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Abstract

Current decarbonization policies neglect damages from local air pollutants. We analyze the trade-off between complementary taxation of carbon emissions and local air pollution. We quantify results for the European power market until 2050. Taxing only air pollution results in social cost of 5,890 billion € and fosters nuclear deployment. Taxing only carbon yields social cost of 716 billion € and promotes CCS deployment. Taxing both yields cost of 1,118 billion €. Moderate carbon taxation can be complementary to a primary policy of air pollution abatement. On the contrary, a primary policy of decarbonization stands in trade-off with air pollution abatement in the long-term.

JEL Code: C61, H21, H23, H43, L94

Keywords: Taxation, 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 reductions of CO_2 emissions to keep global warming below 2° Celsius (Paris Agreement, 2015), but 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) and analyze possible co-benefits and trade-offs when jointly mitigating the two.

With more than 40%, electricity and related heat generation are the biggest contributors of the 36.3 Gt of energy-related CO_2 emissions.[1] Electricity generation and its role for emitting CO_2 significantly increased over the last decades. It is expected to assume an ever bigger share in the future 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 0.914 Gt in the period 2013 to 2021.[2] The European Union even proposes more ambitious targets to achieve carbon neutrality by 2045. However, European actions alone will not 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.[3]

Air pollution emissions, in turn, have local impacts and every country should undertake efforts to internalize those local damages by means of appropriate taxation at the respective marginal 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. Moreover, each electricity generation technology has a unique profile of carbon and air pollution intensity. This allows sensitive response of the optimal technology mix to different scenarios of internalizing social cost. Some climate neutral technologies such as biomass with carbon capture and storage (bio-CCS) reflect internalization trade-offs as they bind CO_2 emissions but are heavily locally air-polluting, giving way to interesting questions about how to design a technology mix with both low carbon and low air pollution emissions.

We internalize SCC and SCAP via taxes and implement this strategy in the EUREGEN model, a multi-region partial equilibrium model of the European power market that optimizes investments, decommissioning, and dispatch of multiple generation, storage, and transmission technologies until 2050 (Weissbart and Blanford, 2019). We use air pollution emission factors (Cai et al., 2012, EPA, 1995, EEA, 2019, UBA, 2019), calibrate the DICE model (Nordhaus, 2014) to deliver SCC that

[1] See `https://www.iea.org/reports/global-energy-review-co2-emissions-in-2021-2`.

[2] See `https://ec.europa.eu/clima/news-your-voice/news/emissions-trading-greenhouse-gas-emissions-73-2021-en`.

[3] The literature developed and analyzed multiple approaches how to mitigate the problem of free-riding (e.g., Barrett, 1994, Nordhaus, 2015) but those approaches have not been globally implemented so far.

match population projections from the World Bank[4] as well as GDP projections from EUREGEN's CGE model calibration (Mier et al., 2020, 2022, Siala et al., 2022), and obtain SCAP from the externE project series (Friedrich and Bickel, 2001, Pietrapertosa et al., 2009).

There exists an array of literature on emissions and resulting damages of electricity generation, among which several papers also consider local air pollutants.[5] Klaassen and Riahi (2007) apply MESSAGE-MACRO to internalize air pollution damages but unlike in our analysis they refrain from internalizing climate damages (from CO_2 emissions). They also use SCAP estimates from the externE project series (that are similar but less recent than ours). However, two of our core technologies, bio-CCS and gas-CCS, are not part of their technology set. Nam et al. (2010) find, using a CGE analysis for 18 European countries, fundamental welfare losses (2%) from air pollution. Barteczko-Hibbert et al. (2014) integrate life cycle assessment and electricity generation but focus on greenhouse gases and less on local damages from air pollution. Shindell (2015) extends the SCC framework to incorporate (local) damages from air pollutants. He finds annual damages of 330 to 970 billion $ for US electricity generation. 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 annual damages fell from 245 billion $ in 2010 to 133 billion $ in 2017. Burtraw et al. (2014) look at the introduction of CO_2 emissions regulation in the US in addition to existing air pollution regulation (only covering SO_2) under different policy scenarios by using a power market model. Their analysis focuses on quantifying (consumer) surplus depending on the policy instrument used. Driscoll et al. (2015) find co-benefits for human health from improvements in air quality following from CO_2 emissions regulation scenarios by using US power market models. However, they do not quantify health benefits in monetary terms and do not take into account social damages beyond human health (as we do). Their scenarios differ by options to reduce CO_2 emissions and only one of their scenarios uses SCC in the sense of carbon taxation. Moreover, Driscoll et al. (2015) only allow for carbon-capture-and-storage (CCS) in coal-fired plants. We allow for this technology as well but identify CCS on the basis of biomass (bio-CCS) and natural gas-fired power plants (gas-CCS) as key technologies to manage the trade-offs between damages from CO_2 emissions and local air pollutants.[6] Millstein et al. (2017) carry out a retrospective quantification of avoided CO_2 and air pollution emissions via substitution effects of renewable energy generation in the US. However, they do not allow for insights from optimization trade-offs in the long-run.

Our contribution delivers insights into how the long term technology and emission mix of the European power system varies under different internalization strategies or taxation choices (no taxation, sole air pollutant taxation, sole CO_2 taxation, joint CO_2 and air pollutant taxation), respectively. We test robustness of results by varying assumptions about SCC, SCAP, air pollutant

[4]See `https://databank.worldbank.org/source/population-estimates-and-projections`.

[5]This paper is a substantial expansion of Mier et al. (2021) but focuses on the complementary taxation of carbon emissions and local air pollutants only. The effect of diverging private and social discount rates is analyzed in another succeeding work.

[6]In fact, coal-CCS is absent in our optimized equilibrium because capture rates are worse and cost are considerably higher than for gas-CCS.

emission factors, and technological progress of wind power. Focusing solely on CO_2 taxation leads to accumulated SCC of 281 billion € in the 30 years from 2021 to 2050. Accumulated SCAP of 435 billion € are not internalized (sum of 716 billion €). The relation of SCC to SCAP turns when looking at discounted values (194 billion € of accumulated SCC vs. 92 billion € for accumulated SCAP) because CO_2 emissions are initially high and become even negative in the long-run, while the relative dominance of carbon damages yield considerably higher (and more costly) air pollution. Those late air pollutant emission damages, in turn, are discounted heavily so that the discounted values are below the ones from CO_2 emissions. When only taxing air pollution, 5,547 (1,340) billion € of (discounted) accumulated SCC remain non-internalized and SCAP are reduced to 343 (92) billion € (in discounted terms). Our results show that sole CO_2 taxation yields tremendously lower social cost compared to taxing solely air pollution, underlining that the mitigation of carbon emissions should dominate the policy making.

Interestingly, jointly mitigating the two yields accumulated SCC (SCAP) of 923 (195) billion €. In discounted values, we obtain cost of 307 or 53 billion €, respectively. Thus, the efficient combination of CO_2 and air pollution yield higher SCC but lower SCAP; adding air pollution taxation to existing carbon taxation thus inherits a trade-off for mitigating damages from CO_2, whereas adding carbon taxation to existing air pollution taxation comes with a substantial co-benefit. We further determine trade-offs and co-benefits of taxation choices when adding imperfect taxation choices for one emission type (e.g., air pollution) to the perfect taxation choices for the other emission type (e.g., CO_2). In particular, adding air pollution taxation to existing carbon taxation always comes with a trade-off because accumulated SCC increase substantially. Adding CO_2 taxation to already existing air pollution taxation in turn comes with some co-benefits as long as the carbon tax level is not above the efficient one, i.e., total air pollutant damages become lower. Increasing the carbon tax above the efficient level in turn increases air pollution and related damages. Such non-linear effects stem from the substantial diverging emission profiles of electricity generation technologies. In particular, high CO_2 taxes lead to a technology switch from gas-CCS to bio-CCS, whereas low or no air pollution taxes substitute nuclear by bio-CCS. High air pollution taxes in turn reverse this shift away from nuclear at cost of CCS technologies. Finally, low CO_2 taxes foster the usage of conventional gas technologies. Policy makers can use those findings to shape policies according to their preferences. When the main goal is to primarily reduce CO_2 emissions and related SCC, additional air pollution taxation creates mitigation trade-offs. When the the primary goal is to reduce air pollution and SCAP, moderate additional carbon taxation can further contribute to this.

Section 2 introduces the modeling strategy. Section 3 presents the calibration by focusing on emissions and social cost. Section 4 presents results and tests for robustness. Section 5 discusses, summarizes, and extends most important results from the previous section. Section 6 concludes.

2. Modeling strategy

Notation. Suppose there are generation technologies i, storage technologies j, and transmission technologies k. r indicates regions and rr is an alias of r. We use subscripts i, j, k, r, rr for

technologies as well as regions and parentheses (h, v, t) for time indices—h is the hour, v the year of installation (vintage), and t the current year (period)—to denote parameters (small letters) and variables (capital letters).

$IQ(v)$ are investments from vintage v that translate into currently (in period t) active capacities $Q(v,t)$ (both in GW). Capacity investments are costly, $c^{IQ} > 0$ (in €/GW), as it is holding capacity, $c^{Q} > 0$ (in €/GW and year), so that endogenous decommissioning might be optimal, i.e., $Q(v,t) \leq IQ(v)$. For storage technologies, charge and discharge capacity (e.g., pumps and turbines) are assumed to be the same. We assume that cost of holding capacity apply only for joint charge and discharge capacity but not for the storage size. For transmission technologies, we refer to net transfer capacities (NTC) and distinguish between export and import lines to reflect current political situation of constraining capacities in one of the respective directions.

Y_i is generation, Y_j^+ is storage charge, Y_j^- is storage discharge, and $Y_{k,r,rr}$ is the bilateral trade flow from region r to rr (all in GWh). Generation is costly, $c_i^Y(v,t) > 0$ (in €/GWh), but we assume no further variable cost for storage operations and transmission (only losses for charge, discharge, hourly discharge, and for transmission). $\eta \in (0,1]$ denotes efficiencies. In particular, η_i is the burning efficiency of generation technologies. Finally, the overall target is to meet electricity demand d but it could to optimal to allow for lost load L (both in GWh) at cost $c^L > 0$ (in €/GWh).

Objective. The objective is to minimize the net present value of total system cost ($\delta(t)$ is the discount factor) from investments (**IQ** is the vector of investment decisions for all generation, storage, transmission technologies), holding capacity (**Q** the vector of capacity decisions), and dispatch (**Y** is the vector of dispatch decisions) over all regions and time periods:

$$\begin{aligned}
\min_{\mathbf{IQ},\mathbf{Q},\mathbf{Y}} \sum_{t,r} \delta(t) \Bigg[& c_r^L(t) \sum_h L_r(h,t) + \\
& \sum_i \left(\sum_{v=t} c_{ir}^{IQ}(v)\, IQ_{ir}(v)\, \Gamma_i(v,t) + \sum_{v \leq t} c_{ir}^{Q}(v,t)\, Q_{ir}(v,t) + \sum_{v \leq t} c_{ir}^{Y}(v,t) \sum_h Y_{ir}(h,v,t) \right) + \\
& \sum_j \left(\sum_{v=t} c_{jr}^{IQ}(v)\, IQ_{jr}(v)\, \Gamma_j(v,t) + \sum_{v \leq t} c_{jr}^{Q}(v,t)\, Q_{jr}(v,t) \right) + \\
& \sum_{k,rr} \left(\sum_{v=t} c_{k,r,rr}^{IQ}(v)\, IQ_{k,r,rr}(v)\, \Gamma_k(v,t) + \sum_{v \leq t} c_{k,r,rr}^{Q}(v,t)\, Q_{k,r,rr}(v,t) \right) \Bigg],
\end{aligned} \tag{1}$$

where $\Gamma(v,t)$ is the fraction of investment cost that should be considered within the planning horizon (from t until t^{end}). In particular, $\Gamma(v,t) = 1$ when the depreciation time of an investment is completely within the planning horizon and $\Gamma(v,t) < 1$ when the depreciation time of an investment spans above the planning horizon (depreciates longer than t^{end}). This endeffect is calculated on the basis of private discount rates and the time exceeding the planning horizon. The

first line of (1) after the square bracket reflects cost of lost load, the second line reflects generation cost, the third line reflects storage cost, and the fourth line reflects transmission cost.

Internalization of social cost. We suppose that a social planner internalizes social cost from carbon emissions and air pollution by setting tax rates according to the respective marginal damages. We can thus directly include those marginal damages—the specific SCC and the specific SCAP—into our objective function via generation cost. Denote by $scc(t)$ the specific SCC and by $scap_{r,ap}(t)$ the specific SCAP (both in €/ton) with ap being different air pollutants. SCC and SCAP change over time. Moreover, SCAP are region-specific, whereas SCC refer to a global value. Carbon emission factors $\xi^{car}(v)$, air pollution emission factors $\xi^{air}_{i,ap}(v)$ (both in ton/GWh thermal), and power plant efficiencies $\eta_i(v)$ depend on the vintage, that is, older vintages have lower efficiencies and higher emission factors leading to higher emissions. In particular, $\sum_{v\leq t}\sum_h \frac{1}{\eta_i(v)} Y_{ir}(h,v,t)$ is total fuel used per technology in period t (in GWh thermal) with $p_{ir}(t)$ beeing the time-varying fuel price in region r for technology i. Multiplying this total fuel used with the respective emission factors yields CO_2 emissions and local air pollution (in ton). We can now derive the generation cost as

$$c^Y_{ir}(v,t) \;=\; c^{var}_{ir}(v) + \left[p_{ir}(t) + scc(t)\,\xi^{car}_i(v) + \sum_{ap} scap_{r,ap}(t)\,\xi^{air}_{i,ap}(v)\right]\sum_{v\leq t}\sum_h \frac{1}{\eta_i(v)}. \quad (2)$$

Variable cost c^{var} are independent of efficiencies. Cost from fuel, SCC, and SCAP in turn depend on those efficiencies, while the latter two are also subject to their respective emission factors.

Optimization constraints. The minimization problem is subject to multiple constraints that we abstain from showing here but Appendix A contains the full set of demand, generation, storage, and transmission constraints of the optimization problem.

3. Calibration

3.1. Setup

We *quantify* the trade-offs and potential benefits of internalizing damages from CO_2 and air pollutant emissions with EUREGEN (Weissbart and Blanford, 2019). EUREGEN is a multi-region partial equilibrium model of the European power market that intertemporally optimizes (i.e., assumes perfect foresight) overall system cost (from investments, holding and decommissioning of capacity, and dispatch of multiple generation, storage, and transmission technologies) from 2015 (base year) to 2050 (end year). We work with an adjusted 2015 calibration to account for real-world developments until 2020. In particular, we assume that taxation choices in 2015 and 2020 reflect real-world policies, i.e., CO_2 prices follow from the EU ETS and there is no air pollution tax

in place.[7] From 2021 onwards, we change policies to either not tax at all, tax only air pollution, only CO_2 emissions, or both (at the respective efficient levels).

The CGE model PACE delivers annual electricity demand and major fuel prices.[8] CO_2 emissions follow from an emission factor and EUREGEN applies either a carbon price (e.g., Mier et al., 2022) or a quantity target (e.g., Weissbart, 2020, Mier and Weissbart, 2020, Azarova and Mier, 2021). We extend the EUREGEN model by emission factors for different air pollutants (Subsection 3.3). We refrain from using carbon prices resulting from the CGE calibration or quantity targets as imposed for instance by the EU ETS and instead apply optimal carbon or air pollution taxes that follow from specific SCAP (Subsection 3.4) and SCC (Subsection 3.5) from 2021 onwards.[9]

EUREGEN can switch between implementations of different discount and interest rates, investor types, and spatial resolutions (Mier and Azarova, 2021a,b). We opt for a discount rate of 7%. Furthermore, we apply the *normal* investor that carries cost of investments within the period of investment and uses endeffects if the investment's depreciation extends beyond the model horizon (and thus neglects the role of different interest rates). 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 for numerical feasibility.[10]

3.2. Considered technologies

Our generation technologies burn either biomass, coal, lignite, natural gas, and uranium or use wind, solar, geothermal, and hydro power to generate electricity. We further consider steam turbines, gas turbines, combined-cycle gas turbines, and engines. In particular, we consider steam turbines "burning" biomass (*bioenergy*), steam turbines "burning" biomass with carbon-capture and storage (*bio-CCS*), steam turbines "burning" *coal*, *coal-CCS*, steam turbines "burning" *lignite*, and steam turbines "burning "natural gas (*gas-ST*).[11] We further consider open-cycle gas turbines burning natural gas (*gas-OCGT*), combined-cycle gas turbines burning natural gas (*gas-CCGT*), the same with carbon-capture and storage (*gas-CCS*), and gas turbines or engines, respectively, using oil and other non-biomass non-natural gas fuels (*oil*). We restrict the annual level of burnable biomass to 2,045 thermal TWh (half of the total available sustainable biomass potential) but have no further limits for other fuels. Moreover, We do not account for combined-heat-and-power (CHP) plants due to the considerable transformation in the heating sector that is driven by

[7] Except 2015, all periods reflects 5 years, i.e., 2020 considers the years 2016 to 2020, ..., and 2050 the year 2046 to 2050.

[8] Appendix B contains detailed values. See Mier et al. (2020, 2022), Siala et al. (2022) for applications of the very same calibration.

[9] Optimality refers to full internalization of the social cost.

[10] 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 timeseries to match annual demand and full-load hours of all intermittent technologies.

[11] Indeed, steam turbines only use the steam generated from burning the respective fuel and are not burning it directly.

decarbonization efforts and demands for not burning fossil fuels anymore. Such transformations make most existing CHP plants obsolete. Moreover, heating electrification is considered by the CGE calibration.

We further consider steam turbines using uranium (*nuclear*) and *geothermal* power plants. Out of the group of intermittent technologies, we model run-in-the-river power plants (*hydro*), *wind onshore*, *wind offshore*, and *solar PV* by means of hourly-varying availability. Regarding wind onshore and wind offshore we assume that the existing fleet has hub heights of 80m, while we consider hub heights of 100m for future vintages. Hydro cannot be expanded beyond the existing level. Nuclear, lignite, and coal expansion is restricted to countries that already use those technologies. Wind and solar expansion is constrained by resource potential quality classes (high, mid, and low). Appendix C summarizes efficiencies, emission factors, and investment cost of those technologies. We further model three storage technologies (pump hydro, batteries, and power-to-gas), where expansion of pump hydro is again restricted to existing capacities. Transmission technologies are represented by AC lines as well as DC cables.[12]

3.3. Emissions from electricity generation

CO_2 emissions are the major source of pollution from electricity generation. We additionally focus on 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).[13] We aim for fleet average emission factors for existing plant vintages, which are calculated via annual statistics of total emissions and total fuel consumption. The literature provides lower and upper bounds as well as medium range emission factors (EPA, 1995, Cai et al., 2012, EEA, 2019, UBA, 2019).

We choose medium emission factors for existing vintages. Where applicable, we include linear improvements in average abatement efficiency for future vintages, so that 2050 vintages across all regions achieve abatement efficiencies of today's most modern plants. Table 1 summarizes emission factors of different technologies for 2020 vintages. 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 emitted. 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.[14]

3.4. Social cost of air pollution

Air pollution leads 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

[12]DC cables mainly apply to connect countries that are divided by water.

[13]EEA (2019) provides information on how these air pollutants occur, and what general measures exist to mitigate their air release.

[14]Biomass emission factors 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).

Table 1: 2020 emission factors (in ton/GWh electric)

	NO_x	SO_2	$PPM_{2.5}$	PPM_{10}	NH_3	NMVOC	All AP	CO_2
Bio-CCS	1.719	0.243	0.629	0.716	0.086	0.164	3.557	-855
Bioenergy	1.376	0.194	0.503	0.573	0.023	0.132	2.801	
Gas-CCGT, Gas-ST		0.001	0.005	0.005		0.001	0.201	341
Gas-CCS		0.001	0.007	0.007		0.002	0.253	41
Gas-OCGT		0.001	0.008	0.008		0.002	0.287	484
Coal	0.582	0.509	0.027	0.062	0.002	0.008	1.190	763
Coal-CCS	0.728	0.509	0.034	0.077	0.009	0.010	1.367	91
Lignite	0.545	0.686	0.024	0.059	0.002	0.011	1.327	838
Oil		0.825	0.225	0.294		0.027	2.031	910

Appendix D contains the full set of emission intensities (in g/GJ). We combine those with technology- and vintage-specific plant efficiencies (Table C.4 in Appendix C) to arrive at a sophisticated representation of actual emission factors (in ton/GWh electric). For CCS technologies, we further consider increased NH_3 emissions occurring during the capture process (Heo et al., 2015) and reflect overall slightly increased emissions for NO_x, NMVOC, and PPM due to increased fuel consumption via decreased efficiencies of CCS plants compared to their non-CCS counterparts.

(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 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 apply results from the NEEDS project (part of the externE project series) that provides specific SCAP (in current 2000-€) for six air pollutants (NH_3, NMVOC, NO_x, PPM_{10}, $PPM_{2.5}$, SO_2) for five categories (human health, loss of biodiversity, regional crops, materials, and international damages) in the 28 countries under investigation.[15] We take the estimates for high release heights (as suggested in the user manual for electricity generation) that are calculated for meteorological conditions of 2010. NEEDS authors suggest increasing the specific SCAP by a rate according to GDP growth. GDP of the 28 countries under consideration grew by 25.84% between 2000 and 2015. We apply the same increase to translate the values from current 2000-€ to current 2015-€.[16] Growth rates for 2020 onwards are based on country-level projections from our CGE calibration.[17]

Table 2 shows average SCAP (in current €/ton), weighted by 2020 country annual electricity demand, for the six air pollutants and the damage categories. The category *International* accumulates the impact of those air pollutants outside of the 28 countries under consideration and

[15]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/`.

[16]We increase specific SCAP by 1.2584 to reflect GDP growth and then divide again by 1.3334. In fact, 2000-€ SCAP have the same absolute value as do 2015-€ SCAP.

[17]See Table E.6 in Appendix E for GDP projections.

Table 2: 2020 specific SCAP (€/ton) by impact category and air pollutant

	NO_x	SO_2	$PPM_{2.5}$	PPM_{10}	NH_3	NMVOC
Human health	8,516	10,490	24,538	1,081	17,561	1,100
Loss of biodiversity	1,672	612			6,197	-136
Regional crops	382	-118			-302	337
Materials	124	463				
International	234	498	282	4	5	640
Total global cost	10,928	11,945	24,820	1,084	23,461	1,940

The presented values follow from weighting country-specific values with 2020 country-specific annual demand. The depicted values are measured in current €. Country level data is available in Appendix F. The international damage is the same for each country and we thus refrain from presenting it in Appendix F.

is uppermost relevant for NMVOC (33% of NMVOC damages). Observe that (regional) human health impacts dominate with shares of 57% (for NMVOC) to almost 100% (for PPM_{10}). Moreover, NH_3 and $PPM_{2.5}$ are the most damaging air pollutants, followed by NO_x and SO_2.[18]

3.5. Social cost of carbon

We apply a slightly adjusted version of DICE-2016R-091216a to calculate specific SCC (in current €/ton).[19] DICE maximizes the net present value of utility (from consumption) and thus the specific SCC is calculated according to the fraction of the marginal of the emission equation (in utility units per ton) and the consumption equation (in utility units per $). Utility units are in present values, so that the division of present value utility (per ton) by present value utility (per $) leaves specific SCC in current $/ton. We can thus use the calculated specific SCC directly again in another discounting framework that uses current values to minimize the net present value of cost via discounting. Table 3 presents calibration (GDP, population) and selected output (SCC, CO_2 emissions, and temperature increase). We calculate specific SCC of 206 $/ton in 2050. Observe that CO_2 emissions drop from 39.6 Gt in 2020 to 25.3 Gt in 2050. The associated temperature increase is 1.99°C in 2050.[20]

[18]The SCAP values grow with GDP per capita (per country) so that 2050 values would be around 60% higher than 2020 values.

[19]We transform the 2015 world GDP of 105.5 trillion 2010-US$ to 86.1 trillion 2015–US$ and total factor productivity by 0.8254 to obtain real-world 2020 CO_2 emission of 39.6 Gt. Moreover, we adjust population growth and total factor productivity from 2020 to 2050 to obtain population projections from the World Bank and GDP projections from the CGE model used to calibrate EUREGEN (see DICE calibration in Table 3). We further reduce the DICE default pure rate of time preference from 1.5% to 0.04% (Drupp et al., 2018). Original GAMS code is available at `http://www.econ.yale.edu/~nordhaus/homepage/homepage/DICE2016R-091916ap.gms`. The adjusted version is available upon request from the corresponding author.

[20]The maximum temperature increase is indeed 3.36°C.

Table 3: DICE calibration and output

		2020	2030	2040	2050
Calibration	Gross world GDP (trillion 2015-$)	101	134	175	224
	World population (billion)	7.75	8.50	9.14	9.68
Output	SCC ($/ton)	94	123	160	206
	CO_2 emissions (Gt)	39.60	31.03	29.05	25.26
	Atmosphere temperature increase (°C)	1.02	1.36	1.68	1.99
Conversion in €	SCC (€/ton)	86	112	145	187

We apply an exchange rate of 1.1 to convert US-$ into €, i.e., 1 € is worth 1.1 US-$ in 2015.

3.6. Comparison of carbon and air pollution taxes

Setting carbon or air pollutant taxes equal to their respective marginal damages (specific SCC and SCAP) and calculating the respective tax rate per technology by employing efficiencies and emission factors yields results in Table 4. The first block shows carbon taxes and the second one shows air pollution taxes for each of the relevant technologies. We present taxes for 2025, 2030, 2040, and 2050. Remember that carbon and air pollution taxes in 2015 and 2020 are assumed to reflect real-world conditions with carbon taxes of 7.75 €/ton (in 2015) and 15 €/ton (in 2020), while there is no air pollution tax in place. Periods 2035 and 2045 are not shown for sake of parsimony. The chosen unit (€/MWh electric) makes tax rates directly comparable across technologies and between carbon and air pollution taxes.

Table 4: Technology-specific carbon and air pollution taxes (in €/MWh electric)

	Carbon tax				Air pollution tax			
	2025	2030	2040	2050	2025	2030	2040	2050
Bioenergy					31.92	32.53	34.08	36.52
Bio-CCS	-80.13	-89.66	-112.09	-139.34	41.32	42.16	44.24	47.49
Gas-CCGT, Gas-ST	32.30	36.29	47.19	60.94	2.33	2.41	2.69	3.06
Gas-CCS	4.01	4.58	5.95	7.68	2.92	3.02	3.37	3.84
Gas-OCGT	44.30	49.53	63.02	81.38	3.20	3.29	3.59	4.09
Coal	69.68	77.71	101.06	130.49	12.61	12.55	13.11	13.78
Coal-CCS	8.93	10.20	13.26	17.12	14.53	14.48	15.20	16.09
Lignite*	81.88	93.50	121.59	157.01	16.43	17.51	20.11	23.47
Oil*	88.89	101.50	131.99	170.44	25.44	27.09	31.01	36.18

Values refer to state-of-the-art capacities from the respective vintage. *Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results.

Remember that bioenergy is carbon-neutral and thus not subject to carbon taxes. Bio-CCS in turn delivers negative carbon emissions so that the carbon tax is negative, i.e., a subsidy that grows from 80.13 to 139.34 €/ton from 2025 to 2050. The air pollution tax in turn is positive but grows only slightly from 41.32 to 47.49 €/ton due to two reasons. First, the specific SCAP grow with GDP

by 60% from 2015 to 2050, while specific specific SCC more than double. Second, technological improvements with regard to efficiencies and emission factors reduce the underlying damage and thus have dampening effects on the optimal air pollution tax. However, air pollution taxes cannot fully cover the benefits from the carbon subsidy for bio-CCS, which is highly negative (and even higher than the average electricity price, around 70 €/MWh). Among the other technologies, coal, lignite, and oil have by far the highest carbon tax and also air pollution tax rates are high. Gas in turn has considerably lower carbon tax rates and air pollution rates are even lowest among technologies, making gas technologies a viable option in the optimized technology mix. However, gas-CCS combines the best of the two worlds with quite low carbon taxes and only marginally higher air pollution taxes than the corresponding comparable conventional gas technology. Coal-CCS in turn seems to be by far less competitive than gas-CCS due to considerably higher air pollution taxes.

4. Results

We now analyze the generation and emission mix when a social planner decides for no taxation, only taxing either air pollution or CO_2, and jointly taxing air pollution and CO_2 (Subsection 4.1). We test sensitives of our results with regard to specific SCC and SCAP. We further test sensitivities with regard to diverging air pollution emission factor assumptions and then analyze the impact of wind power technology improvements on the generation and emission mix to ensure that our findings are robust against more optimistic technology projections (all Subsection 4.2). Finally, we summarize technology substitution patterns for those diverging tax choices as well as SCC and SCAP levels (Subsection 4.3).

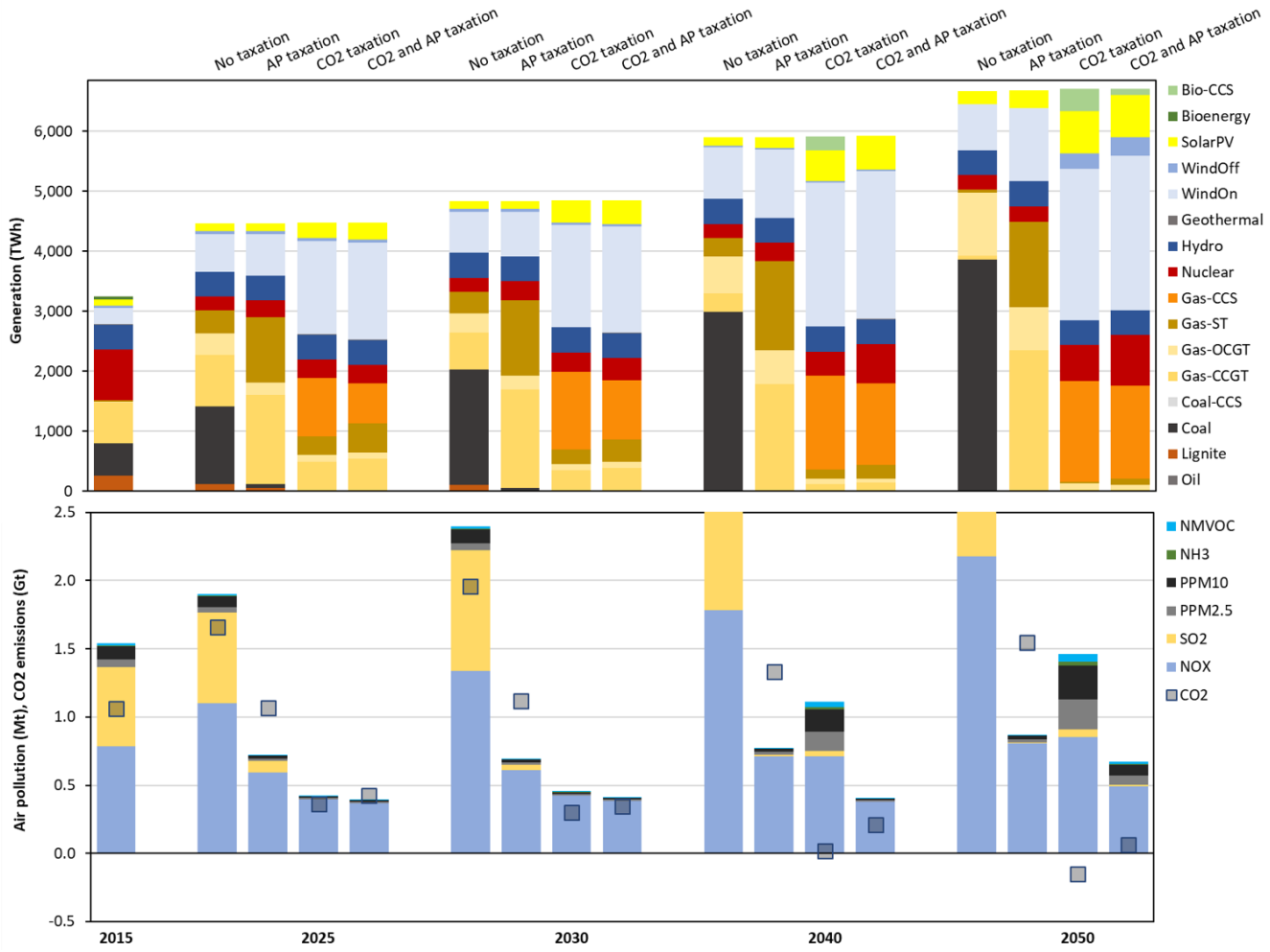
4.1. Taxation choice

Figure 1 visualizes taxation choice results. The stacked bars in the upper panel depict annual generation by technology (in TWh). The stacked bars in the lower panel show annual emissions by air pollutant (in Mt) and the gray diamonds depict annual CO_2 emissions (in Gt). 2015 serves as calibration year. Different model specifications are grouped for periods 2025, 2030, 2040, and 2050.[21] Assuming no air pollution taxes and CO_2 prices of 7.75 €/ton (2015 EU ETS average) in our *calibration year* 2015, the technology mix is dominated by nuclear (836 TWh, 25.8%), conventional gas (720 TWh, 22.2%), and coal (538 TWh, 16.6%). Hydro (418 TWh, 12.9%), wind (306 TWh, 9.4%), lignite (245 TWh, 7.6%), and solar (109 TWh, 3.4%) contribute relevant shares (above 2%). CO_2 emissions are at 1.06 Gt and air pollution at 1.54 Mt, stemming mainly from NO_x and SO_2. PPM and NMVOC are the remaining air pollutants and NH_3 amounts are negligible due to the absence of CCS technologies.

From 2025 onwards, taxation choices across specifications differ. *No taxation* (first column of each grouping) encourages the short-run deployment of conventional gas technologies (from 720

[21] EUREGEN optimizes in five-year steps. For parsimony, we refrain from presenting 2020, 2035, and 2045 outcomes.

Figure 1: Generation (upper panel) and emission (lower panel) mix for different taxation choices



TWh in 2015 to 1,225 TWh in 2025 to 1,171 TWh in 2050) at the cost of nuclear (from 836 TWh to 351 TWh to 235 TWh), and promotes massive deployment of coal in the short-run as well as long-run (from 538 to 1,286 to 3,862 TWh, generation shares of 16.6%, 28.8%, and 57.9%). However, also wind generation more than doubles from 306 TWh (2015, 9.4%) to 763 TWh (2050, 11.4%). Solar PV shares remain constant (3.4%, generation increases from 109 to 227 TWh). CO_2 emissions increase already in 2025 to 1.66 Gt and continue to grow to 3.21 Gt in 2050. Also related air pollution increases from 1.9 Mt in 2025 to 3.81 Mt in 2050.[22] The composition of the air pollution mix does not change much over time, NO_x and SO_2 emissions from burning coal thus remain the dominant air pollutants.

[22]Observe that the bars and squares for no taxation leave the scale of the lower panel in 2040 already.

The generation mix completely changes when imposing *AP taxation* (second column). Coal is almost absent already in 2025 (small shares remain active until 2045). In turn, conventional gas technologies start dominating in 2025 with a generation share of 62.2% (22.2% in 2015) that increases to 67.2% in 2050. Nuclear generation drops from 2015 to 2025 (285 TWh) as well but then remains almost constant until 2050 (261 TWh). Wind generation quadruples and solar generation triples from 2015 to 2050. However, the 2050 generation shares of wind and solar are still low at 18.3% and 4.4%. The reliance on technologies burning natural gas is reflected in the air pollution mix. Total air pollutant emissions drop to 0.72 Mt in 2025 already, whereas CO_2 emissions see almost no change. Also the air pollution composition changes away from high SO_2 and substantial PPM emissions to a completely NO_x dominated system (82.22%). After 2025, both CO_2 and air pollutant emissions then slightly increase, but the increase of CO_2 is more pronounced (to 1.55 Gt in 2050). The composition further changes so that SO_2 is almost absent and NO_x is more or less the only (air) pollution source (93.15%).

The substitution of coal by conventional gas technologies is the dominant change when adding air pollution taxation to a policy regime of no taxation. Adding instead only *CO_2 taxation* (third column) or exchanging air pollution by CO_2 taxes, respectively, yields a substantially more diverse substitution pattern. There is no one single dominating technology anymore. Instead, gas-CCS (21.8%) and wind (35.9%) overtake the major generation part in 2025. This dynamic even intensifies over time. Gas-CCS generation grows to 1,674 TWh (share of 25%) and wind generation to 2,775 TWh (41.4%) in 2050. Additionally, nuclear generation rises from 302 TWh in 2025 to 604 TWh in 2050 (shares of 6.8% or 9%, respectively). Conventional gas contribution is only 2.4%. Solar PV (714 TWh, 10.7% in 2050) and bio-CCS (362 TWh, 5.4%) are the remaining relevant technologies. Turning to the emission mix, observe that CO_2 and air pollution emissions immediately drop to 0.36 Gt or 0.42 Mt, respectively, in 2025. The air pollution level remains low until bio-CCS is introduced to the technology mix in 2040. We can now observe substantial amounts of SO_2, PPM, NMVOC, and also NH_3, all stemming mainly from burning biomass. The CO_2 in turn is captured, so that the European power system is carbon neutral already in 2040. The spread in the development between air pollutant and CO_2 emissions grows with bio-CCS usage until 2050, so that final air pollution is at 1.46 Mt, whereas CO_2 emissions are at -0.15 Gt.

The joint taxation of CO_2 and air pollution (*CO_2 and AP taxation*, fourth column) shows similar patterns as sole CO_2 taxation in 2025 and 2030. The gas-CCS share is slightly lower, while conventional gas and wind generation is slightly higher. Those small differences yield slightly higher CO_2 and slightly lower air pollutant emissions. However, the composition of air pollutants remains the same. Major differences start in 2040 again, when sole CO_2 taxation starts deploying bio-CCS, while additional air pollution taxation discourages bio-CCS in the optimized system. However, the CO_2 price increases further from 145 to 187 €/ton until 2050, making small amounts of bio-CCS (103 TWh, 1.5%) competitive in the generation mix. CO_2 emissions drop from 0.18 to 0.06 Gt, whereas air pollution increases from 0.44 to 0.67 Mt. Air pollution composition is comparable to sole taxation of CO_2. The lower bio-CCS and gas-CCS generation is substituted by substantially higher nuclear generation (12.6% compared to 9% in 2050) and more wind deployment (42.9% vs. 41.4%).

Different taxation choices for CO_2 and air pollutants impose vastly different optimal technology and emission mixes. The taxation of air pollutants fosters conventional gas technologies. Those technologies burn natural gas, which comes at substantially lower SO_2 and PPM emissions. Carbon taxation in turn encourages the deployment of intermittent renewable energies such as wind and solar and, additionally, the deployment of CCS technologies that capture carbon and permanently store it. As a result, gas-CCS is almost carbon-neutral and bio-CCS is even carbon-negative. There is little need for nuclear when only taxing CO_2 because other emission types do not matter. Adding air pollution taxation to already existing CO_2 taxation in turn incentivizes nuclear deployment because the dispatchable carbon-neutral (gas-CCS) or carbon-negative (bio-CCS) technologies still come with substantial air pollution (and at the related cost). However, also wind power is fostered by air pollution taxation.

4.2. Sensitivity analysis

Despite careful calibration, some uncertainty remains regarding specific SCAP and SCC as well as air pollution emission factors.[23] We address this uncertainty by additionally modifying specific SCAP and SCC levels to 25%, 50%, 200%, 400%, and 800% of the default level. We use the joint taxation specification *CO_2 and AP taxation* as a benchmark for this task, where we modify either SCC or SCAP to alternative levels, while the other one stays at the 100% default level. For air pollution emission factors, we additionally develop a low and a high emission factor scenario. The low scenario starts at same values as our benchmark but assumes more optimistic technological progress of pollution abatement than the benchmark. The high scenario in turn is less optimistic than our default scenario. We apply those scenarios on sole air pollution taxation as well as joint CO_2 and air pollution taxation. Appendix G contains visualizations of our sensitivity analysis.

Specific SCAP. Bio-CCS embodies an emission trade-off, as it is severely locally air polluting but tremendously reduces CO_2 emissions. As a result, cheap air pollution at 25% SCAP encourages full usage of the biomass potential in terms of bio-CCS in 2050. The 50% SCAP scenario exploits almost the total biomass potential in 2050 (but 2040 and 2045 deployment is substantially lower). 200% SCAP ends up with negligible bio-CCS generation in 2050 (0.2%). Higher SCAP levels prevent bio-CCS altogether. Gas-CCS contributes 24.2% (23.4%, 20.9%, 17%, 9.1%) and nuclear 9.4% (10.4%, 15%, 17.7%, 27%) for 25% (50%, 200%, 400%, 800%) SCAP. Wind (41.6% for 25% SCAP, 44% for 800% SCAP) and solar (10.6% for 25% SCAP, 8.1% for 800% SCAP) are less affected by changing specific SCAP. Lower SCAP thus foster CCS technologies, yield more air pollution but lowest CO_2 emissions. Higher SCAP in turn foster nuclear and wind, leading to a lower air pollution but higher CO_2 emissions.

Specific SCC. 25% and 50% SCC are insufficient to induce competitiveness of CCS technologies. Instead, conventional gas technologies substitute for bio-CCS, gas-CCS, substantial parts of nuclear

[23] Carbon emission factors are not modified as they mainly depend on the plant efficiency and fuel used, which are both explicitly modeled. Air pollution emission factors additionally depend for instance on the firing/furnace technology and a broad but diverse set of available abatement technologies. See EEA (2019) for an overview.

(for 25% and 50% SCC), and considerable wind generation (only 30.2% in 2050 for 25% SCC). Not relying on CCS technologies leaves 25% and 50% SCC with a substantially lower air pollution burden but tremendously higher CO_2 emissions (1.11 Gt for 25% SCC and 0.75 Gt for 50% SCC in 2050). 200% SCC uses almost the entire biomass potential for CCS from 2030 onwards. 400% and 800% SCC use almost the entire potential already from 2025 onwards. This biomass usage makes the European power system carbon-negative from 2025 onwards when doubling the underlying SCC. Associated air pollution in turn skyrockets to 2015 levels with substantially higher shares of PPM, NMVOC, and NH_3 (SO_2 share is smaller due to the absence of oil, lignite, and coal). Increasing SCC above 200% does not change much in the overall CO_2 emission level because biomass usage is limited. Instead, there is a substantial shift from gas-CCS to nuclear to avoid even the small remaining CO_2 emissions associated with gas-CCS. As a consequence, also air pollution decreases again for very high SCC values. Wind (42.2% for 50% SCC and 42% for 800% SCC) and solar shares (10.7% for 25% SCC and 8.1% for 800% SCC) are impacted considerably less.

Air pollution emission factors. Start with sole air pollution taxation. The impact on the technology mix is minor. 2050 wind, solar, and conventional gas generation is slightly lower for the low scenario, while there is a small amount of coal generation in 2050 (3.3%). The high scenario comes with slightly higher nuclear generation that substitutes for conventional gas (+0.3 or –0.4%, respectively). Resulting CO_2 emissions are lowest for the high scenario (1.51 Gt) and highest for the low scenario (1.65 Gt). Air pollution effects are reversed and the relative differences are substantially higher. Now turn to joint taxation. Interestingly, 2050 CO_2 emissions are now highest (0.14 Gt) and air pollution lowest (0.39 Mt) for the high air pollution emission factor scenario because the high emission factors prevent bio-CCS from being competitive. In contrast, small amounts of bio-CCS are introduced in 2050 for the other two emission factor scenarios. As a consequence, wind and nuclear generation is slightly higher in the high scenario. The results show that emission factor assumptions have substantial impact when a certain threshold is reached as it is the case for coal (under sole air pollution taxation with low emission factors) and bio-CCS (under joint taxation with high emission factors).

Technology boost. We observe stable 2050 wind deployment across taxation choices (shares of 41.4% when taxing CO_2 only and 42.9% when adding air pollution taxation), specific SCAP levels (41.6% for 25% SCAP and 44% for 800% SCAP), specific SCC levels (42.2% for 50% SCC and 42% for 800% SCC), and air pollution emission factor scenarios (42.2% for low and 43.6% for high under joint taxation).[24] This consistency in deployment indicates that the economically viable potential of wind does not differ much across the underlying specifications and in turn promotes nuclear expansion as alternative emission-free technology. We test for this effect by

[24]Deciding for no taxation (11.4%), sole air pollution taxation with low (17.3%), mid (18.3%), and high emission factor assumptions (18.2%) as well as deciding to internalize only 25% of the SCC (30.2%) yield indeed substantially lower wind deployment rates. However, those options are also furthest away from realistic policy options in Europe, where substantial carbon pricing plays a key role.

introducing a technology boost in 2040—i.e., full-load hours (FLH) of wind onshore and offshore increase (see Appendix H for details)—and apply joint CO_2 and air pollution taxation. 2050 wind generation increases to 62.2% (42.9% without boost), nuclear contributes only 3.4% (12.6%), gas-CCS 16.5% (23.1%), bio-CCS 0.5% (1.5%), and solar 8.1% (10.6%). The higher wind potential thus reduces nuclear shares, hinting that wind and nuclear are deployed by the model as emission-free technological substitutes. However, higher wind potential also reduces CCS shares so that overall air pollution is brought down to 0.39 Mt (compared to 0.67 Mt without boost), whereas CO_2 emissions are slightly higher with boost (0.104 vs. 0.063 Gt).

4.3. Substitution patterns

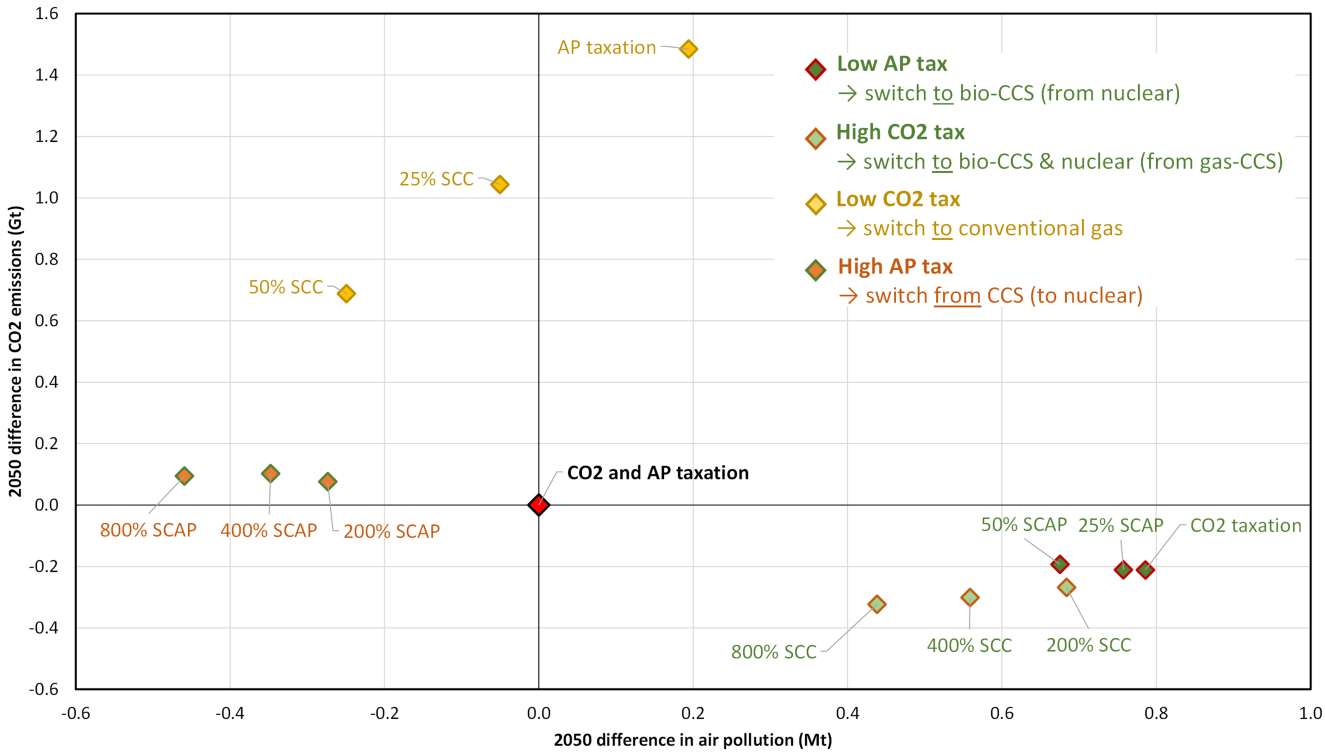
From the previous results it is apparent that technology switch patterns are of high relevance when accounting for local air pollution. We thus analyze general behavioral patterns and trends of technology deployment in this subsection. This allows us to synthesize technological substitution effects in relation to system profiles of CO_2 emissions and air pollution. In particular, we group specifications into policy clusters and analyze for each cluster which technologies systematically gain and lose most in the final 2050 mix compared to our benchmark *CO_2 and AP taxation* (at 100% SCAP and SCC levels). We exploit the fact that the (relative) taxation intensity of CO_2 vs. air pollution varies across all our specifications. This is achieved by different taxation choices, varying specific SCAP and SCC.[25] We can therefore sort specifications into clusters of high air pollution taxes, low air pollution taxes, high CO_2 taxes, and low CO_2 taxes. Figure 2 depicts all clustered specifications in a scatter plot. The y-axis measures 2050 CO_2 emissions and the x-axis measures 2050 air pollution emissions, each in absolute differences to the benchmark.[26] The color scheme indicates cluster membership and emphasizes the technologies that are at the center of the cluster's technology switch.

Clusters *Low AP tax* and *High CO_2 tax* both exhibit a distinct switch towards bio-CCS. For *Low AP tax*, the switch takes place away from emission-neutral nuclear, whereas for *High CO_2 tax* the substitution happens away from gas-CCS to fully avoid this technology's residual CO_2 emissions. However, observe that the resulting CO_2 and air pollution profiles of the systems are very similar for both clusters despite very different taxation regimes. *High AP tax* is marked by specifications that shift away from air polluting CCS technologies (bio-CCS and gas-CCS) towards emission-neutral nuclear. This substitution pattern under aggressive air pollution taxation is associated with a nearly horizontal movement along the x-axis, and thus hardly impacts CO_2 intensity of the system. *Low CO_2 tax* is characterized by an extensive shift from various technologies to conventional gas. Such a regime of cheap CO_2 emissions does not only increase CO_2 emissions but also increasingly enhances local air pollution when burning natural gas.

[25] We spare the technology boost here because it hampers comparability of results. For the same reason, we also spare the emission factor scenarios as they structurally shift the intensity and composition of the air pollution profile of technologies.

[26] Note that social damages from CO_2 are proportional to the CO_2 intensity of the system. This is not the case for air pollution, as we depict the total aggregate of all air pollutants for complexity reasons here. Across specifications, the composition of total air pollution might change between more or less harmful compositions.

Figure 2: 2050 emissions in relation to benchmark and clustered by technology switch



CO_2 and air pollutant emissions are displayed in absolute difference to the benchmark of joint *CO_2 and AP taxation* at 100% SCC and SCAP.

It is interesting to note that excessive taxing of either of the emission types, i.e., clusters *High CO_2 tax* and *High AP tax*, is also at the expensive of the solar PV generation share. The intuition behind this implies that both clusters switch away from dispatchable gas-CCS generation, whose low but nevertheless existing emissions are heavily taxed. This leaves the system at a lack of a flexible (low-emission) technology to balance intermittent renewable generation. For cluster *High CO_2 tax*, bio-CCS as a dispatchable carbon-negative technology is expanded. However, the biomass limits constrain usage to compensate large-scale fluctuating renewable supply. As a result, the model in both clusters slightly cuts down on intermittent solar PV and relies more on emission-neutral nuclear.

5. Discussion

Our results indicate that joint taxation schemes bear important mitigation dynamics. We thus discuss accumulated (discounted and non-discounted) social cost under different taxation choices as well as co-benefits of complementary taxation in the remainder of this section.

Table 5 presents accumulated CO_2 emissions (in Gt) and air pollution (in Mt) as well as corresponding social cost (in billion €, discounted values in parentheses) from 2021 to 2050 for our

four main specifications Observe that accumulated CO_2 and air pollutant emissions are by far the highest for no taxation. Further, CO_2 emissions drop when taxing air pollution. SCC decrease by more than 5,000 billion €, while SCAP are reduced by around 1,000 billion € only. Social cost are considerably lower when taxing only CO_2 emissions, as are accumulated CO_2 emissions (3.3 Gt). At the same time, accumulated air pollution is only slightly higher than when solely taxing air pollution (27 vs. 23.1 Mt). However, discounted accumulated SCAP are at the same level because the time profile of air pollutant emissions differs considerably. Air pollution taxation reduces air pollution in later periods. In contrast, CO_2 taxation has quite an extensive impact (by means of reducing air pollution) in the mid-term, whereas in the long-run air pollution is substantially higher (due to bio-CCS usage). We observe a similar effect for accumulated SCC when adding air pollution taxation to existing CO_2 taxes. Here, accumulated non-discounted SCC increase by 642 billion €, but discounted SCC only by 115 billion €. Again, differences in emissions and related social cost manifest mainly in the long-run due to the deployment of bio-CCS.

Table 5: Accumulated emissions and social cost as well as electricity price range from period 2025 to 2050

	CO_2 (Gt)	SCC* (billion €)	AP (Mt)	SCAP* (billion €)	Electricity price** (€/MWh)
No taxation	73.1	10,636 (2,449)	87.9	1,420 (346)	51.44–47.04 (2025)
AP taxation	38.8	5,547 (1,340)	23.1	343 (92)	53.78–52.03 (2025)
CO_2 taxation	3.3	281 (194)	27.0	435 (92)	78.39–77.84 (79.91, 2035)
CO_2 and AP taxation	7.4	923 (311)	13.7	195 (53)	80.41–79.03 (81.07, 2045)

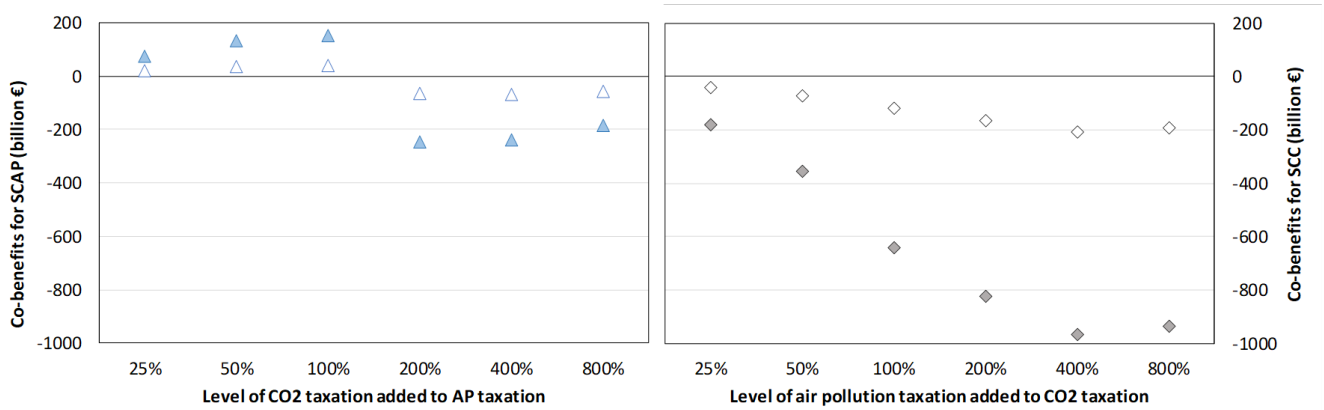
CO_2, SCC, air pollution (AP), and SCAP values are accumulated values from period 2025 to 2050 (30 years because 2025 reflects years 2021–2025). *The values for SCC and SCAP in parentheses show discounted social cost. **We present ranges of electricity prices with the first value referring to 2025 and the second one to 2050. Parentheses show the maximum electricity price with the respective year.

Furthermore, electricity prices are lowest for no taxation and air pollution taxation increase them only by 5% (in 2025) to 10% (in 2050). However, CO_2 taxes have a overarching effect on prices that are no more than 50% higher than in the no taxation case and also almost 50% higher than in the policy regime of taxing air pollution only. Combining air pollution and carbon taxes finally result in highest prices.

The intuition that joint taxation schemes significantly reduce social cost is not generally true because the model takes into account related abatement cost when minimizing the net present value of system cost. However, the composition of cost (SCAP vs. SCC) fundamentally changes. Such findings open up discussions about co-benefits of complementary taxation. Moreover, in practice it may not be necessary, feasible, or intended to heavily tax both emission types and nor may "the more the better" lead to efficient returns from taxation. With the goal of understanding how long a way co-mitigation effects go, we analyze the co-benefits of CO_2 and air pollution taxation on the respective other emission type. For instance, if taxing air pollution as a measure to internalize local damages also has positive benefits for ongoing CO_2 emission mitigation, this would be a useful instrument to complement existing policies of carbon pricing.

Starting with sole CO_2 taxation (at 100% SCC level) as benchmark, we iteratively add increasing levels of air pollution taxation (as done implicitly by 25% to 800% SCAP). The co-benefits are the amount of (non-discounted, unless stated otherwise) CO_2 emission damages (expressed at the 100% SCC level) that are additionally avoided compared to the benchmark. For example, sole CO_2 taxation leads to 281 billion € of aggregate SCC (see Table 5). When air pollution taxation is added as a complementary instrument at 25% SCAP level, this leaves a system with 182 billion € higher aggregate SCC. The co-benefit of added air pollution taxation on SCC would then be –182 billion €. Increasing air pollution taxation to 50% SCAP level yields an even more negative co-benefit of –356 billion €. We continue this exercise until arriving at 800% SCAP (co-benefit is –937 billion €) and repeat it vice versa for sole air pollution taxation and added levels of CO_2 taxation. Figure 3 presents results. The left panel shows the dynamics of adding CO_2 taxation to existing air pollution taxation. The co-benefit (filled blue triangles) is thus expressed in avoided accumulated SCAP. Hollow triangles show discounted co-benefits. The right panel presents the outcome of adding air pollution taxation to existing CO_2 taxation. The co-benefit (filled gray diamonds) is measured in avoided accumulated SCC. Hollow diamonds show discounted co-benefits.

Figure 3: Co-benefits of complementary taxation as accumulated social damages avoided



The left panel shows AP taxation with diverging levels of CO_2 taxation. The right panel shows CO_2 taxation with diverging levels of AP taxation. Co-benefits are expressed in 100% SCC or SCAP levels, respectively. Filled markers represent non-discounted values; hollow markers represent discounted values.

Coming from existing air pollution taxation (left panel), adding mild to moderate carbon pricing has increasingly positive co-mitigation effects on local air pollution. Such taxation schemes discourage the deployment of technologies that exhibit residual emissions of both types (e.g., conventional gas, gas-CCS). Co-benefits grow from 74 billion € at 25% to a peak of 148 billion € at 100% CO_2 taxation. Co-benefits are however strongly non-linear so that beyond 100% CO_2 taxation, the co-benefits actually turn into mitigation trade-offs. Indeed, co-benefits drop to –250 billion € for 200% and then slightly improve to –185 billion € for 800%. Aggressive CO_2 taxation leads to a technology mix that accepts increased air pollution damages for extensive mitigation of carbon emissions, e.g., via bio-CCS usage towards the end of the model horizon. Hence, in case the primary policy goal is mitigation of local air pollution, the mitigation benefits can be even

increased by low to moderate carbon pricing as a complementary policy.

Coming from a taxation scheme that fully internalizes CO_2 emission damages already (right panel), CO_2 emissions cannot be further decreased through complementary air pollution taxation. For all our specifications with additive air pollution taxation, co-mitigation effects on CO_2 are negative (overall effect on social damage mitigation may still be positive). Yet again, co-benefit effects are non-linear, such that they are slightly negative for mild air pollution taxation (–182 billion € at 25% air pollution taxation) and floor at –966 to –937 billion € for high to very high levels of air pollution taxation. Note that these numbers are aggregate co-benefits covering the long term optimization horizon. It is important to keep in mind that timing of co-benefit effects matters strongly here for two reasons. (1) The negative co-benefits of CO_2 are strongly driven by bio-CCS usage in later periods, which can turn positive mid term co-benefits into negative co-benefits in the cumulative long-term. (2) As the negative co-benefits driven by bio-CCS occur in later periods, they are heavily discounted in the optimization process. This causes an increasing gap between discounted co-benefits and non-discounted co-benefits for excessive air pollution taxation. This divergence should be taken into account when assessing actual generational (i.e. non-discounted) damages of different policy regimes.

6. Conclusion

We derive emissions factors of six local air pollutants (NH_3, NMVOC, NO_x, PPM_{10}, $PPM_{2.5}$, and SO_2) for multiple electricity generation technologies (e.g., bio-CCS, coal, gas-CCGT, gas-CCS) depending on fuel used (e.g., biomass, coal, natural gas) and underling technological characteristics as well as the year of installation to reflect potential air pollution of the current and future power plant fleet in Europe (Cai et al., 2012, EPA, 1995, EEA, 2019, UBA, 2019). We then use estimates of the social cost of air pollution (SCAP) from the externE project series that are tailored to electricity generation technologies (Friedrich and Bickel, 2001, Pietrapertosa et al., 2009). We further derive social cost of carbon (SCC) from an own calibration of DICE-2016R-091216a (Nordhaus, 2014). We implement air pollution emission factors and pollution taxes (equal to the respective SCAP and SCC) in EUREGEN (Weissbart and Blanford, 2019) to quantify the impact of accounting for air pollution for the European power market until 2050.[27] In particular, we match SCAP and SCC estimates with EUREGEN's CGE calibration by accounting for country-specific GDP growth and the underlying population projections from the World Bank. We then analyze different internalization strategies of social cost by either deciding for no taxation, only taxing air pollution or CO_2, respectively, or jointly taxing both emission types. We additionally test for sensitivities of SCC levels, SCAP levels, air pollution emission factors, and technological progress of wind power to gain insight into technological substitution patterns when deciding for taxing air pollution and/or CO_2 emissions. We finally calculate the social cost occurring from different taxation choices and determine whether or not adding CO_2 (or air pollution) taxation to already existing air pollution

[27]EUREGEN is a multi-region partial equilibrium model of the European power market that optimizes investments, decommissioning, and dispatch of multiple generation, storage, and transmission technologies.

(CO_2) taxation comes with co-benefits (or trade-offs) by means of reduced (increased) damages from air pollution (CO_2). Our key findings are fourfold.

First, we determine the technology and emission mix occurring under different taxation choices. No taxation fosters coal deployment. Air pollution taxation fosters the usage of conventional gas technologies and comes with significant reductions in air pollution, whereas carbon emissions increase. CO_2 taxation yields considerable amounts of nuclear as well as gas-CCS and employs air polluting bio-CCS up to the biomass limit. Consequently, air pollution increases considerably when introducing bio-CCS but overall carbon emissions indeed drop to negative levels in the long-run. Binary decisions to tax either air pollution or carbon thus come with completely diverging emission profiles, mainly due to the employment of bio-CCS (and secondarily also due to gas-CCS). The technology and emission mix when jointly taxing air pollution and CO_2 is dominated by carbon taxes. However, additional air pollution taxation halves the total air pollution by reducing usage of CCS technologies, whereas nuclear generation is substantially higher.

Second, we test robustness of results by changing the underlying SCC and SCAP levels and thus the respective taxation levels. We use those results to systematically assess technological substitutions patterns. The results of this task underline that high air pollution taxes foster nuclear at the cost of bio-CCS and gas-CCS. Low air pollution taxes in turn substitute nuclear by bio-CCS only. High CO_2 taxes foster nuclear at the expense of gas-CCS because gas-CCS still emits residual amounts of CO_2. Moreover, bio-CCS is fostered, too, as long as the biomass limit is not reached already. Low CO_2 taxes in turn foster conventional gas technologies.

Third, we scrutinize accumulated social cost as well as electricity prices in the period 2021 to 2050 under different taxation choices. No taxation comes with lowest electricity prices (47 €/MWh in 2050) but social cost accumulate to 12,056 billion €, which amounts to more than 400 billion €/a and is close to the 2022 annual government budget of Germany—the biggest country within the European power market. Sole air pollution taxation more than halves those damages, whereas electricity prices increase only by 10% in the long-run. Interestingly, air pollution taxation reduces the burden of SCC from 10,636 to 5,547 billion €. CO_2 taxation actually yields lowest overall damages (281 billion € from CO_2 and 435 billion € from air pollution). Here, air pollution (damage) is only around 16% (92 billion €) higher. Electricity prices increase tremendously by around 26 €/MWh (+48%). Those results show some complementarity in the mitigation of CO_2 and air pollutants emissions. However, the socially optimal policy regime is joint taxation of both emission types. Such a policy regime in fact increases the overall social cost from 716 to 1,118 billion € but comes at similar electricity prices (compared to sole CO_2 taxation). However, the objective is not to minimize social cost but the net present value of total system cost; thus abatement cost play a role as well. In particular, the discounted social cost increase only from 286 to 364 billion €. Notably, discounting plays a fundamental role when assessing damages from CO_2 and air pollution because different taxation choices impose a completely different time profile of emissions. For example, only taxing CO_2 yields 55% higher social cost from air pollution than from carbon emissions but, when looking at discounted values, damages from air pollution are actually 53% lower than those from CO_2. Bio-CCS again plays a fundamental role here because it reduces carbon emissions in late periods (little benefits for discounted social cost of carbon),

whereas it increases air pollution in those periods (high undiscounted social cost of air pollution).

Fourth, we determine co-benefits from different taxation regimes. In particular, we do not observe large power systems that jointly internalize damages from CO_2 and air pollution. For example, the United States mainly focus on air pollution regimes, thereby neglecting damage mitigation from CO_2. Europe in turn predominantly focuses on CO_2 mitigation. However, the internalization of local damages from air pollution should be undertaken by each country on their own iniative because free-riding does not matter. This might lead to situations where additional air pollution (in Europe) possibly reduces also (global) damages from CO_2. In turn, one argument to employ carbon pricing in the United States might be that there is also a related benefit in terms of reduced air pollution. We quantify those scenarios and find that there is indeed a co-benefit when CO_2 taxation is added to existing air pollution taxation as long as the level of CO_2 taxation is not above the efficient one. However, adding air pollutant taxes to existing carbon taxes always comes with negative co-benefits for CO_2 mitigation.

Our paper shows that the interpretation of modeling results and their consideration by policy makers requires careful review of the assumptions about taxes, underlying technological characteristics, and prioritization of policy goals. Our findings inform about impacts of different taxation choices and levels on resulting emissions, associated damages and technology switch patterns. Our results also emphasize how sensitive the optimal system reacts to different versions of complementary taxation schemes. Interestingly, nuclear plays a key role because wind and solar deployment at competitive spots is naturally limited and thus nuclear is the only remaining (competitive and expandable) emission-neutral 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. Our findings also inform about policies that do not appropriately internalize CO_2 or air pollutant damages, respectively, and underline that the focus on decarbonization should leave space also for co-internalization of air pollutant damages. This is particularly important once CCS technologies become competitive. We also deliver insights into how much potential is borne in complementary taxation schemes to yield co-benefits for an existing primary mitigation goal. Those co-mitigation effects need to be carefully handled by policy makers as they are non-linear. To summarize, we advise policy makers to use mild carbon pricing as additional tool to reduce air pollution but not to use air pollution taxes as a tool to reduce carbon emissions. However, from a holistic system perspective it is best to jointly internalize both emission types. This joint taxation also means that ambitions to decarbonize economies must be reviewed in the sense that one of the most powerful carbon-negative technologies, biomass in combination with carbon-capture and storage, is problematic regarding its air pollution impact.

Our analysis comes with some limitations. 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 emissions trade-offs of CCS technologies are 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 avoiding CCS technologies. Moreover, the quite prominent role of nuclear is fostered by the fact that we do not account (for short- and long-term) radiation damages from using 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. Finally, we apply the very same discount rate to evaluate damages from carbon and air pollutant emissions. There are at least some arguments that promote that air pollutant damages might be evaluated at higher discount rates than social cost of carbon, because the damages of local air pollution are immediate and not as long-lasting (over several generations) as are those from emitting CO_2.

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Appendix

Appendix A. Optimization constraints

Demand constraints. Equation (A.1) ensures to meet an exogenous given demand $d_r(h,t)$, which can be reduced by allowing for lost load $L_r(h,t)$ (*demand-equals-supply constraint*). The difference of demand and lost load is final consumption. Total supply from generation $\sum_{i,v} Y_{ir}(h,v,t)$, storage operations (discharge including discharge losses $\eta^-_{jr}(v)$ less charge, second line), and transmission operations (imports including import losses $\eta_{k,rr,r}$ less exports including export losses $\eta_{k,r,rr}$, third line; $\mu_{k,r,rr}$ describes the mapping of regions that are eligible for transmission exchange) must be higher than consumption by distribution grid losses $\eta^{loss}_r(t)$.

Equation (A.2) ensures that there is sufficient back-up capacity in every region to meet demand and refrains from accounting for the possibility of lost load (*resource adequacy constraint*). We work with capacity credits α that indicate the secured amount of capacity for each technology. Storage charge and exports does not play any role here due to the fact that those operations hamper to meet the adequacy target.

$$\begin{aligned}
\frac{d_r(h,t) - L_r(h,t)}{\eta^{loss}_r(t)} &= \sum_{i,v} Y_{ir}(h,v,t) \\
&+ \sum_{j,v\le t} \left(Y^-_{jr}(h,v,t)\,\eta^-_{jr}(v) - Y^+_{jr}(h,v,t)\right) \\
&+ \sum_{\mu_{k,rr,r}} Y_{k,rr,r}(h,t)\,\eta_{k,rr,r} - \sum_{\mu_{k,r-rr}} \frac{Y_{k,r,rr}(h,t)}{\eta_{k,r,rr}} \quad \forall \quad (h,r,t), \qquad \text{(A.1)}
\end{aligned}$$

$$\begin{aligned}
\frac{d_r(h,t)}{\eta^{loss}_r(t)} &= \sum_{i,v} \alpha_i Q_{ir}(h,v,t) \\
&+ \sum_{j,v\le t} \alpha_j Q^-_{jr}(h,v,t)\,\eta^-_{jr}(v) \\
&+ \sum_{\mu_{k,rr,r}} \alpha_k Q_{k,rr,r}(h,t)\,\eta_{k,rr,r} \quad \forall \quad (h,t). \qquad \text{(A.2)}
\end{aligned}$$

Generation constraints. Equation (A.3) restricts generation by available capacity (*capacity constraint*). $\beta_{irnw(i),r}(h,v) \in [0,1]$ is hourly availability of the subset of intermittent renewables $irnw(i)$ (solar PV, wind onshore, wind offshore, hydro), $\gamma_{\text{not } irnw,r}(h,v) \in [0,1]$ is hourly availability for all other technologies (bioenergy, bio-CCS, gas-OCGT, gas-CCGT, gas-ST, gas-CCS, coal, coal-CCS, lignite, oil, nuclear, and geothermal) following from monthly generation patterns and reliability assumptions. We further have $\beta_{\text{not}irnw(i)} = \gamma_{irnw(i)} = 1$.

Equations (A.4) and (A.5) describe the movement of capacity over time (*capacity stock constraints*). Equation (A.4) describes the movement of existing capacities $q^{base}_{ir}(v)$ that is still active at t^{base} (the beginning of the planning horizon). Equation (A.5) describes the movement of added

capacity. $\Lambda_i(v,t) \in [0,1]$ is a lifetime parameter that describes the respective active share of capacity. Endogenous decommissioning is permitted from $t^{base}+1$ onward. We relinquish to show the respective constraints that avoid early decommissioning of existing capacities in t^{base} already. Existing or added capacity, respectively, is capable of reaching the end of the specified lifetime. Additionally, 50\% might be still active 5 years later, and 30% even 10 years later. We further specify $\Lambda\left(t^{base}\right), \Lambda\left(t^{base}+1\right)=1$ for existing capacities to avoid distortions from enforced decommissioning in early periods although those existing capacities are still active in reality. We then apply the 50% or 30% metric with one period lag.

Equation (A.6) enforces monotonic decommissioning of capacity (*monotonicity constraint*), that is, ensures that already decommissioned capacity cannot be build up again. Equation (A.7) enforces that overall capacity does not exceed a certain limit $q_{ir}^{lim}(t)$ (*capacity limit constraint*). Equation (A.8) enforces investments that are already planned or under construction but not commissioned yet $iq_{ir}(v)^{pipe}$ (*pipeline constraint*). This constraint is particular important in $t^{base}+1=2020$ for wind and solar investments but also in later periods when it is about ongoing nuclear projects. We work with an adapted 2015 calibration that already contains lots of investments until the end of 2020 that are enforced in the model by this pipeline constraint. Equation (A.9) restricts expansion of intermittent renewable energies according to their resource potential by quality class (*resource potential constraint*). In particular, we consider three classes (high, mid, low) of wind onshore, wind offshore, and solar PV potential. $\mu_{irnw(i)}(class)$ is the mapping of the respective intermittent technology to its class. $q_{ir}^{lim}(class)$ is then the upper limit of the respective quality class (GW). Equation (A.10) restricts annual usage of biomass (*biomass constraint*). $bio(i)$ is the subset of technologies using biomass, $\sum_{bio(i)}\sum_{h,v\leq t}\frac{1}{\eta_{ir}(v)}Y_{ir}(h,v,t)$ is used biomass, and $bio_r^{lim}(t)$ the annual limit per region (both in GWh thermal). Equation (A.11) restrict overall storage of carbon in the ground (*stored carbon constraint*). $ccs(i)$ is the subset of carbon-capture-and-storage (CCS) technologies, $\epsilon_{ir}^{CCS}$the capture rate (ton/GWh electric), and sc_r^{lim} is the region-specific potential of storing carbon in the ground (ton).

$$Y_{ir}(h,v,t) \leq \beta_{ir}(h,v)\,\gamma_{ir}(h,v)\,Q_{ir}(v,t) \quad \forall \quad (i,r,h,v \leq t,t)\,, \tag{A.3}$$

$$Q_{ir}(v,t) \leq q_{ir}^{base}(v)\,\Lambda_i(v,t) \quad \forall \quad \left(i,r,v \leq t^{base},t\right), \tag{A.4}$$

$$Q_{ir}(v,t) \leq IQ_{ir}(v)\,\Lambda_i(v,t) \quad \forall \quad \left(i,r,t^{base} < v \leq t,t\right), \tag{A.5}$$

$$Q_{ir}(v,t) \geq Q_{ir}(v,t+1) \quad \forall \quad \left(i,r,v \leq t,t < t^{end}\right), \tag{A.6}$$

$$\sum_{v \leq t} Q_{ir}(v) \leq q_{ir}^{lim}(t) \quad \forall \quad (i,r,t)\,, \tag{A.7}$$

$$IQ_{ir}(v) \geq iq_{ir}^{pipe}(v) \quad \forall \quad \left(i,r,t^{base} < v\right), \tag{A.8}$$

$$\sum_{\mu_{irnw(i)}(class)} \sum_{v \leq t} Q_{ir}(v,t) \leq q_{ir}^{lim}(class) \quad \forall \quad \left(\mu_{irnw(i)}(class),r,t\right), \tag{A.9}$$

$$\sum_{bio(i)} \sum_{h,v \leq t} \frac{Y_{ir}(h,v,t)}{\eta_{ir}(v)} \leq bio_r^{lim}(t) \quad \forall \quad (r,t)\,, \tag{A.10}$$

$$\sum_{ccs(i)} \sum_{h,v,t} \epsilon_{ir}^{CCS}(v)\,Y_{ir}(h,v,t) \leq sc_r^{lim} \quad \forall \quad (r)\,. \tag{A.11}$$

Storage constraints. Equation (A.12) restricts storage charge by storage capacity (*charge constraint).* Equation (A.13) restricts storage discharge by storage capacity (*discharge constraint*). Equation (A.14) restricts the storage balance by storage size (*size constraint*). For parsimony, we assume a fixed relation between charge and discharge capacity to the storage size with $hours_{jr}(v)$ being a constant parameter (in hours) for each technology-region pair. Equation (A.15) describes the movement of stored energy over time (*balance constraint*), including hourly storage losses $\eta_{jr}^{h}(v)$ and charge losses $\eta_{jr}^{+}(v)$ (discharge losses $\eta_{jr}^{-}(v)$ enter the demand-equals-supply constraint (A.1)). Equations (A.16) and (A.17) are the *capacity stock constraints*, Equation (A.18) is the *monotonicity constraint*, Equation (A.19) the *capacity limit constraint*, and Equation (A.20) the *pipeline constraint*. Those five constraints mirror equations (A.4) to (A.8) from the set of generation constraints.

$$Y_{jr}^{+}(h,v,t) \leq Q_{jr}(v,t) \quad \forall \quad (j,r,h,v \leq t,t), \tag{A.12}$$

$$Y_{jr}^{-}(h,v,t) \leq Q_{jr}(v,t) \quad \forall \quad (j,r,h,v \leq t,t), \tag{A.13}$$

$$B_{jr}(h,v,t) \leq Q_{jr}(v,t) \cdot hours_{jr}(v) \quad \forall \quad (j,r,h,v \leq t,t), \tag{A.14}$$

$$\begin{aligned} B_{jr}(h,v,t) &= B_{jr}(h-1,v,t)\,\eta_{jr}^{h}(v) \\ &+ Y_{jr}^{+}(h,v,t)\,\eta_{jr}^{+}(v) - Y_{jr}^{-}(h,v,t) \quad \forall \quad (j,r,h,v \leq t,t), \end{aligned} \tag{A.15}$$

$$Q_{jr}(v,t) \leq q_{jr}^{base}(v)\,\Lambda_j(v,t) \quad \forall \quad \left(j,r,v \leq t^{base},t\right), \tag{A.16}$$

$$Q_{jr}(v,t) \leq IQ_{jr}(v)\,\Lambda_j(v,t) \quad \forall \quad \left(j,r,t^{base} < v \leq t,t\right), \tag{A.17}$$

$$Q_{jr}(v,t) \geq Q_{jr}(v,t+1) \quad \forall \quad \left(j,r,v \leq t, t < t^{end}\right), \tag{A.18}$$

$$\sum_{v \leq t} IQ_{jr}(v) \leq q_{jr}^{lim}(t) \quad \forall \quad (j,r,t), \tag{A.19}$$

$$IQ_{jr}(v) \geq iq_{jr}^{pipe}(v) \quad \forall \quad (j,r,v). \tag{A.20}$$

Transmission constraints. Equation (A.21) restricts transmission between eligible region pairs to the overall amount (over all vintages) of transmission capacity (*trade constraint*). Equations (A.22) and (A.23) are the *capacity stock constraints*, Equation (A.24) is the *monotonicity constraints*, Equation (A.25) is the *limit constraint*, and Equation (A.26) is the *pipeline constraint*. Those five constraints mirror equations (A.4) to (A.8) from the set of generation constraints. $q_{k,r,rr}^{lim}$ is the upper limit of possible transmission expansion and grows over time to account for the political will to increase interchange in Europe but still limits expansion to a socially acceptable level. $iq_{k,r,rr}^{pipe}$ refects plans of transmission system operators to reach a 25% interconnectivity target and contains already planned projects.

$$Y_{k,r,rr}(h,t) \leq \sum_{v \leq t} Q_{k,r,rr}(v,t) \quad \forall \quad (\mu_{k,r,rr},h,t), \tag{A.21}$$

$$Q_{k,r,rr}(v,t) \leq q_{k,r,rr}^{base}(v)\,\Lambda_k(v,t) \quad \forall \quad \left(\mu_{k,r,rr}, v \leq t^{base},t\right), \tag{A.22}$$

$$Q_{k,r,rr}(v,t) \leq IQ_{k,r,rr}(v)\,\Lambda_k(v,t) \quad \forall \quad \left(\mu_{k,r,rr}, t^{base} < v \leq t,t\right), \tag{A.23}$$

$$Q_{k,r,rr}(v,t) \geq Q_{k,r,rr}(v,t+1) \quad \forall \quad \left(\mu_{k,r,rr}, v \leq t, t < t^{end}\right), \tag{A.24}$$

$$\sum_{rr,v \leq t} IQ_{k,r,rr}(v) \leq q_{k,r,rr}^{lim}(t) \quad \forall \quad (\mu_{k,r,rr},t), \tag{A.25}$$

$$IQ_{k,r,rr}(v) \geq iq_{k,r,rr}^{pipe}(v) \quad \forall \quad (\mu_{k,r,rr},v). \tag{A.26}$$

Appendix B. Electricity demand and fuel prices from the CGE calibration

Table B.1: 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 B.2: Exemplary fuel prices for Germany (€/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

Bioenergy, lignite, and uranium prices are the same for each country. Coal, gas, and oil prices slightly differ reflecting results from the CGE calibration. However, differences are not decisive with regard to overall competitiveness of technologies in certain regions.

Appendix C. Technology parameters

Table C.3: Efficiencies of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bioenergy	0.20	0.20	0.21	0.21	0.21	0.22	0.22	0.23
Bio-CCS	0.16	0.16	0.17	0.17	0.17	0.18	0.18	0.18
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
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
Lignite*	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
Oil*	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Geothermal	0.09	0.11	0.11	0.12	0.13	0.13	0.14	0.14
Nuclear	0.59	0.60	0.61	0.62	0.62	0.62	0.62	0.62

Values refer to state-of-the-art capacities from the respective vintage. *Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results.

Table C.4: Carbon emission factors (ton/GWh electric) of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bio-CCS	-855	-855	-805	-805	-805	-760	-760	-760
Gas-CCGT, Gas-ST	347	341	335	330	330	330	330	330
Gas-CCS	42	41	40	39	39	39	39	39
Gas-OCGT	507	484	473	463	463	453	453	453
Coal	797	763	747	732	732	732	732	732
Coal-CCS	94	91	89	86	86	86	86	86
Lignite	838	838	838	838	838	838	838	838
Oil	910	910	910	910	910	910	910	910

Values refer to state-of-the-art capacities from the respective vintage. *Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results. Bioenergy, geothermal, and nuclear are emission neutral.

Table C.5: Investment cost (€/kW) of generation technologies

	2015	2020	2025	2030	2035	2040	2045	2050
Bioenergy	4,322	4,236	4,149	4,149	4,106	4,063	4,063	4,020
Bio-CCS	6,322	6,236	6,149	6,149	6,106	6,063	6,063	6,020
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
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
Lignite*	1,640	1,640	1,640	1,640	1,640	1,640	1,640	1,640
Oil*	822	822	822	822	822	822	822	822
Geothermal	12,364	11,993	11,622	11,498	11,251	11,127	11,004	11,004
Nuclear**	7,600	7,006	6,346	6,082	5,818	5,488	5,488	5,356
Solar	1,300	1,027	936	858	819	780	741	715
Wind offshore	3,600	3,024	2,700	2,520	2,376	2,268	2,160	2,088
Wind onshore	1,520	1,397	1,368	1,339	1,325	1,310	1,310	1,296

Values refer to state-of-the-art capacities from the respective vintage. *Lignite and oil values refer to 2015 vintages in the respective period because we do not observe any lignite and oil expansion in our results. **Social cost of nuclear are often neglected in energy system analysis, in particular, decommissioning cost and storing nuclear waste. Given cost estimates of around 6,000 €/kW for installing nuclear facilities, estimates are around 1,000 €/kW for decommissioning them. However, the timing of those cost at the very end of the respective life times impedes their appropriate consideration. In fact, a discount rate of 7% leads to the consideration of only 100 €/kW decommissioning cost. We thus opt for an approach, where firms need to pay a decommissioning premium of 1,000 €/kW into a decommissioning fund at time of construction, so that 2020 investment cost are at 7,000 (instead of 6,000) €/kW.

Appendix D. Air pollution emission intensities (g/GJ thermal)

	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

Emission intensities are displayed for each vintages and thus include technological progress of mitigation measures that differ for each air pollutant.

Appendix E. GDP and population projections

Table E.6: GDP projections (billion 2015-€)

	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 E.7: 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 F. Specific SCAP

Table F.8: 2020 weighted average of specific 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

Table F.9: 2020 weighted average of specific SCAP (€/ton) by impact category and air pollutant (2)

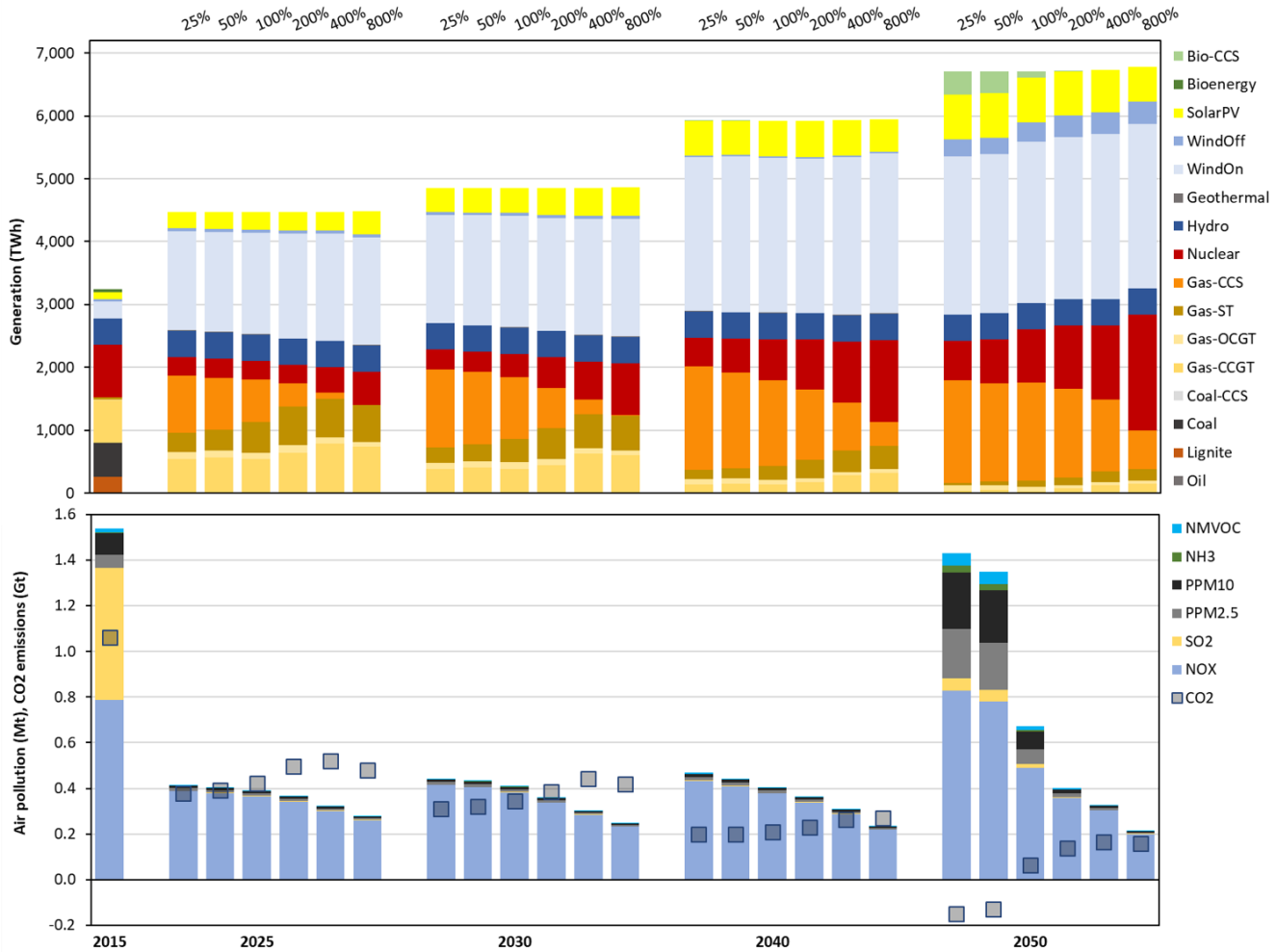
	ES	HU	FI	FR	HR	HU	IE	IT	LT	LU
Human health										
NH_3	6,024	22,941	5,302	14,423	19,968	22,941	3,028	16,842	7,296	29,975
NMVOC	546	810	294	1,178	992	810	859	857	547	2,554
NO_x	3,034	11,998	1,905	10,928	9,590	11,998	4,149	8,406	5,868	11,334
PPM_{10}	489	1,119	74	1,040	819	1,119	384	1,073	366	1,355
$PPM_{2.5}$	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

Table F.10: 2020 weighted average of specific 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

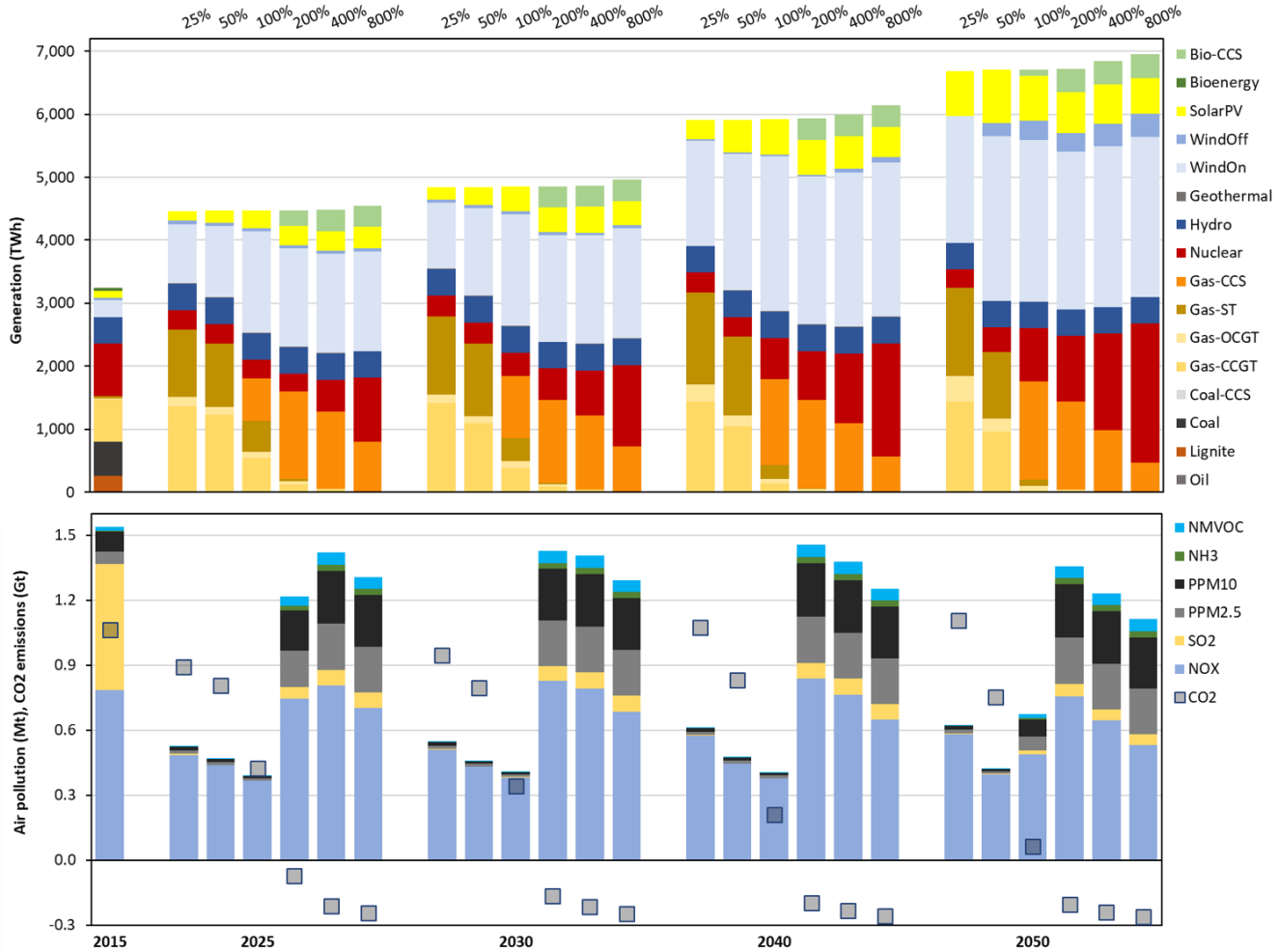
Appendix G. Visualizations of sensitivity analysis

Figure G.1: Generation (upper panel) and emission (lower panel) mix for SCAP sensitivity



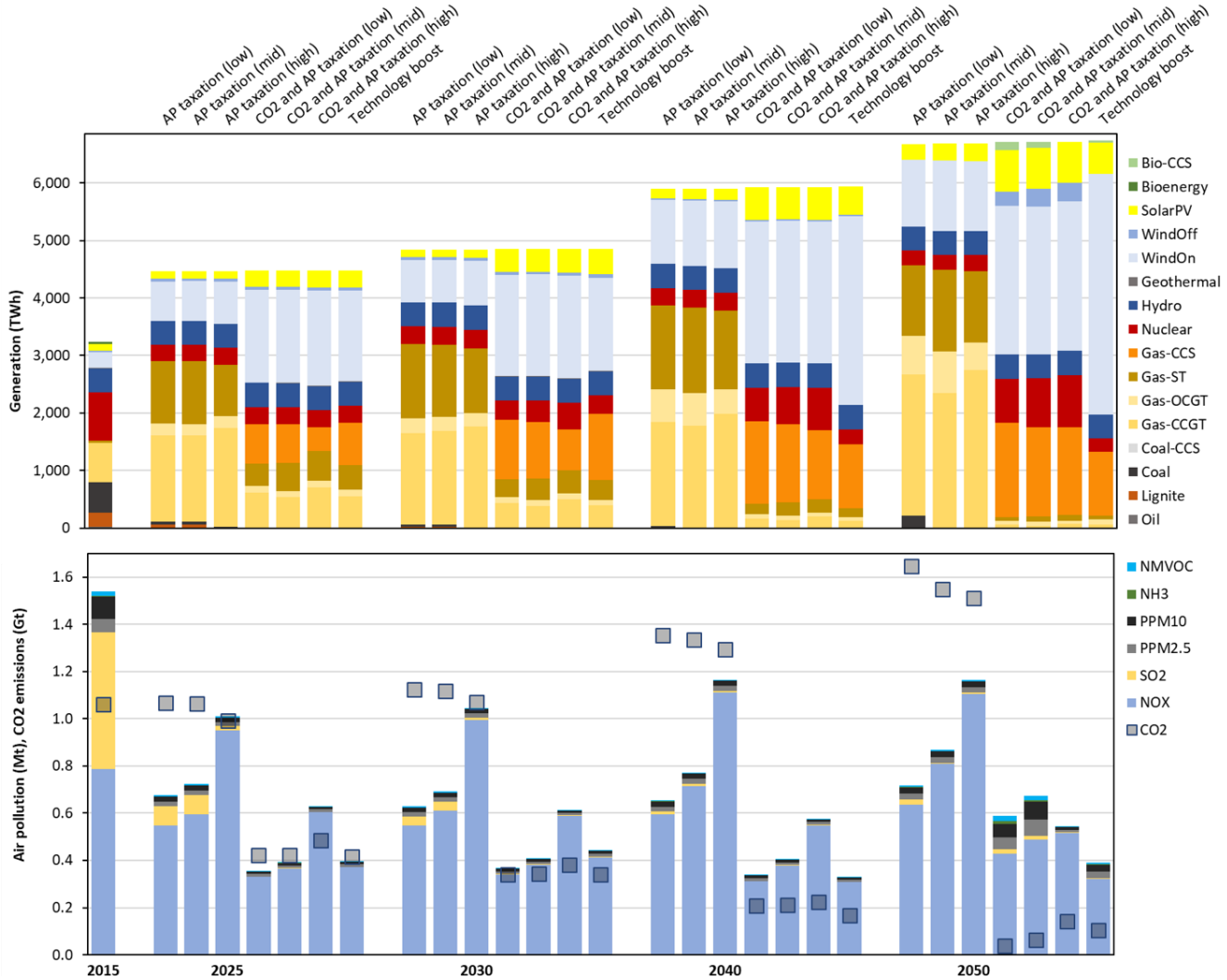
The percentage values reflect a change in specific SCAP and the respective air pollution taxes from 2025 onwards. The specific SCC and respective carbon tax remains unchanged.

Figure G.2: Generation (upper panel) and emission (lower panel) mix for SCC sensitivity



The percentage values reflect a change in specific SCC and the respective carbon tax from 2025 onwards. The specific SCAP and respective air pollution taxes remain unchanged.

Figure G.3: Generation (upper panel) and emission (lower panel) mix for air pollution emission factor sensitivity and the technology boost



Low, mid, and high in brackets present the respective air pollution emission factor scenarios. The mid scenario is used for all prior specifications. The low scenario starts at very same 2015 emission factors as the mid scenario but assumed technological progress is higher, so that emission factor decrease more. The high scenario starts at higher 2015 emission factors (less optimistic assumptions about current fleet) and technological progress is less optimistic as well (compared to the mid scenario). The technology boost indeed uses joint CO_2 and air pollution taxation with emission factors from the mid scenario.

Appendix H. Technology boost

The Table H.11 shows the total theoretical potential by wind resource class as well as corresponding average (potential-weighted) full-load hours (FLH) for wind onshore (see Table H.12 for country-specific potentials). Wind offshore is less relevant in the technology mix. We thus refrain from showing it here (see Tables H.13 and H.14 for details). Observe that total wind onshore potential in the *high* resource class is 585 GW. The potential above 3,000 FLH is just 275 GW. The technology boost increases this potential to 946 GW, whereas FLH increase by 23% in the *high* class and by 49% in the *mid* class.

Table H.11: Potential and full-load hours of wind onshore by resource class (low, mid, high) without and with technology boost

Resource class	low	mid	high
Total 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%

Table H.12: Potential (GW) of wind technologies by country and resource class (low, mid, high)

	Wind offshore			Wind onshore		
	low	mid	high	low	mid	high
Austria				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				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				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	0	0	0	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 H.13: Full-load hours of wind technologies by resource class (low, mid, high) without technology boost

	Wind offshore			Wind onshore		
	low	mid	high	low	mid	high
Austria				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 Republic				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				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				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	1,368	1,632	2,211	620	1,619	2,821
Romania	1,112	1,336	1,667	512	1,010	2,518
Slovak Republic				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	709	1,391	3,003	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 H.14: Full-load hours of wind technologies by resource class (low, mid, high) with technology boost

	Wind offshore			Wind onshore		
	low	mid	high	low	mid	high
Austria				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 Republic				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				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				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	1,237	1,970	2,413	968	2,847	3,646
Romania	1,240	1,583	1,844	832	1,752	2,881
Slovak Republic				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	796	1,796	3,200	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