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Abstract

Current policies focus on reducing CO_2 emissions, neglecting the existence and impact of other air pollutants such as NO_2, NH_3, NMVOC, PPM_{10}, $PPM_{2.5}$, and SO_2. We devise a strategy to model those emissions and related social cost accounting for diverging social and private discount rates in an intertemporal optimization framework that aims to predict firm behavior. We derive optimal CO_2 and air pollution taxes above the social cost of carbon or social cost of air pollution, respectively, when social discount rates are below private ones. We implement the modeling strategy in the EUREGEN model to determine the technology and emission mix of the European power market until 2050 and quantify aggregated social cost. No taxation yields aggregated social cost of 5,145 billion € in the period 2020 to 2050. Taxing CO_2 emissions only leads to aggregated social cost of 794 billion € and promotes the deployment of CCS technologies. Taxing air pollution only results in aggregated social cost of 2,091 billion € and fosters the deployment of nuclear. Taxing both reduces cost to 622 billion €. Wind and solar are almost unaffected by internalization choices.

JEL Code: C61, C68, Q40, Q41
Keywords: Taxation, intertemporal optimization, social cost, air pollution, carbon emission, externality, energy system model, power market model, decarbonization

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1. Introduction

Climate change calls for prompt action by policymakers, firms, and consumers. The overarching goal is to reduce CO_2 emissions in order to keep global warming far below 2° Celsius. However, a focus on CO_2 emissions and climate change neglects local effects from related air pollution and associated damages on human health or loss of biodiversity, respectively. We address this issue by showing how power system transformations and related social cost change when accounting for social cost of air pollution (SCAP) as well as social cost of carbon (SSC).

With more than 40%, electricity generation is the biggest contributor of the 33.4 Gt of energy-related CO_2 emissions (IEA, 2020). Electricity generation and its role for emitting CO_2 significantly increased over the last decades—leaving aside a pandemic-driven drop in 2020—and is expected to assume an ever bigger share due to electrification trends (digitization, air conditioning, electric mobility, economic development). Thus, many policies focus on decarbonizing electricity generation. For example, the European Union Emission Trading System (EU ETS) reduced—among other supplementary policies—CO_2 emissions from power generation from 1.191 to 0.844 Gt in the period 2013 to 2020. The European Union even proposes more ambitious targets to achieve carbon neutrality by 2045. However, European actions alone will never completely suffice to reduce CO_2 emissions in other parts of the world and, more importantly, climate change's global impact. The characteristic of CO_2 emissions as public bad (or reducing them as public good) allows for free riding and hampers the binding and enforceable implementation of goals and targets. Air pollution emissions, in turn, have local impacts and every country should undertake efforts to internalize those local damages. Thus, shifting the focus away from sole mitigation of CO_2 emissions towards the internalization of air pollution might be a complementary policy to partly resolve the free riding problem. Additionally, some climate neutral technologies such as bio-CCS (biomass with carbon capture and storage) deprive CO_2 emissions but still pollute, giving way to interesting questions about how to design a technology mix with low carbon and low air pollution emissions.

We develop a strategy to depict SCC and SCAP in an intertemporal optimization framework, thereby accounting for diverging discount rates when evaluating firms' cash flows (investment, fixed, and variable cost), SCC, and SCAP. The underlying assumption is that SCC require lowest (social) discount rates due to the long-lasting intergenerational impact of CO_2 emissions and firms face highest (private) discount rates. Damages from air pollution emissions would be (socially) discounted in the meantime because their impact is immediate and not as long-lasting and intergenerational, as is the case for CO_2 emissions. We implement this strategy in the EUREGEN model, a partial equilibrium model of the European power market that optimizes investments, dispatch, and decommissioning of multiple generation, storage, and transmission technologies from 2020 to 2050 (Weissbart and Blanford, 2019). We obtain air pollution emission factors from EPA (1995), Cai et al. (2012), EEA (2019), UBA (2019). We calibrate the DICE model (Nordhaus, 2014) to deliver SCC that match population projections from the World Bank (https://databank.worldbank.org/source/population-estimates-and-projections) as well as GDP projections from EUREGEN's CGE calibration (Mier et al., 2020, Siala et al., 2020). We obtain SCAP from the externE project series (Friedrich and Bickel, 2001).

Our general theoretical contribution demonstrates how diverging social and private discount rates can be implemented simultaneously in an intertemporal optimizing framework (such as integrated assessment, energy system, and power market models). This makes it possible to evaluate firm cash flows differently from social cost occurring when emitting either CO_2 or one of the air pollutants under investigation. Social discount rates below private ones and the existence of emissions requires taxing CO_2 emissions and air pollution at rates above their marginal damages, SCC or SCAP, respectively. For example, assuming SCC of 62 €/ton in 2050, a social discount rate of 1.5%, and a private discount rate of 7%, demands for an optimal CO_2 tax of 354 €/ton to enforce full internalization of cost because firms discount cash flows including taxes (in their variable cost) differently to a social planner.

Our numerical contribution delivers insight on three subjects. First, we calculate how the European power system varies under different internalization specifications (no taxation, CO_2 taxation, air pollutant taxation, CO_2 and air pollutant taxation). We test robustness of results by varying assumptions about emission factors, SCC, SCAP, and technological progress of wind power. Second, we determine the impact of diverging discount rates on the technology mix, emissions, and social cost. Third, we analyze distributional and trade effects by running different specifications that differ in the weighting of SCAP across countries, biomass limits, and tradability of biomass.

Focusing solely on the internalization of SCC, leads to aggregate total SCC of 345 billion € until 2050. Total SCAP come to 449 billion € (sum of social cost of 794 billion €). When only internalizing SCAP, total SCC come to 1,761 billion € and total SCAP are at 330 billion € (sum of 2,091 billion €). Internalizing SCC as well as SCAP, leads to aggregate total SCC (SCAP, sum) of 456 (166, 622) billion €. Thus, solely internalizing SCAP is a bad substitute for internalizing SCC. However, also internalizing SCAP additionally to SCC leads to lowest social cost, where total SCC are higher (compared to only internalizing SCC) but total SCAP are substantially lower than for the case where we internalize SCAP only. Thus, SCC internalization is a good complement of SCAP internalization.

We find that wind and solar deployment is almost unaffected by internalization choice, emission factor assumptions, SCC, and SCAP specifications. The economically viable wind and solar potential is used even when SCC values (and corresponding optimal tax rates) are low. Thus, increasing or decreasing them does not lead to relevant changes. In turn, we observe a CCS-nuclear substitution. Higher SCAP foster nuclear expansion at the cost of CCS technologies because those technologies still emit air pollutants that come at fundamental cost. High SCC as well as relaxing biomass limits and trade barriers in turn result in the promotion of bio-CCS while reducing wind, gas-CCS, and nuclear.

Section 2 relates our contribution to the literature. Section 3 introduces the modeling strategy within an intertemporal optimization framework and optimal taxation following from diverging discount rates. Section 4 presents the calibration by focusing on emissions, social cost, and the role of discounting and resulting taxation. Sections 5, 6, and 7 show results. Section 5 describes the impact of different internalization choices and tests sensitivity of emission factor assumptions, SCC, and SCAP, as well as assumptions about the technological progress of wind power. Section 6 presents the role of discounting when internalizing social cost by intertemporal taxation. Section

7 analyzes distributional effects, the role of biomass limits, and the impact of biomass tradability. Section 8 discusses results by showing general substitution patterns and aggregated levels of social cost. Section 9 concludes.

2. Literature

Our paper relates to the literature about models aiming to internalize externalities, about discount rates in (integrated assessment, energy system, or power market) models, and about optimal taxation of emissions when social and private discount rates differ. Our paper does not relate to literature about technological details when it comes to CO_2 and air pollutant emission factors (see Subsection 4.1). We also do not discuss how (not) to determine SCC (e.g., Nordhaus, 2014), SCAP (e.g., Douthwaite et al., 2003), or other social cost from electricity generation (e.g., Sheldon et al., 2015).[1] We deploy existing models (SCC) or estimates (SCAP) to determine SCC and SCAP (see Subsection 4.2). Moreover, we also do not contribute to the discussion whether to apply constant or hyperbolic discount rates (e.g., Arrow et al., 2014), time-inconsistency problems arising from intertemporal taxation and different forms of discount rates (e.g., Strulik, 2021), the general level of (social) discount rates (e.g., Drupp et al., 2018), or how to discount climate change (e.g., Stern, 2008).[2]

The literature agrees that social and private discount rates differ (von Below, 2012, Belfiori, 2017, 2018, Barrage, 2018). Climate change impact should be discounted with the lowest possible discount rate due to its long-lasting and intergenerational effects (Weitzman, 1998). In turn, firm discount rates follow from capital market interest rates (Steinbach, 2015). However, given that CO_2 emissions, air pollutant emissions, and investment, fixed, and variable cost of firms have diverging discount rates, we encounter a problem of setting optimal intertemporal tax rates on CO_2 and air pollutant emissions. We show that intertemporal models aiming to reflect firm behavior need to tax CO_2 and air pollutant emissions at rates above their marginal damage (SCC, SCAP) because those emissions' social discount rates lie below those of firms. This finding corresponds to those of Belfiori (2017) and Barrage (2018). Belfiori (2017) shows that the optimal carbon tax does not equal in general the SCC and that social discount rates are below those of private individuals. Barrage (2018) highlights that social planners and households discount the future differently. Additional intertemporal effects distort optimal decisions in general equilibrium, requiring massive taxation decisions to restore efficiency. In our partial equilibrium modeling task, we do not have general equilibrium distortions, however, we do have diverging discount rates between social planner (for

[1] Owen (2004), Roth and Ambs (2004), Owen (2006), National Research Council (2010), Galetovic and Muñoz (2013), McCubbin and Sovacool (2013), Thopil and Pouris (2015), Rhodes et al. (2017) focus on the determination of final cost of electricity generating technologies, whereas Sundqvist (2004) explains differences in estimates by reviewing the past literature. See also Hazilla and Kopp (1990) for a discussion of differences between social and private cost from environmental quality regulations.

[2] For parsimony, we simply assume in our standard specification social discount rates of 1.5% to discount SCC and 3% to discount SCAP, and private discount rates of 7% to discount firm cash flows from investments, fixed, and variable cost including tax payments.

SCC and SCAP) and firms. The result are intertemporal tax rates above SCC and SCAP (when SCC and SCAP discount rates of the social planner are below those of firms).

Only few papers address the issue of discount rates in energy system models. Steinbach (2015) argues that social discount rates differ from private ones and gives guidance on how to determine those rates. García-Gusano et al. (2016) and Mier and Azarova (2021) show that diverging discount rates considerably impact results. This is supported by Shindell (2015) who presents results for different discount rates and concludes that some air pollutant damages dominate for low and others when assuming high rates. However, he refrains from analyzing the role of applying different discount rates for CO_2 and air pollutant emissions simultaneously as done in our paper. The authors are not aware of any contribution attempting to implement multiple discount rates in one intertemporal optimization framework and how to deal with the resulting internalization (taxation) problem.

Klaassen and Riahi (2007) apply MESSAGE-MACRO to internalize air pollution damages but refrain from internalizing climate damages (as we do). They also take SCAP estimates from the externE project series (that are similar but older than ours). However, their focus is completely different since we focus on the internalization decomposition, the role of intertemporal taxation, and distributional as well as trade effects. Additionally, our most important technologies for SCC and SCAP internalization, bio-CCS and gas-CCS, are not part of their technology set. Final results can thus no longer be compared. Nam et al. (2010) find, using CGE analysis for 18 European countries, fundamental welfare losses (2%) from air pollution. Barteczko-Hibbert et al. (2014) integrate life cycle assessment (LCA) and electricity generation but focus on greenhouse gases and less on local damages from air pollution. Like our paper, Shindell (2015) extends the SCC framework to incorporate (local) damages from air pollutants. He finds environmental damages of 330 to 970 billion \$/year for US electricity generation. Our 2020 damages estimates are fundamentally lower, but the underlying message is similar: also accounting for damages from air pollutants considerably changes final social cost. Also, Holland et al. (2020) use local and global damages from CO_2 emissions and air pollution. Using an integrated assessment model, they find that damages fell from \$245 billion in 2010 to \$133 billion in 2017. Our 2020 annual damages are at 40 billion € when not internalizing social cost (by taxation). However, US CO_2 emissions are approximately double those of the European power market and thus damages are fundamentally higher in Holland et al. (2020).

3. Modeling Strategy

Power market models in general minimize the stream of cost $C(t)$ from investments, operation and maintenance, and dispatch by choosing to install capacities $\mathbf{Q}$ and generation $\mathbf{Y}$ for all time periods t. Intertemporal models—such as EUREGEN—additionally discount cash flows by using the discount factor $\delta(t)$, i.e., the minimization problem is given by

$$\min_{\mathbf{Q},\mathbf{Y}} \sum_{t} \delta(t)\, C(t)\,. \tag{1}$$

We add social cost by using different discount factors. $\delta^{car}(t)$ is the time-varying discount factor for CO_2 emissions and $\delta^{air}(t)$ is the one for air pollution. We assume that $\delta^{car}(t) \leq \delta^{air}(t) \leq \delta(t)$ to reflect the long-lasting (intergenerational) impact of CO_2 emissions (lowest discount rate) and the myopic behavior of firms (highest discount rate). We use subscripts i, r to denote technologies and regions, respectively, and parentheses for vintages v (year of installation) and periods t (current time period). For example, $Y_{ir}(v,t)$ is generation from technology i in region r in period t whose capacity is installed in period v. Denote by $SCC(t)$ the social cost of carbon and by $SCAP_{r,ap}(t)$ the region-specific social cost of air pollution by air pollutant ap (both in €/ton). CO_2 emission factor $\xi_i^{car}(v)$, air pollution emission factor $\xi_{i,ap}^{air}(v)$, and power plant efficiency $\eta_i(v)$ depend on the vintage. Older vintages have lower efficiencies and higher emissions factors, which results in higher emissions. Discounted total social cost $SC_\delta(t)$ follow from

$$\begin{aligned} SC_\delta(t) &= \delta^{car}(t) \sum_{v \leq t} \sum_{i,r} SCC(t) \times \xi_i^{car}(v) \frac{Y_{ir}(v,t)}{\eta_i(v)} + \\ & \quad \delta^{air}(t) \sum_{v \leq t} \sum_{i,r} \sum_{ap} SCAP_{r,ap}(t) \times \xi_{i,ap}^{air}(v) \frac{Y_{ir}(v,t)}{\eta_i(v)}. \end{aligned} \tag{2}$$

The first term are discounted total SCC and the second term discounted total SCAP in period t. $\frac{Y_{ir}(v,t)}{\eta_i(v)}$ represents region- and technology-specific fuel usage and $\xi_i(v)\frac{Y_{ir}(v,t)}{\eta_i(v)}$ related emissions. Multiplying emissions with respective social cost, SCC or $SCAP$, yields total social cost (of carbon or air pollution, respectively). Weighting social cost with the discount factor yields $SC_\delta(t)$. The resulting minimization problem is

$$\min_{\mathbf{Q},\mathbf{Y}} \sum_t \left(\delta(t) C(t) + SC_\delta(t)\right). \tag{3}$$

We internalize those social cost within a firm equilibrium by imposing a carbon tax $\tau^{car}(t)$ as well as air pollution taxes $\tau_{r,ap}^{air}(t)$. Denote by $E^{car}(t) = \sum_{v \leq t} \sum_{i,r} \xi_i^{car}(v) \frac{Y_{ir}(v,t)}{\eta_i(v)}$ CO_2 emissions and by $E_{r,ap}^{air} = \sum_{v \leq t} \sum_i \xi_{i,ap}^{air}(v) \frac{Y_{ir}(v,t)}{\eta_i(v)}$ regional air pollution by air pollutant. The cost minimization problem changes to

$$\min_{\mathbf{Q},\mathbf{Y}} \sum_t \delta(t) \left(C(t) + \tau^{car}(t) E^{car}(t) + \sum_r \sum_{ap} \tau_{r,ap}^{air}(t) E_{r,ap}^{air}(t) \right). \tag{4}$$

Problem (3) and (4) are equivalent when the social planner sets optimal intertemporal tax rates of

$$\tau^{car}(t)^* = SCC(t)\frac{\delta^{car}(t)}{\delta(t)}, \quad (5)$$

$$\tau^{air}_{r,ap}(t)^* = SCAP_{r,ap}(t)\frac{\delta^{air}(t)}{\delta(t)}. \quad (6)$$

Observe that those tax rates are higher than the respective social cost by $\frac{\delta^{car}(t)}{\delta(t)} \geq 1$ or $\frac{\delta^{air}(t)}{\delta(t)} \geq 1$ due to the assumptions of $\delta^{car}(t) \leq \delta^{air}(t) \leq \delta(t)$ because firms discount cash flows more than a social planner discounts CO_2 and air pollutant emission damages.[3]

4. Calibration

EUREGEN is a partial equilibrium model of the European power market, which optimizes investments, decommissioning, and dispatch of multiple generation, storage, and transmission technologies intertemporally from 2020 to 2050, while 2015 serves as base year.[4] EUREGEN uses the CGE model PACE to calibrate for annual electricity demand and major fuel prices.[5] EUREGEN calculates CO_2 emissions from an emission factor and either implements a carbon price (e.g., Mier et al., 2020) or a quantity target (e.g., Azarova and Mier, 2021). We extend the EUREGEN model by emission factors for different air pollutants and run different specifications to account for technology heterogeneity and uncertain technological developments in future (Subsection 4.1). We refrain from using carbon prices resulting from the CGE calibration or quantity targets as imposed, e.g., by the EU ETS and, instead, apply SCC and SCAP as described in Subsection 4.2. EUREGEN chooses between different discount and interest rates, investor types, and spatial resolutions (Mier and Azarova, 2021). Subsection 4.3 describes the applied discounting and tax rates. We opt for the *normal* investor that carries cost of investments within the period of investment and uses endeffects when the investment's depreciation extends above the model horizon. Moreover, we apply the maximum spatial resolution of 28 countries (EU27 less the island states of Cyprus and Malta, including Norway, Switzerland, and United Kingdom) and an hour choice algorithm to reduce temporal resolution of the year (to keep the model numerically feasible).[6]

[3]We are aware of the time inconsistency problem of intertemporal taxation under discounting, i.e., optimal 2025 to 2050 tax rates from 2020 perspective differ from optimal 2025 to 2050 tax rates from 2025 perspective. However, we keep the rates as they are because they underline the problems of handling private and social discount rates within one intertemporal optimization framework. Moreover, resulting carbon taxes are indeed necessary to achieve carbon neutrality by the mid of the century.

[4]See Weissbart and Blanford (2019) for the basics of the model and Weissbart (2020) and Mier and Weissbart (2020) for applications.

[5]See Appendix A.3 and Mier et al. (2020) and Siala et al. (2020) for details.

[6]The hour choice algorithm selects and weights hours that present the extremes of load, wind onshore, wind offshore, solar, and hydro generation. We obtain 280 hours and finally scale load and intermittent renewables timeseries to match annual demand and full-load hours, respectively.

4.1. Emissions from Electricity Generation

CO_2 emissions are the major source of pollution from electricity generation. Its emission factor depends on the carbon content of fuel. We also concentrate on other air pollutants and their role for electricity generation. The most important ones are ammonia NH_3, non-methane volatile organic compounds NMVOC, nitrogen oxides NO_x, particulate matter PPM_{10} as well as the finer $PPM_{2.5}$, and sulfur dioxide SO_2 (or SO_x expressed in SO_2 equivalents). EEA (2019) provides information on how these air pollutants occur, and what general measures exist to mitigate their air release.

NMVOC is emitted due to incomplete combustion and its emission factor is negatively correlated with plant size. NO_x emissions can be reduced by around 30% by applying single primary measures such as low NO_x burner technologies. This can be complemented by secondary measures like selective catalytic reduction or non-selective catalytic reduction, achieving up to 50 to 80% reduction. NH_3 is added for NO_x abatement purposes and finally emitted due to incomplete reaction. PPM_{10} and $PPM_{2.5}$ decrease with plant size. The most common abatement techniques are electrostatic precipitation and fabric filters. The emission intensity of SO_2 depends on the fuel's sulfur content. Most common abatement techniques are flue gas desulfurization processes, reaching control levels of more than 90%. Technologies for SO_2 abatement also contribute to very effective PPM abatement.

The actual (CO_2 and air pollution) emission intensity of one electricity unit produced depends on three factors. The first is the type of fuel used, the second any of the applied counter measures above, and the third are the plant-specific efficiency and underlying combustion technology. We therefore distinguish emission factors according to fuel type and technology (comprising combustion technology and the underlying counter measure) to address these three factors. We consider steam turbines burning biomass with carbon capture and storage (bio-CCS), steam turbines burning biomass (bioenergy), steam turbines burning coal (coal), coal-CCS, combined-cycle gas turbines burning natural gas (gas-CCGT), steam turbines burning natural gas (gas-ST), open-cycle gas turbines burning natural gas (gas-OCGT), gas-CCS, steam turbines burning lignite (lignite), and gas turbines using oil and other non-biomass non-natural gas fuels (oil). In the following, we refrain from presenting values for bioenergy, coal-CCS, lignite, and oil because those technologies are not relevant for the final technology mix.

We express all emission factors under consideration in emissions per thermal fuel input unit (g/GJ), which allows us to explicitly account for the role of plant efficiency on emission intensity in the consequent modeling process. We achieve this by combining emission factors with technology- and vintage-specific plant efficiencies (see equation (2) in Section 3 and Table A.1 in Appendix A.3). By doing so, we arrive at a sophisticated representation of actual emission intensities per electricity output unit (ton/GWh electric). Due to the wide-spread application of the abatement technologies indicated above, we abstain from using air pollution emission factors that do not assume any emission control. Rather, we aim for fleet average emission factors for existing plant vintages, which are calculated via annual statistics of total emissions and total fuel consumption. Thereby, an averaged abatement efficiency is considered. For CCS technologies we further consider increased NH_3 emissions occurring during the capture process. We reflect overall slightly increased emissions for NO_x, NMVOC, and PPM due to increased fuel consumption by decreased efficiencies of CCS plants compared to their non-CCS counterparts.

We construct three emission factor specifications—*low*, *mid*, and *high*—that differ by the assumed emissions factors for existing and future vintages. The literature provides lower and upper bounds as well as medium range emission factors (EPA, 1995, Cai et al., 2012, EEA, 2019, UBA, 2019). Our benchmark specification *mid* uses medium emission factors of existing vintages. Where applicable, for future vintages we include linear improvements in average abatement efficiency so that 2050 vintages across all regions achieve abatement efficiencies of modern plant fleets. The *low* specification uses the same emission factors for existing vintages, whereas improvements for future vintages are more ambitious. In this specification, 2050 vintages in all regions achieve lower bound abatement levels of today's technology frontier. The third specification *high* applies upper bound emissions factors for existing vintages. Where applicable, for future vintages we implement a linear improvement path so that 2050 vintages achieve abatement levels, comparable to existing vintages in the *mid* specification. Tables A.3 to A.5 in Appendix A.2 contain the full set of emission factors (in ton/GJ) as compiled from EPA (1995), Cai et al. (2012), EEA (2019), UBA (2019).[7]

Table 1 summarizes emission factors of different technologies. Observe that CO_2 emission factors are by far the highest. Among the air pollutants NO_x, PPM_{10}, and $PPM_{2.5}$ are most relevant. Gas technologies do not emit relevant amounts of NH_3, and sulfur-content of natural gas is almost negligible. In general, technologies burning natural gas are the cleanest, whereas biomass technologies are the most emission intensive.

Table 1: 2015 emission factors (ton/GWh electric) for the *mid* specification

	NH_3	NMVOC	NO_x	PPM_{10}	$PPM_{2.5}$	SO_2	CO_2
Bio-CCS	0.086	0.164	1.719	0.716	0.629	0.243	-710
Coal	0.002	0.008	0.582	0.062	0.027	0.509	760
Gas-CCGT, Gas-ST		0.001	0.189	0.005	0.005	0.001	340
Gas-OCGT		0.002	0.268	0.008	0.008	0.001	480
Gas-CCS		0.002	0.236	0.007	0.007	0.001	40

Emission factors displayed here are already subject to technology-specific efficiencies as shown in Table A.1 in Appendix A.1. We refrain from presenting values for bioenergy, coal-CCS, lignite, and oil here and in the following because those technologies do not play a relevant role in the final technology mix.

4.2. Social Cost

Social cost of carbon. The CGE model used to calibrate the EUREGEN model also projects GDP development (see Table A.9 in Appendix A.5). The underlying population projections are from the world bank (see Table A.8 in Appendix A.4). In DICE-2016R-091216a, 2015 world GDP is

[7] A note is to be added on biomass emission factors, which are quite dispersed in range. This reflects the availability of different abatement techniques in combination with the variation in emission intensity from using heterogeneous fuels or fuel compositions (wood, crops and agricultural residues, waste), respectively.

105.5 trillion 2010-US$.[8] We change this value to 86.1 trillion 2015–US$. Additionally, we need to scale total factor productivity by 0.8254 to match 2020 CO_2 emission of 39.6 Gt. We further adjust population and total factor productivity from 2020 to 2050 to precisely match world bank (population) and CGE (GDP) projections. Finally, we use DICE standard discounting with pure time preferences of 1.5%.

We obtain SCC of 28 €/ton in 2020 and 62 €/ton in 2050. Table 2 presents the exact values and further parameters. Observe that (global) carbon emissions remain almost constant, leading to a temperature increase of above 1.5° (2.0°) Celsius already in 2040 (2050). We are aware that those predictions does not correspond targets from the Paris Agreement (2015) but are in line with recent findings of Dietz et al. (2021), who also find that the *optimal* path leads to more than 2° Celsius warming. Indeed, SCC values are even lower in Dietz et al. (2021) compared to the outcome from DICE-2016R-091216a. We thus decide to stick with the above-mentioned version of the DICE model.

Table 2: SCC and other parameters from final DICE calibration

	2020	2030	2040	2050
SCC (US$/ton)	30.48	39.79	52.37	68.53
SCC (€/ton)	27.71	36.18	47.61	62.30
CO_2 emissions (Gt)	39.60	39.30	40.50	40.95
Temperature increase (°C)	1.02	1.37	1.71	2.06
Gross world GDP (trillion 2015-US$)	99.7	131.5	171.7	216.6
World population (billion)	7.75	8.50	9.14	9.68

We apply an exchange rate of 1.1 to convert US-$ into €, i.e., 1 € is worth 1.1 US-$ in 2015. We refrain from showing 2015 values because they are not relevant for calculating results. We further refrain from showing 2025, 2035, and 2045 for better readability.

Social cost of air pollution. Air pollution (from electricity generation) can lead to higher mortality, discomfort, and productivity loss (e.g., Markandya and Wilkinson, 2007, Dedoussi and Barrett, 2014, Dedoussi et al., 2020). Value of life concepts (e.g., Viscusi and Aldy, 2003) such as disabled adjusted life years (e.g., Murray, 1994, Anand and Hanson, 1997, Murray et al., 2012), monetize those damages. The externE project series calculates and monetizes those damages by employing life cycle assessment (e.g., Klöpffer, 1997), the impact pathway approach (e.g., Douthwaite et al., 2003), diffusion patterns of air pollutants, as well as meteorological, geological, demographic, and health data. We take SCAP from the NEEDS project (part of the externE project series) that provides SCAP (in 2000-€) for six air pollutants (NH_3, NMVOC, NO_x, PPM_{10}, $PPM_{2.5}$, SO_2), the 28 countries under investigation, and for five categories (human health, loss of biodiversity,

[8] GAMS code is available at http://www.econ.yale.edu/ nordhaus/homepage/homepage/DICE2016R-091916ap.gms.

regional crops, materials, and rest of the world damages).[9] We take the high height of release values (as suggested in the user manual for electricity generation) that are calculated for meteorological conditions for 2010. We recalculate the values from 2000-€ in 2015-€ by using the ratio 1.3334. NEEDS authors suggest increasing the SCAP by a rate according to GDP growth. We assume that real GDP grew by 25.84% between 2000 and 2015. Growth rates for 2020 onwards are based on country-level projections from our CGE calibration (see Table A.10 in Appendix A.5).

Table 3 shows the country (annual electricity demand-weighted) averages for the six air pollutants and the categories for 2015. Country level data is available in Tables A.14 to A.16 in Appendix A.6. The difference between total regional and total global cost in Table 3 is the rest-of-the-world impact. This impact is negligible for NH_3, NO_x, PPM_{10}, $PPM_{2.5}$, and SO_2) (below 5%) and only relevant for NMVOC (global impact, see Subsection 4.1). Observe that (regional) human health impacts dominate with shares of 56.81% (for NMVOC) to 99.61% (for PPM_{10}). Moreover, NH_3 and $PPM_{2.5}$ are the most expensive air pollutants, followed by NO_x and SO_2. Total cost of NMVOC and PPM_{10} seem to be negligible. However, final emissions will determine whether the levels are crucial for the relative competitiveness of technologies. We thus calculate SCC and SCAP per technology in the next paragraph.

Table 3: 2015 average SCAP by impact category and air pollutant

	NH_3	NMVOC	NO_x	PPM_{10}	$PPM_{2.5}$	SO_2
Human health	16,543	1,039	8,003	1,019	23,105	9,844
Loss of biodiversity	5,790	-129	1,570			583
Regional crops	-281	319	356			-112
Materials			116			435
Total regional cost	22,052	1,229	10,045	1,019	23,105	10,750
Total global cost	22,057	1,829	10,265	1,023	23,370	11,217

2015 average SCAP follow from weighting 2015 country-specific SCAP with 2015 country-specific annual demand. The rest of the world category value is the differences between regional and global cost.

Technology-specific social cost. We now compare SCC and SCAP values by applying efficiencies (see Table A.1 in Appendix A.1) and emission factors (see Tables A.3 to A.5 in Appendix A.2) of different technologies. We obtain the values in Table 4. Remember that SCC are at 28 €/t in 2020 and at 62 €/t in 2050. Moreover, SCAP values grow with GDP to a similar extent (see Table A.10 in Appendix A.5). Start with bio-CCS. Negative CO_2 emissions yield negative SCC values, growing from -20 €/MWh in 2020 to -44 €/MWh in 2050. In turn, SCAP grow from 39 to 47 €/MWh in 2050. In aggregate, the competitiveness of bio-CCS increases over time, that is, growing SCC and SCAP values does not fully neutralize each other. Among the remaining

[9]See https://cordis.europa.eu/project/id/502687/de for details. The project page, https://needs-project.org, is no longer available. Data and further documents can be now accessed via the project page of the University of Stuttgart, https://www.ier.uni-stuttgart.de/forschung/modelle/ecosense/.

technologies observe that SCAP have higher impact than SCC only for gas-CCS. For all other technologies, SCC dominate. Those magnitudes conform to recent findings of Dedoussi et al. (2019) that calculate 20% higher social cost when additionally accounting for mortality caused by air pollutants.

Table 4: SCC and average SCAP (€/MWh electric) by vintage and technology

	2020	2030	2040	2050
Bio-CCS				
SCC	-20	-26	-34	-44
SCAP	39	42	44	47
Coal				
SCC	20	25	33	43
SCAP	12	13	13	14
Gas-CCGT, Gas-ST				
SCC	9	12	15	20
SCAP	2	2	3	3
Gas-OCGT				
SCC	13	16	21	27
SCAP	3	3	4	4
Gas-CCS				
SCC	1	1	2	3
SCAP	3	3	3	4

SCAP follow from average SCAP and emission factors from the *mid* specification. Summing up over all air pollutants and applying efficiencies yields the respective values. For SCC we only need to apply efficiencies and emission factor to obtain the respective values.

4.3. Discounting and Taxation

Discounting. The standard discounting in EUREGEN applies a discount rate of 7% to evaluate all cash flows. We follow the interpretation of discount rates and factors from the DICE model as stated in Nordhaus (2014), and thus relinquish the distinction between discount rates and rates of pure time preferences. More specifically, we either assume constant consumption or a non-existent elasticity of marginal utility. Following the discussion in Nordhaus (2014) and supported by Drupp et al. (2018), we apply 1.5% to discount SCC. Moreover, we believe that air pollution damages should be discounted slightly lower (i.e., higher discount rate) due to their immediate effect, which is not long-lasting. We thus decide to discount SCAP with 3%. Table 5 shows the respective discount factors reflecting all periods from 2020 onwards covering 5 years in total.

Table 5: Discount factors following from different discount rates

Discount rate		2020	2030	2040	2050
Private discount rate	7%	4.10	2.08	1.06	0.54
Social discount rate for air pollution	3%	4.58	3.41	2.54	1.89
Social discount rate for CO_2 emissions	1.5%	4.78	4.12	3.55	3.06

Discount factors follow from $\delta(t) = \frac{(1+\nu)^{t_{step}(t)}-1}{\nu(1+\nu)^{t-t_{base}}}$ with ν as discount rate, $t_{step}(t)$ as the number of years in period t, and $t_{base} = 2015$. Note that $\delta(2015) = 1$ because $t_{step}(2015) = 1$.

Taxation. Different discount rates for SCC and firm cash flows require for taxation as derived in Equation (5) in Section 3. The carbon tax thus predicts this optimal tax rate that needs to be implemented in the power market model to strive for efficient internalization of cost. We present results for such a constellation in Section 5 but also change discount rate differentials in Section 6. Observe from Tables 2 and 6 that a moderate SCC of 62 €/ton in 2050 reaches 354 €/ton when implementing the optimal tax rate in an intertemporal optimization context.

Accordingly, the relative magnitudes of effects in Table 4 change to those presented in Table 6. Observe that the role of the carbon tax grows comparatively to those of the air pollution tax. Moreover, the carbon tax now clearly dominates for bio-CCS from 2040 onwards. In the long-run, carbon and air pollution taxes are similarly important for gas-CCS. For all other technologies, the dominance of SCC actually grows through carbon taxation.

5. Internalization

We start presenting results in Subsection 5.1 by focusing on different outcomes depending on the internalization of SCC and/or SCAP, respectively. This enables us to analyze both the decomposed effects of both types of social cost as well as their joint internalization effect. We additionally test the role of assumptions about the underlying air pollution emission factor (Subsection 5.2), the level of SCC (Subsection 5.3) and SCAP (Subsection 5.4), and finally changes emanating from further technological advancements of wind turbines, called *technology boost* (Subsection 5.5).

5.1. Decomposition of Internalization Choices

Figures 1 and 2 visualize our results for installed capacities, generation, CO_2 emissions, and total SCAP and SCC (Figure C.9 in Appendix C.1 displays CO_2 and air pollution emissions). Figure 1 consists of an upper and a lower panel where different model specifications are clustered by periods from 2020 to 2050. The upper panel shows installed capacities (in GW, left axis) and the lower one generation (in TWh, left axis) by technology type. The lower panel additionally displays CO_2 emissions (in Gt, right axis). Figure 2 presents total social cost from air pollution (in billion €, left axis) and from CO_2 emissions (in billion €, right axis). We consider six different specifications reflecting different levels of internalization and assumptions about emission factors: (1) *No internalization* of SCC nor SCAP, (2) *Only SCAP* internalization given the *mid* emission

Table 6: Optimal CO_2 and air pollution taxes by year (€/ton) or vintage and technology (€/MWh electric)

	2020	2030	2040	2050
CO_2 tax (€/ton)	32	72	160	354
Bio-CCS				
CO_2 tax (€/MWh electric)	-23	-51	-114	-252
Air pollution tax (€/MWh electric)	43	69	106	166
Coal				
CO_2 tax (€/MWh electric)	24	50	111	246
Air pollution tax (€/MWh electric)	14	21	31	48
Gas-CCGT, Gas-ST				
CO_2 tax (€/MWh electric)	11	23	52	115
Air pollution tax (€/MWh electric)	2	4	6	11
Gas-OCGT				
CO_2 tax (€/MWh electric)	15	32	69	154
Air pollution tax (€/MWh electric)	3	5	9	14
Gas-CCS				
CO_2 tax (€/MWh electric)	1	3	7	15
Air pollution tax (€/MWh electric)	3	5	8	13

Air pollution taxes are specific to air pollution emissions factors that depend on vintage and technology as well as SCAP and thus cannot be simply displayed in €/ton. We use average SCAP to determine air pollution taxes, that is, air pollution taxes might be lower for some countries and higher for others.

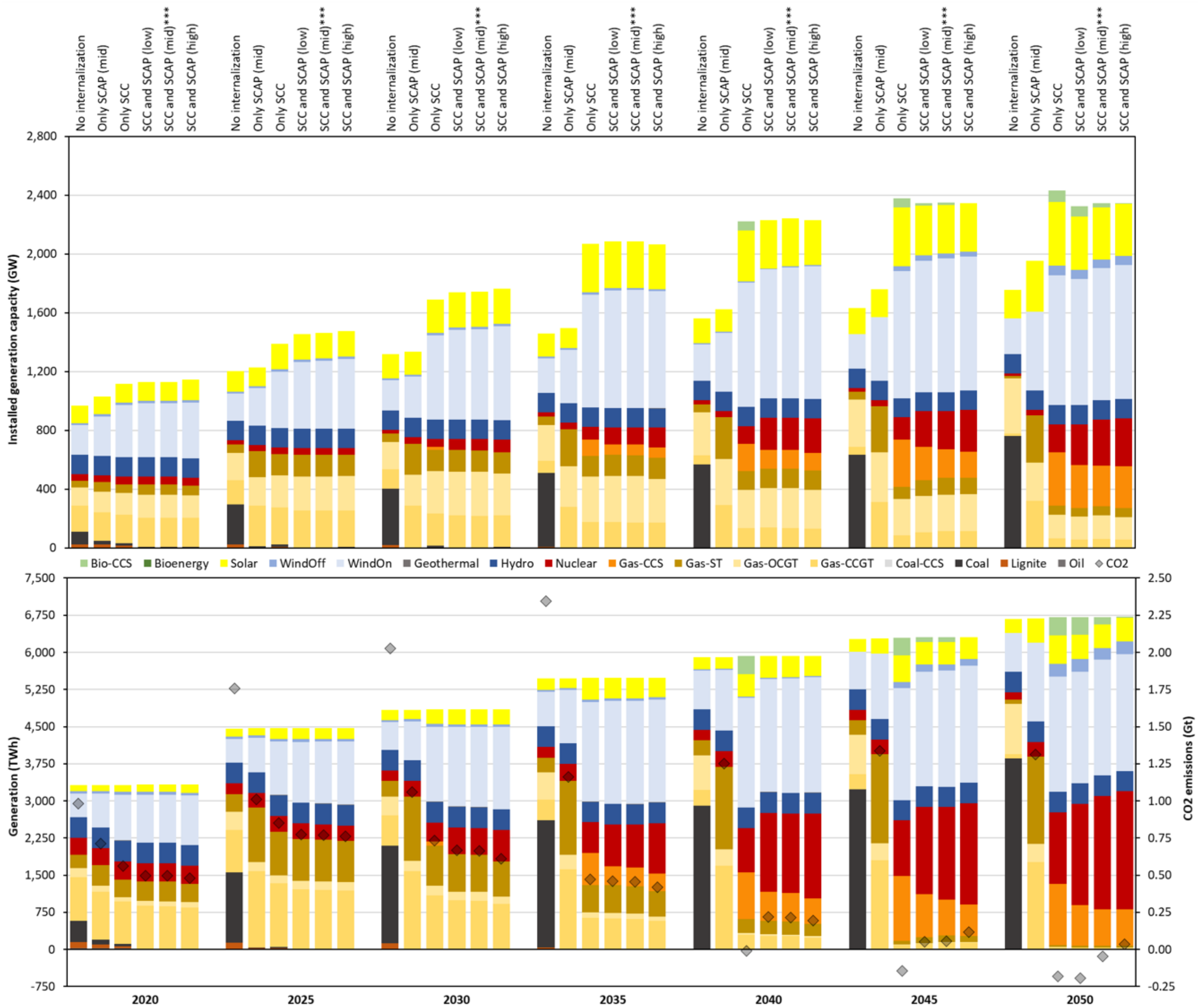
factor assumptions, (3) *Only SCC* internalization, (4) *SCC and SCAP* internalization given the *low* emission factors, (5) *SCC and SCAP* internalization given the *mid* emission factors, and finally (6) *SCC and SCAP* internalization given the *high* emission factors for air pollution. The numbers in parentheses reflect the column of each cluster in Figure 1. Figure 2 (and C.9 in Appendix C.1) refrains from showing the first specification for better comparability of the other specifications.

We start with decomposing the impact when internalizing SCC and/or SCAP by optimal intertemporal taxation in this subsection. There, we consider specifications (1), (2), (3), and (5). Specifications (4), (5), and (6) test emission factor sensitivity and are subject of the next subsection.

No internalization (first column of each cluster) reflects the extreme case. Coal capacity increases from 85 GW in 2020 to 762 GW in 2050 (+797%) and thus the generation share increases from 13 to 58%. Other dirty technologies are phased out by by 2040 (oil) or 2050 (lignite), respectively. Nuclear is successively phased out as well (capacity drops from 46 to 18 GW in 2050). Generation from wind (solar) increases from 525 TWh (129 TWh) to 781 TWh (289 TWh) but its generation share drops from 16 to 12% (remains constant). Conventional gas (gas-CCGT, gas-ST, gas-OCGT) capacity rises just slightly (from 347 to 407 GW) but its generation share drops from 40 to 18%. Observe that CCS technologies are entirely irrelevant due to the lack of incentives for CO_2 abatement. Resulting CO_2 emissions leave the scale of the axis from 2040 onwards and are finally at 3.21 Gt (+227% compared to 2020). Moreover, the resulting generation mix is associated with severe NO_x (2.2 Mt) and SO_2 emissions (1.4 Mt, see also Figure C.9 in Appendix C.1). This leaves the 2050 system with annual cost of 200 billion € from CO_2 and 71 billion € from air pollution emissions, mostly caused by NO_x (40 billion €), SO_2 (28 billion €), and $PPM_{2.5}$ (3 billion €). This extreme case does not serve as a good benchmark for analysis of more realistic internalization choices. We opt for *SCC and SCAP (mid)* as a decisive benchmark, i.e. our standard specification, to evaluate the impact of internalizing SCC (difference to *Only SCAP (mid)*) and SCAP (difference to *Only SCC*). The benchmark is labelled with *** to improve readability of Figure 1.

In *SCC and SCAP (mid)*, wind capacity increases from 385 GW in 2020 to 957 GW in 2050, so that the final generation share increases from 31% in 2020 to 38% in 2050. Solar capacity even increases from 126 to 352 GW (generation share almost doubles from 4 to 7%). Nuclear, gas-CCS, hydro, and some bio-CCS accompany wind and solar in the long-run. Hydro capacity and generation remain (as in all other specifications) constant at 131 GW and around 415 TWh). The biomass potential—which is 376 TWh assuming efficiencies of the 2050 vintage—is not fully exploited so that bio-CCS plays a minor role with just 147 TWh (share of 2.2%) in 2050. Gas-CCS starts being employed from 2035 onwards, making up 279 GW or a generation share of 11% in 2050. Nuclear is the other major generation source besides wind. Nuclear capacity increases from 54 to 314 GW (generation share increases from 11 to 34%).[10] Observe that final CO_2 emissions

[10]Note that the nuclear share was 26% in 2015 (in a non-optimized system) and drops until 2025 to 7% when applying optimization given existing capacities and pipeline investments.



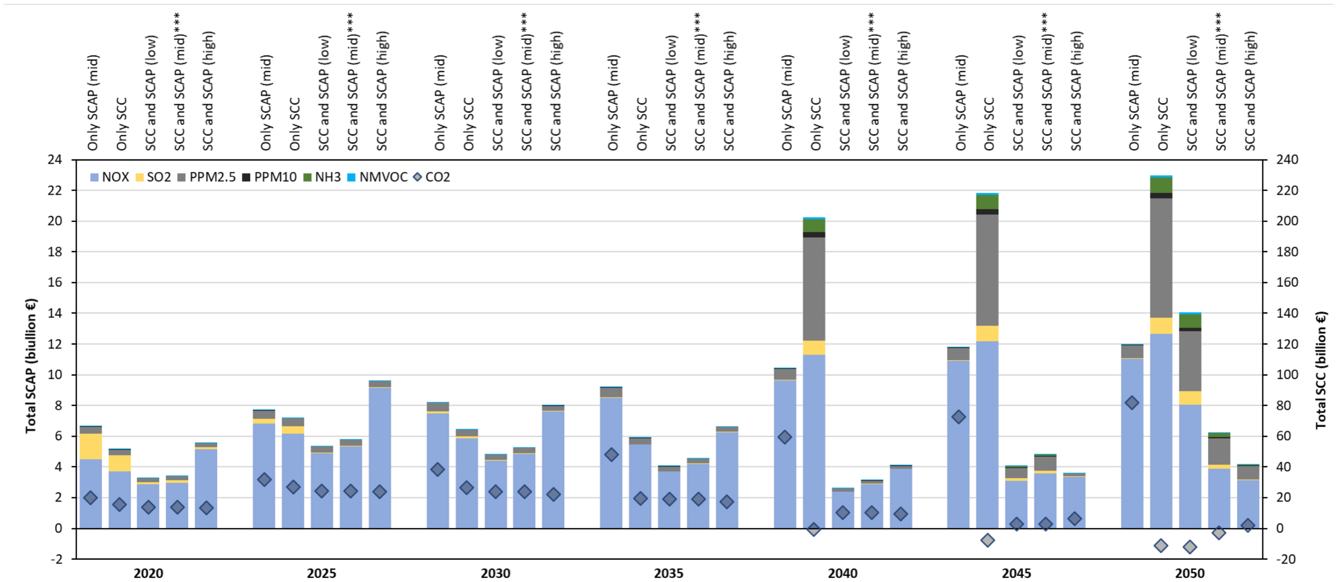
***SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

Figure 1: Installed capacity (upper panel) and generation with CO2$_2$ emissions (lower panel) for different levels of internalization and emission factor assumptions

are negative (-0.05 Gt) and thus this internalization specification is a good reflection of what a carbon-neutral electricity system might look like. Note that carbon-neutral (carbon-negative) systems come at no (negative) total SCC. Observe from Figure 2 that total SCC increase from 14 billion € in 2020 to 24 billion € in 2030 and then drop to -3 billion € in 2050. Total SCAP in turn increase from 3 billion € (almost only NO_x) to 6 billion € (also $PPM_{2.5}$). Related air pollution is mainly proportional to social cost but PPM_{10} and NMVOC do not play a role in the absolute level of social cost (see also Figure C.9 in Appendix C.1).

The differences from our benchmark to *Only SCAP (mid)* is the effect of internalizing SCC. Observe that gas-CCS and bio-CCS do not play a role at all. Additionally, nuclear plays a minor role, contributing just 4% (compared to 34%) to the 2050 generation mix, and coal phases out completely in 2030. Instead, conventional gas technologies constitute the major share with 58%. However, the role of wind remains at least constant (22% in 2020, 24% in 2050), reflecting almost a doubling in capacity (from 283 to 536 GW). Not internalizing SCC and just SCAP comes at increasing CO_2 emissions (from 0.71 to 1.31 Gt). Air pollution, in turn, remains almost constant but its decomposition slightly changes away from some SO_2 (from coal generation) to more NO_x (from gas generation). However, total SCAP double from 6 to 12 billion €.

Differences to *Only SCC* (third column) can be adhered to the SCAP internalization effect. Observe that effects are fundamentally smaller compared to the effect from SCC internalization. Wind plays a similar a role (-4% generation in 2020, same in 2050) but solar becomes more important (+20% generation in 2050). Additionally, the biomass potential is fully exploited from 2040 onwards (365 TWh), making the bio-CCS share 5.4% in 2050 (compared to 2.2%). Higher solar and bio-CCS generation comes at benefits of gas-CCS (+68% compared to the benchmark) and deprives nuclear (-36%). Combined gas-CCS and nuclear generation drops from 45 to 40% in 2050. Final CO_2 emissions drop to -0.18 Gt. However, related air pollution increases from 0.4 to 1.3 Mt leading to fundamentally higher social cost (see Figure 2). In particular, $PPM_{2.5}$ takes a fundamental share due to the extensive use of bio-CCS and higher gas-CCS generation compared to our benchmark case. Additionally, NH_3 now plays a considerable role due to bio-CCS.



***SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

Figure 2: Total SCAP and SCC for different levels of internalization and emission factor assumptions

We can shortly summarize the main trends when looking at different internalization strategies. First, SCC internalization fosters gas-CCS and bio-CCS. Gas-CCS and bio-CCS are powerful technologies to mitigate CO_2 emissions but still additionally emit air pollutants to some extent that come at their very own costs. Second, SCAP internalization hampers gas-CCS and bio-CCS at the benefit of nuclear power. Such a specification accounts for considerable air pollution and related social cost of CCS technologies. Besides nuclear, the other emission-neutral solutions are wind and solar. However, current technological projections (potential, full-load hours, cost) limit the expansion of wind and solar and require nuclear capacity to fill the gap to annual demand (that more than doubles to around 6.700 TWh in 2050). Third, wind and solar shares are almost unaffected due to expansion limits and technological projections of those technologies. We conclude that internalization of SCAP is not a complement for the internalization of SCC. In total, SCC are around the factor 5 more relevant (see the scale of the axes in Figure 2) and thus the internalization of SCC dominates the system. However, only SCC is also a poor complement for SCAP as soon as bio-CCS becomes relevant. Bio-CCS provides negative CO_2 emissions at cost of high air pollution (and related cost). So, bio-CCS drives the adverse behavior of internalizing SCC and SCAP, while finally the internalization of SCC is more important for ending in a cost optimal system.

5.2. Varying Emission Factors

We now focus on specifications (4), (5), and (6) in Figures 1 and 2 to analyze the role of assumptions about emission factors. Remember from Subsection 4.1 that current and future technologies differ in air pollution emission factors. The CO_2 emission factor follows from the carbon content of the underlying fuel and predictions of those are quite consistent across different studies. Predictions about air pollutants in turn are not. We thus analyze the three diverging assumptions described in Subsection 4.1. The *mid* assumptions serve as benchmark as in the prior subsection.

Start with *low*. Lower air pollution emission factors decrease the role of SCAP in internalizing social cost because technologies become cleaner. The effect grows over time because the emission factor differential increases from 2020 to 2050 compared to *mid* assumptions. Difference in the expansion of wind and solar capacity and related generation are negligible. In turn, bio-CCS and gas-CCS play a bigger and nuclear a smaller role. Bio-CCS is almost used to its maximum potential (351 TWh or 3% higher generation share in 2050, compared to 147 TWh). Gas-CCS generation share is 1.2% higher and nuclear share 3.4% lower. Higher CCS usage comes at higher air pollution (NO_x +52%, SO_2 +128%, $PPM_{2.5}$ +29%) and higher related social cost (+108%, +217%, +125%). CO_2 emissions in turn are at -0.19 Gt.

High emission factors again do not impact wind and solar deployment. In turn, bio-CCS share drops to 0.4%, gas-CCS remains almost constant at 11%, and nuclear share increases to 35.4% in 2050. Final CO_2 emissions are at 0.03 Gt and thus the entire system is still almost carbon neutral. However, air pollution is fundamentally lower, mainly due to less bio-CCS, and related 2050 social cost sum up to 4 billion €. Interestingly, combined social cost (total SCC plus total SCAP) are lowest for the *high* emissions assumptions.

Intuitively, lower emission factors should lead to lower emissions and higher ones to higher emissions. We reveal how this intuition is wrong. Lower emission factors promote the expansion of air pollution emission-intensive technologies (such as bio-CCS and gas-CCS), leading to more pollution and more social cost. In turn, higher emission factors in turn hamper the deployment of bio-CCS so that final air pollution and related social cost are lowest. Again, wind and solar deployment is almost unaffected. However, nuclear generation differs by considerable amounts (2050 generation shares of 30.5%, 33.9%, and 35.4% for low, mid, and high emission factor assumptions).

5.3. Varying Social Cost of Carbon

Now, we test the sensitivity of results regarding the SCC level additionally applying 25%, 50%, 200%, 400%, and 800% of the SCC level in SCC and SCAP (mid) (see Figures C.10 to C.12 in Appendix C.2 for visualization).

SCC 25% (carbon price below 90 € in 2050) is insufficient for introducing CCS technologies. In turn, conventional gas technologies substitute for gas-CCS and substantial parts of nuclear generation, making up a generation share of 27% in 2050 (45% in 2020). Wind (solar, nuclear) share increases from 25% (4%, 11%) in 2020 to 39% (10%, 18%) in 2050. CO_2 emissions even increase from 0.61 Gt in 2020 to 1.04 Gt in 2035 and then drop to 0.61 Gt in 2050 again. For SCC 50% (carbon price of around 175 € in 2050), gas-CCS is employed from 2045 onwards but its generation share is only at 7% in 2050 (compared to 11% for our benchmark SCC and SCAP (mid)). Wind (solar, nuclear) contributes 40% (7%, 32%) in 2050, and is thus already quite close to the benchmark case with 38% (7%, 34%). Interestingly, bio-CCS is not in the system whereas our benchmark has 2.2% of generation from bio-CCS. Thus, it requires intertemporal carbon tax rates between 175 and 350 €/ton to induce a small amount of bio-CCS in 2050. Increasing SCC values to 200%, 400%, and 800% increases bio-CCS (up to its maximum potential, 5% generation share in 2050) and nuclear at cost of gas-CCS. Wind and solar remain almost unaffected with shares of 38% (41%, 41%) and 6% (6%, 6%) in 2050 for SCC 200% (400%, 800%). Nuclear and gas-CCS make up to 35% and 9% in 2050 for SCC 200%. 2050 gas-CCS share is fundamentally lower at 2% (2%) and nuclear share higher at 39% (41%) for 400% (800%). 2050 CO_2 emissions are at 0.19 Gt for SCC 50% (-0.05 for in our benchmark) and drop even further in SCC level to -0.23 Gt (-0.26 Gt, -0.26 Gt) for SCC 200% (400%, 800%).

Note that wind shares do not differ much across SCC levels (between 38% and 41%). Despite 10% solar generation for SCC 25%, fostered by higher conventional gas capacity, solar is at a similar level as well. Remaining differences lie in the employment of CCS technologies and nuclear. Interestingly, higher SCC level do not automatically foster gas-CCS. Gas-CCS shares first increase in higher SCC levels but then drop for very high SCC levels again because gas-CCS still emits CO_2. In turn, nuclear as carbon-neutral technology is highest for highest SCC level, whereas the bio-CCS share already reaches its maximum for carbon prices between 350 and 700 €/ton so that CO_2 does not drop much further when increasing SCC above 200% of the benchmark value.

Total SCC are directly proportional to the CO_2 emission and the corresponding SCC level, that is, highest for SCC 25% (9 billion € in 2050) and lowest for SCC 800% (-130 billion € in 2050). More interestingly, total SCAP differ fundamentally between SCC levels and even show some non-linear effects. Total SCAP is at 6 billion €in 2050 for SCC 25%, drops to 3 billion € for SCC 50%, increases to 6 billion € for our benchmark again, and then heavily increases to 19 (18, 17) billion € for SCC 200% (400%, 800%) due to full bio-CCS usage.

We conclude that the CCS-nuclear substitution effect is not valid anymore for very high SCC levels. However, our previous finding that solar and wind shares are almost unaffected across specifications holds for different SCC levels as well. Moreover, total SCAP are again dominated by bio-CCS deployment.

5.4. Varying Social Cost of Air Pollution

Despite careful calibration, some uncertainty remains regarding SCAP. We address this uncertainty by testing on modified SCAP. We thus mirror the sensitivity in the prior subsection by applying the same sensitivity magnitudes on SCAP (see Figures C.13 to C.15 in Appendix C.3 for visualization).

SCAP 25% (50%) lead to full usage of the biomass potential (5% generation share) from 2045 onwards (in 2050). Our benchmark (SCAP 200%) still applies some bio-CCS with 2050 generation share of 2.2% (1.5%). Higher SCAP in turn prevent bio-CCS from being part of an optimized system. Gas-CCS contributes 15% (12%, 11%, 7%, 3%, 2%) and nuclear (26%, 29%, 34%, 38%, 42%, 43%) for SCAP 25% (50%, our benchmark, 200%, 400%, 800%). Wind (38% for SCAP 25%, 42% for SCAP 800%) and solar (8% for SCAP 25%, 6% for SCAP 800%) are almost unaffected from changing SCAP levels. Final CO_2 emissions are driven by bio-CCS shares. SCAP 25% and 50% reach -0.2 Gt and -0.19 Gt, our benchmark and SCAP 200% are slightly negative at -0.05 and -0.02 Gt, and finally SCAP 400% and 800% are almost carbon neutral at 0.04 Gt. There is adverse behavior of air pollution emissions, that is, air pollution emissions are highest when CO_2 emissions are lowest (for SCAP 25% and 50%) and lowest when CO_2 are highest (for SCAP 400% and 800%). In turn, resulting total SCAP demonstrate non-linear behavior. 2050 total SCAP double from 5 to 10 billion € when doubling SCAP levels from 25% to 50%. Remember that 25% and 50% both use the entire biomass potential, resulting in similar final emissions but double total SCAP for the 50% specification. Our benchmark (SCAP 200%) lead to 6 (7) billion € total SCAP. Bio-CCS share is higher for our benchmark but cost higher for SCAP 200%. The resulting total SCAP level is thus similar. Finally, SCAP 400% and 800% have lowest 2050 total SCAP (2.8 and 3.4 billion €) due to similar technology mix driven by no bio-CCS deployment.

Varying SCAP mainly impacts the deployment of bio-CCS, gas-CCS, and nuclear. Lower SCAP foster CCS deployment. Higher SCAP in turn lead to more nuclear. Note that this CCS-nuclear trade-off is quite important although the final CO_2 emissions do not differ much in absolute terms. Those results are in line with those for internalization decomposition and lower/higher emission factors but differ from the sensitivity of SCC.

5.5. Technology Boost

We observe fairly constant 2050 wind deployment across internalization strategies (38% for *Only SCC* and *SCC and SCAP (mid)*), emission factor assumptions (37% for *low*, 39% for *high*), SCC sensitivity (39% for SCC 25% and 41% for SCC 800%), and SCAP sensitivity (38% for SCAP 25%, 42% for SCAP 800%). This almost constant deployment indicates that the economically usable potential of wind (see Table A.17 in Appendix A.7 for theoretical potential by resource class by country) does not differ much from the underlying specifications and in turn promotes nuclear expansion (2050 generation share of 34% in our benchmark specification *SCC and SCAP (mid)*). We test for this effect by introducing a technology boost in 2040, that is, wind turbines are now up to 140 meters high delivering higher full-load hours (FLH) than before (see Tables A.18 and A.19 in Appendix A.7).

In EUREGEN, wind expansion (for onshore and offshore) works with potentials reflecting high, mid, and low resource classes. By assumptions, high and low resource class are of the same size, whereas the mid class is three times the size. Full-load hours (FLH) and timeseries of respective wind turbines follow from this assumption. It is possible that countries with high wind speeds have higher FLH in their mid or low resource class, respectively, than countries with low wind speeds in their high resource class.

Table 7 shows the total theoretical potential by class as well as corresponding average (potential-weighted) FLH. Observe that total wind onshore (offshore) potential in the *high* resource class is 585 GW (1,724 GW). The potential above 3,000 FLH (4,250 FLH) is just 275 GW (0 GW), whereas 2050 capacity in our benchmark specification is at 898 GW (58 GW). Thus, wind offshore potential is rarely used but wind onshore potential quite extensively (there is no wind capacity installed in the low class). The technology boost increases this potential to 946 GW (288 GW), where *high* FLH increase by 23% (13%) in the high class and by 49% (4%) in the mid class.

Table 7: Potential and full-load hours of wind technologies by resource class (low, mid, high) without and with technology boost

Resource class	low	mid	high
Wind offshore			
Total theoretical potential (GW)	1,724	5,178	1,724
Potential (GW) $\geq$ 4250 FLH without boost	0	0	0
Potential (GW) (GW) $\geq$ 4250 FLH with boost	0	0	288
Average FLH without boost	1,450	2,135	2,601
Average FLH with boost	1,577	2,230	2,937
Difference in FLH	8.78%	4.42%	12.93%
Wind onshore			
Total theoretical potential (GW)	585	1,756	585
Potential (GW) $\geq$ 3000 FLH without boost	0	0	275
Potential (GW) $\geq$ 3000 FLH with boost	50	487	409
Average FLH without boost	1,089	1,725	2,898
Average FLH with boost	1,776	2,578	3,558
Difference in FLH	63.08%	49.49%	22.78%

Now we look at the outcome (capacities, generation, emissions, social cost) when modeling the technology boost (see Figures C.16 to C.18 in Appendix C.4 for visualization). 2050 wind capacity increases to 1,457 GW (1,340, 1,396 GW, 1,488 GW) for *SCC and SCAP (mid)* (only SCC, low, high), reflecting generation shares of 64% (60%, 62%, 65%) . Nuclear in turn drops to 14% (8%, 11%, 15%) compared to 34% (22%, 31%, 35%). Thus, the final realization of wind (and eventually also solar) shares depends on technological assumptions and thus substitutes for nuclear. However, the overall pattern, particularly regarding social cost and emissions, remains consistent despite the reduced role for nuclear and the increased one for wind.

6. Discounting and Taxation in Intertemporal Optimization Frameworks

We discuss the impact of different discount rates and optimal taxation in intertemporal optimization frameworks already in Subsection 4.3. Previously, we assume that firms discount cash flows with 7% and the social planner SCAP with 3% and SCC with 1.5%. Resulting carbon taxation is shown in the last line of Table 8, i.e., 2050 SCC of 62 €/ton translate into an optimal carbon tax of 354 €/ton.

We now analyze three specifications with homogeneous discount (and interest) rates for firms' cash flows, SCAP, and SCC but differ the level, i.e., 7/7/7 applies 7% discount and interest rates for all three categories, 3/3/3 applies 3%, and 1.5/1.5/1.5 applies 1.5%. We obtain carbon prices presented in the first line of Table 8. We additionally analyze three specifications with heterogeneous discount factors (applying 7% interest rate). 7/3/3 applies 7% discount rate for firms' cash flows and discount SCC as well as SCAP at 3%. The resulting carbon tax is shown in the second line of Table 8. 7/1.5/1.5 discounts SCC and SCAP at 1.5% resulting in a carbon tax as shown in the third line of Table 8 but structurally higher taxes for air pollution emissions. 7/3/1.5 is our benchmark specifications (and marked with *** in the following) with the same carbon tax as 7/1.5/1.5.

Table 8: Optimal carbon tax (€/ton) for different discount rates for firms' cash flows and SCC

	2020	2030	2040	2050
Equal discount rates	27.71	36.18	47.61	62.30
7% vs. 3%	30.95	59.14	113.93	218.23
7% vs. 1.5%***	32.32	71.53	159.55	353.90

***7% vs. 1.5% is the specification applied in our benchmark specification SCC and SCAP (mid).

Let us start with the three specifications applying homogeneous rates. Differences between those specifications can be traced back to the absolute level of discount rates.[11] Figure 3 mirrors Figure 1 for the changed discount rate specifications. Observe that the overall amount of installed capacity is highest for 1.5/1.5/1.5 (2,581 GW in 2050) and lowest for 7/7/7 (2,387 GW). Intuitively, discounting cash flows at lower rates places more emphasis on later generation cost than on early investment cost. Thus, investments (and total installed capacity) increase with lower rates from 2020 onwards, and the differences remain consistent, although they drop over time. Wind capacity increases from 487 GW (448 GW, 373 GW) in 2020 to 1,072 GW (1,005 GW, 797 GW) in 2050

[11] We also change interest rates at the same level as private discount rates, but the impact of diverging interest rate is negligible for early investments and only minor for later ones.

for 1.5/1.5/1.5 (3/3/3, 7/7/7), whereas solar capacity is around 550 GW in 2050 for all three specifications. Further structural differences exist in the level of nuclear (146 GW in 2050 for 1.5/1.5/1.5 vs. 49 GW for 7/7/7) and gas (686 GW vs. 872 GW). 2050 wind generation shares are 41% (39%, 33%) for 1.5/1.5/1.5 (3/3/3, 7/7/7), those of nuclear 16% (15%, 4%), and those of solar at 10% (11%, 11%). Gas contributes 26% (29%, 46%) in 2050. CCS technologies are not part of the mix for all three specifications because carbon prices following from homogeneous rates (see first line in Table 8 in Subsection 4.3) are not sufficient to induce CCS technologies. Lower air pollution taxes (that generally foster CCS deployment) are thus not dominating in establishing CCS technologies. 2050 CO_2 emissions are at 0.59 Gt (0.62 Gt, 1.02 Gt). Looking at social cost in Figure 4, 2050 total SCAP are at 5 (6, 10) billion € and 2050 total SCC at 37 (41, 64) billion € for 1.5/1.5/1.5 (3/3/3, 7/7/7). The composition of social cost does not change much over time and in between different levels of homogeneous rate specifications because no CCS technologies are employed. Observe that SO_2 cost drop out due to the phase out of coal.

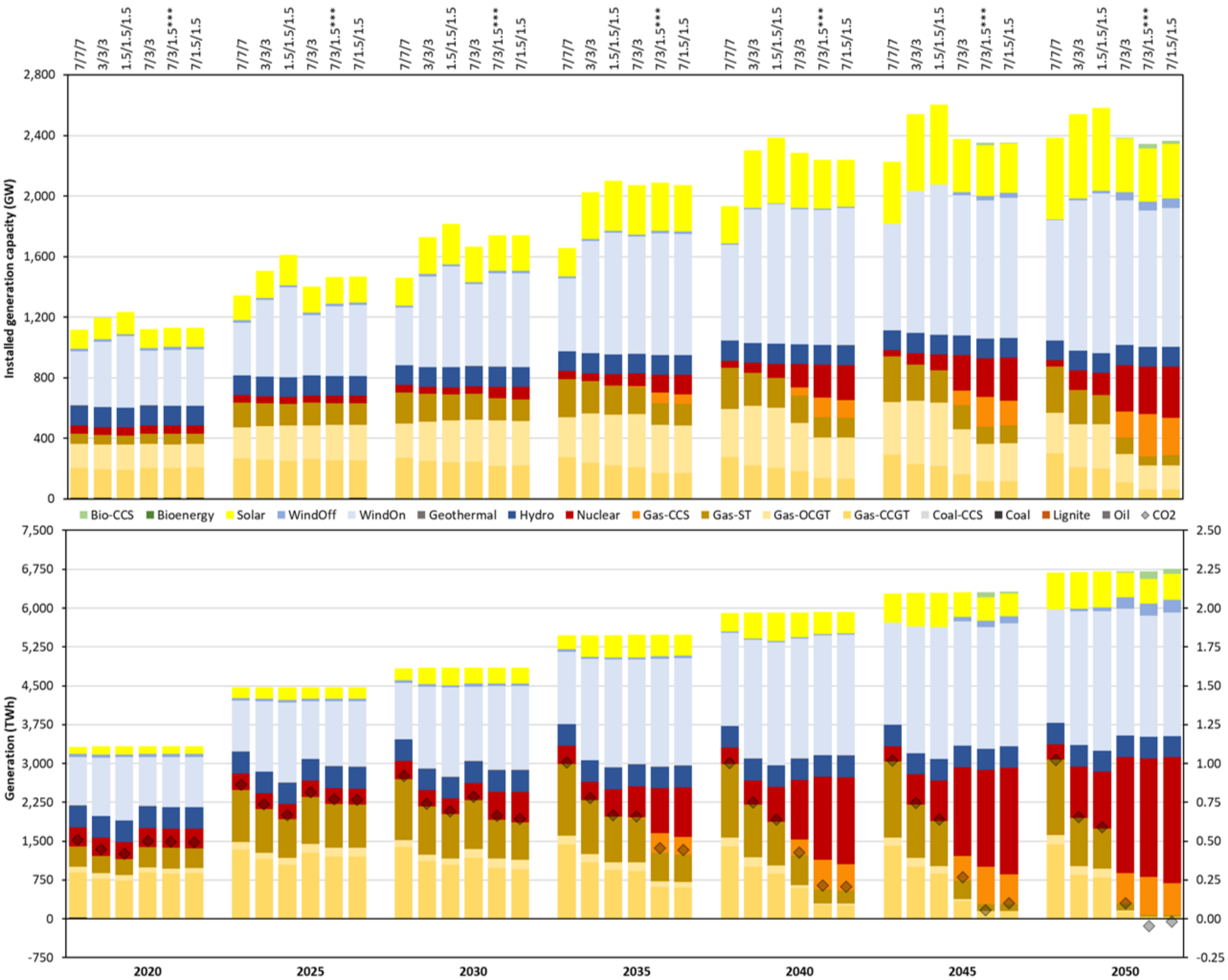
Now consider the three specifications with heterogeneous rates. Wind, solar, and nuclear capacities are at similar 2050 levels (around 1,000 GW, 355 GW, and 320 GW), leading to generation shares of 40% (38%, 39%) for wind, 7% (7%, 7%) for solar, and 33% (34%, 36%) for nuclear for 7/3/3 (7/3/1.5, 7/1.5/1.5). Bio-CCS contributes 0.5% (2.2%, 1.5%) and gas-CCS 9% (11%, 9%) in 2050. Those small differences in the technology mix yield CO_2 emissions of -0.02 Gt (-0.05 Gt, 0.1 Gt). Absolute levels (3, 6, and 4 billion €) of total SCAP in turn fundamentally differ due to diverging CCS shares. Carbon taxes of 218 €/ton (7/3/3) are indeed sufficient to introduce a small amount of bio-CCS. The bio-CCS share drops when applying lower discount rates for SCAP (7/1.5/1.5) because air pollution damages are weighted higher.

The lower carbon price is the main driving force behind differences between homogeneous and heterogeneous discount rates. Lower discount rates in general foster decarbonization by expanding wind capacity and nuclear capacity, whereas higher rates rely more on conventional gas. Remember that 7/3/3 induces lower carbon prices than 7/3/1.5 and 7/1.5/1.5 (almost by factor 2). However, resulting decarbonization and technology mix differ only slightly because bio-CCS shares remain small and economically best wind potentials are already used.

7. Distributional Effects and the Role of Biomass

7.1. Distributional and Growth Effects

Country differences in SCAP are based on the meteorological and geological conditions but also demographics (age structure, population density, health system). SCAP differences neglect diverging welfare across countries due to ethical reasons. The default life cycle analysis assumes that all countries face the same value for disabled adjusted life years (DALY). Indeed, GDP per capita normally serves as a benchmark to determine diverging DALY per country. Moreover, SCAP grow country-specifically with GDP per capita. Finally, we avoid arbitrage effects by equalizing SCAP across all regions by applying an electricity demand-weighted average of regional SCAP. Based on these facts, we develop five additional specifications beside our benchmark to analyze distributional effects: (2) *SCAP equal* neglects country differences in SCAP by using average

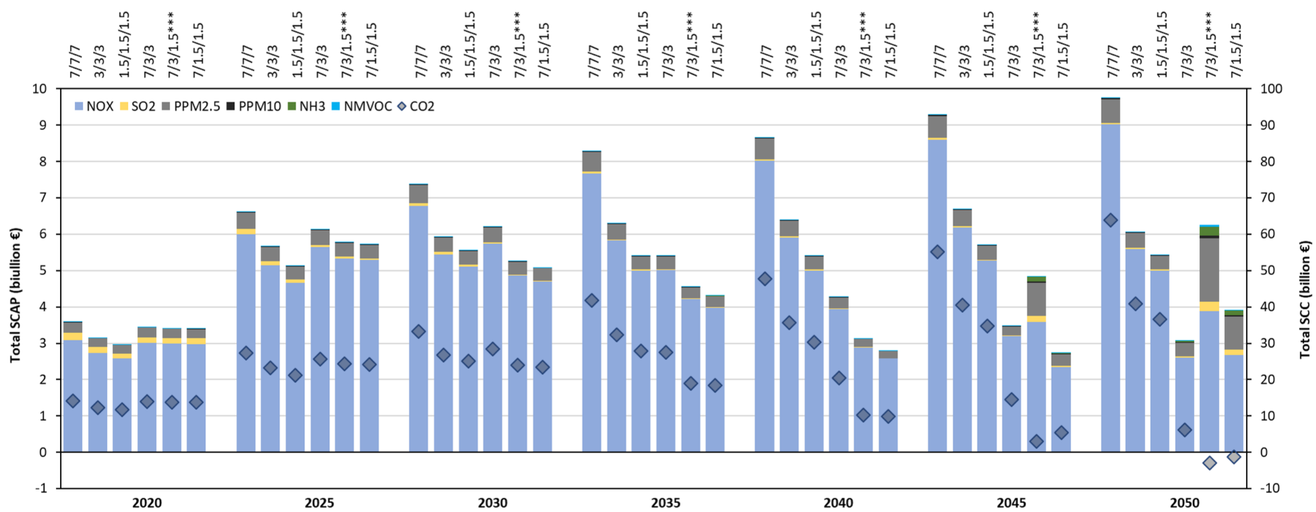


***7/3/1.5 is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure 3: Installed capacity (upper panel) and generation with CO2 emissions (lower panel) for different discount and interest rates

(demand weighted) SCAP for each country. (3) *SCAP distributional* adjusts SCAP accordingly to a index reflecting GDP per capita differences, i.e., countries with higher GDP per capita face higher (see Table A.13 in Appendix A.5) SCAP due to higher assumed DALY. (4) *SCAP equal and distributional* combines the two previous ones by taking average SCAP and then scale those simply by the index reflecting GDP per capita differences. (5) *SCAP no GDP growth* neglects that SCAP rise with GDP per capita, i.e., SCAP are constant for each country over time. Finally, (6) *SCAP equal and no GDP growth* takes the same SCAP for every country for all time periods.

Figures 5 to C.20 show installed capacities, generation, CO_2 emissions, social cost, and air

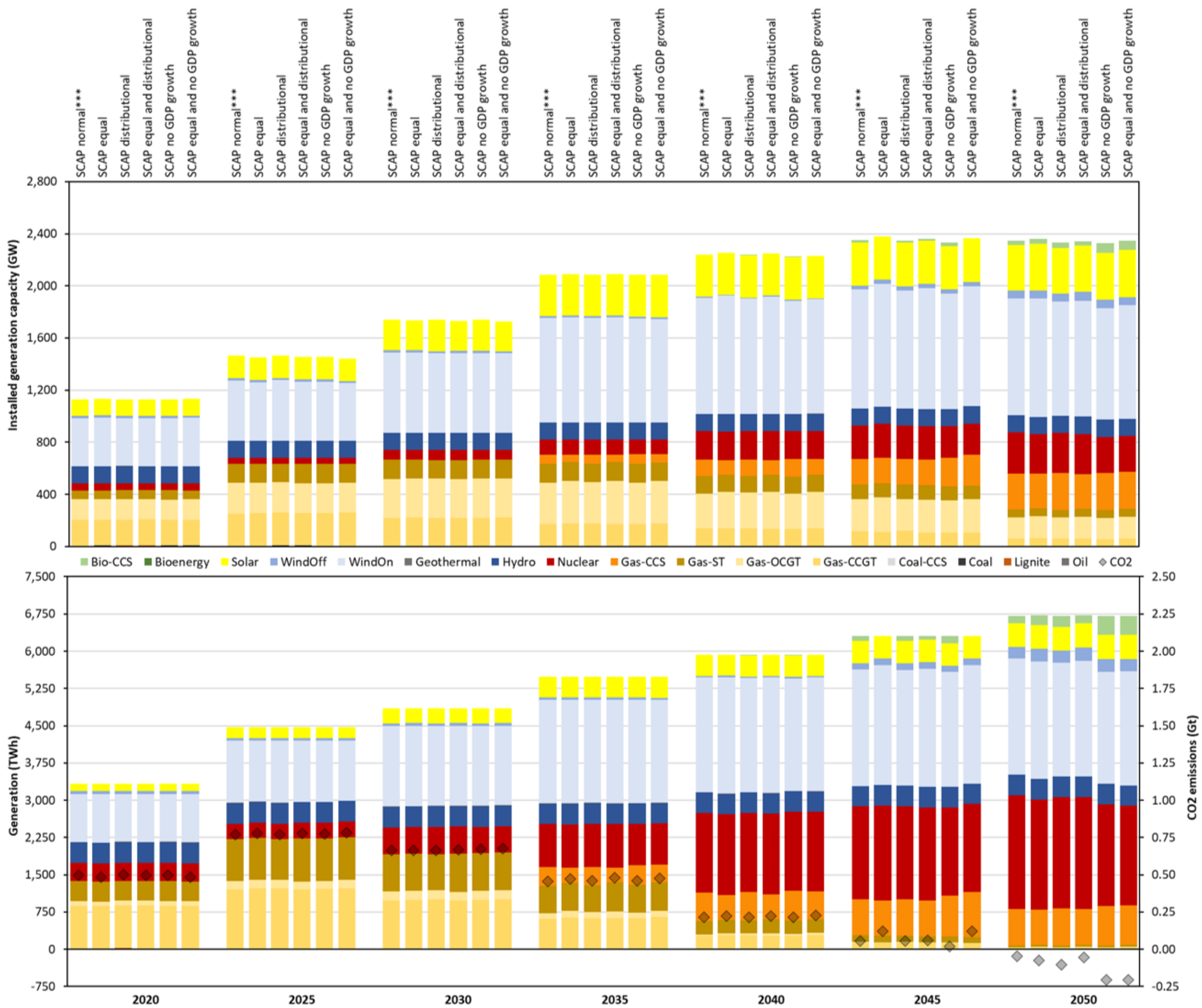


***7/3/1.5 is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure 4: Total SCAP and SCC for different discount and interest rates

pollution for the six specifications. SCC and SCAP (mid) serves as benchmark again and is called *SCAP normal* for parsimony in the following and marked by *** in Figures5 to C.20. In 2050, remember that installed wind (solar, bio-CCS, nuclear, gas-CCS) capacity is 957 GW (352 GW, 30 GW, 314 GW, 279 GW) and the corresponding generation share is 38% (7%, 2.2%, 34%, 10.9%), resulting in -0.05 Gt CO_2 emissions, -3 billion € total SCC and 6 billion € total SCAP, whereas SCAP are dominated by NO_x and $PPM_{2.5}$ damages.

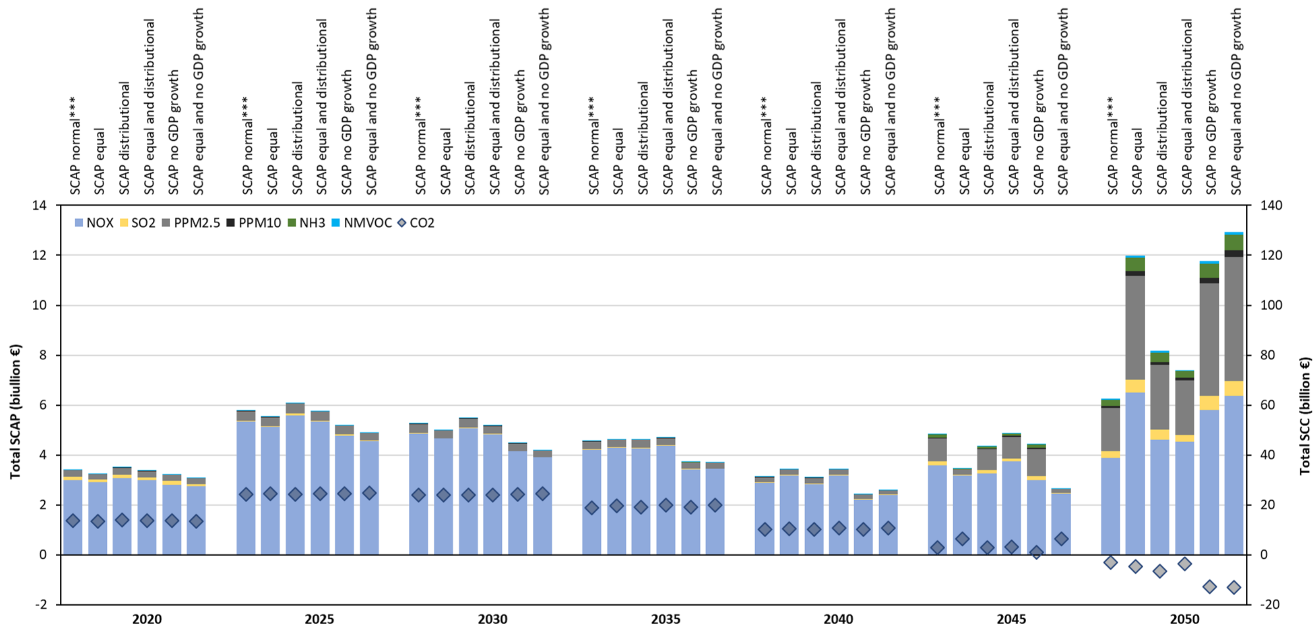
Now turn to the analysis of *SCAP equal*. Intuitively, equalizing SCAP across countries reduces SCAP of "very expensive" countries and increases those of "cheaper" ones. As result, there are less arbitrage effects, that is, producing with "dirty" SCAP technologies (i.e., bio-CCS and gas-CCS) in cheap countries. At first sight, hardly any relevant differences in capacity and generation mix can be observed between the different specifications until 2040. Even in 2050, the differences in system composition appear only minor. For example, 2050 wind (solar, bio-CCS, nuclear, gas-CCS) capacity grows by +12 GW (+7 GW, +10 GW, -11 GW, -14 GW). Final generation share is at 39% (7%, 2.8%, 33%, 10.6%) and CO_2 emissions are at -0.08 Gt. We observe slightly more bio-CCS but less gas-CCS. However, looking at the associated emissions and their social costs, the specifications can be clearly distinguished from one another. Total SCAP double to 12 billion €, whereas overall air pollution just increases by 16% from 0.6 to 0.7 Mt. This effect can be explained by the model's near-lacking ability under equalized SCAP to arbitrage between regional SCAP levels when making location choices for pollution intensive generation capacities. Thus, the aforementioned intuition is not wrong, but effects are more diverse. When looking just at capacities and generation, one might neglect the overall impact of taking equalized SCAP for each country. However, total SCAP show that arbitrage effects play a fundamental role because the doubling of total SCAP is not reflected in total generation share changes and air pollutant emissions.



***SCAP normal is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure 5: Installed capacity (upper panel) and generation with CO2 emissions (lower panel) for different SCAP specifications

The next specification, *SCAP distributional*, constrains arbitrage opportunities (for SCAP) compared to the benchmark but does not remove them altogether (as does *SCAP equal*). In 2050, wind (solar, bio-CCS, nuclear, gas-CCS) capacity drops by 21 GW (-1 GW, +13 GW, -5 GW, +2 GW) and the corresponding generation share is 38% (7%, 3.4%, 33%, 11.1%). Intuitively, we expect that the SCAP differences across countries and thus arbitrage effects grow, resulting in higher air pollution but lower overall social cost. This intuition is wrong. Air pollution is higher at



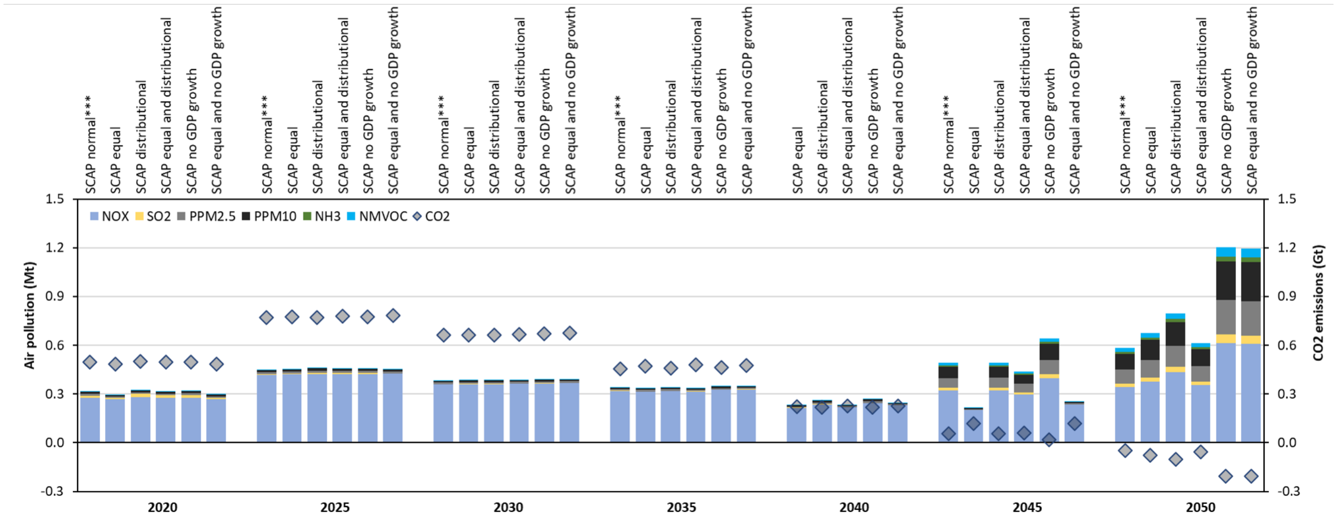
***SCAP normal is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure 6: Total SCAP and SCC for different SCAP specifications

0.8 Mt (compared to 0.6 Mt in our benchmark, +37%) and resulting total SCAP grow by a similar level to 8 billion € (+31%). However, higher shares for CCS technologies and higher air pollution indicate that overall arbitrage effects grow slightly, making CCS technologies more competitive. As a result, constrained SCAP arbitrage opportunities drive the need for negative SCC, so that we likewise observe slightly increased bio-CCS capacities as it is the case for *SCAP equal*.

When combining equalized SCAP and distributional effects, as done in *SCAP equal and distributional*, we observe that 2050 wind (solar, bio-CCS, nuclear, gas-CCS) capacity remains constant (+6 GW, +1 GW, -3 GW, -12 GW) and its generation share is at 39% (7%, 2.4%, 33%, 10.8%). Air pollution is comparable to our benchmark (0.6 Mt) but fundamentally lower compared to *SCAP distributional*. However, total SCAP are at 7 billion € and thus higher than our benchmark but lower than *SCAP distributional*. It appears that jointly applying two dimensions that work in opposite directions (regarding fostering or hampering arbitrage effects related to air pollution) leads to a slightly cleaner system. Equalized SCAP reduce air pollution and distributional effects reduce related total SCAP.

Now turn to the specifications neglecting GDP growth. Start with *SCAP no GDP growth*. 2050 wind (solar, bio-CCS, nuclear, gas-CCS) capacity drops by -37 GW (+11 GW, +44 GW, -36 GW, +7 GW) and generation share is at 37% (7%, 5.5%, 30%, 11.9%). We now observe that SCAP indeed impact wind deployment to the benefit of CCS technologies. Neglecting GDP growth leads to fundamentally lower SCAP values in 2045 and 2050, so that bio-CCS is used to its maximum potential and gas-CCS capacity/shares likewise increase fundamentally. Final



***SCAP normal is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure 7: Air pollutant and carbon emissions for different SCAP specifications

air pollution emissions are at 12 Mt and related social cost at 12 billion €. When additionally applying equalized SCAP, as done in *SCAP equal and no GDP growth*, we obtain wind (solar, bio-CCS, nuclear, gas-CCS) capacity changes of -21 GW (+9 GW, +39 GW, -38 GW, +4 GW) and shares of 38% (7%, 5.6%, 30%, 11.9%). Observe that generation differences between the two GDP growth specifications are negligible, as is related air pollution, but total SCAP are higher, again indicating that arbitrage effects of producing in "cheap" countries are reduced.

To summarize, we again observe a structural CCS-nuclear shift when SCAP become effectively lower (distributional scaling, no GDP growth). Interestingly, there is a small wind substitution effect when applying no GDP growth. SCAP values are then fundamentally lower, and CCS technologies far more competitive. Overall, the effect of taking equalized SCAP across countries impact the technology mix and related air pollution only to a minor extent but shows considerable impact when looking at total SCAP. However, benefits from reducing carbon emissions still partially outweigh changes in SCAP because total SCC are higher in magnitude until 2045 (and similar in 2050).

7.2. Biomass Limits and Trade

Biomass, its costs, and the maximum usage are key for sustainable development due to biomass with carbon capture and storage (bio-CCS). Such technology uses carbon-neutral biomass and additionally (captures and) stores CO_2 so that the final CO_2 emission factor is negative. Assuming an efficiency of 16%, the resulting factor is -0.71 ton/MWh electric. Indeed, cost assumptions, assumptions about the efficiency, and emission factor assumptions are important, but decisive for the role of bio-CCS for future decarbonization is the biomass limit eligible for usage in electricity generation. Our standard calibration assumes a European wide biomass limit of 2,045 TWh per year (resulting in generation of around 376 TWh for the 2050 vintage). We compile long-term economic annual harvesting potentials for agricultural, wooden, and waste biomass from Scarlat et al. (2011), Dees et al. (2017) and Thees et al. (2017) and convert them to biomass potentials. The country-level values and related maximum generation are depicted in Table A.20 in Appendix A.8.

We take our benchmark and vary the regional biomass limit by factors two and four, respectively. We also provide for biomass tradability across Europe, allowing for arbitrage effects when trading biomass from an "expensive" into a "cheap" (in terms of SCAP) country. Additional to our benchmark, we analyze five specifications: *European trading* takes the standard biomass limits and allows for trading across Europe. *Double regional* takes the twofold limits. *Double European trading* allows to trade the twofold limits. *Fourfold regional* take the fourfold limits. Finally, *Fourfold European trading* makes it possible to trade the fourfold limits. Note that there is no direct trade costs. Visual results are shown in Figures C.21 to C.23 in Appendix C.7.

Higher regional biomass limits allow "cheap" countries already using their maximum potential to increase biomass usage and related bio-CCS production. Increasing the limits by factor two (four), increases 2050 bio-CCS capacity from 30 GW to 59 GW (111 GW) and the related generation shares from 2.2% to 4.4% (8.7%). Thus, doubling the limits doubles capacity and generation, but does not enforce maximum usage. Allowing for European trade of biomass with simple (double, fourfold) limits increase capacity to 71 GW (128 GW, 249 GW) and generation share to 5.4% (10,8%, 21.7%). Subsequently, the entire European potential is used by trading it into the "cheap" countries that used completely its regional potential already. Interestingly, higher bio-CCS usage reduces nuclear generation from 34% to 32% (33%, 30%, 31%, 25%) and gas-CCS generation from 10.9% to 10.7% (10.5%, 10.2%, 10.1%, 9.3%) for *European trading* (*Double regional*, *Double European trading*, *Fourfold regional*, *Fourfold European trading*). Interestingly, even wind shares drop from 38% to 37% (38%, 35%, 36%, 30%). Final CO_2 emissions are hugely negative due to massive bio-CCS usage (-1 Gt *Fourfold European trading*). Air pollution emissions are negatively correlated to CO_2 emissions, since low CO_2 emissions due to high bio-CCS usage come at high air pollutant emissions.

However, resulting total SCAP does not fully reflect air pollutant emissions due to tremendous arbitrage effects when allowing for European biomass trade. Thus, the European-wide trade of biomass (instead of just using just the regional limits) increases arbitrage effects, that is, biomass would be traded in "cheap" countries so that resulting total SCAP are reduced. Moreover, bio-CCS substitutes for gas-CCS, nuclear, and even wind power. This substitution effect is not observed in the prior analysis.

7.3. Biomass Trade and Arbitrage

Bio-CCS appeared to be a key lever in the model's ability to steer social cost via earnings from negative CO_2 emissions. In particular, arbitrage effects when using biomass in "cheap" countries (with regard to SCAP) are considerably important. We test the prior findings by running the same specifications (limits, tradability) as before but assume equalized SCAP. This reduces SCAP arbitrage opportunities especially in the specifications with trade.

2050 bio-CCS shares now increase from 2.8% (in the *SCAP equal* specification) to 5.5% (5.4%, 11.2%, 9.8%, 13.7%) compared to 2.2% to 5.4% (4.4%, 10.8%, 8.7%, 21.7%) for *European trading* (*Double regional*, *Double European trading*, *Fourfold regional*, *Fourfold European trading*). Interestingly, bio-CCS shares without European trade are even higher than for normal SCAP. Conversely, the impact of trade is now much lower. *Fourfold European trading* delivers only 13.7% generation compared to the previous 21.7%. Thus, the overall biomass potential is no longer fully exploited.

8. Discussion

Diverging total social cost (of carbon and air pollution) and substitution effects between technologies are the key differences of the analyzed specifications. We thus compare aggregated social cost in Subsection 8.1 and cluster substitution effects according to resulting CO_2 and air pollutant emissions in Subsection 8.2.

8.1. Aggregated Social Cost

Table 9 presents aggregated social cost from air pollutant and CO_2 emissions for the 35 years from period 2020 to period 2050, thereby considering that each period reflects five years, for selected specifications.[12] Start with the first group that contains information about internalization strategies and the technology boost. Observe that aggregated social cost are at 5,145 billion € for *no internalization*. Internalizing *only SCAP (mid)*, reduces cost by more than 60%. However, accounting for *only SCC* reduces aggregate social cost to 794 (compared to 2,091 for only internalizing SCAP). Consequently, SCC internalization plays a dominating role in the reduction of social cost. However, only internalizing SCAP results in fundamentally lower aggregated SCAP (330 billion € compared to 449 billion € for *only SCC*). Combining both internalization strategies in *SCC and SCAP (mid)* engenders additional benefits for aggregated SCAP (that reduce to 166 billion €), whereas aggregated SCC increase from 345 to 456 billion € (compared to *only SCC*). Only internalizing SCAP is thus a bad complement for SCC internalization but additional SCAP internalization a useful tool to reduce social cost. Interestingly, when applying the technology boost (that increases 2050 wind shares from 38% to 64%) aggregate social cost even increase by 7 billion € due to slightly higher bio-CCS and gas-CCS usage (whereas shares of other SCC- and SCAP-free technologies such as nuclear drop).

Now turn to discounting and intertemporal taxation in the second block. We selected 7/7/7, 7/3/3, and 7/1.5/1.5 due to their diverging underlying optimal tax rates (see Table 8 in Section 6). 7/7/7 implements lowest tax rates (for CO_2 and air pollution) and increases aggregated social cost to 1,684 billion €. The increase mainly stems from increasing SCC (1,416 billion €). Intuitively, the tax drop for SCAP is less pronounced than for SCC because SCC is discounted with 1.5% and SCAP with 3% in our benchmark. 7/3/3 just increases the discount rate for SCC, leading to similar aggregated SCAP but considerably higher aggregated SCC (683 vs. 456 billion €). Finally, increasing tax rates for air pollution emissions (discount rate of 1.5% instead of 3%)

[12] Tables B.21 and B.22 in Appendix B.1 present the full set of specifications.

Table 9: Aggregated social cost (billion €) from period 2020 (2016 to 2020) to 2050 (2045 to 2050)

	SCAP	SCC	Sum
Internalization and technology boost			
No internalization	1,494	3,650	5,145
Only SCAP (mid)	330	1,761	2,091
Only SCC	449	345	794
SCC and SCAP (mid)***	166	456	622
SCC and SCAP (mid) with boost	153	476	629
Discounting and taxation			
7/7/7	268	1,416	1,684
7/3/3	160	683	843
7/1.5/1.5	140	468	608
Distributional effects, biomass limits, and trade			
SCAP equal	186	469	656
SCAP distributional	177	441	618
European trading	187	356	543
Double regional	194	404	598
Double European trading	243	205	448
Fourfold regional	249	302	551
Fourfold European trading	345	-35	310
Fourfold European trading and SCAP equal	359	304	662

***SCC and SCAP (mid) is the same as 7/3/1.5 and regional biomass limits. SCC and SCAP (mid) serve as benchmark for comparisons with other specifications.

changes aggregated SCAP only slightly to 140 billion €. Aggregated social cost remain almost unaffected. Discount rates strongly impact the resulting technology mix and the related emission levels, but aggregated SCC react more sensitively towards changes. Again, this underlines the dominance of SCC in contrast to SCAP for the optimal technology mix and emission levels, and the complementing feature of additional SCAP internalization.

Finally, equalized SCAP and distributional effects impact aggregate social cost only to a minor extent. *SCAP equal* increases social cost by 34 billion € (Compared to the benchmark). *SCAP distributional*, that is, higher SCAP level for richer countries, in turn even reduces aggregated social cost by 4 billion €. Biomass limits and tradability of biomass across European countries in turn impact results tremendously. *European trading* allows for higher bio-CCS usage so that aggregated SCAP increase by 21 billion € but aggregated SCC drop by 100 billion €. Arbitrage effects across countries from "cheap" SCAP regions are at 79 billion € (more than two billion € per year). Those arbitrage effects even increase when assuming double (fourfold) biomass limits with European trading to 174 (312) billion €. However, all benefits are destroyed when assuming equalized SCAP across European countries although underlying bio-CCS shares increase.

8.2. Substitution Effects

Many of our specifications either make CO_2 or air pollutant emissions cheaper or more expensive. We do this explicitly by internalization choices (Subsection 5.1), changing SCC (Subsection 5.3) or SCAP (Subsection 5.4), or implicitly by changing emission factors (Subsection 5.2), underlying discount rates (Section 6), or allowing for tradability of biomass (Subsection 7.2). We now proceed to identify behavioral patterns in the resulting 2050 technology mix by comparing CO_2 and air pollutant emissions as well as generation shares. In particular, we analyze for each specification which technologies gain and lose most in the 2050 mix compared to our benchmark *SCC and SCAP (mid)*. Based on the pattern of technology switches, we identify four clusters: (1) medium dominance of SCC, (2) strong dominance of SCC, (3) biomass dominance, (4) little or no dominance of SCC, and (5) dominance of SCAP.

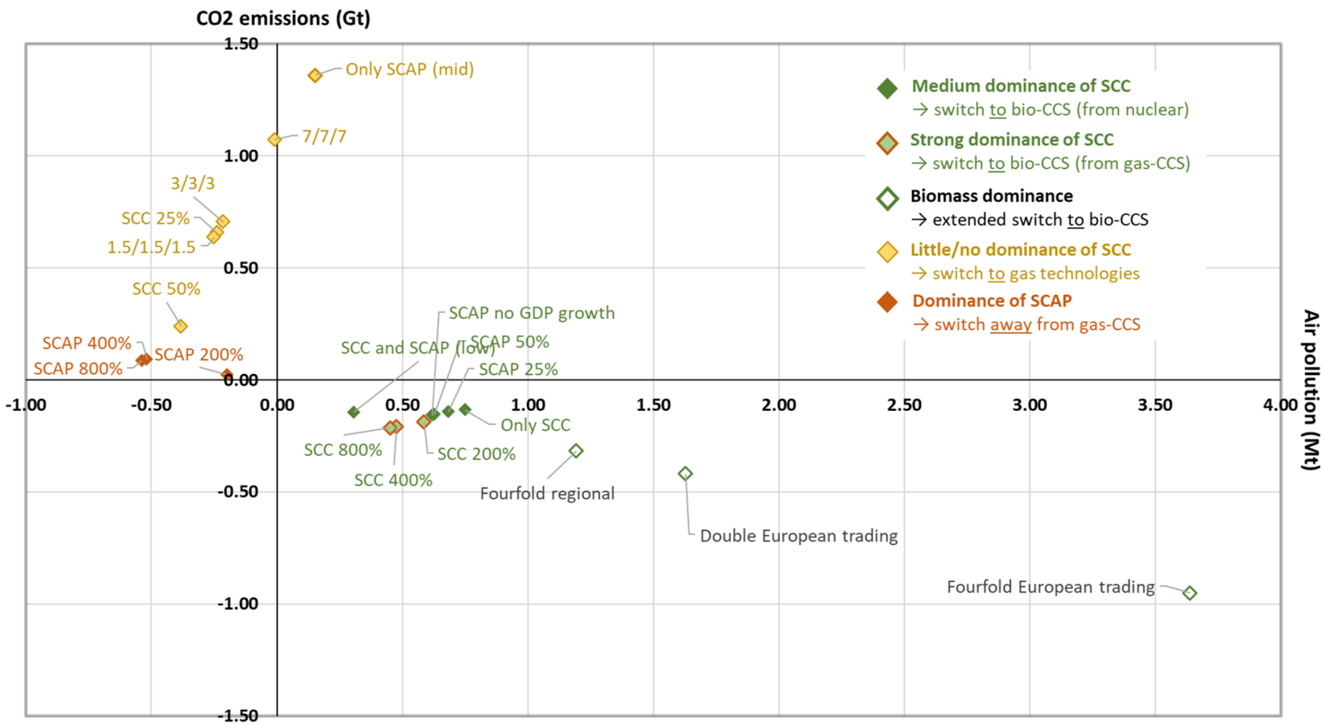
In the first two clusters, SCC dominate SCAP compared to our benchmark, and they all exhibit a technology switch to bio-CCS. In cluster *median dominance of SCC* the difference between air pollution taxes and carbon taxes is relatively mild and the switch happens from nuclear to bio-CCS. In cluster *strong dominance of SCC* carbon taxes are significantly higher than air pollution taxes, with the switch happening from gas-CCS towards bio-CCS, while nuclear becomes a co-winning technology. Cluster *biomass dominance* resembles the first two clusters in the way that it exhibits distinct technology switches from nuclear to bio-CCS. However, the distinction to *median dominance of SCC* is that this switch is not driven by changes in emission taxes but by significant increases to the biomass potentials and consequential arbitrage opportunities. Cluster *little or no dominance of SCC* is marked by specifications where carbon taxes are low. The technology switch defining this cluster is a significant shift to conventional gas. The last cluster *dominance of SCAP* comprises specifications with higher air pollution taxes than our benchmark, which switch away from gas-CCS towards emission-free technologies like nuclear and wind. Wind and solar shares in the generation mix remain essentially unaffected by the technology switches in most of the clustered specifications.[13]

Figure 8 depicts all clustered specifications in a scatter plot relative to our benchmark specification.[14]. The y-axis measures 2050 CO_2 emissions and the x-axis measures 2050 air pollution emissions as absolute differences to the benchmark. The color scheme indicates cluster membership and emphasizes the technology, which is at the center of the cluster's technology switch. Observe that each cluster is associated with distinct movement roughly along one of the axes. Cluster *median dominance of SCC* is scattered along the positive x-axis range, thus represents increased air pollution emissions. Cluster *strong dominance of SCC* is the same but with only slightly decreased CO_2 emissions, as biomass potentials for negative CO_2 emissions are limited. Cluster *biomass dominance* extends this trend towards increased air pollution but gravitates towards the

[13]Table B.23 in Appendix B.2 gives an overview of the clustered specifications and respective technology switching. Several specifications have not been clustered despite presenting similar technology switching trends as the clusters above because their technology switching pattern is not pronounced enough. Tables B.24 and B.25 in Appendix B.2 summarize the entire set of specifications.

[14]See Figure C.27 in Appendix C.9 for a full scatter plot with all specifications (except for technology boost).

center of the fourth quadrant thanks to increased bio-CCS switches with negative CO_2 emissions. We can interpret cluster *little or no dominance of SCC* as movement along the positive range of the y-axis, i.e., increased CO_2 emissions due to the conventional gas-switch. The movement is not strictly vertical, as conventional gas also bears a fair amount of air pollution, which therefore changes slightly accordingly. Finally, cluster *dominance of SCAP* marks movement along the negative range of the x-axis. This represents decreases in air pollution emissions from the switch away from gas-CCS to emissions-free technologies. This movement is one dimensional, that is, leaving CO_2 emission unaffected, as gas-CCS is a carbon-neutral technology.



Note that CO_2 and air pollutant emissions are displayed in absolute difference to our benchmark SCC and SCAP (mid)—which is the same as 7/3/1.5 and Regional biomass limits.

Figure 8: 2050 emissions of selected specifications in relation to benchmark specification – clustered by technology switch

From the clustering and resulting scatter plot, we can conclude that low air pollution taxes (or low air pollution emission factors) and high carbon taxes both have the same effect of fostering bio-CCS deployment (clusters *median dominance of SCC* and *strong dominance of SCC*). This can be further promoted by enhancing biomass exploitation and trade (cluster *biomass dominance*). While it is straightforward and well-known that low carbon taxes lead to overinvestments into conventional gas (cluster *little or no dominance of SCC*), high air pollution taxes make gas-CCS noncompetitive (cluster *dominance of SCAP*).

9. Conclusion

We develop a modeling strategy to account for social cost of carbon (SCC) and social cost of air pollution (SCAP) in intertemporal optimization frameworks. In particular, we derive optimal intertemporal taxation to internalize CO_2 and air pollutant emissions given diverging social and private discount rates for SCC, SCAP, and firms' cash flows. We implement the theoretical framework in the EUREGEN model that intertemporally optimizes capacity expansion and generation of the European power market until 2050. We use data from the DICE model to determine SCC and from the externE project series for SCAP. We start with decomposing the effect of internalizing SCC and SCAP on the technology mix, emissions, and social cost. We additionally test for sensitivities of emission factors, SCC level, SCAP level, and technological assumptions of wind turbines. Next, we vary discount and interest rates to find the impact of varying rates and resulting intertemporal taxation. Finally, we analyze distributional effects by testing different specifications for SCAP calculation, varying biomass limits, and allow for tradability of biomass across European countries.

We run 42 specifications of diverging internalization choices for SCC or SCAP, respectively, with internalization differing either explicitly or implicitly. Our key findings are threefold. First, we find that intertemporal tax rates of CO_2 and air pollutant emissions are higher than their marginal damages, SCC or SCAP, by the ratio of social (for SCC or SCAP) to private (for firms' cash flows) discount rates. For example, assuming social discount rates of 1.5% for damages from CO_2 emissions and private discount rates of 7% for firms' cash flows, yields an (intertemporally) optimal 2050 carbon tax of 354 €/ton whereas marginal damages, that is, SCC, are at 62 €/ton only. Assuming the same discount rates leads to carbon tax rates equal to SCC.

Second, we determine how different internalization choices, discount rates, distributional assumptions, and the tradability of biomass impact aggregated social cost until 2050. Only accounting for SCAP yields social cost of 2,091 billion €. Cost drop to 794 billion € when accounting for SCC instead. Jointly internalizing SCC and SCAP reduces social cost to 622 billion €.[15] Increasing social discount rates or decreasing tax rates for CO_2 or air pollutants, respectively, yields fundamentally higher aggregate social cost. Assuming the same SCAP values for each country or adjusting them according to their GDP per capita only has a minor impact on the overall social cost level. Increasing biomass limits or allowing for European trade of biomass in turn impacts social cost tremendously. For example, assuming a doubled limit and allowing for trade reduces aggregated social cost until 2050 by 174 billion €, whereas aggregate SCAP increase—due to extensive biomass usage in low-SCAP countries—and aggregate SCC decrease—due to negative CO_2 emissions from a technology switch to bio-CCS.

Third, we examine patterns of technology switches and analyze substitution effects when accounting for higher or lower SCC and SCAP. We find five substitution clusters. Medium (strong) dominance of SCC internalization over SCAP internalization fosters bio-CCS deployment while reducing nuclear (gas-CCS). Increasing biomass limits and tradability of biomass always promotes

[15] We use carbon prices that nearly lead to carbon neutrality by 2050 in our benchmark specification.

bio-CCS usage in substitution for nuclear. For extensive expansions of bio-CCS usage even wind energy is substituted. All those specifications lead to rising air pollutant and falling CO_2 emissions, driven by bio-CCS deployment. Subsequently, little or no dominance of SCC, that is, low CO_2 taxes, lead to increasing CO_2 emissions. The dominant switch is from nuclear to gas. Finally, dominance of SCAP, that is very high taxes on air pollution, promotes the substitution of gas-CCS for nuclear under decreasing air pollution and increasing CO_2 emissions.

Our paper shows that the interpretation of modeling results and their consideration by policy makers requires careful review of the assumptions about discount rates, taxes, and what the respective model tries to determine. Some models seek for the social optimum, others depict firm equilibria, and others in turn do not even make any explicit statement about this. We model a situation where a social planner tries to set carbon and air pollutant tax rates to push firms for intertemporally optimal investment and generation decisions. Our first key result, i.e., that emission tax rates are to be set above marginal damages, also underlines that social planners need to consider tax rates or emission prices above marginal damages instead of trying to argue for equality. Quantity targets overcome such a problem, that is, models could determine the optimal quantity target that would then be necessary to get imposed by policy makers. As result, we would obtain tax rates as described in our paper. Our second key result informs about welfare losses of policies when not appropriately internalizing CO_2 or air pollutant damages, respectively, and underlines that the focus on decarbonization should leave space also for co-internalization of air pollutant damages, in particular, when CCS technologies become competitive. Our third key result describes technology switch patterns. Interestingly, nuclear plays a dominant role because wind and solar deployment at competitive spots is naturally limited and thus nuclear is the only remaining emission-neutral (CO_2 and air pollutants) technology. As a consequence, accounting for air pollutant damages shifts the focus back towards nuclear in the choice set of policy makers. In addition, bio-CCS is the dominant technology that drives air pollutant damages but reduces those of CO_2 emissions. This trade-off challenges the role of bio-CCS as panacea to achieve a deep decarbonization. Regional biomass limits reinforce that challenge and trading biomass into low-SCAP countries opens discussions on fair burden sharing of decarbonization.

Our analysis comes with some limitations. First, we do not address the time inconsistency problem when re-setting intertemporal optimal tax rates in succeeding periods. To do so, we would need to run the model on a rolling horizon until arriving at 2050. However, the objective of our analysis is to highlight flaws of current modeling when interpreting results and, thus, we refrain from undergoing this computationally intense task. Second, we use a European power market model to quantify results. Consequently, quantification of social cost is only valid for Europe which is quite densely populated and thus carries quite high damages from air pollutants. However, technology cost are similar across the globe and the determined substitution effects and the problem of CCS technologies is generally applicable. Moreover, wind and solar potential in time and space is limited under current electricity demand projections. Other world regions without that scarcity might overcome the entire air pollutant relevance by not using CCS technologies. Third, the quite prominent role of nuclear is fostered by the fact that we do not explicitly account for social cost of nuclear. Considering them could be a useful topic for future work. However, reduced nuclear capacities come with higher reliance on CCS technologies, which in turn makes the role of air pollutant damages and their appropriate taxation even more severe.

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Appendix A. Supplementary Data

Appendix A.1. Technology Parameters

Table A.1: Efficiencies of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bio-CCS	0.16	0.16	0.17	0.17	0.17	0.18	0.18	0.18
Bioenergy	0.20	0.20	0.21	0.21	0.21	0.22	0.22	0.23
Coal	0.45	0.47	0.48	0.49	0.49	0.49	0.49	0.49
Coal-CCS	0.36	0.37	0.38	0.39	0.39	0.39	0.39	0.39
Gas-CCGT, Gas-ST	0.59	0.60	0.61	0.62	0.62	0.62	0.62	0.62
Gas-CCS	0.47	0.48	0.49	0.50	0.50	0.50	0.50	0.50
Gas-OCGT	0.42	0.44	0.45	0.46	0.46	0.47	0.47	0.47
Geothermal	0.09	0.11	0.11	0.12	0.13	0.13	0.14	0.14
Lignite	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
Nuclear	0.59	0.60	0.61	0.62	0.62	0.62	0.62	0.62
Oil	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31

Table A.2: Investment cost (€/kW) of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bio-CCS	4,450	4,361	4,272	4,272	4,228	4,183	4,183	4,139
Bioenergy	4,322	4,236	4,149	4,149	4,106	4,063	4,063	4,020
Coal	1,500	1,500	1,440	1,410	1,395	1,380	1,380	1,365
Coal-CCS	3,415	3,415	3,278	3,210	3,176	3,142	3,142	3,108
Gas-CCGT, Gas-ST	850	850	850	850	850	850	850	850
Gas-CCS	1,495	1,495	1,495	1,495	1,495	1,495	1,495	1,495
Gas-OCGT	437	437	437	437	437	437	437	437
Geothermal	12,364	11,993	11,622	11,498	11,251	11,127	11,004	11,004
Lignite	1,640	1,640	1,640	1,640	1,640	1,640	1,640	1,640
Nuclear	6,600	6,006	5,346	5,082	4,818	4,488	4,488	4,356
Oil	822	822	822	822	822	822	822	822
Solar	1,300	1,027	936	858	819	780	741	715
Wind off	3,600	3,024	2,700	2,520	2,376	2,268	2,160	2,088
Wind on	1,520	1,397	1,368	1,339	1,325	1,310	1,310	1,296

Appendix A.2. Emission Factors

Table A.3: Air pollution emissions (g/GJ) from the low scenario

	2015	2020	2025	2030	2035	2040	2045	2050
NH_3								
Bio-CCS	3.84	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Bioenergy	1.28	1.28	1.28	1.28	1.28	1.28	1.28	1.28
Coal	0.30	0.29	0.28	0.27	0.26	0.25	0.24	0.23
Coal-CCS	0.90	0.87	0.84	0.81	0.78	0.75	0.72	0.69
Gas-CCGT, Gas-OCGT, Gas-ST, Oil	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gas-CCS	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Lignite	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
NMVOC								
Bio-CCS, Bioenergy	7.31	7.31	7.31	7.31	7.31	7.31	7.31	7.31
Coal, Coal-CCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
Lignite	1.40	1.35	1.31	1.26	1.21	1.17	1.12	1.07
Oil	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30
NO_x								
Bio-CCS, Bioenergy	76.42	73.77	71.13	68.48	65.84	63.19	60.55	57.90
Coal, Coal-CCS	72.50	69.90	67.30	64.70	62.10	59.50	56.90	54.30
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	31.01	28.61	26.21	23.81	21.40	19.00	16.60	14.20
Lignite	72.50	69.90	67.30	64.70	62.10	59.50	56.90	54.30
Oil	56.60	54.57	52.54	50.51	48.49	46.46	44.43	42.40
PPM_{10}								
Bio-CCS, Bioenergy	31.81	29.72	27.63	25.55	23.46	21.37	19.28	17.20
Coal, Coal-CCS	7.70	6.78	5.87	4.95	4.04	3.12	2.21	1.29
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	7.90	6.81	5.72	4.63	3.53	2.44	1.35	0.26
Oil	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20
$PPM_{2.5}$								
Bio-CCS, Bioenergy	27.94	26.10	24.26	22.41	20.57	18.73	16.89	15.05
Coal, Coal-CCS	3.40	3.08	2.76	2.44	2.11	1.79	1.47	1.15
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	3.20	2.78	2.36	1.94	1.52	1.10	0.68	0.26
Oil	19.30	19.30	19.30	19.30	19.30	19.30	19.30	19.30
SO_2								
Bio-CCS, Bioenergy	10.80	10.24	9.68	9.12	8.57	8.01	7.45	6.89
Coal	63.45	55.41	47.38	39.34	31.31	23.27	15.24	7.20
Coal-CCS	50.76	44.33	37.90	31.47	25.05	18.62	12.19	5.76
Gas-CCGT, Gas-OCGT, Gas-ST	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Gas-CCS	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Lignite	91.20	79.20	67.20	55.20	43.20	31.20	19.20	7.20
Oil	70.70	68.69	66.67	64.66	62.64	60.63	58.61	56.60

Table A.4: Air pollution emissions (g/GJ) from the mid scenario

	2015	2020	2025	2030	2035	2040	2045	2050
NH_3								
Bio-CCS	3.84	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Bioenergy	1.28	1.28	1.28	1.28	1.28	1.28	1.28	1.28
Coal	0.30	0.29	0.28	0.27	0.26	0.25	0.24	0.23
Coal-CCS	0.90	0.87	0.84	0.81	0.78	0.75	0.72	0.69
Gas-CCGT, Gas-OCGT, Gas-ST, Oil	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gas-CCS	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Lignite	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
NMVOC								
Bio-CCS, Bioenergy	7.31	7.31	7.31	7.31	7.31	7.31	7.31	7.31
Coal, Coal-CCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
Lignite	1.40	1.35	1.31	1.26	1.21	1.17	1.12	1.07
Oil	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30
NO_x								
Bio-CCS, Bioenergy	76.42	73.77	71.13	68.48	65.84	63.19	60.55	57.90
Coal, Coal-CCS	72.50	71.23	69.96	68.69	67.43	66.16	64.89	63.62
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	31.01	30.62	30.24	29.85	29.46	29.07	28.69	28.30
Lignite	72.50	71.64	70.78	69.92	69.07	68.21	67.35	66.49
Oil	56.60	54.57	52.54	50.51	48.49	46.46	44.43	42.40
PPM_{10}								
Bio-CCS, Bioenergy	31.81	31.81	31.81	31.81	31.81	31.81	31.81	31.81
Coal, Coal-CCS	7.70	6.85	6.00	5.15	4.30	3.45	2.60	1.75
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	7.90	6.85	5.80	4.75	3.71	2.66	1.61	0.56
Oil	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20
$PPM_{2.5}$								
Bio-CCS, Bioenergy	27.94	27.94	27.94	27.94	27.94	27.94	27.94	27.94
Coal, Coal-CCS	3.40	3.14	2.87	2.61	2.35	2.09	1.82	1.56
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	3.20	2.81	2.43	2.04	1.65	1.26	0.88	0.49
Oil	19.30	19.30	19.30	19.30	19.30	19.30	19.30	19.30
SO_2								
Bio-CCS, Bioenergy	10.80	10.24	9.68	9.12	8.57	8.01	7.45	6.89
Coal	63.45	59.74	56.03	52.32	48.60	44.89	41.18	37.47
Coal-CCS	50.76	47.79	44.82	41.85	38.88	35.91	32.95	29.98
Gas-CCGT, Gas-OCGT, Gas-ST	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Gas-CCS	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Lignite	91.20	81.44	71.68	61.92	52.16	42.40	32.64	22.88
Oil	70.70	68.69	66.67	64.66	62.64	60.63	58.61	56.60

Table A.5: Air pollution emissions (g/GJ) from the high scenario

	2015	2020	2025	2030	2035	2040	2045	2050
NH_3								
Bio-CCS	3.84	3.84	3.84	3.84	3.84	3.84	3.84	3.84
Bioenergy	1.28	1.28	1.28	1.28	1.28	1.28	1.28	1.28
Coal	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
Coal-CCS	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Gas-CCGT, Gas-OCGT, Gas-ST, Oil	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gas-CCS	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Lignite	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
NMVOC								
Bio-CCS, Bioenergy	7.31	7.31	7.31	7.31	7.31	7.31	7.31	7.31
Coal, Coal-CCS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
Lignite	1.40	1.40	1.40	1.40	1.40	1.40	1.40	1.40
Oil	2.30	2.30	2.30	2.30	2.30	2.30	2.30	2.30
NO_x								
Bio-CCS, Bioenergy	115.70	112.94	110.19	107.43	104.67	101.91	99.16	96.40
Coal, Coal-CCS	143.17	133.07	122.98	112.88	102.79	92.69	82.60	72.50
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	59.01	55.01	51.01	47.01	43.01	39.01	35.01	31.01
Lignite	123.14	115.91	108.67	101.44	94.20	86.97	79.73	72.50
Oil	56.60	54.57	52.54	50.51	48.49	46.46	44.43	42.40
PPM_{10}								
Bio-CCS, Bioenergy	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00
Coal, Coal-CCS	20.82	18.95	17.07	15.20	13.32	11.45	9.57	7.70
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	22.67	20.56	18.45	16.34	14.23	12.12	10.01	7.90
Oil	25.20	25.20	25.20	25.20	25.20	25.20	25.20	25.20
$PPM_{2.5}$								
Bio-CCS, Bioenergy	133.00	133.00	133.00	133.00	133.00	133.00	133.00	133.00
Coal, Coal-CCS	17.47	15.46	13.45	11.44	9.43	7.42	5.41	3.40
Gas-CCGT, Gas-OCGT, Gas-ST, Gas-CCS	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Lignite	22.60	19.83	17.06	14.29	11.51	8.74	5.97	3.20
Oil	19.30	19.30	19.30	19.30	19.30	19.30	19.30	19.30
SO_2								
Bio-CCS, Bioenergy	10.80	10.80	10.80	10.80	10.80	10.80	10.80	10.80
Coal	72.50	71.21	69.91	68.62	67.33	66.04	64.74	63.45
Coal-CCS	58.00	56.97	55.93	54.90	53.86	52.83	51.79	50.76
Gas-CCGT, Gas-OCGT, Gas-ST	0.28	0.26	0.24	0.22	0.20	0.18	0.16	0.14
Gas-CCS	0.22	0.21	0.19	0.18	0.16	0.14	0.13	0.11
Lignite	346.38	309.92	273.47	237.02	200.56	164.11	127.65	91.20
Oil	70.70	68.69	66.67	64.66	62.64	60.63	58.61	56.60

Appendix A.3. Annual Electricity Demand and Fuel Prices

Table A.6: Annual electricity demand (TWh)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	63	64	78	91	137	147	156	163
Belgium	83	82	96	107	131	157	181	196
Bulgaria	30	30	35	36	37	39	41	43
Croatia	16	16	17	18	18	20	23	25
Czech Republic	59	63	116	121	125	133	141	149
Denmark	32	32	37	35	39	47	52	56
Estonia	7	8	9	11	12	12	13	14
Finland	80	73	83	79	80	82	87	91
France	448	450	759	768	813	868	926	986
Germany	528	534	832	843	843	874	910	950
Greece	52	53	58	54	58	63	68	71
Hungary	38	37	44	53	67	71	75	81
Ireland	26	26	31	32	39	42	45	49
Italy	297	319	421	562	597	644	689	735
Latvia	6	7	8	9	10	12	12	13
Lithuania	10	12	18	18	17	18	19	20
Luxembourg	6	6	7	8	11	14	15	17
Netherlands	109	113	148	186	189	199	210	226
Norway	119	124	131	126	158	168	179	190
Poland	139	143	164	179	229	267	280	293
Portugal	47	52	61	62	66	70	73	76
Romania	47	47	54	58	60	67	74	80
Slovak Republic	25	27	34	39	48	56	58	60
Slovenia	13	13	15	17	19	22	23	24
Spain	239	247	313	367	494	523	543	568
Sweden	128	133	159	161	232	248	265	282
Switzerland	58	61	67	71	117	128	139	151
United Kingdom	311	317	358	389	435	489	533	595

Table A.7: Fuel prices for Germany (EUR/MWh thermal)

	2015	2020	2025	2030	2035	2040	2045	2050
Bioenergy	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
Coal	8.35	8.22	8.09	7.94	7.79	7.68	7.58	7.49
Lignite	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00
Gas	20.65	20.34	20.01	19.63	19.27	18.99	18.74	18.53
Oil	40.26	40.84	41.18	41.58	42.14	42.74	43.51	44.34
Uranium	2.33	2.33	2.33	2.33	2.33	2.33	2.33	2.33

Appendix A.4. Population Projections

Table A.8: Population projections (million)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	8.64	8.92	8.98	9.04	9.07	9.06	9.01	8.93
Belgium	11.27	11.54	11.70	11.83	11.93	12.01	12.06	12.09
Bulgaria	7.18	6.92	6.66	6.38	6.10	5.84	5.59	5.36
Croatia	4.20	4.04	3.93	3.82	3.70	3.56	3.43	3.30
Czech Republic	11	11	11	11	11	11	11	11
Denmark	5.68	5.83	5.94	6.03	6.10	6.17	6.21	6.25
Estonia	1.32	1.33	1.30	1.27	1.24	1.21	1.18	1.15
Finland	5.48	5.53	5.56	5.55	5.52	5.50	5.48	5.45
France	66.55	67.20	68.01	68.54	68.87	69.09	69.18	69.09
Germany	81.69	83.15	82.55	82.22	81.72	80.93	79.80	78.53
Greece	10.82	10.66	10.38	10.15	9.93	9.71	9.48	9.20
Hungary	9.84	9.74	9.58	9.40	9.18	8.94	8.73	8.52
Ireland	4.70	4.98	5.14	5.27	5.38	5.50	5.60	5.68
Italy	60.73	60.18	59.51	58.59	57.64	56.62	55.29	53.59
Latvia	1.98	1.89	1.81	1.73	1.66	1.60	1.55	1.50
Lithuania	2.90	2.76	2.64	2.54	2.44	2.35	2.26	2.18
Luxembourg	0.57	0.63	0.66	0.69	0.72	0.74	0.76	0.78
Netherlands	16.94	17.38	17.55	17.65	17.67	17.61	17.48	17.29
Norway	5.19	5.39	5.62	5.83	6.03	6.21	6.37	6.52
Poland	37.99	37.91	37.57	36.95	36.09	35.09	34.12	33.19
Portugal	10.36	10.25	10.11	9.95	9.77	9.57	9.34	9.08
Romania	19.82	19.25	18.82	18.35	17.84	17.31	16.82	16.30
Slovak Republic	5.42	5.46	5.44	5.39	5.30	5.19	5.07	4.96
Slovenia	2.06	2.09	2.08	2.06	2.03	2.00	1.97	1.93
Spain	46.44	47.13	46.87	46.46	45.93	45.30	44.51	43.49
Sweden	9.80	10.34	10.61	10.83	11.01	11.19	11.38	11.55
Switzerland	8.28	8.63	8.90	9.13	9.32	9.47	9.59	9.68
United Kingdom	65.12	67.16	68.44	69.54	70.48	71.36	72.13	72.74
World	7,339	7,754	8,140	8,501	8,836	9,145	9,426	9,676

Appendix A.5. GDP Projections

Table A.9: GDP projections (billion 2015 EUR)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	436	474	511	546	589	636	683	728
Belgium	528	566	606	654	719	797	877	960
Bulgaria	56	62	67	71	75	79	83	86
Croatia	57	62	65	69	75	82	88	94
Czech Republic	204	223	238	258	277	297	317	338
Denmark	346	388	429	463	499	542	590	643
Estonia	26	29	31	33	35	38	40	41
Finland	271	287	303	323	350	382	413	445
France	2,841	3,066	3,270	3,488	3,763	4,094	4,435	4,820
Germany	3,850	4,091	4,328	4,490	4,640	4,855	5,097	5,334
Greece	234	241	246	256	275	295	306	316
Hungary	137	148	165	180	194	207	217	231
Ireland	250	282	306	333	363	393	420	455
Italy	2,132	2,273	2,409	2,556	2,733	2,939	3,144	3,385
Latvia	31	35	39	42	44	47	50	52
Lithuania	47	54	57	58	59	63	67	71
Luxembourg	65	74	84	95	108	123	138	154
Netherlands	876	938	987	1,028	1,083	1,153	1,230	1,317
Norway	507	555	601	654	715	785	861	936
Poland	542	622	698	769	826	881	919	947
Portugal	228	245	266	281	296	309	319	330
Romania	198	222	243	261	278	297	317	338
Slovak Republic	99	114	128	144	156	164	169	173
Slovenia	49	53	58	62	65	70	74	78
Spain	1,376	1,510	1,652	1,793	1,936	2,061	2,141	2,264
Sweden	570	630	697	765	847	937	1,033	1,131
Switzerland	700	776	859	950	1,055	1,172	1,300	1,430
United Kingdom	2,984	3,188	3,366	3,611	3,948	4,354	4,780	5,215
World	78,242	90,573	104,038	119,466	136,834	155,959	175,894	196,762

Table A.10: GDP growth (2015 = 1)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	1.00	1.09	1.17	1.25	1.35	1.46	1.57	1.67
Belgium	1.00	1.07	1.15	1.24	1.36	1.51	1.66	1.82
Bulgaria	1.00	1.11	1.20	1.27	1.34	1.42	1.48	1.53
Croatia	1.00	1.09	1.15	1.22	1.32	1.45	1.56	1.66
Czech Republic	1.00	1.09	1.17	1.26	1.36	1.45	1.55	1.65
Denmark	1.00	1.12	1.24	1.34	1.44	1.57	1.70	1.86
Estonia	1.00	1.10	1.18	1.26	1.34	1.42	1.50	1.56
Finland	1.00	1.06	1.12	1.19	1.29	1.41	1.52	1.64
France	1.00	1.08	1.15	1.23	1.32	1.44	1.56	1.70
Germany	1.00	1.06	1.12	1.17	1.21	1.26	1.32	1.39
Greece	1.00	1.03	1.05	1.09	1.18	1.26	1.31	1.35
Hungary	1.00	1.08	1.20	1.32	1.42	1.50	1.58	1.68
Ireland	1.00	1.13	1.22	1.33	1.45	1.57	1.68	1.82
Italy	1.00	1.07	1.13	1.20	1.28	1.38	1.47	1.59
Latvia	1.00	1.14	1.25	1.34	1.41	1.52	1.60	1.68
Lithuania	1.00	1.14	1.20	1.22	1.25	1.32	1.41	1.50
Luxembourg	1.00	1.14	1.29	1.46	1.67	1.90	2.13	2.37
Netherlands	1.00	1.07	1.13	1.17	1.24	1.32	1.40	1.50
Norway	1.00	1.10	1.19	1.29	1.41	1.55	1.70	1.85
Poland	1.00	1.15	1.29	1.42	1.52	1.62	1.70	1.75
Portugal	1.00	1.07	1.16	1.23	1.29	1.35	1.40	1.45
Romania	1.00	1.12	1.23	1.32	1.40	1.50	1.60	1.70
Slovak Republic	1.00	1.15	1.29	1.46	1.57	1.65	1.70	1.75
Slovenia	1.00	1.08	1.17	1.25	1.33	1.41	1.49	1.58
Spain	1.00	1.10	1.20	1.30	1.41	1.50	1.56	1.65
Sweden	1.00	1.11	1.22	1.34	1.49	1.64	1.81	1.99
Switzerland	1.00	1.11	1.23	1.36	1.51	1.67	1.86	2.04
United Kingdom	1.00	1.07	1.13	1.21	1.32	1.46	1.60	1.75
World	1.00	1.16	1.33	1.53	1.75	1.99	2.25	2.51

Table A.11: GDP per capita (2015er EUR)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	50,447	53,122	56,882	60,422	65,003	70,194	75,788	81,573
Belgium	46,828	49,070	51,840	55,235	60,281	66,345	72,752	79,463
Bulgaria	7,803	9,019	10,132	11,173	12,313	13,600	14,814	16,033
Croatia	13,509	15,280	16,584	18,081	20,279	23,080	25,765	28,542
Czech Republic	19,358	20,822	22,175	24,141	26,129	28,101	30,103	32,170
Denmark	60,879	66,439	72,165	76,820	81,782	87,851	94,885	102,893
Estonia	20,076	21,880	23,948	26,147	28,492	31,077	33,531	35,882
Finland	49,532	51,818	54,551	58,276	63,441	69,427	75,519	81,745
France	42,691	45,624	48,086	50,883	54,629	59,248	64,105	69,772
Germany	47,135	49,193	52,425	54,606	56,777	59,991	63,868	67,926
Greece	21,604	22,635	23,679	25,213	27,670	30,369	32,275	34,361
Hungary	13,942	15,235	17,188	19,197	21,174	23,094	24,924	27,096
Ireland	53,216	56,603	59,576	63,162	67,411	71,445	74,920	79,977
Italy	35,102	37,764	40,479	43,621	47,415	51,914	56,867	63,155
Latvia	15,730	18,725	21,552	23,975	26,410	29,484	32,223	34,792
Lithuania	16,343	19,524	21,609	22,797	24,225	26,780	29,687	32,691
Luxembourg	113,650	116,861	126,423	137,335	150,763	166,092	181,310	196,353
Netherlands	51,708	53,969	56,222	58,261	61,312	65,459	70,373	76,168
Norway	97,625	102,975	107,016	112,177	118,729	126,534	135,089	143,682
Poland	14,268	16,396	18,568	20,816	22,882	25,092	26,945	28,535
Portugal	22,057	23,866	26,304	28,285	30,263	32,250	34,193	36,397
Romania	10,012	11,528	12,933	14,245	15,567	17,173	18,853	20,750
Slovak Republic	18,267	20,830	23,476	26,750	29,386	31,575	33,242	34,887
Slovenia	23,876	25,521	27,837	29,894	32,227	34,789	37,430	40,341
Spain	29,631	32,047	35,251	38,599	42,143	45,492	48,099	52,061
Sweden	58,129	60,914	65,647	70,643	76,911	83,714	90,796	97,892
Switzerland	84,554	89,900	96,469	104,057	113,187	123,741	135,521	147,763
United Kingdom	45,828	47,469	49,174	51,931	56,019	61,017	66,270	71,700
World	10,661	11,682	12,781	14,052	15,485	17,054	18,661	20,335

Table A.12: GDP per capita growth (2015 = 1)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	1.00	1.05	1.13	1.20	1.29	1.39	1.50	1.62
Belgium	1.00	1.05	1.11	1.18	1.29	1.42	1.55	1.70
Bulgaria	1.00	1.16	1.30	1.43	1.58	1.74	1.90	2.05
Croatia	1.00	1.13	1.23	1.34	1.50	1.71	1.91	2.11
Czech Republic	1.00	1.08	1.15	1.25	1.35	1.45	1.56	1.66
Denmark	1.00	1.09	1.19	1.26	1.34	1.44	1.56	1.69
Estonia	1.00	1.09	1.19	1.30	1.42	1.55	1.67	1.79
Finland	1.00	1.05	1.10	1.18	1.28	1.40	1.52	1.65
France	1.00	1.07	1.13	1.19	1.28	1.39	1.50	1.63
Germany	1.00	1.04	1.11	1.16	1.20	1.27	1.36	1.44
Greece	1.00	1.05	1.10	1.17	1.28	1.41	1.49	1.59
Hungary	1.00	1.09	1.23	1.38	1.52	1.66	1.79	1.94
Ireland	1.00	1.06	1.12	1.19	1.27	1.34	1.41	1.50
Italy	1.00	1.08	1.15	1.24	1.35	1.48	1.62	1.80
Latvia	1.00	1.19	1.37	1.52	1.68	1.87	2.05	2.21
Lithuania	1.00	1.19	1.32	1.39	1.48	1.64	1.82	2.00
Luxembourg	1.00	1.03	1.11	1.21	1.33	1.46	1.60	1.73
Netherlands	1.00	1.04	1.09	1.13	1.19	1.27	1.36	1.47
Norway	1.00	1.05	1.10	1.15	1.22	1.30	1.38	1.47
Poland	1.00	1.15	1.30	1.46	1.60	1.76	1.89	2.00
Portugal	1.00	1.08	1.19	1.28	1.37	1.46	1.55	1.65
Romania	1.00	1.15	1.29	1.42	1.55	1.72	1.88	2.07
Slovak Republic	1.00	1.14	1.29	1.46	1.61	1.73	1.82	1.91
Slovenia	1.00	1.07	1.17	1.25	1.35	1.46	1.57	1.69
Spain	1.00	1.08	1.19	1.30	1.42	1.54	1.62	1.76
Sweden	1.00	1.05	1.13	1.22	1.32	1.44	1.56	1.68
Switzerland	1.00	1.06	1.14	1.23	1.34	1.46	1.60	1.75
United Kingdom	1.00	1.04	1.07	1.13	1.22	1.33	1.45	1.56
World	1.00	1.10	1.20	1.32	1.45	1.60	1.75	1.91

Table A.13: GDP per capita index (European 28 = 1)

	2015	2020	2025	2030	2035	2040	2045	2050
Austria	1.34	1.32	1.32	1.31	1.31	1.30	1.30	1.28
Belgium	1.24	1.22	1.20	1.20	1.21	1.23	1.24	1.25
Bulgaria	0.21	0.22	0.24	0.24	0.25	0.25	0.25	0.25
Croatia	0.36	0.38	0.38	0.39	0.41	0.43	0.44	0.45
Czech Republic	0.51	0.52	0.51	0.52	0.53	0.52	0.51	0.51
Denmark	1.62	1.65	1.68	1.67	1.65	1.63	1.62	1.62
Estonia	0.53	0.54	0.56	0.57	0.57	0.58	0.57	0.56
Finland	1.32	1.29	1.27	1.26	1.28	1.29	1.29	1.29
France	1.13	1.13	1.12	1.10	1.10	1.10	1.10	1.10
Germany	1.25	1.22	1.22	1.18	1.14	1.11	1.09	1.07
Greece	0.57	0.56	0.55	0.55	0.56	0.56	0.55	0.54
Hungary	0.37	0.38	0.40	0.42	0.43	0.43	0.43	0.43
Ireland	1.41	1.41	1.38	1.37	1.36	1.32	1.28	1.26
Italy	0.93	0.94	0.94	0.95	0.95	0.96	0.97	0.99
Latvia	0.42	0.47	0.50	0.52	0.53	0.55	0.55	0.55
Lithuania	0.43	0.49	0.50	0.49	0.49	0.50	0.51	0.51
Luxembourg	3.02	2.90	2.93	2.98	3.03	3.08	3.10	3.09
Netherlands	1.37	1.34	1.31	1.26	1.23	1.21	1.20	1.20
Norway	2.59	2.56	2.48	2.43	2.39	2.34	2.31	2.26
Poland	0.38	0.41	0.43	0.45	0.46	0.46	0.46	0.45
Portugal	0.59	0.59	0.61	0.61	0.61	0.60	0.58	0.57
Romania	0.27	0.29	0.30	0.31	0.31	0.32	0.32	0.33
Slovak Republic	0.49	0.52	0.54	0.58	0.59	0.59	0.57	0.55
Slovenia	0.63	0.63	0.65	0.65	0.65	0.64	0.64	0.64
Spain	0.79	0.80	0.82	0.84	0.85	0.84	0.82	0.82
Sweden	1.54	1.51	1.52	1.53	1.55	1.55	1.55	1.54
Switzerland	2.25	2.23	2.24	2.26	2.28	2.29	2.32	2.33
United Kingdom	1.22	1.18	1.14	1.13	1.13	1.13	1.13	1.13
World	0.28	0.29	0.30	0.30	0.31	0.32	0.32	0.32

Appendix A.6. Detailed SCAP

Table A.14: Demand-weighted average SCAP (€/ton) by impact category and air pollutant (1)

	Average	AT	BE	BG	CH	CZ	DE	DK	EE	EL
Human health										
NH_3	16,543	19,650	36,698	9,475	14,214	28,161	21,930	11,964	8,563	7,149
NMVOC	1,039	1,702	2,633	-87	1,301	980	1,394	957	273	259
NO_x	8,003	11,803	9,576	7,235	20,071	9,885	11,574	5,131	1,903	2,553
PPM_{10}	1,019	789	2,441	634	549	939	1,493	591	241	500
$PPM_{2.5}$	23,105	24,759	33,185	15,381	26,800	27,356	36,745	11,805	7,360	11,544
SO_2	9,844	11,300	13,504	7,551	16,003	11,381	13,067	6,214	5,397	7,207
Loss of biodiversity										
NH_3	5,790	6,483	3,342	1,382	14,710	8,897	10,510	2,297	5,585	1,118
NMVOC	-129	-80	-60	-14	-177	-146	-356	-82	-50	-17
NO_x	1,570	1,276	1,100	229	2,567	2,413	2,435	1,426	941	325
PPM_{10}	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	583	402	480	32	424	731	944	630	349	69
Regional crops										
NH_3	-281	-97	-133	-125	-207	-211	-106	-149	-11	-318
NMVOC	319	119	432	35	254	228	470	334	51	51
NO_x	356	324	1	214	784	390	629	212	55	149
PPM_{10}	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	-112	-73	-111	4	-214	-100	-195	-127	-26	-5
Materials										
NH_3	0	0	0	0	0	0	0	0	0	0
NMVOC	0	0	0	0	0	0	0	0	0	0
NO_x	116	141	78	82	120	203	156	121	52	88
PPM_{10}	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	435	355	461	178	387	850	733	425	165	142
Total regional cost										
NH_3	22,052	26,036	39,906	10,732	28,717	36,847	32,334	14,112	14,137	7,949
NMVOC	1,229	1,741	3,005	-66	1,379	1,061	1,507	1,209	274	293
NO_x	10,045	13,544	10,755	7,760	23,543	12,891	14,794	6,890	2,950	3,115
PPM_{10}	1,019	789	2,441	634	549	939	1,493	591	241	500
$PPM_{2.5}$	23,105	24,759	33,185	15,381	26,800	27,356	36,745	11,805	7,360	11,544
SO_2	10,750	11,985	14,335	7,766	16,601	12,862	14,548	7,142	5,885	7,414
Total global cost										
NH_3	22,057	26,041	39,911	10,736	28,721	36,852	32,339	14,116	14,141	7,954
NMVOC	1,829	2,341	3,605	534	1,979	1,661	2,107	1,809	874	893
NO_x	10,265	13,764	10,975	7,980	23,763	13,111	15,014	7,110	3,170	3,335
PPM_{10}	1,023	792	2,445	637	552	943	1,497	594	244	503
$PPM_{2.5}$	23,370	25,024	33,449	15,645	27,065	27,620	37,009	12,070	7,624	11,809
SO_2	11,217	12,451	14,801	8,232	17,068	13,328	15,015	7,609	6,352	7,881

Table A.15: Demand-weighted average SCAP (€/ton) by impact category and air pollutant (2)

	ES	HU	FI	FR	HR	HU	IE	IT	LT	LU
Human health										
NH_3	6,024	22,941	5,302	14,423	19,968	22,941	3,028	16,842	7,296	29,975
NMVOC	546	810	294	1,178	992	810	859	857	547	2,554
NO_x	3,034	11,998	1,905	10,928	9,590	11,998	4,149	8,406	5,868	11,334
PPM_{10}	489	1,119	74	1,040	819	1,119	384	1,073	366	1,355
$PPM_{2.5}$	11,273	27,537	4,921	27,382	23,825	27,537	9,386	22,115	10,308	32,757
SO_2	7,391	10,882	3,742	10,548	11,005	10,882	7,651	10,455	6,809	14,702
Loss of biodiversity										
NH_3	2,705	5,335	3,090	5,224	7,844	5,335	635	9,755	3,905	11,331
NMVOC	-43	-82	-55	-95	-100	-82	-34	-130	-49	-136
NO_x	851	1,822	1,266	1,570	2,167	1,822	668	1,894	940	2,541
PPM_{10}	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	197	475	641	950	562	475	251	265	241	996
Regional crops										
NH_3	-451	-280	-4	-529	-336	-280	-279	-447	-19	-285
NMVOC	139	144	50	376	234	144	206	327	59	564
NO_x	438	659	59	389	1,121	659	438	590	171	891
PPM_{10}	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	-80	-34	-31	-162	-108	-34	-112	-62	-75	-261
Materials										
NH_3	0	0	0	0	0	0	0	0	0	0
NMVOC	0	0	0	0	0	0	0	0	0	0
NO_x	31	298	36	126	120	298	53	93	124	175
PPM_{10}	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0
SO_2	69	817	144	420	387	817	118	188	324	755
Total regional cost										
NH_3	8,278	27,997	8,388	19,117	27,476	27,997	3,384	26,150	11,182	41,020
NMVOC	641	872	290	1,460	1,126	872	1,032	1,054	557	2,981
NO_x	4,354	14,777	3,266	13,013	12,998	14,777	5,309	10,983	7,103	14,940
PPM_{10}	489	1,119	74	1,040	819	1,119	384	1,073	366	1,355
$PPM_{2.5}$	11,273	27,537	4,921	27,382	23,825	27,537	9,386	22,115	10,308	32,757
SO_2	7,577	12,140	4,495	11,755	11,846	12,140	7,907	10,846	7,299	16,192
Total global cost										
NH_3	8,283	28,002	8,393	19,122	27,481	28,002	3,389	26,155	11,186	41,024
NMVOC	1,241	1,472	890	2,060	1,726	1,472	1,632	1,654	1,157	3,581
NO_x	4,573	14,997	3,486	13,233	13,218	14,997	5,528	11,203	7,323	15,160
PPM_{10}	493	1,123	78	1,044	823	1,123	388	1,076	369	1,358
$PPM_{2.5}$	11,538	27,802	5,185	27,646	24,090	27,802	9,650	22,379	10,573	33,022
SO_2	8,044	12,607	4,962	12,222	12,313	12,607	8,374	11,313	7,765	16,659

Table A.16: Demand-weighted average SCAP (€/ton) by impact category and air pollutant (3)

	Average	LV	NL	NO	PL	PT	RO	SE	SI	SK	UK
Human health											
NH_3	6,024	8,096	28,196	4,273	16,194	4,958	11,039	10,224	22,073	25,327	21,596
NMVOC	546	497	2,038	461	758	521	489	482	1,399	653	1,093
NO_x	3,034	3,995	8,678	3,585	6,510	916	8,508	3,693	9,935	10,156	4,807
PPM_{10}	489	348	2,388	191	1,012	328	917	170	843	928	1,136
$PPM_{2.5}$	11,273	8,838	36,246	6,012	24,798	7,080	18,976	6,421	23,387	23,614	20,252
SO_2	7,391	5,891	12,927	2,093	10,981	4,831	9,108	4,833	12,333	10,576	8,858
Loss of biodiversity											
NH_3	2,705	5,220	5,929	1,399	6,486	1,737	3,963	2,403	13,424	9,157	1,042
NMVOC	-43	-59	-107	-74	-90	-17	-36	-68	-150	-99	-53
NO_x	851	994	1,760	825	1,781	270	675	1,638	2,965	1,656	1,020
PPM_{10}	0	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0	0
SO_2	197	249	1,223	463	-54	86	101	967	748	524	377
Regional crops											
NH_3	-451	-14	-279	-36	-160	-361	-192	-33	-321	-216	-406
NMVOC	139	67	645	146	192	91	75	111	262	156	521
NO_x	438	60	-263	360	236	102	326	191	922	644	-30
PPM_{10}	0	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0	0
SO_2	-80	-39	-200	-47	-13	-42	-9	-74	-189	-47	-102
Materials											
NH_3	0	0	0	0	0	0	0	0	0	0	0
NMVOC	0	0	0	0	0	0	0	0	0	0	0
NO_x	31	78	137	120	220	19	222	53	215	273	70
PPM_{10}	0	0	0	0	0	0	0	0	0	0	0
$PPM_{2.5}$	0	0	0	0	0	0	0	0	0	0	0
SO_2	69	216	827	387	880	49	644	186	576	813	320
Total regional cost											
NH_3	8,278	13,302	33,846	5,636	22,520	6,334	14,810	12,594	35,176	34,268	22,232
NMVOC	641	504	2,577	534	860	595	528	525	1,510	710	1,562
NO_x	4,354	5,127	10,313	4,890	8,747	1,308	9,730	5,574	14,038	12,729	5,866
PPM_{10}	489	348	2,388	191	1,012	328	917	170	843	928	1,136
$PPM_{2.5}$	11,273	8,838	36,246	6,012	24,798	7,080	18,976	6,421	23,387	23,614	20,252
SO_2	7,577	6,318	14,777	2,896	11,794	4,925	9,844	5,912	13,469	11,866	9,452
Total global cost											
NH_3	8,283	13,307	33,851	5,640	22,525	6,338	14,815	12,599	35,181	34,272	22,237
NMVOC	1,241	1,104	3,177	1,134	1,460	1,195	1,128	1,125	2,110	1,310	2,162
NO_x	4,573	5,347	10,533	5,110	8,967	1,527	9,950	5,794	14,258	12,948	6,086
PPM_{10}	493	351	2,392	194	1,016	332	920	174	846	931	1,139
$PPM_{2.5}$	11,538	9,102	36,511	6,277	25,063	7,345	19,240	6,686	23,651	23,878	20,517
SO_2	8,044	6,784	15,244	3,362	12,261	5,392	10,311	6,379	13,936	12,333	9,919

Appendix A.7. Technology boost

Table A.17: Potential (GW) of wind technologies by country and resource class (low, mid, high)

	Wind off (low)	Wind off (mid)	Wind off (high)	Wind on (low)	Wind on (mid)	Wind on (high)
Austria	0	0	0	10	30	10
Belgium	1	2	1	3	9	3
Bulgaria	12	36	12	14	43	14
Croatia	19	57	19	7	22	7
Czech Republic	0	0	0	10	29	10
Denmark	36	108	36	5	16	5
Estonia	13	38	13	5	16	5
Finland	27	82	27	40	119	40
France	119	358	119	71	214	71
Germany	19	58	19	43	128	43
Greece	167	502	167	17	50	17
Hungary	0	0	0	12	36	12
Ireland	148	444	148	9	28	9
Italy	178	535	178	37	111	37
Latvia	10	30	10	8	24	8
Lithuania	2	7	2	8	25	8
Luxembourg				0	1	0
Netherlands	22	67	22	4	12	4
Norway	321	963	321	35	106	35
Poland	10	31	10	40	119	40
Portugal	110	329	110	12	36	12
Romania	10	31	10	31	92	31
Slovak Republic				6	18	6
Slovenia				2	7	2
Spain	195	585	195	67	201	67
Sweden	53	159	53	53	158	53
Switzerland				5	14	5
United Kingdom	252	756	252	31	92	31
Sum	1,724	5,178	1,724	585	1,756	585

Table A.18: Full-load hours of wind and solar technologies by resource class (low, mid, high) without wind technology boost

	Wind off (low)	Wind off (mid)	Wind off (high)	Wind on (low)	Wind on (mid)	Wind on (high)
Austria	0	0	0	558	1,675	2,814
Belgium	2,758	2,763	3,255	2,197	2,292	2,930
Bulgaria	594	1,203	1,523	479	1,337	2,555
Croatia	462	1,107	915	284	619	2,288
Czech	0	0	0	1,894	2,326	2,812
Denmark	2,800	3,312	4,106	1,376	2,764	2,992
Estonia	2,248	2,160	3,420	1,299	1,836	2,903
Finland	1,151	2,033	2,683	742	940	3,462
France	1,671	2,735	3,414	1,462	2,003	2,889
Germany	2,617	3,190	3,267	1,757	2,105	2,403
Greece	610	1,440	2,133	259	718	2,201
Hungary	0	0	0	637	848	2,686
Ireland	2,061	3,557	4,046	2,131	2,682	3,324
Italy	664	979	956	255	970	1,849
Latvia	1,809	2,833	3,375	648	2,265	2,704
Lithuania	1,885	2,708	1,881	485	1,580	2,317
Luxembourg	0	0	0	1,862	2,087	2,254
Netherlands	2,959	3,116	3,728	1,929	2,135	2,513
Norway	1,114	2,218	2,070	664	2,317	3,303
Poland	2,196	2,751	3,149	1,883	2,032	3,406
Portugal				620	1,619	2,821
Romania	1,112	1,336	1,667	512	1,010	2,518
Slovakia				679	1,620	2,834
Slovenia	685	685	457	331	894	1,722
Spain	752	1,084	1,574	1,602	2,328	3,295
Sweden				325	947	3,258
Switzerland				1,499	1,793	2,501
United Kingdom	2,912	3,150	4,148	1,901	2,700	3,019
Average	1,450	2,135	2,601	1,089	1,725	2,898

Table A.19: Full-load hours of wind and solar technologies by resource class (low, mid, high) with wind technology boost

	Wind off (low)	Wind off (mid)	Wind off (high)	Wind on (low)	Wind on (mid)	Wind on (high)
Austria	0	0	0	831	2,719	3,753
Belgium	2,964	2,970	3,489	3,269	3,247	3,616
Bulgaria	881	1,333	1,685	732	2,120	3,242
Croatia	893	923	996	472	966	2,975
Czech	0	0	0	2,722	3,178	3,834
Denmark	3,037	3,567	4,353	1,876	4,083	4,443
Estonia	2,459	2,978	3,654	1,888	2,573	4,328
Finland	1,190	1,695	2,901	1,419	1,776	3,886
France	1,833	2,964	3,638	3,053	3,003	3,708
Germany	2,836	2,573	3,661	2,893	2,977	3,003
Greece	773	1,270	2,318	456	1,060	2,896
Hungary	0	0	0	965	1,271	3,575
Ireland	2,217	3,980	4,214	2,797	3,737	3,895
Italy	735	1,058	1,886	394	1,498	2,401
Latvia	1,970	3,065	3,607	1,012	3,550	3,664
Lithuania	2,044	2,891	3,205	766	2,644	3,216
Luxembourg	0	0	0	2,523	2,660	2,903
Netherlands	3,175	3,338	3,956	2,843	3,251	3,331
Norway	1,244	1,843	2,167	940	3,271	3,835
Poland	2,110	2,973	3,390	2,873	3,263	4,314
Portugal				968	2,847	3,646
Romania	1,240	1,583	1,844	832	1,752	2,881
Slovakia				1,010	2,209	3,652
Slovenia	761	761	507	515	1,509	2,417
Spain	832	1,511	2,499	2,578	3,031	3,928
Sweden				550	1,770	3,704
Switzerland				2,141	2,520	2,838
United Kingdom	3,127	3,375	4,324	2,387	3,642	3,615
Average	1,577	2,230	2,937	1,776	2,578	3,558

Appendix A.8. Biomass Limits

Table A.20: Country-level biomass limits (TWh)

TWh th.:	Standard	Double	Fourfold	TWh el.:	Standard	Double	Fourfold
Austria	52	103	207		10	19	38
Belgium	21	42	85		4	8	16
Bulgaria	37	73	146		7	13	27
Croatia	16	31	62		3	6	11
Czech Republic	61	121	242		11	22	45
Denmark	17	34	69		3	6	13
Estonia	18	35	70		3	6	13
Finland	101	202	404		19	37	74
France	300	600	1,200		55	110	221
Germany	263	526	1,053		48	97	194
Greece	21	42	84		4	8	15
Hungary	54	107	215		10	20	39
Ireland	37	75	149		7	14	27
Italy	114	228	456		21	42	84
Latvia	28	56	111		5	10	20
Lithuania	22	44	88		4	8	16
Luxembourg	3	5	11		0	1	2
Netherlands	18	36	72		3	7	13
Norway	23	46	93		4	9	17
Poland	161	322	643		30	59	118
Portugal	35	69	139		6	13	26
Romania	122	245	490		23	45	90
Slovak Republic	22	44	88		4	8	16
Slovenia	14	27	55		3	5	10
Spain	160	320	640		29	59	118
Sweden	148	296	592		27	54	109
Switzerland	13	27	54		2	5	10
United Kingdom	166	332	664		31	61	122
Sum	2,045	4,091	8,182		376	753	1,505

We take regional economic harvesting potentials in kilo tons (metric) for agricultural biomass, wooden biomass, and waste, out of which we assume 50% to be available for electricity generation. We use net calorific values of 18 MJ/kg (agricultural crops), 19 MJ/kg (wood), and 15 MJ/kg (dry matter waste) to convert biomass potentials to bioenergy potentials.
The three columns on the left show thermal limits (TWh th.) and the three columns on the right generation limits (TWh el.) when assuming technology parameters of the 2050 vintage.

Appendix B. Supplementary Tables

Appendix B.1. Additional Tables for Subsection 8.1

Table B.21: Aggregated social cost (billion €) from 2016 to 2050 (1)

	SCAP	SCC	Sum
Internalization choices and emission factor assumptions			
No internalization	1,494	3,650	5,145
Only SCAP (mid)	330	1,761	2,091
Only SCC	449	345	794
SCC and SCAP (low)	192	414	605
SCC and SCAP (mid)***	166	456	622
SCC and SCAP (high)	208	474	682
Varying SCC level			
SCC 25%	242	321	562
SCC 50%	185	451	636
SCC 100%***	166	456	622
SCC 200%	353	-34	320
SCC 400%	486	-998	-512
SCC 800%	576	-2,727	-2,151
Varying SCAP level			
SCAP 25%	89	369	458
SCAP 50%	130	417	548
SCAP 100%***	166	456	622
SCAP 200%	249	446	695
SCAP 400%	322	382	704
SCAP 800%	408	285	693
Technology boost			
No internalization with boost	1,340	3,251	4,591
Only SCAP (mid) with boost	280	1,460	1,740
Only SCC with boost	430	375	805
SCC and SCAP (low) with boost	174	441	615
SCC and SCAP (mid) with boost	153	476	629
SCC and SCAP (high) with boost	200	483	683

***SCC and SCAP (mid) is the same as SCC 100%, SCAP 100%, 7/3/1.5, SCAP normal, and regional biomass limits. Those serve as benchmark for comparison with other specifications.

Table B.22: Aggregated social cost (billion €) from 2016 to 2050 (2)

	SCAP	SCC	Sum
Discounting and taxation			
7/7/7	268	1,416	1,684
3/3/3	201	1,058	1,259
1.5/1.5/1.5	178	937	1,115
7/3/3	160	683	843
7/3/1.5***	166	456	622
7/1.5/1.5	140	468	608
Distributional and growth effects			
SCAP normal***	166	456	622
SCAP equal	186	469	656
SCAP distributional	177	441	618
SCAP equal and distributional	174	464	638
SCAP no GDP growth	176	401	578
SCAP equal and no GDP growth	170	435	605
Biomass limits and trade			
Regional biomass limits***	166	456	622
European trade	187	356	543
Double regional	194	404	598
Double European trade	243	205	448
Fourfold regional	249	302	551
Fourfold European trade	345	-35	310
Biomass trade and arbitrage			
Regional biomass limits and SCAP equal (mid)	186	469	656
European trade and SCAP equal (mid)	230	426	656
Double regional and SCAP equal (mid)	230	428	658
Double European trade and SCAP equal (mid)	319	341	660
Fourfold regional and SCAP equal (mid)	297	363	660
Fourfold European trade and SCAP equal (mid)	359	304	662

***SCC and SCAP (mid) is the same as SCC 100%, SCAP 100%, 7/3/1.5, SCAP normal, and regional biomass limits. Those serve as benchmark for comparison with other specifications.

Appendix B.2. Additional Tables for Subsection 8.2

Table B.23: Technology switching clusters A to D compared to benchmark specification SCC and SCAP (mid)

Specifications by cluster	from	to
Median dominance of SCC		
SCC and SCAP (low)	Nuclear	**Bio-CCS**
SCAP 50%	Nuclear	**Bio-CCS**
SCAP no GDP growth	Nuclear	**Bio-CCS**
Only SCC	Nuclear	**Bio-CCS**. Gas-CCS
SCAP 25%	Nuclear	**Bio-CCS**.Gas-CCS
Strong dominance of SCC		
SCC 200%	Gas-CCS	**Bio-CCS**
SCC 400%	Gas-CCS	**Bio-CCS**. Nuclear
SCC 800%	Gas-CCS	**Bio-CCS**. Nuclear
Biomass dominance		
Double European trading	Nuclear. Wind	**Bio-CCS**
Fourfold regional	Nuclear	**Bio-CCS**
Fourfold European trading	Nuclear. Wind	**Bio-CCS**
Little or no dominance of SCC		
No internalization	Nuclear. Wind	**Gas**
SCC 50%	Gas-CCS	**Gas**
SCC 25%	Nuclear	**Gas**
Only SCAP	Nuclear. Wind	**Gas**
7/7/7	Nuclear. Wind	**Gas**. Solar
3/3/3	Nuclear	**Gas**. Solar
1.5/1.5/1.5	Nuclear	**Gas**. Solar
Dominance of SCAP		
SCAP 200%	**Gas-CCS**	Nuclear
SCAP 400%	**Gas-CCS**	Nuclear
SCAP 800%	**Gas-CCS**	Nuclear. Wind

Table B.24: Change in 2050 emissions in comparison to benchmark specification SCC and SCAP (mid) (1)

Change in 2050 emissions	**Air pollution (in Mt)**	**Carbon (in Gt)**	**Air pollution (magnitude)**	**Carbon (magnitude)**
Internalization choices and emission factor assumptions				
No internalization	3.24	3.26	+++	+++
Only SCAP	0.15	1.36	+	+++
Only SCC	0.75	-0.13	++	-
SCC and SCAP (low)	0.31	-0.14	+	-
SCC and SCAP (high)	-0.12	0.08	-	+
Varying SCC level				
SCC 25%	-0.24	0.66	-	++
SCC 50%	-0.38	0.24	--	+
SCC 200%	0.59	-0.19	++	-
SCC 400%	0.48	-0.21	+	-
SCC 800%	0.45	-0.21	+	-
Varying SCAP level				
SCAP 25%	0.68	-0.14	++	-
SCAP 50%	0.63	-0.16	++	-
SCAP 200%	-0.20	0.02	-	+
SCAP 400%	-0.52	0.09	---	+
SCAP 800%	-0.54	0.09	---	+
Technology boost				
No internalization with boost	2.52	2.64	+++	+++
Only SCAP (mid) with boost	-0.08	0.94	-	++
Only SCC with boost	0.64	-0.14	++	-
SCC and SCAP (low) with boost	0.15	-0.10	+	-
SCC and SCAP (mid) with boost	-0.06	0.00	-	+
SCC and SCAP (high) with boost	-0.20	0.09	-	+

***SCC and SCAP (mid) is the same as SCC 100%, SCAP 100%, 7/3/1.5, SCAP normal, and regional biomass limits. Those serve as benchmark for comparison with other specifications.

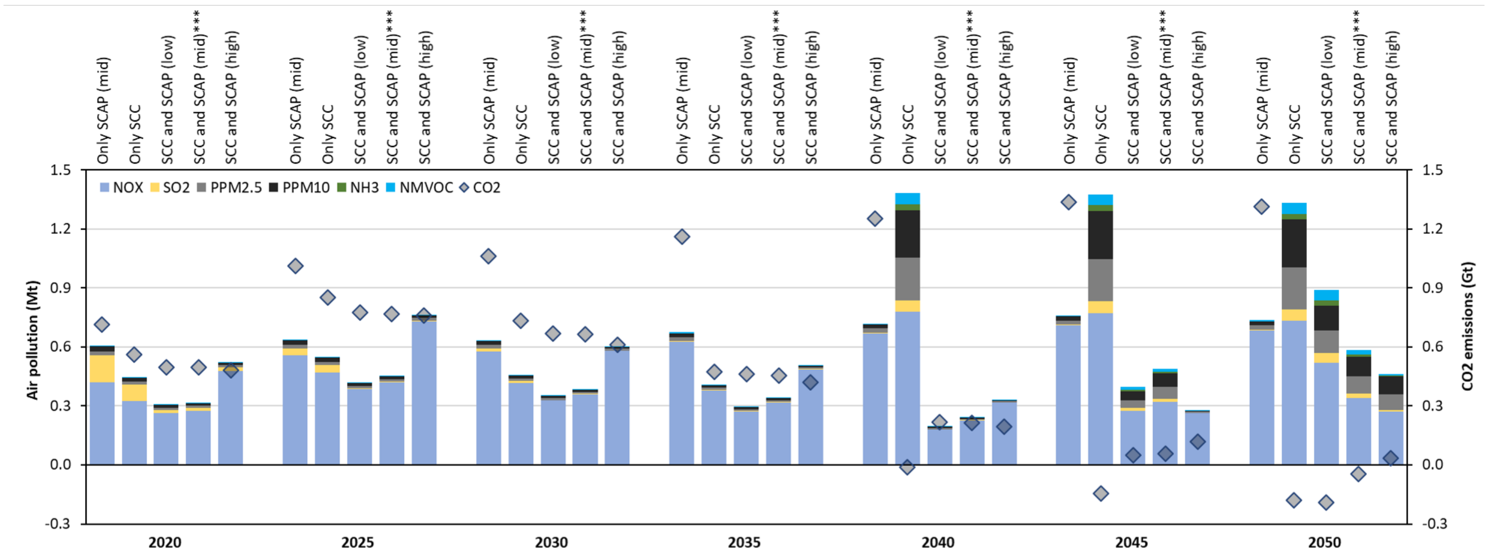
Table B.25: Change in 2050 emissions in comparison to benchmark specification SCC and SCAP (mid)

Change in 2050 emissions	**Air pollution (in Mt)**	**Carbon (in Gt)**	**Air pollution (magnitude)**	**Carbon (magnitude)**
Discounting and taxation				
7/7/7	-0.01	1.07	-	+++
3/3/3	-0.21	0.70	-	++
1.5/1.5/1.5	-0.25	0.64	--	++
7/3/3	-0.31	0.15	--	+
7/1.5/1.5	-0.16	0.03	-	+
Distributional and growth effects				
SCAP equal	0.09	-0.03	+	-
SCAP distributional	0.21	-0.06	+	-
SCAP equal and distributional	0.03	-0.01	+	-
SCAP no GDP growth	0.62	-0.16	++	-
SCAP equal and no GDP growth	0.61	-0.16	++	-
Biomass limits and trade				
European trading	0.61	-0.16	++	-
Double regional	0.39	-0.11	+	-
Double European trading	1.63	-0.42	+++	--
Fourfold regional	1.19	-0.32	+++	--
Fourfold European trading	3.64	-0.95	+++	---
Biomass trade and arbitrage				
European trading and SCAP equal	0.57	-0.17	++	-
Double regional and SCAP equal	0.57	-0.16	++	-
Double European trading and SCAP equal	1.56	-0.44	+++	--
Fourfold regional and SCAP equal	1.32	-0.37	+++	--
Fourfold European trading and SCAP equal	2.00	-0.56	+++	---

***SCC and SCAP (mid) is the same as SCC 100%, SCAP 100%, 7/3/1.5, SCAP normal, and regional biomass limits. Those serve as benchmark for comparison with other specifications.

Appendix C. Supplementary Visualizations

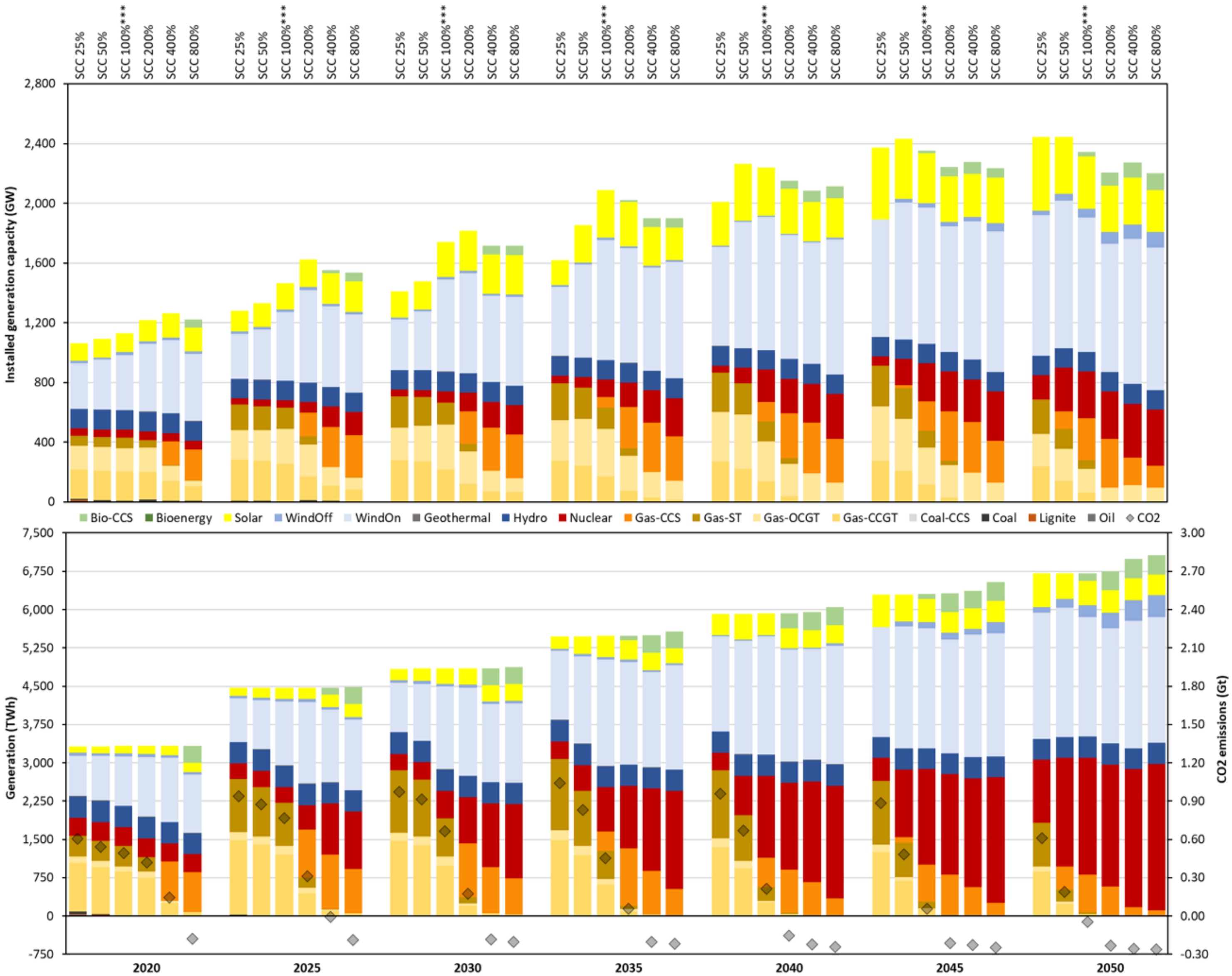
Appendix C.1. Additional Figures for Subsection 5.1



***SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

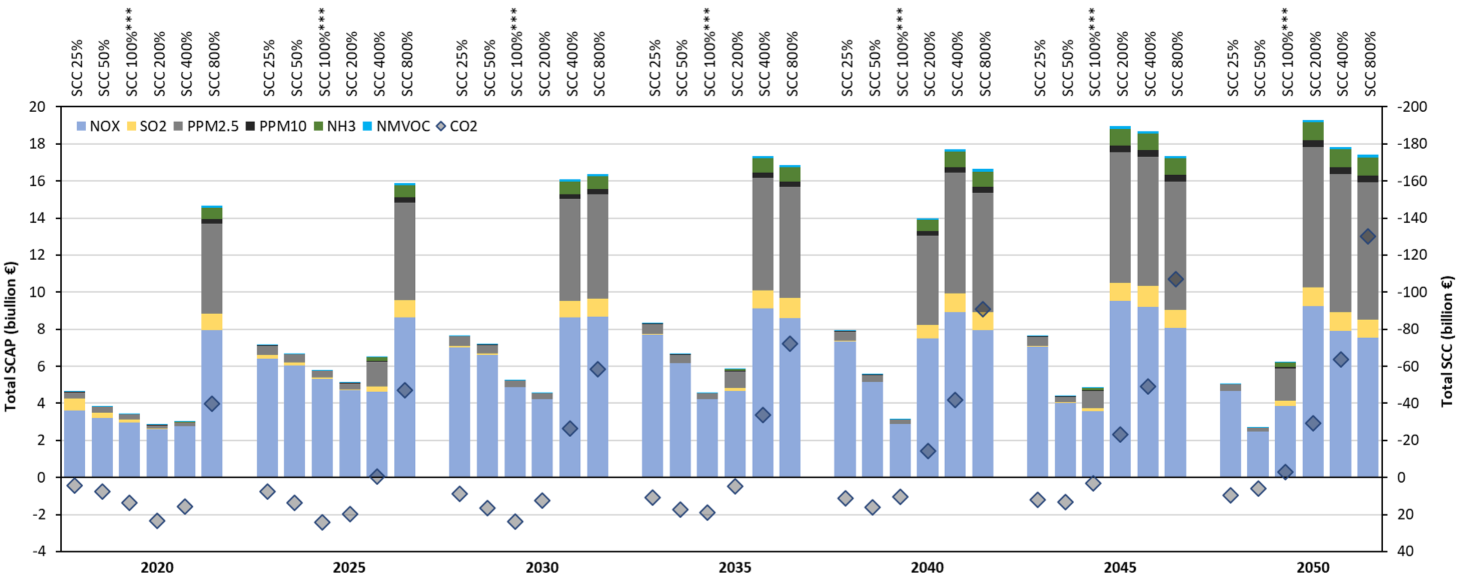
Figure C.9: Air pollutant and carbon emissions for different internalization strategies and emission factor scenarios

Appendix C.2. Additional Figures for Subsection 5.3



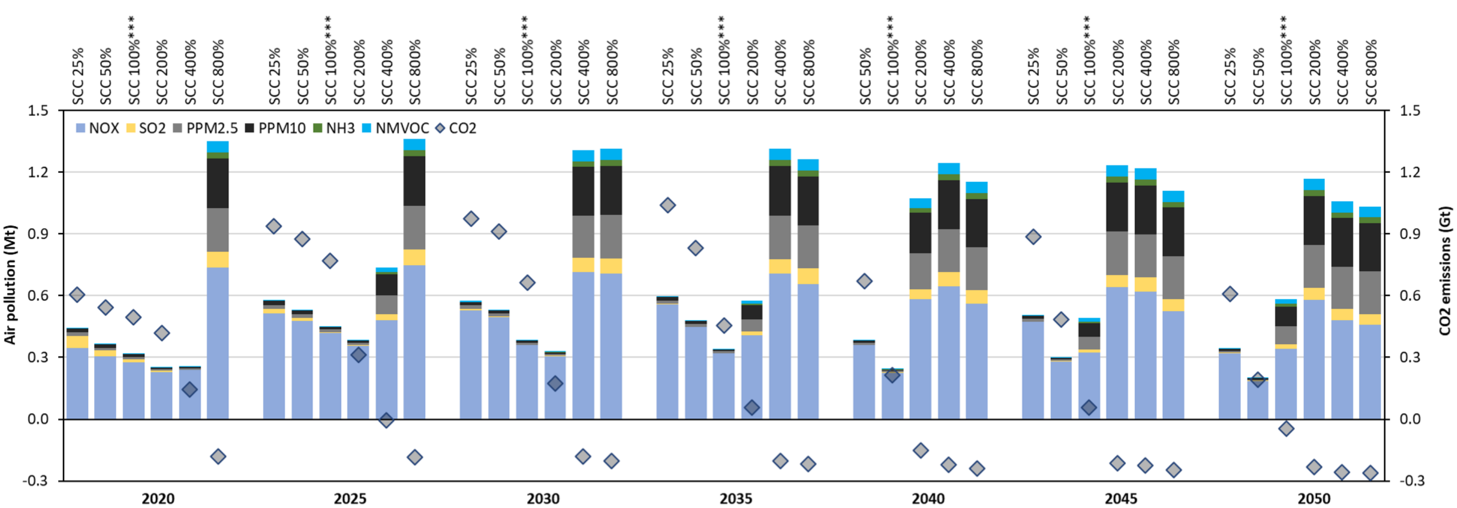
***SCC 100% is the same as SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

Figure C.10: Installed capacity (upper panel) and generation with CO2 emissions (lower panel) for different SCC assumptions



***SCC 100% is the same as SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

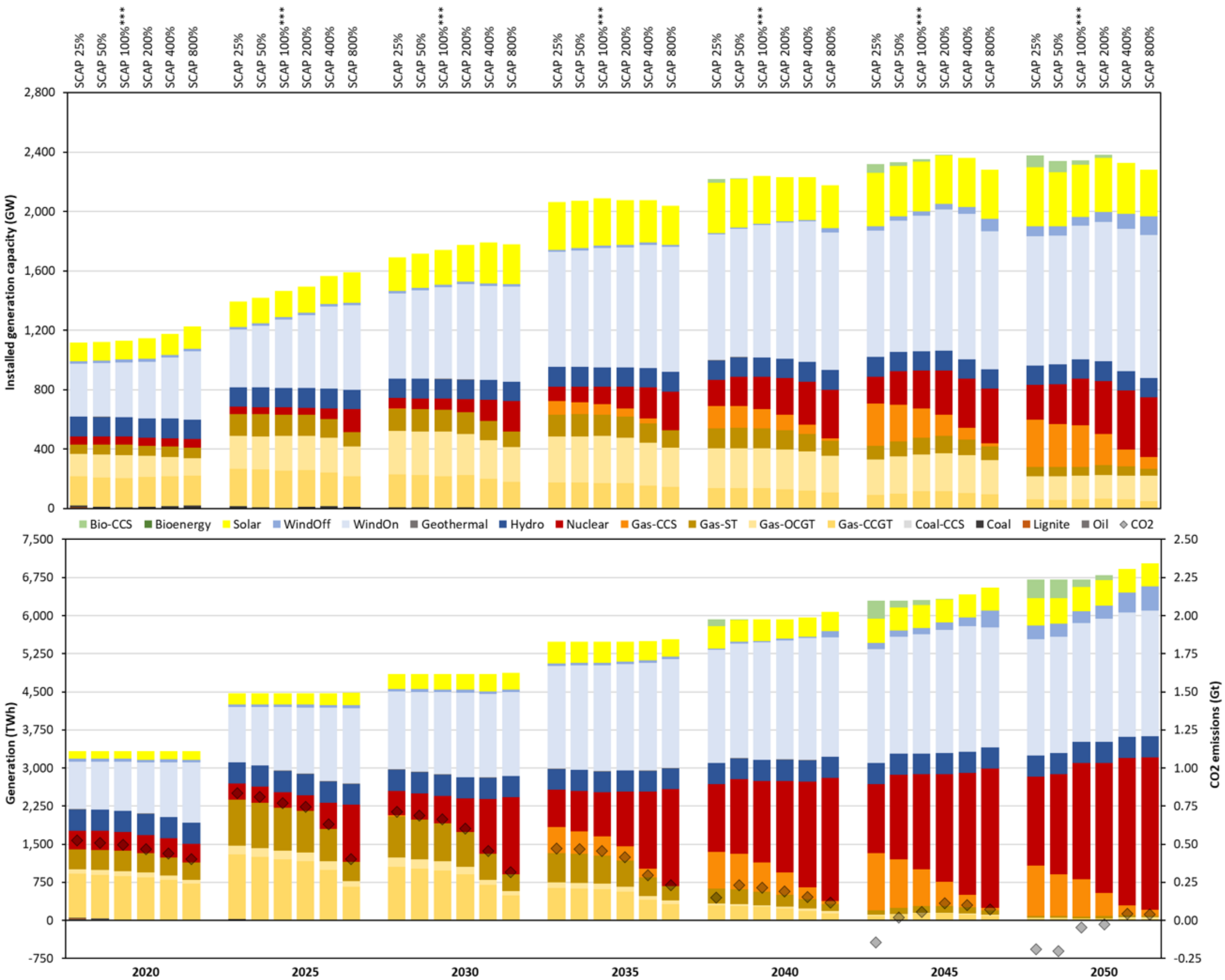
Figure C.11: Total SCAP and SCC for different SCC assumptions



***SCC 100% is the same as SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

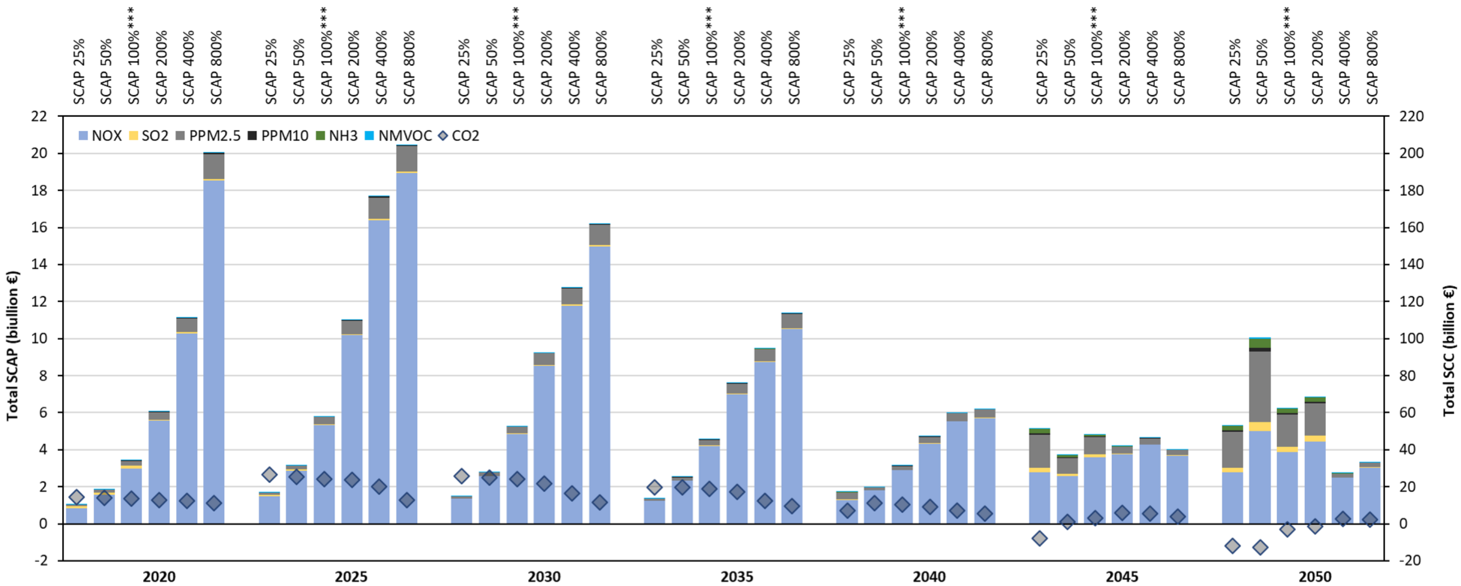
Figure C.12: Air pollutant and carbon emissions for different SCC assumptions

Appendix C.3. Additional Figures for Subsection 5.4



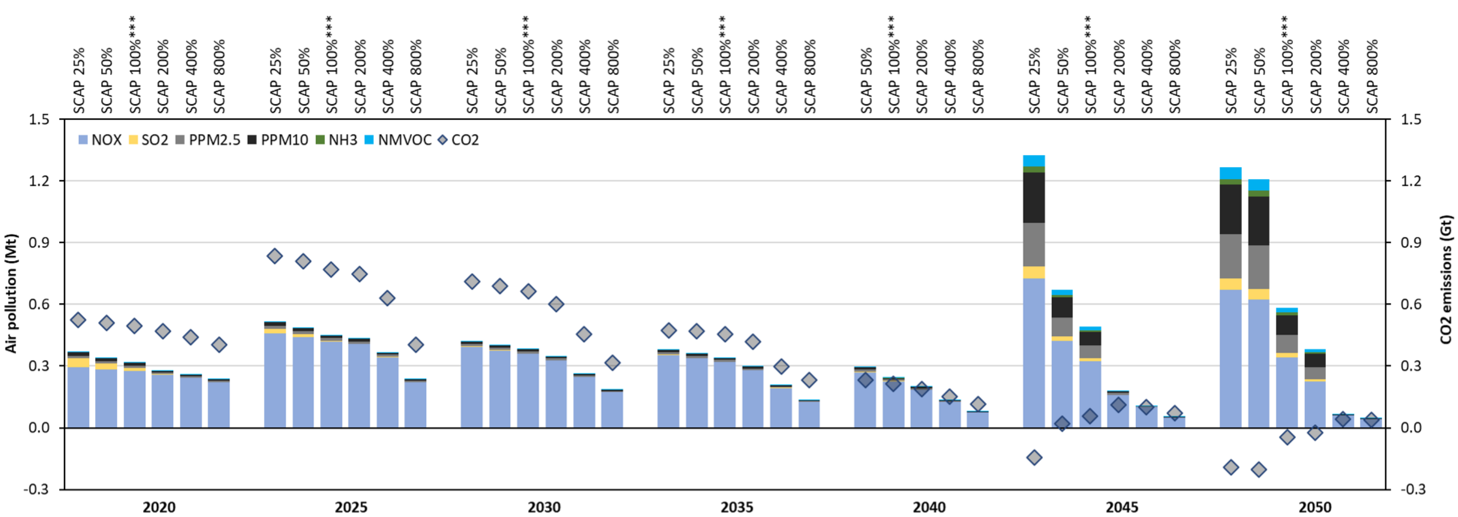
***SCAP 100% is the same as SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

Figure C.13: Installed capacity (upper panel) and generation with CO2 emissions (lower panel) for different SCAP assumptions



***SCAP 100% is the same as SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

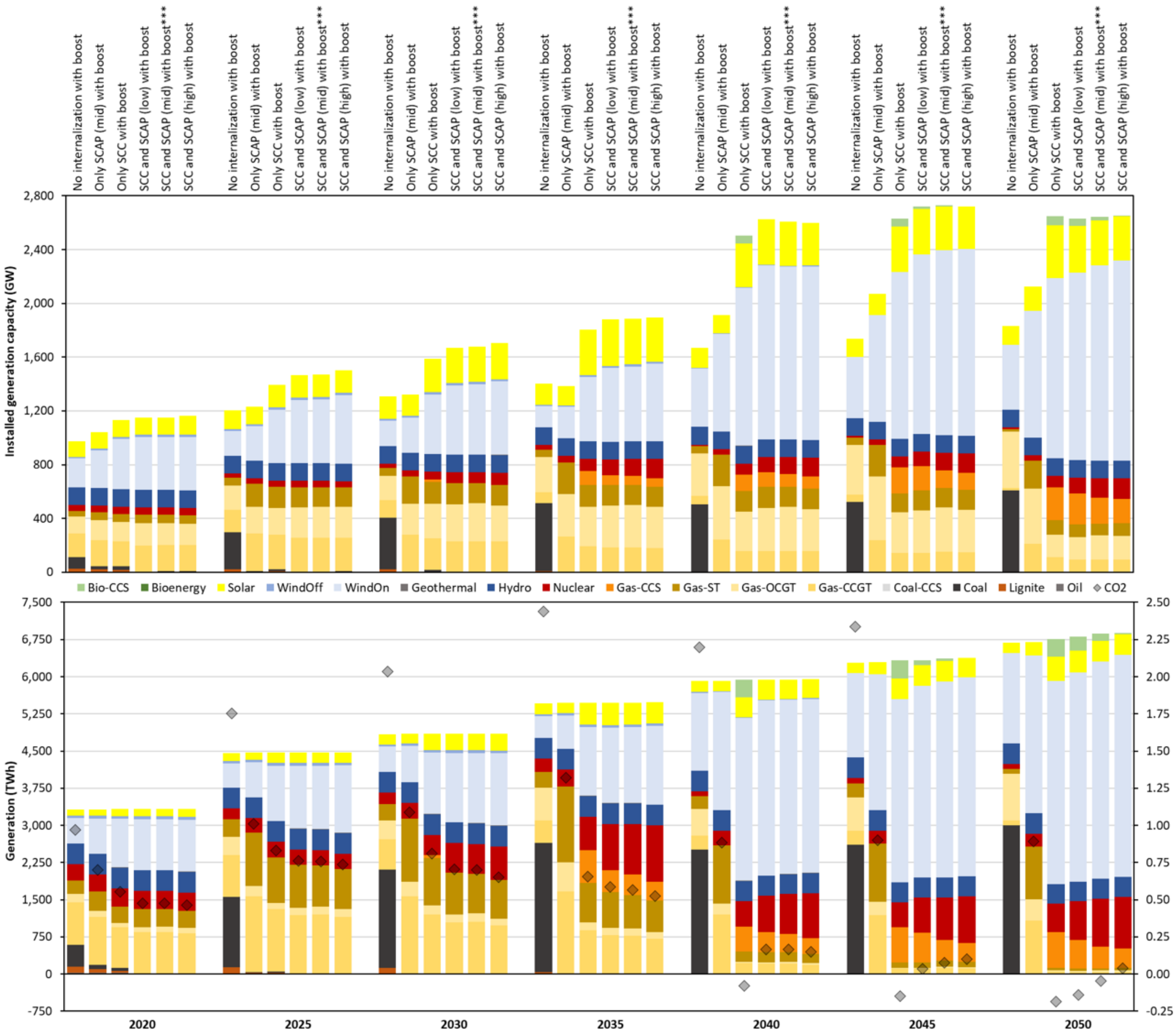
Figure C.14: Total SCAP and SCC for different SCAP assumptions



***SCAP 100% is the same as SCC and SCAP (mid) serves as benchmark for comparisons with other specifications.

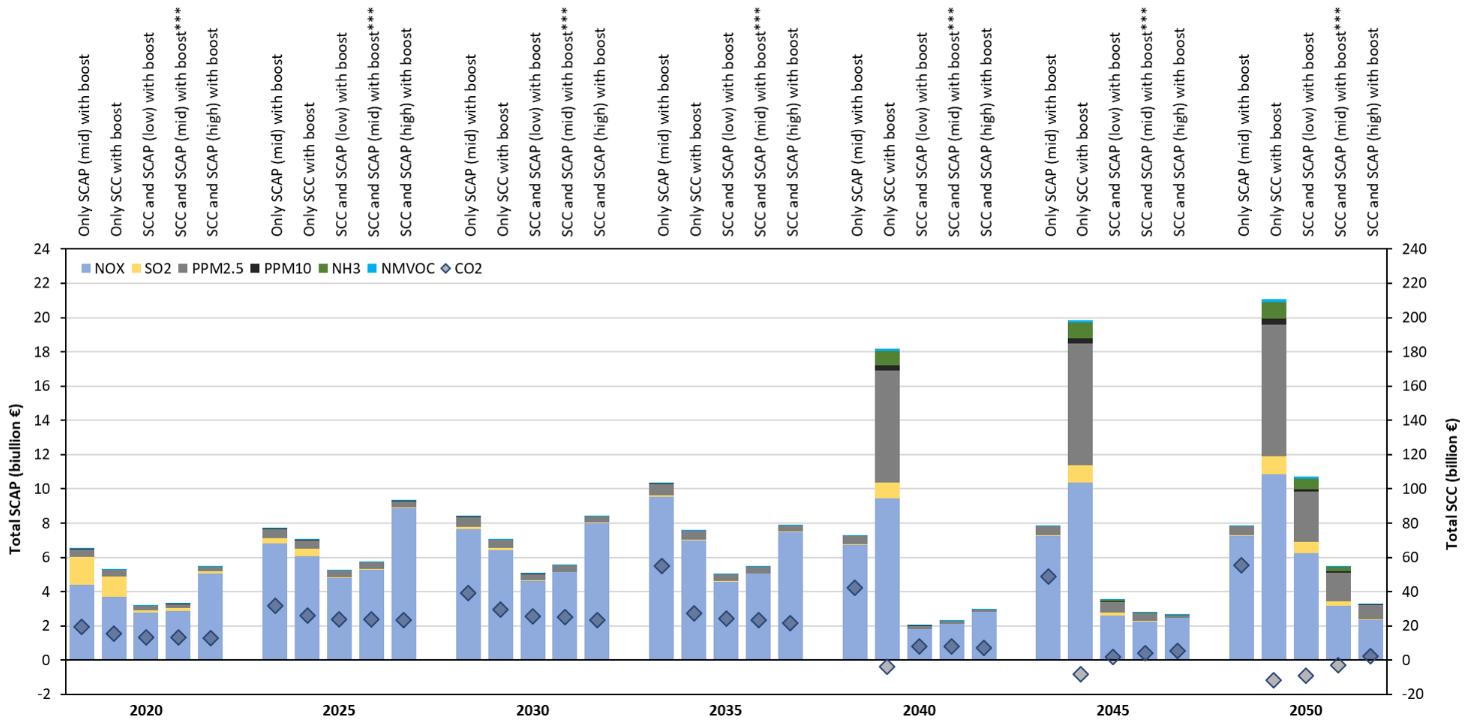
Figure C.15: Air pollutant and carbon emissions for different SCAP assumptions

Appendix C.4. Additional Figures for Subsection 5.5



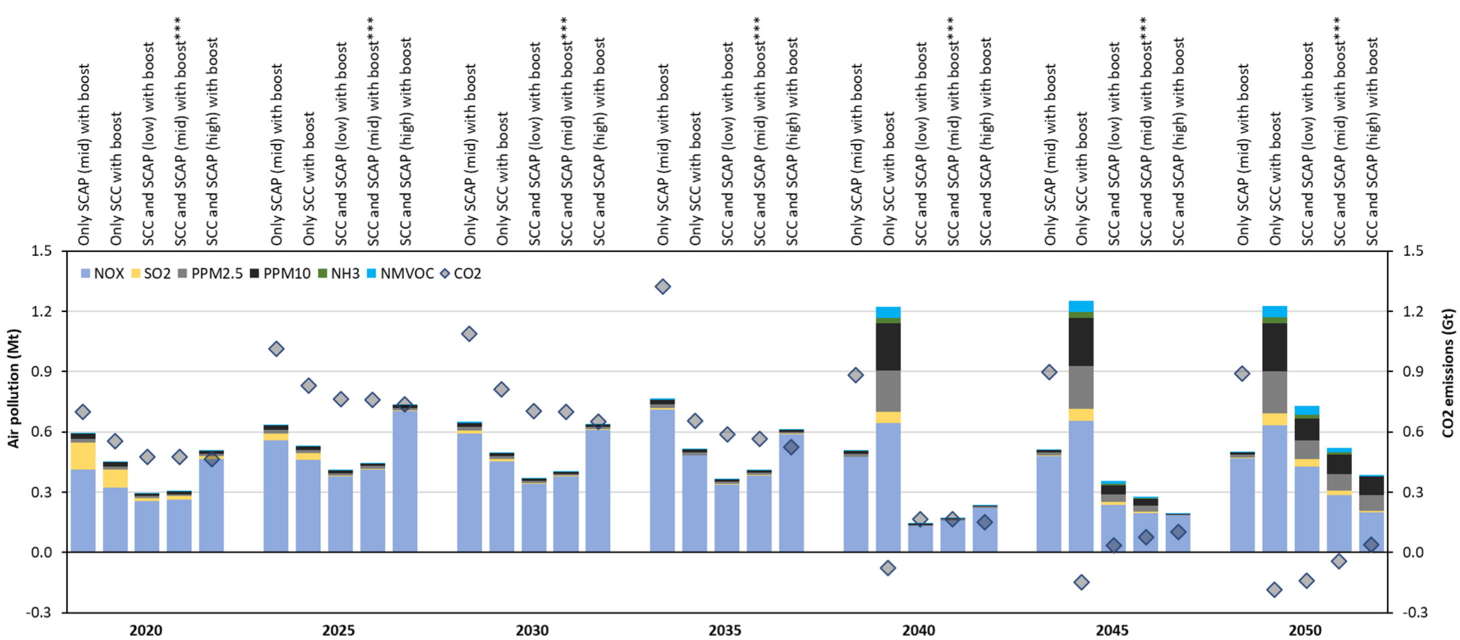
***SCC and SCAP (mid) with boost serves as benchmark for comparisons with other specifications.

Figure C.16: Installed capacity (upper panel) and generation with CO2 emissions (lower panel) for different levels of internalization and emission factor assumptions assuming higher full-load hours for wind from 2040 onwards



***SCC and SCAP (mid) with boost serves as benchmark for comparisons with other specifications.

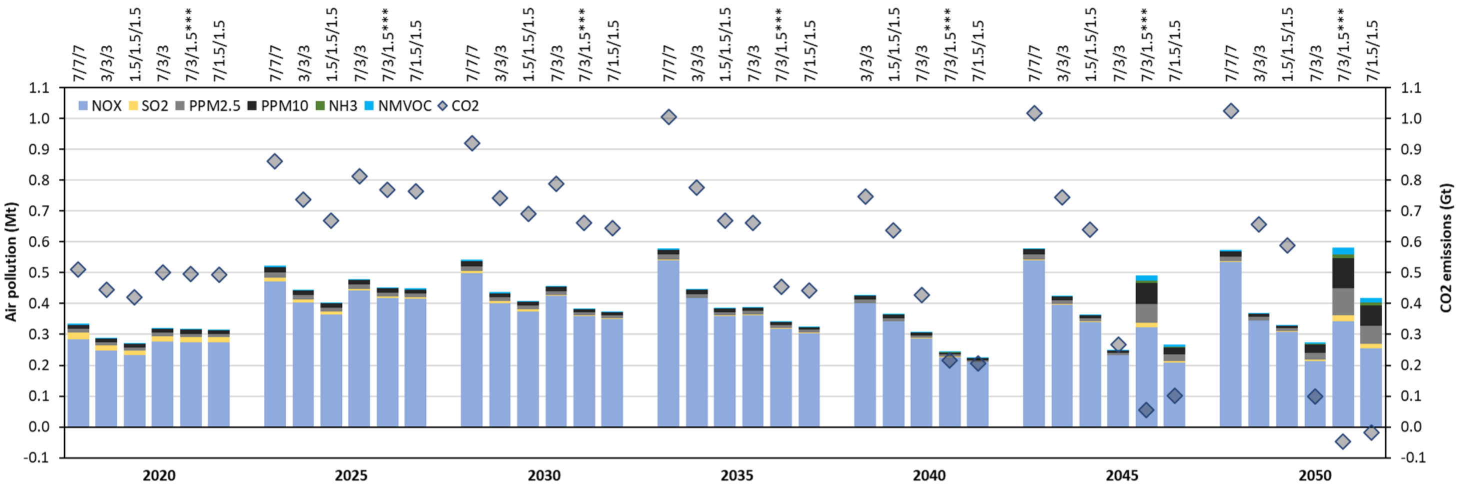
Figure C.17: Total SCAP and SCC for different levels of internalization and emission factor assumptions assuming higher full-load hours for wind from 2040 onwards



***SCC and SCAP (mid) with boost serves as benchmark for comparisons with other specifications.

Figure C.18: Air pollutant and carbon emissions for different levels of internalization and emission factor assumptions assuming higher full-load hours for wind from 2040 onwards

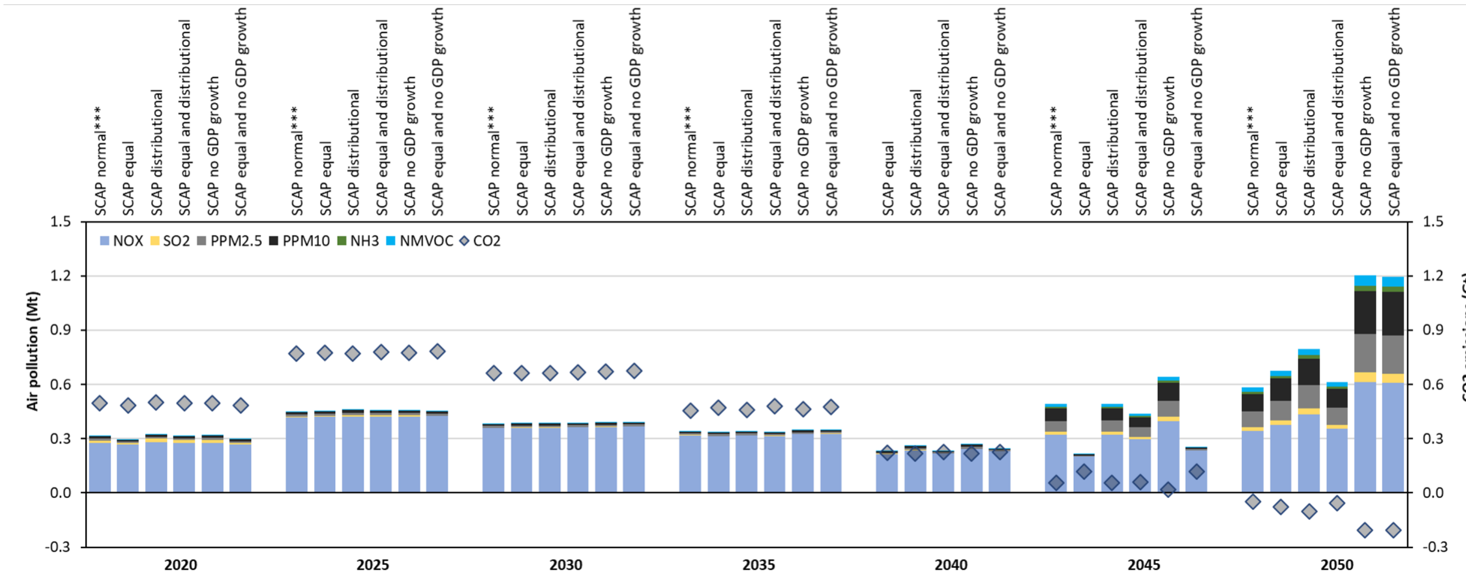
Appendix C.5. Additional Figures for Section 6



***7/3/1.5 is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure C.19: Air pollutant and carbon emissions for different discount and interest rates

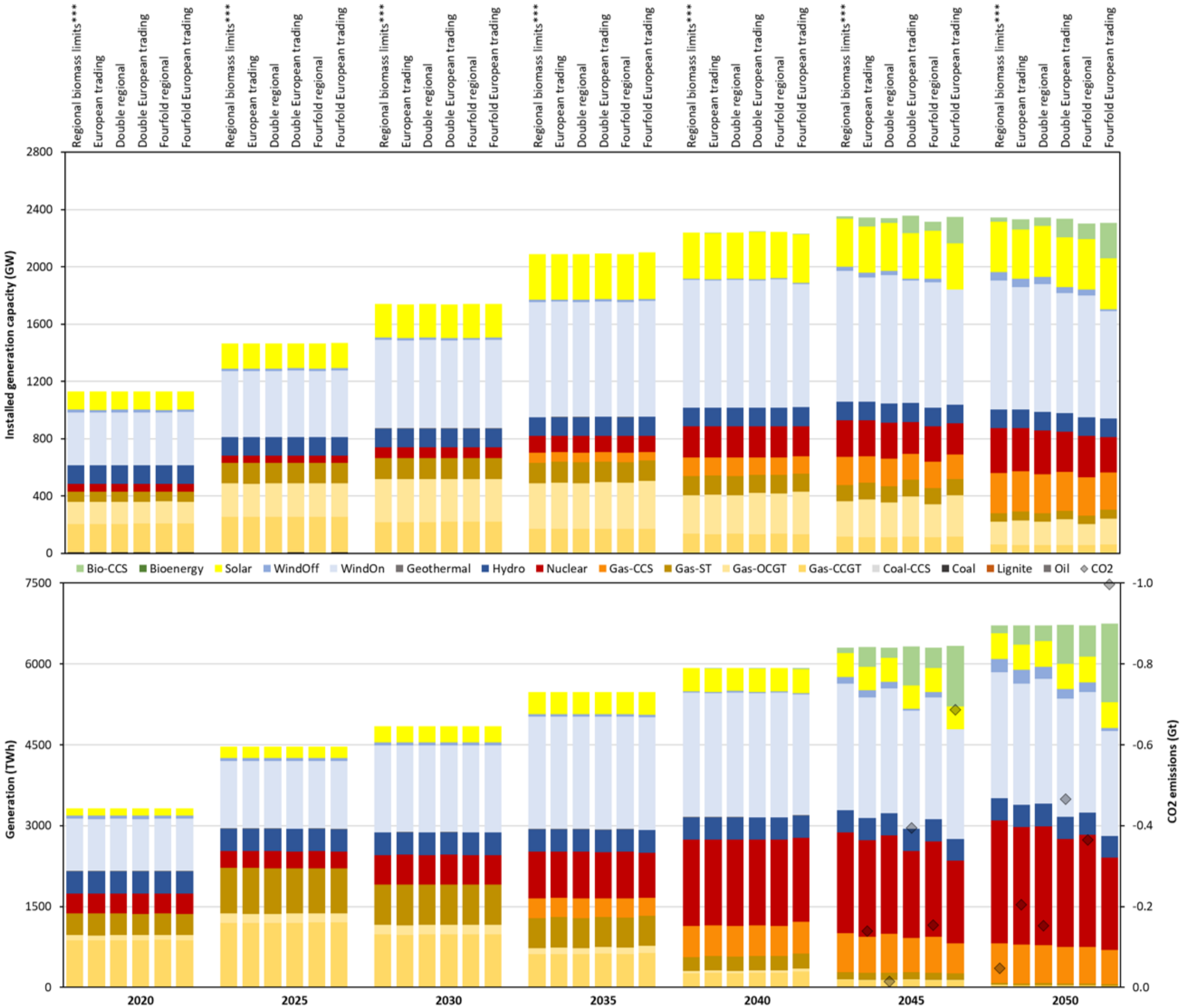
Appendix C.6. Additional Figures for Subsection 7.1



***SCAP normal is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

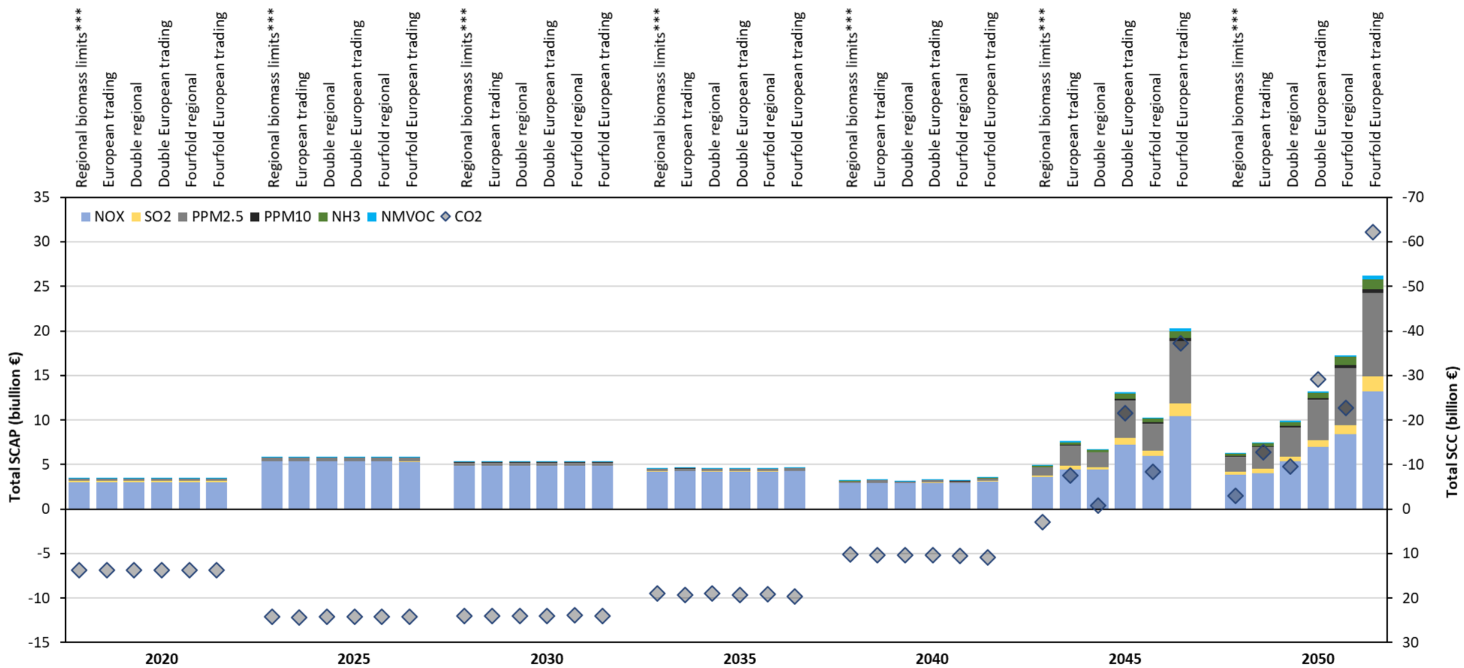
Figure C.20: Air pollutant and carbon emissions for different SCAP specifications

Appendix C.7. Additional Figures for Subsection 7.2



***Regional biomass limits is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure C.21: Installed capacity (upper panel) and generation with CO2 emissions (lower panel) for different biomass limits



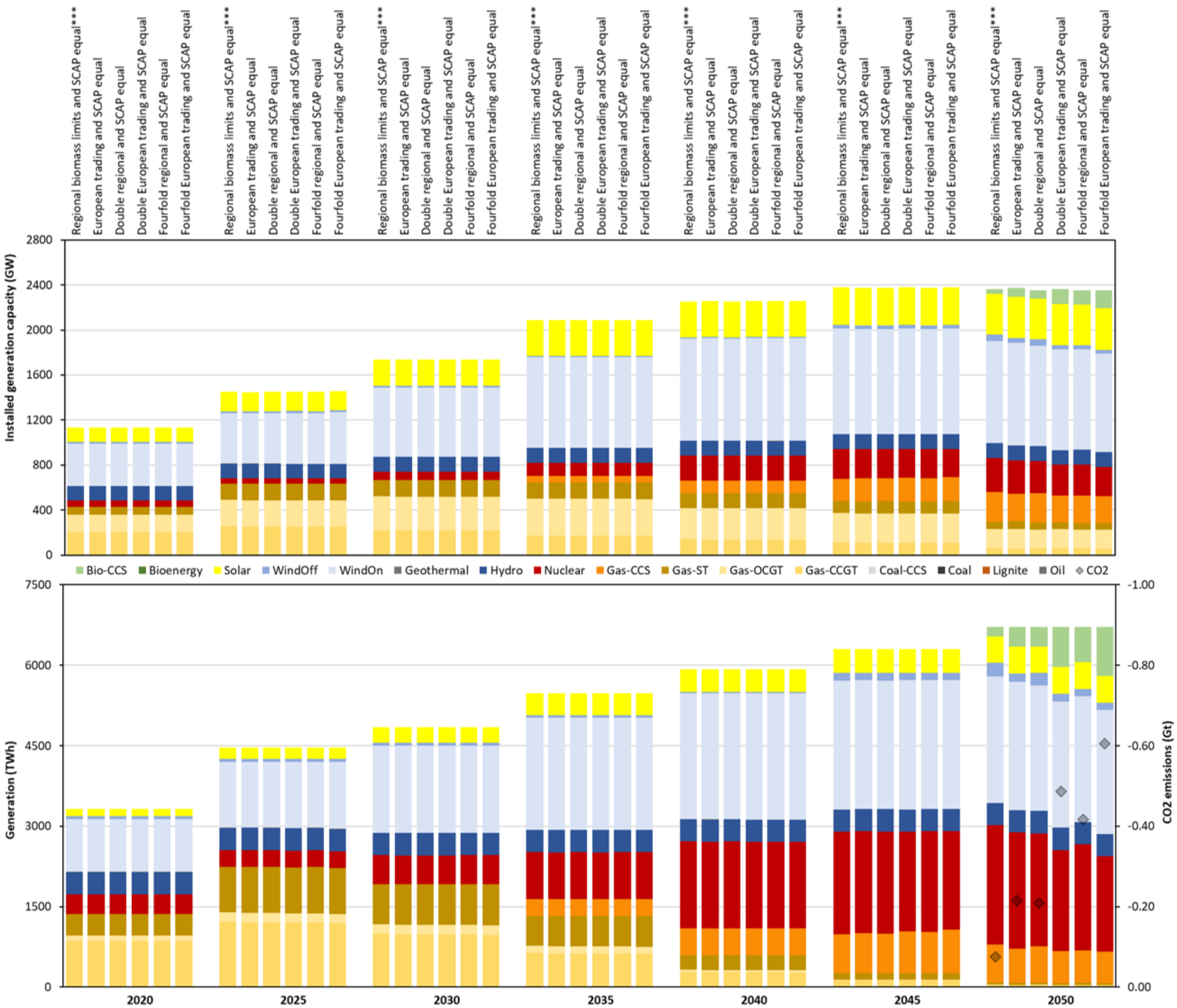
***Regional biomass limits is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

Figure C.22: Total SCAP and SCC for different biomass limits

***Regional biomass limits is the same as SCC and SCAP (mid) and serves as benchmark for comparisons with other specifications.

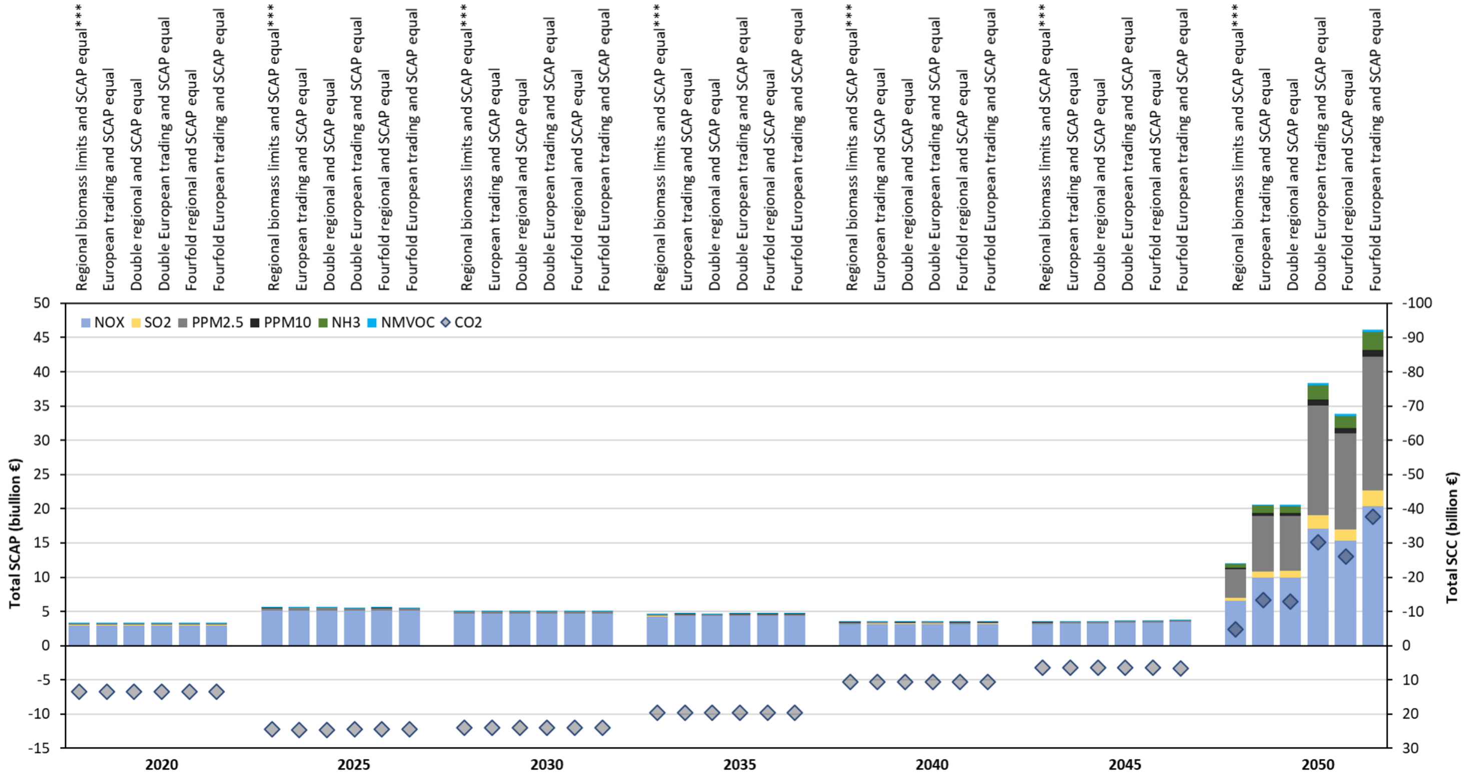
Figure C.23: Air pollutant and carbon emissions for different biomass limits

Appendix C.8. Additional Figures for Subsection 7.3



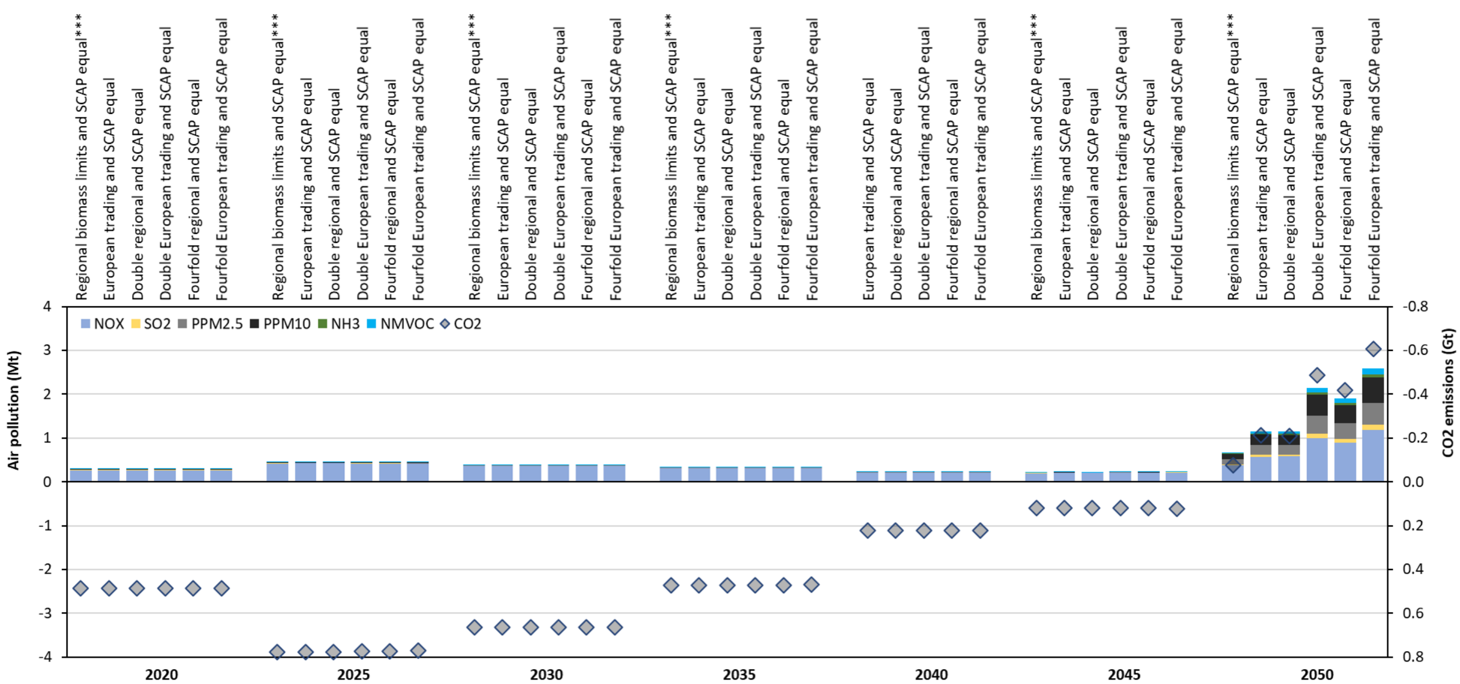
***Regional biomass limits and SCAP equal is the same as SCAP equal and serves as benchmark for comparisons with other specifications.

Figure C.24: Installed capacity (upper panel) and generation with CO2 emissions (lower panel) for different biomass limits when assuming equal SCAP across countries



***Regional biomass limits and SCAP equal is the same as SCAP equal and serves as benchmark for comparisons with other specifications.

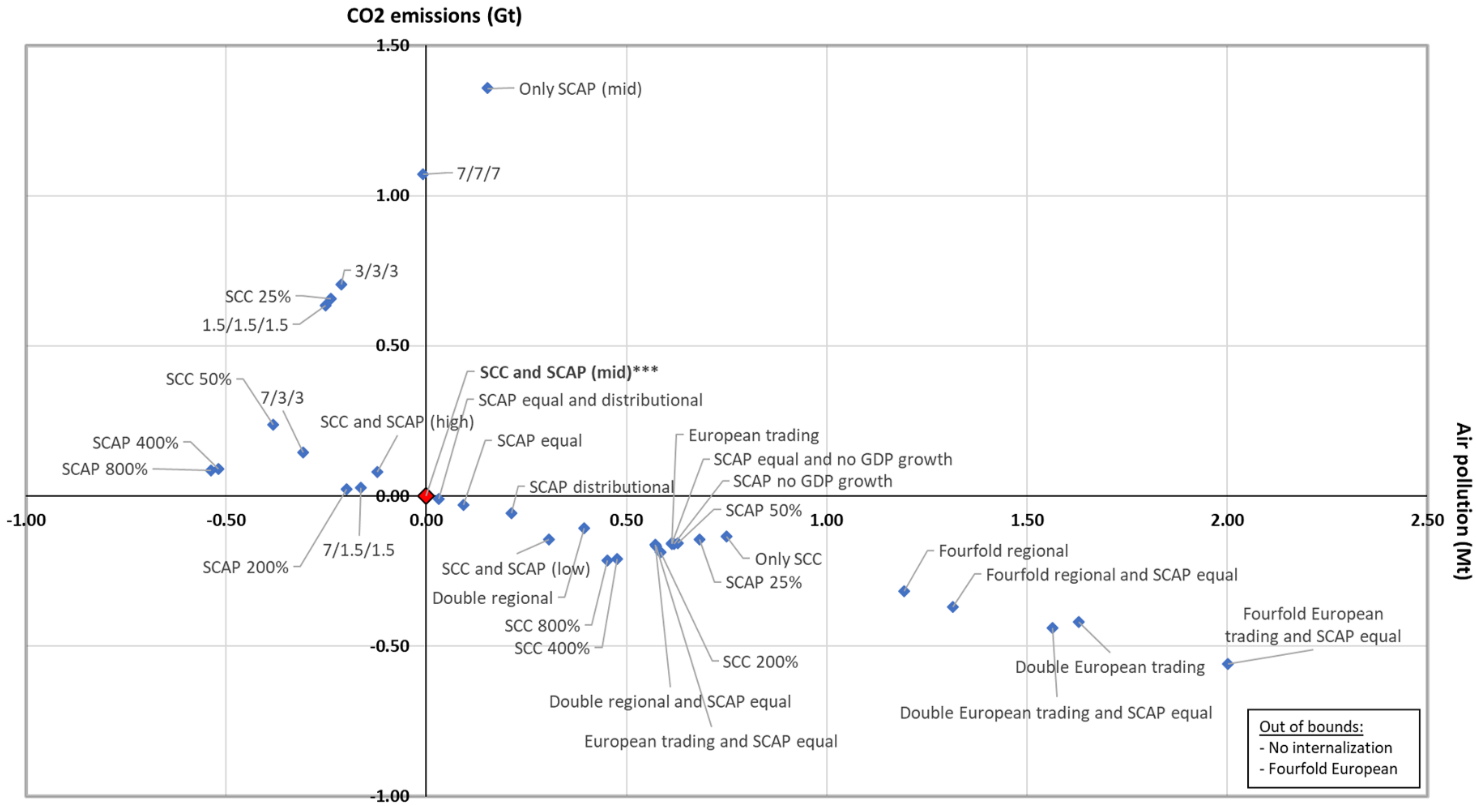
Figure C.25: Total SCAP and SCC for different biomass limits when assuming equal SCAP across countries



***Regional biomass limits and SCAP equal is the same as SCAP equal and serves as benchmark for comparisons with other specifications.

Figure C.26: Air pollutant and carbon emissions for different biomass limits when assuming equal SCAP across countries

Appendix C.9. Additional Figures for Subsection 8.2



Note that both CO_2 and air pollutant emissions are displayed in absolute difference to our benchmark specification SCC and SCAP (mid)***. Technology boost specifications are excluded for readability purposes as they do not change any emission-related or social-cost related assumptions.

Figure C.27: 2050 emissions of all specifications in relation to benchmark specification