nature energy

Article

https://doi.org/10.1038/s41560-024-01606-7

Reducing the cost of capital to finance the energy transition in developing countries

Received: 16 May 2023

Accepted: 15 July 2024

Published online: 27 September 2024

Check for updates

M. Calcaterra [1,2,3], L. Aleluia Reis [2,3], P. Fragkos [4], T. Briera [5], H. S. de Boer[6], F. Egli [7,8], J. Emmerling [2,3], G. Iyer [9], S. Mittal [10,11], F. H. J. Polzin [12], M. W. J. L. Sanders [13], T. S. Schmidt [8,14], A. Serebriakova[13], B. Steffen [15], D. J. van de Ven [16], D. P. van Vuuren [6,17], P. Waidelich [15] & M. Tavoni [1,2,3]

Climate stabilization requires the mobilization of substantial investments in low- and zero-carbon technologies, especially in emerging and developing economies. However, access to stable and affordable finance varies dramatically across countries. Models used to evaluate the energy transition do not differentiate regional financing costs and therefore cannot study risk-sharing mechanisms for renewable electricity generation. In this study, we incorporated the empirically estimated cost of capital differentiated by country and technology into an ensemble of five climate–energy–economy models. We quantified the additional financing cost of decarbonization borne by developing regions and explored policies of risk premium convergence across countries. We found that alleviating financial constraints benefits both climate and equity as a result of more renewable and affordable energy in the developing world. This highlights the importance of fair finance for energy availability, affordability and sustainability, as well as the need to include financial considerations in model-based assessments.

As highlighted in the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report, finance is one of the critical enablers for accelerating climate action[1]. However, access to finance is fundamentally unequal across countries[2] and, as a result, it can be a barrier to mitigation and adaptation investment[1]. Developing countries and renewable energy sources (RES) in particular face high investment risks that are reflected in a high cost of capital (CoC) for projects. Managing such costs is thus a key challenge in mobilizing (private) funding for the energy transition in the developing world[3].

This is a critical topic in terms of policy relevance[4], financial fairness[5] and energy justice[6,7]. Indeed, a key issue raised by the clean energy transition is how to make renewable energy more widely accessible, particularly to low-income populations[6], as energy is fundamental for social and economic development[8]. Therefore, suitable public support is required, which can be achieved by ensuring access to capital through low-cost finance and financial de-risking[9]. This problem is particularly acute, given the recent global rise in interest rates, which is putting developing countries' finances under pressure[10], and the high

[1]Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Milan, Italy. [2]Euro-Mediterranean Center on Climate Change (CMCC), Lecce, Italy. [3]RFF-CMCC European Institute on Economics and the Environment, Milan, Italy. [4]E3Modelling, Athens, Greece. [5]CIRED, AgroParisTech, Nogent-sur-Marne, France. [6]PBL Netherlands Environmental Assessment Agency, The Hague, the Netherlands. [7]School of Social Sciences and Technology, Technical University of Munich, Munich, Germany. [8]Energy and Technology Policy Group, ETH Zurich, Zurich, Switzerland. [9]Joint Global Change Research Institute, Pacific Northwest National Laboratory and University of Maryland, College Park, MD, USA. [10]Grantham Institute for Climate Change and the Environment, Imperial College London, London, UK. [11]CICERO Center for International Climate Research, Oslo, Norway. [12]Utrecht University School of Economics (USE), Utrecht, the Netherlands. [13]Department of Macro, International and Labour Economics (MILE), School of Business and Economics, Maastricht University, Maastricht, the Netherlands. [14]Institute of Science, Technology and Policy, ETH Zurich, Zurich, Switzerland. [15]Climate Finance and Policy Group, ETH Zurich, Zurich, Switzerland. [16]Basque Centre for Climate Change (BC3), University of the Basque Country, Leioa, Spain. [17]Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, the Netherlands. e-mail: matteo.calcaterra@polimi.it

https://doi.org/10.1038/s41560-024-01606-7

capital intensity of clean energy technologies. Despite their evident relevance, the CoC and appropriate de-risking policies are currently not well represented in the models generating the scenarios reviewed by the IPCC. In this paper, we show that they are a key tool for ensuring a just climate transition[9,11–13].

Thus, in this study, we empirically estimated[14] and incorporated real-world CoC[15] into five integrated assessment models (IAMs), thereby improving their representation of investment conditions. The CoC (and thus investment risks) were previously assumed to be the same across countries and technologies, leading to biases in model-based projections[16,17]. Indeed, RES deployment is not only driven by physical factors and costs[18–22] but, importantly, also by varying investment risks across countries[23–25], technologies[14] and time. Due to their capital intensity, the uptake of RES is much more affected by higher financing costs than fossil fuel-based plants[26] because some of these technologies are still perceived as not fully mature and therefore face a higher risk premium, which will decrease with greater confidence and deployment over time[27–29]. This methodological improvement allowed us to explore the effects of a stylized policy of international convergence to equitable finance for the energy transition in a model ensemble.

This paper contributes to the literature on justice in modern energy access[6,7,9] and in global cost-effective mitigation investment[5], and to that on the inclusion of realistic financial costs and barriers in energy and climate transition models[17]. It builds on previous articles showing the importance of modelling differentiated CoC values[30–35] as well as the benefits of their exogenous reduction[21,36–40] on the cost of the transition and on climate. Going beyond the existing literature, we provide evidence on the energy justice implications of the assumed financial transition scenario.

To obtain our results we leveraged an ensemble of coupled climate–economy models (GCAM[41], IMACLIM[42], IMAGE[43], TIAM[44] and WITCH[45]) under different climate policies. Multi-model exercises offer distinct advantages over single-model results. They provide a broader spectrum of perspectives and assumptions, reducing the likelihood of bias that might be inherent in any single modelling framework. The model ensemble includes simulation and optimization frameworks, energy systems, general equilibrium and hybrid approaches. This diversity captures a range of uncertainties, allowing stakeholders to understand the potential outcome variability. Furthermore, by comparing and contrasting different models, consistent patterns and results can be identified, lending greater confidence to certain projections or findings.

We found that financing costs are a key determinant of the effectiveness and fairness of the climate transition. International convergence in the CoC reduces emissions and fosters access to affordable energy, especially in developing countries, substantially contributing to a just transition.

Empirical work and study design

We started our analysis by deriving empirical values for the CoC for electricity generation technologies, measured by the weighted average CoC. Two main approaches were distinguished (which were also used in ref. 29): for fossil fuel-based power generation and hydro, we derived the CoC from the financing costs of a major set of energy utilities per country (based on balance sheet finance), while for non-hydro RES, we determined the costs of debt and equity as driven by the country and sector level and the technology level (project finance)[14,46]. Furthermore, we deconstructed the CoC into different components (for example, country risk and technology risk) to impute financing costs for countries and technologies where no data were available.

We obtained values for many country–technology pairs. The values are presented in Extended Data Fig. 1 and Supplementary Table 1. The developed world shows the lowest CoC values, while, within developing countries, industrialized Asian countries have a lower CoC than the remaining high-CoC countries, which were our focus in this study. In particular, we found that the CoC in the high-CoC region is, for a given technology, on average 4% higher than that of the low-CoC region. Accordingly, for the analysis of our results, we aggregated countries into three macro-regions (Extended Data Fig. 1).

Equipped with this improved empirical basis, we recalibrated the models. First, we introduced the actual region- and technology-specific CoC values. We also added a time dimension through financing experience curves, which describe the learning process of finance providers becoming acquainted with new technologies[27,29]. This was implemented as a learning-by-doing process for the CoC using the rates estimated in ref. 29. Therefore, in models with endogenous learning, the CoC reduces as technology uptake increases; the median technology–region pathway is used exogenously by the other models (see 'Full set of scenarios' in Methods for more details). Financial experience has a strong effect on CoC development over time, decreasing the CoC for renewables by 1–2% by 2100 in low-CoC countries and by 1–4% in high-CoC countries (Fig. 1a). These improvements in the models allow a realistic time evolution of the CoC for renewable electricity generation technologies (differentiated by country) and can therefore be regarded as our 'CoC-reference' scenario, against which we compare our scenario of interest. This calibration is one of the key results of our methodology as it enables a realistic representation of future global CoC development.

Our main scenario of interest was the 'CoC-convergence' scenario, in which the CoC for energy generation in developing countries converges to that of developed countries. Each generation technology's CoC higher than the one in the Global North is assumed to converge linearly to the CoC of that technology in the European Union and the United States, reaching parity by 2050. We assumed that this reduction affects only the country risk component of the CoC. However, we also assumed that the technology risk component would still be affected by financing experience, that is, the CoC convergence pathway is not exactly linear. Convergence reduces the CoC in high-CoC countries by around 4 percentage points compared with the starting point, the interaction with learning having a small further effect (Fig. 1a; see Extended Data Fig. 2 for greater granularity). This scenario therefore depicts a future world in which international access to energy financing is equal. To achieve such a world in 25 years, policy makers would need to put in place, among others, policies that imply international risk pooling and global diversification. This is far from trivial, but our exercise is meant to illustrate what might be achieved through this ambition.

We evaluated the role of the CoC under two climate policies. In the nationally determined contributions (NDC) scenario, countries are assumed to fulfil their NDC by 2030 and to apply an equivalent level of climate effort thereafter[47]. This entails continued mild mitigation efforts that do not include net-zero pledges and result in a temperature warming outcome of approximately 2.6 °C by the end of the century[48]. We compare this with an idealized scenario consistent with keeping the global temperature below 1.5 °C of warming (denoted the 1.5D scenario). This scenario involves imposing a carbon budget of 500–600 $GtCO_2$ (depending on the model) for the period of 2020–2100, achieving the NDC through 2030 and assuming a cost-minimizing uniform carbon tax rising over time thereafter (Extended Data Fig. 3). We also included additional scenarios for robustness, including one where the financing of risks spills over between countries and is transferred. In total, we explored five scenarios (see Extended Data Table 1 for a summary of the scenarios involved in this study).

Results of CoC convergence policies

The effects of the modelled CoC-convergence scenario are multifaceted. The direct outcome is the substantial reduction in the CoC in the Global South (Fig. 1a). This leads to interesting dynamics in the climate–economy and equity domains. More renewable electricity is generated in developing countries, which increases mitigation or reduces its cost, depending on the climate policy scenario. Moreover,

https://doi.org/10.1038/s41560-024-01606-7

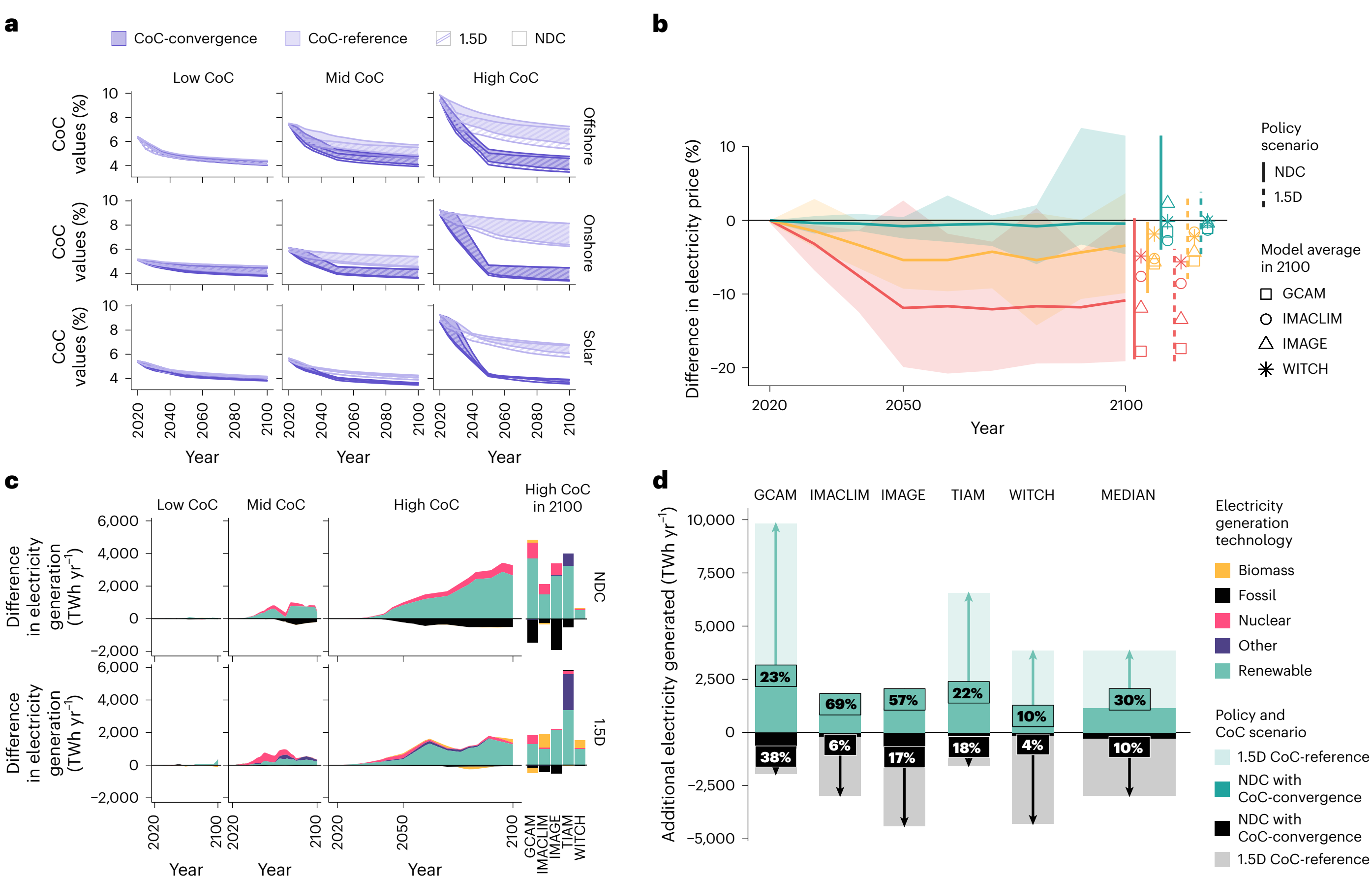


Fig. 1 | Energy consequences of CoC convergence. **a**, Projected CoC for technologies and scenarios with learning. **b**, Percentage difference in the price of electricity between the CoC-reference and CoC-convergence scenarios over time. Left: the lines report the aggregated median value across models, region and policy scenario. The shading represents, for each macro-region, the range across regions and models. Regional aggregation: red, high CoC (Africa, Latin America, Middle East, non-EU Eastern European and transition countries); yellow, mid CoC (China, India, rest of Asia); green, low CoC (Europe, North America, countries of the Pacific OECD). Right: the vertical lines express the ranges of values for each macro-region and policy scenario in 2100. The points on the lines represent the average across regions for each model (the model TIAM is absent as it does not report the price of electricity). **c**, Left: difference in electricity generation between the CoC-reference and CoC-convergence scenarios across macro-regions and time for both NDC and 1.5D scenarios, expressed as the median values across models. Right: breakdown by model for high-CoC countries in 2100 under the NDC and 1.5D scenarios. 'Renewable' includes solar and wind, 'Fossil' includes coal, oil and gas, and 'Other' includes geothermal, hydro and ocean. **d**, Additional electricity generated in an average year by energy source in high-CoC countries. The bars show the absolute additional electricity generated in the NDC CoC-convergence (dark shading) and 1.5D CoC-reference scenarios (light shading) with respect to the CoC-reference NDC scenario with learning. The median column compares the median NDC CoC-convergence with the median 1.5D CoC-reference. The values indicate the ratio between the two bars.

these changes clearly improve the energy justice of the green transition by decreasing inequality along dimensions such as energy expenditure and, by extension, access to modern electricity generation. In short, we found that CoC convergence has substantially positive effects in terms of mitigation, access to energy and inequality in developing countries.

More specifically, the main effect of a financing cost convergence scenario is to make renewable energy cheaper than fossil generation technologies. This is because renewable energy sources are more capital intensive than fossil fuel-based plants and, therefore, more sensitive to financing costs[26]. Thus, RES are installed more and generate more electricity, which is critical because electrification is at the core of decarbonization scenarios. Figure 1c shows that, when the CoC converges, the increase in clean electricity production is located in high-CoC countries and rises over time. In particular, in the NDC scenario, fossil fuel generation is reduced while renewable generation is boosted. In contrast, in the 1.5D scenario, the growth of renewable generation is maintained, but fossil fuels are excluded due to high carbon pricing. The relative magnitude of the increase in renewables is different: demand for renewable electricity in the two scenarios increases by 10% and 5%, respectively (Extended Data Fig. 4) when the CoC converges. The described change in the energy mix, that is, power generation that is more reliant on renewables in developing countries, implies lower emissions there (Extended Data Fig. 5). Usually, this has been interpreted as a higher 'mitigation effort'. However, this further reduction in emissions for poorer countries derives entirely from the higher cost efficiency of renewables[49]. The size of the effect varies across models, with different models displaying different levels of sensitivity to the change in the CoC.

The large effect observed in the NDC scenario hints at the enabling potential of a policy pooling financing risks in the energy transition. Figure 1d shows how much CoC convergence can fill the gap between NDC and a 1.5 °C world in countries with a high CoC, both in terms of the increase in RES uptake and the reduction in fossil sources. Across models, the renewable electricity gap is filled on average by 30%, while the fossil fuel phase-out gap is filled by 10% by 2050. Nevertheless, the models vary in the size of the change needed to be compliant with a warming of 1.5 °C and, as discussed above, in the change in electricity generated by various technologies. Thus, renewables fill from 10%

https://doi.org/10.1038/s41560-024-01606-7

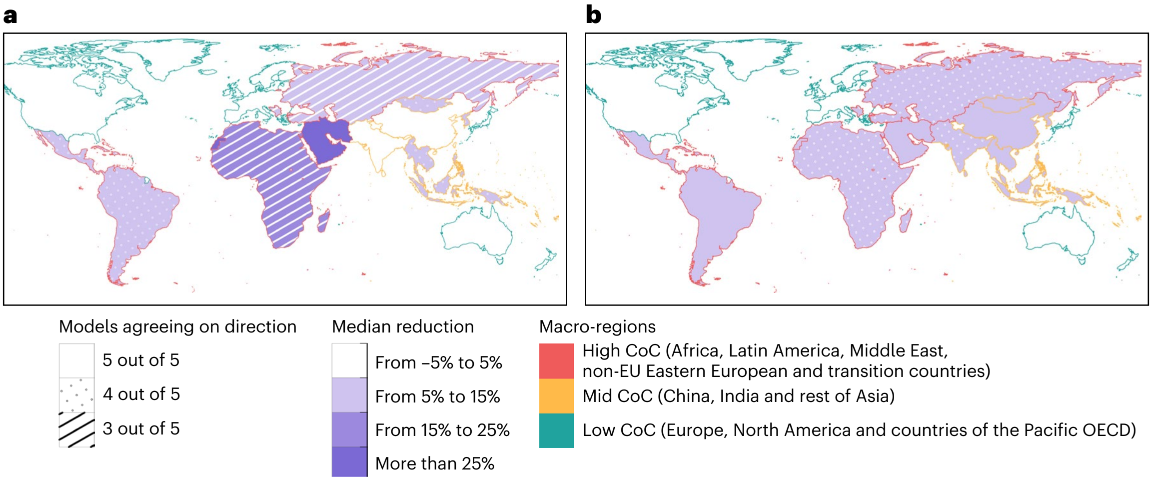


Fig. 2 | Price and quantity effects of CoC convergence. a, Percentage difference in the carbon intensity of electricity between the CoC-convergence and CoC-reference scenarios under the NDC climate policy. The underlying values are provided in Extended Data Fig. 6. **b**, Percentage difference in the policy cost between the CoC-convergence and CoC-reference scenarios under the 1.5D climate policy. Costs were computed as GDP loss (IMACLIM and WITCH), additional total energy system cost (TIAM) and area under the marginal abatement cost curve (GCAM and IMAGE). The underlying values are provided in Extended Data Fig. 7. In **a** and **b**, the colour shading shows the intensity of the reduction, with a darker colour indicating a higher reduction; the patterning illustrates the confidence of the results. OECD, Organisation for Economic Co-operation and Development. Data from ref. 86 with administrative boundaries from EuroGeographics. Figure created with https://ropengov.github.io/giscoR.

to 69% of the positive gap, while fossil fuels fill from 4% to 38% of the negative gap. It is important to note that this wide range does not undermine the validity of our results. On the contrary, it underscores the complexity of the problem at hand and the multitude of factors that can influence the outcome. It also highlights the importance of using an ensemble approach in such studies as it allows for a more holistic understanding of the system under investigation.

There are also substantial co-benefits. Not only is more renewable electricity generated but it is also cheaper. As shown in Fig. 1b, converging financing costs considerably lower the price that high-CoC countries pay for electricity. The decline is gradual following CoC convergence, stabilizing at a median price reduction of ~10% relative to the CoC-reference scenario. The direction of the effect is consistent across models and scenarios, ranging from a reduction of around 20% in some regions and models to a small and temporary positive increase in others.

Following the above, as with any cost reduction, there are both price and quantity effects. Here, a greater amount of renewable electricity is generated and the price of electricity is reduced. In terms of the quantity effect, the combined effect of energy and emissions in the NDC scenario is shown in Fig. 2a: the carbon intensity, that is, the ratio between the CO_2 emitted and the electricity produced, is clearly reduced in high-CoC countries by policies towards CoC convergence. This reduction in carbon intensity occurs robustly only in the NDC scenario as the carbon budget of the 1.5D scenario itself forces extensive decarbonization of electricity production (Extended Data Fig. 6). As a consequence, for the 1.5D scenario, the benefits of CoC convergence are not the lower emissions, but the lower cost of achieving stringent climate policies (Fig. 2b and Extended Data Fig. 7). This result can be estimated only by considering an ensemble of models as individual models are volatile across time and only by contrasting them can the signal be robustly identified, ruling out complementary scenario-variable combinations. Policy costs are reduced not only in developing regions but also in areas where financing costs are currently not the main barrier, such as in the Middle East and Russia. Indeed, those regions face considerable economic risks from a concerted climate mitigation policy as a result of falling revenues from fossil fuel exports.

In either scenario, convergence lowers energy spending in developing countries. On average, Africa and Latin America reduce their energy expenditures as a proportion of gross domestic product (GDP) by 5%, and India+ by 2.5% (Fig. 3a). This, and all of the results presented so far, substantiate the energy justice benefits embedded in a CoC convergence scenario. Indeed, we found that policies towards convergence, enacted following the principle of responsibility, have positive effects in terms of energy availability, affordability and sustainability, as well as intra- and intergenerational equity[7]. Moreover, they reduce inequalities in access to modern energy, which is an integral part of a just transition[6,9] and sustainable development[8]. Inequality in per capita renewable energy generation is on average 4% lower in the NDC scenario and 2% lower in the 1.5D scenario (Fig. 3b), as measured by the 80:20 ratio. Moreover, the renewable capacity Lorenz curves[50] shown in Fig. 3c show that, across climate policies, CoC convergence increases the equity of renewable capacity by up to 2 points in the Gini index and that the changes are spread across the whole distribution.

Discussion

The results of this empirically validated modelling exercise unambiguously show that international convergence in the CoC for energy financing is an important solution to enable the greening of the energy system and increase the justice of the transition.

Our most important contribution has been to explore the effects of a generic policy that creates a level playing field in terms of country risk premia for energy investments by the middle of the century. Such a policy is justified on both justice and efficiency grounds. Efficient global renewable energy plans should build capacity where there is the highest potential. A just global energy system should fairly disseminate both the benefits and the costs of energy services[7]. And accordingly, fair finance should flow from developed countries to developing countries[5], even if country-level risks are a barrier[1,3]. This is vital because access to modern energy is necessary to achieve sustainable development and is mutually reinforcing with other Sustainable Development Goals[8]. In particular, policies towards a convergence of CoC have the potential to yield the triple dividend of increasing energy access, enhancing social and economic benefits, and advancing climate goals[9]. The question of fair access to finance is particularly urgent in

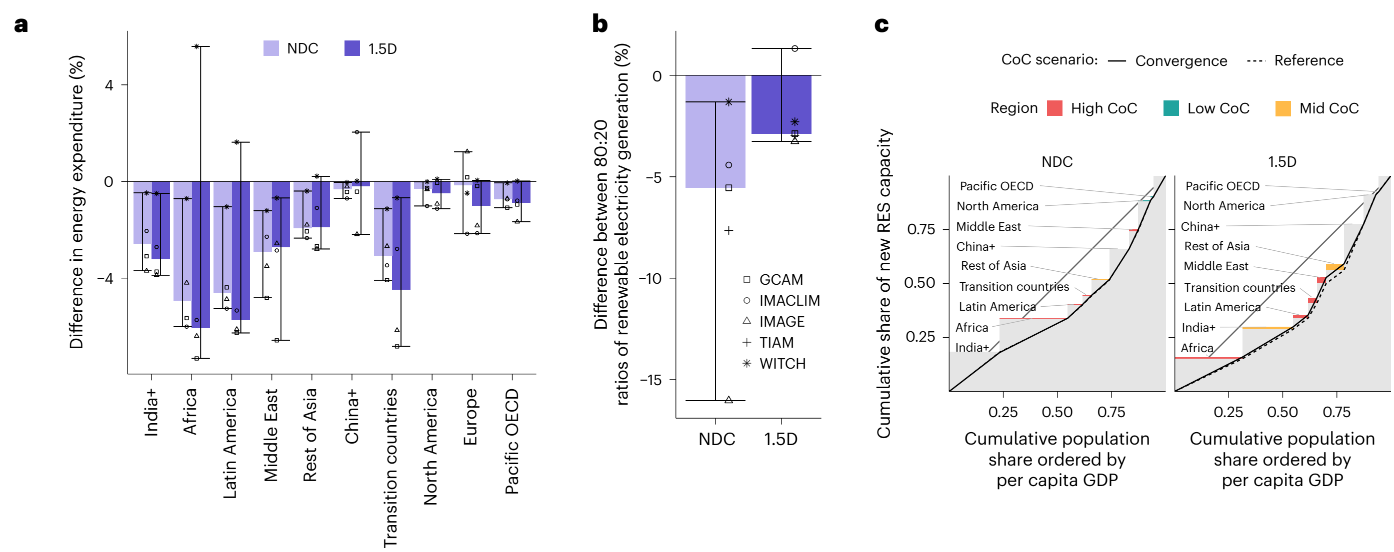


Fig. 3 | Inequality consequences of CoC convergence. a, Percentage change in energy expenditure as a proportion of GDP for CoC-convergence with respect to CoC-reference in 2100 for the NDC and 1.5D scenarios. The bars indicate the median reduction across models and the error bars show the minimum and maximum across four models (the model TIAM is absent as it does not report the price of energy). **b**, Percentage difference in the 80:20 ratio of per capita renewable electricity generation for CoC-convergence with respect to CoC-reference across models for the NDC and 1.5D scenarios. The ratio is obtained by calculating the electricity per capita generated by the two regions with the highest per capita GDP (Europe and Pacific OECD) and dividing it by the amount generated by the two poorest regions (India+ and Africa) in 2100. Then the percentage difference between the CoC-reference and CoC-convergence scenarios is calculated. The bars indicate the median across models and the error bars show the minimum and maximum across five models. **c**, Lorenz curves of the renewable capacity in 2100. The differences in the bars and curves show the additional RES generation in the CoC convergence scenarios, helping to close the gap to an equal distribution of renewable sources (line at 45°). In the NDC scenario, the two scenario lines almost overlapping.

the context of the climate transition, given the tilted distribution of historical responsibilities, physical climate risks and access to energy among industrialized and developing economies.

The ambition of reducing the CoC in developing countries towards that of today's developed world should not be underestimated. The country risk premium depends on factors such as the quality of institutions, macroeconomic stability and financial sector maturity[51], which are also desirable from a development perspective but not completely under the control of policymakers. Our scenario is agnostic with regard to the specific policies that would need to be implemented to bring about the assumed convergence. The policy provisions of Article 6 of the Paris Agreement[52] provide a framework for this. Nevertheless, besides working towards a generally lower country risk, we highlight that there might also be energy sector-specific (or even renewable energy-specific) policy levers[51]. For instance, there is evidence that the design of energy system support policies can lower the cost of renewable energy deployment by around 30% (ref. 37) and that risk-sensitive renewable energy policies have the potential to reduce the levelized cost of energy (LCOE) by 10–30% (ref. 53). Policies that improve financing conditions can include auctions[54] fostered by multilateral guarantee mechanisms, which have the potential to reduce the CoC by 6–7%[55]. Numerical simulations in other studies have shown that a multilateral sovereign guarantee fund could be compatible with the public budgets of developing countries and even impact guarantors' accounts positively[56]. Multilateral development banks are particularly important in this regard as they provide low-interest finance blended with guarantees to developing countries and are increasingly aligning their portfolios with the Paris goals[9,57,58]. Nevertheless, they have been urged to enhance their performance and contribution to the climate cause[59], and mechanisms to fund projects without issuing new debt have been suggested[60].

In this context, a general purpose policy such as the one simulated here is a useful starting point of analysis. However, policies have costs and might have effects besides the intended CoC reduction. Our analysis must be complemented by a more detailed analysis on a case-by-case basis for a tailored set of policies focused on access to and deployment of energy finance. In particular, the absence of possible risk spillovers to the CoC of the Global North is a limitation of the current design. However, we partly explored this in the sensitivity analysis. In particular, we assumed the empirical CoC to increase in the European Union and the United States, thus also impacting the CoC-convergence target for other countries. Given that we have focused only on the power sector, we do not expect the spillover to be large and, were it to be sizeable, to considerably influence our primary conclusions. Indeed, with a risk spillover of 1%, the magnitude of the results is reduced, but the direction is robust (Extended Data Fig. 8). However, future research could benefit from considering these spillover effects.

Coupled energy–economy–climate models play an important role in informing policy design and mitigation strategies at the national and international level. These models explore the response of complex systems in a consistent framework, necessarily by making simplifying assumptions[61], for example, on technology cost development constraints[62,63], the granular representation of storage technologies[64] and the treatment of variable renewable energy[65]. In particular, with respect to the last two points, this study did not focus explicitly on financing enabling infrastructure such as grid transmission, energy storage and hydrogen. These technologies will play a critical role in a renewable-based transition such as the one depicted here and are considered to different extents in the participating models. Nevertheless, their financing was not the focus of this study, given the prerogative of the public sector in infrastructure. Grid development is taken on by public utilities, whose CoC and rating are closely linked to the sovereign state[66] and thus hardly influenced by energy sector-specific policies (the cost of borrowing for grid development is still one of the main barriers in emerging markets[67]). Meanwhile, hydrogen and storage are at an early stage of development and currently need active public support[68,69], that is, for the CoC, and the private sector will play a role only further into the future. These are fundamental elements that have limited the scope of this study but open up critical avenues for future research.

In summary, our research has shown that policies that help the CoC of the power sector in developing countries to converge to the levels of developed countries play an important role in greening electricity generation, lowering the cost of mitigation and improving equity. By eliminating spreads in country risk premia in the CoC for energy financing, such policies create a level playing field, easing access to renewable energy technologies in countries that traditionally have a higher CoC. Our results are robust across models and the sizeable benefits justify investigations by policymakers to develop tools to bring about the modelled convergence. Methodologically, the approach shown here can be taken up by models that evaluate national and international climate policies and thus help to better represent financial dynamics in transition models and scenarios.

Methods

Empirical construction of the CoC

Large-scale energy and climate models that optimize pathways usually employ uniform discount rates (for example, ref. 70). These rates are intended to capture the time value of money, for example, the societal preference of consuming today compared with in the future. As such, these rates can be used to derive theoretically socially optimal pathways to achieve set climate targets in a set target year. In the case of energy system transitions, these pathways imply substantial investments in different kinds of energy assets (for example, renewable versus conventional generation technologies) in different regions of the world. In reality, these investments contain different risks and investors price these risks by demanding different returns[71]. As such, investments in the same technology face different capital costs and investments in different technologies in the same country may do so too. Because the purpose of this study was to illustrate the implications of real-world investment conditions compared with a social optimum reflected by a uniform social discount rate, we developed a method to estimate country- and technology-specific weighted average CoC (WACC).

Investments can be financed via equity or debt. Usually, these sources of capital are combined and debt is preferred because the cost of debt is less than the cost of equity as debt is serviced before equity in the case of financial distress[72]. Hence, any representation of the WACC requires a cost of debt (for example, the interest rate to be paid on a bank loan) and a cost of equity (for example, the internal return expectation, or hurdle rate, of the asset owner). In addition, an input of debt share, that is, how much debt a project or a company is able to attract, is required.

The methodology used to calculate the WACC is described in the literature[73]. Specifically, the authors show that interest expenses can be used as a viable proxy for the cost of debt, and the cost of equity can be proxied by dividend payments.

$$\mathrm{WACC}_{it} = L_{it} \times r_{\mathrm{D}it} \times (1 - \mathrm{TaxRate}_{it}) + (1 - L_{it}) \times r_{\mathrm{E}it} \tag{1}$$

For company i in year t, this shows that the cost of debt, $r_{\mathrm{D}it}$, is weighted by the leverage ratio, L_{it}, and (one minus) the country's tax rate. The cost of equity, $r_{\mathrm{E}it}$, is weighted by the complement of the leverage ratio, which is defined as:

$$L_{it} = \frac{\text{Total Debt}_{it}}{\text{Total Debt}_{it} + \text{Total Equity}_{it}} \tag{2}$$

This approach was used to calculate the CoC for renewable energy projects in ref. 16 and to obtain differentiated country-level utility WACC values for Europe in ref. 71. These data were used in the modelling in this study. In addition, we calculated differentiated country-level utility CoC for the period 2009–2018 for a representative set of major and emerging economies (United States, Japan, Canada, Brazil, China, India, South Korea and Russia). We first describe in detail how WACC for project finance was computed, followed by country-level utility WACC.

Renewable energy CoC

Non-hydro renewable energy assets are predominantly realized in project finance structures and the described approach to estimate WACC in such structures follows the approach proposed by the International Renewable Energy Agency using publicly available data sources with the intention to allow replicability and provide full transparency[74,75]. The empirical literature shows that the costs of both debt and equity are determined by drivers at (1) the country and sector level, (2) the technology level and (3) the project or company level[17]. For this study, we abstracted from individual projects or companies. Accordingly, for debt, we added three components on top of the global risk-free rate, reflecting country risk (that is, the country default spread) and risk specific to the technology or the type of asset (that is, the general risk of a project finance infrastructure investment and the potential additional risk of that asset's technology being relatively new). For equity, we again added three components to the global risk-free rate, reflecting the additional risk of equity markets (that is, the equity premium), the country risk above that of the United States in equity markets (that is, the country premium) and a technology risk, as in debt. Equations (3) and (4), respectively, show the list of components for the cost of debt and the cost of equity used in equation (1).

$$\begin{aligned} r_{\mathrm{D}it} = (&\text{Global Risk Free Rate} + \text{Country Default Spread} \\ &+ \text{Infrastructure Premium} + \text{Technology Premium}) \end{aligned} \tag{3}$$

$$\begin{aligned} r_{\mathrm{E}it} = (&\text{Global Risk Free Rate} + \text{Equity Risk Premium} \\ &+ \text{Country Equity Premium} + \text{Technology Premium}) \end{aligned} \tag{4}$$

The global risk-free rate, equity risk premium, country default spread and country equity premium were taken from data publicly available at the NYU Stern School of Business[76]. The global risk-free rate is the nominal yield on a 10-year US treasury bond (1.68% as of March 2021). The equity risk premium reflects the additional risk, measured in volatility, of the S&P 500 index above the US treasury bond. The country default spread is the spread between a country's bond yield and the US bond yield: depending on data availability, these spreads are calculated using country ratings as proxies. For example, for countries that have not issued US dollar- or euro-denominated bonds, it is calculated via the ratings from Moody's and S&P, the two largest rating agencies. The country equity premium is higher than the country default spread because it reflects the additional risk of a country's equity market compared with US equities (that is, S&P 500), which are inherently riskier than government bonds. The country equity premium is based on the default spread (see above) multiplied by the volatility of the leading equity index of the country in question, more precisely multiplied by the ratio of the standard deviation of the leading national index relative to the standard deviation of the country bond. The infrastructure premium for the cost of debt is based on a hedonic approach outlined in the literature[77], corroborated by industry reports[78], because data on the cost of private infrastructure debt are not readily available. It varies slightly across regions (2–2.2%, post-2015 values).

Debt share (L_{it} in equation (1)) and technology premium vary by technology maturity in the respective country. We defined technology maturity using thresholds for the share of wind and solar photovoltaics (PV) in the overall generation capacity by country (see ref. 77), whereby the threshold is slightly lower for offshore wind to account for the fact that the technology is expected to attract low-cost finance faster because it arrived at a later stage when market formation had already occurred and the financing ecosystem was more established. Thus, we defined mature markets with a threshold of 10% of installed generation capacity (data taken from the CIA's *The World Factbook 2020*[79]) for onshore wind and solar PV and 6% for offshore wind, and we defined intermediate markets with a threshold of 5% for onshore wind and solar PV and 3% for offshore wind. More mature markets are generally able to draw in higher debt shares[27] (Supplementary Table 2). Based on the report of Blanc-Brude and Yim[77], we calibrated the debt share to 80% for mature markets and to 60% for immature markets (choosing the average of 70% for intermediate markets), which corresponds well with academic findings[80]. Technology premiums were set to 1.5% for mature markets, 2.375% for intermediate markets and 3.25% for immature markets based on a report on offshore wind financing conditions, which observed a reduction from 3.25% to 1.5% above the London Inter-Bank Offered Rate in North West Europe[81]. These values correspond well with academic findings on onshore wind and solar PV in Germany, Italy and the United Kingdom, where risk premia dropped from over 3% to an average of 1.7% as renewable capacity shares rose from around 4% in 2008 to around 16% in 2016[80]. Because the infrastructure premium includes a technology component, we chose whichever was higher of the infrastructure and technology premium to calculate the cost of debt. Finally, the technology premium includes a technology risk wedge that is independent of maturity levels because the literature has shown that there can be technology-specific risks[14,80], independent of maturity (for example, due to different operational risks depending on moving parts or differences in the precision of resource estimates). Comparing the empirical risk premium across technologies at similar maturity levels in the literature[14,82], we found a premium for onshore wind above solar PV at similar maturity levels, but no such premium between onshore wind and offshore wind. Based on the empirical values in Germany, the only market with empirical values available for all three technologies at high levels of maturity, we set a premium of 0.1% on the cost of debt and 0.6% on the cost of equity for onshore and offshore wind above solar PV.

Country-level utility CoC

Non-renewable and large hydro energy production is usually not financed on a project basis but on balance sheet by both publicly owned and private utilities. These utilities also finance their balance sheet with debt and equity and the WACC for their investments can be computed by taking data from their financial statements. Specifically, we used:

$$r_{\mathrm{D}it} = \frac{\text{Interest Expense}_{it}}{\text{Total Debt}_{it}} \tag{5}$$

$$r_{\mathrm{E}it} = \frac{\text{Total Cash Dividends Paid}_{it}}{\text{Total Equity}_{it}} \tag{6}$$

The TRBC Sector Classification database[83] was used to extract the above variables to compute the firm-level WACCs (for a complete list of variables, including descriptions, see Supplementary Table 3). They have a respectable methodology for exhaustively classifying companies into industry groups based on primary sources, local expertise and proprietary algorithms[83]. The firms defined as utilities in the database report that between 80% and 100% of their revenue comes from managing utilities. While this database is extensive and covers the financial statements and data of utility companies in each country of interest, it is not without inconsistencies, missing observations and strange input from smaller firms. Problems emerged from firms with negative entries for total equity (that is, companies that are in essence insolvent or bankrupt), which led to negative WACC values, or outlandish imbalances between debt and equity, which led to WACC values of over 100%. Neither are realistic extremes for the CoC and were excluded.

Another issue was posed by firms with many missing values in some, but not in all years. To maintain a balanced panel of data, the chosen solution was to drop such firms from the sample as well (although in the Russian data, this led to the deletion of most of Gazprom's subsidiaries). In both the cases of extremes and missing values, the firms responsible made up no more than 1% of the energy market in their country. This left us confident that the resulting sample is still representative of the utility-level energy production in each country.

Once the firm-level WACC values had been computed, the country-level utility CoC could be calculated by weighting each firm-level WACC by the share of revenue of that firm in the total revenue of the country's utilities market. This procedure resulted in 191 country–year observations based on 428 utilities in 21 countries.

The WACC represents the CoC for utilities, which is the rate of return that these utilities offer their investors. Arbitrage in financial markets ensures that this rate of return must include the risk-free rate of return, r_f, a premium for country c's risk (default spread), p_c, a technology T's risk premium, p_T, and other idiosyncratic risk premia of utilities ε_{ct} that we assumed are normally distributed around zero.

$$\mathrm{WACC}_{ct} = r_{\mathrm{f}t} + p_{\mathrm{T}} + p_c + \varepsilon_{ct} \tag{7}$$

To estimate the technology-specific risk premia, we first subtracted the risk-free rate and country risk component from the country utilities' WACC. As for the project finance WACC, we took the US long-term government bond rate as the risk-free rate and used the spread between a country's long-term interest rate and the US long-term bond as the country risk premium[76]. To isolate technology-specific risk premia, we ran an ordinary least-squares regression with the pure technology component of the country utilities' WACC as the dependent variable and the share of generation per technology per country as independent variables (suppressing the constant because shares of technologies add up to 1 and weighting the variables by country GDP so that large countries have a larger impact on the estimated coefficients β_{0-8}):

$$\begin{aligned}
&\mathrm{WACC}_{ct} - r_{\mathrm{f}t} - p_c \\
&\quad = \beta_0 \times \mathrm{ShareCoal}_{ct} + \beta_1 \times \mathrm{ShareGas}_{ct} + \beta_2 \times \mathrm{ShareOil}_{ct} \\
&\quad + \beta_3 \times \mathrm{ShareNuclear}_{ct} + \beta_4 \times \mathrm{ShareHydro}_{ct} + \beta_5 \times \mathrm{ShareBio}_{ct} \\
&\quad + \beta_6 \times \mathrm{ShareSolar}_{ct} + \beta_7 \times \mathrm{ShareWind}_{ct} + \beta_8 \times \mathrm{ShareOther}_{ct} + \varepsilon_{ct}
\end{aligned} \tag{8}$$

The estimated coefficients measure the average increase in the CoC (and return on investment in a country's average utility) for a 1% increase in the share of a technology in that country's (and therefore the country's average utility's) WACC, where we assumed that the average utility generation mix equals the country generation mix. With the coefficients from the this regression, we constructed the WACC for all technologies in all countries (Supplementary Table 4). The resulting values can be found in Supplementary Table 1.

Finally, 2018 was chosen as the base year for the multi-model analysis for differentiated CoC.

Full set of scenarios

To explore our research questions, we implemented modelling improvements in multiple steps, as described below.

First, the DEF (default) scenario, comprising the original CoC assumptions for each of the models (before this implementation). For some of the models, the CoC was fixed and common to all regions and technologies; for others, it was implicit and equal to the marginal productivity of capital.

Second, the BASE scenario, in which the original assumptions about the CoC were replaced by empirical CoC values. The CoC in this scenario does not have a time dimension, which means that the CoC values are constant.

Third, the LRN (financial learning) scenario, in which a time dimension is introduced, reducing technology risk. Specifically, in this scenario, the finance sector becomes more accurate in judging RES projects over time, thus lowering the required safety margins[27].

 https://doi.org/10.1038/s41560-024-01606-7

This scenario models a more realistic development of RES risk premia over time (without needing specific enabling policies). We applied the learning rates estimated in ref. 29, namely, a 5% reduction in capital cost for each doubling of domestic capacity for the technology. Therefore, technology risk is endogenously reduced by financing experience. Consistent with a financing experience rate of 5%, the learning by financing factor, b_T, is obtained from $b_T = \log_2(1 - 0.05) \cong -0.074$. The CoC values at time t for country n and technology T are obtained by multiplying the differentiated CoCs by the ratio of domestic cumulative technology deployment, Y_T, elevated by b_T:

$$\mathrm{CoC}_{t,n,\mathrm{T}} = \mathrm{CoC}_{0,n,\mathrm{T}} \times \left(\frac{Y_{t,n,\mathrm{T}}}{Y_{0,n,\mathrm{T}}}\right)^{b_\mathrm{T}} \tag{9}$$

This dynamic has been modelled endogenously by three of the five models that were used in the study, namely, IMACLIM, IMAGE and WITCH. The models that could not technically implement endogenous learning, namely, GCAM and TIAM, used an exogenous CoC trajectory equal to the median LRN scenario generated by the other models for each technology, region and year. This is the reference scenario, referred to as CoC-reference in the main text.

Fourth, the CONV (convergence due to a reduction in the CoC) scenario is the scenario of interest and is referred to as CoC-convergence in the main body of the paper. It shows the result of the CoC linearly converging to the level of developed countries (namely, to the average CoC of the European Union and United States) by 2050. The scenario also includes endogenous learning, so the CoC pathways are not exactly linear (Extended Data Fig. 2). The two elements can be combined because financial learning is assumed to reduce only the technology risk component of the CoC, while CoC convergence can be safely assumed to implicitly reduce only the country risk component. Similarly to the LRN scenario, models that do not include endogenous learning (GCAM and TIAM) use an exogenous CoC trajectory equal to the median CONV scenario generated by the other models for each technology, region and year.

Last, the SPILL (CoC spillover) robustness scenario, in which it is assumed that the generic policies necessary for convergence affect the risk premia of the policymakers, that is, the risk spills over. Essentially, enacting a policy to reduce CoC for developing countries increases the empirical CoC values for the European Union and United States by 1% from 2020 onwards for each technology. This also implies that all of the countries that benefit from convergence are affected as the final level of convergence is 1% higher. In other words, the risk is not just reduced, it is to some extent transferred. This scenario has been run for robustness only for the WITCH model.

The response of the models to including the empirical CoC is diverse, depending on the default values and the implemented improvement (Supplementary Fig. 1, difference between DEF and BASE scenarios). The price of electricity increases or decreases depending on the model. In addition, for some models, the reduction is particularly large for both low- and high-income countries characterized by a low CoC. This is caused by the greater difference between the default CoC value, equal across countries, and the country-specific value. Consequently, the CoC was overestimated in some models. The effect on emissions is strong for high-CoC countries in the 1.5D scenario: in the median, a realistic CoC increases the total emissions from 2020 to 2100 by 10%. However, emissions for countries with a lower CoC are not meaningfully affected in the aggregate. The median changes in the energy mix consist of an increase in the use of biomass in the NDC scenario and a similar decrease in the 1.5D scenario. Such ambiguous changes are the result of contrasting mechanisms across models.

The inclusion of financial learning has sizeable effects. Electricity price is reduced in every model and region, emissions are generally reduced and more renewables are installed. Therefore, including financing experience in IAMs is necessary to accurately depict the transition.

CoC implementation

Using the BASE scenario, we applied region- and technology-specific CoCs. The empirical data were translated from country-level to regional-level based on a GDP-weighted average. The implementation across models was tailored to the model characteristics, as described below.

By default, the CoC in GCAM is represented as a fixed change rate (FCR) that annualizes the capital cost of power infrastructure. We adapted the interpretation of this FCR according to ref. 30, which depends on various variables, including the CoC:

$$\mathrm{FCR}_{i,t,T} = \frac{\mathrm{CoC}_{i,t,T}}{1-(1+\mathrm{CoC}_{i,t,T})_{i,T}^{\mathrm{Lifetime}}} \times \frac{1-(\mathrm{TaxRate}\times\mathrm{PresentValue}_{\mathrm{Depreciation}})}{1-\mathrm{TaxRate}} \tag{10}$$

In this study, we adapted the CoC values according to the model region (weighted by GDP for aggregated regions) and technology, as well as the technology lifetimes assumed in the model. For the right-hand term in equation (10), we assumed a value of 1.1, which is in line with the average for the United States[84].

In IMACLIM-R's power sector, electricity generation technologies compete according to their LCOE, in which the CoC is used as a proxy for the discount factor. Thus, the CoC values replace the usual discount factor assumption in the LCOE formula. The default value for the discount factor of electricity generation technologies was 10%. LCOEs serve as arguments for a multinomial logit equation to determine the market shares of electricity generation technologies.

In the IMAGE power sector representation, the CoC values are used to annualize investment costs. These annualized costs are used to determine the LCOE per technology. This LCOE is used when determining market shares for power sector investments in a multinomial logit equation: technologies with lower costs get larger market shares. The default CoC value used in the DEF scenario was 10%. Technologies not represented in the data have been given a regional average (weighted on capacities installed in 2018). In the LRN scenario, no spillover rates or floors were applied. For the 1.5D variations, a global carbon tax was introduced. This carbon tax was optimized so that the carbon budget (600 $GtCO_2$ from 2020 to 2100) was reached at the lowest achievable policy costs. For the NDC scenario, we implemented the regional NDC emission goals (before the Glasgow levels) by introducing regional carbon taxes. The regional carbon taxes differ for the DEF, BASE, LRN and CONV variations because the different scenario settings make the model respond differently to carbon taxes. To achieve the same emissions goal, different taxes are required.

In the TIAM model, we input a global discount rate, which is used to discount all future costs back to the model's base year. In addition to the global discount rate, we input a technology-specific financial hurdle rate. The financial hurdle rate can be defined as the WACC. These specific hurdle rates are used for uplifting the level of the capital cost of generation (or end-use) assets in the model by increasing the total capital recovery over the project lifetime. Operation and maintenance costs are unaffected by this hurdle rate. This hurdle rate reflects how an increased cost of finance would affect capital costs.

The WITCH model uses an implicit interest rate for discounting, equal to the marginal product of capital. Therefore, to apply exogenous values for the CoC, we adjusted the CoC values using the factor $\mathrm{CoC}_{\mathrm{adj}}$, calculated by removing the endogenous interest rate values according to the following expression:

$$\mathrm{CoC}_{\mathrm{adj}_{c,t,T}} = \frac{\sum_{tt=t}^{\mathrm{Lifetime}_T}(1+\mathrm{InterestRate}_{c,tt})^{-tt\times(tt-t)}}{\sum_{tt=t}^{\mathrm{Lifetime}_T}(1+\mathrm{CoC}_{c,tt,T})^{-tt\times(tt-t)}} \tag{11}$$

The adjusted factor obtained then substitutes the relative discount factor and updates the installation cost of plants as an additional hurdle rate.

Data availability

The empirical CoC input data and integrated assessment model outputs are available at Zenodo via https://doi.org/10.5281/zenodo.11545407 (ref. 85). Source data are provided with this paper.

Code availability

The code availability for the individual models used in this paper varies and contact should be made with the individual modelling groups. The models are documented in the common IAM documentation (https://www.iamcdocumentation.eu/index.php/IAMC_wiki), and some code has been published on open source platforms, for example, GCAM (https://github.com/JGCRI/gcam-core) and WITCH (https://github.com/witch-team/witchmodel). The code for processing model output is available at Zenodo via https://doi.org/10.5281/zenodo.11545407 (ref. 85).

References

1. IPCC *Climate Change 2023: Synthesis Report* (eds Core Writing Team, Lee, H. & Romero, J.) (IPCC, 2023); https://www.ipcc.ch/report/ar6/syr/
2. Kreibiehl, S. et al. in *Climate Change 2022: Mitigation of Climate Change* (eds Shukla, P. R. et al.) Ch. 15 (IPCC, Cambridge Univ. Press, 2022); https://doi.org/10.1017/9781009157926.017
3. *Derisking Renewable Energy Investment* (United Nations Development Programme, 2013); https://www.undp.org/publications/derisking-renewable-energy-investment
4. Guterres, A. Guterres leads call to make Africa 'renewable energy superpower'. *UN News* https://news.un.org/en/story/2023/09/1140362 (2023).
5. Pachauri, S. et al. Fairness considerations in global mitigation investments. *Science* **378**, eadf0067 (2022).
6. Carley, S. & Konisky, D. M. The justice and equity implications of the clean energy transition. *Nat. Energy* **5**, 569–577 (2020).
7. Sovacool, B. K., Heffron, R. J., McCauley, D. & Goldthau, A. Energy decisions reframed as justice and ethical concerns. *Nat. Energy* **1**, 16024 (2016).
8. Fuso Nerini, F. et al. Mapping synergies and trade-offs between energy and the Sustainable Development Goals. *Nat. Energy* **3**, 10–15 (2018).
9. Sagar, A. D. et al. Mission Energy Access for a just and sustainable future for all. *Nat. Energy* **8**, 1171–1173 (2023).
10. Schmidt, T. S. et al. Adverse effects of rising interest rates on sustainable energy transitions. *Nat. Sustain.* **2**, 879–885 (2019).
11. Keppo, I. et al. Exploring the possibility space: taking stock of the diverse capabilities and gaps in integrated assessment models. *Environ. Res. Lett.* **16**, 053006 (2021).
12. Sanders, M. et al. Representation of financial markets in macro-economic transition models-—a review and suggestions for extensions. *Environ. Res. Lett.* **17**, 083001 (2022).
13. Battiston, S., Monasterolo, I., Riahi, K. & van Ruijven, B. J. Accounting for finance is key for climate mitigation pathways. *Science* **372**, 918–920 (2021).
14. Steffen, B. Estimating the cost of capital for renewable energy projects. *Energy Econ.* **88**, 104783 (2020).
15. Egli, F. et al. Financing the energy transition: four insights and avenues for future research. *Environ. Res. Lett.* **17**, 051003 (2022).
16. Egli, F., Steffen, B. & Schmidt, T. S. Bias in energy system models with uniform cost of capital assumption. *Nat. Commun.* **10**, 4588 (2019).
17. Lonergan, K. E. et al. Improving the representation of cost of capital in energy system models. *Joule* **7**, 469–483 (2023).
18. Bosmans, J. et al. Determinants of the distribution of utility-scale photovoltaic power facilities across the globe. *Environ. Res. Lett.* **17**, 114006 (2022).
19. *Africa Energy Outlook 2022* (IEA, 2022); https://www.iea.org/reports/africa-energy-outlook-2022
20. Lindahl, J., Lingfors, D., Elmqvist, Å. & Mignon, I. Economic analysis of the early market of centralized photovoltaic parks in Sweden. *Renew. Energy* **185**, 1192–1208 (2022).
21. Sweerts, B., Longa, F. D. & van der Zwaan, B. Financial de-risking to unlock Africa's renewable energy potential. *Renew. Sustain. Energy Rev.* **102**, 75–82 (2019).
22. Angelopoulos, D. et al. Risks and cost of capital for onshore wind energy investments in EU countries. *Energy Environ.* **27**, 82–104 (2016).
23. Ondraczek, J., Komendantova, N. & Patt, A. WACC the dog: the effect of financing costs on the levelized cost of solar PV power. *Renew. Energy* **75**, 888–898 (2015).
24. Labordena, M., Patt, A., Bazilian, M., Howells, M. & Lilliestam, J. Impact of political and economic barriers for concentrating solar power in sub-Saharan Africa. *Energy Policy* **102**, 52–72 (2017).
25. Agutu, C., Egli, F., Williams, N. J., Schmidt, T. S. & Steffen, B. Accounting for finance in electrification models for sub-Saharan Africa. *Nat. Energy* **7**, 631–641 (2022).
26. Schmidt, T. S. Low-carbon investment risks and de-risking. *Nat. Clim. Change* **4**, 237–239 (2014).
27. Egli, F., Steffen, B. & Schmidt, T. S. A dynamic analysis of financing conditions for renewable energy technologies. *Nat. Energy* **3**, 1084–1092 (2018).
28. Kempa, K., Moslener, U., Schenker, O. & Oliver, S. The cost of debt of renewable and non-renewable energy firms. *Nat. Energy* **6**, 135–142 (2021).
29. Polzin, F. et al. The effect of differentiating costs of capital by country and technology on the European energy transition. *Climatic Change* **167**, 26 (2021).
30. Iyer, G. C. et al. Improved representation of investment decisions in assessments of CO_2 mitigation. *Nat. Clim. Change* **5**, 436–440 (2015).
31. Bachner, G., Mayer, J. & Steininger, K. W. Costs or benefits? Assessing the economy-wide effects of the electricity sector's low carbon transition—the role of capital costs, divergent risk perceptions and premiums. *Energy Strategy Rev.* **26**, 100373 (2019).
32. Halstead, M., Donker, J., Longo, F. D. & van der Zwaan, B. C. C. The importance of fossil fuel divestment and competitive procurement for financing Europe's energy transition. *J. Sustain. Finance Invest.* **9**, 349–355 (2019).
33. García-Gusano, D., Espegren, K., Lind, A. & Kirkengen, M. The role of the discount rates in energy systems optimisation models. *Renew. Sustain. Energy Rev.* **59**, 56–72 (2016).
34. Schyska, B. U. & Kies, A. How regional differences in cost of capital influence the optimal design of power systems. *Appl. Energy* **262**, 114523 (2020).
35. Ekholm, T., Ghoddusi, H., Krey, V. & Riahi, K. The effect of financial constraints on energy–climate scenarios. *Energy Policy* **59**, 562–572 (2013).
36. Ameli, N. et al. Higher cost of finance exacerbates a climate investment trap in developing economies. *Nat. Commun.* **12**, 4046 (2021).
37. May, N. & Neuhoff, K. Financing power: impacts of energy policies in changing regulatory environments. *Energy J.* **42**, 4 (2021).
38. Schinko, T. & Komendantova, N. De-risking investment into concentrated solar power in North Africa: impacts on the costs of electricity generation. *Renew. Energy* **92**, 262–272 (2016).
39. Komendantova, N., Schinko, T. & Patt, A. De-risking policies as a substantial determinant of climate change mitigation costs in developing countries: case study of the Middle East and North African region. *Energy Policy* **127**, 404–411 (2019).

40. Paroussos, L. et al. Climate clubs and the macro-economic benefits of international cooperation on climate policy. *Nat. Clim. Change* **9**, 542–546 (2019).
41. Calvin, K. et al. GCAM v5.1: representing the linkages between energy, water, land, climate, and economic systems. *Geosci. Model Dev.* **12**, 677–698 (2019).
42. Sassi, O. et al. IMACLIM-R: a modelling framework to simulate sustainable development pathways. *Int. J. Glob. Environ. Issues* **10**, 5–24 (2010).
43. van Vuuren, D. et al. The 2021 SSP scenarios of the IMAGE 3.2 model. Preprint at https://eartharxiv.org/repository/view/2759/ (2021).
44. Loulou, R. & Labriet, M. ETSAP-TIAM: the TIMES integrated assessment model. Part I: model structure. *Comput. Manage. Sci.* **5**, 7–40 (2008).
45. Emmerling, J. et al. *The WITCH 2016 Model—Documentation and Implementation of the Shared Socioeconomic Pathways* Working Paper No. 2016.42 (Fondazione Eni Enrico Mattei, 2016); https://ideas.repec.org//p/fem/femwpa/2016.42.html
46. Helms, T., Salm, S. & Wüstenhagen, R. in *Renewable Energy Finance: Investor-Specific Cost of Capital and Renewable Energy Investment Decisions* 85–111 (World Scientific Publishing, 2020).
47. van Soest, H. L. et al. Global roll-out of comprehensive policy measures may aid in bridging emissions gap. *Nat. Commun.* **12**, 6419 (2021).
48. Meinshausen, M. et al. Realization of Paris Agreement pledges may limit warming just below 2 °C. *Nature* **604**, 304–309 (2022).
49. Rao, N. D. Towards a “fair-efforts” metric for climate pledges. *PLOS Clim.* **1**, e0000069 (2022).
50. Baker, E. et al. Metrics for decision-making in energy justice. *Annu. Rev. Environ. Resourc.* **48**, 737–760 (2023).
51. Steffen, B. & Waidelich, P. Determinants of cost of capital in the electricity sector. *Prog. Energy* **4**, 033001 (2022).
52. *Report of the Conference of the Parties on its Twenty-first Session, Held in Paris from 30 November to 13 December 2015. Addendum. Part Two: Action Taken by the Conference of the Parties at its Twenty-first Session* (UNFCCC Secretariat, 2016); https://unfccc.int/documents/9097
53. Klessmann, C. et al. Policy options for reducing the costs of reaching the European renewables target. *Renew. Energy* **57**, 390–403 (2013).
54. Đukan, M. & Kitzing, L. The impact of auctions on financing conditions and cost of capital for wind energy projects. *Energy Policy* **152**, 112197 (2021).
55. Matthäus, D. & Mehling, M. De-risking renewable energy investments in developing countries: a multilateral guarantee mechanism. *Joule* **4**, 2627–2645 (2020).
56. Hourcade, J. C., Dasgupta, D. & Ghersi, F. Accelerating the speed and scale of climate finance in the post-pandemic context. *Clim. Policy* **21**, 1383–1397 (2021).
57. *The EIB Group Climate Bank Roadmap 2021–2025* (European Investment Bank, 2020); https://www.eib.org/en/publications/the-eib-group-climate-bank-roadmap
58. *Climate Change Action Plan 2021–2025* Technical Report (World Bank, 2021); https://www.miga.org/sites/default/files/2021-08/CCAP-2021-25-2.pdf
59. Mottley, M. *Urgent and Decisive Action Required for an Unprecedented Combination of Crises: The 2022 Bridgetown Initiative for the Reform of the Global Financial Architecture* (Bridgetown Initiative, 2022).
60. Demertzis, M. Concessional climate finance: the Bridgetown Initiative. *Bruegel* https://www.bruegel.org/comment/concessional-climate-finance-bridgetown-initiative (2023).
61. Riahi, K. et al. in *Climate Change 2022: Mitigation of Climate Change* (eds Shukla, P. R. et al.) 295–408 (IPCC, Cambridge Univ. Press, 2023); https://www.cambridge.org/core/books/climate-change-2022-mitigation-of-climate-change/mitigation-pathways-compatible-with-longterm-goals/7C750344E39ECA3BD5CB14156FCEEFE9
62. Shiraki, H. & Sugiyama, M. Back to the basic: toward improvement of technoeconomic representation in integrated assessment models. *Climatic Change* **162**, 13–24 (2020).
63. Way, R., Ives, M. C., Mealy, P. & Farmer, J. D. Empirically grounded technology forecasts and the energy transition. *Joule* **6**, 2057–2082 (2022).
64. Levin, T. et al. Energy storage solutions to decarbonize electricity through enhanced capacity expansion modelling. *Nature Energy* **8**, 1199–1208 (2023).
65. Pietzcker, R. C. et al. System integration of wind and solar power in integrated assessment models: a cross-model evaluation of new approaches. *Energy Econ.* **64**, 583–599 (2017).
66. Almeida, H., Cunha, I., Ferreira, M. A. & Restrepo, F. The real effects of credit ratings: the sovereign ceiling channel. *J. Finance* **72**, 249–290 (2017).
67. International Energy Agency *Electricity Grids and Secure Energy Transitions: Enhancing the Foundations of Resilient, Sustainable and Affordable Power Systems* (OECD, 2023); https://www.oecd-ilibrary.org/energy/electricity-grids-and-secure-energy-transitions_455dd4fb-en
68. IEA *Global Hydrogen Review 2023* (OECD, 2023); https://www.oecd-ilibrary.org/energy/global-hydrogen-review-2023_cb2635f6-en
69. Miller, L. & Carriveau, R. A review of energy storage financing—learning from and partnering with the renewable energy industry. *J. Energy Storage* **19**, 311–319 (2018).
70. Metcalf, G. E. & Stock, J. H. Integrated assessment models and the social cost of carbon: a review and assessment of US experience. *R. Environ. Econ. Policy* **11**, 80–99 (2017).
71. Polzin, F., Egli, F., Steffen, B. & Schmidt, T. S. How do policies mobilize private finance for renewable energy? A systematic review with an investor perspective. *Appl. Energy* **236**, 1249–1268 (2019).
72. Egli, F. M. *The Role of Finance in Mitigating Climate Change: Insights for Public Policy*. Doctoral thesis, ETH Zurich (2020); https://www.research-collection.ethz.ch/handle/20.500.11850/424913
73. Kling, G., Volz, U., Murinde, V. & Ayas, S. The impact of climate vulnerability on firms’ cost of capital and access to finance. *World Dev.* **137**, 105131 (2021).
74. *The Cost of Financing for Renewable Power* Technical Report (International Renewable Energy Agency, 2023); https://mc-cd8320d4-36a1-40ac-83cc-3389-cdn-endpoint.azureedge.net/-/media/Files/IRENA/Agency/Publication/2023/May/IRENA_Cost_of_financing_renewable_power_2023.pdf?rev=6b95edc23fa5468190745975681a71cc
75. IRENA & CPI *Global Landscape of Renewable Energy Finance* (International Renewable Energy Agency, 2023); https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2023/May/IRENA_The_cost_of_financing_renewable_power_2023.pdf
76. Damodaran, A. Country default spreads and risk premiums. *Stern* https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ctryprem.html (2022).
77. Blanc-Brude, F. & Yim, J.-L. *The Pricing of Private Infrastructure Debt—A Dynamic Approach* (EDHEC Infrastrcture Institute, 2019); https://edhec.infrastructure.institute/paper/the-pricing-of-private-infrastructure-debt/
78. *Infrastructure Debt: Creating Resilient Cashflows Through Secured Lending* (DWS, 2021); https://www.dws.com/AssetDownload/Index?assetGuid=73317bab-9aa8-4902-abd8-7aeb7d9ae26c&consumer=E-Library

79. *The World Factbook 2020* (CIA, 2020); https://www.cia.gov/the-world-factbook/
80. Egli, F. Renewable energy investment risk: an investigation of changes over time and the underlying drivers. *Energy Policy* **140**, 111428 (2020).
81. *Financing Offshore Wind* (PWC, 2020); https://www.pwc.nl/nl/actueel-publicaties/assets/pdfs/pwc-invest-nl-financing-offshore-wind.pdf
82. Roth, A. et al. *Renewable Energy Financing Conditions in Europe: Survey and Impact Analysis* (AURES, 2021).
83. *TRBC Sector Classification* (LSEG, 2020); https://www.lseg.com/en/data-analytics/financial-data/indices/trbc-business-classification
84. Vimmerstedt, L. et al. *2022 Annual Technology Baseline (ATB) Cost and Performance Data for Electricity Generation Technologies* (NREL, 2022); https://data.openei.org/submissions/5716
85. Calcaterra, M. et al. Reducing cost of capital to finance the energy transition in developing countries. *Zenodo* https://doi.org/10.5281/zenodo.11545407 (2024).
86. *Eurostat Regional Yearbook* 2023 edn (Eurostat, (2023); https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Geographical_information_system_of_the_Commission_(GISCO)

Acknowledgements

This project received funding from the European Union's Horizon Europe research and innovation programme (grant agreement nos. 101081604 (PRISMA, to J.E. and M.T.), 101056873 (ELEVATE, to L.A.R.), 730403 (INNOPATHS, to F.H.J.P., M.W.J.L.S. and S.S.), 101022622 (ECEMF, to P.F. and J.E.) and 101056306 (IAM COMPACT, to P.F., S.M. and D.J.v.d.V.)). As part of the PRISMA project, B.S., T.S.S. and P.W. received funding from the Swiss State Secretariat for Education, Research and Innovation (SERI, contract no. 22.00541). S.M., F.H.J.P., M.W.J.L.S., A.S. and D.J.v.d.V. acknowledge support from the Horizon Europe R&I programme project DIAMOND (grant no. 101081179). This article is part of a project that has received funding from the European Union's Horizon 2020 research and innovation programme (Marie Skłodowska-Curie grant agreement no. 870245, to M.C.). B.S. and P.W. received funding from an ERC Starting Grant awarded by the European Research Council (ERC) (grant agreement nos. 948220 and GREENFIN).

Author contributions

M.C., P.F., L.A.R., F.H.J.P. and M.W.J.L.S. designed the research and experiments. F.E., F.H.J.P., M.W.J.L.S., T.S.S., A.S., B.S. and P.W. performed the empirical analysis. M.C., L.A.R., T.B., H.S.d.B., J.E., S.M. and D.J.v.d.V. ran the scenarios. M.C. performed the data analysis. M.C. and M.T. wrote the first draft of the paper. M.C., L.A.R., P.F., T.B., H.S.d.B., F.E., J.E., G.I., S.M., F.H.J.P., M.W.J.L.S., T.S.S., A.S., B.S., D.J.v.d.V., D.P.v.V., P.W. and M.T. provided critical feedback and contributed to the final paper.

Competing interests

The authors declare no competing interests

Additional information

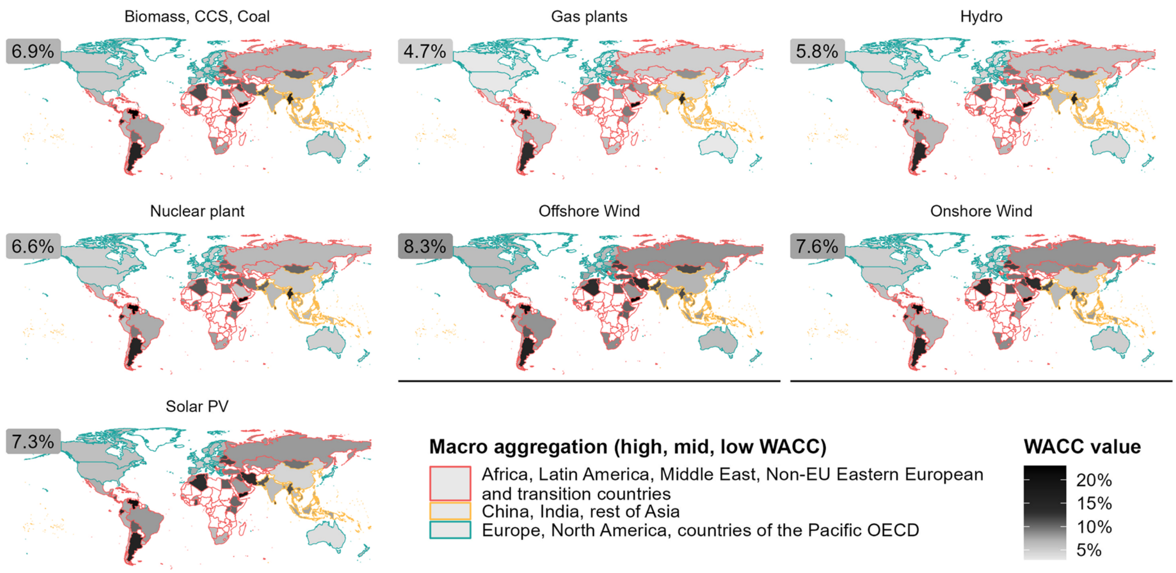
Extended data is available for this paper at https://doi.org/10.1038/s41560-024-01606-7.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41560-024-01606-7.

Correspondence and requests for materials should be addressed to M. Calcaterra.

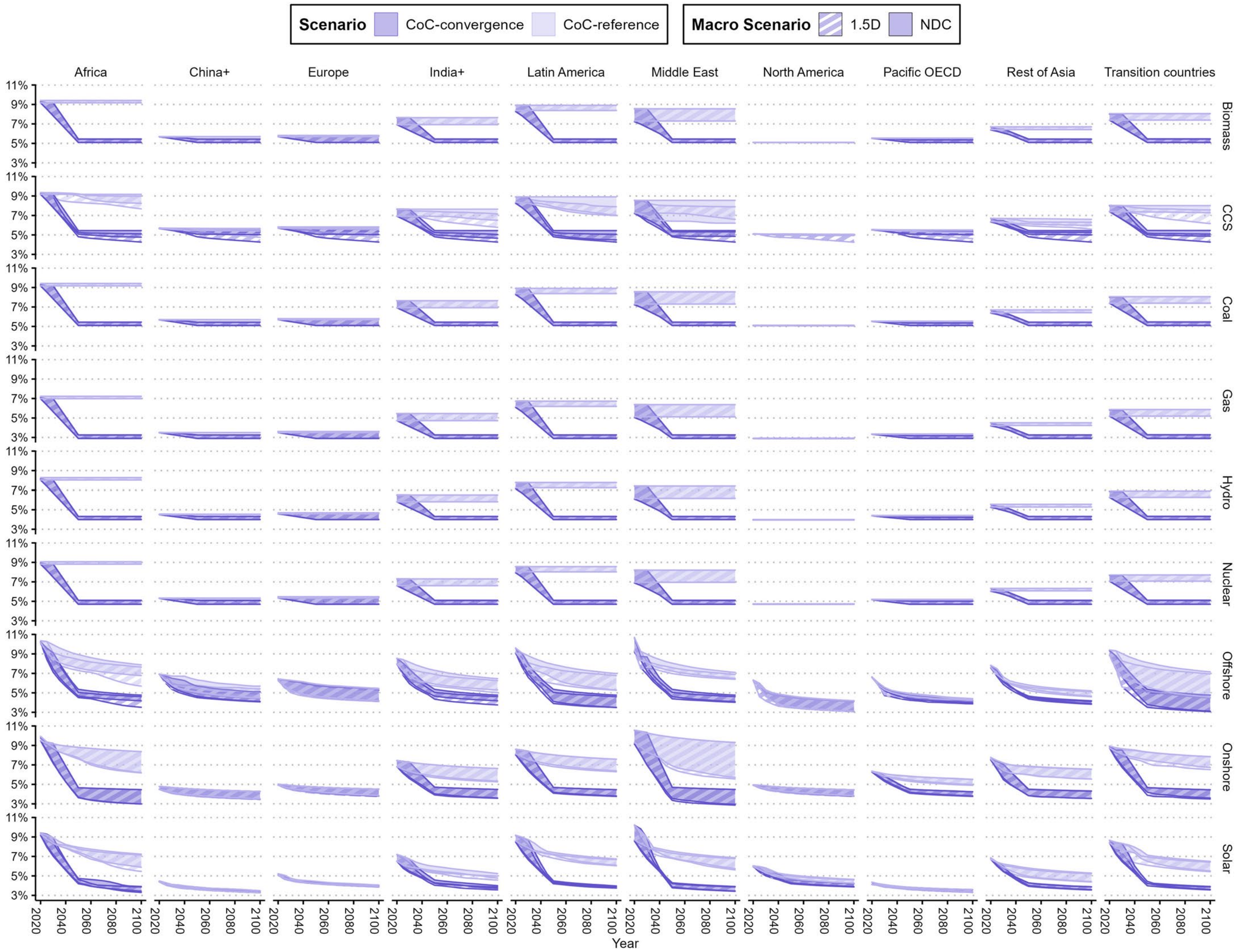
Peer review information *Nature Energy* thanks Omar Guerra, Conor Hickey, Rahel Mandaroux and Wenji Zhou for their contribution to the peer review of this work.

https://doi.org/10.1038/s41560-024-01606-7



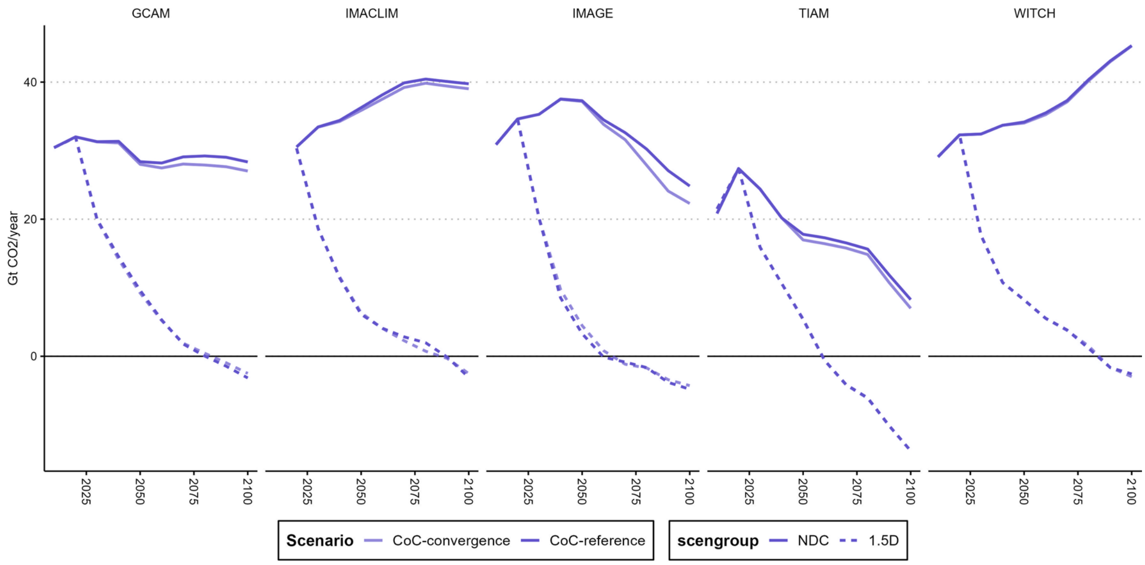
Extended Data Fig. 1 | Empirically calibrated WACC values by technology and country. Values have been aggregated in three macro-region with similar characteristics. In red, developing countries with a higher CoC on average. In yellow, Asian developing countries with a lower CoC on average. In green, the developed world, which exhibits on average the lowest CoC. The label in the top left of each panel displays the median CoC value for that technology. WACC stands for Weighted Average Cost of Capital, while CoC stands for Cost of Capital. © EuroGeographics for the administrative boundaries.

https://doi.org/10.1038/s41560-024-01606-7



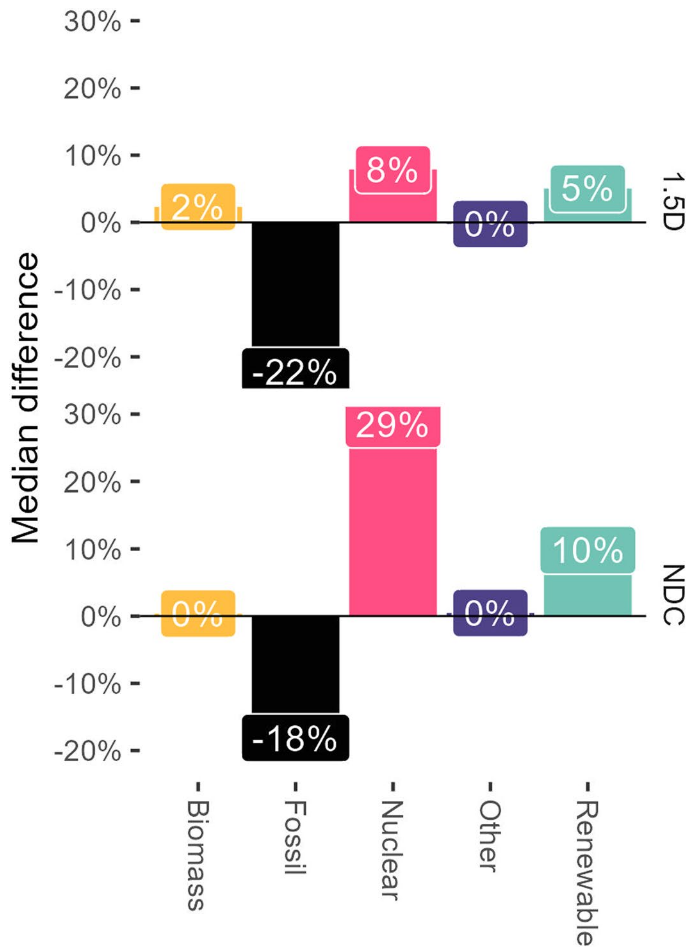
Extended Data Fig. 2 | Range of CoC values' development across time for models with learning. Small differences arise across models in the starting values due to different original regional aggregations and differences in modelling. CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions, CCS stands for Carbon Capture and Storage.

https://doi.org/10.1038/s41560-024-01606-7



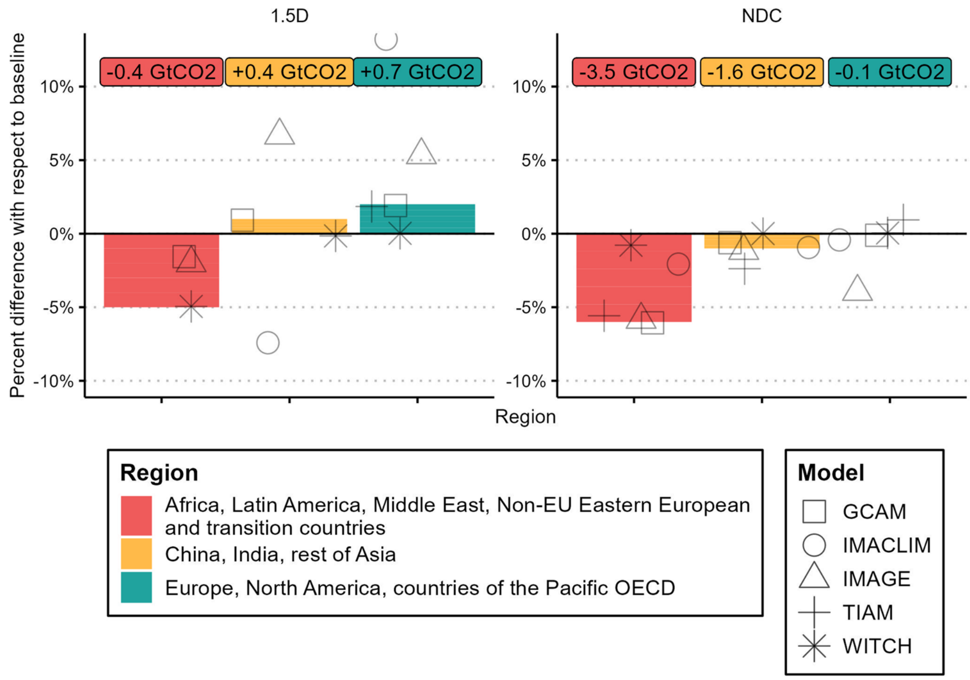
Extended Data Fig. 3 | Global emissions across models and scenarios. CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions.

https://doi.org/10.1038/s41560-024-01606-7



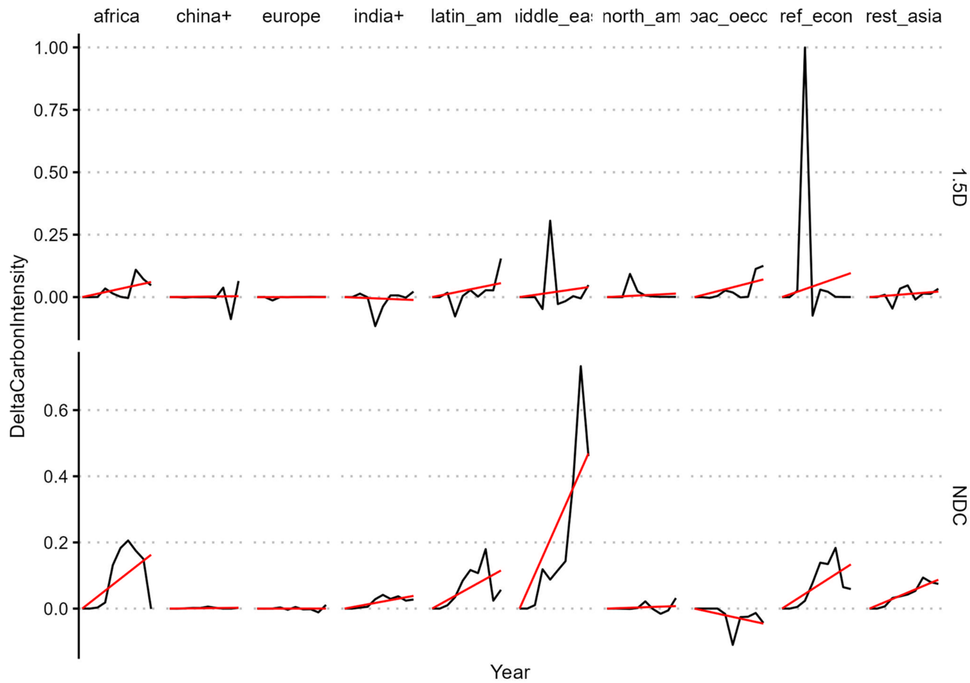
Extended Data Fig. 4 | Percentage difference between CoC-reference and CoC-convergence in electricity generation. Bars report the 2100 model median for the high CoC region. CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions.

 https://doi.org/10.1038/s41560-024-01606-7



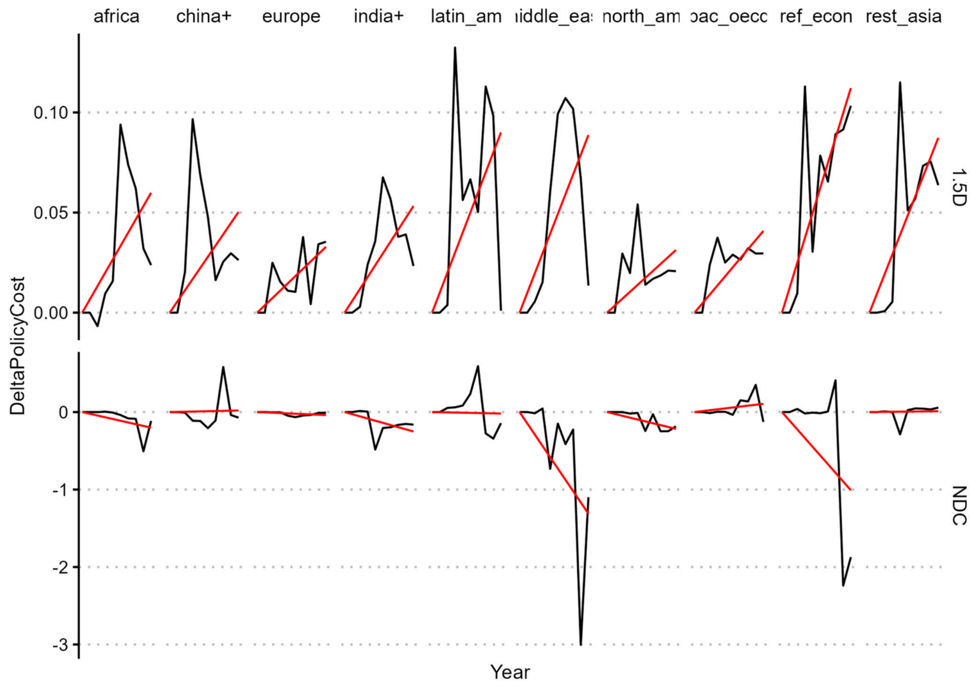
Extended Data Fig. 5 | Emissions from the energy sector. Changes in percentage value (bar height) and absolute value (label) between CoC-reference and CoC-convergence, total emissions up to 2100. The marker for TIAM in the red macro-region for the 1.5D scenario is hidden because the reduction is below -100% (net negative emissions). CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions.

https://doi.org/10.1038/s41560-024-01606-7



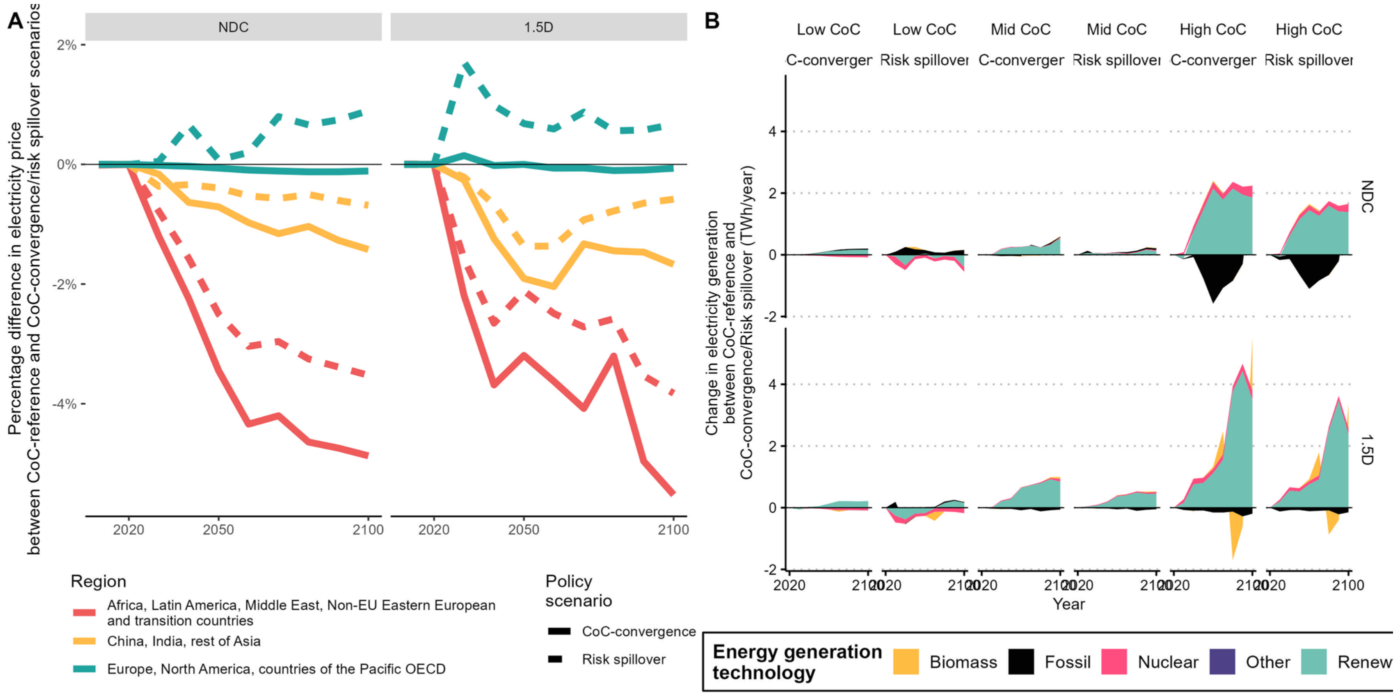
Extended Data Fig. 6 | In the NDC scenario, CoC-convergence reduces carbon intensity. Linear interpolation across time for the median by model of delta carbon intensity CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions.

 https://doi.org/10.1038/s41560-024-01606-7



Extended Data Fig. 7 | In the 1.5D scenario, CoC-convergence reduces policy cost. Linear interpolation across time for the median by model of delta policy cost. CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions.

https://doi.org/10.1038/s41560-024-01606-7



Extended Data Fig. 8 | Robustness scenario. The WITCH model is run in a risk-spillover scenario (more details in Methods). This is compared to a normal CoC-convergence run in difference with respect to the CoC-reference scenario. The magnitude of the resulting dynamics is reduced with risk spillover, but the direction is robust. **a**, Percentage difference in the price of electricity between the CoC-reference and CoC-convergence scenarios over time. **b**, Difference in electricity generation between the CoC-reference and CoC-convergence scenarios across macro-regions and time. CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions.

https://doi.org/10.1038/s41560-024-01606-7

Extended Data Table 1 | Short description of the scenarios implemented

CoC scenarios ⇩	Macro scenarios ⇨ Description	NDC: Countries fulfil their NDCs by 2030 and apply an equivalent level of effort thereon	1.5D: Countries transition to a decarbonized world under a global 500-600 GtCO2 carbon budget
DEF	*Default* run of each model	✓	✓
BASE	Models *rebased* with empirical CoC, differentiated across region and technology, constant over time	✓	✓
LRN CoC-reference	CoC is reduced by financial *learning* over time, the higher the cumulative capacity installed the higher the reduction Technology risk is reduced endogenously	✓	✓
CONV CoC-convergence	CoC linearly *converges* to the average of EU and USA by 2050 by effect of a mechanism *reducing the CoC*, together with learning Country risk is reduced exogenously	✓	✓
SPILL Robustness	All CoC of EU and USA are 1pp higher from 2020 onwards due to risk *spillover* from CoC convergence policy	✓	✓

The analysis in the main part of the paper is done referring to the LRN scenario as CoC-reference and CONV scenario as CoC-convergence. More details on scenario implementation in Methods CoC stands for Cost of Capital, NDC stands for Nationally Determined Contributions.