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Technological Uncertainty in Meeting Europe's Decarbonisation Goals

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Abstract

In response to the challenge of managing the risks of a changing climate, there is no single optimal transition path for energy technology due to uncertainty in several dimensions. In this paper, we use the MERGE model, a long-term optimization model of the global energy and climate systems with regional and technological detail, enhanced in this paper with a more detailed representation of investment and dispatch detail in Europe's electric sector, to explore a wide range of possible technology futures under alternative emissions reduction goals. We find that, based on the revised modeling approach, wind energy is attractive for Europe in all scenarios, but to a varying extent ranging from under 15% to over 75%. One of its key disadvantages is to impose lower capacity factors on other technologies, an effect that can be partially mitigated with flexible operations such as joint production of hydrogen and electricity via gasification with CCS. Solar PV is almost never attractive for Europe as a whole, unless CCS and other technologies are significantly limited.

[1] This paper has benefited from the remarks and suggestions given by Paul Koutstaal, Jan Ros, and two anonymous referees on an earlier version of this paper. The authors are grateful for all the suggestions given by these referees.

Introduction

In response to the challenge of managing the risks of a changing climate, the European Union has set several goals for the reduction of greenhouse gases over the coming decades, primarily through decarbonisation of its energy system. While many technological options for emissions abatement have been identified, most are in early stages of deployment, and all are subject to uncertainty about future costs, performance, and availability. Moreover, the role of one region with respect to the global ambition for limiting atmospheric greenhouse gas concentrations depends on choices and outcomes in other parts of the world. Thus Europe's political commitment to emissions reductions cannot be mapped unambiguously to a single optimal transition path for energy technology.

Recent inter-model comparison studies have explored the sensitivity of mitigation strategy to assumptions about technology cost, performance, and availability. In particular, two studies organized by the Stanford Energy Modeling Forum (EMF), one with a global scope (EMF27) and one focusing on Europe (EMF28), specified coordinated scenarios run by participating models with variation along both policy and technology dimensions. In EMF27, Krey et al (2014) found a wide range of decarbonisation strategies in the electric sector and emphasized electrification at the end-use and the role of bioenergy with CCS (BECCS) deployment in the long run for meeting very tight targets. In EMF28, Knopf et al (2013) found that wind energy plays a significant role in decarbonisation scenarios for Europe, and that solar PV achieves a comparatively modest share in the electricity mix. They also concluded that CCS plays an important role when available but is not necessarily required to meet the mitigation target of reducing greenhouse gas (GHG) emissions by 80% by 2050, and finally that BECCS will only become important beyond 2050.

The focus of EMF28 was on the primary energy mix and the share of low-carbon electricity, rather than on the interactions between specific electric generation technologies. Most (though not all) models in EMF28, and large-scale integrated assessment models in general, account for variability of renewable energy as it impacts electric sector investments only implicitly through stylized constraints (Edenhofer et al, 2013). Global models are beginning to introduce more sophisticated formulations, such as Sullivan et al (2013), but there is a fundamental trade-off between the breadth of coverage and detail of specification. Single-region or single-sector models can afford more detailed modeling approaches, but can also miss important interactions with mitigation in other parts of the global economy. For Europe, examples include Hirth (2013a), who employs a stylized numerical dispatch and investment model of the interconnected Northwestern European power system, and Ueckerdt et al (2014), who demonstrate a reduced-form approach for Germany.

In this paper, we use the MERGE model to extend this area of the literature. MERGE is a long-term optimization model of the global energy and climate systems with regional and technological detail, with several innovations designed to improve the representation of interactions in the energy system while retaining a compact formulation. In particular, we introduce a new electricity generation module similar in design to that described by Ueckerdt et al (2014) that explicitly accounts for the intermittency of renewable resources and is linked to the supply and demand of hydrogen as an intermediate and end-use fuel. The new version of MERGE includes the detailed electric module in Europe will retaining its conventional formulation in other global regions. A wide range of technology and policy scenarios is explored using this enhanced modeling framework.

Our results confirm that wind generation capacity will very likely be an attractive investment in Europe under any policy limiting carbon, with some variation in the extent to which it is optimally deployed in alternative technology cases. On the other hand, solar photovoltaic generation is much less likely to be an attractive investment in Europe, even with aggressive policy targets, notwithstanding certain local situations below the level of aggregation of our model. Coal-based generation with carbon capture and storage (CCS), if it is available, could be a valuable complement to wind energy, especially if it can be combined with hydrogen production for end use. We also find that bioenergy with CCS is potentially valuable both as a complement to wind, particularly at higher carbon prices due to its negative emission flow. Both coal and bioenergy CCS have an advantage over nuclear in a system with heavy penetration of wind, which inevitably lowers capacity factors for other generation assets, because of their lower fixed to variable cost ratio. When CCS is not available, we observe a more diverse and more expensive energy mix relying on other technologies with more steeply decreasing returns to scale.

Model

Our starting point is the MERGE model as applied in the EMF27 global study (see Blanford et al, 2014a). In MERGE, the economy is represented by a nested production function of capital, labor, and electric and non-electric energy, with consumption defined as an aggregate of macro consumption and passenger vehicle services. There is a bottom-up representation of the energy supply sector, in which choices are made among specific activities for the generation of electricity and for the production of non-electric energy, including an option to produce electricity from bioenergy with carbon capture and storage (BECCS), thereby creating a negative emissions flow. Non-CO2 and non-energy-related emissions are also modeled using marginal abatement cost curves, and aerosol emissions are calculated based on exogenous assumptions about air pollution policies and fossil emissions rates. The accumulation of gases in the atmosphere and the subsequent effects on radiative forcing and temperature are described in a simple climate module. The time horizon extends to 2200, although we focus on results in the first century and in particular on the transition through 2050.

Modeling Electricity

For this study, we significantly extend MERGE by re-formulating the electric generation sector. To replace the conventional linear process model in which technologies are characterized only by levelized costs and the mix is governed to a large extent by limits on expansion and decline rates and other share constraints, we introduce a reduced-form capacity and dispatch formulation. Instead of specifying, for technology i in region r in year t, one decision variable for total electric energy supplied, the new formulation specifies one variable for installed electric capacity and a separate set of variables for dispatch of installed capacity to meet load in each segment s. This is a standard formulation for detailed electric system models, but it is less frequently employed in large global models due to the additional computational costs. A key advantage of this formulation is that the capacity factor is an endogenous outcome and the timing of dispatch is explicitly considered, whereas in the previous simple MERGE implementation, levelized cost parameters were calculated based on an exogenously assumed average capacity factor with no consideration of dispatch. Though certainly many aspects of electricity markets are still omitted, as discussed below, this is a more realistic setting and better reflects the economics of the sector. The primary challenge with implementing this type of formulation in a large model is to capture sufficient information about the intra-annual variation of both electricity demand and the availability of intermittent renewable resources in a computationally tractable number of segments.

Electricity demand varies both diurnally and seasonally, which given the relatively high cost of electricity storage is a fundamental driver of the economics of power generation investments. Consistent with minimization of total costs, current systems have evolved to include a mix of high-fixed-cost / low-variable-cost technologies (often called "base load" capacity) and low-fixed cost / high-variable cost technologies (often called "peaking" capacity). To capture this pattern in a model, it is sufficient to introduce only a small number of segments, say three to five, describing base, peak, and intermediate or "shoulder" load conditions, often in "typical" days for winter and summer. However, to accurately reflect the economics of intermittent renewable technologies, such a setting is inadequate due to the much greater and interdependent variation in wind and solar availability. Including a segment for all 8,760 hours of the year would be ideal, but it is not practical in the context of a large, multi-sector, multi-region model.

Instead we employ an approach based on the method introduced by Ueckerdt et al (2014), which characterizes the variability of renewable resources in a reduced-form model in terms of their effect on the residual load duration curve. A duration curve refers to an annual hourly series sorted in decreasing order. Residual load refers to electricity demand less output from intermittent resources, that is, load that must be met with dispatchable resources. Thus the residual load duration curve is *re-sorted* load after deducting the contribution of renewables. It is determined by the installed capacity of wind and solar and their co-variation with load; it in turn determines the capacity factors for other technologies. In our approach we first derive hourly residual load curves for several intermittent resource types in the Europe model region, and second develop parameterized estimates of the shape of those curves as a function of installed intermittent capacity. Our estimation procedure is similar in purpose but analytically distinct from that used by Ueckerdt et al (2014). Our approach is summarized here and described in detail in the Appendix B.

Three classes of wind are considered: one series describing standard continental Europe on-shore wind, one for premium on-shore locations bordering the North Sea, and one for off-shore locations in both the North Sea and Baltic Sea. We consider a single solar series, based mainly on Southern Europe. Our hourly load series is a sum over countries (as reported by ENTSO-E, 2014), while the wind and solar series are weighted averages across potential resource locations of profiles constructed from meteorological reanalysis data (see Appendix A for a detailed description). Hourly residual load duration curves are calculated for the hypothetical introduction of each class of wind and solar respectively in increments of 100 GW up to 1000 GW by re-sorting the resulting residual load series for each increment in renewable capacity. These curves are plotted for the continental wind class in Figure 1(a). Corresponding plots for other resource types are provided in Appendix B.

The key input to the model is the contribution to load of renewable output at each point along the sorted hourly distribution, or "contribution to sorted load," defined as the amount by which residual load in each sort position is decreased relative to full load, expressed as a percentage of installed capacity. This result, a simple transformation of the residual load duration curve, is illustrated for the continental wind class in Figure 1(b) (and for other renewable categories in Appendix B). The intercept with the y-axis reflects the contribution to the residual peak (the 100th percentile of residual load), while the values on the right side reflect the contribution to the residual minimum. The area underneath each "contribution to sorted load" curve equals the annual potential average capacity factor and is constant in increasing capacity. However, as wind capacity increases, the contribution is increasingly skewed toward hours with low residual load. A similar pattern holds for solar (see corresponding plots in Appendix B). Our approach is to estimate the "contribution to sorted load" at each sort position as a polynomial function of installed capacity for each resource class. We also account for interaction between wind and solar, although the underlying hourly data suggests this is a minor effect. A detailed description of the estimation procedure is provided in Appendix B.

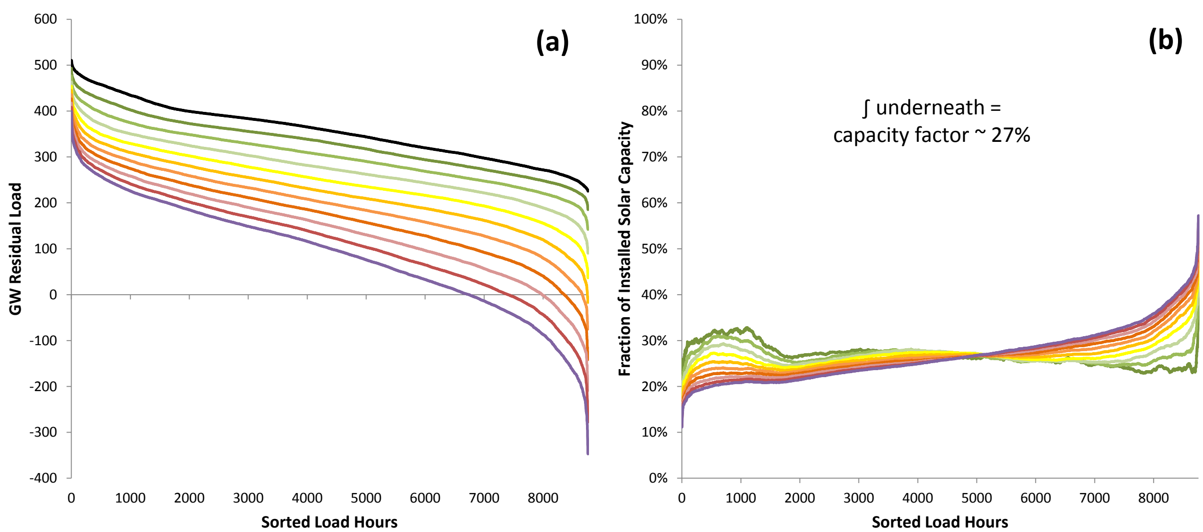

Figure 1. Residual Load Duration Curves (a) and Contribution to Sorted Load (b) for different levels of wind penetration in the EU (based on hourly data). The color spectrum reflects increasing installed wind capacity, with dark green indicating 100 GW, and purple indicating 1000 GW. The black line in panel (a) reflects the total load duration curve.

To enable a compact implementation, we estimate the contribution to load for 21 points corresponding to every 5th percentile (beginning with the peak or 100th %-ile, the 95th, 90th, … , 5th, and minimum or 0th %-ile). The estimated contributions to each percentile, illustrated in Appendix B, are a close approximation to the actual hourly contributions shown in Figure 1(b). In each segment, corresponding to percentiles of sorted load, the residual load is equal to full load less the sum across intermittent resource classes of the contribution fraction multiplied by installed capacity (an endogenous variable). Note that the contribution from intermittent resources is incorporated as an inequality constraint, so that curtailment or "spill" in segments with surplus output is possible. Dispatchable generation is subject to availability factors to capture maintenance in the case of thermal technologies and resource utilization patterns in the case of hydro. These factors are always less than 1 but are higher in high load segments.

This formulation is comparatively parsimonious and can be shown to reproduce closely key summary statistics about the viability of wind and solar investments, such as a marginal value curve, derived from hourly data (see Blanford, 2014). In particular the low contribution of wind and solar capacity to peak ensures that sufficient dispatchable or "back-up" capacity is present (either retained from the extant endowment or added in future time steps), and the high contribution to low-load hours ensures that possible "spill" events are accounted for. Our implementation also offers more granularity in capturing the shape of the residual load curve than that suggested by Ueckerdt et al (2014), who use a more stylized representation with only four segments that vary in both width and height. Nonetheless the approach has several shortcomings. Because the duration curve is sorted, hourly chronology is lost, which makes the approach unsuitable in a multi-region context, since transmission between regions cannot be modeled if the hours in each region are sorted differently.[2] Thus we implicitly assume a fully connected network across Europe, which is assuredly not the case. However, this simplification is countered by the introduction of a quadratic cost term as a function of renewable penetration, implying a rising cost of grid integration (in terms of incremental transmission investments) with a rising share of intermittent generation. This term can be calibrated so that the marginal value curve matches results from an underlying hourly model that does include inter-regional transmission. Still, value opportunities specific to certain sub-regions will be missed by the aggregation and must be modeled in a more detailed context.

Another consequence of the loss of chronology is that electricity storage cannot be explicitly modeled – although the model could be allowed to shift load from one segment to the next, the accumulation of the dynamic storage balance cannot be tracked, thus precluding explicit accounting of the corresponding storage capacity requirement. However, the underlying hourly model does include the option for storage in the value calculation, and the calibration of the reduced-form model's marginal value curve can in principle implicitly reflect the impact of storage. Analysis with the hourly model suggests that unless electricity storage becomes far cheaper than it is today, this option does not fundamentally change the economics of intermittent renewable energy. Still, there are potentially important interactions between storage and intermittent renewable energy, particularly solar, and representing this relationship explicitly is a key direction for future work. Finally, the model cannot explicitly capture the increased size and frequency of ramping and shut-down cycles to which dispatchable thermal technologies would be subjected in the presence of a large deployment of intermittent resources, which would likely have the effect of increasing costs for coal and nuclear technologies. A still more detailed formulation employing unit-level detail and integer variables describing unit commitment is required to account for these costs and constraints, although they are

[2] For example, an alternative reduced-form approach was developed for US-REGEN, a multi-region dynamic optimization model, in which roughly 100 representative hours are selected and weighted. See EPRI (2013) and Blanford et al (2014b) for details.

sometimes handled with a simple cost mark-up (e.g. Ueckerdt et al, 2013, Hirth et al, 2013). These studies suggest that the additional costs associated with ramping, as well as other effects such as short-term balancing, are small compared to the first-order effect on capacity utilization, which is treated explicitly by the residual load duration curve approach.

Modeling Hydrogen

This version of MERGE has also added a hydrogen production activity integrated with the electricity dispatch formulation. Like electricity, hydrogen is a potential energy carrier, requiring energy inputs for conversion but resulting in a higher value end-use fuel. We consider five conversion technologies: coal gasification with and without CCS, natural gas steam-reforming with and without CCS, and electrolysis. These technologies have two close links with electricity production. First, hydrogen production from coal is essentially equivalent to the first stage of an integrated gasification and combined cycle (IGCC) electric plant. Thus one may envision an IGCC technology producing a steady stream of syngas with the option either to deliver it to a second stage turbine or create a flow of hydrogen than can be stored relatively cheaply (see for example Domenichini et al, 2012). This configuration allows the gasification plant to achieve a higher capacity factor by producing hydrogen directly when the price of electricity falls below its dispatch cost. By representing the co-production technology in an optimization framework with segment-level resolution, the value of this option can be assessed. The second link is with the electrolysis technology, which uses electricity as an input. The new formulation allows the model to choose which segments to use electric output to produce hydrogen and to weigh capital costs against the endogenous capacity factor of the electrolysis plant (a similar approach is used by Ueckerdt et al, 2014). This formulation implicitly assumes that it is essentially costless to maintain an inventory of hydrogen, as the shape of its end-use demand is not modeled. Hydrogen can either be used in the non-electric sector to offset liquids and gas or as a fuel in passenger transportation. To reflect infrastructure needs, expansion constraints are placed on the penetration of hydrogen as an end-use fuel and a cost premium is added for non-electric use. Additionally, we assume that it cannot supply more than half of non-electric, non-passenger-transport energy demand.

Despite the compactness of the new electricity-hydrogen module, in the context of a multi-region, intertemporal optimization problem over a long time-horizon, it still imposes a significant computational burden (the model is solved in GAMS using CONOPT with a starting basis specified). For this reason, in this paper we apply the new module only in the model region describing Europe (covering EU27 plus EFTA countries). Furthermore we describe the rest of the global economy using only four other regions: USA, Other OECD, China, and Rest of World (ROW). In the other four regions, electricity production follows previous model versions, and hydrogen production is not explicitly modeled (although a non-electric backstop technology is included). As the new formulation is further refined, and as the performance of computational software and hardware continually improves, it is expected that future versions of MERGE will extend the new formulation to all regions. One promising approach for improved solve time is the decomposition algorithm described by Rutherford and Böhringer (2009).

Scenarios

In this analysis we define a range of scenarios in both the policy and technology dimensions. In the policy dimension, we include (1) a baseline with no greenhouse gas (GHG) policies; (2) a "weak" policy case based on the Reference Policy scenario design in the AMPERE project (Kriegler et al, 2014) in which current pledges for the 2020 timeframe are extended into the future but no long-term target is enforced; and (3) a globally harmonized policy scenario aiming for a long-run target for atmospheric GHG concentrations of 550 ppm CO2-e (for Kyoto gases only). This is roughly consistent with a likely maximum global average surface temperature increase of between 2 and 2.5 °C (see Clarke et al, 2014).

Along the technology dimension, we first define a default case with mainly optimistic assumptions about technology costs and availability, and then consider many sensitivity cases in which cost decline paths and availability constraints for particular technologies are varied. Some of these binary switches may have no effect on scenario results when explored relative to the default case, but in the presence of other variants may turn out to be influential. Our scenario space is designed to explore combinations that result in qualitatively different energy mix results. This represents a methodological extension from previous technology scenario analyses, e.g. recent EMF studies, in which only a few prescribed combinations were analyzed. The resulting sensitivity analysis thus covers a wide range of possible outcomes that demonstrates both heterogeneity and robustness of certain elements with respect to technological uncertainty for a given policy scenario.

Table 1 summarizes our default assumptions for electric generation technologies, which are based on (though not identical to) assumptions in the World Energy Outlook (IEA ,2012). The capital costs are applied directly in the Europe model region, while in other regions using the simpler electricity formulation levelized costs based on these figures are used. The sensitivity dimensions in which the technology scenarios will be constructed (see Table 2 below) are summarized as follows:

On-shore wind: with installed capacity already in excess of 100 GW, wind's on-shore footprint in densely populated European countries is under increasing scrutiny. We consider the impact of an upper bound on on-shore wind capacity of 400 GW based on local siting opposition.

Off-shore wind: off-shore wind sites offer higher capacity factors and to a certain extent more valuable profiles, but they come with a cost premium for both initial investment and ongoing maintenance and a potentially shorter lifetime. While in the default case, declining costs make off-shore wind attractive relative to on-shore in the long run, we also consider the possibility of no significant cost improvements.

Solar: manufacturing costs for photovoltaic panels have fallen steeply in recent years, and further improvements seem likely, if not at the same rate. In the default case we assume costs fall from roughly $2000/kW to $1000/kW over the next three decades. We also consider a case in which costs fall faster and further, reaching $1200/kW in 2030 and $750/kW in 2050.

Integration costs: the penetration of intermittent renewable sources must be accompanied by expanded transmission infrastructure to accommodate their spatial and temporal variability. Although our model does not have high enough resolution to capture transmission explicitly, we include as a proxy a cost term that rises linearly with the share of wind and solar. In the default case this cost reaches \$15/MWh at high penetration levels. If the expansion of transmission is limited due to siting difficulties, the implicit cost of integrating intermittent supply with demand could rise much more steeply. Thus we also consider a case in which this cost is doubled. Note that the implications of temporal variation for the value of energy and capacity are explicitly modeled in the Europe region.

Table 1. Default Scenario Technology Capital Cost Assumptions (\$/kW)

	2020	2030	2040	2050+
Coal (Pulverized)	\$2,100	\$2,100	\$2,100	\$2,100
Coal Integrated Gasification Combined Cycle (IGCC)	\$2,400	\$2,300	\$2,200	\$2,200
Coal IGCC with CCS	\$3,500	\$3,000	\$2,700	\$2,700
Gas Single Cycle	\$625	\$625	\$625	\$625
Natural Gas Combined Cycle (NGCC)	\$900	\$900	\$900	\$900
NGCC with CCS	\$1,620	\$1,500	\$1,350	\$1,350
Nuclear (Gen III)	\$4,000	\$4,000	\$4,000	\$4,000
Nuclear (Gen IV)	N/A	N/A	N/A	\$5,600
Biomass	\$2,300	\$2,200	\$2,100	\$2,100
Biomass with CCS	\$3,400	\$3,200	\$3,000	\$3,000
Wind On-shore	\$1,700	\$1,700	\$1,700	\$1,700
Wind Off-shore	\$2,500	\$2,200	\$2,100	\$2,000
Solar PV	\$2,000	\$1,600	\$1,200	\$1,000

Note: costs are expressed in year 2005 USD.

Bioenergy: large-scale annual production flows of bioenergy will have major impacts on land use and land-related activities such as agriculture and forestry. We assume a maximum of biomass production of 275 EJ, which is based on the average of 100-450EJ, see PBL (2012). Ultimately these interactions will limit the extent to which bioenergy can be sustainably produced, that is, without indirect carbon emissions from land cover change. Although MERGE does not explicitly model land use, we model the supply of purpose-grown energy crops with a rising supply curve and place an upper bound on the annual total in each region based on estimates in the literature. Trade in biofuels is allowed, although biomass for electric generation may be more difficult to transport due to low energy density and high costs. In the default case, biomass must be consumed in the region in which it is produced, implying an upper bound on biomass-based generation (with or without CCS) in Europe of around 1000 TWh. We also consider a case in which solid biomass can be traded among regions with a transport cost of $2/GJ.

Nuclear: while new investments in nuclear in Europe may not be cost-effective in the default case, nuclear plays a much larger mitigation role in fast-growing regions such as China and other non-OECD countries. Because the deployment of nuclear depends on a range of political and social decisions that extend beyond private investment economics, we consider a case in which nuclear expansion is limited to projects currently under construction. On the other hand, expanded deployment of nuclear requires scaling up the extraction of uranium, at least until an advanced reactor able to recycle fuel is available (which we assume does not occur until 2050). We also consider a case in which constraints on this scale-up are relaxed, significantly slowing the rate at which global uranium prices rise with increased production.

CCS: despite some commercial experience with carbon capture and long-term underground storage, the viability of this technology at large scale remains uncertain. The model includes regional constraints on geologic reservoir capacity (roughly 400 billion tons of CO_2 for Europe) with rising unit costs with cumulative storage. To reflect the possibility that for technical or public acceptance reasons, the practice is simply not viable, we consider a case in which CCS options for electric generation, hydrogen production, and cement manufacture are omitted.

Co-production of hydrogen: while it is straightforward from a design perspective to envision the flexible IGCC configuration outlined above, it remains unproven and may encounter unforeseen technical obstacles. We therefore consider a case in which the co-production technology is not available, that is, the ability for hydrogen production and electricity generation to "share" the same gasification plant. In this case both IGCC and hydrogen from coal gasification are available individually.

Demand for hydrogen: it is also unproven whether hydrogen can become a widespread end-use fuel, either in transportation or stationary applications such as industrial process heat. In contrast to the default case in which the costs of fuel-cell passenger vehicles decline rapidly and hydrogen can supply up to 50% of non-electric, non-passenger-transport demand (with a price premium for delivery infrastructure), we consider a case in which fuel-cell vehicles remain expensive relative to other options and hydrogen can supply up to only 10% of other non-electric demand.

Demand for electricity: the future pathway for electricity demand depends on several uncertain factors, such as the rate of economic growth, the rate of decline in energy intensity, and the extent of electrification. While it is not possible in this study to consider a comprehensive scenario space covering possible ranges for this collection of factors, we did explore the cost of battery technology for electric vehicles, a potentially important avenue for substitution with non-electric energy. The result is a small increase in overall electricity demand without significant effects on the supply-side mix.

Table 2. Key Technology Sensitivity Cases

Label on Figures 9 & 10	Description (see Scenarios section above)
Bio Trade	Solid biomass can be traded internationally
Default	Default scenario
Pes. On-Shore	On-shore wind is limited to 400 GW total
Pes. Off-Shore	Off-shore wind costs do not decline over time
Hi Int. Costs	Integration cost term is doubled relative to default scenario
No New Nuc	No new nuclear capacity is allowed
No Co-H2	IGCC+CCS with co-production of hydrogen is not allowed
No CCS	CCS is not allowed
… + Opt. Solar	No CCS plus optimistic assumptions about the cost of solar PV
… + Off-shore	No CCS + Opt. Solar plus no decline in off-shore wind costs
… + No Nuc	No CCS + Opt. Solar + Pes. Off-shore plus no new nuclear
… + On-shore	No CCS + Opt. Solar + Pes. Off-shore + No New Nuc + limited on-shore wind

Results

Emissions

We first present results on global total greenhouse gas (GHG) emissions for each policy scenario in the left panel of Figure 3.[3] In the case of the weak policy scenario, emissions targets are prescribed in each region (banking is not allowed), so the pathway for global emissions is the same regardless of the resolution of technological uncertainty. By contrast, in the harmonized stabilization scenario, the emissions path depends on technology, as the path can shift in time while satisfying roughly the same total budget.[4] The baseline scenario is largely independent of the dimensions of technological uncertainty discussed here; only the pathway for the default technology scenario is shown. In the weak policy case, emissions roughly return to recent levels by the end of the century. In the more stringent stabilization case, global emissions fall to half their recent level by 2050, which corresponds roughly to the goal articulated by the former G8 group of countries (G8, 2009). Because the potential reduction in non-CO2 emissions is assumed to be limited to a relatively small fraction of their baseline, particularly for agricultural sources (USEPA, 2014), the scenarios entail greater proportional reductions in carbon emissions than in the carbon-equivalent total, reaching near-zero levels by the end of the century in the stabilization scenario.

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[3] Emissions reporting in MERGE excludes carbon emissions due to anthropogenic land-use change. However, the carbon cycle is calibrated using the assumption that this emissions flow is offset by fertilization-induced increases in the terrestrial biosphere.

[4] Note that if the policy scenarios had been specified in terms of prices rather than quantities, there would be more variation in the emissions path with respect to technological uncertainty. With a quantity-based policy implementation, variation in technology realizations translates instead into variation in costs.

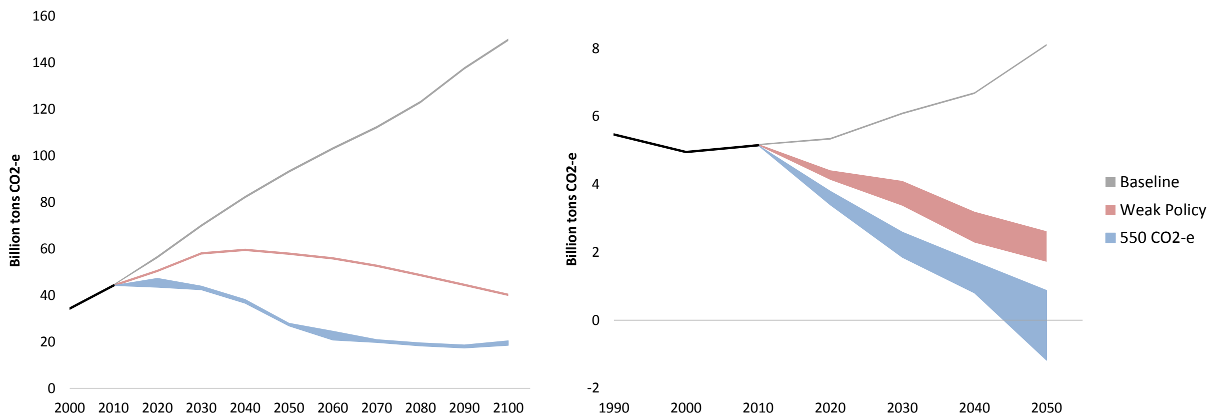

Figure 2: Global CEQ Emissions (left) and Europe CEQ Emissions (right).

We now turn the focus on to the Europe region in the first half of the century, shown on the right panel of Figure 2. The baseline emissions path for Europe reflects the evolution of an energy system with no further control of greenhouse gas emissions. Note that this is not necessarily a likely future, given the many political commitments to the contrary; rather it is a hypothetical "counterfactual" or "counter-expectation" scenario used to illustrate the magnitude and impact of efforts to reduce emissions. In this setting, continued fossil fuel use keeps carbon intensity roughly constant, while energy intensity declines at a rate similar to historical experience (more slowly than economic growth), leading to growth in total energy use and rising emissions. In the weak policy scenario, the targets for Europe follow in broad terms its articulated goals: a 20% reduction relative to 1990 by 2020, and an 80% reduction by 2050. However, trade in emissions credits is allowed with other regions in the weak policy scenario, the extent of which varies across the range of technology scenarios – essentially, Europe imports more credits with more pessimistic assumptions about technology. Thus while the global path is fixed, there is variation at the regional level, and Europe is always a net importer, leading to realized emissions above the nominal goal. Still, the target implies significant mitigation relative to baseline for Europe and thus is not necessarily "weak" per se – the label refers to the global level of ambition relative to that required for stringent long-term climate scenarios. In the 550 ppm CO2-e scenario, total GHG emissions in Europe fall even more rapidly, with net carbon emissions becoming negative by mid-century in some technological instances.

Electric Generation

To meet current objectives for emissions reductions, or even more ambitious pathways consistent with stringent global climate outcomes, a transformation must occur in the electric generation mix. Although emissions from fossil use in the electric sector account for only a third of total emissions, there are more and better options for alternatives than in most other sectors, thus the relative cost of abatement is lower. Studies of cost-efficient mitigation strategies nearly always indicate a larger share of reductions in electric generation than in the economy as a whole (see for example Krey et al, 2013 and Knopf et al, 2013). However, abatement costs for electricity are nonetheless convex, and in particular renewable energy technologies exhibit decreasing returns to scale as they penetrate the market due primarily to their temporal variation (Blanford, 2014; Mills and Wiser, 2014; Hirth, 2013b). In the updated formulation described here, these effects can be captured, revealing a broad range of the optimal levels of deployment of the various low-carbon electric options depending on the technological scenario.

Default Technology Scenario

In the default case, for both the weak and stringent policies, we find that wind energy plays a major role, complemented by a combination of CCS technologies (see Figure 3). Wind provides low-cost carbon-free energy with a profile that in Europe is better correlated with electricity demand than in other regions. Nonetheless its contribution to capacity needs is limited, and its energy is delivered disproportionately in low-value segments. Dispatchable technologies provide capacity and energy to fill in wind's gaps. These include integrated coal gasification and combined cycle (IGCC) with CCS and bioenergy with CCS (BECCS). Both of these technologies, in addition to providing firm capacity to counter wind's inconvenient profile, provide other benefits as well. While the presence of wind in the system drives down the capacity factor of dispatchable technologies, in the case of IGCC the co-production of hydrogen allows the gasification phase to operate at full capacity. Thus when hydrogen has value as an end-use fuel, and when it can be relatively cheaply stored, the economics of this option for electric generation are improved. Nonetheless, the residual emissions of fossil-based CCS diminish its role in our stringent policy scenario. In the case of BECCS, provided that the feedstock is carbon-neutral with respect to induced land-use change, a negative emissions flow is created, which in a carbon policy scenario represents an additional revenue stream. At high carbon prices, this stream may dominate the value of electricity produced. Even at modest carbon prices it confers on BECCS an advantage over competing technologies, regardless of whether total net emissions are negative..

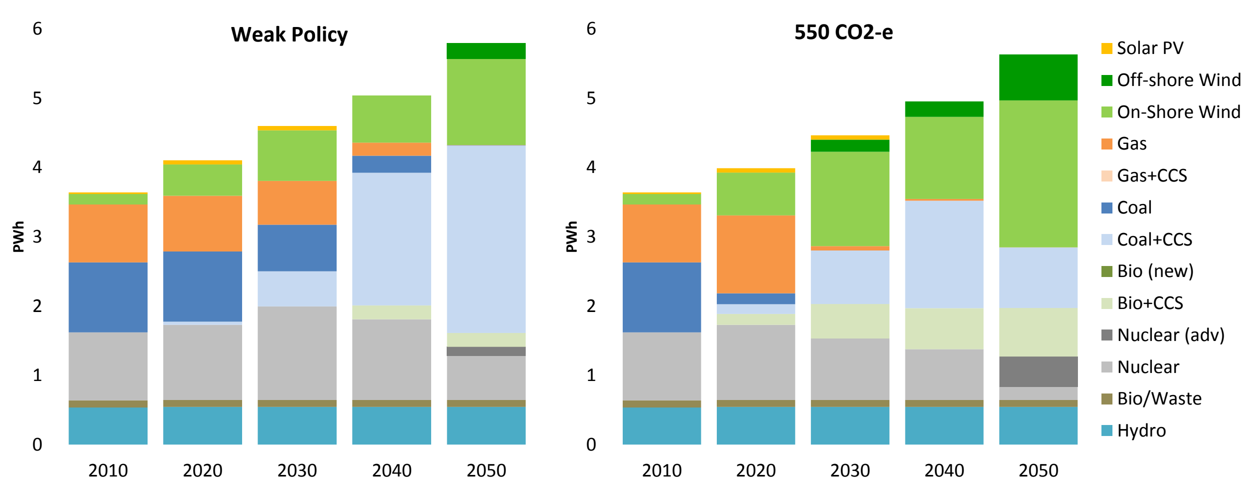

Figure 3. Electric Generation in Europe under Default Technology Scenario.

To illustrate the implications of temporal variation for the economics of renewable energy in the electric generation mix, Figure 4 shows electricity dispatch across the load segments corresponding to percentiles of the ranked load duration curve for both 2010 (simulated) and 2050 in the weak policy case under the default technology scenario.[5] The 2010 panel illustrates the current conventional system in which coal operates mainly in base load, gas in shoulder and peaking mode, with only a minor effect on the shape from wind and solar. In the 2050 policy case, installed wind capacity has expanded to approximately 550 GW by 2050 (as compared to less than 100 GW in 2010) and constitutes 25% of electricity generation. Peak load is roughly 970 GW, and peak residual load (net of the contribution of wind), is 870 GW. That is, firm capacity needs are reduced by 100 GW or roughly 18% of installed wind capacity. The shift in the residual load curve from the contribution of wind results in lower capacity factors for the remaining technologies, in particular the nearly 200 GW of gas-fired capacity, which is essentially used only during the peak. A dispatchable technology's capacity factor can be roughly inferred from the chart by comparing the average height of dispatch across all segments to the height in the peak segment, during which all available capacity is fully dispatched as a condition of optimality. However, only 80-90% of installed capacity is available at the peak. The left panel of Figure 5 illustrates the capacity factor for coal with CCS in the 2050 weak policy case, which is 51%. In the 550 CO2-e scenario (described below), installed capacity and capacity factor for coal with CCS are both half as large, implying only a quarter of generation, while installed wind capacity (and generation) are nearly double.

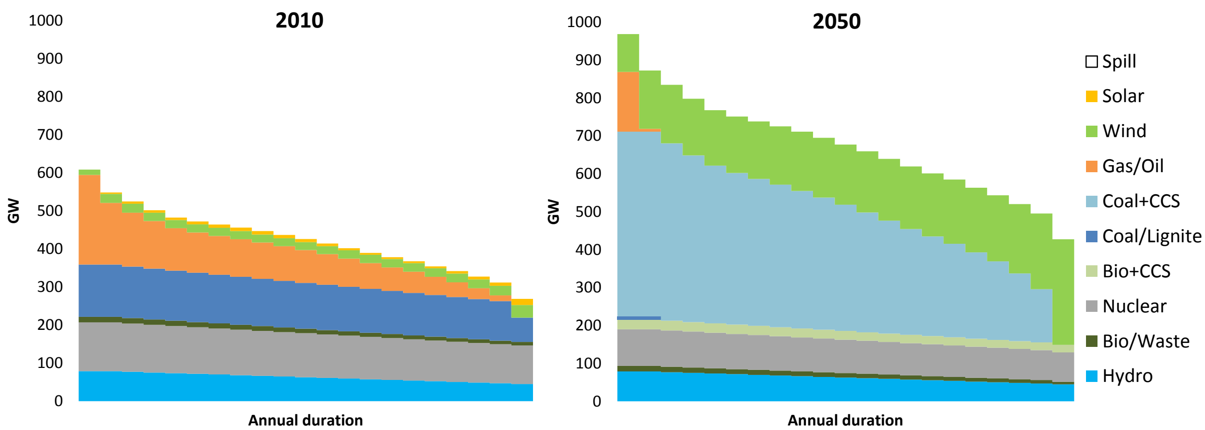

Figure 4. Electricity Dispatch in Europe in 2010 vs. 2050 Weak Policy Scenario (default technology). Note: the width of the peak segment is exaggerated for illustrative purposes. In the model it is weighted with a single hour.

[5] Note that the peak load segment is weighted by a single hour, with the second-highest segment weighted by 437 hours. The remaining 19 segments are weighted by 438 hours each for a total of 8760. Thus the graphics in Figure 5 and Figure 7 are slightly mis-scaled as the width of the peak segment is exaggerated for illustrative purposes.

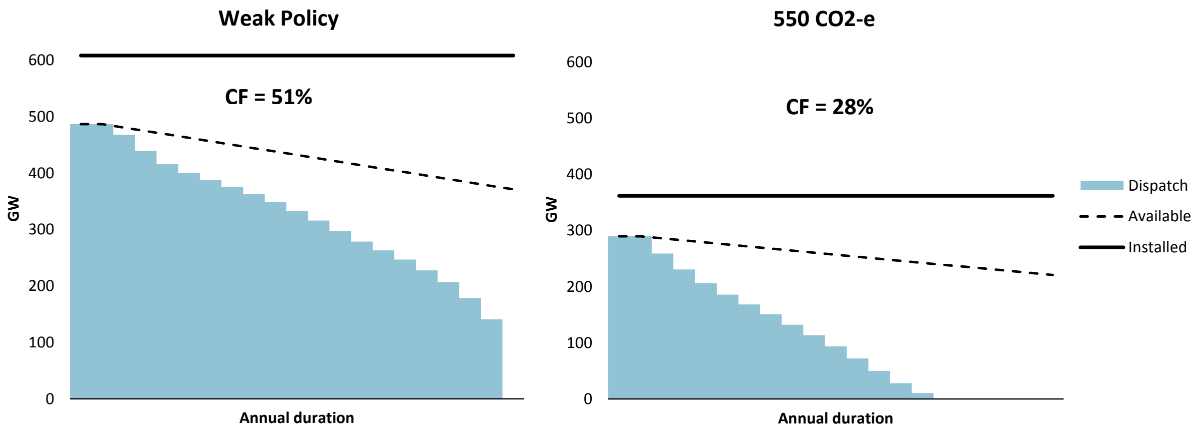

Figure 5. Dispatch and Capacity Factor of Coal with CCS in 2050 in Weak Policy and 550 CO2-e Scenarios (default technology). The dashed line reflects installed capacity adjusted for an availability factor in each segment as discussed above. Note the width of the peak segment is exaggerated for illustrative purposes. In the model it is weighted with a single hour.

Absent from the default generation mix are solar and natural gas-fired generation, and nuclear's share does not expand. In Europe, solar is a particularly difficult technology from a value perspective, given the low capacity factor due to Europe's northern latitudes and frequent cloud cover as well as its profile relative to load, which is even more inconvenient than wind. In particular, solar provides zero capacity value given Europe's winter evening peak in electricity load (driven by heating demand). While it is currently heavily supported by subsidies in several European countries, when carbon mitigation is efficiently priced, solar struggles to compete with other options even under default assumptions of rapid cost declines to $1000/kW by 2050. In the case of nuclear, its high capital costs become a significant penalty when the presence of wind in the system forces lower capacity factors on other technologies. Moreover, rising global prices of uranium increase its variable costs as well. Although the model considers a public cost that rises with the share of nuclear to reflect acceptability concerns, this factor is dominated in the default case by private investment economics. Natural gas plays a transitional role in the near to medium term, but in the long run it is not viable without CCS under moderate or stringent carbon prices. With CCS it is out-competed by coal-based technology, particularly given the value of the co-production of hydrogen available with IGCC. However, single cycle gas turbines continue to play an important role in providing capacity, albeit with very few operating hours.

Alternative Technology Scenarios

While wind, CCS, bioenergy, and hydrogen emerge as the main elements of a least-cost decarbonisation pathway for Europe with a default set of assumptions, many future parameter values are uncertain. Given the significant role played by CCS technologies in the default case, we begin with the sensitivity scenario in which CCS is not available. In this case, electric generation from coal and bioenergy with CCS is replaced by a combination of energy efficiency (i.e. reduced demand), natural gas, and a much heavier reliance on wind, both on-shore and off-shore. Additionally, there is a larger initial investment in advanced nuclear in 2050, although the build-out of new conventional nuclear capacity before 2050 is similar. One key consequence of a larger share from wind is low capacity factors for gas and some remaining coal, but also for nuclear and even for wind itself. This interaction is fundamental to the economics of intermittent renewable technologies, but can only be captured with a more detailed representing of the electric sector such as the one implemented here. . Notably, even under these circumstances solar capacity is not "in the money" with its default cost trajectory. We return to the issue of solar below.

Another scenario in which CCS plays a smaller role is with limitations on either the co-production of hydrogen or the market for hydrogen as an end-use fuel. Without the enhanced economics of co-production, coal-based CCS is still in the mix, but at around half its level in the default case. Without the opportunity to produce hydrogen during non-dispatch hours, coal-based CCS needs a higher capacity factor in the electricity market to be a viable investment. Interestingly, this leads not only to less coal with CCS but also slightly less wind energy, because its intermittent profile is less easily absorbed and thus less valuable without the flexible co-production technology. Instead, BECCS and conventional nuclear have expanded roles, and there is a small increase in natural gas. This pattern is also observed when the co-production technology is available but the share of hydrogen in non-electric end-use demand is assumed to be limited. Without such constraints, hydrogen produced from coal gasification with CCS is an attractive alternative to liquid fuels under a carbon policy on the basis of price, even accounting for a storage and delivery premium of $3/GJ.

In a sensitivity case combining the constraint on CCS with the fast cost decline path for solar, a relatively small block of solar capacity (around 30 GW) is added by 2050 when costs have fallen to $750/kW. Adding to this case also the sensitivity that off-shore wind costs do not improve much, the contribution of solar grows a little larger to around 50 GW, but the main effect is an increase in on-shore wind. Adding to this further a restriction on new nuclear builds, around 120 GW of solar is added by 2050. Still it provides less than 5% of the energy provided by wind in this case. The most solar deployment occurs in a case with all of the above restrictions, plus the pessimistic upper bound of 400 GW on on-shore wind, in the 550 CO2-e policy scenario. In this case there are 300 GW of installed solar, accounting for 8% of energy. The extent of solar deployment in 2050 across the various technology sensitivity cases is shown in Figure 6. The dispatch of electricity for the extreme case of 300 GW is shown in Figure 7.

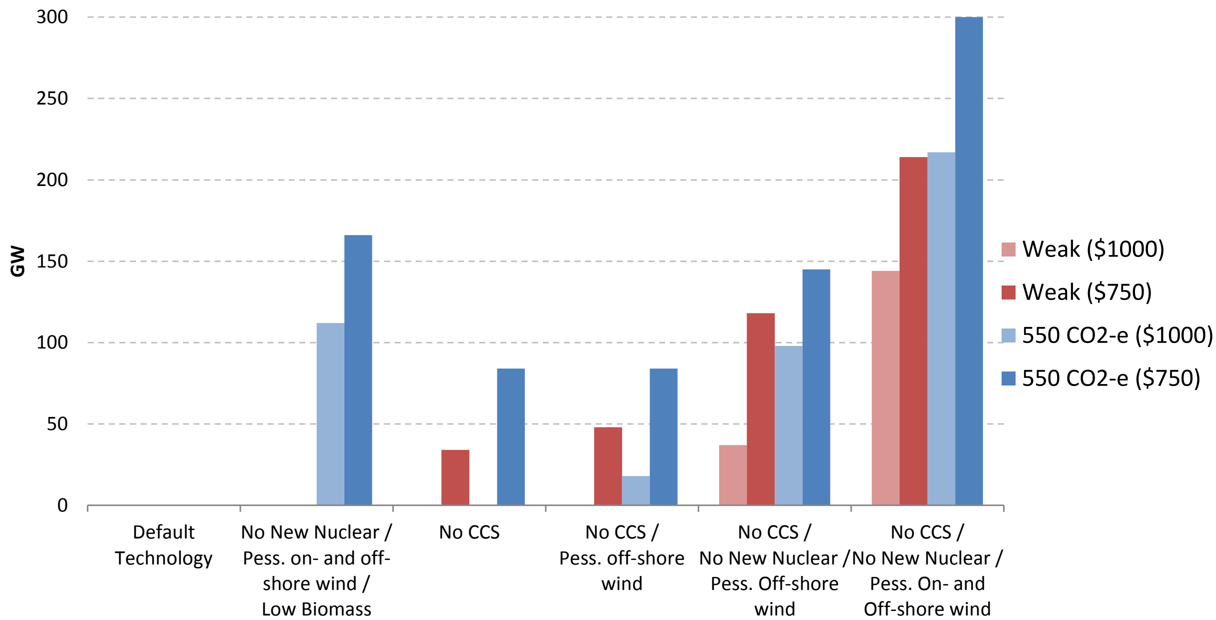

Figure 6. Solar Deployment in 2050 in Europe with default costs of $1000/kW and optimistic costs of $750/kW under alternative policy scenarios. In the highest deployment level of 300 GW on the far right, solar provides 8% of electric generation.

Next we explore a branch of sensitivity cases in which wind energy is limited, first by higher integration costs, and second by assuming that potential capacity additions of on-shore wind in Europe are limited to 400 GW or approximately 1000 TWh. With higher integration costs, optimal deployment of wind falls from roughly 500 GW in 2050 to 250 GW, with the difference made up by coal with CCS and BECCS. By contrast, when potential additions are limited, deployment is reduced by roughly 100 GW with the difference made up mainly by off-shore wind and a slight increase in BECCS. If we add pessimistic assumptions about off-shore wind and a constraint on new nuclear builds to this scenario, the CCS share becomes even larger.

In a policy environment mandating faster reductions consistent with a global stabilization effort, some of the insights described above remain valid while some distinct patterns emerge. First, the transition away from existing coal begins much sooner, with a large fraction replaced by gas in the first decision period, i.e. by 2020. By contrast, in the weak policy case, only about 40% of coal capacity is retired early, and this occurs in 2040 and 2050. In the default case for the stringent target, wind and BECCS expand more quickly, while coal with CCS expands more slowly and there are very few additions of conventional nuclear. The value of the BECCS negative emissions stream and its lower capital intensity relative to nuclear make it a better match with large amounts of wind in a deep decarbonisation scenario. Figure 7 shows the dispatch of electricity in the 550 CO2-e scenario under both the default technology case and the limited case described above (and in the last row of Table 2) in which solar's role emerges. In this case excess electricity produced at the lower end of the residual load curve is used for hydrogen production via electrolysis. However, some energy is still spilled, as it is not cost-effective to over-build electrolysis capacity to absorb large amounts of excess energy for a small number of hours.

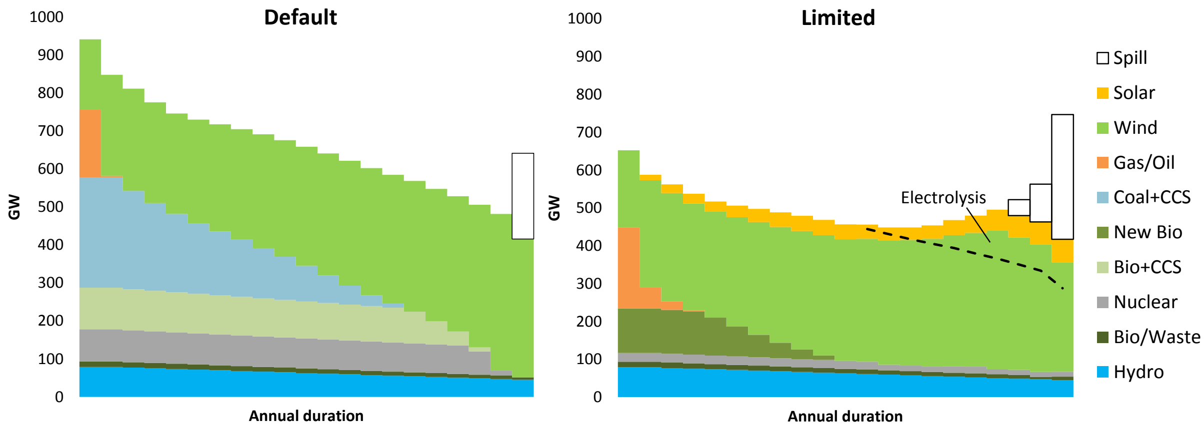

Figure 7. Electricity Dispatch in Europe in 2050 in 550 CO2-e Policy Scenario for default technology and the "limited" case with no CCS, no new nuclear, no cost improvements in off-shore wind, and an upper bound of 400 GW for on-shore wind, but with more rapid cost declines for solar. Electric generation above the black dotted line, excluding the "spill" quantities, is used for hydrogen production via electrolysis. Note: the width of the peak segment is exaggerated for illustrative purposes. In the model it is weighted with a single hour.

A final dimension to consider is that of price. In Figure 8, the average wholesale electricity price in 2050 is plotted against the 2050 carbon price for each technology scenario listed in Table 2. In the weak policy scenarios, the price of electricity is roughly twice the baseline price with carbon prices more or less than \$100/tCO2. The most expensive cases in the upper right of the group correspond to the No CCS cases. For the 550 CO2-e scenarios, carbon prices are much higher in the range of \$400-\$500/tCO2, and electricity prices are also higher, though not proportionally with the carbon price as most of the system has become carbon-free. Still, the most expensive no-CCS cases, such as that depicted as "limited" in Figure 7, are in the upper right corner with electricity prices more than three times the baseline level.

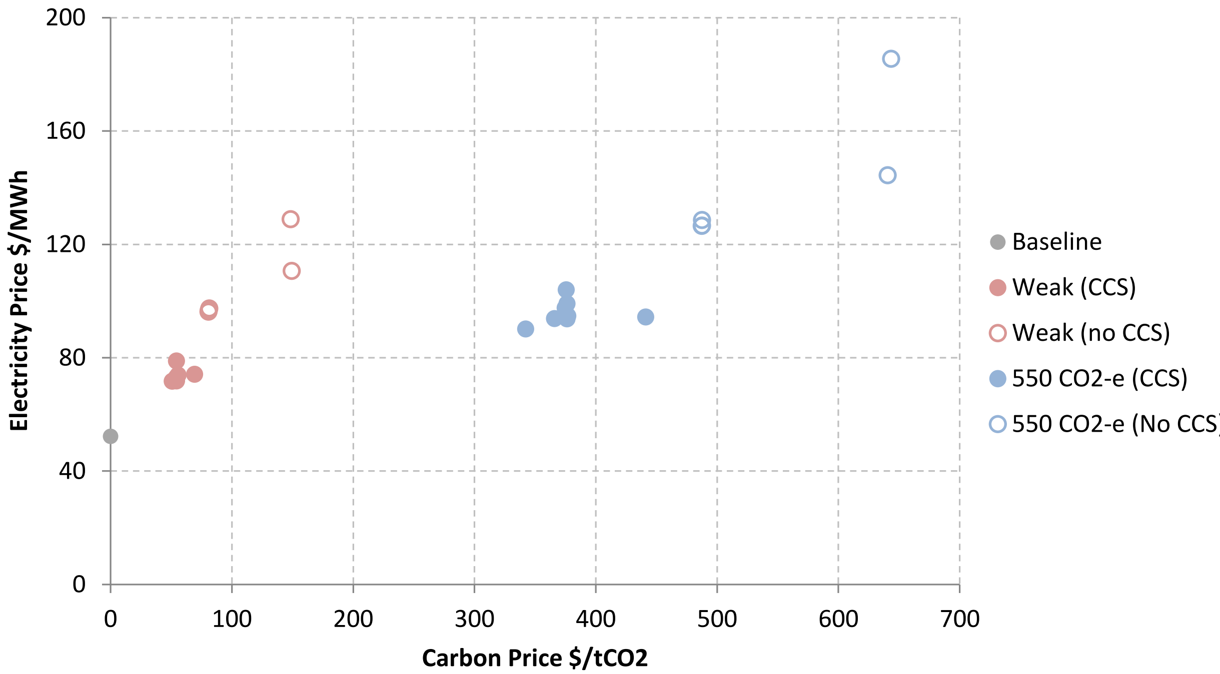

Figure 8. 2050 Europe Electricity price (average wholesale price) plotted against carbon price for all technology scenarios in the Weak Policy and 550 CO_2-e policy sensitivity analysis. Solid dots reflect scenarios in which CCS is available; open dots reflect scenarios in which CCS is not available.

Discussion and Conclusions

We have explored a wide range of potential decarbonisation scenarios in the context of a global model with an explicit representation of investment and dispatch detail in Europe's electric sector. The emphasis of our analysis is on the heterogeneity of potential outcomes in terms of technology mix over the next several decades as a result of uncertainty about costs and constraints on available options. A wide range of technology scenarios have been explored under alternative policy specifications. Figure 9 and Figure 10 summarize the key sensitivity cases explored for the weak policy and 550 CO_2-e scenarios, respectively, in terms of the 2050 generation mix (see Table 2 for precise definitions of the sensitivity cases). From the analysis a number of robust results emerge.

One robust finding is that wind energy is a prominent feature of essentially every scenario. The profile of wind energy in Europe provides a better match to the shape of load than in other regions, such as the US (see for example EPRI, 2013), and although its average capacity factor is lower than in the US, its advantageous shape means that the marginal value of incremental capacity erodes more slowly with increased penetration.[6]

[6] This confirms the results of Hirth (2013), who showed that high wind shares will result if there are high CO_2 prices, restrictions on nuclear, and large cost reductions for wind. In the default case there are no restrictions on nuclear. Nevertheless we see no nuclear expansion in Europe. The nuclear expansion in other regions than Europe depletes the uranium resource and pushes the price nuclear power and thus limits the use of nuclear in Europe.

Still, wind faces challenges, such as transmission requirements and public siting opposition, which could limit its deployment. Moreover, its shape is only *relatively* advantageous: it nonetheless contributes disproportionately to low-load hours, forcing dispatchable technologies to operate at lower capacity factors and lowering the value of energy when they are operating. For this reason wind's presence in the system makes flexible technologies like co-production of electricity and hydrogen from coal gasification more valuable and capital-intensive technologies like nuclear less valuable.

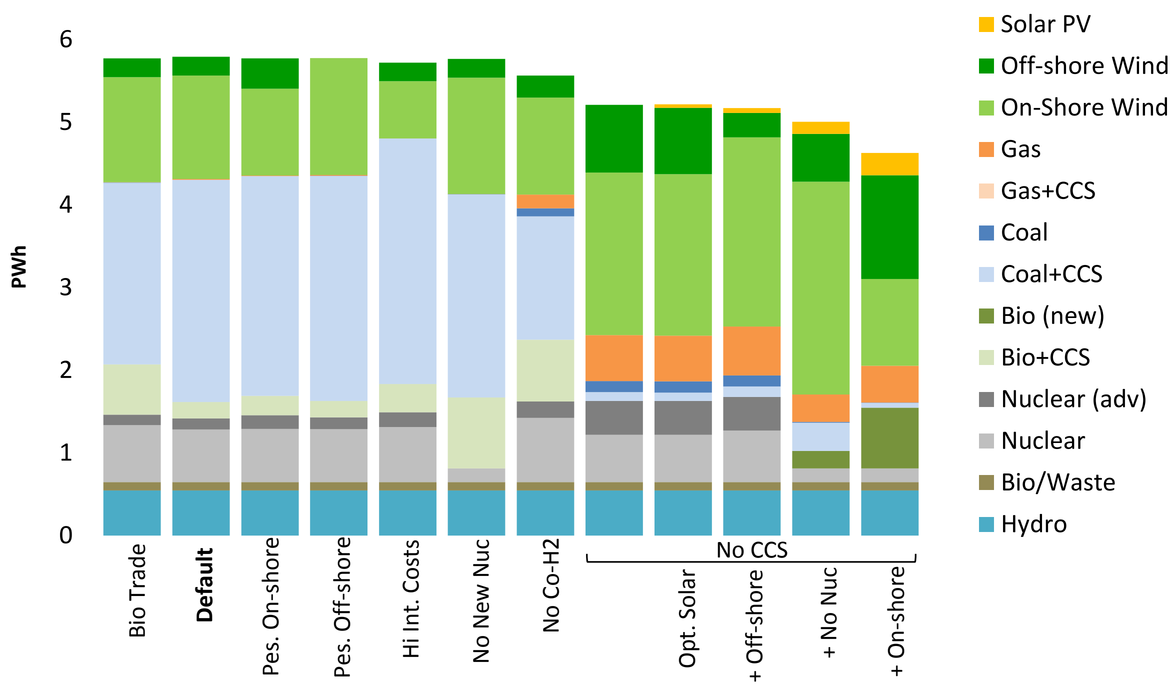

Figure 9. 2050 Generation Mix in Europe under Weak Policy Scenario for a range of Technology Cases.

Another robust finding is that CCS is the preferable complement to wind, if it is available. This result arises in our model because CCS technologies have more value at low capacity factors than alternatives such as nuclear, rather than because of operational flexibility (discussed further below). Particularly for moderate (rather than stringent) emissions reduction goals, the best application of CCS is with coal in co-production mode. If this is not possible, due either to supply or demand side limitations on hydrogen, coal-based CCS is considerably less attractive while BECCS is more attractive.[7] Especially if there is a policy goal to rapidly reduce emissions, BECCS is the best application, contingent on sufficient capacity to produce sustainably carbon-neutral bioenergy, along with the potential for international trade. When developing regions with large potential bioenergy production but smaller electric systems can supplement Europe's supply through trade, BECCS plays a much more significant role, especially in

[7] In this analysis, gas with CCS only enters the mix in the 550 CO2-e case when co-production of hydrogen is not allowed. However, we do not fully explore alternative cost assumptions (or alternative gas price scenarios) that might make it more attractive.

the 550 CO2-e case (see Figure 10). This is consistent with Knopf et al. (2013), who find that BECCS will play a limited role to 2050 as long as there is no or little trade in bioenergy. In terms of its effect on the character of the optimal energy mix in a decarbonized European electric sector, CCS is a pivotal technology. If it is not available, a different system emerges with a much greater reliance on renewables and stronger price signals for energy efficiency investments.

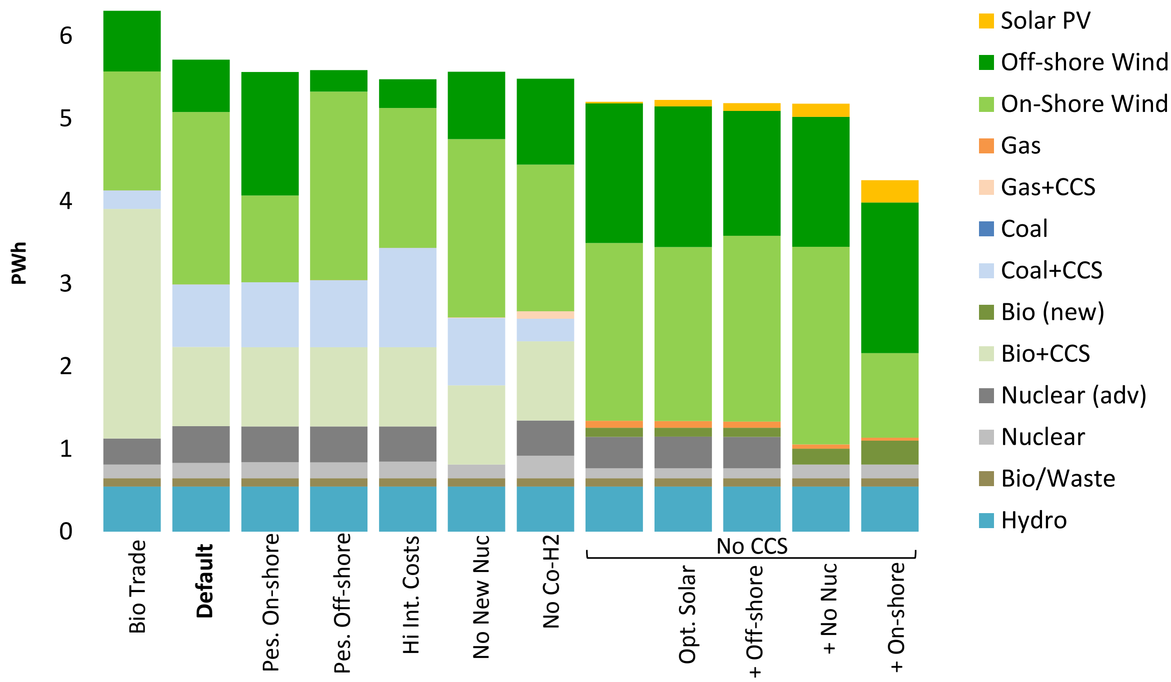

Figure 10. 2050 Generation Mix in Europe under 550 CO2-e Scenario for a range of Technology Cases.

In Knopf et al (2013) nuclear energy becomes more important if no CCS is allowed in electricity generation. In this analysis, new nuclear energy plays a more muted role than CCS. A major reason is that the opportunity for base load generation, nuclear's traditional role as a high-fixed-cost, low-variable-cost technology, is squeezed by the penetration of wind energy as more and more of its potential hours are supplanted by the steeply falling residual load curve (an argument lacking in most of the models applied in Knopf et al., 2013). That is, even assuming the possibility of flexible operation, a low capacity factor discourages investment in nuclear on capacity utilization grounds alone. Another reason is that variable costs rise as the price of uranium responds to a large increase in demand globally, especially in the stabilization scenario, further undercutting its traditional advantage. Nonetheless in the default case there are new investments in 2020 and 2030 in conventional (i.e. third generation) nuclear plants, partially replacing the retirement of existing units. Perhaps counter-intuitively, more new nuclear is built under a moderate policy than under a stringent policy because of increased competition with wind and BECCS in the latter case. In the long run, an advanced nuclear technology with a closed fuel cycle could be important, especially if CCS is limited and if carbon emissions in Europe are to be eliminated by 2050.

Finally, we find that solar PV, in a least-cost setting with efficient pricing of carbon and electricity, is unlikely to play a significant role in Europe's decarbonisation. Its profile is more inconvenient than wind's, and its capacity factor lower, suggesting that only with the combination of pessimistic assumptions about several other technologies is it economically attractive, and then only when its costs fall well below $1,000 per kW.

An important caveat to these results, particularly concerning the value of wind, is that even though they have been derived from a representation of electric generation that is much more sophisticated and closer to reality than previous versions of the MERGE model and similar energy-economy models, they nonetheless omit an important effect of intermittent generation, namely operational constraints. The first-order effect of reducing capacity factors is effectively captured by the residual load curve. However, additional costs and constraints associated with low-capacity-factor dispatch may be incurred at the unit level, below the aggregation of our model. Although unit commitment modeling is an active area of research, a tractable method for incorporating the implied economics of unit commitment into a reduced-form intertemporal investment and dispatch model is not yet available.

In addition to this important next step, the electric sector formulation applied here for Europe should be extended to other model regions. This step requires an underlying regional model with hourly and spatial detail for calibration, which presents data challenges for a global application. Extending the formulation to the US or possibly other OECD countries is likely straightforward, but data availability is more complicated for countries such as China and India. Additionally, aggregate regions that are not geographically contiguous or electrically interconnected could be difficult to represent. Finally, a representation of endogenous technical change through learning, research, and spillovers could provide important insights given the strong dependence of the results on cost reductions over time; carbon technologies are likely to improve faster in a policy environment where more abatement effort is being undertaken. Nonetheless, the methodology and results presented build upon recent advances in the ability of models to portray the economics of decarbonisation in the electric sector.

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Appendix A: Data Development for Wind and Solar Profiles in MERGE

The newly developed version of the electric sector in MERGE (currently applied only in the Europe region) used a reduced-form representation of intra-annual variability to reflect intermittent renewable resources such as wind and solar. The underlying data is based on hourly time series for solar and six-hour average time series for wind at the grid cell level in 2011. The series reflect output as a percentage of nameplate capacity based on observed meteorology and technological parameters.

Construction of wind data

For wind, we use the 2011-ECMWF's ERA-40 reanalysis data at 10 m height as our primary resource.[8] The wind speeds at 10 meter height, V_{10}, were derived from the 10 meter height wind speed in the U (10U) and V (10V) direction with magnitude $\sqrt{(10U)^2 + (10V)^2}$. Subsequently, we converted these 10-meter-height wind speeds to the wind speed at hub height, V_H, using the logarithmic wind profile for neutral conditions (Hoogwijk et al., 2004)

$$V_H = V_{10}\left(\frac{\ln(H/z_0)}{\ln(10/z_0)}\right)$$

Here, H denotes the hub height in meters and z_0 denotes the roughness length expressed in meters. Expected hub heights are based on recent practice and are 100m onshore and 120m offshore. The roughness length z_0 is based on the Corine Land Cover database 2000 (CLC) as in EEA (2009).[9] From these wind speeds at hub height, we constructed for each grid point in the reanalysis dataset the generated power (kW) using a power-velocity curve of a 2 MW wind turbine.[10]

Construction of solar data

For solar, we use the 2011-KNMI's radiation dataset as our primary resource.[11] Using data on direct and indirect (diffuse) radiation on the horizontal plane, we first construct an estimate of the hourly radiation on a titled plane for each grid point and time unit in the data set. Subsequently, we use this estimate together with ambient temperature, to determine the output of a south-facing hypothetical PV module.

[8] ECMWF ERA-40 = European Centre for Medium-Range Weather Forecasts Reanalysis40.
[9] EEA = European Environmental Agency.
[10] We used curve P_nom = 2.0_3 depicted in Figure 2.2 of EEA (2009).
[11] KNMI = Koninklijk Nederlands Meteorologisch Instituut. See http://msgcpp.knmi.nl/mediawiki/index.php/MSG_Cloud_Physical_Properties_%28CPP%29 for a more detailed description.

Let N denote the day of the year, $N = 1, \ldots, 365$. The solar declination, δ, which is the angular distance of the sun's rays north of the equator, is then given by

$$\delta = 23.45 \sin\{\frac{2\pi}{365}(284 + N)\}. \tag{1}$$

Notice that declinations north of the equator are positive. At the spring and autumn equinoxes the declination is 0°, whereas it is $+23.45^{\circ}$ at the summer solstice and -23.45° at the winter solstice. Next, determine the hour angle h in degrees by

$$h = 0.25(\text{Number of minutes from local solar noon}), \tag{2}$$

where the local solar noon is equal to 12.00 hours (winter time). Thus the hour angle at the local solar noon is zero and 1 h is equivalent to $0.25 * 60 = 15^{\circ}$, afternoon hours designated as positive. The time in the KNMI database is UTC irrespective of longitude. Local time t_{local} is given by

$$t_{local} = t_{UTC} + (l_{local} - l_{UTC})\frac{24}{360}, \tag{3}$$

where t_{UTC} is the time in the KNMI database, and l_i is the respective longitude. To illustrate, suppose $t_{UTC} = 13$, $l_{UTC} = 0°$ and $l_{local} = 18°$. Then, t_{local} is 14 hours and 12 minutes. The KNMI data base contains beam (*sds*) and diffuse (*sds_diff*) radiation on the horizontal plane. Denote these variables by G_B and G_D respectively. Total radiation on a titled plane at time t, G_t, is then given by

$$\begin{aligned} G_t &= G_{Bt} + G_{Dt} + G_{Gt} \\ &= G_B \frac{cos(\theta)}{cos(\Phi)} + G_D[\frac{1 + cos(\beta)}{2}] + (G_B + G_D)\rho_G[\frac{1 - cos(\beta)}{2}] \end{aligned} \tag{4}$$

where G_{Bt}, G_{Dt} and G_{Gt} have been defined implicitly and denote the beam, diffuse and ground reflected solar radiation on the titled plane at time t, respectively. In Eq. (4), θ denotes the incidence angle, which is the angle between the sun's rays and the normal on a surface. The solar zenith angle Φ is defined as the angle between the sun's rays and the vertical (the normal on a horizontal plane). The surface tilt angle β measures the angle of the PV module with the horizontal plane. Finally, ρ_g is ground albedo. The incidence and solar zenith angles are related to the latitude L, the surface tilt angle β, the solar declination δ, the hour angle h and the surface azimuth angle Z_s. Assuming a south-facing module, we have

$$\frac{cos(\theta)}{cos(\Phi)} = \frac{sin(L - \beta)sin(\delta) + cos(L - \beta)cos(\delta)cos(h)}{sin(L)sin(\delta) + cos(L)cos(\delta)cos(h)}. \tag{5}$$

The output of a PV module at time t is now calculated as

$$P_t = A_c G_t \eta_{PV,t}(G_t, T_{ct}), \tag{6}$$

where A_c is the surface area of the PV panel (which we will take to be 1 m^2), $\eta_{PV,t}$ is the conversion efficiency in the solar sell, which depends on radiation G_t and cell temperature T_{ct} as follows:

$$\eta_{PV,t} = \eta_r \eta_{pc}[1 - \gamma(T_{ct} - T_{cref})], \quad (7)$$

where η_r is the reference module efficiency which is set to 15%, T_{cref} is the reference cell temperature, γ is the so-called generator efficiency temperature coefficient, and η_{pc} is the power condition efficiency. Finally, the temperature of the solar cell can be obtained through

$$T_{ct} = 30 + 0.0175(G_t - 300) + 1.14(T_{at} - 25), \quad (8)$$

where T_{at} is the ambient temperature at time t. As hourly temperature data is not available for Europe, we construct country-specific estimates of hourly temperature from the minimum, maximum and daily average temperature by using Method 1 in Reicosky et al. (1989).[12] Table A1 summarizes all parameters and data values that have been used in the computations.

Table A1. Parameters and Data used for Solar Output Calculations

Parameter/Data	Value	Source
$\boldsymbol{L}$,$\boldsymbol{G_B}$ **and** $\boldsymbol{G_D}$		KNMI: See ftp://msgcpp-ogc-archive.knmi.nl/ (for 2011-today)
$\boldsymbol{\beta}$		Fixed Tilt Table on www.macslab.com/optsolar.html#other
$\boldsymbol{\rho_G}$	0.2	Van der Borg and Wiggelinkhuizen (2012)
$\boldsymbol{Z_s}$	0	Assume optimal facing
$\boldsymbol{A_c}$	1	Standardization
$\boldsymbol{T_a}$		www.ecad.eu/ensembles
$\boldsymbol{\gamma}$	0.0045	Average value as listed in Skoplaki (2009)
$\boldsymbol{T_{cref}}$	25	Kalogirou (2009), Ch. 9, p. 480.
$\boldsymbol{\eta_{pc}}$	1	We implicitly assume the use of a perfect maximum power tracker.

[12] The temperature data was downloaded from http://www.ecad.eu/download/ensembles/ensembles.php.

Aggregation of Gridded Data

Grid cells were aggregated into categories referring to top 10%, bottom 10%, and middle 80% in each European country. For the wind and solar technologies included in MERGE, a representative series was constructed as a weighted average from the categories of gridded data. The weights were chosen based on ad hoc judgment with the intention of reflecting a plausible distribution across countries and sites below the level of aggregation in the model. Factors such as resource quality, geography, population density, economic activity, and national policy priorities were considered in the selection of weights.

Three classes of wind are considered: one series describing standard continental Europe on-shore wind, one for premium on-shore locations bordering the North Sea, and one for off-shore locations in the North Sea. One class of solar PV corresponding to deployment on the European continent is considered. These classes were constructed as follows:

Standard (Continental) On-Shore Wind

For this class, an equal weighting on the top 10% and middle 80% categories was applied to a weighted average across countries in western and central continental Europe. The weighting excluded countries with inaccessible terrain (e.g. Switzerland) and very low-quality resources (e.g. land-locked southeastern Europe). Finally, the constructed average series was reduced uniformly by 10% to reflect wake effects and losses between the turbine and the grid.

	Weight	Top 10% CF	Mid 80% CF
Germany	0.21	37%	17%
Spain	0.21	36%	13%
France	0.21	43%	17%
Italy	0.10	38%	13%
Poland	0.10	32%	17%
Netherlands	0.05	43%	24%
Greece	0.05	38%	17%
Portugal	0.05	29%	12%
Belgium	0.02	27%	19%
Resulting Weighted Average:		**30%**	
Resulting Weighted Average -10%:		**27%**	

Premium (North Sea) On-Shore Wind

For this class, a 2:1 weighting on the top 10% and middle 80% categories respectively was applied to a weighted average across countries in the North Sea area. The middle 80% category was included in the weighting based on the assumption that not all of the land in the best grid cells will be accessible for development. Finally, the constructed average series was reduced uniformly by 10% to reflect wake effects and losses between the turbine and the grid.

	Weight	Top 10% CF	Mid 80% CF
Norway	0.20	46%	19%
Sweden	0.20	42%	21%
England	0.20	51%	34%
Denmark	0.12	47%	34%
Ireland	0.12	51%	34%
Northern Ireland	0.04	47%	34%
Scotland	0.04	53%	37%
Estonia	0.04	45%	28%
Latvia	0.04	43%	25%
Resulting Weighted Average:		**44%**	
Resulting Weighted Average -10%:		**39%**	

North Sea Off-Shore Wind

For this class, an equal weighting on the top 10% and middle 80% categories was applied to a weighted average across countries in the North Sea area, including along the southern shore. The constructed average series was reduced uniformly by 10% to reflect wake effects and losses between the turbine and the grid.

	Weight	Top 10% CF	Mid 80% CF
Germany	0.17	53%	46%
France	0.17	46%	34%
England	0.17	60%	53%
Norway	0.08	56%	49%
Sweden	0.08	48%	43%
Denmark	0.08	47%	43%
Poland	0.07	45%	43%
Ireland	0.05	61%	54%
Netherlands	0.05	49%	45%
Estonia	0.03	47%	44%
Latvia	0.03	46%	41%
Scotland	0.02	61%	57%
Resulting Weighted Average:		**48%**	
Resulting Weighted Average -10%:		**43%**	

Standard (Continental) Solar PV

For this class, an equal weighting on the top 10% and middle 80% categories was applied to a weighted average across countries in continental Europe. Weights were chosen so that the sum across the eastern countries equaled the sum across western countries. Note that the reported capacity factor includes a reduction of 25% to account for inverter losses.

	Weight	Top 10% CF	Mid 80% CF
West			
Germany	0.13	13%	12%
Spain	0.13	17%	16%
France	0.13	16%	13%
Italy	0.07	17%	15%
Portugal	0.03	17%	16%
Switzerland	0.01	15%	14%
East			
Greece	0.13	17%	15%
Austria	0.06	14%	13%
Poland	0.06	12%	11%
Romania	0.06	14%	13%
Bulgaria	0.06	14%	14%
Hungary	0.06	14%	13%
Czech Republic	0.04	13%	12%
Slovakia	0.03	13%	13%
Resulting Weighted Average:		**14%**	

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Appendix B: Estimation of Load Contribution Coefficients for Wind and Solar

Hourly residual load series were constructed for each resource type for a range of hypothetical installed capacity levels, in increments of 100 GW up to 1000 GW. For continental wind and solar PV, joint residual load series were constructed, i.e. 100 series representing each combination of capacity increments in wind and solar. For the on-shore and off-shore North Sea wind classes, residual load series were constructed based on varying the respective capacity in the class individually, i.e. 10 series for each class. These residual load series were each re-sorted, and the resulting values in each sort position were subtracted from the full load duration curve to calculate the "contribution to sorted load", the key quantity to be estimated. Figures B1 – B4 show the residual load curves for increasing capacity in each resource class (panel a) and the "contribution to sorted load" (panel b). (Figure B1 is a re-production of Figure 1 in the main text.)

Both wind and solar are delivered disproportionately at low-load hours, with additional skewedness (i.e. sloping to the right, implying an increasing share of energy during low-load hours) as penetration increases. The solar pattern is accentuated by the fact that its distribution is effectively truncated to zero for roughly half the hours of the year; as installed solar capacity increases, the hours with low residual load become predominantly daylight hours. Overall capacity factors, as well as the contribution during peak and near-peak hours, are considerably higher for North Sea wind locations than for the average over continental wind locations.

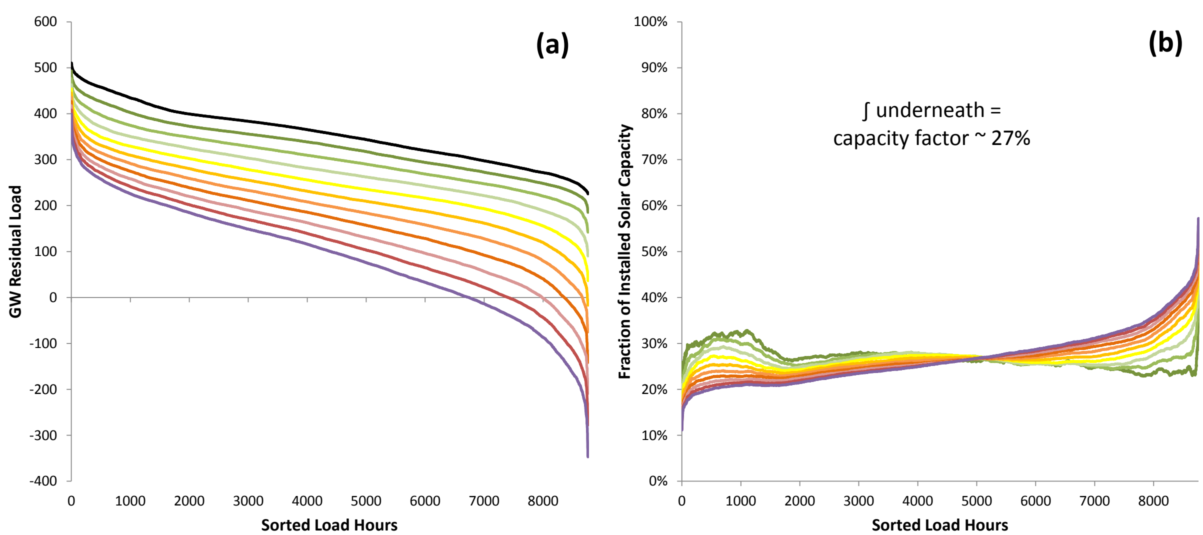

Figure B1 (Figure 1 in main paper). **Continental Wind**: Residual Load Duration Curves (a) and Contribution to Sorted Load (b) for different levels of wind penetration in the EU (based on hourly data). The color spectrum reflects increasing installed wind capacity, with dark green indicating 100 GW, and purple indicating 1000 GW. The black line in panel (a) reflects the total load duration curve.

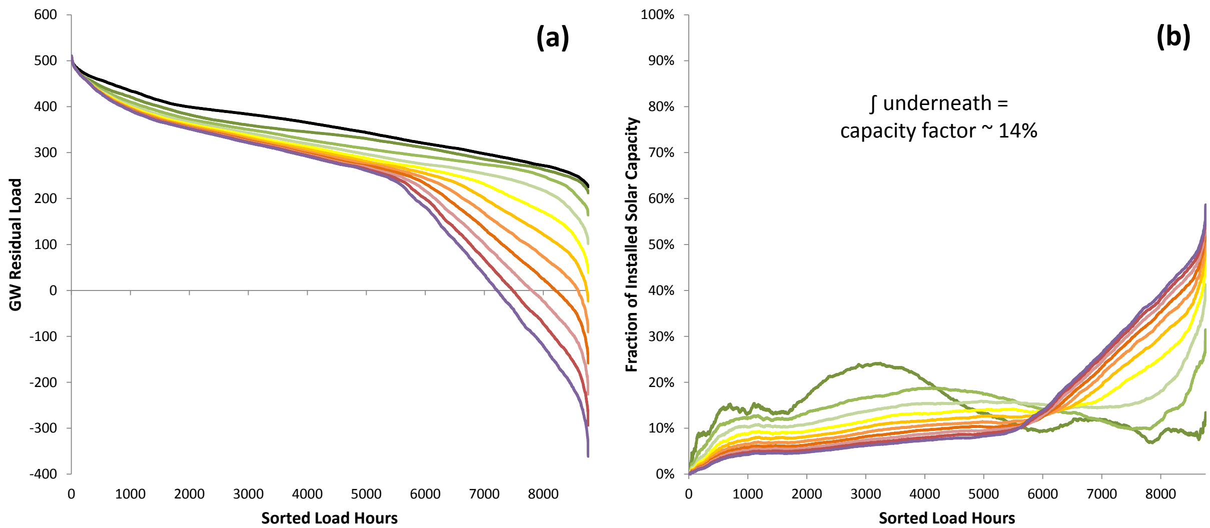

Figure B2. **Continental Solar PV**: Residual Load Duration Curves (a) and Contribution to Sorted Load (b) for different levels of solar PV penetration in the EU (based on hourly data). The color spectrum reflects increasing installed solar PV capacity, with dark green indicating 100 GW, and purple indicating 1000 GW. The black line in panel (a) reflects the total load duration curve.

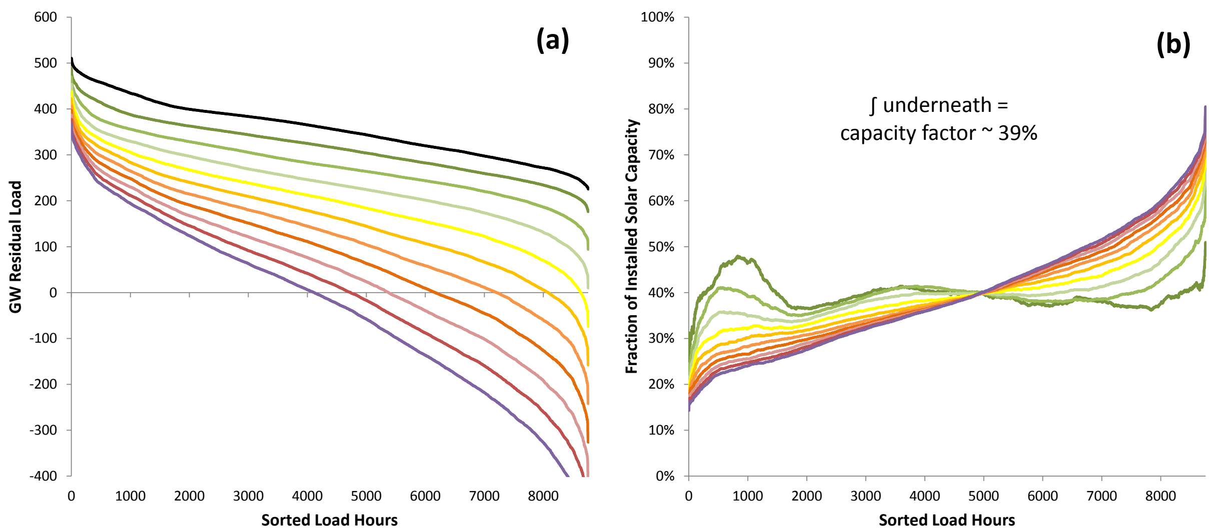

Figure B3. **North Sea On-Shore Wind**: Residual Load Duration Curves (a) and Contribution to Sorted Load (b) for different levels of wind penetration in the EU (based on hourly data). The color spectrum reflects increasing installed wind capacity, with dark green indicating 100 GW, and purple indicating 1000 GW. The black line in panel (a) reflects the total load duration curve.

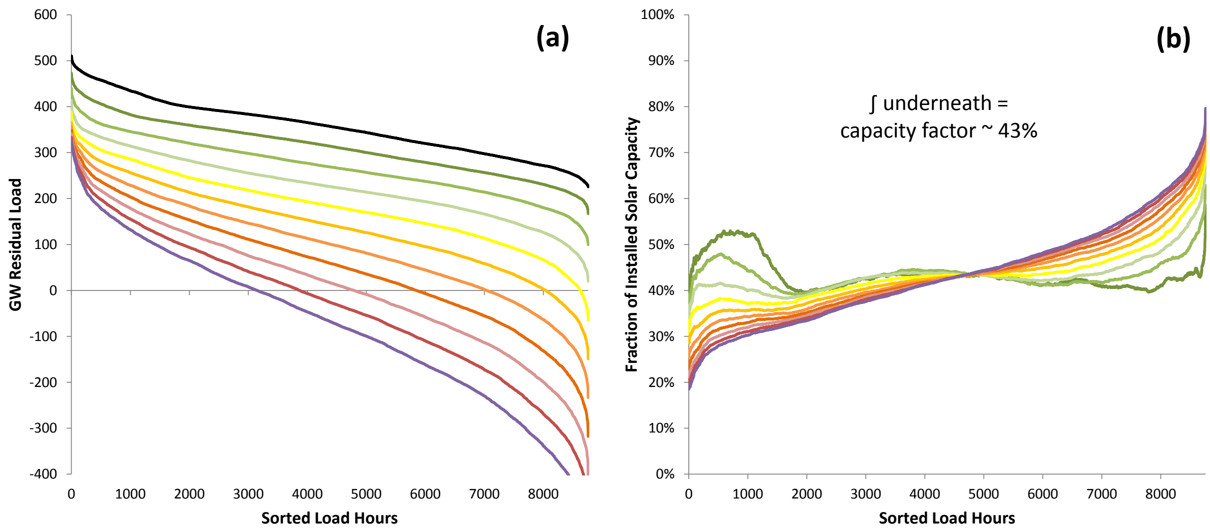

Figure B4. **North Sea Off-Shore Wind**: Residual Load Duration Curves (a) and Contribution to Sorted Load (b) for different levels of wind penetration in the EU (based on hourly data). The color spectrum reflects increasing installed wind capacity, with dark green indicating 100 GW, and purple indicating 1000 GW. The black line in panel (a) reflects the total load duration curve.

In the preceding figures, only variation against "own-capacity" is shown. Figure B5 illustrates the extent of interaction effects between continental wind and solar, showing the "contribution to sorted load" for wind @ 300 GW for increasing solar capacity (panel a) and for solar @ 300 GW for increasing wind capacity (panel b). There is a noticeable effect in both cases shifting hours away from minimum load to near-minimum load as high penetration levels of the other technology are reached. Still, the effect is minor compared to the variation with respect to "own-capacity" increases.

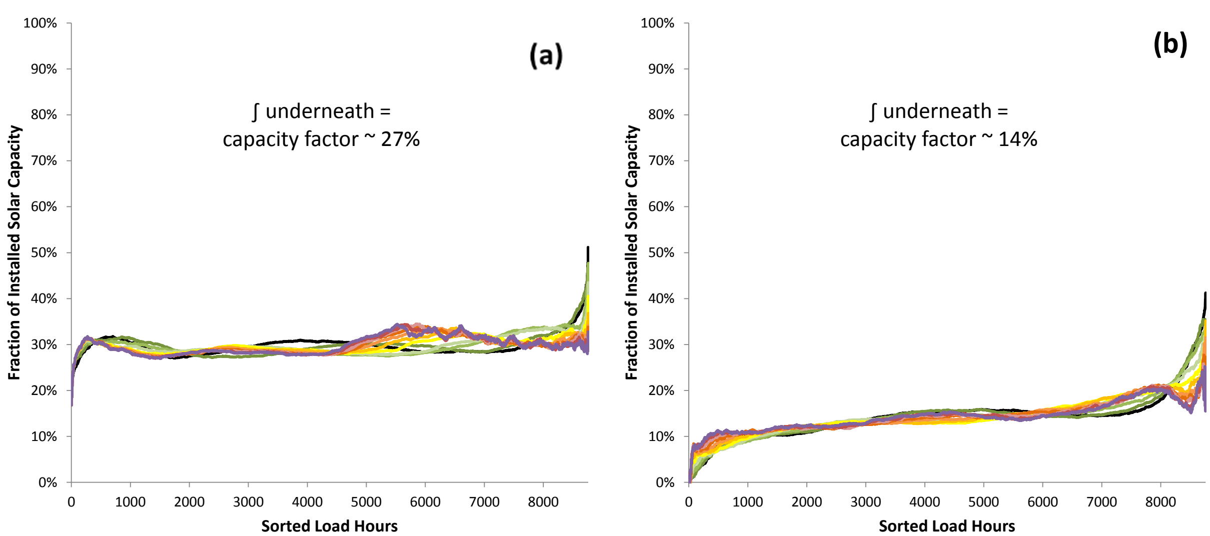

Figure B5. **Continental Wind vs. Solar PV**: Contribution to Sorted Load for wind @ 300 GW with different levels of solar penetration (a) and for solar @ 300 GW with different levels of wind penetration in the EU (based on hourly data). The color spectrum reflects increasing installed capacity (in the interacting technology), with black indicating 0 GW, dark green indicating 100 GW, and purple indicating 1000 GW.

Next, the 21 points corresponding to every 5th percentile (beginning with the peak or 100th %-ile, the 95th, 90th, … , 5th, and minimum or 0th %-ile) in the "contribution to sorted load" series were identified. The objective of the estimation procedure was to capture the variation across installed capacity in "contribution to sorted load" for each of these 21 points in the hourly distribution. The hourly-based functions (of "contribution" vs. installed capacity), against which error for the estimated functions was measured, are shown in black for the 100th, 75th, 50th, 25th, and 0th percentile of wind and solar in Figures B6 and B7 respectively. Although the estimation was conducted for installed capacity levels between 100 and 1000 GW in 100 GW increments, the "contribution to sorted load" for lower capacity levels can also be calculated. The black lines in Figures B6 and B7 include data for the range between 10 and 100 GW at 10 GW increments. For both wind and solar there is strong non-linear behavior over this range around the high and low percentiles. However, caution should be used in interpreting this result, as small increments are more subject to idiosyncrasies in the hourly data.

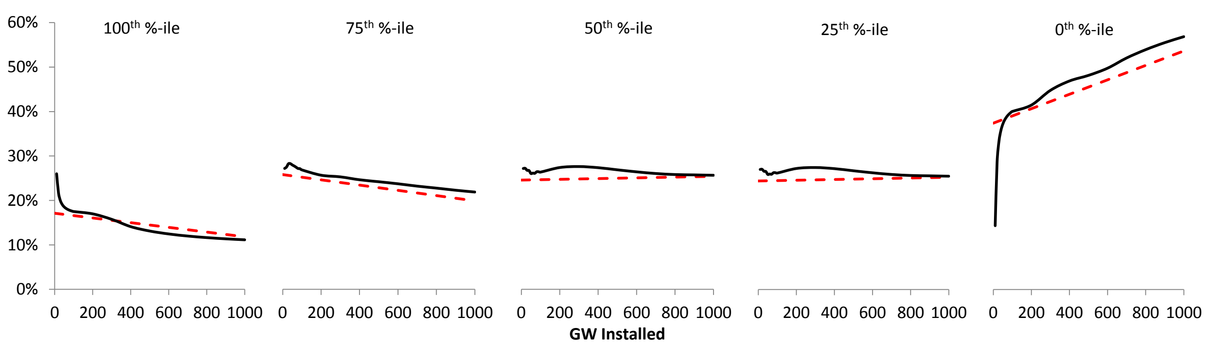

Figure B6. Continental Wind: Contribution to Sorted Load at different percentiles as a function of installed wind capacity in the EU. Solid black line reflects hourly data, dashed red line reflects estimated coefficients.

A least squares error-estimation procedure was used to find polynomial coefficients for which the renewable output based on the estimated function of capacity most closely matched the "contribution to sorted load" in each of these 21 points. The results of the estimation are shown in Figures B6 and B7 as dashed red lines. Wind output was estimated with linear and quadratic terms, which become constant and linear terms respectively when normalized by capacity in Figure B6 and B7. Solar was estimated with an additional cubic term, which becomes a quadratic term when normalized by capacity, to better fit the underlying hourly data.[13] For continental wind and solar, the estimation was conducted

[13] It is worth noting that the estimation procedure is easier for a region like Europe in which electricity demand peaks in winter after sunset, thus implying that solar has a zero contribution to peak regardless of its penetration

over the joint residual load curves, so that the coefficients are chosen taking into account interaction effects. Thus for example the estimated contribution in the minimum load percentile for solar does not precisely follow the hourly contribution of solar alone because it is designed to best match solar's contribution as it varies over the wind capacity domain. However, the interaction term itself was found to have little effect and hence was omitted in the current simulations. For the North Sea classes, the estimation included only linear and quadratic "own-capacity" terms. Ideally, all interactions would be explored in the estimation, but this proved too dimensionally complex for the initial implementation and was left for future work. Similarly, future work should check for the robustness of the estimation to multiple years of data.

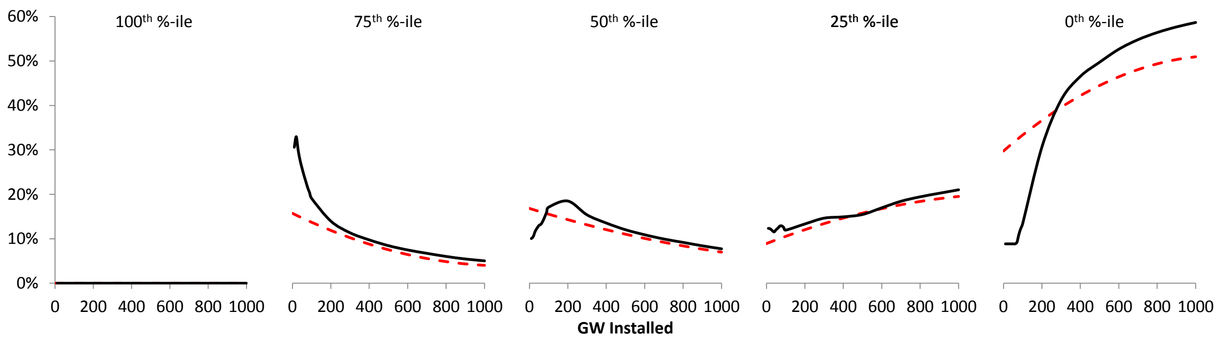

Figure B7. Continental Solar PV: Contribution to Sorted Load at different percentiles as a function of installed wind capacity in the EU. Solid black line reflects hourly data, dashed red line reflects estimated coefficients.

Several additional constraints were placed on the estimation. First, the coefficients must preserve the average capacity factor for any penetration level. This constraint is typically satisfied by ensuring that the linear coefficients have a weighted sum[14] equal to the average capacity factor and the higher-order coefficients have a weighted sum equal to zero. Thus the linear term (i.e. constant when expressed as a coefficient on capacity) in each segment reflects the contribution to sorted load when capacity is zero, or the marginal contribution of the first unit of capacity. Second, to ensure that the marginal contribution to sorted load in all segments remains positive throughout the domain of installed capacity, we require the first derivative of the polynomial function of output in each segment to be non-negative. This constraint avoids a situation in which adding wind or solar capacity above a certain level could require an input of energy in one segment in order to get output in others. Such a situation cannot occur by construction in the hourly series. Finally we require the linear coefficients to be non-negative, and we fix the solar coefficients in the peak segment to zero.

level. In a region like the US with a summer afternoon system peak, solar initially contributes significantly to the peak, but as penetration increases, the *residual* peak shifts to a nighttime hour, driving the solar peak contribution abruptly to zero. Such a pattern is more challenging to capture with a polynomial estimator.

[14] Each segment is weighted by its number of hours, 438 = 8760 / 20 for all but the top two segments, which are equal to 1 for the peak and 437 for the second segment. Thus the sum of the 21 weights equals 8760.

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