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The impact of financing conditions on global deep decarbonization

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The impact of financing conditions on global deep decarbonization

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ABSTRACT

Integrated assessment models (IAMs) shape mitigation pathways and policies but usually neglect differences in financing conditions across countries, sectors, and time. Recent studies highlight how this omission distorts outcomes concerning electricity generation but ignore other sectors. Here, we estimate and implement dynamic, country-specific cost of capital (CoC) for nine energy and industry sectors in the IMAGE IAM. Accounting for developing countries' investment risks increases global mitigation costs through 2100 for staying well below +2 °C by over 10% and shifts cost-effective mitigation efforts to lower-risk regions. Sector-level analysis shows that using granular CoC estimates reduces grid investments in developing countries, shifts centralized heat production toward natural gas, and raises green hydrogen costs due to higher electricity prices and sector-specific risks, slowing electrolysis uptake. In industries such as steel and cement, sector and country risks hinder capital-intensive carbon capture and electricity-based technologies. Our results reveal biases from omitting country-specific financing conditions and highlight the need for climate finance beyond electricity generation to facilitate global deep decarbonization.

Introduction

As global warming rapidly approaches +1.5°C, climate change mitigation is increasingly urgent, requiring deep decarbonization across all economic sectors[1, 2]. For public and private decision-makers alike, prudent climate policy and investment decisions require a good understanding of feasible and affordable decarbonization pathways for each climate-relevant sector. Integrated assessment models (IAMs) of climate change are a key tool to identify and assess such pathways, and have strongly informed reports by the Intergovernmental Panel on Climate Change (IPCC) on mitigation[3, 4], as well as assessments of climate targets[5], transition risks[6], and sectoral investment needs[7, 8]. Therefore, the accuracy of how technologies and climate-relevant sectors are represented in IAMs, including relevant feasibility constraints, is central to our understanding of deep decarbonization and is subject to extensive research[9, 10, 11, 12, 13].

A key feasibility constraint for the low-carbon transition is the cost of capital (CoC), defined as the rate of return expected by investors and debt providers to compensate them for the risks involved[14]. A higher CoC can substantially reduce the cost competitiveness of low-carbon technologies, such as renewable energy technologies or heat pumps, which are more capital-intensive than their fossil fuel-based alternatives[15, 16, 17, 18, 19]. In addition, higher interest rates and return expectations make new investments overall less attractive, thus favoring the prolonged use of existing, typically more carbon-intensive assets[20]. Despite the CoC's importance, IAMs—and energy system and industry decarbonization models alike[21, 22]—have historically represented financing conditions through uniform CoC assumptions that abstract from risk differences between countries, sectors, and technologies[21, 23, 24]. While such an approach was, among other things, motivated by modeling complexity, as well as a lack of data and best practices[21], it may bias results considerably[25].

Recent studies have begun to address this issue by augmenting models with more granular CoC estimates for

electricity generation, highlighting important implications for developing countries in particular[26, 27, 28, 29, 30, 31]. However, the narrow scope of these studies omits CoC effects on electricity networks, the remaining energy sector, and other climate-relevant sectors such as industry. Notably, electricity generation accounts for only a quarter of global greenhouse gas emissions[2] and, compared to other climate-relevant sectors, has systematically lower market risks[32] and abatement costs[3]. Therefore, assessing how accounting for granular sector and country risks in CoC assumptions affects sectors beyond electricity generation is crucial to evaluating the overall impact of granular financing cost estimates on mitigation pathways and costs, which remains unknown so far.

In this paper, we address this gap in the extant literature through three contributions. First, we estimate empirical, sector- and country-differentiated CoC for nine climate-relevant energy and industry sectors, such as hydrogen production, cement, and steel. By doing so, we expand the narrow sectoral scope of the literature, thus enabling conclusions about how CoC differences shape overall emissions and mitigation costs. Importantly, the methodology underlying our CoC estimates can also be applied to other sectors that may emerge in the future, such as large-scale direct air carbon capture. Second, we introduce an empirically calibrated feedback effect of developing countries' economic growth on investment risks, whereas extant studies either ignore this feedback or use coarse and stylized assumptions, such as uniform long-term convergence to risk levels of high-income countries[27, 30]. Similar to our CoC estimates, this feedback mechanism can be easily applied to different IAMs and similar models to endogenize future country risk. Lastly, by implementing our dynamic, region- and sector-specific CoC into a well-established IAM with high geographic and technological resolution, the IMAGE model[33], we provide a detailed assessment of how capturing sector and country risks affects deep decarbonization in energy and industry, overall emissions, and mitigation costs. Importantly, our assessment also covers the spillover effects of CoC-related energy price shifts on other sectors, such as transportation.

Results

Estimating financing costs of climate-relevant sectors worldwide

While IMAGE, unlike many other IAMs, explicitly represents the CoC in modeling investment decisions, its default version uses a CoC assumption uniform across regions, sectors, and time[33, 34]. To augment the model, we build on and advance the approaches and data sources used by recent studies that incorporate granular CoC for electricity generation in IAMs and similar models[30, 28, 27, 31, 26, 21]. To capture risk differences, we take country risk premiums based on sovereign ratings (Fig. 1a) and sector-specific risk measures based on stock price patterns (Fig. 1b) from a widely used financial market database[32] and apply them to IMAGE by aggregating country variables to model regions and matching database industry groups to IMAGE's sectors. This procedure yields region- and sector-specific estimates of current financing costs, revealing substantial heterogeneity (Fig. 1c). For instance, the financing costs of the electricity and steel sectors in the United States (US) differ by approximately two percentage points, which is equivalent to the difference between electricity generation projects in the US and those in emerging markets such as India or Indonesia. Notably, country risk differences can be even larger, with the electricity CoC in high-risk regions, such as Eastern Africa or Ukraine, being around three times higher than in the US. We categorize IMAGE's model regions as high-, mid-, or low-risk based on their CoC for the electricity sector (dashed lines in Fig. 1c). To capture how the CoC may evolve in the future, we estimate the empirical relationship between country risk premiums and income per capita growth, a key determinant of sovereign ratings in empirical studies[35, 36, 37], and translate regions' projected economic growth into CoC reductions (Fig. 1d; for details, see Methods).

We run IMAGE in two settings to explore the impacts of differentiating the CoC by region, sector, and over time, either using our *Differentiated CoC* estimates or by emulating the *Uniform CoC* approach predominantly used by IAMs through a uniform, time-constant 5% value. This approach broadly corresponds to an emission-weighted average of our empirical estimates for a low-risk country (e.g., the US) across all sectors considered. Therefore, the *Uniform CoC* abstracts from sector risk differences between electricity generation and other climate-relevant sectors while omitting country risk and its reduction due to economic growth. We explore CoC effects in a current policies pathway and a pathway with a carbon budget that ensures global warming remains well below 2°C in line with the Paris Agreement, which result in +2.8°C and +1.7°C of global warming by 2100, respectively. Notably, in

the well below +2°C pathway, the model adjusts climate policy stringency (in the form of global carbon pricing) endogenously to ensure that the climate target is met.

CoC effects on overall emissions and mitigation costs

Between 2030 and 2100, the global mitigation cost of keeping global warming well below +2°C increases gradually over time, reaching almost USD 2 trillion per year by the end of the century under the *Uniform CoC* approach (Supplementary Fig. S4). Introducing our *Differentiated CoC* estimates that vary by sector, region, and time increases cumulative mitigation costs by roughly 15% from USD 62 to 71 trillion (Fig. 2a). We decompose this increase into different components by first holding climate policy stringency constant at the levels of the *Uniform CoC* approach and introducing our CoC differentiation elements step by step ("CoC changes") before finally allowing the model to adjust climate policy endogenously to still comply with the carbon budget of well below +2°C despite higher CoC in many countries ("policy reaction"). Doing so reveals that sectoral risk differentiation lowers mitigation cost (primarily through lower electricity prices; see the next section), while the increase in mitigation cost is primarily driven by the addition of country risk (+6%) and only mildly mitigated by future economic growth. Notably, the higher CoC in developing countries due to their country risk makes mitigation options less financially viable and, when holding climate policy stringency constant, increases global warming through 2100. Allowing the model to increase policy stringency endogenously negates this additional warming but increases cumulative mitigation costs considerably (+11%).

The emission-increasing effect of our *Differentiated CoC* estimates is shown in Fig. 2b. Under current policies, global cumulative CO_2 emissions through 2100 increase by roughly 50 Gt, which is equivalent to more than one additional year of current emission levels and overwhelmingly driven by high-risk regions. Under the well below +2°C pathway, emission increases due to differentiating the CoC are even higher without a climate policy reaction. In part, these increases are driven by the electricity sector, in line with previous studies' finding that the introduction of country risk shifts this sector toward less capital-intensive technologies using fossil fuels and raises power prices[27, 30, 28, 18, 15, 16, 26, 25]. In addition, current-policies emissions increase in other energy supply sectors, in industry, and, notably, in sectors for which we do not implement differentiated CoC estimates, such as transport and heating, due to spillover effects of power price changes. If the model's endogenous climate policy reaction is included, the shift in total cumulative emissions is approximately zero. This is because the additional transport and industry emissions in higher-risk regions, which become increasingly costly to abate, are now offset by additional abatement in the electricity sector, particularly in low- and mid-risk regions where abatement efforts under *Current Policies* are not too high.

As a result, these additional mitigation efforts increase cumulative mitigation cost in higher-risk regions and also in most mid- and low-risk regions, except Western Europe, where *Current Policies* are relatively ambitious compared to other low-risk regions (Fig. 2c). As expected, the effect is most pronounced for regions where key economies have persistently poor credit ratings. However, mitigation cost increases are also substantial for major low-risk economies, such as the US and China (both +13%).

CoC effects on the energy sector

When breaking down these main findings by sector, we generally omit the climate policy reaction to identify the pure CoC effect on sectoral outcomes. For electricity generation, our results largely corroborate the extant literature's findings. Introducing country risk reduces the share of renewables and nuclear in high-risk regions' long-term electricity mix to the benefit of fossil fuels, primarily natural gas (Supplementary Fig. S5)—which is less capital-intensive and hence less sensitive to CoC increases than coal[18]. Moving beyond previous studies, we find that differentiating the CoC reduces developing countries' investments in electricity grids both in the current policies and the well below +2°C pathway if we isolate the CoC effect by omitting the climate policy reaction (Fig. 3a). This finding is highly relevant given that the grid sector has similarly high or even higher net-zero investment needs than electricity generation[38] and plays a key role for energy access in developing countries[39].

Some of these grid investment reductions reflect a lower electricity demand, as the higher CoC for electricity generation and networks in mid- and high-risk regions increases the average electricity price between 2030–2100—

whereas low-risk regions exhibit price reductions due to the sector's below-average market risk (Fig. 3b). These price shifts due to CoC differentiation are typically more pronounced for the well below +2°C scenario, which involves a higher penetration of capital-intensive renewables, increasing the sensitivity of average levelized cost to the CoC. For hydrogen prices, the differences between the current policies and the well below +2°C scenario show no such clear pattern. However, price increases due to the *Differentiated CoC* overall are even more pronounced than for electricity and affect nearly every region, with increases well-above 20% for key regions like Western Africa that are often envisaged as potential hydrogen exporters[40].

The strong hydrogen price effect of the CoC has two reasons. First, hydrogen production is currently dominated by companies associated with the chemical sector, which exhibits a relatively high sector risk (Fig. 1b). Second, in the case of electrolysis, hydrogen production is fully exposed to CoC-induced shifts in electricity prices, which either drive up effective input prices or the opportunity cost of using power produced on-site for electrolysis rather than selling it. For these reasons, global hydrogen production using electrolysis drops substantially when sector and country risks are properly taken into account (Fig. 3c). By contrast, the decrease in the current incumbent technology, natural gas-based steam methane reforming, is less pronounced—except in low-risk regions where differentiating the CoC increases power prices only modestly or decreases them (Supplementary Fig. S6). As hydrogen, on average, becomes more CO_2-intensive and costly, it becomes less attractive for decarbonizing other sectors, such as transport, industry, and electricity generation, whose global end-of-century hydrogen usage under the well below +2°C scenario drops accordingly (Supplementary Fig. S7).

Differentiating the CoC also shifts centralized heat production in the model (i.e., district heating and combined heat and power generation) away from biomass and coal toward natural gas, particularly in high-risk regions under the current policies pathway (Fig. 3d). While this fuel shift and the higher CoC translate into higher heat prices in mid- and high-risk regions, the increase is less pronounced than for electricity (Supplementary Fig. S8). As a result, the (modest) global volume of centralized heat production by 2100 under the well below +2°C scenario increases from 7.4 to 7.9 EJ (1.4 to 1.8 EJ in high-risk regions) as purchasing heat becomes less expensive for companies and households relative to on-site generation using heat pumps. Taken together, these CoC-driven shifts away from electrified heat, electrolysis-based hydrogen, and low-carbon electricity sources result in the energy sector's emission increases displayed in Fig. 2b.

CoC effects on industry and fuel mixes

When exploring the sectoral effects of differentiated CoC estimates for the four climate-relevant industry sectors covered by our CoC estimates (i.e., cement, iron and steel, pulp and paper, and food processing), we focus on the well below +2°C scenario because, unlike for electricity generation, industry decarbonization efforts in the current policies scenario are limited (Supplementary Fig. S9) due to the more challenging underlying economics[41,3]. For the cement sector, which accounts for about 7% of current global CO_2 emissions[42], using the *Differentiated CoC* substantially alters the sector's technology mix (Fig. 4a). Under the well below +2°C scenario, the sector rapidly switches from the incumbent standard kiln technology to more efficient new-build kilns using the best available technology in IMAGE, in most cases augmented with carbon capture and storage (CCS). However, country and sector risks limit and slow down this transition. As a result, the global market share of inefficient standard kilns without CCS by 2100 almost doubles compared to the *Uniform CoC* setting.

Our findings for the iron and steel sector, which accounts for roughly 8% of current global CO_2 emissions[43], corroborate these patterns (Fig. 4b). Overall, the sector's higher CoC translates into higher market shares of the main incumbent technology, which reduces iron ore in coke-fueled blast furnaces before refining it to crude steel in basic oxygen furnaces (BOF). Importantly, BOF is considerably more carbon-intensive than the alternative electric arc furnaces (EAF), which produce crude steel either from recycled scrap or direct-reduced iron (DRI) using natural gas for the reduction process[42]. Differentiating the CoC reduces the uptake of CCS for both DRI EAF and BOF, leading to a higher market share of unabated technology versions, and further reduces the small market share for novel, less carbon-intensive technologies like electrowinning/EAF or direct reduction using hydrogen. Notably, scrap-based EAF in IMAGE is primarily determined by rising scrap availability[44]—which the model estimates based on past steel usage and average product lifetimes[45]—and hence remains largely unaffected by the CoC. Overall, the

amount of industrial CCS by the cement and steel sectors decreases substantially, which is overwhelmingly driven by high-risk regions (Fig. 4c).

Beyond the discussed technology choices and CCS deployment, differentiating the CoC also affects the fuel mix in climate-relevant industries and, through spillover effects of energy price shifts, in other non-energy sectors, with a substantial effect on transportation emissions in particular (Fig. 2b). In cement and steel, higher power prices due to country risk reduce electricity usage, which is primarily replaced by fossil fuels and, in the case of cement, biomass (Fig. 4d). Food processing and pulp and paper, the two other industrial sectors with explicit CoC representation in IMAGE, also exhibit a similar shift from electricity to biomass usage and, for food processing, fossil fuels. Notably, the latter allows the continued use of existing assets and, therefore, becomes more attractive if a higher CoC makes greenfield investments in new assets more costly. Beyond the industrial sector, the power price shifts induced by differentiating the CoC also delay the transportation sector's switch to electricity and increase the use of oil-based fuels in high-risk regions (Fig. 4e), particularly in passenger vehicles and trucking. These delays in transport and industry electrification, as well as CCS deployment, increase emissions and, to meet the climate target, require additional climate policy stringency, thereby contributing to the rise in mitigation costs. Notably, such spillover effects of energy price shifts are not easily captured in single-sector techno-economic models, highlighting the need for IAMs' broad sectoral coverage to assess how the CoC affects overall decarbonization.

Discussion

The results in this paper have important takeaways for IAMs and, more generally, modelers studying global mitigation pathways. We show that not capturing CoC differences across sectors, and particularly countries, may lead to underestimated mitigation costs. This result is partially driven by CoC-related price shifts in electricity and clean hydrogen, which, unlike fossil fuels, are not (yet) global commodities and hence more exposed to domestic country risk. In the energy sector, omitting country and sector risk differences may result in too optimistic assessments of grid expansion, electrification, and the potential of green hydrogen and its derivatives (e.g., synthetic aviation fuels) for deep decarbonization. For the industrial sector, above-average sector risks, potentially amplified by country risk, reduce the economic viability of technology upgrades and industrial CCS.

Therefore, studies using uniform, energy sector-based CoC assumptions, including most IAM-based scenario runs informing the IPCC reports and important industry decarbonization models[22], should revise their CoC assumptions, particularly in higher-risk developing countries. To this end, modelers can leverage the values and methodologies presented here, which can be readily applied to other sectors and models with varying geographical resolution. In addition, our results indicate that CoC-driven technology and fuel shifts in other climate-relevant sectors, including in industry, have a similar or even higher magnitude than for electricity generation. This novel finding may reflect that while the lever of the CoC on levelized cost may be higher for renewable power generation due to their capital intensity[18, 16], cost-minimizing decarbonization pathways in other sectors are much more uncertain and, therefore, more sensitive to the financing conditions assumed.

Regarding policy implications, our results suggest that the economic growth of developing countries, although important, is likely insufficient to mitigate the vast current CoC differences between countries fully—unless such growth is accompanied by improvements in other sovereign risk determinants that do not scale with economic growth[35]. At the same time, we show that country risk in particular hinders mitigation across sectors and increases costs, which underscores the strong need for international climate finance to de-risk investments across all climate-relevant sectors in developing countries. Currently, a majority of international mitigation finance flows into low-carbon electricity generation[46]. Given the overall role of the CoC in mitigation, international climate funds, development finance institutions, and climate finance donor countries should consider expanding their capital provision for sectors other than power generation, including grids and industry decarbonization. In addition, our results highlight de-risking needs particularly in low- and lower-middle-income countries with poor sovereign ratings where multilateral development banks and other climate finance providers can be hesitant to lend due to concerns about their risk exposure and credit ratings[47]. Even in lower-risk countries, targeted de-risking interventions such as (carbon) contracts for difference[48] or public credit and off-take guarantees[49, 40] may be required to reduce the high

CoC for industry decarbonization and clean hydrogen production.

These important insights notwithstanding, the findings presented in this study are accompanied by some caveats. While we expand the scope of differentiated CoC considerably vis-à-vis previous, electricity generation-focused studies, we model CoC-induced energy price effects but not explicit CoC impacts on the transport, agriculture, and some industrial sectors, most notably chemicals. This limitation is driven by the less explicit CoC representation in IMAGE for these sectors[33] and, for transportation, the sector-specific role of consumer finance and income segment-specific financing conditions[50], as well as leasing. Such financing conditions are not easily covered by the methodology presented here and would require more granular data on households' creditworthiness and opportunity cost, which goes beyond the scope of this study. Furthermore, we estimate the CoC based on recent history and, for future years, consider only changes introduced by expected economic growth but no potential trends in sectoral risks—for instance, if steel decarbonization reshuffles supply chain structures that alter the industry's overall risk structure[51]. In addition, given the notorious volatility of region-specific estimates[52], our estimates of current sectoral risks are based on global averages, which may underestimate sectoral risks in developing countries. Lastly, our CoC estimates capture overall *market* conditions and rates. In higher-risk developing countries, these market rates are somewhat mitigated by existing international climate finance[26] and other financial policy interventions, which are typically not represented in IAMs.

Future research can address these shortcomings in multiple ways, for instance, by expanding the scope of CoC differentiation to sectors not included here, most notably chemicals and transportation. In addition, model intercomparison studies leveraging multiple IAMs could corroborate and further contextualize the numerical findings presented here, for instance, by exploring how CoC-induced shifts in low-emission pathways vary with the availability of scalable bioenergy CCS and direct air capture across IAMs. Concerning estimating the CoC, scholars could explore ways to translate expected shifts in sectoral risks, institutional quality, and international climate finance into existing CoC estimates and could also consider integrating the physical risks of climate change[53]. In addition, future studies should incorporate more detailed representations of policy interventions targeting the CoC[54] to examine the potential effects on decarbonization outcomes and costs across various sectors. Such exercises would further advance the understanding of CoC-induced impacts and shifts beyond the results of this study.

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Author contributions statement

All authors designed the research and developed the methodology and scenarios. P.W. performed the empirical analysis. H.S.d.B. and C.C. ran the scenarios. P.W. analyzed the scenario results and wrote the first draft of the paper. B.S. and D.v.V. acquired funding. All authors provided feedback and editing for the final paper.

Competing interests statement

P.W. advises European energy network operators on regulatory matters, including issues related to their cost of capital. All other authors declare no conflict of interest.

Figures

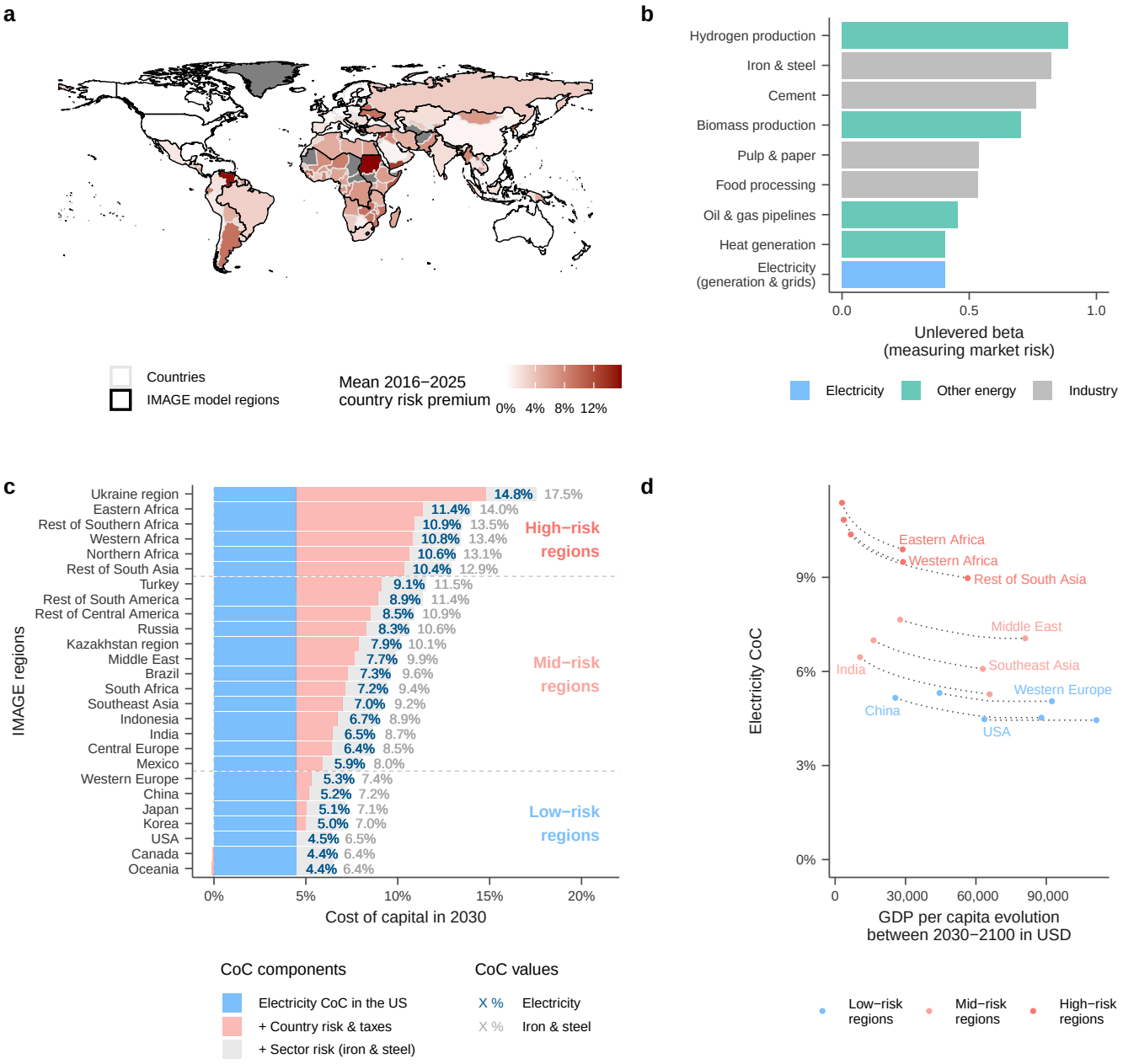


Figure 1. Deriving dynamic region- and sector-specific CoC estimates for the IMAGE model. **(a)** Mean 2016–2025 country risk premium (start-of-year)[32], with IMAGE model regions (countries) marked in black (grey). For territories colored in grey, data is not available. **(b)** Unlevered beta estimates of market risk by IMAGE sectors based on global industry-specific averages[32]. **(c)** Resulting CoC estimates (nominal, after-tax) for two example sectors (electricity and iron & steel), disaggregated into the CoC without country risk for the US electricity sector (blue), CoC changes due to country risk and taxes (red; calculated as regional electricity CoC minus US electricity CoC), and additional sector risk (grey; calculated as regional iron & steel CoC minus regional electricity CoC). **(d)** CoC reduction due to GDP per capita growth (SSP2) between 2030–2100 for an example sector (electricity), displayed for three example IMAGE model regions with the highest 2025 population per macro region (high-/mid-/low-risk).

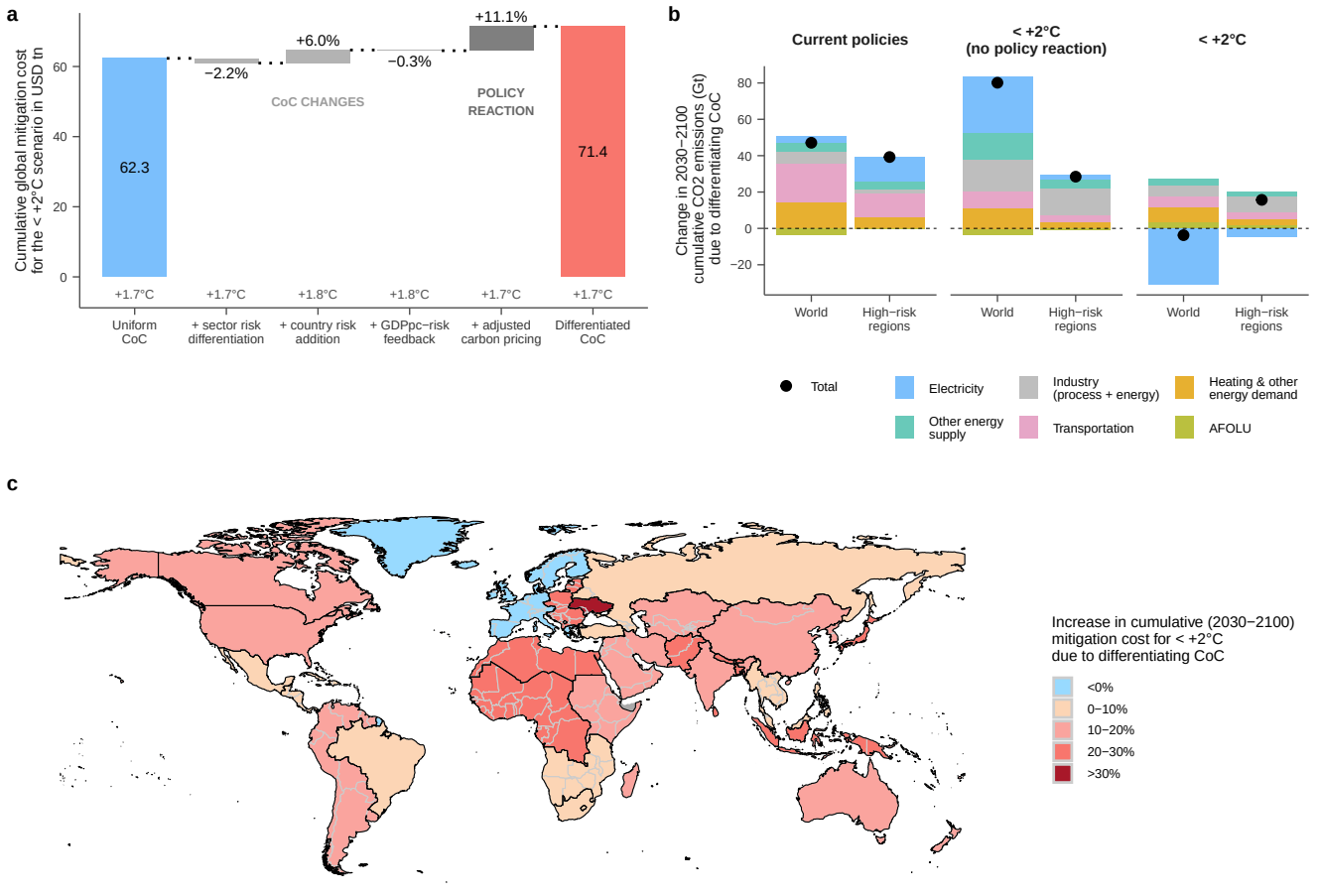


Figure 2. Effect of differentiated CoC on CO_2 emissions and mitigation costs. **(a)** Global cumulative mitigation cost (2030–2100) under the well below +2°C scenario for the *Uniform CoC* (blue) and the *Differentiated CoC* (red) scenarios. "+X°C" labels below the bars indicate the change in global mean surface temperature by 2100 vis-a-vis pre-industrial. **(b)** Change in global cumulative (2030–2100) CO_2 emissions between the *Uniform CoC* and the *Differentiated* CoC scenario by sector (bars) and across all sectors (black dots) for the current policies scenario and the well below +2°C with and without climate policy reacting to the CoC changes. AFOLU denotes agriculture, forestry, and other land uses. **(c)** Relative shift in the region-specific cumulative mitigation cost (2030–2100) between *Uniform CoC* and the *Differentiated CoC* scenario.

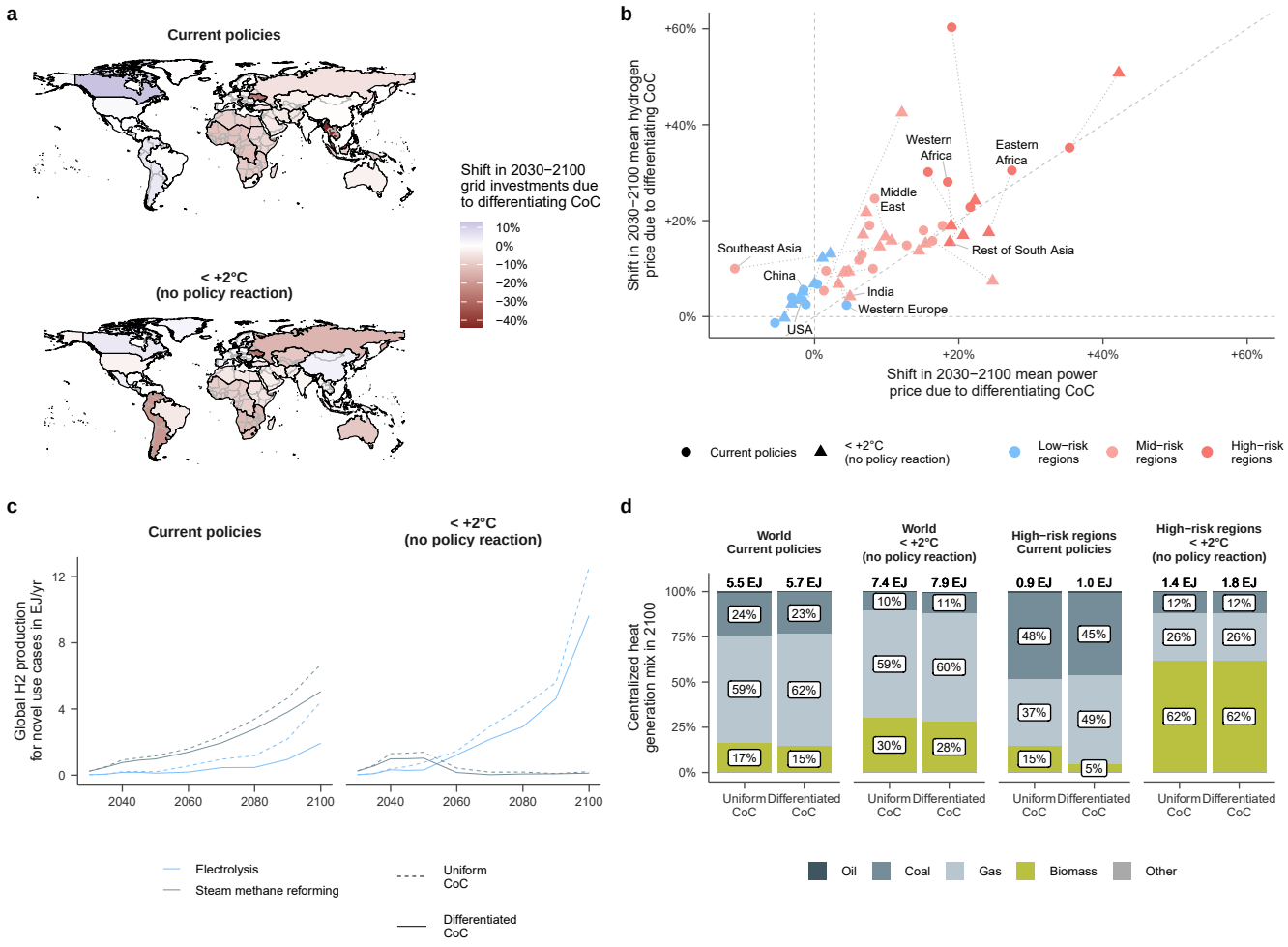


Figure 3. Effect of differentiating the CoC on grid investments, energy prices, as well as hydrogen and heat generation under the current policies and the well below +2°C scenario without policy reaction. **(a)** Shift in the cumulative investments in electricity grids (2030–2100) between *Uniform CoC* and the *Differentiated CoC*. **(b)** Shift in the mean 2030–2100 hydrogen (y-axis) and electricity (x-axis) prices between *Uniform CoC* and the *Differentiated CoC*. **(c)** Global hydrogen production for novel use cases by technology (color) and CoC setting (linetype). "Steam methane reforming" includes plants with and without CCS. "Electrolysis" comprises proton exchange membrane, solid oxide, and alkaline electrolyzers. Other IMAGE technologies (i.e., partial oxidation of oil and gasification of biofuels and coal) are omitted because of negligible production volumes. Hydrogen production for legacy use-cases (e.g., ammonia, refineries) is not covered by IMAGE. **(d)** Centralized heat generation mix in 2100 worldwide and for the High-risk macro region. "Other" comprises geothermal and hydrogen. Bold labels denote the total heat generation.

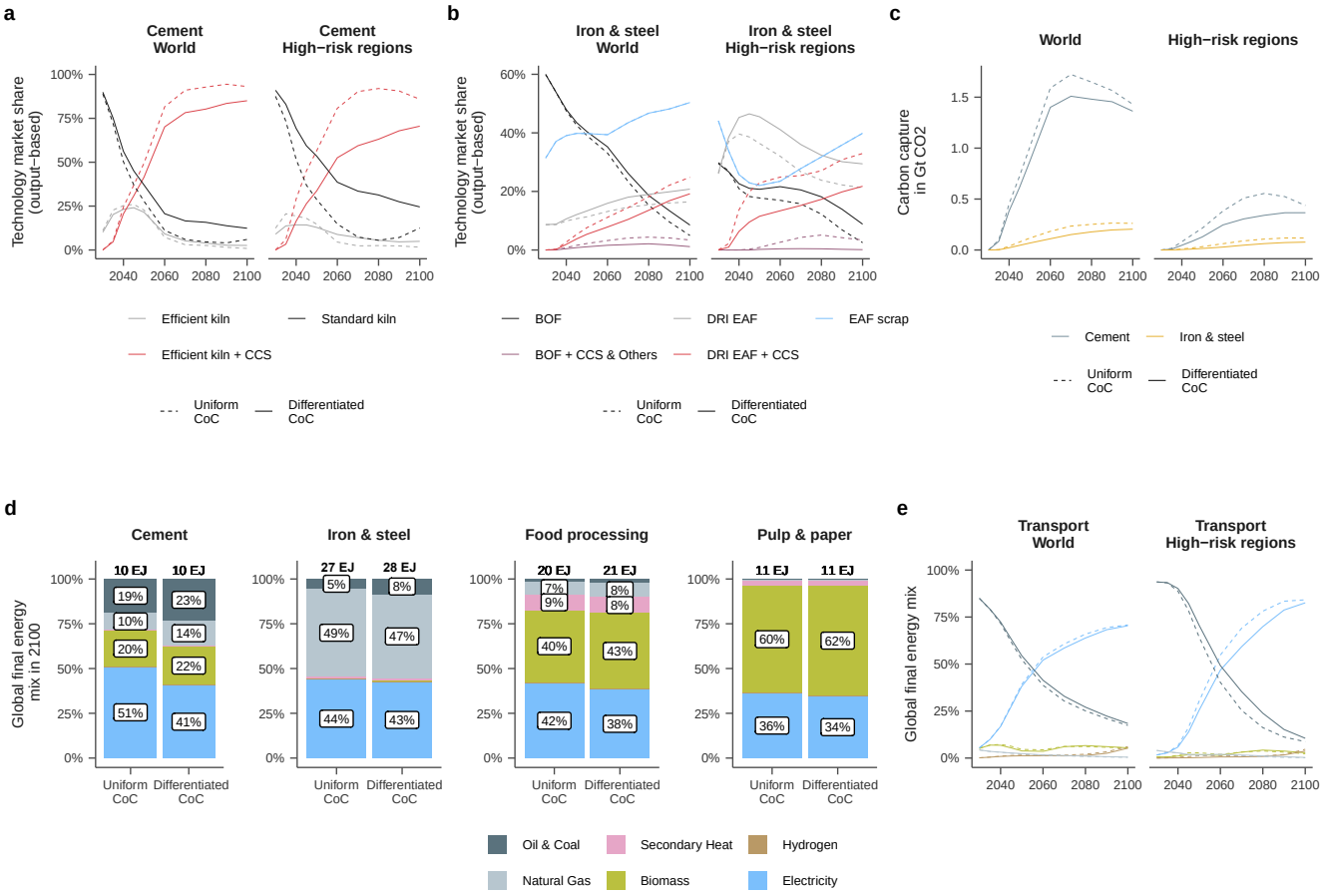


Figure 4. Effects of differentiating the CoC on industry technology and fuel mixes for the well below +2°C scenario without climate policy reaction. **(a)** Technology share in cement production (measured in tonnes of cement) worldwide and for the High-risk macro region. "Efficient kiln + CCS" comprises pre-combustion oxy CCS, post-combustion monoethanolamine CCS, and on-site direct separation CCS. **(b)** Same as Panel a but for the iron and steel sector. "BOF + CCS & Others" comprises BF/BOF with CCS, H-DRI/EAF, and Electrowinning/EAF. Note that EAF scrap production in IMAGE is primarily constrained by scrap availability and, therefore, does not vary with the CoC in a decarbonization scenario. **(c)** Carbon capture by the cement and steel sector (process and energy emissions) worldwide and for the High-risk macro region. **(d)** Fuel mix of different industry sectors. Bold labels denote the total final energy demand. **(e)** Same as Panel d but for the transport sector (comprising domestic and international passenger and freight transport via road, air, and ship) and displayed over time.

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Methods

The IMAGE model IMAGE (Integrated Model to Assess the Global Environment) is a comprehensive integrated assessment model that simulates the environmental impacts of human activities worldwide, covering topics such as climate change, biodiversity, and resource use. The framework links socioeconomic developments with changes in the Earth system, enabling scenario analysis for sustainability and policy assessment. IMAGE covers 26 regions from 1970 through 2100 in yearly time steps; however, in line with the harmonized IAM reporting framework, we use output data in five-year (ten-year) intervals through (after) 2050 and, where necessary, interpolate linearly. The core model takes socioeconomic drivers from the Shared Socioeconomic Pathways (SSPs) and translates them into agriculture and land use projections using a land use model and energy supply, conversion and demand projections using the TIMER energy system model. TIMER simulates year-to-year investment decisions based on bottom-up engineering information and defined investment rules, rather than optimizing for perfect foresight. Its submodels cover energy demand, energy conversion, fossil and non-fossil fuel supply, energy trade, and emissions. Key mechanisms include price-driven fuel and technology substitution, cost reductions through learning-by-doing, resource depletion modeled with long-term supply curves, and explicit simulation of trade barriers across regions. Overall, different technologies and energy carriers compete based on their costs and are chosen via a multinomial logit function. Costs include operating expenses and capital expenses, with the latter being transformed into an annuity based on asset lifetime and the cost of capital (CoC). Notably, IMAGE does not include a bottom-up representation of all energy and industrial sectors, such that CoC effects for a few climate-relevant (sub)sectors (e.g., chemicals, glass) cannot be explored without overhauling the current model structure. As a result, CoC effects for these sectors fall outside the scope of this paper. Throughout the paper, we use SSP2 for all model runs and all monetary model results are given in 2010 USD PPP unless specified otherwise. For more details on the model, we refer to the model documentation[33].

For visual conciseness, we aggregate the 26 regions of IMAGE into three macro regions based on the electricity CoC, with implied thresholds at 5.5% (which effectively separates non-Latin American OECD countries and China from the rest of the world) and 10% (which separates emerging markets from high-risk regions, including African countries except South Africa and model regions that include only few countries with persistently poor sovereign ratings, such as the Ukraine region). Macro regions are shown in Supplementary Fig. S3.

Scenarios for climate policy ambition and CoC We use two different scenarios capturing a range of different climate policy ambitions, which in IMAGE is primarily represented via carbon pricing: i) the current policies scenario in which there is no carbon price beyond current policies, which are extended until the end of the simulation[55]; ii) the well below +2°C mitigation run, in which the model solves the optimization problem of reaching respective carbon budgets (1,000 $GtCO_2$ between 2020–2100[56]) at the lowest achievable policy costs by setting a global carbon tax. Each of these scenarios is paired with two different scenarios for how the CoC in IMAGE is implemented. Under the *Uniform CoC* scenario, all regions and technologies use a static, uniform 5% value, which is broadly consistent with the emission-weighted average for the US (typically used as a risk-free benchmark country) across all sectors considered here. Under the *Differentiated CoC* scenario, we implement dynamic region- and sector-specific CoC (for details, see below), which i) adds country risk for all countries not rated at risk-free levels, ii) adds sector risk to most sectors (but reduces the CoC for the lowest-risk sectors, such as electricity and heat) and iii) accounts for the potential reducing effect of continued economic growth on countries' risk premiums. As IMAGE is calibrated to historical data for past years, we modify the model's CoC assumptions from 2030 onward. Under the well below +2°C scenario, the model endogenously revises the carbon pricing to ensure that the carbon budget is not violated ("with climate policy reaction"). To isolate the CoC effect, we re-run the well below +2°C pathway with our *Differentiated CoC* estimates while holding the carbon price schedule of the *Uniform CoC* run constant ("no climate policy reaction") and use these results when exploring sector-specific CoC effects (Fig. 3–4).

Weighted average cost of capital To derive country- and sector-specific CoC estimates, we use financial market data and assessments by credit rating agencies to quantify overall average risk profiles of the different climate-relevant sectors represented in IMAGE. We rely on the NYU Damodaran database[32], which provides rating-based

country risk premiums and industry-specific financial variables (e.g., betas or equity shares) with annual updates and is widely used in the extant literature[27, 30, 28, 57]. To estimate financing costs, we calculate the nominal weighted average cost of capital (WACC) after taxes for country i and sector a as follows:

$$\mathrm{WACC}_{i,a} = \underbrace{(1-\mathrm{DS}_a)}_{\text{Equity share}} \times \underbrace{\left(\mathrm{RF}+\mathrm{CRP}_i^E+\beta_a \times \mathrm{ERP}\right)}_{\text{Cost of equity}} + \underbrace{\mathrm{DS}_a}_{\text{Debt share}} \times \underbrace{\left(\mathrm{RF}+\mathrm{CRP}_i^D+\mathrm{DP}_a\right)}_{\text{Cost of debt (pre-tax)}} \times \underbrace{(1-\tau_i)}_{\text{Tax shield}} \quad (1)$$

Here, DS denotes the sector-specific debt share in the capital structure, while $1-DS$ is the share of equity. Industry-specific debt shares are taken from the NYU Damodaran database as global average values and calculated as the ratio of firms' total debt used (incl. lease debt) to the sum of total debt and market capitalization.

The cost of equity has the following components:

- **Risk-Free Rate** (RF): We use the 2015–2024 arithmetic average of US 10-year Treasury bond yields provided by the OECD[58], $RF = 2.48\%$. Notably, this value is considerably lower than Treasury bond yields observed in the first half of 2025, which exceed 4%. Therefore, an implicit assumption is that in the medium to long run, interest rate levels revert to values that are more representative of the past decade.

- **Country Risk Premiums** (CRP): Year- and country-specific country risk premiums (relative to a country considered risk-free) are derived from sovereign credit ratings, which typically operate as a "sovereign ceiling" on domestic firms' credit rating[59]. Local currency ratings (as of 1 January) and the corresponding risk premiums, following the methodology outlined in ref.[60], are obtained from ref.[32]. For non-rated countries, ref.[60] imputes the country risk premium based on a country's composite risk score by Political Risk Services. To reflect that equity is inherently riskier than debt, the country risk premium for equity (CRP^E) features an adder of approximately 1.35, which ref.[52] estimates based on the relative volatility of stock and bond returns in emerging markets (where country risk is most prevalent), such that $\mathrm{CRP}^E = 1.35 \times \mathrm{CRP}^D$. To avoid individual years dominating the assumed value, we take country risk premium estimates from the NYU Damodaran database for 2016–2025 and average them.

- **Equity Risk Premium** (ERP): We use a global value of $\mathrm{ERP} = 5\%$, in line with the long-term global estimate by ref.[61] and consistent with survey estimates and premiums implied by stock market data listed in Table 27 of ref.[52]. Notably, this approach is not country-specific because while a uniform ERP does not reflect equity risk differences between markets, confidence intervals around market-specific ERP estimates are usually so large that they severely limit their usability, particularly for less mature stock markets[52].

- **Levered Industry Betas** (β): Unlevered industry-specific betas, which do not reflect risks due to indebtedness, are taken from ref.[32] as global averages estimated based on five years of stock return data. Betas are relevered at the country level using $\beta = \beta_{a,\text{unlevered}} \times \left[1+(1-\tau_i) \times \frac{\mathrm{DS}_a}{1-\mathrm{DS}_a}\right]$ where τ_i denotes the country-specific corporate tax rate (more details below). Since betas are multiplied by the ERP, $\beta > 1$ denotes industries that are riskier than the overall market, while $\beta < 1$ denotes less risky industries. We use global beta estimates because, similar to the ERP, country- or region-specific betas are subject to large uncertainties and can lead to underestimated risk measures for emerging markets with low weights in global indices[52]. Doing so means that the estimated CoC differences between low- and high-risk regions arise solely from differences in country risk premiums and taxes, which is conservative.

In addition, the cost of debt has the following components:

- **Debt Premium** (DP): Debt markups on the risk-free rate are estimated based on the volatility of stocks in a given industry and taken from ref.[32]. Values range between 1.54% and 2.24% for the sectors considered here.

- **Corporate Tax Rates** (τ): Country-specific corporate tax rates for 2025 are sourced from ref.[32] and, for countries with missing entries, from an international database compiled by PwC[62] to account for the so-called "tax shield" since debt repayments are tax-deductible, which reduces the effective cost of debt financing accordingly.

Lastly, in electricity generation, renewable energy projects are predominantly structured as stand-alone project companies, with lenders having no recourse to the project sponsors in case of default[57, 63]. This financing structure creates a direct link between technology characteristics and overall risk profiles[14], leading to WACCs varying within the same sector (electricity generation) by technology[64]. Therefore, we assess technology-specific WACC spreads using a recent database of renewable energy financing conditions[65] and, based on the results in Supplementary Note 1, apply a conservative WACC premium of +0.8 percentage points to Equation 1 for offshore and other not-yet-matured renewable energy technologies in IMAGE (i.e., concentrated solar power and wave) vis-a-vis other electricity generation technologies (Supplementary Note 1).

Country-to-region aggregation and sector mapping We aggregate sector-specific WACC estimates from the country level to IMAGE model regions using World Bank WDI data on GDP PPP[66] for 2024 (or, if this is not available, the last available year) as weights. As a result, a handful of countries without available GDP information in the World Bank data (e.g., Venezuela) are effectively excluded from regional averages. The same holds for countries that are missing in the Damodaran database altogether; however, these countries tend to be small and thus would have a very low weight in our GDP-weighted regional averages. For a few countries, corporate tax rates are missing. In this case, we take country-specific values from PwC's Worldwide Tax Summaries[62] and, if those are also not available, we impute missing country values with the GDP-weighted average tax rate in a country's IMAGE region (Supplementary Table S6).

For sector-specific values with subscript a from the NYU Damodaran database (β, DP, and DS), we map the sectors in IMAGE to the industry groups distinguished in the database (Supplementary Table S2). Where this is not straightforward, we identify the best corresponding industry by first identifying the major publicly listed firms worldwide in the respective sector of interest through desk research and then identifying the Damodaran database industry group of these firms, using the four-eyes principle. Notably, only publicly listed firms are included in the database and hence in Supplementary Table S2. For additional details, see Supplementary Note 1.

Projecting changes in country risk premiums Estimates for CRP in Equation 1 reflect *current* financing conditions. Studies assessing the main determinants of sovereign credit ratings consistently rank (log-transformed) GDP per capita as the main predictor[35, 36], which will increase over time. Therefore, we take country risk premiums from ref.[32] for all available years starting in 2001 and combine them with World Bank data on real GDP per capita (PPP) available through 2024[67]. Then we regress the country risk premium for debt of country i in year t as follows:

$$CRP^{D}_{i,t} = \beta_1 \ln\mathrm{GDPpc}_{i,t-1} + \beta_2 CRP^{D}_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

where $lnGDPpc$ denotes the log-transformed GDP per capita from the previous year (as CRP is based on start-of-year ratings), α_i and δ_t denote country and year fixed effects ($N = 164$ countries, $T = 25$ years, unbalanced panel), and $\varepsilon_{i,t}$ is the error term. The model features a lagged value of the dependent variable ($CRP^{D}_{i,t-1}$) to account for the stickiness in country ratings, while further lags are not statistically significant but reduce the effective sample size (Supplementary Table S5). To avoid very small countries with unusual GDP per capita values (e.g., Monaco) driving our results and in line with our GDP-weighted CoC estimates, our main specification weights countries by their current GDP[66]. As robustness checks, we also weight countries by current population or equally, add a country-specific linear time trend, and exclude post-pandemic years by using only years prior to 2020 (Supplementary Table S4). Our conservative main specification suggests a 0.59 percentage point decrease in the country risk premium per one-unit increase in log-transformed GDP per capita (which ranges between 7–12). Additional information on the regressions is provided in Supplementary Note 2.

Notably, the relationship between country risk premium and log-transformed GDP per capita is broadly linear through lnGDPpc = 11 (i.e., a GDP per capita of roughly 60,000 USD) before flattening out (Supplementary Fig. S1), in line with the extant literature[36]. This flattening-out effect cannot be captured by our fixed effects regression model since using country fixed effects effectively discards all countries for which the country risk premium is consistently at zero (e.g., the US). Therefore, we further assume that the relationship between log-transformed GDP per capita and the country risk premium no longer persists once this income level is reached.

Noting that differentiating Equation 1 with respect to CRP^D yields

$$\psi_{i,a} = 1.35(1 - DS_a) + DS_a(1 - \tau_i), \tag{3}$$

this means that we project future reductions in WACCs due to lower regional risk premiums for debt in IMAGE as follows:

$$\mathrm{WACC}_{r,a,t} = \mathrm{WACC}_{r,a,2025} - \psi_{r,a} \times 0.0059 \times \left(\min\{11,\ \mathrm{lnGDPpc}_{r,t}\} - \min\{11,\ \mathrm{lnGDPpc}_{r,2025}\}\right) \tag{4}$$

Here, $\psi_{r,t,a}$ is calculated at the country level following Equation 3 and aggregated to the region level using GDP weighting (equivalent to the WACCs). In addition, we floor $\mathrm{WACC}_{r,a,t}$ at the initial WACC estimated for the US ($\mathrm{WACC}_{US,a,2025}$) for which $CRP^D = 0$. As a result, regions with relatively low current income levels can improve their financing conditions through continued economic growth. In contrast, regions relatively close to or above the cut-off value of 11 that are not AAA-rated (e.g., Western Europe due to, among others, Italy) maintain their risk premium, which is in line with this premium being related to factors other than general economic development.

Data availability

Data from the NYU Damodaran database[32] is available here: https://pages.stern.nyu.edu/~adamodar/. OECD data on US Treasury bond yields[58] is available here: https://fred.stlouisfed.org/series/IRLTLT01USM156N. PwC data on corporate tax rates[62] is available here: https://taxsummaries.pwc.com/interactive-map. GDP and GDP per capita data from the World Bank WDI database[67, 66] are available here: https://databank.worldbank.org/source/world-development-indicators. Upon acceptance, all additional input data, the cost of capital estimates, and the IMAGE output data will be published to a permanent repository.

Code availability

Information on the IMAGE model and the principles of its source code can be found in ref.[33]. The code for the empirical analysis, for processing IMAGE outputs, and for creating the figures and tables in this study will be published to a permanent repository upon acceptance.

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Supplementary Information

Supplementary Note 1: Additional information on the CoC estimates

Technology risk premium for higher-risk, project-financed renewable energy technologies. Overall, our methodology to estimate the CoC assumes on average similar financing conditions for projects carried out by the same sponsors and, therefore, estimates sector-level CoC based on sector-specific average risks and indebtedness (see Methods). Unlike fossil fuel-based technologies and most industries, however, power generation using renewable energy (RE) technologies is predominantly financed via project finance, that is, stand-alone project companies with lenders having no recourse to the project sponsors[63, 57]. Therefore, for the same project sponsors, financing conditions can and do vary by technology due to differences in risk-return profiles related to time-constant technology-inherent characteristics and time-varying market maturity[14, 64]. Previous studies have addressed this by estimating RE CoC by technology, for instance, by using utility-specific financial and portfolio data, using country-level deployment as proxies for market maturity with thresholds informed by expert interviews, or estimating technology differences based on average CoC spreads between technology-specific CoC estimates in the extant literature[28, 27].

While the power generation sector is not the primary focus of this paper, we investigate how recent CoC estimates suggest the need for technology-specific risk premiums. Specifically, we leverage a recently published database of CoC estimates for solar PV, onshore and offshore wind for 68 countries between 2010–2022[65] and regress the available nominal after-tax WACC estimates on technology dummies, adding country, year, and study fixed effects to reduce omitted variable bias. To ensure that findings are not driven by outdated data points (reflecting a market immaturity that may no longer apply) or methodological differences between data points for different technologies, we also explore results for subsetting the sample to estimates for the last five years and to studies that cover all three technologies (i.e., the fixed effects model effectively averages within-study between-technology spreads).

Results are shown in Supplementary Table S1 and indicate that, on average, offshore wind commands the highest CoC of the technologies, while onshore wind commands the lowest. This finding aligns with previous studies which document that onshore wind matured the earliest among the three RE technologies, while solar PV's technology risks have decreased substantially throughout the 2000s and 2010s amid a sharp ramp-up in deployment[68, 69] and, in some markets like Germany, converged against those of onshore wind[70]. By contrast, offshore wind is considered a high-CoC technology due to construction complexities and ownership structures, with previous studies documenting a CoC premium of +1.3 percentage points[71] and widespread public financial support for the technology[69, 49]. Similarly, our estimates for offshore wind vary between 0.8–1.4 percentage points across specifications but remain statistically significant. By contrast, the p-value for the solar PV premium exceeds 5% if we subset the sample to the most recent years and becomes statistically insignificant and lower if we only consider studies covering all three RE technologies.

Doing so effectively reduces the sample to selected OECD countries, China, and Vietnam, in which offshore wind and solar PV deployment is relatively advanced compared to most markets. Therefore, using this subset implies a lower risk of conflating technology-specific, time-constant risk premiums with premiums due to (past) market immaturity that may have changed by now or may change in the near-term future. Therefore, we apply a conservative +0.8% CoC premium to offshore wind projects but no similar premium to solar PV. Offshore wind featured a technology readiness level (TRL) of nine through 2022 in the International Energy Agency's technology classification (on a scale between 1–11)[72]. Therefore, we also apply the +0.8% premium to IMAGE's other less mature higher-risk renewable energy technologies with a current IEA TRL of nine or lower (i.e., concentrated solar power, and wave power) because for these technologies, a lack of technology-specific CoC estimates hinders the estimation of robust technology premiums.

CoC differences between lower-risk project-financed RE technologies and overall power generation. Importantly, the results in Supplementary Table S1 do not speak to differences between lower-risk renewable energy technologies and financing conditions for other technologies that do not primarily use project finance (e.g., fossil fuels and nuclear). In general, project finance typically features a higher debt share of around 70–80% facilitated by better corporate governance, easier assessments by lenders, and the conclusion of long-term power purchase

Table S1. Assessing technology spreads in published CoC estimates

Dependent Variable:	WACC (nominal, after-tax) in decimals			
	Full Sample	2019–	All 3 Tech	All 3 Tech (2019–)
Model:	(1)	(2)	(3)	(4)
Variables				
technology = SolarPV	0.0051*	0.0071·	0.0032	0.0032
	(0.0024)	(0.0038)	(0.0023)	(0.0020)
technology = Windoffshore	0.0144***	0.0105**	0.0081**	0.0080**
	(0.0036)	(0.0034)	(0.0027)	(0.0027)
Fixed-effects				
country	Yes	Yes	Yes	Yes
financing_year	Yes	Yes	Yes	Yes
study	Yes	Yes	Yes	Yes
Fit statistics				
Observations	366	150	39	30
R^2	0.76441	0.82969	0.86869	0.91288
Within R^2	0.04106	0.05778	0.29717	0.37524
BIC	-1,347.3	-541.27	-238.08	-198.38

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

agreements that reduce market risk[63]. However, current CoC estimates for RE technologies also include substantial de-risking through feed-in tariffs and other support policies that may be discontinued or at least reduced throughout IMAGE's modeling period. Therefore and to be conservative, we abstract from these differences and use our general power generation CoC estimate for lower-risk project-financed renewable energy technologies in IMAGE (i.e., solar PV, onshore wind, and biomass), noting that past IAM studies suggest that RE deployment in decarbonization deployment is relatively robust to moderate CoC changes[27].

Sectoral mapping for biomass production For the biomass sector, publicly listed companies fall into various database categories with no clear-cut match. However, we note that the derived unlevered beta 0.70 and equity share of 68% (resulting in a relevered beta of 0.96 for a corporate tax rate of 20%) based on most companies' categorization aligns with company-specific levered beta estimates sourced from Yahoo Finance on 21 May 2025 for the largest companies, such as ADM (0.67), Green Plains (1.19), Valero (0.95), FutureFuel (0.84), Drax (0.75), and Enviva (0.84)—particularly when keeping in mind that Drax and ADM are primarily active in sectors like electricity generation and food processing, which have lower sectoral risk[32].

Supplementary Note 2: Additional information on estimating the GDPpc-risk premium feedback

The country-level panel data set was collected from ref.[32] and the World Bank's WDI database[67]. For country risk premiums (CRPs), data cleaning was performed to discard duplicate values and, for some countries and years, additional (lower) estimates for the country as a center for offshore banking instead of domestic economic activities (e.g., the Cayman Islands). For the United Arab Emirates, values for individual emirates were discarded to ensure that we have only one country risk premium per ISO3 code and year. Summary statistics for the resulting sample are displayed in Supplementary Table S3. The observed country risk premiums range between 0% for AAA-rated

	IMAGE sector	Industry in the Damodaran database	Unlevered beta	Equity share	Publicly listed example companies
1	Electricity	Power	0.41	51%	NextEra, The Southern Company, Enel, Uniper, Iberdrola, RWE, EnBW, Fortum, Korea Electric Power Corporation, Tokyo Electric Power *Note: Some companies (e.g., Engie) are also listed as "Utility (General)", which has the same beta and only a slightly higher equity share (56%).*
2	Electricity networks	Power	0.41	51%	Redeia, Terna, Elia, Admie, Fortis, Xcel Energy, Power Grid Corporation of India Power Grid Bangladesh, Hydro One *Note: Some companies (e.g., National Grid, E.ON) are also listed as "Utility (General)".*
3	Centralized heat generation	Power	0.41	51%	Fortum, Uniper, EnBW, Orsted *Note: Some companies (e.g., Engie, Veolia, E.ON) are also listed as "Utility (General)"*
4	Hydrogen production	Chemical (Specialty)	0.89	81%	Linde, Air Products, Air Liquide, Jiangsu Huachang *Note: Some key companies are also listed as "Chemical (Diversified)" (BASF; beta: 0.77, equity share: 61%) or "Oil/Gas Integrated" (Sinopec; beta: 0.81, equity share: 83%)*
5	Biomass production	Oilfield Svcs/Equip.	0.70	68%	*For bioethanol:* Valero, Green Plains, Cosan, CropEnergies, Aemetis, Cardinal Ethanol, Highwater Ethanol, Ubon Bio Ethanol *For biodiesel:* Renewable Energy Group, FutureFuel, Longyan Zhuoyue New Energy, Aemetis, Neste *Note: Some companies (ADM, Wilmar, 3Tentos) are also listed as "Farming/Agriculture" (beta: 0.52, equity share: 61%). Leading pellet producers are listed either as "Coal & Related Energy" (Enviva; beta: 1.05, equity share: 84%) or "Green & Renewable Energy" (Drax, which primarily deals in power generation; beta: 0.57, equity share: 58%)*
6	Oil & gas pipelines	Oil/Gas Distribution	0.46	61%	The Williams Companies, Enbridge, Kinder Morgan, TC Energy, Fluxys
7	Cement	Construction Supplies	0.76	73%	Holcim, CEMEX, CRH, Buzzi, UltraTech, Grasim, Anhui Conch, Heidelberg Cement, Ambuja
8	Food processing	Food Processing	0.54	73%	Nestle, Mondelez, Hershey, Kraft Heinz, Danone, General Mills, Lindt & Sprüngli *Note: Some key companies (Unilever) are also listed as "Transportation" (beta: 0.65, equity share: 64%)*
9	Iron and steel	Steel	0.82	65%	ArcelorMittal, Nippon Steel, HBIS, Shagang, POSCO, Shougang, Tata Steel, JSW Steel Limited, JFE, Nucor
10	Pulp and paper	Paper/Forest Products	0.54	55%	UPM-Kymmene, Suzano, Svenska Cellulosa, Stora Enso, Celulosa Argentina, Mondi, Holmen *Note: Some companies (International Paper) are also listed as "Food Processing"*

Table S2. Matching of climate-relevant technologies/subsectors to the industry groups in the NYU Damodaran database

countries and up to 18% for high-risk countries, such as Sudan, Venezuela, and Yemen. Log-transformed GDP per capita ranges between 6.9 and 11.9 (roughly 1,000 and 150,000 USD, respectively). Missing values for the GDP (per capita) and the population variables arise from the 2025 year (for which only start-of-year country risk premiums are observed) and from a few countries not included in the underlying World Bank WDI database, such as Venezuela.

Table S3. Summary statistics for the regression sample

	Mean	N	St.Dv.	Min	Max
year	2014.48	3412	7.15	2001	2025
crp_debt_defaultspread (decimals)	0.03	3412	0.03	0.00	0.18
ln_gdp_pc	9.68	3031	1.03	6.90	11.86
gdp (billion)	930.06	3031	2728.54	0.63	33 597.90
pop (million)	48.34	3159	165.90	0.03	1450.94

Results for the regression model outlined in the Methods section are displayed in Supplementary Table S4, with standard errors two-way clustered by country and year. Consistent with the literature, we find that increases in log-transformed GDP per capita are significantly associated with decreases in the country risk premium, both before (col. 1) and after introducing fixed effects (col. 2). Controlling for last year's country risk premium halves the effect to about 0.59 percentage points per one-unit increase in log-transformed GDP per capita (col. 3), as countries' ratings in adjacent years are strongly correlated. We find no clear evidence for a non-linear effect (col. 4). Introducing country-specific linear time trends (col. 5), or altering the weighting of observations (col. 6 and 7), increases the point estimate or leaves it roughly unaltered. The same holds for discarding the (post-)pandemic

years from 2020 on, although dropping more than 20% of our sample unsurprisingly increases the p-value. To be conservative and given that country-specific trends may overfit the data, we opt for the main specification in col. 3.

Notably, studies predicting sovereign credit ratings typically identify a range of determinants, including government debt, inflation, unemployment, fiscal balance, current account balances, default history, and institutional quality (see Table 1 in ref.[35] for an overview). As these other determinants are not easily captured in IMAGE and the underlying SSP scenarios, our model abstracts from them and, by doing so, loads all effects of correlated determinants (net of fixed effects and, potentially, time trends) onto the GDP per capita variable as a catch-all predictor. However, we note that a 0.59 percentage point reduction in country risk per one-unit increase in log-transformed GDP per capita is consistent with effect sizes of rating upgrades of 1–2 notches reported by previous studies[37, 73], as a one-notch upgrade approximately yields a 0.3 percentage point reduction for investment grade-rated countries, with substantially higher spread effects for sub-investment-grade countries (see the default spreads by rating category reported by ref.[32]).

Table S4. Regressing country risk premiums on log-transformed GDP per capita

Dependent Variable:	crp_debt_defaultspread							
Model:	noFEs (1)	+ FEs (2)	main (3)	+ quadratic (4)	+ lin. trend (5)	unweighted (6)	POP-weighted (7)	noCovid (8)
Variables								
Constant	0.1412***							
	(0.0351)							
l(ln_gdp_pc,1)	-0.0127***	-0.0138*	-0.0059*	0.0187	-0.0308*	-0.0131***	-0.0063*	-0.0062.
	(0.0033)	(0.0051)	(0.0024)	(0.0250)	(0.0133)	(0.0033)	(0.0022)	(0.0034)
l(crp_debt_defaultspread,1)			0.6188***	0.6169***	0.4242***	0.6399***	0.6491***	0.6156***
			(0.0729)	(0.0735)	(0.0907)	(0.0624)	(0.0672)	(0.1092)
l(ln_gdp_pc,1) square				-0.0014				
				(0.0014)				
Fixed-effects								
iso3		Yes	Yes	Yes	Yes	Yes	Yes	Yes
year		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Varying Slopes								
year (iso3)					Yes			
Fit statistics								
Observations	2,860	2,860	2,860	2,860	2,860	3,023	2,866	2,054
R^2	0.28841	0.83212	0.89687	0.89712	0.91649	0.90528	0.91648	0.91696
Within R^2		0.06155	0.42349	0.42491	0.26874	0.46674	0.44580	0.48848
BIC	-12,464.3	-15,216.9	-16,593.1	-16,594.7	-15,813.3	-17,935.2	-16,775.9	-12,232.6

Clustered (iso3 & year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table S5. Adding further lags of the dependent variable

Dependent Variable:	crp_debt_defaultspread				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
l(ln_gdp_pc,1)	-0.0059*	-0.0046*	-0.0045·	-0.0058*	-0.0057*
	(0.0024)	(0.0018)	(0.0021)	(0.0024)	(0.0024)
l(crp_debt_defaultspread,1)	0.6188***	0.6229***	0.6076***	0.6136***	0.6087***
	(0.0729)	(0.0670)	(0.0638)	(0.0721)	(0.0844)
l(crp_debt_defaultspread,2)		0.0703	0.1005	0.1146	0.1471
		(0.0504)	(0.0833)	(0.0925)	(0.1213)
l(crp_debt_defaultspread,3)			-0.0539	-0.0766	-0.1093
			(0.0611)	(0.1141)	(0.1332)
l(crp_debt_defaultspread,4)				0.0228	0.0662
				(0.0932)	(0.1419)
l(crp_debt_defaultspread,5)					-0.0486
					(0.0435)
Fixed-effects					
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	2,860	2,693	2,528	2,364	2,201
R^2	0.89687	0.90242	0.90655	0.90777	0.90812
Within R^2	0.42349	0.44883	0.44654	0.44368	0.43435
BIC	-16,593.1	-15,502.9	-14,690.8	-13,755.0	-12,833.2

Clustered (iso3 & year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

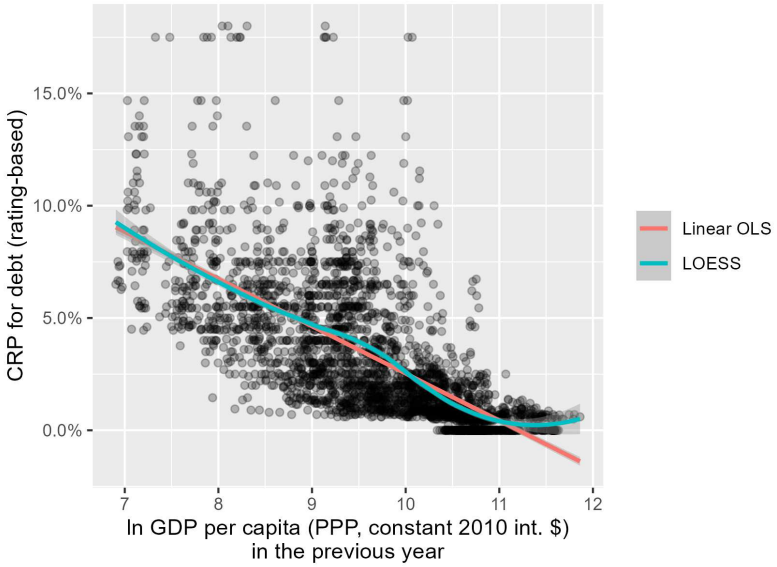


Figure S1. Scatter plot and simple OLS and LOESS regression lines (excl. fixed effects and time trends) for the link between country risk premiums (start-of-year) and GDP per capita

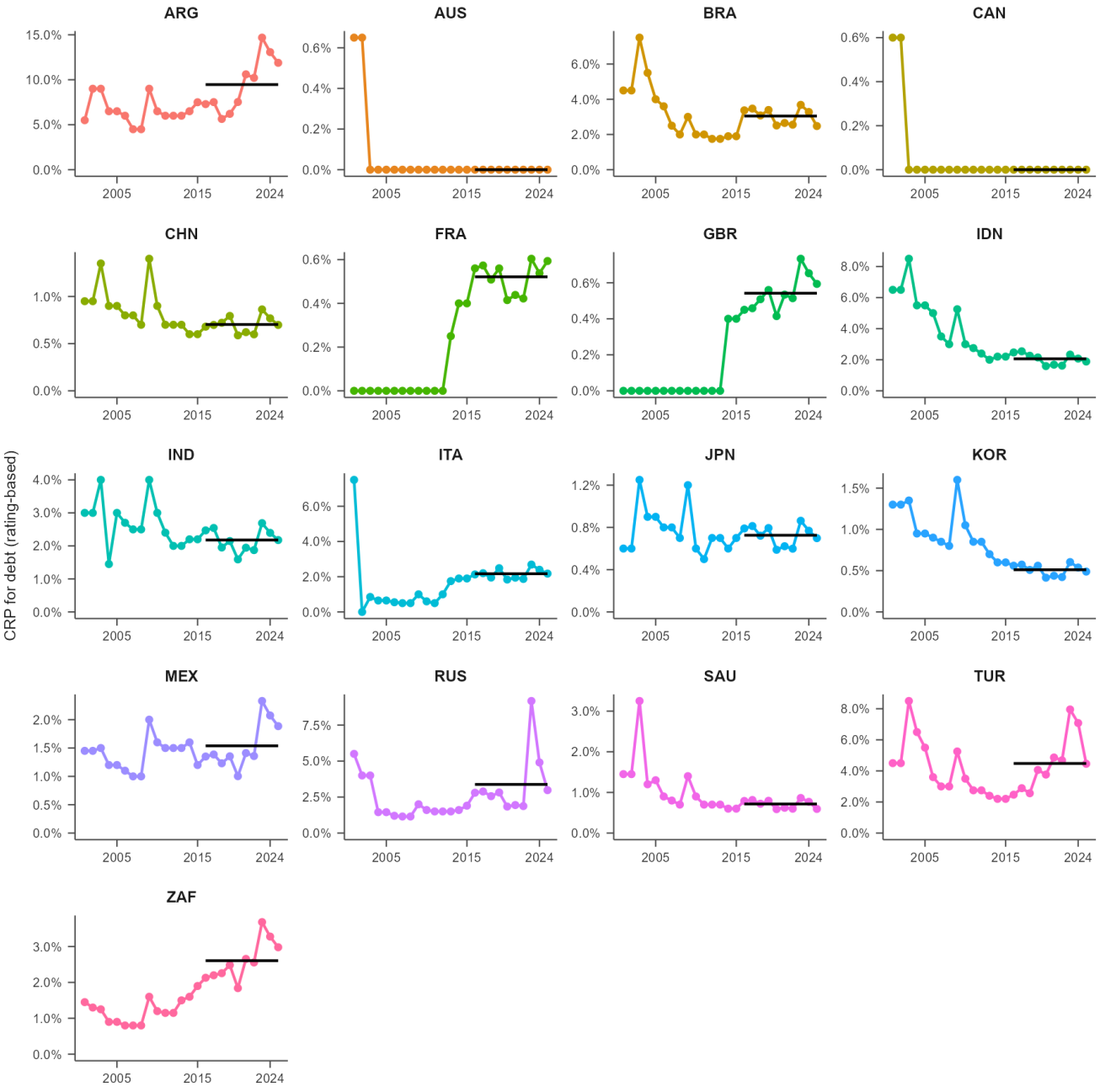


Figure S2. Rating-based country risk premiums for debt over time and the 2016–2025 mean used for our CoC estimates (black line), displayed for G20 countries (excluding Germany and the US, which have a consistent country risk premium of 0%)

Other Supplementary Figures and Tables

	Imputed countries	IMAGE region	Country peers in the same region used for imputation
1	Sudan, Somalia	E. Africa	Ethiopia, Kenya, Madagascar, Mauritius, Rwanda, Uganda
2	North Korea	Korea	South Korea
3	Iran, Syria, Yemen	Middle East	United Arab Emirates, Bahrain, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia
4	Haiti	Rest C. America	Aruba, Bahamas, Belize, Bermuda, Barbados, Costa Rica, Cuba, Curaçao, Cayman Islands, Dominican Republic, Guatemala, Honduras, Jamaica, Montserrat, Nicaragua, Panama, El Salvador, Turks & Caicos Islands, Trinidad & Tobago, St. Vincent & Grenadines
5	Malawi, Zimbabwe	Rest S. Africa	Angola, Botswana, Mozambique, Namibia, Eswatini, Tanzania, Zambia
6	Guinea, Gambia, Guinea-Bissau, Liberia, Sierra Leone	W. Africa	Benin, Burkina Faso, Côte d'Ivoire, Cameroon, Congo - Kinshasa, Congo - Brazzaville, Cape Verde, Gabon, Ghana, Mali, Niger, Nigeria, Senegal, Togo

Table S6. Imputation of corporate tax rates

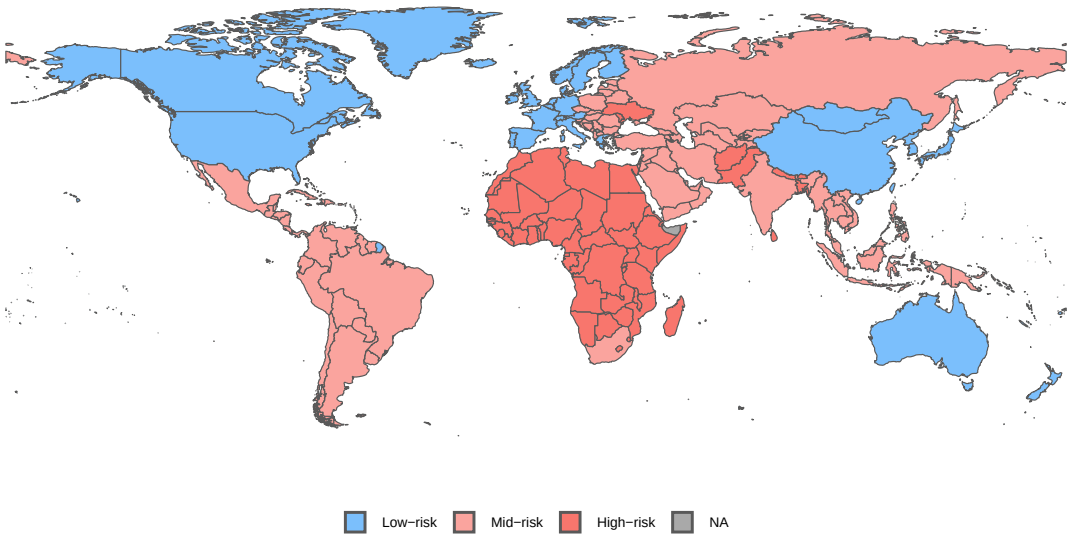


Figure S3. CoC-based macro regions to which the 26 IMAGE regions are aggregated. Country-level territories in grey are not (explicitly) represented in IMAGE.

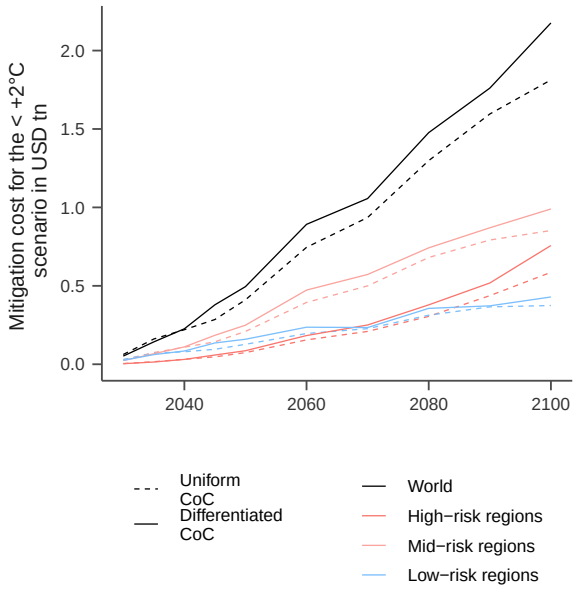


Figure S4. Mitigation cost for the well below +2°C scenario worldwide and by macro region

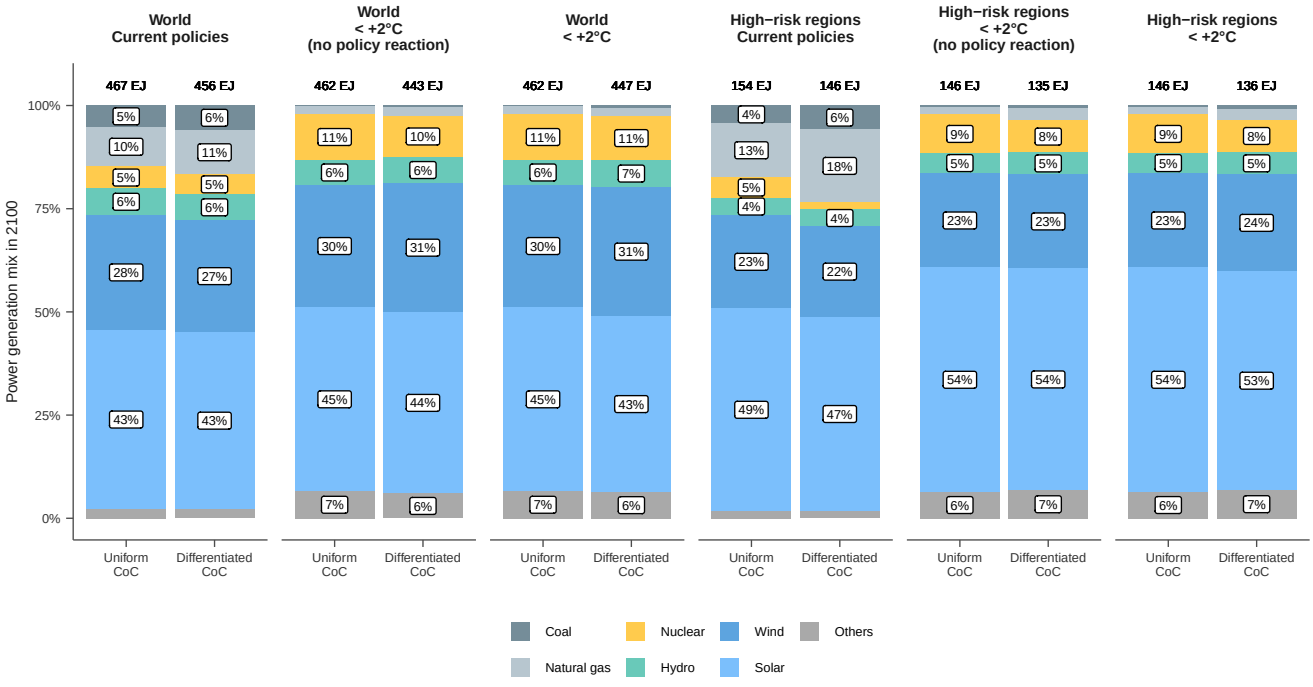


Figure S5. Power generation mix by 2100 worldwide and in high-risk regions

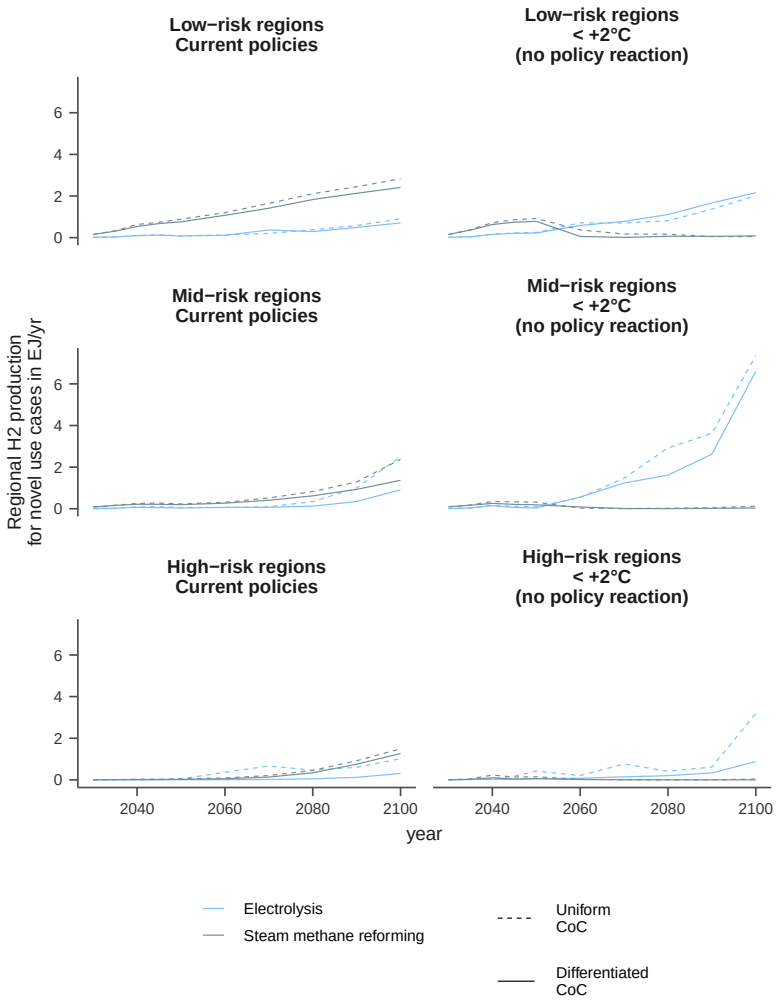


Figure S6. Hydrogen production by macro region and scenario (excluding legacy use cases that are not covered by the IMAGE model)

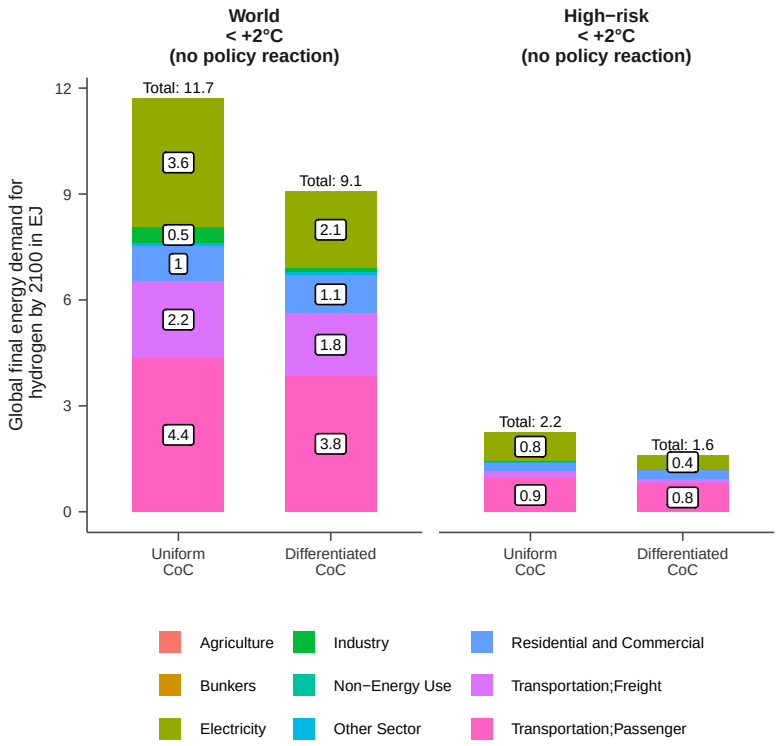


Figure S7. Final energy demand in hydrogen by sector under the well below +2°C scenario. Note that legacy use cases of hydrogen (e.g., as a feedstock in chemicals or in refineries) are not shown because they are not covered by the IMAGE model.

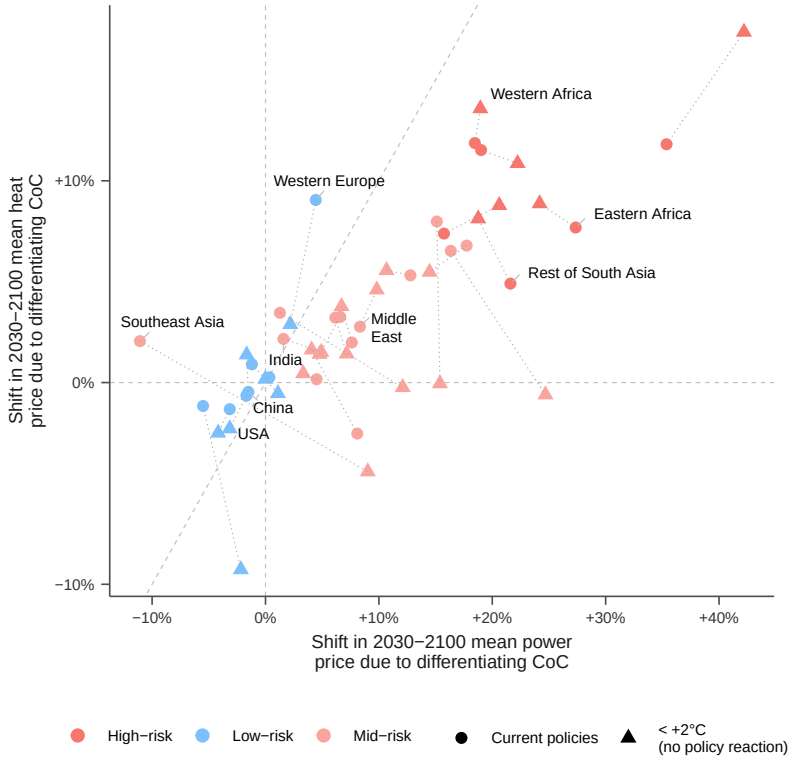


Figure S8. Impact of cost of capital differentiation on mean 2030–2100 power and heat prices

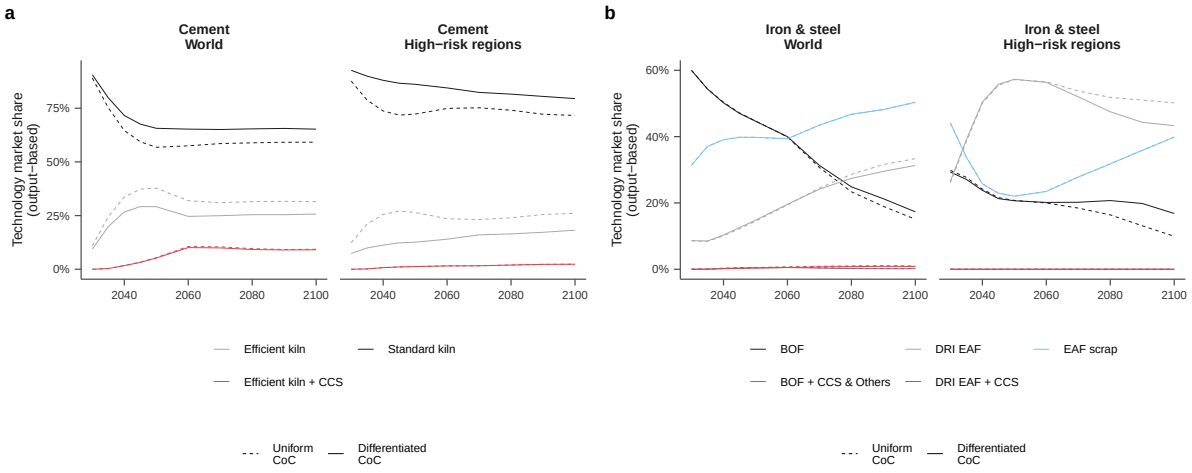


Figure S9. Cement and steel market shares by technology under the current policies scenario. “BOF” denotes the blast furnace basic oxygen furnace route. “EAF” and “DRI” denote electric arc furnace and direct reduced iron, respectively.

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Supplementary Files

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