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How uncertainty in technology costs and CDR availability affects climate mitigation pathways

Anastasis Giannousakis, Jérôme Hilaire, Gregory F. Nemet, Gunnar Luderer, Robert C. Pietzcker, Renato Rodrigues, Lavinia Baumstark, Elmar Kriegler

Abstract

Limiting global warming to "well below 2 °C" as stated in the Paris Agreement requires ambitious emissions reductions from all sectors. Rapid technology cost declines in the energy sector are changing energy investment and emissions, even with only weak climate policies at present. We assess how energy supply costs and carbon dioxide removal (CDR) availability affect mitigation pathways by performing an efficient large-scale sensitivity analysis with the technology-rich energy-economy model REMIND. We use new scenarios with carbon price paths that aim at reducing the frequently seen temperature overshoot. Further, we measure the sensitivities of important mitigation indicators to the costs of technologies across economic sectors. We assess the sensitivity to nine techno-economic parameters: the costs of wind, solar, bioenergy, gas, coal, oil, and nuclear, as well as CDR¹ rates and costs of electric/hydrogen vehicles. While technology costs play a role in shaping optimal pathways, we find that transport sector costs affect the economics of deep decarbonization, whereas costs of renewables are more important for scenarios under weak climate policies. This further highlights the character of renewable energy deployment as a no-regret option of climate policy. In terms of the sensitivity of model outputs, economic indicators become more sensitive to costs than emissions, with increasing policy stringency.

Keywords: technology costs, electromobility, carbon dioxide removal

1. Introduction

The energy sector accounts for the largest share of greenhouse gas (GHG) emissions (Papadis and Tsatsaronis, 2020) and holds the greatest decarbonization potential (Luderer et al., 2018). Thus, investments in energy transformation technologies are key factors shaping climate mitigation pathways (Kumar et al., 2020; Kriegler et al., 2014; Pietzcker et al., 2014; Hirth and Steckel, 2016). The uncertainty associated with the costs of energy technologies constitutes an important component of the overall uncertainty present in mitigation pathways (van Vuuren et al., 2020; Bosetti et al., 2015; Mouratiadou et al., 2015; Bosetti et al., 2012; Candelise et al., 2013)

Energy investment costs have changed drastically over time and vary considerably across space (Baker et al., 2015). Solar and onshore wind have leveled costs of electricity (LCOE) that are in some regions lower than the long-run-marginal-cost (LRMC) of standing coal capacity, but analysts suggest a strong policy signal (in the form of carbon price or efficiency standard) is still needed for a fast decarbonization of the power sector (Bistline and Blanford, 2020; Wang et al., 2019; Liu et al., 2018; Bertram et al., 2015; Tietjen et al., 2016; Creutzig et al.,

¹Carbon dioxide removal.

2017). At the same time, the decarbonization of the transportation sector is proceeding (Knobloch et al., 2020) and depends on the cost of electric and fuel-cell vehicles (van der Zwaan et al., 2013; Haasz et al., 2018; Hoekstra, 2019), as well as oil prices (Zimmer and Koch, 2017) and policies (Solaymani, 2019).

Given recent changes, what are the differences in global mitigation pathways using 2015 technology cost projections versus 2019 cost projections? How are CDR demands and individual sectors affected? What is the relative importance of the costs of technologies when compared with each other, and which mitigation indicators are affected the most by these costs? In this paper, we tackle these uncertainties by performing a sensitivity analysis of mitigation indicators on energy technology costs, under various levels of climate policy ambition. We assess the sensitivity of nine techno-economic parameters: renewable energy (wind, solar photovoltaics and concentrated solar power (CSP)) technology costs, nuclear power plant costs, cost curves for fossil fuel extraction (gas, coal, oil), bioenergy supply costs, as well as rates of injecting carbon dioxide (CO₂) into the ground for carbon capture and storage (CCS). The CO₂ injection rate crucially determines the mitigation potential of BECCS² (bioenergy with CCS³), the most important CDR technology. We also consider costs of electric and hydrogen-fueled vehicles, as alternatives to oil in the transport sector. We further contrast scenarios including large-scale CDR with scenarios where CDR—other than reforestation and afforestation—is not allowed. Apart from being a useful tool for answering the above questions, sensitivity analysis is good scientific practice for enhancing transparency and the credibility of model results for informing societal decisions (Saltelli et al., 2020; Drouet et al., 2015).

The remainder of the paper is structured as follows. In the next section, we describe the scenarios and methods used here: the climate policy scenarios, the technology cost ranges, and the sensitivity analysis method. We then present the results starting with the insights gained from the effect that technology costs have on global outcomes across sectors, followed by a ranking of important mitigation indicators with respect to their relative sensitivity to technology costs. Section 5 summarizes and concludes. We compute all scenarios with the large-scale and technologically detailed energy-economy model REMIND, see Appendix A.1 for a detailed description.

2. Scenarios and methods

2.1. Climate policy scenarios

Table 1 shows the scenarios considered, which feature an extensive coverage of climate policy ambition, and use SSP2⁴ socio-economic assumptions. The scenarios range from a no-policy baseline (BASE) to a continuation of the currently announced Paris pledges (NDC) and three different scenarios (B900, B1100, B1300) assuming global CO₂ emissions are constrained by a budget of 900, 1100 and 1300 Gt CO₂ in the time period 2011-peak year, respectively. With "peak-year" we refer to the year where global mean temperature peaks.

Typical budget scenarios usually feature carbon prices⁵ increasing exponentially until the end of the century, and tend to show increased demand for CDR and an overshoot in temperature. Here, newly developed scenarios (Rogelj

²Bioenergy with carbon capture and storage

³Carbon capture and storage

⁴Shared socio-economic pathways (O'Neill et al., 2014)

⁵climate policy in all our scenarios is enforced via a global, uniform, lump-sum carbon price, covering also CH₄ and N₂O emissions.

These are also reduced in policy scenarios, but by prescribed paths.

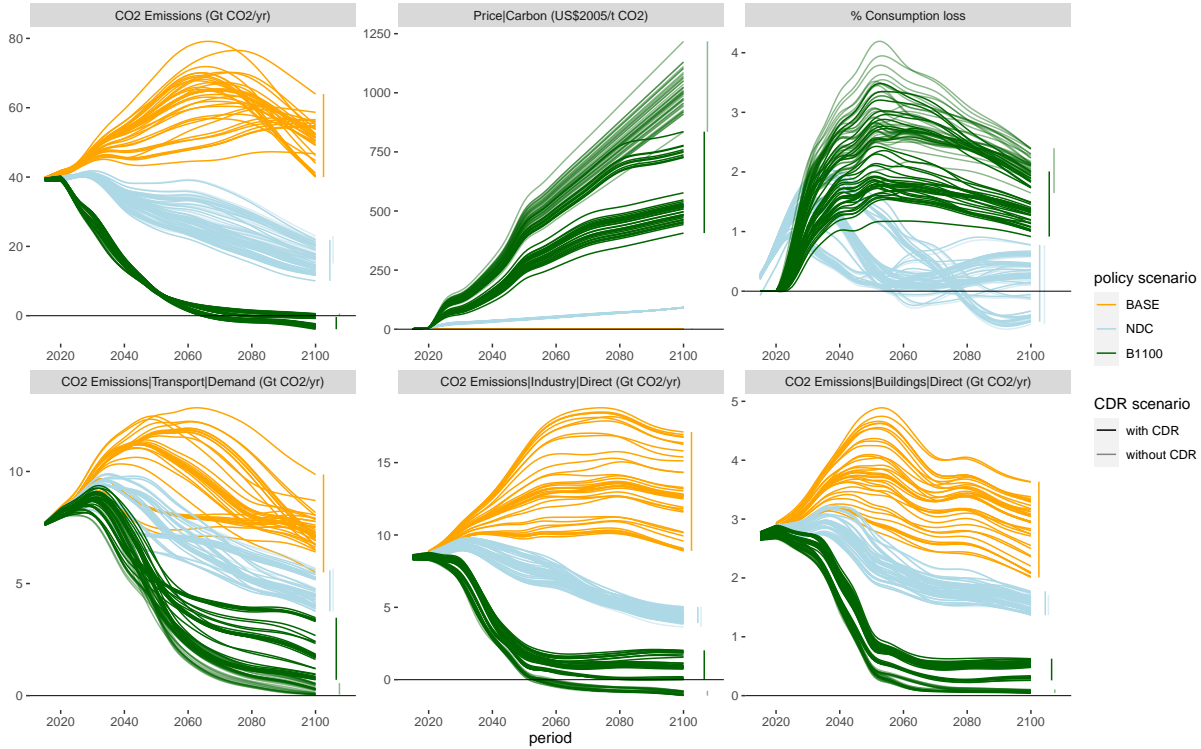


Figure 1: Impact of technology uncertainty on mitigation. The ensemble of scenarios for the no-policy baseline, NDC continuation, and B1100 scenarios, see Table 1. Indicators shown are emissions (total and by sector), policy costs, and carbon price. Technology costs are the source of uncertainty of all policy scenarios. Vertical lines on the right show the uncertainty range. Sectors (lower row of indicators) feature similar uncertainty range, but transport has a stronger variation in the stringent policy case (B1100; transport is also the only sector with rising short-term emissions). The NDC scenarios clearly fall short of adequate emissions reductions for reaching ambitious climate goals. Uncertainty in economics increases with policy stringency, while uncertainty in emissions decreases. CDR availability increases the uncertainty range (vertical lines), giving more flexibility to the system. The same graph including also the B900 and B1300 scenarios is found in the Appendix.

et al., 2019) with carbon prices increasing steeply until net carbon emissions become zero (this point corresponds also to roughly the peak temperature point), and increase slowly afterwards, see Fig. A.8 of the Appendix. This carbon price trajectory leads to a moderate need for CDR and a reduced overshoot in the global mean temperature, and is more in line with the interpretation of the Paris climate targets as not-to-exceed limits (Streffer et al., 2020).

To isolate the effect of energy technology costs from CDR availability, we consider scenarios with and without additional CDR technologies⁶(enhanced weathering, direct air capture and BECCS). The full ensemble of approx. 400 scenarios is found in the Appendix. Fig. 1 visualizes the technology cost uncertainty by showing CO₂ emissions (by sector and total), carbon prices, and consumption losses for the baseline, NDC, and B1100 policy scenarios. For each indicator, policy, and CDR availability scenario, a different spread is observed in the computed values. Quantifying and understanding this uncertainty is the goal of this paper. Due to space constraints, we focus on our main scenario B1100; other scenarios are described in the Appendix.

⁶CDR from exogenous reforestation and afforestation scenarios is always allowed

Table 1: Number of model runs—per policy and CDR availability scenario—needed for the extended one-factor-at-a-time method used here, and scenario description. Explanation of numerical values: 3 refers to the reference cases (all factors at reference value/all factors at high/all factors at low), 9 to the number of factors (BIO, CCS, COAL, etc.), and 4 to the sensitivity cases (factor value at high/low/others-high/others-low). Temperature increase is global mean surface-air temperature increase compared to the mean of 1850-1900 in 2100, CO₂ budgets are given in the period 2011-2100.

	with CDR	without CDR	Description
No-policy baseline	3+9x4	3+9x4	Counterfactual scenario without climate policies
NDC	3+9x4	3+9x4	Nationally Determined Contributions continued without increased ambition
B1300	3+9x4	3+9x4	67% prob. of 2 °C; 1300 Gt CO ₂ in 2011-2100
B1100	3+9x4	3+9x4	"well below" 2 °C; 1100 Gt CO ₂ in 2011-2100
B900	3+9x4	3+9x4	67% prob. of 1.5 °C; 900 Gt CO ₂ in 2011-2100

2.2. Technology cost ranges

The nine (groups of) technologies with uncertain costs (or potential) are shown in Table 2, while an overview of the ranges considered in the sensitivity analysis is given in Fig. A.9, expressed in terms of low, medium, and high scenarios. REMIND computes endogenous resource market prices, thus for the sensitivity of the costs of fossil fuels (oil, coal, gas) we choose the extraction costs according to the SSP scenario variation: SSP1, SSP2, and SSP5 (Bauer et al., 2016), delivering the low, medium, and high cases, respectively. The SSP scenarios feature extraction cost curves for each of REMIND’s world regions, the average of which is shown in Fig. A.9. For the variation of the remaining energy conversion technologies we use capital costs, whereas for CCS we use CO₂ injection rates. Capital cost uncertainty is important also because of a potential rise of interest rates in the future. For renewables we depart from observed investment cost ranges (high, reference, and low; source: LCOE ranges from IRENA (2019)). Nuclear power plant costs are varied by a range derived from observed typical cost overruns during construction. To visualize the resulting ranges we plot the turnkey costs for wind, solar photovoltaics, CSP, nuclear, as they are used in REMIND. We vary simultaneously costs of electric and full-cell vehicles ("ELH2" will be used throughout the paper to refer to the pair) by observed purchase costs (5th and 95th percentile of the cost of a medium size vehicle, Cox et al. (2018)), and the CCS injection rate according to the following values: 0,5% (reference, yielding roughly 60 Mt CO₂ per year), 0,1% (low injection rate, corresponding to the "high" case in the sensitivity analysis, as in "low availability", i.e. high cost; for compatibility with the other varied inputs), 100% (unconstrained injection rate, corresponds to the "low" case in the sensitivity analysis). Finally, biomass extraction costs (also highly uncertain like the CCS injection rate) are varied by 50 per cent higher and lower compared to the reference SSP2 value.

2.2.1. Modelling of energy technology costs

The costs of energy technologies in REMIND, which are balanced in the macro-economic budget equation, consist of those arising from the extraction of energy resources and the investment in—and use of—energy conversion technologies.

First, the costs associated with the extraction of coal, oil, gas, and uranium are represented by regional long-run marginal supply cost curves which relate cumulative resource extraction to marginal costs (Rogner, 1997; Rogner et al., 2012; Bauer et al., 2016). These costs increase with cumulative extraction reflecting the transition from low-costs (e.g. conventional oil) to high-costs mines and deposits (e.g. offshore oil, tight oil, oil shale) (Herfindahl,

Table 2: Technologies with uncertain costs (or potential) considered in the present study. Ranges are shown in Fig. A.9

Technology	Short name	Techno-economic parameter
Wind power converters	WIND	Capital cost
Utility scale solar photovoltaics and CSP	SOLAR	Capital cost
Nuclear power plants	NUCLEAR	Capital cost
Electric and fuel-cell H ₂ vehicles	ELH2	Purchase cost
Carbon Capture and Storage	CCS	CO ₂ injection rate
Bioenergy	BIO	Extraction cost
Coal	COAL	Extraction cost
Gas	GAS	Extraction cost
Oil	OIL	Extraction cost

1967; Rogner, 1997; Aguilera et al., 2009). In addition, the production of fossil fuels is subject to adjustment costs that are represented by quadratic curves and account for the costs increase stemming from short-term changes in production (Bauer et al., 2015). Trade costs are added to the overall production fuel costs (Bauer et al., 2015). Bioenergy costs are also modelled by supply cost curves that capture the time, scale, and region dependent change of bioenergy production costs, as well as path dependencies resulting from past land conversions and induced technological changes in the land-use sector (Klein et al., 2014).

Secondly, each energy conversion technology is characterised by investment costs, operation and maintenance costs, and fuel costs. Investment costs are modelled as turnkey costs and are regionally differentiated. These are computed by adding financing costs that occur over the construction time of technologies to specific overnight capital costs with a view to capture differences in the cost of capital across technologies and regions. Investment costs remain relatively constant for most technologies (e.g. coal power plant) and decrease for some relatively new technologies (e.g. wind and solar photovoltaics, electric/hydrogen vehicles), due to rapid innovation and technological change. Technological change is modelled via learning curves that relate cumulative capacity installation to marginal costs. Operation and maintenance costs are divided into fixed yearly operating and maintenance costs which are estimated as a fraction of investment costs and variable operating costs which scale with energy output. Finally, fuel costs are those arising from the energy resource production described in the previous paragraph.

2.3. Sensitivity Analysis (Method description)

Here, the sensitivity analysis of techno-economic parameters (technology and extraction costs, injection rate, purchase costs of electric/hydrogen vehicles) using the energy-economy-climate model REMIND will be presented. We will refer to the techno-economic parameters as factors (i.e. model inputs in sensitivity analysis jargon). Due to the model size (60+ energy technologies, 12 world regions, 19 time-steps) an extended one-factor-at-a-time method featuring efficient sampling is used here, same as in Marangoni et al. (2017). "Extended" refers to the ability of the method to compute also the factor interaction effect (Borgonovo, 2010), which is computed as follows: each factor is changed to its high (or low) value while all other factors are kept at their reference value, and, additionally, each factor is fixed at its reference value while all other factors are moved to their high (or low) values. The former gives the first-order (or direct) effect of a factor, while the latter—with a change in sign—gives the total effect of the factor in question.

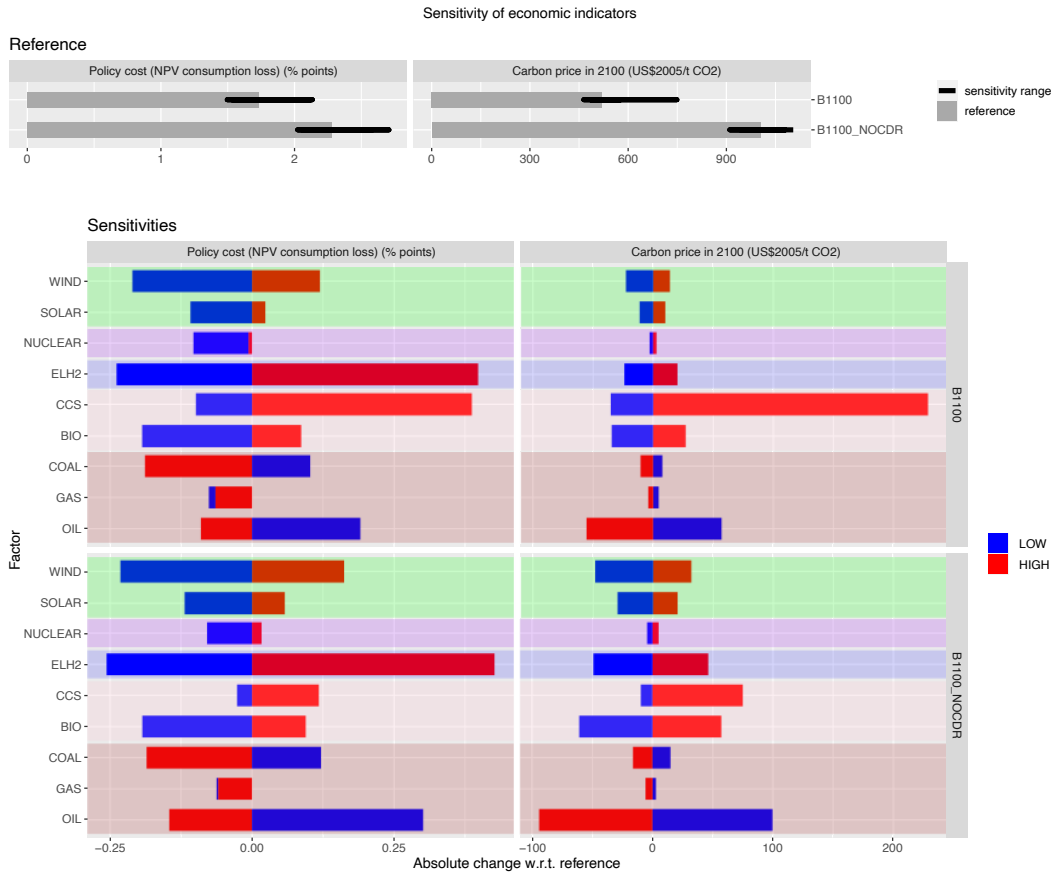


Figure 2: **Modified tornado-diagrams: Economic indicators.** The Sensitivities panel shows absolute change (x axis) in mitigation indicators caused by a one-factor-at-a-time variation of technology costs (y axis). Blue bars correspond to low cost, red bars to high cost (for the CCS injection rate, the only technology where a physical property rather than costs is varied, the colors are used to reflect how "accessible" the technology is—thus red is low rate and blue is high). Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges. Example on how the information on the diagrams is interpreted: "cheap oil and expensive ELH2 lead to increased policy costs in a B1100 scenario", etc. The policy costs are described as net present value consumption losses relative to the baseline, aggregated over the period 2010-2100 and discounted at 5%.

3. The effect of technology costs on mitigation indicators

We present the results in two parts. First, to quantify the sources of uncertainty we show the individual effect of technology costs on selected mitigation indicators. We then compute aggregate measures that summarize the individual effects and compare the sensitivities (in sensitivity analysis jargon: sensitivity indices) of the indicators to answer the question which mitigation indicators are affected the most by technology costs. We separate the mitigation indicators (model outputs) into three groups. The first group relates to the economics of decarbonization, the second contains indicators describing the depth of decarbonization by mid-century, and the third contains the CDR demand and the year of carbon neutrality (YCN, see Table 3 for details).

3.1. Economic indicators

Results for the first indicator group are shown in Fig. 2, which presents a modified tornado-diagram, similar to the ones commonly used in sensitivity analyses. For each factor, it shows the indicator reference value (shown



Figure 3: **Modified tornado-diagrams with sectoral detail.** Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Thin red bars correspond to low price and thick blue bars to high price. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.

separately at the top; grey bars) as well as the magnitude and direction (increase or decrease) of change when going from reference to low or high. It thus illustrates how factors affect the indicators (Note: the same graphs for the baseline, NDC, and B900/B1300 scenarios are found in the Appendix) and consideration or not of CDR. In each of the four panels, the relative importance⁷ of the factors is also seen, by comparing the magnitude of their change. Factors are typically sorted with the most influential at the top, this is what gives the tornado-diagrams their name. Here, we sort them in terms of color-coded clusters: renewables (green), nuclear (purple), low-carbon mobility (light blue), BECCS (pink), and fossils (brown). This way we can visualize thematic results.

An increase of 20% in climate policy costs (net present value of consumption losses in 2011-2100, relative to the no-policy baseline) is observed when low-carbon mobility (electric vehicles and hydrogen-powered fuel-cell vehicles, "ELH2" from now on) is more expensive, and the CCS injection rate is low (red bars). This is the strongest

⁷Seen also in Fig. 5, will be explained in detail later on.

Table 3: Characteristics of mitigation indicators (model outputs).

Group	Indicator	By Sector	Year	Aggregated
1: Economics	Carbon tax	No	2100	No
	Climate policy costs	No	2010-2100	Yes
2: Depth	CO ₂ emissions	Yes	2030-2050 mean	No
	Electricity share of final energy	Yes	2030-2050 mean	No
	Fossil carbon intensity of fuels	Yes	2030-2050 mean	No
3: CDR and YCN	Cumulated CDR	No	2020-2100	Yes
	Year of carbon neutrality	No	—	No

increase, followed by an 8% increase in policy costs if oil extraction would happen at lower costs. The highest cost decrease (9%) comes also from ELH2 being cheaper, followed by wind and bioenergy/coal (8%). Similar dynamics as in the case with CDR hold for the no-CDR case, as seen in the bottom left panel of Fig. 2. Biomass is an important factor also in the absence of CDR. Carbon prices react in a much more sensitive way to CCS availability than policy costs, but the effect of ELH2 and oil remains significant also here, and becomes even more pronounced in the no-CDR case. The other three policy scenarios (and their no-CDR alternatives) show the same behavior in policy costs and carbon prices (in the Appendix). Overall, transport-related costs (ELH2 and oil) alongside BECCS have the largest impact on the economic indicators.

3.2. Depth of decarbonization

Fig. 3 shows the second group of indicators (depth of decarbonization), and adds the sectoral dimension. The indicators describe the average progress made in decarbonization in the period 2030-2050. Sectoral emissions from buildings, industry and transportation exclude indirect emissions from upstream, e.g. electricity. In the total values (Fig. 3b), the impact of ELH2 and CCS is the most pronounced on the emissions (followed by an emissions decrease at low costs for wind and oil). The strong effect the costs of renewables have on the electricity share of final energy is comparable to ELH2, whereas their impact on the fossil carbon intensity is lower than ELH2 and oil.

The breakdown of the total values by demand-sector contributions is shown in Figs. 3 (c-e). The transport sector (e) is showing the highest effect, both in terms of which sector is the most sensitive to technology cost variation, and in terms of factor importance (ELH2 and oil; most of the oil use happens in the transport sector). Electricity supply (f) shows the highest overall sensitivity, combining second-order effects from downstream changes in demand (oil, ELH2, CCS) and direct influence of technology costs (solar, wind, and nuclear). Conversely, fossil resource prices other than biomass show a limited influence on power sector decarbonization (fossil carbon intensity of fuels).

3.3. CDR and year of carbon neutrality

Overall, CDR adds flexibility to the system (see the increase in the uncertainty ranges of Fig. 1, as well as the differences between 3 and A.12), leading to a stronger effect of energy technology costs on mitigation than in the cases without CDR. Fig. 4 shows the impact of costs on CDR use. The CCS injection rate has the highest impact, but in the case of unconstrained injection rate (blue bar) the effect is very limited compared to the case of low injection rate, where CDR is reduced by more than 50%. This shows that the reference value for the injection

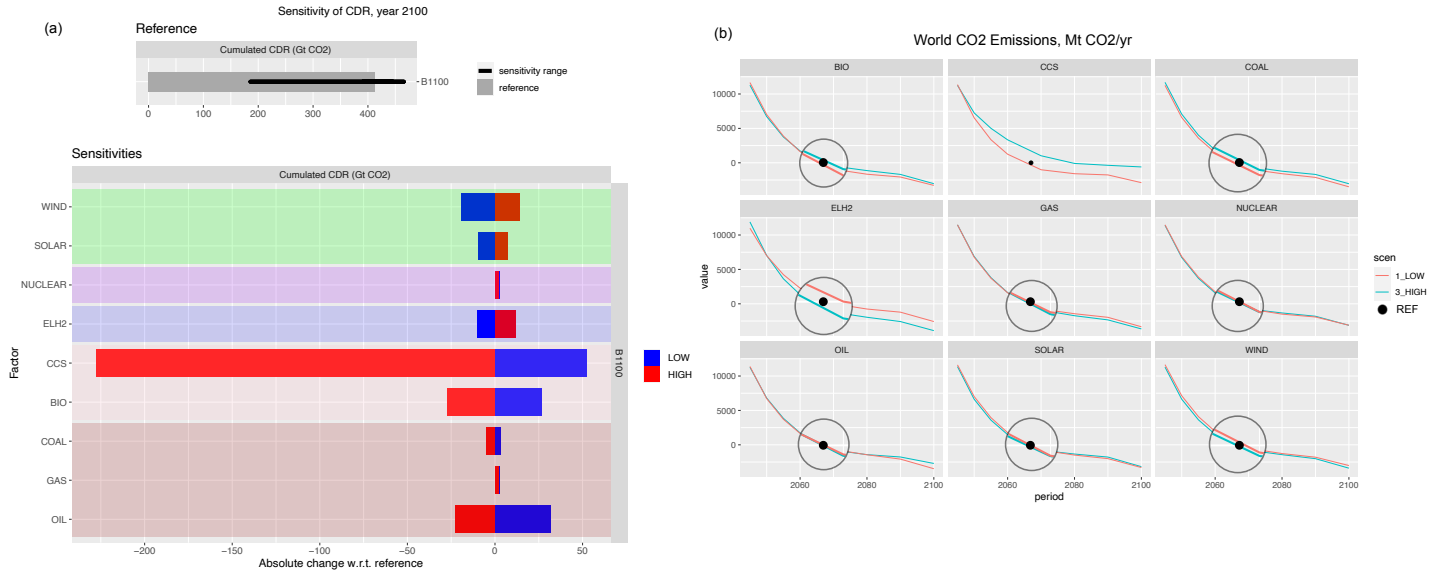


Figure 4: **CDR and year of carbon neutrality** Impact of technology cost uncertainty on the CDR demand (a) and on the shift in the year of carbon neutrality, YCN (b). The reference YCN is denoted by a black dot on the graph.

rate limit leads to CDR use that is close to the economic optimum for the model—constraining injection further has a large effect, but relaxing it does relatively little. Another 12% variation comes from the uncertainty in oil prices. The year of carbon neutrality is also largely unaffected by the variation of the factors, except for CCS and ELH2. Also here an unconstrained injection rate does not have an impact, compared to a strong shift of more than 10 years if the CCS injection rate is low. In the case of ELH2, lower purchase costs would lead to a decrease in emissions in the short-term that would then need to be compensated less by CDR later on, shifting the YCN to the right compared to the reference.

4. Relative sensitivities of indicators

There are several approaches to summarizing sensitivity analysis results. In most cases the so-called sensitivity indices are computed, describing the impact of model inputs on model outputs. We apply two different metrics for the calculation of the sensitivity indices. The first one is described by the direct effect a factor has on the *variance*

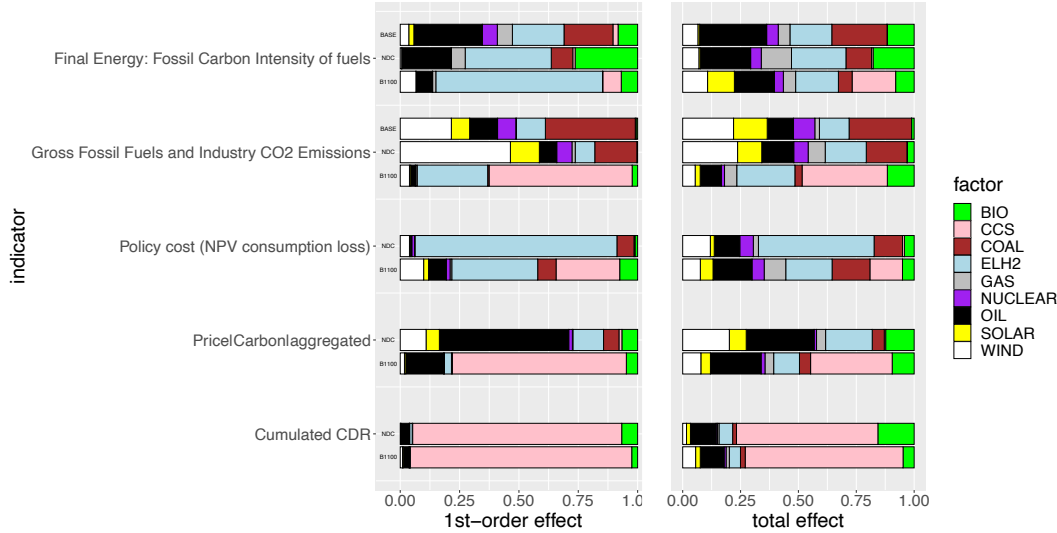


Figure 5: **Sensitivity indices** Left: Sobol’ first order (direct) indices describe the contribution (share) of each factor (model input) to the variance of the model outputs. Right: The total effect describes the direct contribution of each factor to the percent change in outputs plus the effect caused by the interactions of the factor with the other factors. NPV: net present value.

of a certain output and is called first order Sobol’ index (Homma and Saltelli, 1996):

$$S_i = \frac{V_{X_i}(\mathbf{E}_{\mathbf{X}_{-i}}(Y|X_i))}{V(Y)}, \text{ where } i: \text{factor, } \mathbf{X}: \text{vector of factors, } \mathbf{E}: \text{expected value operator, } Y: \text{indicator, and } V: \text{indicator variance.}$$

The second metric is described by the total effect a factor has on the *percent change* of an indicator from the mean; total in this case refers to the sum of the direct effect (like above) *plus* the interaction effect of the factor in question with the rest of the factors. The percent change is given by the following formula

$$\%change = \sum_i 100 \cdot \left(\frac{|Y_{H,i} - Y_R|}{|Y_{H,i}| + |Y_R|} + \frac{|Y_{L,i} - Y_R|}{|Y_{L,i}| + |Y_R|} \right), \text{ where } i: \text{factor, } H: \text{high, } R: \text{reference, } L: \text{low, and } Y: \text{indicator value,}$$

whereas the interaction effect is captured by the method described by Marangoni et al. (2017), consisting of running—alongside scenarios with a normal one-factor-at-a-time variation—scenarios where one factor is maintained at the reference value and all the other factors are changed to the high or low values. These findings are summarized in Fig. 5.

Based on the above computations, an approach to decision-making by analysis of trade-offs is provided in Fig. 6, which compares challenges (climate policy costs) and sustainability concerns related to climate change mitigation (total CDR requirements and total (gross) emissions), in terms of the effect technology costs have on these characteristics of a B1100 scenario with CDR. The effect is measured by computing the total percent change compared to the mean. This way, we visualize the type of model output that each factor is affecting the most.

4.1. Edge cases: Scenarios of full- and no-flexibility

The ”edge cases” of the factor values describe worlds with and without flexibility, i.e. worlds where energy technology options are either very difficult—see also the *LimTech* scenario from Kriegler et al. (2014)—or very easy to reach. Here, these worlds are modelled by taking all the factors at their respective low or high cost value, at the same time. An overview of how the edge cases shape three key mitigation indicators (final energy demand,

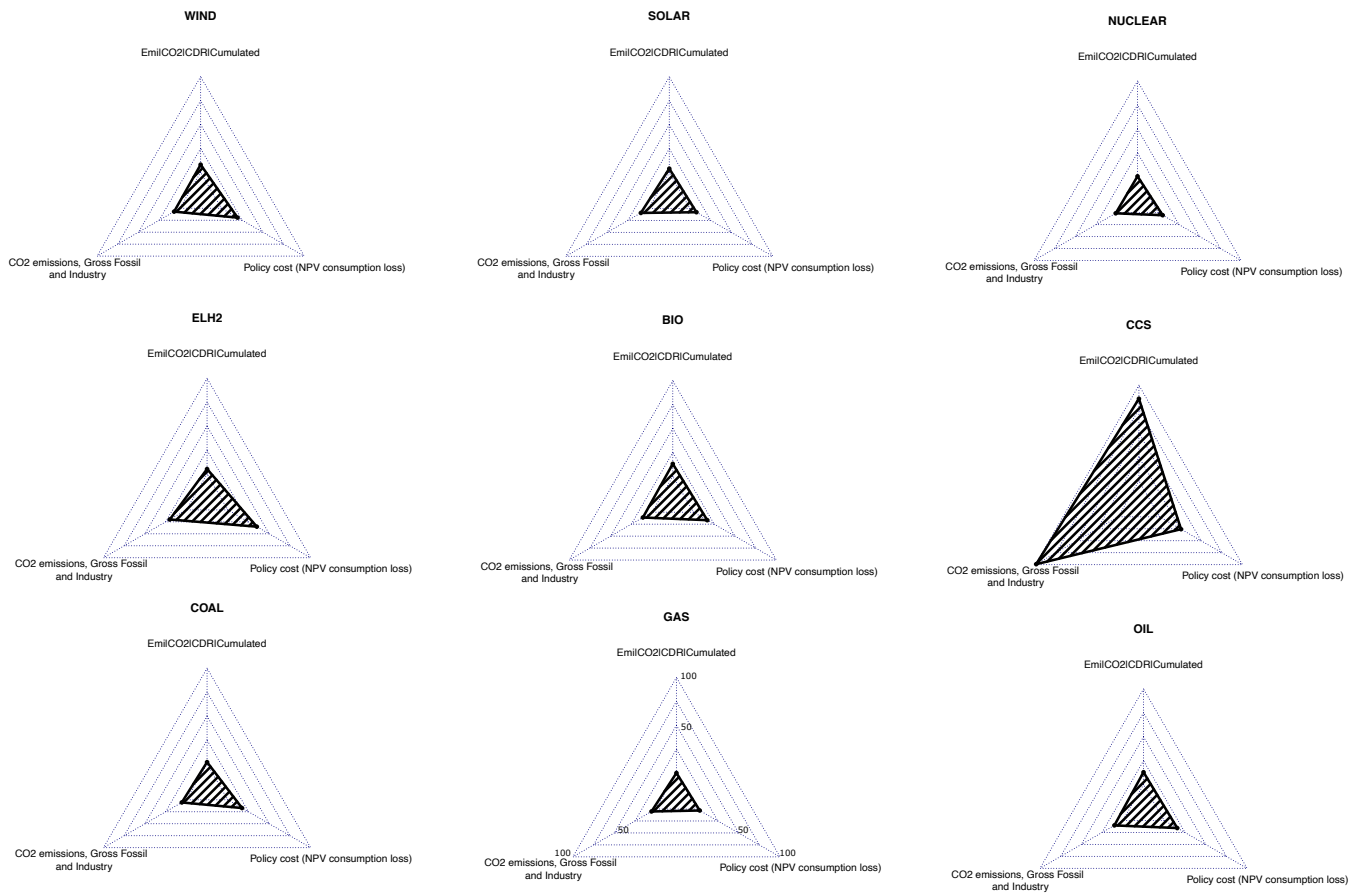


Figure 6: **Comparison of mitigation indicators by individual factor effect.** The mitigation indicators shown here describe challenges (climate policy costs) and sustainability concerns related to climate change mitigation (total CDR requirements and total (gross) emissions). Scenario: B1100 with CDR, year 2100. Reference values (World total CDR/World gross emissions/Policy costs): 413 Gt CO₂/5 Gt/1,74% Net present value of consumption losses 2010-2100

policy costs, carbon price) for the B1100 policy case is given in Fig. 7, where climate policy costs and near-term carbon prices nearly double when going from full- to no-flexibility (“all low” versus “all high”), combined with a 25% average final energy demand response. This gives an intuition about the potential in influencing mitigation pathways of a) a wide spectrum of technology options, and b) policy instruments beyond carbon prices and emissions trading. It is important to note that these edge cases give an indication of the size of the solution space only as it is seen from the viewpoint of a neutral energy/technology “planner”, who does not know which options reduce emissions and which do not. This means that the edge cases do not cover the full range of mitigation outcomes from all the possible technology cost combinations—as the cases of, e.g. all *mitigation* technologies being easily accessible while fossil fuels are expensive, and vice versa, are not considered here. These cases can potentially lead to even stronger variation in mitigation-related outputs as they would be tailored to explicitly favor or hinder mitigation.

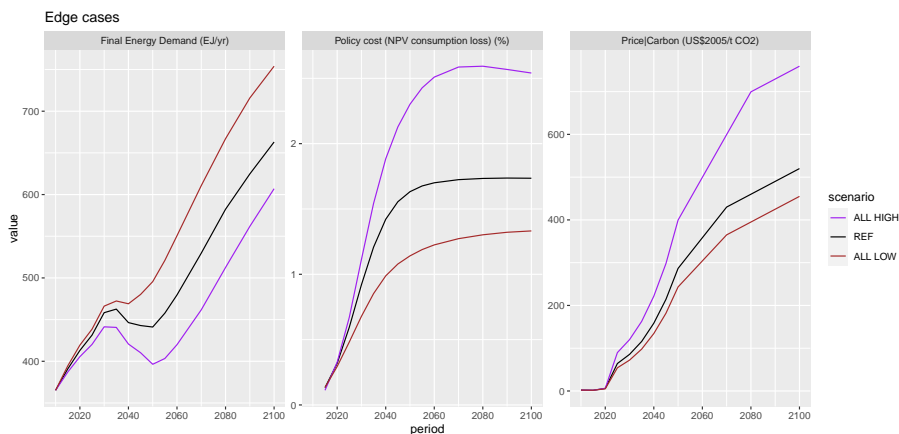


Figure 7: **Edge cases.** Differences between the reference case and worlds with no- and full-flexibility (all technology costs at high and low values, respectively).

5. Summary and conclusions

This sensitivity analysis of technology costs shows that uncertainty in BECCS and transport-related options (ELH2 and oil) have the largest effects on both physical and economic mitigation indicators. This is in line with the strongest variation among technologies resulting from BECCS and energy intensity (transport-related) reported by Luderer et al. (2013) and Kriegler et al. (2014). In the case of BECCS, this happens because this technology directly controls the option to create net negative emissions, but in the case of low-carbon mobility and oil, the explanation is two-fold. First, increasing policy stringency requires a rapid decarbonization of the power sector, which features many complementary options—making one more expensive does not hurt very much. The buildings and industry sectors feature high electrification in the reference scenario, so only the transport sector affects carbon prices. Second, the transport sector emissions are the only ones that keep rising in the short term. These two effects make transport the price-setting sector.

The year of carbon neutrality remains largely unaffected by the variation in costs. This indicates the importance of early action, as even in "favorable" price scenarios, optimal emissions need to reach zero by 2065. On the other hand, the use of CDR is a more sensitive economy-wide physical mitigation indicator, mainly affected by the CCS injection limit and the dipole oil/ELH2. The importance of CCS is highlighted also by the rise in climate policy costs caused by low CCS injection rates, reaching almost the same values as in the scenarios without CDR. Furthermore, the remaining emissions of NDC scenarios with low costs of renewables raise the question of whether falling prices for renewables alone will be sufficient to reach long-term climate targets, such as the well below 2 °C. Finally, the high overall influence of BECCS (with uncertain potential) and transport-related technologies (which are difficult to decarbonize) on the indicators, highlights the need for robust and broad policy support for achieving the goals of the Paris Agreement.

The present study focuses mostly on the energy supply side, thus further research shedding light into demand-side uncertainties are needed to provide additional information to the policy process. Finally, including second-best effects, and further analysing integration constraints and market failures leading to the cost of technologies not reaching the market would enhance the usefulness of the present findings.

Code and data availability. REMIND is open-source: <https://github.com/remindmodel/remind>. The version used here is REMIND v2.1.1.

Declarations of interest: none.

Appendix A.

Appendix A.1. The integrated assessment model REMIND

REMIND (REgional Model of INvestment and Development) is a multi-sector, multi-region integrated assessment model used for global and regional climate policy analysis (Luderer et al., 2015). REMIND has been used extensively in IPCC reports, e.g. IPCC (2014) and IPCC (2018), and major model intercomparison projects, e.g. Kriegler et al. (2014), Pietzcker et al. (2017), Bauer et al. (2018), Luderer et al. (2018), Riahi et al. (2017). It combines a top-down Ramsey-type growth model with a bottom-up energy system model of large technological detail. In the macro-economic core of REMIND, aggregated and discounted intertemporal social welfare is maximized for a number of regions spanning the whole globe, while pathways are derived for savings and investments, factor incomes, as well as energy and material demand. The utility function of REMIND exhibits constant relative risk aversion and has a logarithmic form on consumption. Regions interact by trade in primary energy carriers, emission permits, and a composite good. The detailed representation of the energy system in each region consists of capital stocks for more than 60 technologies for energy conversion, including technologies that are able to generate negative emissions, like bioenergy combined with carbon capture and sequestration.

In REMIND, economic activity results in demand for energy services, which in turn results in GHG emissions from extraction and burning of fossil fuels in different sectors (buildings, industry, transport) and levels (primary, secondary, final, and useful energy). Mitigation scenarios analyse optimal strategies for decarbonization with the use of a carbon tax applied on the economy, resulting in a shift from fossil use to renewable energy. A full portfolio of GHG is considered (CO_2 , CH_4 , N_2O , NH_3 , F-gases, etc.), either via emissions from energy use or via exogenous marginal abatement cost curves (e.g. land-use). Adjustment costs in energy investment and deployment account for policy realism and path dependency. REMIND usually runs in so-called cost-effectiveness mode, not internalizing potential economic damages of climate change, but rather analyzing energy technology portfolios and investment dynamics under given climate targets (carbon budgets, reduction relative to a baseline, carbon taxes, etc.). REMIND features endogenous technological learning for several energy conversion technologies (investment costs decrease with increasing installed capacity).

Appendix A.2. The effect of technology costs on the baseline, NDC, and B900/B1300 scenarios

Fig. A.11 shows the variation of the economic indicators (see 3 for the B900 and B1300 scenarios. We observe the same dynamics as in the B1100 scenario, with the effects of ELH2, oil and CCS becoming more pronounced as target stringency increases from B1300 to B1100 and B900. Conversely, the overall effect of technology uncertainty on emissions is reduced when going from NDC to B1100 and further to B900 (see Fig A.11

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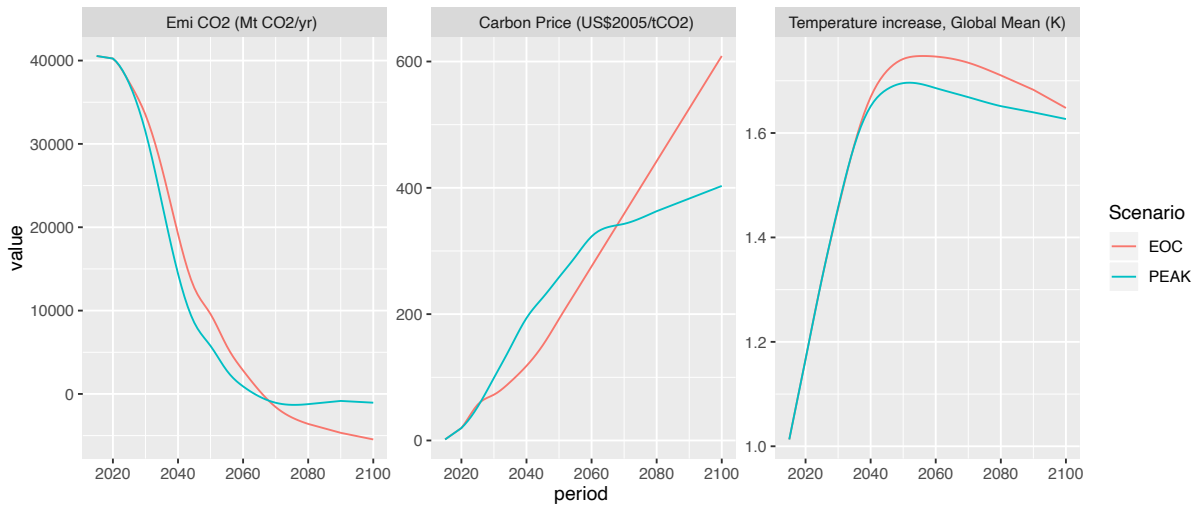


Figure A.8: Differences between End-of-Century and Peak-budget scenarios.

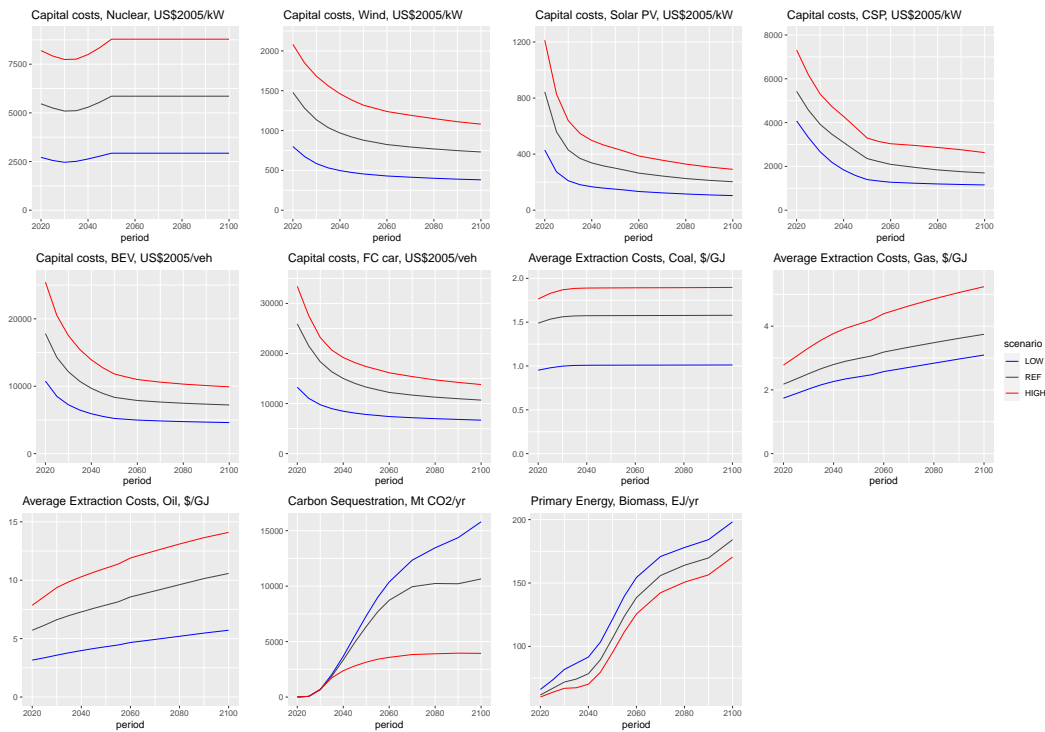


Figure A.9: **Technology cost ranges of the present study.** Turnkey costs for solar photovoltaics, CSP, onshore wind, and nuclear. Average extraction costs for fossil fuels, and purchase costs for hydrogen and electric vehicles. For biomass the effect of the range considered is shown by means of primary energy usage. The CDR curve shows the uncertainty in the CCS injection rate. See the main text for sources.

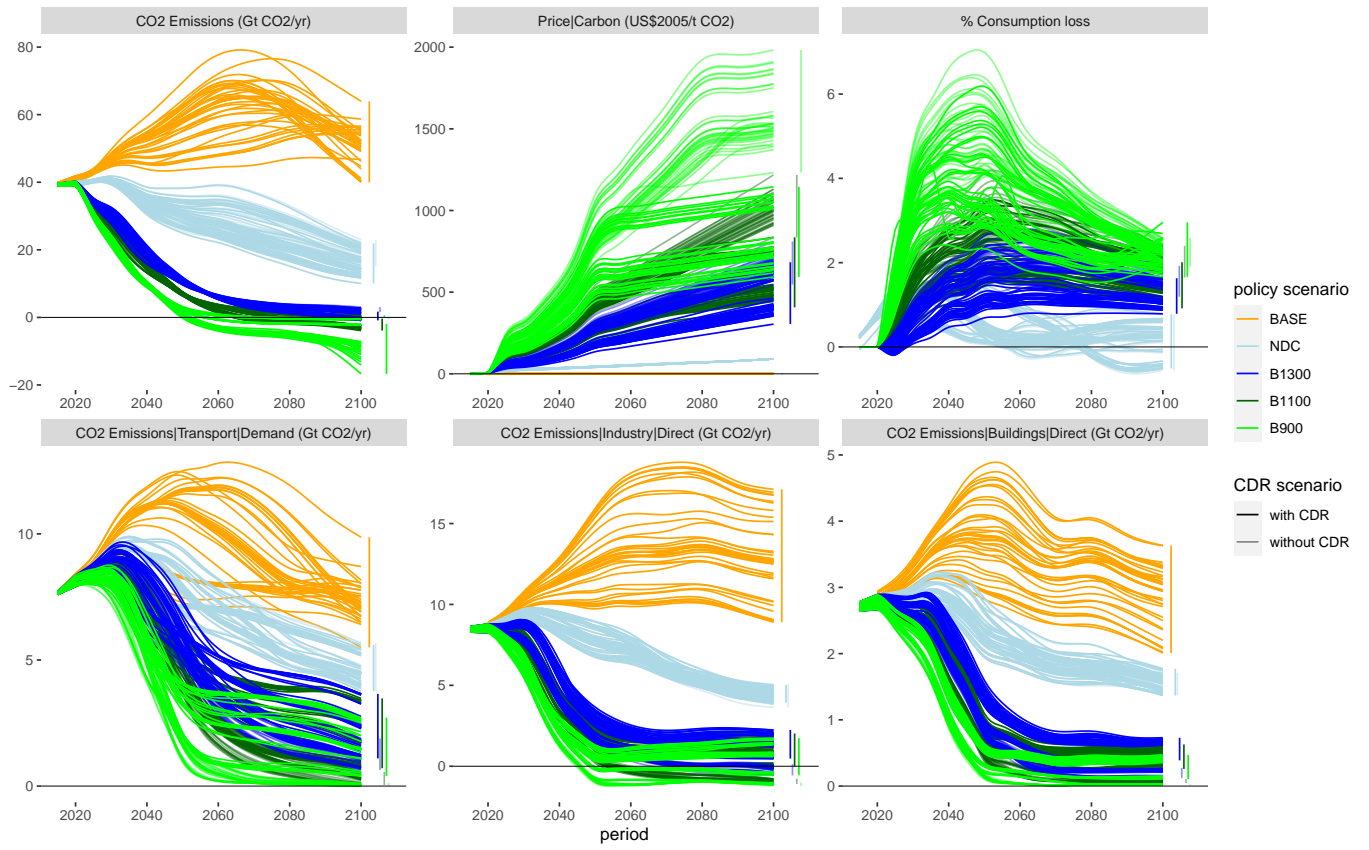


Figure A.10: Ensemble showing all scenarios, with uncertainty ranges

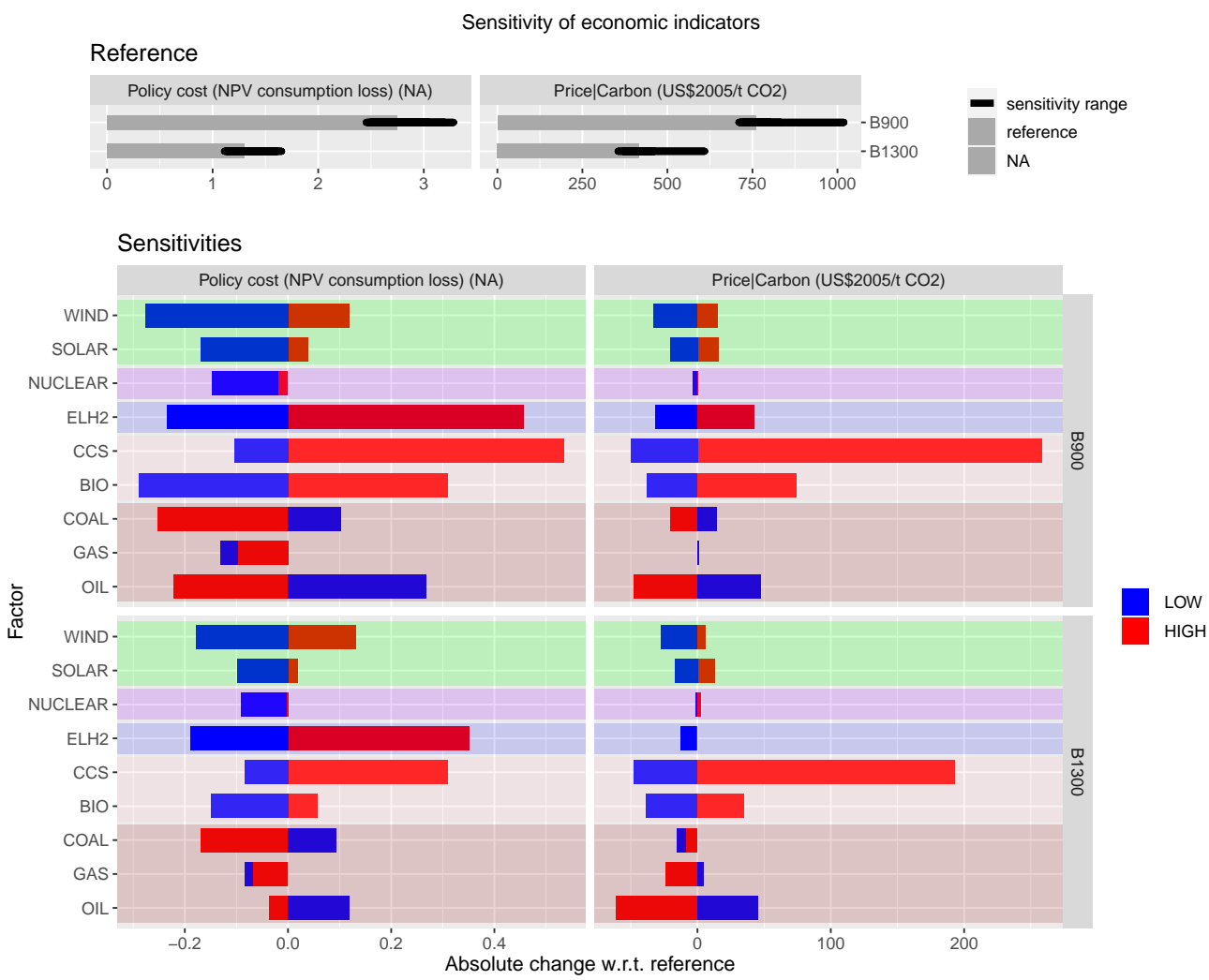


Figure A.11: **Modified tornado-diagrams: Economic indicators for additional policy scenarios.** The Sensitivities panel shows absolute change (x axis) in mitigation indicators caused by one-factor-at-a-time variation of technology costs (y axis). Blue bars correspond to low price, red bars to high price (for the CCS injection rate—the only technology where a physical property rather than costs is varied—the colors are used to reflect how "accessible" the technology is, thus red is low rate and blue is high). Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges. Example on how the information on the diagrams is interpreted: "cheap oil and expensive ELH2 lead to increased policy costs in a B900 scenario", etc. The policy costs are net present value consumption losses relative to the baseline, aggregated over the period 2010-2100 and discounted at 5%.

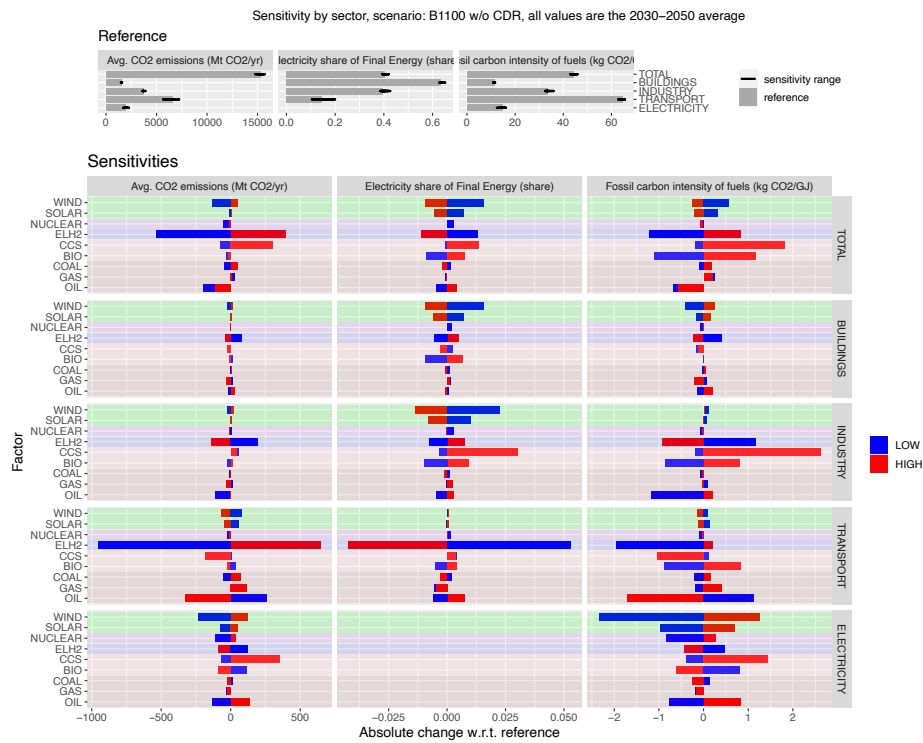


Figure A.12: **Modified tornado-diagrams with sectoral detail, B1100 w/o CDR.** Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Thin red bars correspond to low price and thick blue bars to high price. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.

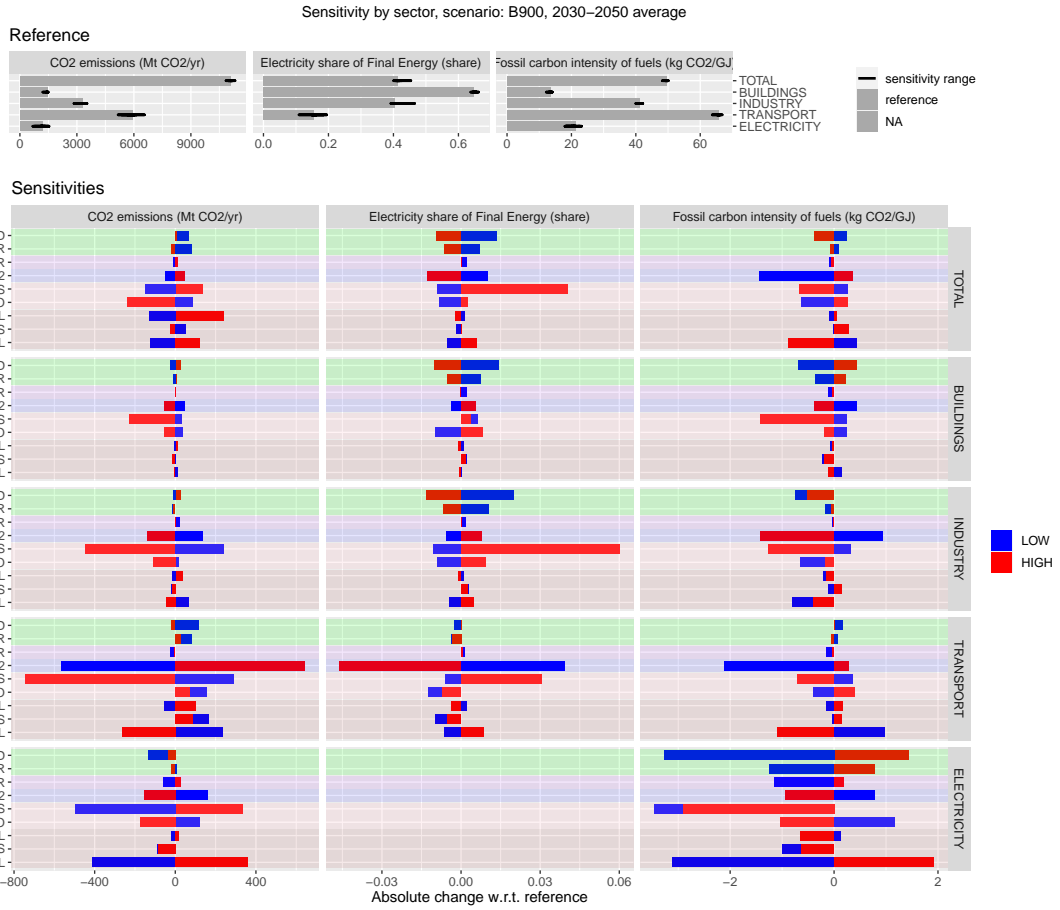


Figure A.13: **Modified tornado-diagrams with sectoral detail, B1100 w/o CDR.** Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Thin red bars correspond to low price and thick blue bars to high price. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.

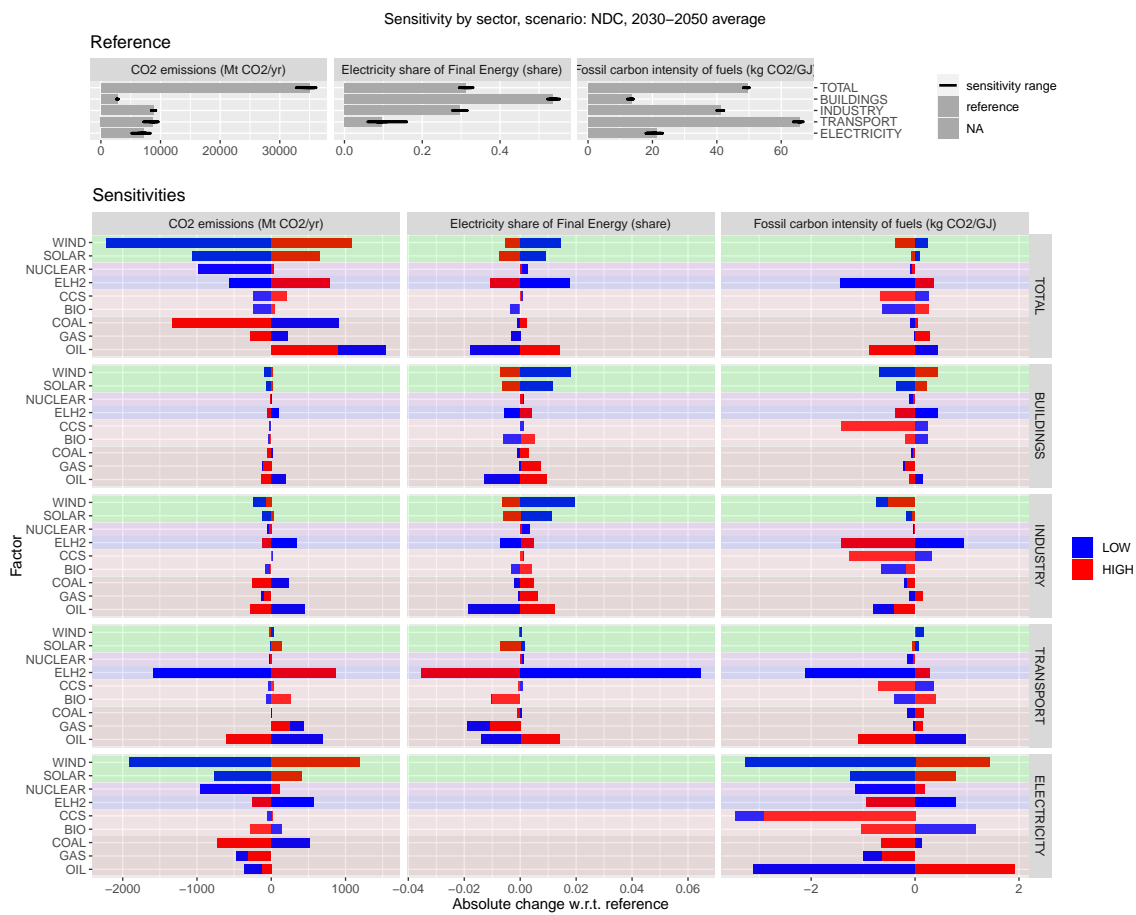


Figure A.14: **Modified tornado-diagrams with sectoral detail, NDC scenario.** Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Thin red bars correspond to low price and thick blue bars to high price. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.