.6	-	78.7
Geothermal	3687	6429	375	-	-	-	-
Nuclear	1300	11800	600	-	7.3	-	100
Onshore Wind	4250	2894	278	-	-	0	-
Offshore Wind	12821	6575	183	-	-	0	-
Oil	930	1300	140	1.5	14.4	-	87.1
PV (utility-scale)	3775	7325	367	-	-	76.7	-
Rooftop PV	3775	13561	740	-	-	76.7	-

Subsidies are assumed to be allocated within the first GCAM time-step (i.e., by 2025), closely reflecting the EC's intention for the funds to be spent the soonest possible (European Commission, 2020a). However, parts of these subsidies will in reality be spent towards the end of this period—or towards technologies that require long construction times (e.g., nuclear, offshore wind)—leading to installed capacity coming online in 2025-2030, especially for technologies with high lead times. As such, we also calculated employment gains up to 2030 using the employment factors presented in Table 5, adapted based on decreasing technology-specific CAPEX and OPEX over time (Giarola et al., 2021), as suggested by Ram et al. (2020).

3.2.4 Portfolio Analysis

The emissions and jobs implications of the 800 recovery scenarios were then used as inputs in AUGMECON-R, a multi-objective optimisation model, to establish dominant portfolio mixes based on combinations of subsidies to the different technologies towards optimising the environmental and employment performance of the green recovery package. Different problems were formulated, to respond to the research questions while enhancing the policy insights depending on the political priorities in terms of the timing and sustainability of returns on the recovery budget spending. Initially, a bi-objective mathematical programming model was formulated (B_1), in which portfolios were optimised by cumulative emissions cuts from 2021 to 2030 ($E_{2021-2030}$), considering that 2030 is a milestone year to achieve the NDC targets, and cumulative jobs created from 2021 to 2025 ($J_{2021-2025}$); this is deemed of political priority and therefore relevant to policymakers as they expect immediate returns on their spendings with a few to achieving swift economic recovery from the pandemic's impacts (Equation 3). Then, a slightly modified problem was formulated (B_2), comprising again cumulative emissions cuts by 2030 and cumulative jobs created from 2021 to 2030 ($J_{2021-2030}$) to account for the total impact of the subsidies and understand longer-term trends (Equation 4), while also exploring to what extent employment gains can be sustained in the longer run. Acknowledging the need to both create near-term jobs and sustain employment gains in the longer run, a third, tri-objective mathematical problem was formulated and solved (T), this time with all three objectives (Equation 5). The three problems were solved independently. This process was critical to identify trends between the different directions triggered by short-term and longer-term employment planning as well as trade-offs and/or synergies among all three priorities. The optimisation problems are defined as follows:

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

$$\max B_1 = [E_{2021-2030}(MtCO_2),\ J_{2021-2025}(job\ years)], \quad subject\ to\ < \$96\ billion\ (€80\ billion) \tag{3}$$

$$\max B_2 = [E_{2021-2030}(MtCO_2),\ J_{2021-2030}(job\ years)], \quad subject\ to\ < \$96\ billion\ (€80\ billion) \tag{4}$$

$$\max T = [E_{2021-2030}(MtCO_2),\ J_{2021-2025}(job\ years), J_{2021-2030}(job\ years)]\ , \quad subject\ to\ < \$96\ billion\ (€80\ billion) \tag{5}$$

3.2.5 Robustness Analysis

To increase policymakers' confidence in the provided portfolio mixes, a robustness analysis framework was employed (Forouli et al., 2020), based on a Monte Carlo simulation, to quantify the uncertainty of the energy system changes, as typically represented by integrated assessment models (Pfenninger et al., 2017; Ellenbeck and Lilliestam, 2019).

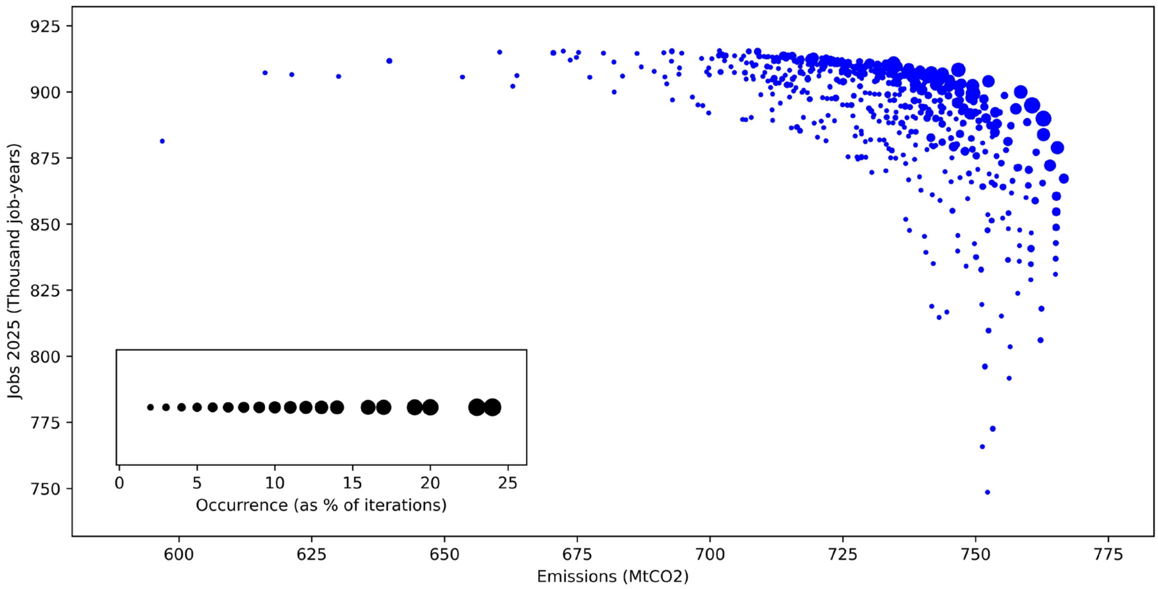
In particular, following a normal distribution with a mean value fixed on the GCAM outputs (and the subsequent employment conversions) and a standard deviation of 5% (Forouli et al., 2019), 100 iterations of the portfolio analysis (in Section 3.2.4) were performed to calculate the vulnerability of the optimal investment portfolios to uncertainties associated with the performance of a single investment in terms of new jobs created and additional emissions cuts achieved. From iteration to iteration, different portfolio mixes typically emerge as dominant, while others are crowded out of the solution space (Pareto front), based on the fluctuating impact of subsidies on emissions and employment. For this reason, here we introduced a robustness metric reflecting the number of iterations each portfolio made it among the dominant solutions (Pareto front) in the total of 100 iterations. The physical interpretation of robustness in this case is that, if a portfolio consistently makes it into the solution space in x iterations, it means that it is more robust than a portfolio appearing in $y < x$ iterations, against the assumed parametric uncertainty in the modelling results.

3.3 Results and Discussion

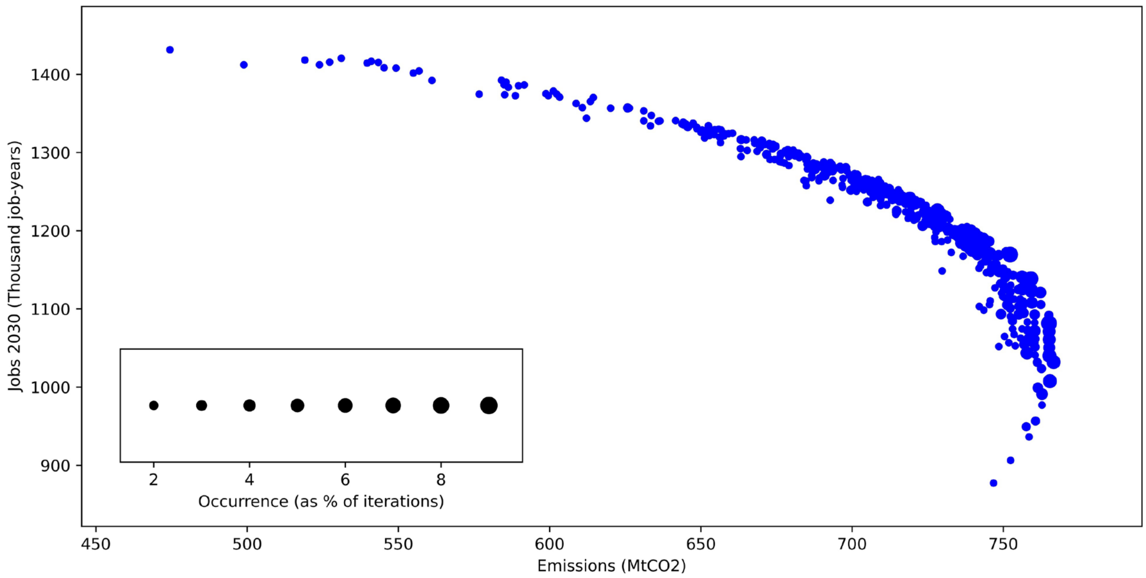
Following the multi-stage methodology presented in Section 3.2, we sought to determine how to optimally spend the green part of the European recovery funding towards further mitigating CO_2 emissions on top of the current policy framework, while maximising energy-sector employment gains, first in the near-term (by 2025) and then in the longer run (by 2030).

In both cases, we observed a clear trade-off between emissions reductions and employment gains, meaning that portfolios performing well in relation to net-positive employment gains were found suboptimal in terms of emissions cuts, and vice versa. In particular, when looking at near-term employment opportunities, we calculated a potential for 766–915 thousand new job-years created in the energy sector by 2025 as well as a capacity for cumulative emissions cuts of 596–748 $MtCO_2$ up to 2030, both compared with the current policy baseline (Figure 11a). Considering this trade-off between emissions and employment gains, the maximum (minimum) potential for new energy-sector jobs by 2025 is 915 (766) thousand job-years, achieved by a green recovery portfolio that can lead to a drop in cumulative CO_2 emissions of 596 (748) $MtCO_2$ by 2030. When maximising employment gains by the end of the decade, instead, we calculated a potential for 877-1,431 thousand job-years created by 2030. Here, opting for longer-term sustainability of new energy employment opportunities did not significantly hamper the range of emissions reductions, which however is now slightly larger (474-766 $MtCO_2$ up to 2030, Figure 11b).

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.



(a)



(b)

Figure 11: Optimal green RRF subsidy portfolios in terms of further emissions cuts (x-axis) and new employment opportunities in the energy sector (y-axis) with (a) short-term planning and (b) long-term planning.

(a) Emphasises employment gians by 2025 and (b) emphasises sustainable new energy jobs by the end of 2030. Bubble size indicates robustness against uncertainty perturbations.

A second insight directly emerging from Figure 11 is that for both time horizons (2025 and 2030), optimal portfolios achieving moderate gains along both objectives (emissions and employment gains) are less prone to uncertainty perturbations compared to portfolios predominantly focusing on either of the two objectives. Similarly, we can observe that in the second case—i.e., when maximising full-decade emissions and employment gains—portfolios appear to be considerably less robust against uncertainties, with all portfolios appearing in less than 10% of iterations (i.e., robustness <10%).

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Third, of the eight considered technologies, most portfolios heavily included investments in onshore wind and, to a smaller degree, in biofuels; these two were occasionally (i.e., across the Pareto front and the assumed uncertainty range) supplemented by small shares of offshore wind and nuclear subsidies. The exact investment mix largely depended on the priorities of the optimisation (Figure 12). In particular, the portfolio achieving most emissions cuts was the same for both time horizons of employment optimisation and relied primarily on onshore wind ($83.8 billion) and less on biofuels ($12 billion). When shifting our focus towards maximising employment, however, the selected portfolios differed among the two bi-objective problems: in the portfolio maximising near-term employment gains, onshore wind retained its $81-billion share but the remainder was now made up by investments in offshore wind ($9.8 billion) and nuclear power ($5.1 billion); on the other hand, optimising longer-term employment gains yielded a portfolio with increased diversification but without straying from the four technologies: offshore wind ($37.2 billion), biofuels ($27.7 billion), nuclear ($22.6 billion) and onshore wind ($8.4 billion).

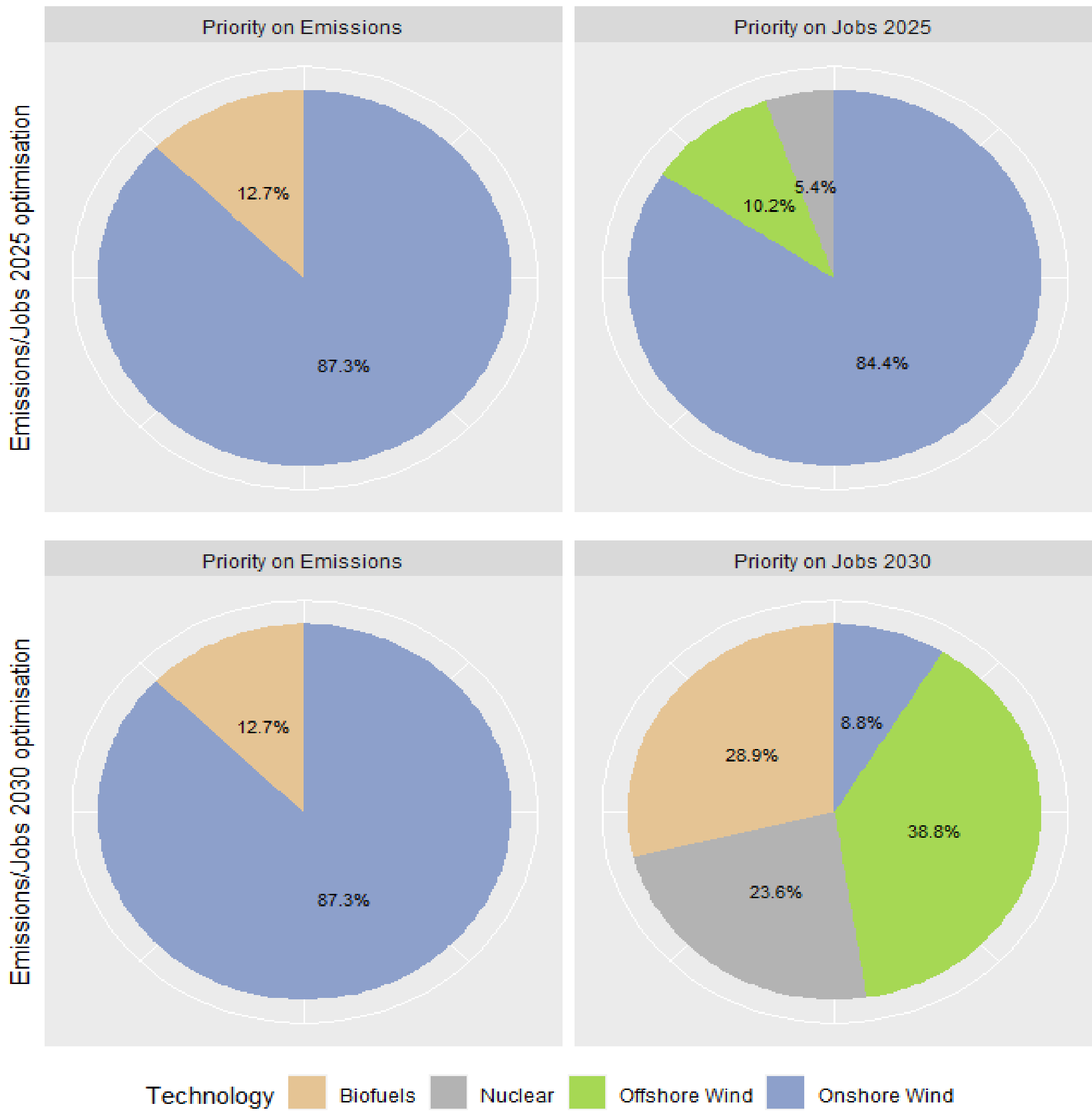


Figure 12: Allocation of the available budget depending on the priority goal (columns) in the two bi-objective optimisation problems (rows).

To better understand these trends, we delve into the returns on the independent subsidisation levels for each

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

technology along the three objectives, in the GCAM-generated recovery scenarios (Figure 13). Onshore wind development dominates the impact on emissions and employment up to 2025 and, although it falls back in terms of employment gains by 2030, it keeps up with the rest of the technologies. Similarly, subsidies in biofuels keep up with onshore wind investments in terms of emissions cuts and have the highest employment returns by 2030. This explains the consistent inclusion of both technologies in optimal portfolios. Offshore wind and nuclear are almost equally as efficient as biofuels, in terms of creating new jobs by the end of the decade; therefore, maximising employment gains by 2030 pinpoints a portfolio comprising a split among the three technologies (bottom-right panel, Figure 12). Given the high competition among technologies, the overall robustness of subsidy portfolios optimising the creation of new jobs by 2030 is relatively low, as no specific investment mix emerges as dominant (Figure 11b). GCAM results show that RRF subsidies in the remaining four technologies (PV, CSP, geothermal, and biomass) fail to have a considerable positive impact across any of the three objectives, thereby ending mostly absent from optimal portfolios. Especially for PV, this contradicts insights from other integrated assessment models and/or for other major economies with announced green recovery packages (van de Ven et al., 2022; Malik and Bertram, 2022). In our case, however, a possible explanation for the poor performance of PV subsidisation can be found in the relative saturation of solar power in the current policy trajectory (Nikas et al., 2021), as well as in the reduced EU-domestic capacity to create jobs in the manufacturing sector, which predominantly takes place in China. These two factors render PV subsidies sub-optimal, in both emissions cuts and employment gains. This insight does not undermine the added value of PV growth in the context of mitigation efforts by 2030; it rather refers to their cost-optimality compared to other options as part of RRF-powered clean energy technology subsidisation.

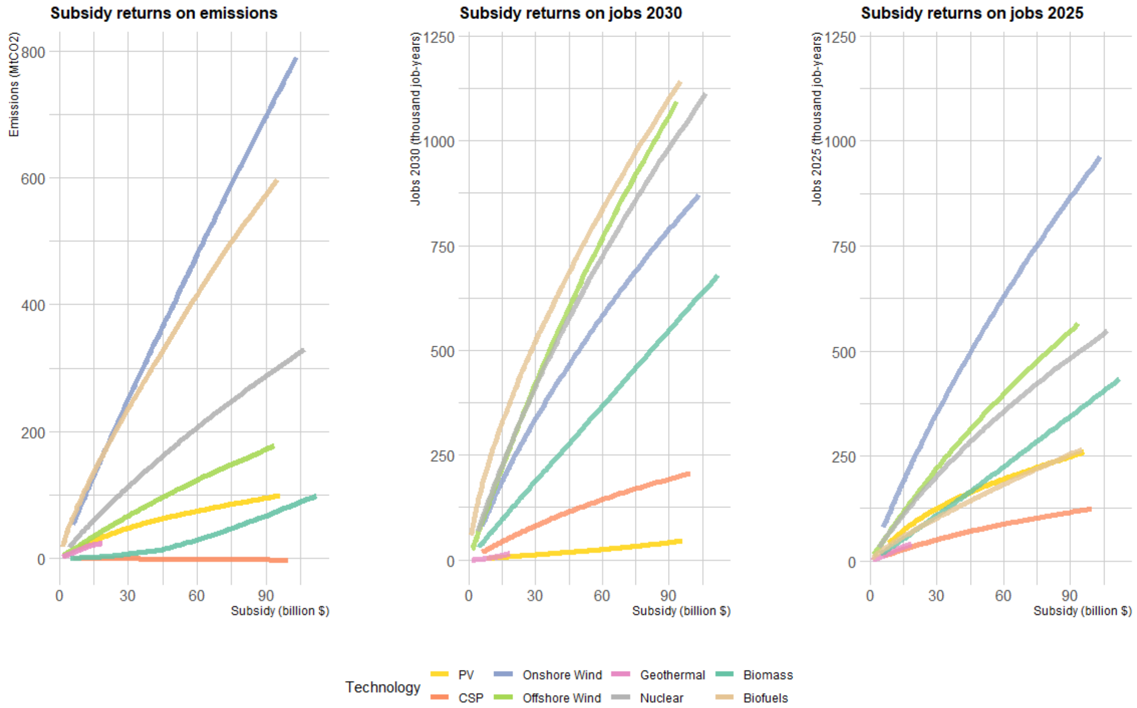


Figure 13: Return on investment/subsidisation level across the eight technologies, in terms of emissions cuts (left), employment by 2030 (centre), and employment by 2025 (right)

Considering the significant differences of the technology mix maximising full-decade employment gains from those optimising the other two goals, we find that the conflict between longer-term and near-term employment gains (as well as between longer-term employment gains and emissions cuts) is higher than the conflict between achieving large cumulative emissions cuts by 2030 and creating new energy-sector jobs by 2025—with onshore

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

wind dominating both cases. This trade-off between near- and longer-term employment gains also shows in the synthesis of optimal portfolios emerging in each of the two problems, tracing back to how investment choices fare against current policies. When focusing on longer-term planning, it was found preferable to subsidise less competitive technologies that would not have been subsidised absent the recovery package; as such, maximum employment gains are mostly observed beyond 2025. In contrast, should policymakers opt for a shorter-term planning with immediate employment returns on recovery funds spending, investments should heavily focus on onshore wind. This technology, however, is already mature and highly competitive in the current policy context, and any investments in it would essentially accelerate the achievement of the current policy targets. Such a strategy would be effective at creating short-term jobs but would quickly lose momentum post-2025, undermining long-term employment gains. Due to relative scarcity for resource-rich onshore wind sites as well as limits to integration of intermittent wind power in the European power mix, a large part of these quickly created jobs would have been created towards the end of the decade regardless of the RRF investments.

Given these dynamics, we further explored if the technological mix of green recovery spending can be diversified towards a better balance between near- and longer-term employment gains, by optimising emissions cuts, employment by 2025, and employment by 2030 simultaneously. After solving the tri-objective problem, we found a similar potential across the three objectives as in the bi-objective problems. This potential ranges between 391-766 $MtCO_2$ emissions reductions by 2030, 843-1,433 thousand cumulative job-years by 2030, and 544-915 thousand cumulative job-years by 2025. Figure 14 displays the solution front of the tri-objective problem, highlighting solutions of any robustness (excluding portfolios occurring only once; Figure 14a), occurring >10% (Figure 14b), >20% (Figure 14c), and 30% (Figure 14d) among the 100 Monte Carlo runs. Despite yielding comparable results, here the trade-off between full-decade employment gains and the other objectives is further highlighted, as the upper end of the range (1.4 million job-years by 2030) cannot be achieved without giving up on the potential for emissions reductions and without losing out on possible employment gains by 2025 (as evident by the outer blue perimeter in the solution front in Figure 14a). Also, shifting to portfolios maximising employment gains by 2030 significantly reduces robustness (Figures 14b-d), as observed in the respective bi-objective problem. Contrary to the latter, however, we now identify portfolios appearing in more than 10% of the iterations (Figure 14b), which can potentially reach up to 1.2 million job-years by 2030 without undermining near-term job gains nor additional emissions reductions.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

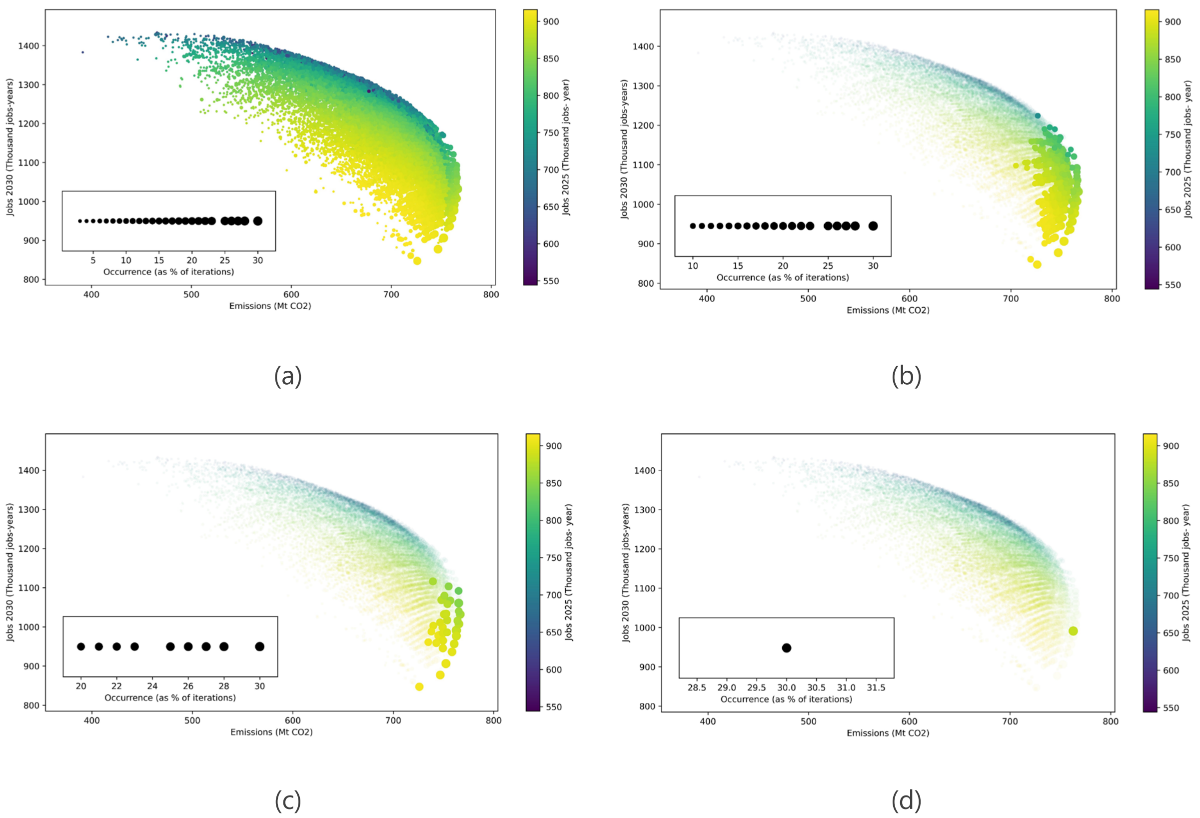


Figure 14: Optimal green RRF subsidy portfolios in terms of further emissions cuts (horizontal axis) as well as long-term (vertical axis) and near-term (colour axis) employment gains in the EU, highlighting only the portfolios occurring in (a) over 1%, (b) over 1

Among portfolios with high robustness (occurrence > 20%, see Figures 14c-d), subsidy portfolios again comprise mostly onshore wind (above $75 billion), biofuels (up to $16 billion), and to a smaller extent nuclear (up to 10$ billion) and offshore wind (up to $3.3 billion). We can, therefore, gain robust insights into which technologies the green part of the RRF spending should flow towards. However, the exact investment mix largely depends on policy priorities in terms of targets, as we have identified a set of 30 portfolios of >20% robustness (Figure 15) that could all be efficiently implemented but with largely different impacts each. In these portfolios, there are strong indications of a positive correlation between subsidies for onshore wind and job gains by 2025 and equally strong indications of a negative correlation between subsidies for onshore wind and job gains by 2030. In fact, every additional $1 billion of investments in onshore wind can increase employment in 2025 by more than 3,000 job-years, but at the same time reduce employment in 2030 by approximately 12,500 job-years. In contrast, biofuels feature opposite trends, with every additional $1 billion having the capacity to increase employment in 2030 by more than 16,000 job-years, while limiting the potential for new employment in 2025 by 5,000 job-years and for further emissions reductions by 4 $MtCO_2$ (whereas there was no indication of a correlation on emissions for onshore wind). The small investment shares on nuclear and offshore wind do not allow extracting meaningful correlations, although there are indications of a positive correlation between nuclear investments and employment gains by 2030.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

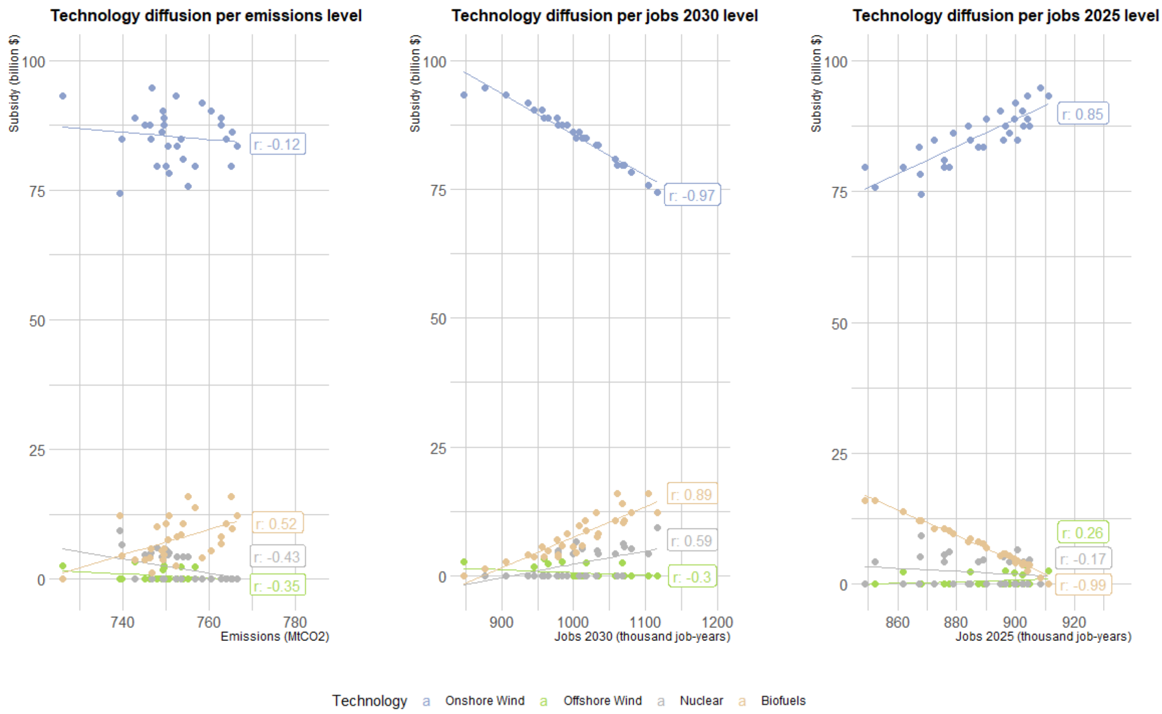


Figure 15: Participation of each technology in the most robust (>20%) portfolios (subsidy) depending on the impact on emissions (left), employment by 2030 (centre), and employment by 2025 (right).

Only one portfolio was found with a robustness level of 30%, which was made up by investments explicitly in onshore wind ($87.5 billion) and biofuels ($8.2 billion), closely resembling the emissions-focused optimal portfolio of the bi-objective models (Figure 12). This does not necessarily imply that it should be the single best choice for policymakers, as robustness is yet another decision criterion and the final decision may depend on other policy priorities. This portfolio has the potential to achieve 763 $MtCO_2$ emissions reductions on top of the current policy mitigation efforts, as well as 883 and 991 thousand job-years created in the energy sector by 2025 and 2030, respectively. Evidently, when optimising all three objectives and strongly emphasising robustness, giving up on near-term employment gains or emissions cuts is found costlier than losing longer-term sustainability of new energy-sector jobs, which is also found relatively uncertain. Still, cumulative employment gains by 2030 can be far from the lower end of the potential range (Figure 11b) and remain above the near-term energy-sector job creation potential, highlighting the potential of continuous (albeit slower) growth of the intended immediate returns on recovery spending. In their pre-pandemic study, Malik et al. (2021) had showed that climate policy efforts could drive an increase in employment in the energy sector by 2025, which however would be followed by a reverse trend post-2025 and beyond, depending on the stringency of climate action (Malik and Bertram, 2022). Here we show that, with a nuanced approach to allocating the COVID-19 recovery packages in the EU with a view to coupling mitigation goals with both near- and longer-term employment planning, this energy-sector unemployment rebound can be mitigated, at least by the end of this decade.

In terms of how these additional jobs are distributed across sectors and technologies/fuels in the most robust portfolio (Figure 16), we find that most employment gains until 2025 are expectedly observed in the manufacturing and construction sectors as well as in onshore wind, which is heavily subsidised. Post-2025, the increase in these sectors could halt, with manufacturing jobs even rebounding; however, the positive net impact is maintained as jobs in the later stages of project pipelines (i.e., O&M) start to increase. As such, continuous policy support (including reskilling) is required beyond the duration of the RRF instrument to ensure these shifts do not lead to job losses post-2025. Interestingly, we also observe a significant increase in PV-related employment within the

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

region, despite the absence of any subsidies. On the other hand, losses in rooftop PVs indicate internal shifts in the solar market as a spillover effect from investments in onshore wind: huge increases in subsidised wind in electricity significantly reduce the electricity price, increasing overall demand for grid electricity and disincentivising distributed generation. Nevertheless, a net positive employment impact for the entire solar sector is maintained. Considering the link between rooftop PV installations and demand-side transformations, including their role in energy democracy and energy poverty alleviation (Rodríguez et al., 2018), careful consideration should be placed on such shifts in the supply sector to control the interplay with other parts of the RRF focusing on the demand side (e.g., energy efficiency in the built environment), as well as broader demand-side shifts—especially in response to Russia's invasion of Ukraine and subsequent energy-planning decisions, such as the introduction of the REPowerEU program, which are expected to significantly affect energy demand.

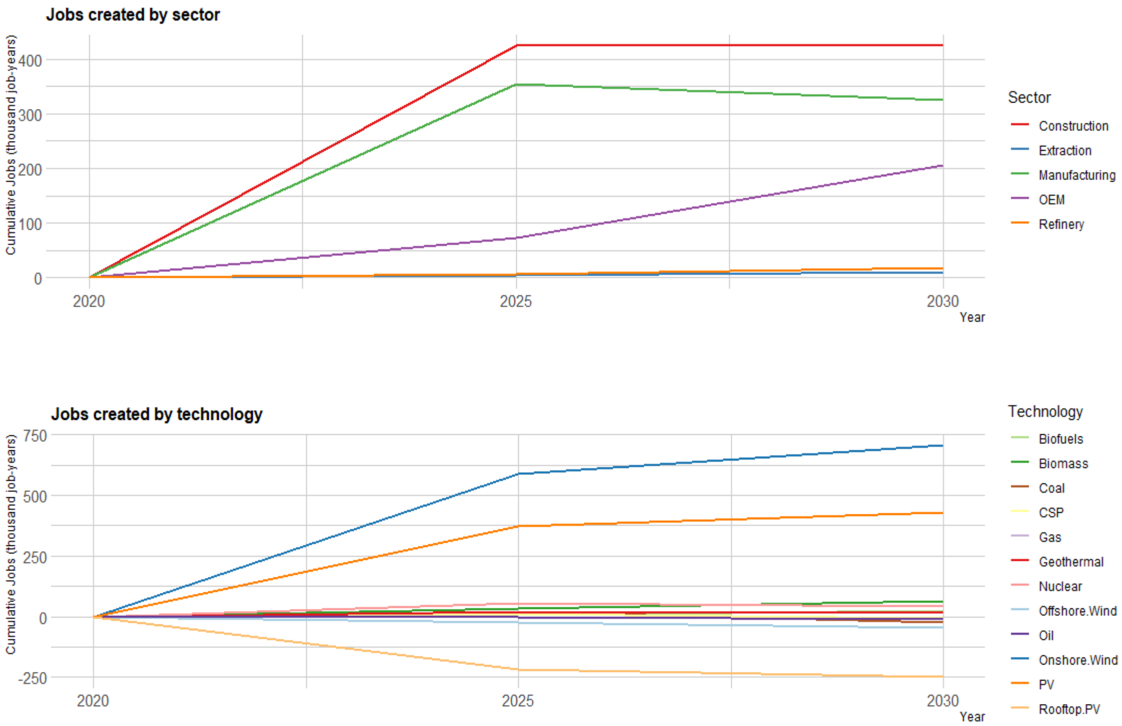


Figure 16: Breakdown of cumulative employment created by sector (top) and by technology/fuel (bottom) in the most robust portfolio (robustness of 30%)

Finally, despite investments being channelled explicitly towards onshore wind and biofuels in the most robust portfolio, the subsidies can have broader implications for the entire energy sector, as evident in the employment boost in solar PVs, including capacity additions in renewables: we calculate that this portfolio could achieve the integration of 108GW of additional installed capacity from renewables by 2030, on top of the current policies reference trajectory. This, however, would fall short of the 200GW target envisaged in the RRF. This inadequacy is further validated when feeding five other indicative portfolios (the three portfolios of Figure 12 and the robustness-weighted average of the portfolios of Figures 14a and 14c) back into GCAM, which would yield an additional renewable energy capacity of 49-118GW by 2030, depending on the technology mix of each portfolio. This additional capacity Recovery plans designed by the Member States should, therefore, account for this shortcoming and pursue domestic investments that could also raise additional funds (i.e., from the private sector) that would help close the gap.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

3.4 Conclusions and Policy Implications

The RRF is a major financial instrument in the EU intended to mitigate and/or alleviate the socioeconomic impacts of the COVID-19 pandemic within the region, while pushing forward the envisaged green transition. At least 37% of the total funds made available to Member States should constitute a green stimulus package, expected to flow towards climate mitigation-compatible investments and clean energy projects. With employment hit especially hard by the pandemic, and notably in the energy sector as the crisis came on top of shifts triggered by climate efforts, key questions arise over the trade-offs between socioeconomic and mitigation potentials of the EU green recovery package, in terms of employment gains in the energy sector and emissions cuts, as well as over the optimal allocation of these funds to maximise both goals. To answer these questions and support policymakers in the EU in designing and implementing their respective recovery and resilience plans, this study employed a multi-stage integrated modelling framework. Delving into the EU (plus the UK's) recovery package, an €80 billion budget was identified as relevant for projects of eight energy technologies, with high competition among them to absorb these funds. The GCAM integrated assessment model was used to calculate 800 recovery scenarios of technology subsidies (100 subsidy levels for each of the eight technologies) that were applied on top of a current policies baseline. After translating the energy system outputs of these scenarios to employment impacts using well-documented employment factor databases in the literature, the AUGMECON-R portfolio analysis model was used to solve three optimisation problems for maximising full-decade additional emissions cuts as well as near- (2025) and longer-term (2030) employment gains in the energy sector. The portfolio analysis was further coupled with a Monte Carlo simulation to identify robust technological mixes among the optimal investment portfolios.

First, we determined a clear trade-off among all three objectives, hinting the conflicting nature of different clean energy projects as well as the challenge in reaching the maximum potential in terms of employment and CO_2 emissions cuts. This trade-off is evident in the overall potential of the green RRF part (achieving approximately 400-770 $MtCO_2$ emissions reduction by 2030, and 550-915 and 850-1,450 thousand energy-sector job-years created by 2025 and 2030 respectively, additionally to what the current policy framework is expected to achieve). Second, the most challenging objective was maintaining employment gains by the end of the decade, as this was found to considerably undermine creating new jobs by 2025 and nearing the EU's NDC target. Indicatively, in the most robust portfolios, achieving about two-thirds of the maximum employment potential by 2030 (1.45 million job-years) enables hitting the upper bound of the other two objectives; aiming for the maximum potential of new energy-sector job-years in the energy sector was found at odds with climate objectives and the main goal of immediate socioeconomic returns on the RRF investments. Third, we found that recovery policy plans could benefit from investments in specific technologies, with a large chunk of optimal portfolios heading towards onshore wind, and then biofuels, nuclear power, and offshore wind.

The exact investment mix should largely depend on the policy priorities: larger investments in onshore wind appear to yield positive impacts on emissions cuts and near-term employment gains, while shifting towards the other three technologies (biofuels, nuclear, and offshore wind) can benefit larger energy-sector employment gains by the end of the decade. In general, investment portfolios favouring already cost-competitive technologies (such as onshore wind) may create the most jobs by 2025 but could quickly lose momentum, leading to negligible jobs gains onwards. This is because certain investments would only pull forward employment opportunities that could have been created anyway within the decade, driven by the policies currently in place. On the other hand, prioritising currently less cost-competitive technologies (such as offshore wind or advanced biofuels) could leverage the opportunity arising from the recovery package and benefit the maturity of these technologies, altering the current policy energy-system trajectory and boosting diversification of technological capacity with an ongoing running positive effect in the future and longer-lasting job opportunities. These trade-offs with the current policies should be an important consideration in interpreting the results of the study. For example, PVs

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

appeared to be a less favourable investment, tracing back to their strong presence in the current policies baseline; however, this does not imply that solar deployment should not be reinforced throughout the decade, but rather that policy efforts should be aligned with the targets set (which includes large PV capacity additions) and complemented with the optimal investment mix identified.

Finally, although an additional 200GW capacity from renewables by 2030 lies among the EU's intentions behind the green RRF package, we estimated that only half of this potential can be achieved based on the available budget, if energy-sector employment should also be prioritised. To close this gap, different criteria should be considered and/or additional funds be raised, as there may be limited capacity to further increase the RRF's share towards clean energy production, considering that it is a multi-purpose mechanism.

This study has undergone significant effort to realistically represent employment impacts of the recovery package in the EU, if centrally coordinated. However, we acknowledge that most socioeconomic impacts from the pandemic are present at the national level, while calculated employment gains may not be equally distributed across Member States (especially considering the earlier stages of project pipelines, as well as domestic renewable energy potentials for the later stage of relevant projects). This is even more so for the UK, the green recovery package of which has been included in the study to align our analysis with the employed model's regional disaggregation, despite it not being a Member State. We also acknowledge that this optimal allocation of the RRF spending requires a level of EU-wide/supranational coordination that may not be reflected in national recovery and resilience plans, which are left flexibly up to Member States. Still, broader insights into a general EU-level direction may be drawn, while future research based on the proposed approach can delve into the national-level spending of the available funds as the implementation of the recovery and resilience plans starts taking shape.

A strong caveat of an approach based on employment factors, such as the one used here, lies in the challenging task of addressing the heterogeneity of unemployment: some people cannot find a job, while some jobs cannot be filled; this further stresses the need to go beyond first-order effects examined here and account for labour mobility and the required reskilling of the workforce, as well as the impact on wage levels in different sectors and regions. Even more so for COVID-19 recovery spending, since initiatives aimed at stimulating the EU economy do not focus solely on the energy sector, but rather aim to create value-added across multiple sectors, including *inter alia* the transportation, residential, food, and agricultural sectors. As such, future research could draw from the optimal portfolios calculated here, introduce them to models with more advanced representation of the entire economic system and the underlying labour markets (including, e.g., production functions, prices and substitution elasticities, input and output markets, trade flows, etc.) to elaborate on broader impacts of both the subsidies as well as the entire recovery package.

Apart from the use of one integrated assessment model, in which capacity factors for power technologies are fixed (while additional renewables in power could potentially push more fossil technologies out of the market through dispatch, see van de Ven et al., 2022), another important caveat of this study lies in the assumption that markets will be the same as today. For instance, the assumption of a fixed market for manufacturing materials in 2030 may be one of the reasons behind PVs being found sub-optimal. Further development of the PV manufacturing supply chain within the EU, for example, may yield different results, considering the employment impact in the early stages of the solar power project pipeline. In this sense, our study provides a baseline scenario of the implications of RFF spending, assuming business-as-usual in terms of interactions and spillover effects between markets, both within and beyond Europe. While the exact investment mix may be subject to these interactions as well as to other uncertainties (such as repercussions from the Ukraine conflict to the European economy), our study shows that the (near-) optimal use of the green part of the RFF can lead to both emissions reductions and short- and long-term jobs in the energy sector, while providing indications of which technologies can be impactful. Future studies could further investigate scenarios of market evolution and employ tools such as agent-based models to examine

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

said interactions between markets and relevant actors in more detail.

Finally, it is also noteworthy that not all relevant technologies have been considered for subsidisation; although the inclusion of some technologies would not have changed the outcome (e.g., hydro, given the limited potential for additional hydropower in the EU), future work should focus on representing options such as hydrogen or infrastructure projects, which may be central in the EU's recovery plans and/or pathway to net-zero. Apart from additional technologies, future research can shed light on spillover effects that the subsidies in specific technologies, such as the ones calculated here, could have–for example, the use of biofuels on land use changes, solar and wind expansion on mineral extraction, and the challenge of end-of-life disposal of wind turbines and PV panels.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Appendix 1: Metadata for Augmecon-Py

Nr	Code metadata description	*Please fill in this column*
C1	Current code version	v1.0.0
C2	Permanent link to code/repository used for this code version	https://github.com/KatforEpu/Augmecon-Py
C3	Permanent link to reproducible capsule	N/A
C4	Legal code license	Apache 2.0 License
C5	Code versioning system used	Git
C6	Software code languages, tools and services used	Python
C7	Compilation requirements, operating environments and dependencies	cycler==0.10.0 et-xmlfile==1.0.1 gurobipy==9.1.1 kiwisolver==1.3.1 matplotlib==3.5.0 nose==1.3.7 numpy==1.20.2 openpyxl==3.0.7 pandas==1.2.4 Pillow==8.2.0 ply==3.11 Pyomo==5.7.3 pyparsing==2.4.7 python-dateutil==2.8.1 pytz==2021.1 PyUtilib==6.0.0 pywin32==300 scipy==1.6.3 seaborn==0.11.1 six==1.15.0 xlrd==2.0.1 XlsxWriter==1.4.3
C8	If available, link to developer documentation/manual	N/A
C9	Support email for questions	kfor@epu.ntua.gr

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Appendix 2: Supplementary material for Chapter 2

Note S1 TIAM-Grantham

Summary: The TIMES Integrate Assessment Model, TIAM-Grantham, is a multi-region, global version of TIMES, which is a modelling platform for local, national or multi-regional energy systems, providing a technology-rich basis for estimating how energy system operations will evolve over a long-term, multiple-period time horizon[1]. These energy system operations include the extraction of primary energy such as fossil fuels, the conversion of this primary energy into useful forms (such as electricity, hydrogen, solid heating fuels and liquid transport fuels), and the use of these fuels in a range of energy service applications (vehicular transport, building heating and cooling, and the powering of industrial manufacturing plants). In multi-region versions of the model, fuel trading between regions is also estimated. The TIMES framework is usually applied to the analysis of the entire energy sector but may also be applied to the detailed study of single sectors (e.g. the electricity and district heat sector).

Recent use cases include (Gambhir et al., 2014), (Napp et al., 2019), and (Realmonte et al., 2019).

Economic rationale: TIAM-Grantham simultaneously calculates the quantity of production and consumption of the different commodities accounted for in the model. These commodities are the different energy forms that are produced to satisfy the related energy service demands. Energy service demands are exogenous to the model, and the price of producing the required commodity affects the decision of which technology use to produce that commodity. TIAM- Grantham operates in a market-clearing manner, such that prices of commodities are consistent with the supply and demand being in balance for all commodities.

TIAM-Grantham most commonly operates on a perfect foresight principle, such that it has knowledge of all current and future technology costs and fuel supply curves. This allows it to reach a cost-minimising level of commodity production and consumption, which is consistent with meeting all current and future energy demands, as well as any imposed emissions constraints. The total energy system cost (including any losses to consumers' welfare as a result of energy price rises) is calculated as a Net Present Value (NPV) cost of the energy system over the whole time period until 2100, using a discount factor to value the costs of the energy system at different time points in the future.

Emissions: The model can calculate the three main sources of GHGs—carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) deriving from the energy system's operations, including some non-energy CO_2 and non-CO_2 gases.

Notes on current policy and subsidy implementation: Energy related (pre-Covid-19, announced until 2020) policies like renewable targets, fuel standards and carbon taxes have been applied in all 6 regions in this study. Non-energy sector's current policies are not implemented in the *current policies* scenarios in TIAM-Grantham. For the Covid-19 recovery package related subsidies to be additional to pre-Covid-19 policies. The technology growth rate assumptions based on the literature are relaxed to capture the impact of subsidy implementation on technology deployment.

Note S2 GCAM-PR 5.3

Summary: The Global Change Assessment Model (GCAM) is a global integrated assessment model that represents both human and Earth system dynamics (Edmonds et al., 1994). It explores the behaviour and interactions between the energy system, agriculture and land use, the economy and climate (Calvin et al., 2019). The model allows users to explore what-if scenarios, quantifying the implications of possible future conditions; these outputs are a way of analysing the potential impacts of different assumptions about future conditions.

GCAM reads in external "scenario assumptions" about key drivers (e.g., population, economic activity, technology,

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

and policies) and then assesses the implications of these assumptions on key scientific or decision-relevant outcomes (e.g., commodity prices, energy use, land use, water use, emissions, and concentrations). It is used to explore and map the implications of uncertainty in key input assumptions and parameters into implied distributions of outputs, such as GHG emissions, energy use, energy prices, and trade patterns.

GCAM has been used to produce scenarios for national and international assessments ranging from the very first IPCC scenarios through the present Shared Socioeconomic Pathways (SSPs) (Calvin et al., 2017). Recent use cases include (Markandya et al., 2018), (Huang et al., 2019), and (Ou et al., 2021). The GCAM-PR variant has been designed to harmonise a large set of assumptions with other models within the PARIS REINFORCE research project (https://www.paris-reinforce.eu/). The details of these assumptions are elaborated in (Giarola et al., 2021).

Economic rationale: The core operating principle for GCAM is that of market equilibrium. The representative agents in the modules use information on prices and make decisions about the allocation of resources. They represent, for example, regional electricity sectors, regional refining sectors, regional energy demand sectors, and land users who have to allocate land among competing crops within any given land region. Markets are the means by which these representative agents interact with one another. Agents indicate their intended supply and/or demand for goods and services in the markets. GCAM solves for a set of market prices so that supplies and demands are balanced in all these markets across the model; in other words, market equilibrium is assumed to take place in each one of these markets (partial equilibrium), and not in the entire economy across all markets (general equilibrium). The GCAM solution process is the process of iterating on market prices until this equilibrium is reached. Markets exist for physical flows such as electricity or agricultural commodities, but they also can exist for other types of goods and services, for example tradable carbon permits.

GCAM is a dynamic recursive model, meaning that decision-makers do not know the future when making a decision today, as opposed to other optimisation models, which assume that agents know the future with certainty when they make decisions. After it solves each period, the model then uses the resulting state of the world, including the consequences of decisions made in that period—such as resource depletion, capital stock retirements and installations, and changes to the landscape—and then moves to the next time step and performs the same exercise. The GCAM version used is typically operated in five-year time steps with 2015 as the final calibration year. However, the model has flexibility to be operated at a different time horizon through user-defined parameters.

Emissions: GCAM endogenously estimates CO_2 fossil-fuel related emissions based on fossil fuel consumption and global emission factors by fuel (oil, unconventional oil, natural gas, and coal). GCAM can be considered as a process model for CO_2 emissions and reductions. CO_2 emissions change over time as fuel consumption in GCAM endogenously changes. Application of Carbon Capture and Storage (CCS) is explicitly considered as separate technological options for a number of processes, such as electricity generation and fertilizer manufacturing. The GCAM, in effect, produces a Marginal Abatement Curve for CO_2 as a carbon-price is applied within the model. The model does also cover a large variety of non-CO_2 emissions, including all greenhouse gases (GHGs), and multiple pollutants.

Notes on current policy and subsidy implementation: Energy and land-related current (pre-Covid-19, until 2020) policies have been applied in all 6 regions in this study. For the Covid-19 recovery package related subsidies to be additional to pre-Covid-19 policies, the latter have been fixed to constant subsidies and/or taxes when modelling the recovery package subsidies. E.g., the same EU-ETS price the model calculated to achieve the ETS targets before applying the recovery package subsidies is also applied in all the subsidy runs.

Note S3: GEMINI-E3

Summary: The General Equilibrium Model of International-National Interactions between Economy, Energy, and

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

the Environment (GEMINI-E3) is a multi-country, multi-sectors, and a recursive computable general equilibrium (CGE) model (Bernard & Vielle, 2008). GEMINI-E3 simulates all relevant domestic and international markets, which are assumed to be perfectly competitive. It implies that the corresponding prices are flexible for commodities (through relative prices), for labour (through wages), and for domestic and international savings (through rates of interest and exchange rates). Time periods are linked through endogenous real interest rates from balancing of savings and the investment. It follows, real exchange rates are endogenously determined by constraining foreign trade deficits or surpluses. These rates link the national and regional scope in the model.

There is one notable, yet usual exception to this general assumption of perfect competition. It relates to foreign trade, where goods of the same sector produced by different countries are not supposed to be perfectly competitive. They are considered as economically different goods, more or less substitute according to the Armington elasticity of substitution. Simulations with GEMINI-E3 result in outputs on a regional and annual basis. These include carbon taxes, marginal abatement costs, prices and net sales of tradable permits, and effective abatement of CO_2 emissions. The model also projects the total net welfare loss and its components (e.g. net loss from terms of trade, pure deadweight loss of taxation, and net purchases of tradable permits), macro-economic aggregates (e.g. production, imports and final demand), real exchange rates and real interest rates, and data at the industrial level (e.g. change in production and in factors of production, and prices of goods).

GEMINI-E3 is available in several versions with different sectors and regions classifications depending on the research question studied. For example, analysing the European burden sharing requires disaggregation of the 28 European member states individually, and the European version is used (see (Vielle, 2020)). In this study, the world economy is divided into five countries (USA, China, India, Brazil, and Russia) and six aggregated regions, including EU-28. The analysis is based on GTAP-10 (Aguiar et al., 2019), a database that accommodates a consistent representation of energy markets in physical units (tons of oil equivalent) and detailed socio-accounting matrices in USD for a large set of countries or regions and bilateral trade flows.

Economic rationale: For each sector and region, GEMINI-E3 computes total demand as the sum of final demand (investment, consumption, and exports) and intermediate consumptions by all sectors. Then, demand is split between imports and domestic production according to the Armington assumption. Domestic production technologies are described through nested Constant Elasticity of Substitution (CES) functions, which differ by sector.

Household behaviour consists of three interdependent decisions: labour supply; savings; and consumption of various goods and services. Both labour supply and the rate of savings are assumed to be exogenous. Demand in the different commodities has consumption prices and "spent" income (i.e. income after savings) that is derived from nested CES utility functions. At the first level of the consumption function, households choose between three aggregates: housing, transport, and other consumptions. Energy consumption is split for transportation and housing purposes, while transport demand is classified into purchased and own transports. The model distinguishes three types of personal vehicles depending on the fuel used. These include electric vehicles, which are mainly dedicated to short or medium distance, and two other types using the same motorisation (i.e. internal combustion using petroleum products, and the other biofuels). Each vehicle is characterised by a vehicle capital and a type of fuel used (refined oil, biofuel, or electricity).

Total government consumption is exogenous. Its level changes over time as it is driven by the growth rates of the main aggregates of the economy. The model splits total consumption between goods, based on fixed budget shares. The exports are the sum of imports by all other countries/regions that are endogenously determined in the model. Investment by products is derived from investment by sectors through a transfer matrix. Sectoral investment is determined from an "anticipated" capital demand using the CES function of each sector. Anticipated

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

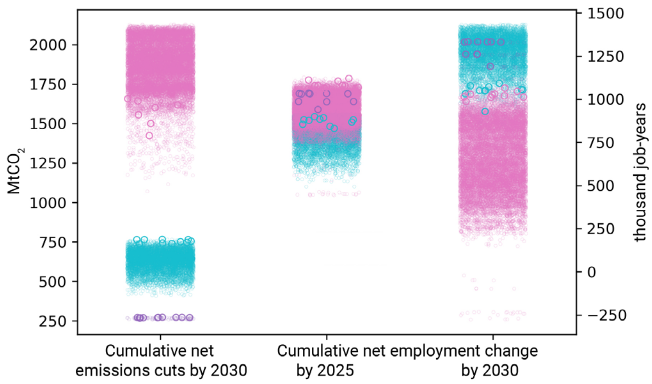
production prices and demands are based on adaptive expectations.

The government surplus or deficit is the difference between revenues accruing from taxation (direct and indirect, including social security contributions) and two types of expenditures (public consumption and transfers to households such as social benefits).

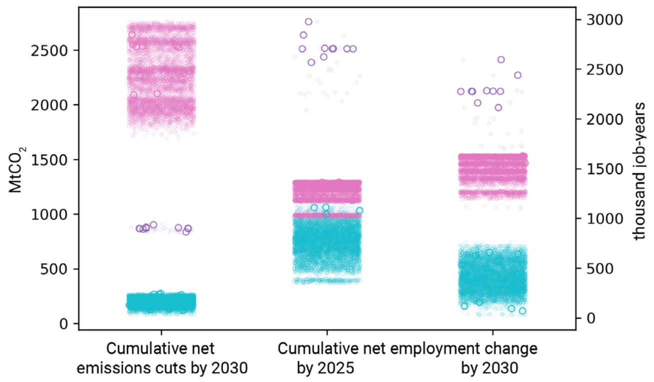
Emissions: GEMINI-E3 computes all GHG emissions included in the Kyoto basket: CO_2, CH_4, N_2O and fluorinated gases. Carbon emissions are directly computed from fossil energy consumption in physical quantities using coefficient factors that differ among firms (i.e. sectors), households, and regions. For non-CO_2 GHG gases, the emissions of each source are linked to an activity level (or an economic driver).

Notes on scenario implementation: Energy and climate policies (pre-Covid-19, until 2020) have been applied in all eleven regions. For the aggregated regions, they mainly refer to renewable electricity targets that have been summed. For the six individual regions, they encompass a much broader set of policies. These policies have been introduced into GEMINI-E3 through taxes (VAT, excises, etc.), subsidies and carbon prices (like the EU ETS price). All these policies define the "current policies scenario" and remain constant under the Covid-19 recovery package, where the new power capacities are added on top of them through additional subsidies.

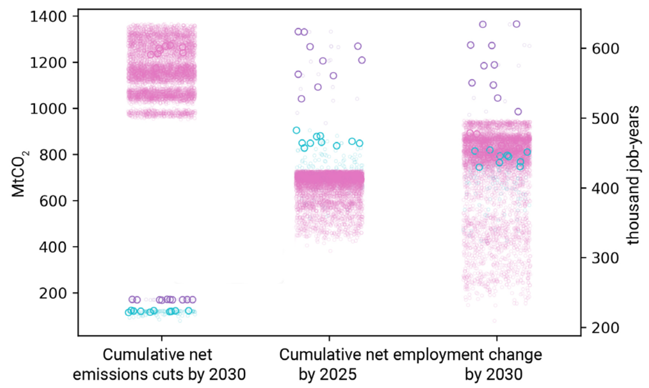
Supplemental Figures



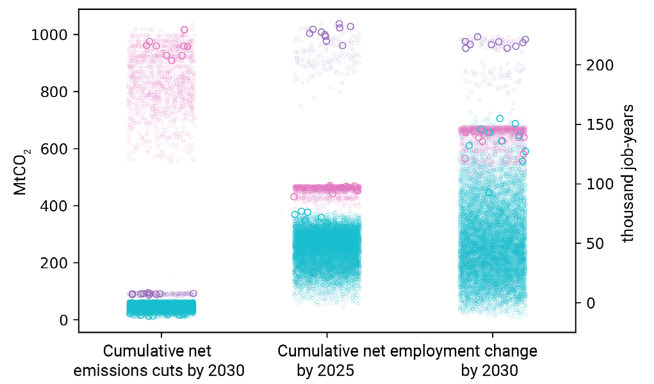
(A) EU



(B) China



(C) USA



(D) India

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

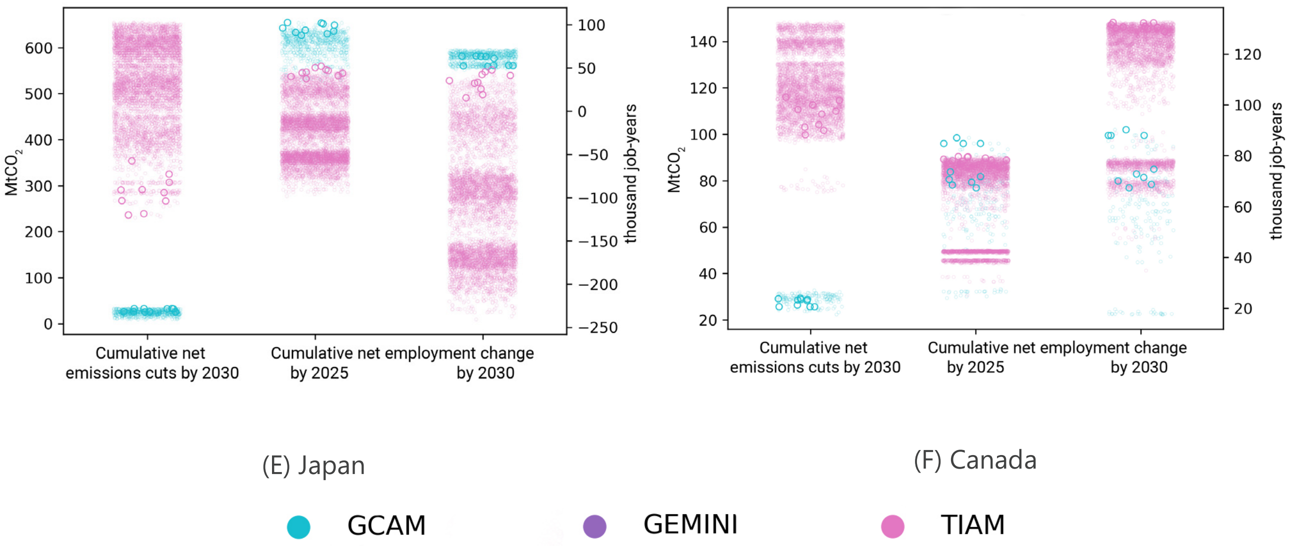


Figure A2.1: Cross-model ranges of Pareto-optimal scenarios for each country, based on three objectives

The first objective refers to the need for further reductions of CO_2 emissions, as articulated in the NDCs of the examined countries, and it is measured in terms of cumulative CO_2 emissions cuts between 2021 and 2030 (MtCO$_2$). The second and third objectives refer to the creation of new energy-sector jobs by 2025 and 2030, respectively, and are measured in terms of cumulative net employment change between 2021 and 2025, and between 2021 and 2030 (thousand job-years), respectively. Panels A – F show ranges of these results for the six different countries/regions examined. Blue colour represents portfolios from GCAM, purple from GEMINI, and pink from TIAM. For each model, the top 10 most robust portfolios have been highlighted with larger bubbles.

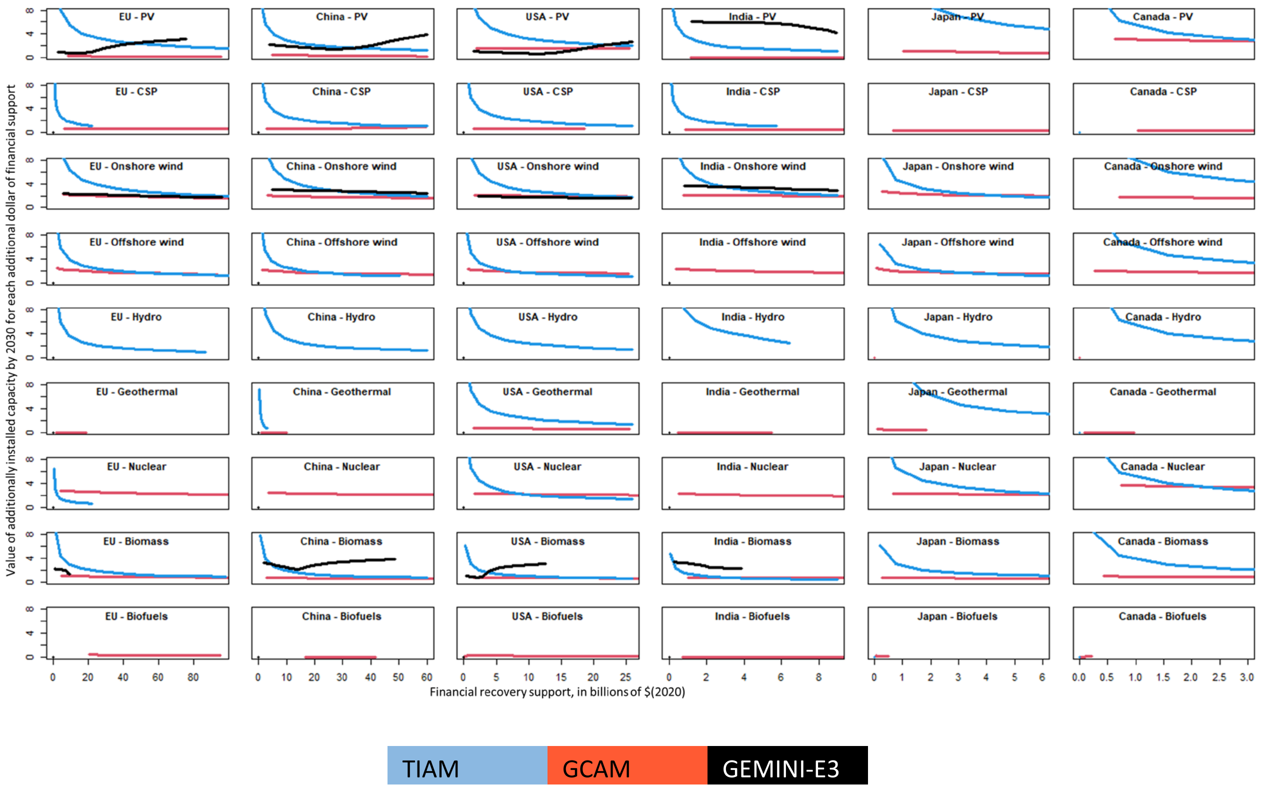
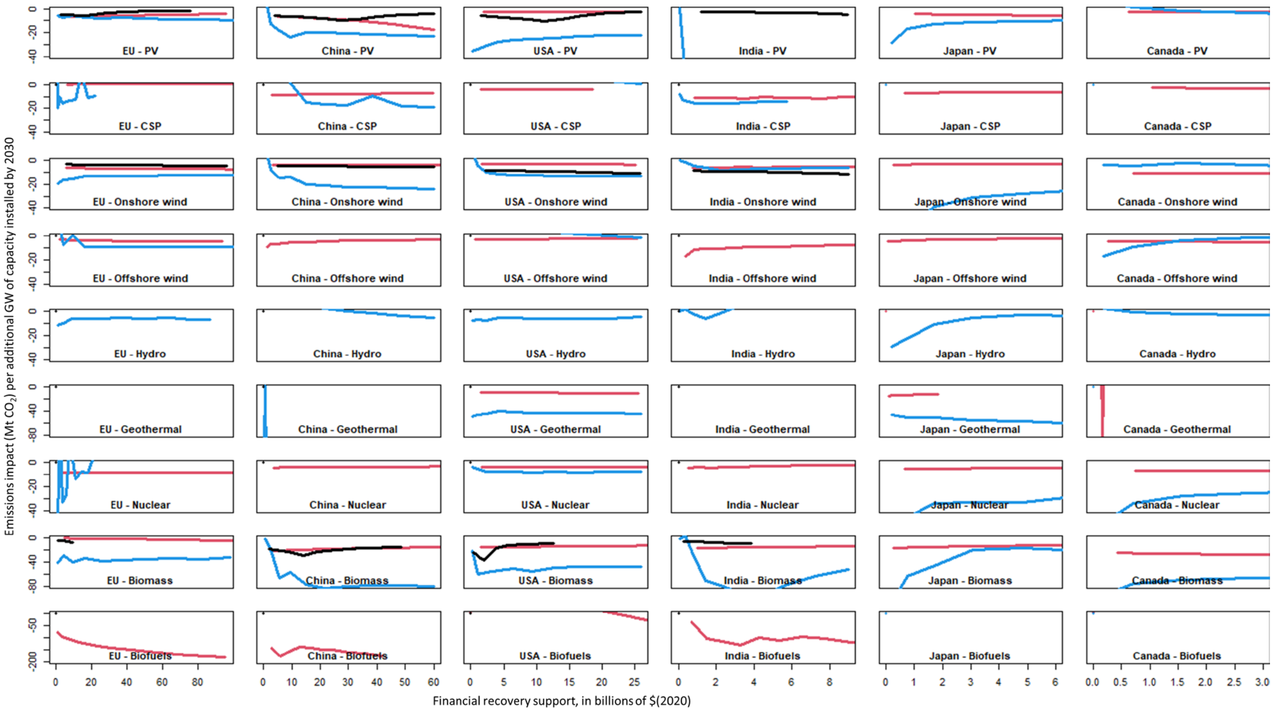


Figure A2.2: Additional value of capacity installed for each dollar of support for each country, technology and applied model

For example, a value of two means that each dollar of supports yields two dollars of additional capacity for that technology. Graphs are capped at country budgets.

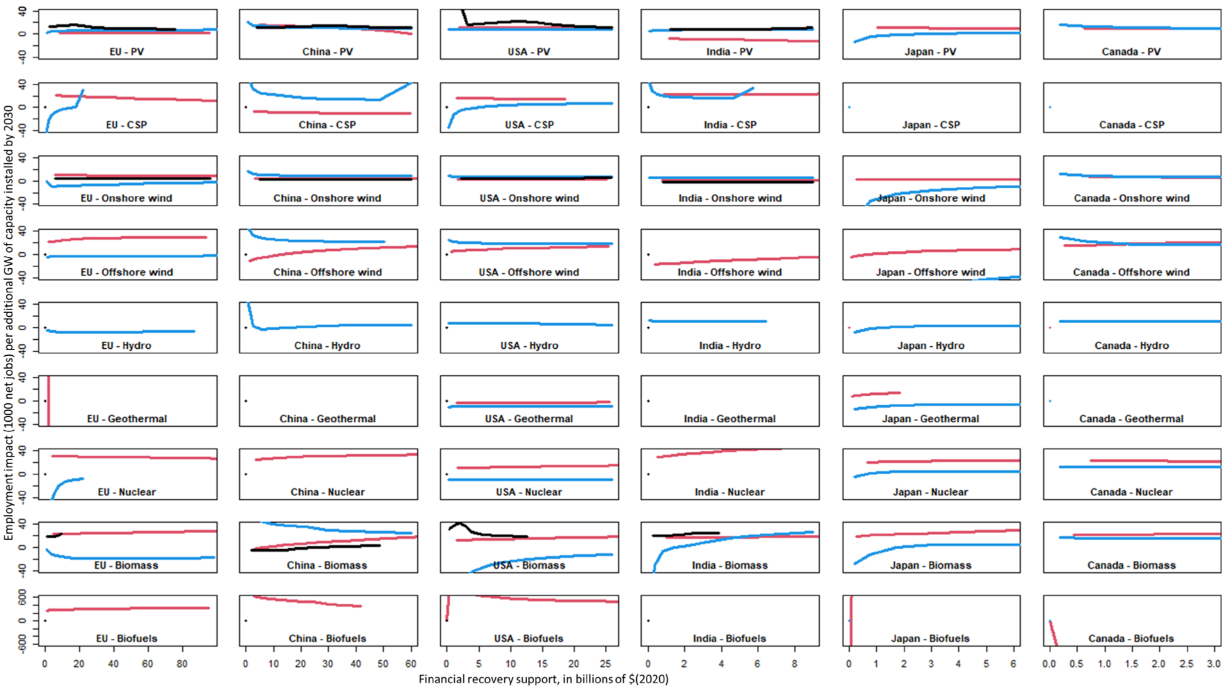
The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.



TIAM | GCAM | GEMINI-E3

Figure A2.3: Emission impacts for each additional unit of capacity (GW) installed by 2030 for each country, technology and applied model.

***For example,** a value of minus ten means that each GW of additional capacity yields a cumulative saving of 10 Mt CO_2.*



TIAM | GCAM | GEMINI-E3

Figure A2.4: Employment impacts for each additional unit of capacity (GW) installed by 2030 for each country, technology and applied model.

For example, a value of ten means that each GW of additional capacity yields a cumulative gain of 10 job-years by 2030..

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

References

Aguiar, A., Chepeliev, M., Corong, E., McDougall, R., & van der Mensbrugghe, D. (2019). The GTAP Data Base: Version 10. Journal of Global Economic Analysis, 4(1), 1–27.

Alves Dias, P., Kanellopoulos, K., Medarac, H., Kapetaki, Z., Miranda-Barbosa, E., Shortall, R., ... & Tzimas, E. (2018). EU coal regions: opportunities and challenges ahead. European Union: Luxembourg. Retrieved from: https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/eu-coal-regions-opportunities-and-challenges-ahead

Andrijevic, M., Schleussner, C.-F., Gidden, M.J., McCollum, D.L., and Rogelj, J. (2020). COVID-19 recovery funds dwarf clean energy investment needs. Science (80-.). 370, 298–300.

Arancibia, A. L., Marques, G. F., & Mendes, C. A. B. (2016). Systems capacity expansion planning: Novel approach for environmental and energy policy change analysis. Environmental modelling & software, 85, 70-79.

Attia, A. M., Ghaithan, A. M., & Duffuaa, S. O. (2019). A Multi-Objective Optimization Model for Tactical Planning of Upstream Oil & Gas Supply Chains. Computers & Chemical Engineering.

Bal, A., & Satoglu, S. I. (2018). A goal programming model for sustainable reverse logistics operations planning and an application. Journal of cleaner production, 201, 1081-1091.

Baran, J., Szpor, A., & Witajewski-Baltvilks, J. (2020). Low-carbon transition in a coal-producing country: A labour market perspective. Energy Policy, 147, 111878.

Bernard, A., & Vielle, M. (2008). GEMINI-E3, a general equilibrium model of international–national interactions between economy, energy and the environment. Computational Management Science, 5(3), 173–206. https://doi.org/10.1007/s10287-007-0047-y

Bertram, C., Riahi, K., Hilaire, J., Bosetti, V., Drouet, L., Fricko, O., Malik, A., Nogueira, L.P., van der Zwaan, B., van Ruijven, B., et al. (2021). Energy system developments and investments in the decisive decade for the Paris Agreement goals. Environ. Res. Lett. 16, 074020.

Bootaki, B., Mahdavi, I., & Paydar, M. M. (2014). A hybrid GA-AUGMECON method to solve a cubic cell formation problem considering different worker skills. Computers & Industrial Engineering, 75, 31-40.

Bootaki, B., Mahdavi, I., & Paydar, M. M. (2016). New criteria for configuration of cellular manufacturing considering product mix variation. Computers & Industrial Engineering, 98, 413-426.

Calvin, K., Bond-Lamberty, B., Clarke, L., Edmonds, J., Eom, J., Hartin, C., Kim, S., Kyle, P., Link, R., Moss, R., McJeon, H., Patel, P., Smith, S., Waldhoff, S., & Wise, M. (2017). The SSP4: A world of deepening inequality. Global Environmental Change, 42, 284–296. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2016.06.010

Calvin, K., Patel, P., Clarke, L., Asrar, G., Bond-Lamberty, B., Cui, R. Y., Di Vittorio, A., Dorheim, K., Edmonds, J., Hartin, C., Hejazi, M., Horowitz, R., Iyer, G., Kyle, P., Kim, S., Link, R., McJeon, H., Smith, S., Snyder, A., ... Wise, M. (2019). GCAM v5.1: representing the linkages between energy, water, land, climate, and economic systems. Geoscientific Model Development, 12(2). https://doi.org/10.5194/gmd-12-677-2019

Cambero, C., & Sowlati, T. (2016). Incorporating social benefits in multi-objective optimization of forest-based bioenergy and biofuel supply chains. Applied Energy, 178, 721-735.

Cambero, C., Sowlati, T., & Pavel, M. (2016). Economic and life cycle environmental optimization of forest-based biorefinery supply chains for bioenergy and biofuel production. Chemical Engineering Research and

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Design, 107, 218-235.

Canales-Bustos, L., Santibañez-González, E., & Candia-Véjar, A. (2017). A multi-objective optimization model for the design of an effective decarbonized supply chain in mining. International Journal of Production Economics, 193, 449-464.

Cazcarro, I., García-Gusano, D., Iribarren, D., Linares, P., Romero, J.C., Arocena, P., Arto, I., Banacloche, S., Lechón, Y., Miguel, L.J., et al. (2022). Energy-socio-economic-environmental modelling for the EU energy and post-COVID-19 transitions. Sci. Total Environ. 805, 150329.

Chaurasiya, P.K., Prasad, V., and Khare, R. (2013). Scenario and risk of hydro power projects in India. Int. J. ChemTech Res. 5, 1068–1075.

Chen, C., Liu, Y., Greig, J.A., Shen, Z., and Shi, Y. (2022). The impacts of COVID-19 on clean energy labor markets: Evidence from multifaceted analysis of public health interventions and COVID-health factors. Energy Policy 164, 112880.

Ciarli, T., and Savona, M. (2019). Modelling the Evolution of Economic Structure and Climate Change: A Review. Ecol. Econ. 158, 51–64.

Claeys, G., Tagliapietra, S., & Zachmann, G. (2019). How to make the European Green Deal work. Bruegel Policy Contribution, 13. Retrieved from: https://www.bruegel.org/wp-content/uploads/2019/11/PC-14_2019-041119.pdf

Clarke, J.F., and Edmonds, J.A. (1993). Modelling energy technologies in a competitive market. Energy Econ. 15, 123–129.

Climate Action Tracker. (2021). Warming Projections Global Update, November 2021.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). Labor Markets During the COVID-19 Crisis: A Preliminary View.

CRS. (2021). Inflation in the Wake of COVID-19.

D'Alessandro, S., Cieplinski, A., Distefano, T., & Dittmer, K. (2020). Feasible alternatives to green growth. Nature Sustainability, 3(4), 329-335.

D'Alessandro, S., Cieplinski, A., Distefano, T., and Dittmer, K. (2020). Feasible alternatives to green growth. Nat. Sustain. 3, 329–335.

Dafnomilis, I., Chen, H.-H., den Elzen, M., Fragkos, P., Chewpreecha, U., van Soest, H., Fragkiadakis, K., Karkatsoulis, P., Paroussos, L., de Boer, H.-S., et al. (2022). Targeted Green Recovery Measures in a Post-COVID-19 World Enable the Energy Transition. Front. Clim. 4.

Dafnomilis, I., den Elzen, M., van Soest, H., Hans, F., Kuramochi, T., & Höhne, N. (2020). Exploring the impact of the COVID-19 pandemic on global emission projections. PBL Netherlands Environmental Agency.

Den Elzen, M. G., Dafnomilis, I., Forsell, N., Fragkos, P., Fragkiadakis, K., Höhne, N., ... & Sperling, F. (2022). Updated nationally determined contributions collectively raise ambition levels but need strengthening further to keep Paris goals within reach. Mitigation and adaptation strategies for global change, 27(6), 1-29.

Distelkamp, M., and Meyer, M. (2019). Pathways to a Resource-Efficient and Low-Carbon Europe. Ecol. Econ. 155, 88–104.

Duggal, R., Rayudu, R., Hinkley, J., Burnell, J., Wieland, C., and Keim, M. (2022). A comprehensive review of energy extraction from low-temperature geothermal resources in hydrocarbon fields. Renew. Sustain. Energy Rev.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

154, 111865.

Edmonds, J. A., Wise, M. A., & MacCracken, C. N. (1994). Advanced Energy Technologies and Climate Change: An Analysis Using the Global Change Assessment Model (gcam) (PNL-9798). Pacific Northwest National Laboratory (PNNL).

Ehrenstein, M., Wang, C. H., & Guillén-Gosálbez, G. (2019). Strategic planning of supply chains considering extreme events: Novel heuristic and application to the petrochemical industry. Computers & Chemical Engineering, 125, 306-323.

Ellenbeck, S., & Lilliestam, J. (2019). How modelers construct energy costs: discursive elements in energy system and integrated assessment models. Energy Research & Social Science, 47, 69-77.

Environment and Climate Change Canada (2021). A Healthy Environment and a Healthy Economy.

European Commission. (2020a). Recovery plan for Europe. Retrieved from: https://ec.europa.eu/info/strategy/recovery-plan-europe_en

European Commission. (2020b). Commission Staff Working Document: Guidance to Member States Recovery and Resilience Plans. Retrieved from: https://ec.europa.eu/info/sites/default/files/3_en_document_travail_service_part1_v3_en_0.pdf

European Commission. (2021). Annual Sustainable Growth Strategy 2021. https://www.eesc.europa.eu/en/our-work/opinions-information-reports/opinions/annual-sustainable-growth-strategy-2021

European Parliament. (2021). Rise in Inflation: Temporary or Sign of a More Permanent Trend?

Eurostat. (2020a). Impact of COVID-19 on employment income - advanced estimates. Retrieved from: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Impact_of_COVID-19_on_employment_income_-_advanced_estimates&stable=1#cite_note-1

Eurostat. (2020b). September 2020 - Euro area unemployment at 8.3%.

Eurostat. (2022). Society And Work. Retrieved from: https://ec.europa.eu/eurostat/web/covid-19/society-work

EY. (2020). A Green Covid-19 Recovery and Resilience Plan for Europe. https://www.ey.com/it_it/news/2020/08/a-green-covid-19-recovery-and-resilience-plan-for-europe

Fauci, A. S., Lane, H. C., & Redfield, R. R. (2020). Covid-19—navigating the uncharted. The New England Journal of Medicine, 382, 1268-1269.

Florios, K., & Mavrotas, G. (2014). Generation of the exact Pareto set in multi-objective traveling salesman and set covering problems. Applied Mathematics and Computation, 237, 1-19.

Forouli, A., Doukas, H., Nikas, A., Sampedro, J., & Van de Ven, D. J. (2019a). Identifying optimal technological portfolios for European power generation towards climate change mitigation: A robust portfolio analysis approach. Utilities Policy, 57, 33-42.

Forouli, A., Gkonis, N., Nikas, A., Siskos, E., Doukas, H., & Tourkolias, C. (2019b). Energy efficiency promotion in Greece in light of risk: Evaluating policies as portfolio assets. Energy, 170, 818-831.

Forouli, A., Nikas, A., Van de Ven, D. J., Sampedro, J., & Doukas, H. (2020). A multiple-uncertainty analysis framework for integrated assessment modelling of several sustainable development goals. Environmental Modelling & Software, 131, 104795.

Forster, P.M., Forster, H.I., Evans, M.J., Gidden, M.J., Jones, C.D., Keller, C.A., Lamboll, R.D., Quéré, C. Le, Rogelj, J.,

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Rosen, D., et al. (2020). Current and future global climate impacts resulting from COVID-19. Nat. Clim. Chang. 10, 913–919.

Fragkos, P., and Fragkiadakis, K. (2022). Analyzing the Macro-Economic and Employment Implications of Ambitious Mitigation Pathways and Carbon Pricing. Front. Clim. 4.

Fragkos, P., and Paroussos, L. (2018). Employment creation in EU related to renewables expansion. Appl. Energy 230, 935–945.

Fragkos, P., Fragkiadakis, K., Paroussos, L., Pierfederici, R., Vishwanathan, S.S., Köberle, A.C., Iyer, G., He, C.M., and Oshiro, K. (2018). Coupling national and global models to explore policy impacts of NDCs. Energy Policy 118, 462–473.

Fragkos, P., Fragkiadakis, K., Sovacool, B., Paroussos, L., Vrontisi, Z., & Charalampidis, I. (2021). Equity implications of climate policy: Assessing the social and distributional impacts of emission reduction targets in the European Union. Energy, 237, 121591.

Fujimori, S., Hasegawa, T., Takahashi, K., Dai, H., Liu, J.Y., Ohashi, H., Xie, Y., Zhang, Y., Matsui, T., and Hijioka, Y. (2020). Measuring the sustainable development implications of climate change mitigation. Environ. Res. Lett. 15.

Gambhir, A., Napp, T. A., Emmott, C. J. M., & Anandarajah, G. (2014). India's CO2 emissions pathways to 2050: Energy system, economic and fossil fuel impacts with and without carbon permit trading. Energy, 77, 791–801. https://doi.org/https://doi.org/10.1016/j.energy.2014.09.055

García-García, P., Carpintero, Ó., and Buendía, L. (2020). Just energy transitions to low carbon economies: A review of the concept and its effects on labour and income. Energy Res. Soc. Sci. 70, 101664.

Gavranis, A., & Kozanidis, G. (2017). Mixed integer biobjective quadratic programming for maximum-value minimum-variability fleet availability of a unit of mission aircraft. Computers & Industrial Engineering, 110, 13-29.

Geels, F. W., & Schot, J. (2007). Typology of sociotechnical transition pathways. Research policy, 36(3), 399-417.

Giarola, S., Mittal, S., Vielle, M., Perdana, S., Campagnolo, L., Delpiazzo, E., Bui, H., Kraavi, A.A., Kolpakov, A., Sognnaes, I., et al. (2021). Challenges in the harmonisation of global integrated assessment models: A comprehensive methodology to reduce model response heterogeneity. Sci. Total Environ. 783, 146861.

Gosens, J., and Jotzo, F. (2020). China's post-COVID-19 stimulus: No Green New Deal in sight. Environ. Innov. Soc. Transitions 36, 250–254.

Government of Canada. (2021). Budget 2021: A Recovery Plan for Jobs, Growth, and Resilience.

Guivarch, C., Le Gallic, T., Bauer, N., Fragkos, P., Huppmann, D., Jaxa-Rozen, M., Keppo, I., Kriegler, E., Krisztin, T., Marangoni, G., et al. (2022). Using large ensembles of climate change mitigation scenarios for robust insights. Nat. Clim. Chang. 12, 428–435.

Habibi, F., Barzinpour, F., & Sadjadi, S. J. (2019). A mathematical model for project scheduling and material ordering problem with sustainability considerations: A case study in Iran. Computers & industrial engineering, 128, 690-710.

Hepburn, C., O'Callaghan, B., Stern, N., Stiglitz, J., and Zenghelis, D. (2020). Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change? Oxford Rev. Econ. Policy 36, S359–S381.

Heuberger, C.F., Staffell, I., Shah, N., and Mac Dowell, N. (2018). Impact of myopic decision-making and disruptive

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

events in power systems planning. Nat. Energy 3, 634–640.

Hiloidhari, M., Baruah, D.C., Kumari, M., Kumari, S., and Thakur, I.S. (2019). Prospect and potential of biomass power to mitigate climate change: A case study in India. J. Clean. Prod. 220, 931–944.

HM Government. (2020). The Ten Point Plan for a Green Industrial Revolution. 1-. https://www.gov.uk/government/publications/the-ten-point-plan-for-a-green-industrial-revolution

Hombach, L. E., & Walther, G. (2015). Pareto-efficient legal regulation of the (bio) fuel market using a bi-objective optimization model. European Journal of Operational Research, 245(1), 286-295.

Huang, Z., Hejazi, M., Tang, Q., Vernon, C. R., Liu, Y., Chen, M., & Calvin, K. (2019). Global agricultural green and blue water consumption under future climate and land use changes. Journal of Hydrology, 574, 242–256. https://doi.org/https://doi.org/10.1016/j.jhydrol.2019.04.046

Hymans, J.E.C. (2021). Losing Steam: Why Does Japan Produce So Little Geothermal Power? Soc. Sci. Japan J. 24, 45–65.

IEA. (2019). Data and statistics. Retrieved from: https://www.iea.org/data-and-statistics/data-tables?country=EU28

IEA. (2020). Covid-19 impact on renewable energy growth.

IEA. (2021a). COP26 climate pledges could help limit global warming to 1.8 °C, but implementing them will be the key.

IEA. (2021b). Global Covid-19 fiscal support and its components: long-term economic and sustainable recovery spending, as of July 2021. https://www.iea.org/data-and-statistics/charts/global-covid-19-fiscal-support-and-its-components-long-term-economic-and-sustainable-recovery-spending-as-of-july-2021.

IEA. (2021c). What is the impact of increasing commodity and energy prices on solar PV, wind and biofuels?

IISD. (2020). Japan Unveils USD 700 Billion Stimulus Package.

IMF. (2021). World Economic Outlook: Recovery During a Pandemic - Health Concerns, Supply Disruptions, and Price Pressures.

Inghels, D., Dullaert, W., & Bloemhof, J. (2016). A model for improving sustainable green waste recovery. Resources, Conservation and Recycling, 110, 61-73.

IRENA (2020a). Measuring the Socio-economics of Transition: Focus on Jobs.

IRENA (2020b). The post-COVID recovery: An agenda for resilience, development and equality.

Jaeger, J., Walls, G., Clarke, E., Altamirano, J.C., Harsono, A., Mountford, H., Burrow, S., Smith, S., and Tate, A. (2021). The Green Jobs Advantage: How Climate-Friendly Investments Are Better Job Creators. World Resour. Inst., 1–44.

Jäger-Waldau, A., Kougias, I., Taylor, N., & Thiel, C. (2020). How photovoltaics can contribute to GHG emission reductions of 55% in the EU by 2030. Renewable and Sustainable Energy Reviews, 126, 109836.

Joshi, S., & Mukhopadhyay, K. (2022). Cleaner the better: Macro-economic assessment of ambitious decarbonisation pathways across Indian states. Renewable and Sustainable Energy Transition, 2, 100027.

Josten, C., and Lordan, G. (2022). Automation and the changing nature of work. PLoS One 17, e0266326.

Ju, Y., Sugiyama, M., Kato, E., Oshiro, K., and Wang, J. (2022). Job creation in response to Japan's energy transition towards deep mitigation: An extension of partial equilibrium integrated assessment models. Appl. Energy 318, 119178.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Keppo, I., Butnar, I., Bauer, N., Caspani, M., Edelenbosch, O., Emmerling, J., Fragkos, P., Guivarch, C., Harmsen, M., Lefevre, J., et al. (2021). Exploring the possibility space: taking stock of the diverse capabilities and gaps in integrated assessment models. Environ. Res. Lett. 16.

Keramidas, K., Fosse, F., Diaz-Vazquez, A., Schade, B., Tchung-Ming, S., Weitzel, M., Vandyck, T., and Wojtowicz, K. (2021). Global Energy and Climate Outlook 2020: A New Normal Beyond Covid-19 (Publications Office of the European Union).

Khalili-Damghani, K., Tavana, M., & Sadi-Nezhad, S. (2012). An integrated multi-objective framework for solving multi-period project selection problems. Applied Mathematics and Computation, 219(6), 3122-3138.

Kikstra, J.S., Vinca, A., Lovat, F., Boza-Kiss, B., van Ruijven, B., Wilson, C., Rogelj, J., Zakeri, B., Fricko, O., and Riahi, K. (2021). Climate mitigation scenarios with persistent COVID-19-related energy demand changes. Nat. Energy 6, 1114–1123.

Kivimaa, P., Laakso, S., Lonkila, A., & Kaljonen, M. (2021). Moving beyond disruptive innovation: A review of disruption in sustainability transitions. Environmental Innovation and Societal Transitions, 38, 110-126.

Koasidis, K., Nikas, A., van de Ven, D. J., Xexakis, G., Forouli, A., Shivika, M., Gambhir, A., Koutsellis, T., & Doukas, H. (2022). Towards a green recovery in the EU: Aligning further emissions reductions with short- and long-term energy-sector employment gains. Energy Policy, in press.

Lahcen, B., Brusselaers, J., Vrancken, K., Dams, Y., Da Silva Paes, C., Eyckmans, J., and Rousseau, S. (2020). Green Recovery Policies for the COVID-19 Crisis: Modelling the Impact on the Economy and Greenhouse Gas Emissions. Environ. Resour. Econ. 76, 731–750.

Lahcen, B., Brusselaers, J., Vrancken, K., Dams, Y., Paes, C. D. S., Eyckmans, J., & Rousseau, S. (2020). Green recovery policies for the COVID-19 crisis: modelling the Impact on the economy and greenhouse gas emissions. Environmental and Resource Economics, 76(4), 731-750.

Le Quéré, C., Jackson, R. B., Jones, M. W., Smith, A. J., Abernethy, S., Andrew, R. M., Friedlingstein, P., Creutzig, F., & Peters, G. P. (2020). Temporary reduction in daily global CO 2 emissions during the COVID-19 forced confinement. Nature Climate Change, 1-7.

Malik, A., & Bertram, C. (2022). Solar energy as an early just transition opportunity for coal-bearing states in India. Environmental Research Letters, 17, 034011.

Malik, A., Bertram, C., Kriegler, E., & Luderer, G. (2021). Climate policy accelerates structural changes in energy employment. Energy Policy, 159, 112642.

Malik, A., Bertram, C., Kriegler, E., and Luderer, G. (2021). Climate policy accelerates structural changes in energy employment. Energy Policy 159, 112642.

Manzanedo, R. D., & Manning, P. (2020). COVID-19: Lessons for the climate change emergency. Science of the Total Environment, 742, 140563.

Markandya, A., Arto, I., González-Eguino, M., and Román, M. V. (2016). Towards a green energy economy? Tracking the employment effects of low-carbon technologies in the European Union. Appl. Energy 179, 1342–1350.

Markandya, A., Sampedro, J., Smith, S. J., Van Dingenen, R., Pizarro-Irizar, C., Arto, I., & González-Eguino, M. (2018). Health co-benefits from air pollution and mitigation costs of the Paris Agreement: a modelling study. The Lancet Planetary Health, 2(3), e126–e133.

Mavrotas, G. (2009). Effective implementation of the ε-constraint method in Multi-Objective Mathematical Programming problems. Appl. Math. Comput. 213, 455–465.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Mavrotas, G. (2009). Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. Applied mathematics and computation, 213(2), 455-465.

Mavrotas, G., & Florios, K. (2013). An improved version of the augmented ε-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems. Applied Mathematics and Computation, 219(18), 9652-9669.

Mavrotas, G., Figueira, J. R., & Siskos, E. (2015a). Robustness analysis methodology for multi-objective combinatorial optimization problems and application to project selection. Omega, 52, 142-155.

Mavrotas, G., Gakis, N., Skoulaxinou, S., Katsouros, V., & Georgopoulou, E. (2015b). Municipal solid waste management and energy production: Consideration of external cost through multi-objective optimization and its effect on waste-to-energy solutions. Renewable and Sustainable Energy Reviews, 51, 1205-1222.

Mavrotas, G., Skoulaxinou, S., Gakis, N., Katsouros, V., & Georgopoulou, E. (2013). A multi-objective programming model for assessment the GHG emissions in MSW management. Waste Management, 33(9), 1934-1949.

Mohammadkhani, N., Sedighizadeh, M., & Esmaili, M. (2018). Energy and emission management of CCHPs with electric and thermal energy storage and electric vehicle. Thermal Science and Engineering Progress, 8, 494-508.

Mohammed, A. M., & Duffuaa, S. O. (2020). A tabu search based algorithm for the optimal design of multi-objective multi-product supply chain networks. Expert Systems with Applications, 140, 112808.

Mousazadeh, M., Torabi, S. A., Pishvaee, M. S., & Abolhassani, F. (2018). Accessible, stable, and equitable health service network redesign: A robust mixed possibilistic-flexible approach. Transportation Research Part E: Logistics and Transportation Review, 111, 113-129.

Musavi, M., & Bozorgi-Amiri, A. (2017). A multi-objective sustainable hub location-scheduling problem for perishable food supply chain. Computers & Industrial Engineering, 113, 766-778.

Napp, T. A., Few, S., Sood, A., Bernie, D., Hawkes, A., & Gambhir, A. (2019). The role of advanced demand-sector technologies and energy demand reduction in achieving ambitious carbon budgets. Applied Energy, 238, 351–367. https://doi.org/10.1016/j.apenergy.2019.01.033

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., and Agha, R. (2020). The socio-economic implications of the coronavirus pandemic (COVID-19): A review. Int. J. Surg. 78, 185–193.

Nikas, A., Elia, A., Boitier, B., Koasidis, K., Doukas, H., Cassetti, G., Anger-Kraavi, A., Bui, H., Campagnolo, L., De Miglio, R., et al. (2021a). Where is the EU headed given its current climate policy? A stakeholder-driven model inter-comparison. Sci. Total Environ. 793, 148549.

Nikas, A., Fountoulakis, A., Forouli, A., & Doukas, H. (2022a). A robust augmented ε-constraint method (AUGMECON-R) for finding exact solutions of multi-objective linear programming problems. Operational Research, 22, 1291–1332.

Nikas, A., Gambhir, A., Trutnevyte, E., Koasidis, K., Lund, H., Thellufsen, J. Z., ... & Doukas, H. (2021b). Perspective of comprehensive and comprehensible multi-model energy and climate science in Europe. Energy, 215, 119153.

Nikas, A., Koasidis, K., Köberle, A. C., Kourtesi, G., & Doukas, H. (2022b). A comparative study of biodiesel in Brazil and Argentina: An integrated systems of innovation perspective. Renewable and Sustainable Energy Reviews, 156, 112022.

Nikas, A., Xexakis, G., Koasidis, K., Acosta-Fernández, J., Arto, I., Calzadilla, A., Domenech, T., Gambhir, A., Giljum, S.,

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Gonzalez-Eguino, M., et al. (2022c). Coupling circularity performance and climate action: From disciplinary silos to transdisciplinary modelling science. Sustain. Prod. Consum. 30, 269–277.

Observer Research Foundation. (2021). Green recovery pathway for India.

Oke, O., & Siddiqui, S. (2015). Efficient automated schematic map drawing using multiobjective mixed integer programming. Computers & Operations Research, 61, 1-17.

Ou, Y., Iyer, G., Clarke, L., Edmonds, J., Fawcett, A. A., Hultman, N., McFarland, J. R., Binsted, M., Cui, R., Fyson, C., Geiges, A., Gonzales-Zuñiga, S., Gidden, M. J., Höhne, N., Jeffery, L., Kuramochi, T., Lewis, J., Meinshausen, M., Nicholls, Z., … McJeon, H. (2021). Can updated climate pledges limit warming well below 2°C? Science, 374(6568), 693–695. https://doi.org/10.1126/science.abl8976

Pai, S., Emmerling, J., Drouet, L., Zerriffi, H., and Jewell, J. (2021). Meeting well-below 2°C target would increase energy sector jobs globally. One Earth 4, 1026–1036.

Patrizio, P., Leduc, S., Kraxner, F., Fuss, S., Kindermann, G., Mesfun, S., Spokas, K., Mendoza, A., Mac Dowell, N., Wetterlund, E., et al. (2018). Reducing US Coal Emissions Can Boost Employment. Joule 2, 2633–2648.

Peng, W., Iyer, G., Bosetti, V., Chaturvedi, V., Edmonds, J., Fawcett, A.A., Hallegatte, S., Victor, D.G., van Vuuren, D., and Weyant, J. (2021). Climate policy models need to get real about people — here's how. Nature 594, 174–176.

Pfenninger, S., DeCarolis, J., Hirth, L., Quoilin, S., & Staffell, I. (2017). The importance of open data and software: Is energy research lagging behind?. Energy Policy, 101, 211-215.

Pollitt, H., Lewney, R., Kiss-Dobronyi, B., and Lin, X. (2021). Modelling the economic effects of COVID-19 and possible green recovery plans: a post-Keynesian approach. Clim. Policy, 1–15.

Purohit, I., Purohit, P., and Shekhar, S. (2013). Evaluating the potential of concentrating solar power generation in Northwestern India. Energy Policy 62, 157–175.

Qiu, R., Zhang, H., Gao, X., Zhou, X., Guo, Z., Liao, Q., & Liang, Y. (2019). A multi-scenario and multi-objective scheduling optimization model for liquefied light hydrocarbon pipeline system. Chemical Engineering Research and Design, 141, 566-579.

Rabbani, M., Saravi, N. A., Farrokhi-Asl, H., Lim, S. F. W., & Tahaei, Z. (2018). Developing a sustainable supply chain optimization model for switchgrass-based bioenergy production: A case study. Journal of cleaner production, 200, 827-843.

Rahimi, Y., Torabi, S. A., & Tavakkoli-Moghaddam, R. (2019). A new robust-possibilistic reliable hub protection model with elastic demands and backup hubs under risk. Engineering Applications of Artificial Intelligence, 86, 68-82.

Ram, M., Aghahosseini, A., and Breyer, C. (2020). Job creation during the global energy transition towards 100% renewable power system by 2050. Technol. Forecast. Soc. Change 151, 119682.

Ram, M., Osorio-Aravena, J.C., Aghahosseini, A., Bogdanov, D., and Breyer, C. (2022). Job creation during a climate compliant global energy transition across the power, heat, transport, and desalination sectors by 2050. Energy 238, 121690.

Rayat, F., Musavi, M., & Bozorgi-Amiri, A. (2017). Bi-objective reliable location-inventory-routing problem with partial backordering under disruption risks: A modified AMOSA approach. Applied Soft Computing, 59, 622-643.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Razm, S., Nickel, S., & Sahebi, H. (2019). A multi-objective mathematical model to redesign of global sustainable bioenergy supply network. Computers & Chemical Engineering, 128, 1-20.

Realmonte, G., Drouet, L., Gambhir, A., Glynn, J., Hawkes, A., Köberle, A. C., & Tavoni, M. (2019). An inter-model assessment of the role of direct air capture in deep mitigation pathways. Nature Communications, 10(1), 3277. https://doi.org/10.1038/s41467-019-10842-5

Resat, H. G., & Unsal, B. (2019). A novel multi-objective optimization approach for sustainable supply chain: A case study in packaging industry. Sustainable Production and Consumption, 20, 29-39.

Rochedo, P.R.R., Fragkos, P., Garaffa, R., Couto, L.C., Baptista, L.B., Cunha, B.S.L., Schaeffer, R., and Szklo, A. (2021). Is Green Recovery Enough? Analysing the Impacts of Post-COVID-19 Economic Packages. Energies 14, 5567.

Rodríguez, L. R., Ramos, J. S., Delgado, M. G., Félix, J. L. M., & Domínguez, S. Á. (2018). Mitigating energy poverty: Potential contributions of combining PV and building thermal mass storage in low-income households. Energy Conversion and Management, 173, 65-80.

Roshan, M., Tavakkoli-Moghaddam, R., & Rahimi, Y. (2019). A two-stage approach to agile pharmaceutical supply chain management with product substitutability in crises. Computers & Chemical Engineering, 127, 200-217.

Rutovitz, J., Dominish, E., and Downes, J. (2015). Calculating Global Energy Sector Jobs: 2015 Methodology Update (prepared for Greenpeace International by the Institute for Sustainable Futures. University of Technology Sydney).

Saadat, S., Rawtani, D., & Hussain, C. M. (2020). Environmental perspective of COVID-19. Science of The Total Environment, 138870.

Saedinia, R., Vahdani, B., Etebari, F., & Nadjafi, B. A. (2019). Robust gasoline closed loop supply chain design with redistricting, service sharing and intra-district service transfer. Transportation Research Part E: Logistics and Transportation Review, 123, 121-141.

Sazvar, Z., Rahmani, M., & Govindan, K. (2018). A sustainable supply chain for organic, conventional agro-food products: The role of demand substitution, climate change and public health. Journal of cleaner production, 194, 564-583.

Schaeffer, S. E., & Cruz-Reyes, L. (2016). Static R&D project portfolio selection in public organizations. Decision support systems, 84, 53-63.

Sedighizadeh, M., Esmaili, M., & Mohammadkhani, N. (2018). Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles. Journal of cleaner production, 195, 301-317.

Shan, Y., Ou, J., Wang, D., Zeng, Z., Zhang, S., Guan, D., and Hubacek, K. (2021). Impacts of COVID-19 and fiscal stimuli on global emissions and the Paris Agreement. Nat. Clim. Chang. 11, 200–206.

Shekarian, M., Nooraie, S. V. R., & Parast, M. M. (2019). An examination of the impact of flexibility and agility on mitigating supply chain disruptions. International Journal of Production Economics.

Sognnaes, I., Gambhir, A., van de Ven, D.J., Nikas, A., Anger-Kraavi, A., Bui, H., Campagnolo, L., Delpiazzo, E., Doukas, H., Giarola, S., et al. (2021). A multi-model analysis of long-term emissions and warming implications of current mitigation efforts. Nat. Clim. Chang. 11, 1055–1062.

Sovacool, B.K., Furszyfer Del Rio, D., and Griffiths, S. (2020). Contextualizing the Covid-19 pandemic for a carbon-

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

constrained world: Insights for sustainability transitions, energy justice, and research methodology. Energy Res. Soc. Sci. 68, 101701.

Spijker, E., Anger-Kraavi, A., Pollitt, H., and van de Ven, D.J. (2020). Evaluating integrated impacts of low-emission transitions in the livestock sector. Environ. Innov. Soc. Transitions 35, 482–492.

Stoll, C., and Mehling, M.A. (2020). COVID-19: Clinching the Climate Opportunity. One Earth 3, 400–404.

Tamba, M., Krause, J., Weitzel, M., Ioan, R., Duboz, L., Grosso, M., & Vandyck, T. (2022). Economy-wide impacts of road transport electrification in the EU. Technological forecasting and social change, 182, 121803.

Tanaka, K., Azar, C., Boucher, O., Ciais, P., Gaucher, Y., and Johansson, D.J.A. (2022). Paris Agreement requires substantial , broad , and sustained policy efforts beyond COVID - 19 public stimulus packages. Clim. Change, 1–10.

Tartibu, L. K., Sun, B. O. H. U. A., & Kaunda, M. A. E. (2015). Optimal design study of thermoacoustic regenerator with lexicographic optimization method. Journal of engineering, design and technology, 13(3), 499-519.

The New York Times (2020). A Look at What's in the Stimulus Package Trump Signed.

Tollefson, J. (2020). Why deforestation and extinctions make pandemics more likely. Nature, 584(7820), 175-176.

Torabi, S. A., Hamedi, M., & Ashayeri, J. (2013). A new optimization approach for nozzle selection and component allocation in multi-head beam-type SMD placement machines. Journal of Manufacturing Systems, 32(4), 700-714.

Vafaeenezhad, T., Tavakkoli-Moghaddam, R., & Cheikhrouhou, N. (2019). Multi-objective mathematical modeling for sustainable supply chain management in the paper industry. Computers & Industrial Engineering.

Van de Ven, D. J., Nikas, A., Koasidis, K., Forouli, A., Cassetti, G., Chiodi, A., ... & Gambhir, A. (2022). COVID-19 recovery packages can benefit climate targets and clean energy jobs, but scale of impacts and optimal investment portfolios differ among major economies. One Earth, 5(9), 1042-1054.

Van de Ven, D. J., Sampedro, J., Johnson, F. X., Bailis, R., Forouli, A., Nikas, A., ... & Doukas, H. (2019). Integrated policy assessment and optimisation over multiple sustainable development goals in Eastern Africa. Environmental Research Letters, 14(9), 094001.

Vieira, M., Pinto-Varela, T., & Barbosa-Póvoa, A. P. (2017). Production and maintenance planning optimisation in biopharmaceutical processes under performance decay using a continuous-time formulation: A multi-objective approach. Computers & Chemical Engineering, 107, 111-139.

Vielle, M. (2020). Navigating various flexibility mechanisms under European burden-sharing. Environmental Economics and Policy Studies, 22(2), 267–313. https://doi.org/10.1007/s10018-019-00257-3

Vyas, M. (2022). India's employment challenge. CMIE. https://www.cmie.com/kommon/bin/sr.php?kall=warticle&dt=20220103135752&msec=816.

Wang, H., Chen, W., Bertram, C., Malik, A., Kriegler, E., Luderer, G., Després, J., Jiang, K., and Krey, V. (2020). Early transformation of the Chinese power sector to avoid additional coal lock-in. Environ. Res. Lett. 15.

Wirl, F. (2000). Lessons from utility conservation programs. Energy J. 21.

World Nuclear Association. (2019). World Uranium Mining Production. Retrieved from: https://www.world-nuclear.org/information-library/nuclear-fuel-cycle/mining-of-uranium/world-uranium-mining-production.aspx

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.

Wouter, B & Paterakis, N. (2021). Doi:10.5281/zenodo.5772549. https://zenodo.org/record/5772549#.YoiquqhBxPY

Xia, F., Lu, X., and Song, F. (2020). The role of feed-in tariff in the curtailment of wind power in China. Energy Econ. 86, 104661.

Xidonas, P., Mavrotas, G., Zopounidis, C., & Psarras, J. (2011). IPSSIS: An integrated multicriteria decision support system for equity portfolio construction and selection. European Journal of Operational Research, 210(2), 398-409.

Xin, S., Liang, Y., Zhou, X., Li, W., Zhang, J., Song, X., ... & Zhang, H. (2019). A two-stage strategy for the pump optimal scheduling of refined products pipelines. Chemical Engineering Research and Design, 152, 1-19.

Zerrahn, A. (2017). Wind Power and Externalities. Ecol. Econ. 141, 245–260.

Zhang, X., Cui, X., Li, B., Hidalgo-Gonzalez, P., Kammen, D. M., Zou, J., & Wang, K. (2022). Immediate actions on coal phaseout enable a just low-carbon transition in China's power sector. Applied Energy, 308, 118401.

The PARIS REINFORCE project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No 820846.