

Supplemental Information

for

100% Clean and Renewable Wind, Water, and Sunlight (WWS) All-Sector Energy Roadmaps for the 50 United States

by

Mark Z. Jacobson, Mark A. Delucchi, Guillaume Bazouin, Zack A.F. Bauer, Christa C. Heavey, Emma Fisher, Sean B. Morris, Diniana J.Y. Piekutowski, Taylor A. Vencill, Tim W. Yeskoo

Energy and Environmental Sciences
2015

OVERVIEW OF THE SUPPLEMENTAL INFORMATION

Our objective and general method

This document contains detailed methodologies for calculating most of the end-result numbers in the main paper. The calculations provided here and all additional calculations for the main paper are detailed further in accompanying spreadsheets (Delucchi et al., 2015).

Our general objective in this document is to estimate the costs and benefits of meeting all end-use energy demand in all 50 U.S. states with wind, water, and solar (WWS) power, compared with a “business-as-usual” (BAU) scenario. We base our BAU scenario on highly detailed projections by the U. S. Energy Information Administration (EIA), because these are the most comprehensive, detailed, well-documented, and well-known energy-use projections for the U.S.

In the following sections we describe how we obtain our estimates of

- 1) Energy use in a 100%-WWS world versus a BAU world
- 2) The difference in the cost of electricity use in the 100% WWS scenario versus the BAU scenario.
- 3) The total damage cost of air pollution from conventional fuels.
- 4) The cost of climate change from fossil-fuel use: damages attributable to and borne by each state.

- 5) Earnings from new construction and operation jobs in a 100% WWS world.
- 6) Projection of state population and GDP.
- 7) The national-average levelized cost of electricity by type of generator.
- 8) Calculation of the cost of electricity by state, year, and scenario.

Construction of “low” and “high” cost scenarios

In order to unify our presentation, we report costs and other results for two general cases: one based on low costs and high benefits (i.e., low net costs or high net benefits) for the 100% WWS scenario, and one based on the reverse, high costs and low benefits (i.e., high net costs or low net benefits) for the 100% WWS scenario. For ease of exposition we use the following abbreviations:

LCHB = low-cost, high benefits for 100% WWS
HCLB = high cost, low benefits for 100% WWS

For each case, all of the component costs and benefits summed to make the total have the same underlying explicit or implicit assumptions regarding the discount rate and other parameters. This means, for example, that in either case we do not add a cost estimate based on a low discount rate to a benefit estimate based on a high-discount rate. This results in the following for the LCHB case (with the opposite for the HCLB case):

Cost or benefit	Discount rate, Low (LCHB) case	Other parameters, Low (LCHB) case
WWS delivered electricity cost	Low value. Results in low annualized capital costs.	Low capital cost of construction. Low operating costs. High capacity factor. High (long) lifetime.
Conventional delivered electricity cost	Low value.	Low capital cost of construction. Low operating costs. High capacity factor. High (long) lifetime. (It is possible that WWS could have low values while conventional has high values, and vice

Storage costs	Low value. Results in low annualized capital costs.	versa, but we do not examine this here.) Low capital cost. Low operating costs. High (long) lifetime.
Long distance transmission costs	Low value. Results in low annualized capital costs.	Shorter transmission distance and other assumptions that result in lower annualized costs.
Cost of energy efficiency improvements	Low value. Results in low annualized cost.	Low initial cost. High (long) life of efficiency improvement.
Change in electricity costs, WWS vs. BAU	Low value, in order to ensure consistency when added with other costs (e.g., climate-change costs).	Low value of parameters affecting cost of delivered electricity and efficiency improvements.
Foregone air-pollution costs (benefit of WWS)	Not specified. (A component of the discount rate, productivity growth per capita, can affect the value of a statistical life [VOSL], such that a low discount rate results in a lower VOSL and hence a lower benefit for WWS, but this effect is small, and we ignore it.)	High air pollution levels. High value of life. High exposure to pollution. High value of non-mortality impacts.
Foregone climate-change costs (benefit of WWS)	Not specified, but implicitly a low value, because low values of the discount rate result in higher present worth of climate-change damages which gives high net benefits (or low net costs) of WWS. Note that whereas the discount rate does not have a major effect on the cost of air pollution, it <i>does</i> have a major effect on the social cost of carbon.	High social cost of carbon, leading to high net benefits (or low net costs) for WWS.

1. ENERGY USE IN A 100% WWS WORLD VS. A BAU WORLD

We estimate energy end-use in a 100% WWS world relative to the EIA's (2014c) *Annual Energy Outlook* (AEO) projections of energy use in its so-called "reference" scenario, which we also refer to as a BAU (Business –As-Usual) scenario. We start with the EIA-based estimates for the BAU and then adjust them for differences between the BAU and the WWS scenario due to extensive electrification in the WWS scenario, the absence of energy use in the industrial sector for petroleum refining to produce energy products in the WWS scenario, and extra end-use energy efficiency measures in the WWS scenario beyond those assumed in the BAU scenario.

Projections of end-use energy by state, sector, and fuel source, BAU

We start with estimates of the use of liquid fuels, natural gas, coal, renewable fuels, and electricity in the residential, commercial, industrial, and transportation sectors of each state in 2010. The EIA's AEO does not project energy use by state, but it does project energy use by sector and fuel source in each of nine Census Divisions covering all 50 states. We therefore project each state's energy use based on the changes projected for the Census Division covering that state. Formally,

$$E_{i,X,S,Y} = E_{i,X,S,2010} \cdot \frac{E_{i,X,R:S \in R,Y}}{E_{i,X,R:S \in R,2010}}$$

where

$E_{i,X,S,Y}$ = end-use of fuel i in sector X in state S in year Y (BTU)

$E_{i,X,S,2010}$ = end-use of fuel i in sector X in state S in year 2010 (BTU) (EIA State Energy Data System, www.eia.gov/state/seds/)

$E_{i,X,R:S \in R,Y}$ = end-use of fuel i in sector X in Census Division R (containing S) in year Y (BTU) (EIA, 2014c; the EIA projects out to 2040, and we extend to 2075 by using a moving 10-year trend extrapolation starting with the estimate for 2031)

$E_{i,X,R:S \in R,2010}$ = end-use of fuel i in sector X in Census Division R (containing S) in year 2010 (BTU) (EIA, 2013b)

Subscripts

i = fuels for which the EIA estimates energy use (liquid fuels, natural gas, coal, renewable energy, electricity)

X = end-use energy sectors (residential, commercial, industrial, transportation)

S = state in the U.S.

Y = target year of the analysis

R = Census region of the U.S. in the EIA's estimates of energy-related CO₂ emissions (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific)

We also re-aggregate the resultant state-level projections to Census-Division-level projections.

Electrification of end uses in the WWS scenario

Partly on the basis of our examination of end-use energy consumption projected in the EIA's AEO, we assume that end-uses are electrified as follows (with the non-electrified fractions producing electrolytic hydrogen as described below):

Sector	Fraction electrified
<i>Residential</i>	
Liquids	1.00
Natural Gas	1.00
Coal	1.00
Electricity (retail)	1.00
Renewables	1.00
<i>Commercial</i>	
Liquids	1.00
Natural Gas	1.00
Coal	1.00
Electricity (retail)	1.00
Renewables	1.00
<i>Industrial</i>	
Liquids	0.95
Natural Gas	0.95
Coal	0.95
Electricity (retail)	1.00
Renewables (incl. biofuels for heat)	1.0
<i>Transportation</i>	
Liquids	0.76
Natural Gas	0.95
Electricity (retail)	1.00

The value for liquids in Transportation is calculated from more disaggregated assumptions, as follows:

<i>Transport mode</i>	<i>% of energy</i>	<i>Fraction electrified</i>
On road gasoline, LPG	61%	95%
On-road diesel	19%	70%
Off-road diesel	1%	65%
Military	0%	20%
Trains	2%	85%
Aircraft	12%	10%
Ships	4%	25%
Lubricants	1%	0%
<i>All liquid in Transport</i>	<i>100%</i>	<i>76%</i>

End uses that are not electrified (e.g., cooking with a flame in the residential and commercial sectors) generally are assumed to use electrolytic hydrogen produced from WWS power, or in the case of aircraft, cryogenic hydrogen produced from WWS power.

Energy use in the industrial sector to refine petroleum into energy products

To estimate energy use in the WWS scenario we deduct from the industrial sector an estimate of the proportion of energy used to refine petroleum (Jacobson and Delucchi, 2011).

Extra end-use energy saving measures in the WWS scenario

As explained in the main text, we assume additional energy-efficiency measures beyond the EIA’s reference case scenario. Our method is to start with one of the EIA’s own higher efficiency scenarios and then make further adjustments that we believe are appropriate.

The EIA (2014c) examines three scenarios in which end-use energy efficiency is higher, and delivered energy use lower, than in the reference-case scenario: “Integrated High Demand Technology,” “Integrated Best Available Demand Technology,” and “Low Electricity Demand.” These three, along with a scenario in which efficiency remains at year-2013 levels (“Integrated 2013 Demand Technology”) are described below and in Table E-1 and Appendix E of EIA (2014c) (with our shortened descriptors shown in parentheses).

Integrated 2013 Demand Technology	Assumes that future equipment purchases in the residential and commercial sectors are based only on the range of equipment available in 2013. Commercial and existing residential building shell efficiency is held constant at 2013 levels. Energy efficiency of new
-----------------------------------	---

(2013Tech) industrial plant and equipment is held constant at the 2014 level over the projection period.

Integrated High Demand Technology (High Efficiency All Sectors – HEAS) Assumes earlier availability, lower costs, and higher efficiencies for more advanced residential and commercial equipment. For new residential construction, building code compliance is assumed to improve after 2013, and building shell efficiencies are assumed to meet ENERGY STAR requirements by 2023. Existing residential building shells exhibit 50% more improvement than in the Reference case after 2013. New and existing commercial building shells are assumed to improve 25% more than in the Reference case by 2040. Industrial sector assumes earlier availability, lower costs, and higher efficiency for more advanced equipment and a more rapid rate of improvement in the recovery of biomass byproducts from industrial processes. In the transportation sector, the characteristics of conventional and alternative-fuel LDVs reflect more optimistic assumptions about incremental improvements in fuel economy and costs, as well as battery electric vehicle costs. Freight trucks are assumed to see more rapid improvement in fuel efficiency. More optimistic assumptions for fuel efficiency improvements are also made for the air, rail, and shipping sectors.

Integrated Best Available Demand Technology (Best Efficiency Residential and Commercial – BEREC) Assumes that all future equipment purchases in the residential and commercial sectors are made from a menu of technologies that includes only the most efficient models available in a particular year, regardless of cost. All residential building shells for new construction are assumed to be code compliant and built to the most efficient specifications after 2013, and existing residential shells have twice the improvement of the Reference case. New and existing commercial building shell efficiencies improve 50% more than in the Reference case by 2040. Industrial and transportation sector assumptions are the same as in the Reference case.

Low Electricity Demand (High Efficiency Electricity Use -- HEEE) This case was developed to explore the effects on the electric power sector if growth in sales to the grid remained relatively low. It uses the assumptions in the Best Available Demand Technology case for the residential and commercial sectors. In addition, input values for the industrial sector motor model are adjusted to increase system savings values for pumps, fans, and air compressors relative to the Reference case. This adjustment lowers total motor electricity consumption by slightly less than 20%. Although technically plausible, this decrease in motor adjustment is not intended to be a likely representation of motor development. As a result of these changes across the end-use sectors, retail sales in 2040 in this case are roughly the same as in 2012.

Here we start with the EIA's HEAS (High Efficiency All Scenarios) scenario, and estimate the ratio of HEAS to Reference energy use by sector (residential, commercial, industrial, and transportation), fuel (petroleum, natural gas, coal, renewable fuel, electricity), Census Division (nine for the U.S.), and year (2011-2075; recall that we use 10-year moving linear trend extrapolation to extend the EIA's projections from 2040 to 2075). We then multiply the resultant HEAS/Reference ratios by *additional* adjustment factors to make the final energy-saving estimates closer to the BERC or HEEU scenario estimates for the residential, commercial and industrial sectors and closer to our own sense of what is reasonable for the transportation sector.

Table S1. Energy Use by Sector and Source for various energy-use scenarios, United States, year 2040

Sector and Source	% change versus EIA Reference						Ref. (quad. BTU)
	2013Tech	HEEU	HEAS	BERC	JD11	This paper	
Residential							
Petroleum, Other Liquids	8.5%	-16.5%	-9.2%	-16.6%	-10%	-12.9%	0.66
Natural Gas	7.9%	-28.2%	-10.8%	-28.3%	-15%	-17.0%	4.21
Renewable Energy	20.5%	-21.7%	-13.2%	-21.6%	-10%	-14.5%	0.42
Electricity	8.8%	-22.2%	-12.9%	-22.8%	-10%	-17.2%	5.65
Delivered Energy	8.9%	-24.1%	-11.9%	-24.5%			10.94
Electricity Related Losses	8.3%	-19.2%	-10.4%	-20.2%			10.55
Total	8.6%	-21.7%	-11.2%	-22.4%			21.48
Commercial							
Petroleum, Other Liquids	0.2%	-4.4%	-4.0%	-4.5%	-5%	-4.0%	0.68
Natural Gas	-3.1%	-0.8%	1.3%	-0.5%	-10%	-0.7%	3.65
Coal	-0.1%	0.3%	0.2%	0.2%	-5%	0.2%	0.04
Renewable Energy	0.0%	0.0%	0.0%	0.0%	-5%	0.0%	0.13
Electricity	9.7%	-21.2%	-17.5%	-21.7%	0%	-19.2%	5.72
Delivered Energy	4.3%	-12.4%	-9.6%	-12.6%			10.22
Electricity Related Losses	9.2%	-18.2%	-15.2%	-19.1%			10.66
Total	6.8%	-15.4%	-12.5%	-15.9%			20.88
Industrial							
Petroleum, Other Liquids	6.3%	0.1%	-2.1%	0.0%	-5%	-2.1%	10.10
Natural Gas and related	10.6%	-0.4%	-0.3%	-0.1%	-5%	-1.3%	11.28
Coal	12.6%	5.5%	-4.0%	4.9%	-5%	-3.9%	1.44
Biofuels Heat Coproducts	-0.2%	0.0%	-0.1%	-0.1%	-5%	-3.9%	0.79
Renewable Energy		1.0%	11.0%	1.0%	-5%	11.0%	2.28

Electricity	10.0%	-16.6%	-2.5%	3.8%	0%	-7.3%	4.34
Delivered Energy	7.6%	-2.1%	-0.5%	0.8%			30.22
Electricity Related Losses	9.5%	-13.4%	0.3%	7.2%			8.10
Total	8.0%	-4.5%	-0.4%	2.2%			38.33
Transportation							
Petroleum, Other Liquids	-0.3%	0.9%	-0.5%	0.8%	-15%	-5.5%	23.73
Natural gas and hydrogen	-1.7%	0.0%	-23.2%	1.1%	-15%	-23.3%	1.71
Electricity	-0.1%	0.5%	8.4%	0.4%	-5%	7.9%	0.06
Delivered Energy	-0.4%	0.8%	-2.0%	0.8%			25.50
Electricity Related Losses	-0.6%	4.3%	11.5%	3.7%			0.12
Total	-0.4%	0.8%	-2.0%	0.8%			25.62
All sectors							
Petroleum, Other Liquids	1.8%	0.2%	-1.2%	0.1%			35.17
Natural gas and related	6.6%	-6.0%	-4.0%	-5.8%			20.85
Coal	12.2%	5.3%	-3.9%	4.8%			1.48
Renewable energy	-1.7%	-1.9%	5.4%	-1.9%			3.62
Electricity	9.4%	-20.2%	-11.6%	-15.0%			15.77
Delivered Energy	4.7%	-5.7%	-3.8%	-4.6%			76.88
Electricity Related Losses	8.9%	-17.1%	-9.1%	-12.2%			29.43
Total	5.9%	-8.8%	-5.3%	-6.7%			106.31
Electric Power generation							
Petroleum, Other Liquids	7.2%	-17.8%	-8.6%	-12.9%			0.19
Natural Gas	7.9%	-25.1%	-20.9%	-19.5%			11.48
Steam Coal	2.8%	-21.2%	-5.3%	-12.9%			17.27
Nuclear / Uranium	9.7%	-4.0%	-2.8%	-4.0%			8.49
Renewable Energy	25.1%	-17.5%	-12.4%	-14.9%			7.44
Non-biogenic Waste	0.0%	0.0%	0.0%	0.0%			0.23
Electricity Imports	21.8%	-20.9%	-12.6%	-16.6%			0.12
Total	9.1%	-18.2%	-10.0%	-13.1%			45.20

Source: our tabulation of results from the EIA's *Annual Energy Outlook 2014 online data tables*: <http://www.eia.gov/oiaf/aeo/tablebrowser/>. 2013Tech = 2013 Technology; HEEU = High Efficiency Electricity Use; HEAS = High Efficiency All Sectors; BERC = Best Efficiency Residential Commercial; JD11 = Jacobson and Delucchi (2011).; Quad. BTU = quadrillion British Thermal Units. Note that JD11 changes are with respect to the EIA AEO 2008 projections for the year 2030. All changes reflect fuel shifting as well as efficiency improvements.

Table S1 shows the EIA's projections of energy use in the U.S. in 2040 by source and sector, for the 2013Tech, HEEU, HEAS, and BERC scenarios versus the EIA Reference case. It also shows Jacobson and Delucchi's (2011) (JD11) assumed energy-use savings for the U.S. in 2030 and the results of our current calculations (described above) for the year 2040. Note that the EIA scenarios in Table S1 reflect the results of fuel shifting as well as the results of efficiency improvements.

As shown in Table S1, the two highest efficiency scenarios, HEEU and BERC, reduce electricity use in the residential and commercial sectors by more than 20%, and reduce NG use in the residential sector by almost 30%, with respect to the Reference case. Overall, the HEEU and BERC scenarios reduce total delivered energy by over 24% in the residential sector and by about 12.5% in the commercial sector. The HEAS scenario, which generally is less aggressive but also presumably more realistic, reduces total delivered energy by 12% in the residential sector and almost 10% in the commercial sector. The assumptions of JD11 are broadly consistent with the results of the HEAS scenario, except that JD11 assumed no reductions in electricity use in the commercial sector.

As mentioned above, we start with the HEAS scenario and make additional adjustments. Overall this results in residential-sector and commercial-sector efficiency improvements greater than in the HEAS scenario but less than in the BERC and HEEU scenarios ("This paper" column of Table S1.)

None of the three EIA high-efficiency scenarios result in significant reductions in delivered energy in the industrial or transportation sectors. The HEEU does result in nearly a 17% reduction in industrial electricity use, but electricity use is a minor fraction of total industrial energy use, and in any event, as indicated above, the EIA implies that the HEEU assumptions for the industrial sector probably are not realistic. In general, it appears that the EIA believes that there is relatively little room to reduce energy use in the industrial sector. JD11 assumed somewhat higher but still modest reductions in energy use in the industrial sector. Our current results are less aggressive than in JD11, and generally follow the EIA's HEAS scenario, except that we do assume modest additional improvements in electricity-use efficiency in the industrial sector.

Only one of the scenarios, HEAS, examines efficiency improvements in the transportation sector. These improvements turn out to be quite modest, resulting in only a 2% reduction in energy use over the Reference case. By contrast, JD11 assumed much greater potential to reduce energy use in transportation. We believe that JD11 overestimated but the EIA underestimated the potential for reductions in energy use in the transportation sector.

Because energy use in the residential and commercial sectors is much less than in the industrial and transportation sectors, and the EIA assumptions result in very little efficiency improvement in the industrial and transportation sectors, the EIA's three high-efficiency scenarios reduce total, all-sectors delivered energy in the U.S. in 2040 by only 4-6% compared with the reference case. Our assumptions, which assume modest efficiency improvements beyond the EIA's HEAS scenario, especially in the transportation sector, result in a 6.7% reduction in overall energy use in 2040.

2) THE DIFFERENCE IN THE COST OF ELECTRICITY USE IN THE 100% WWS SCENARIO VERSUS THE BAU SCENARIO

Method of analysis

The total cost of all energy use in a 100% WWS scenario is different from the total cost in a predominantly fossil-fueled BAU scenario, on account of differences in the types of energy and energy-using equipment. For example, referring to the EIA's fuel end-use categories listed above – liquids, natural gas, coal, renewables, and electricity – in the BAU scenario oil and natural gas are used by combustion devices, such as space heaters or gasoline-engine vehicles, whereas in the WWS scenario these same end uses are powered by electric heat pumps, battery-electric vehicles, and so on. To estimate the BAU-vs.-WWS difference in the cost of energy in the oil, natural gas, and coal end-use categories, one must estimate differences in the in the per-unit cost of delivered energy, the efficiency of energy end-use, and the cost of energy-using equipment in both the BAU and WWS cases. While we do this for the WWS case and for the BAU electricity end-use category, we consider this effort – for the oil, natural gas, and coal end-use categories in non-electricity end-use categories – outside the scope of this paper.

By contrast, it is simpler to estimate the WWS-vs.-BAU cost differences in the electricity end-use category, because the type of energy (electricity) and the end-use equipment are the same in the BAU and the WWS scenarios.

The WWS-vs.-BAU difference in the cost of electricity use is equal to the difference between total electricity end-use expenditures in the BAU scenario and total expenditures for the same end uses in the WWS scenario. Total expenditures are a function of the unit cost of electricity, the quantity of electricity used in the BAU and the WWS scenarios, and the cost of any efficiency improvements that reduce electricity consumption in the WWS compared with the BAU scenario. Formally,

$$\Delta TC_{el,S,Y,BAU-WWS} = TC_{el,S,Y,BAU} - TC_{el,S,Y,WWS}$$

$$TC_{el,S,Y,BAU} = E_{el,S,Y,BAU} \cdot AC_{el,S,Y,BAU}$$

$$TC_{el,S,Y,WWS} = E_{el,S,Y,WWS} \cdot AC_{el,S,Y,WWS} + \Delta E_{el,eff,S,Y,BAU-WWS} \cdot AC_{el,eff(an),S,Y}$$

$$\Delta E_{el,eff,S,Y,BAU-WWS} = E_{el,S,Y,BAU} - E_{el,S,Y,WWS}$$

where

$\Delta TC_{el,S,Y,BAU-WWS}$ = difference in the total cost of electricity use in the BAU vs. the WWS scenario in state S in year Y (\$)

$TC_{el,S,Y,W}$ = the cost of electricity use in state S in year Y in scenario W (\$)

$E_{el,S,Y,W}$ = the use of electricity in state S in year Y in scenario W (kWh) (discussed above)

$AC_{el,S,Y,W}$ = the average cost of electricity in state S in year Y in scenario W (\$/kWh)
(discussed below)

$\Delta E_{el,eff,S,Y,BAU-WWS}$ = the difference in electricity use in the BAU vs. the WWS scenario, due to efficiency improvements, in state S in year Y (kWh)

$AC_{el,eff(an),S,Y}$ = the average annualized cost of the efficiency improvements that provide the electricity savings ΔE in state S in year Y in the WWS scenario (\$/kWh)

The average annualized cost of efficiency improvements is estimated by first estimating the initial cost of an efficiency improvement, as a function of the payback period of the initial investment with respect to the U.S.-average BAU electricity cost, and then annualizing this cost over the life of the improvement. The payback period and the lifetime depend on the end-use sector (residential, commercial, industrial, or transportation). Formally,

$$AC_{el,eff(an),S,Y} = \sum_X C_{el,eff(an),X,S,Y,WWS} \cdot \frac{\Delta E_{el,eff,X,S,Y,BAU-WWS}}{\Delta E_{el,eff,S,Y,BAU-WWS}}$$

$$C_{el,eff(an),X,S,Y,WWS} = \frac{r \cdot IC_{el,eff,X}}{1 - e^{-r \cdot L_{el,eff,X}}}$$

$$IC_{el,eff,X} = AC_{el,US,Y,BAU} \cdot PB_{el,eff,X}$$

$$PB_{el,eff,X} \equiv fr_{PB,X} \cdot L_{el,eff,X}$$

where

$C_{el,eff(an),X,S,Y,WWS}$ = the annualized cost of electricity-use efficiency improvements in sector X in state S in year Y in the WWS scenario (\$/kWh)

$\Delta E_{el,eff,X,S,Y,BAU-WWS}$ = the difference in electricity use in the BAU vs. the WWS scenario, due to efficiency improvements, in sector X in state S in year Y (kWh) (calculated using the data described above)

$IC_{el,eff,X}$ = the initial cost of electricity-use efficiency improvements in sector X (\$)
(constant for all years and states)

$L_{el,eff,X}$ = the lifetime of electricity-use efficiency improvements in sector X (\$) (constant for all years and states) (discussed below)

r = the annual discount rate (discussed below)

$AC_{el,US,Y,BAU}$ = the average cost of delivered electricity in the US in year Y in the BAU scenario (\$/kWh) (calculated as documented below)

$PB_{el,eff,X}$ = the simple (zero-discount-rate) payback period for electricity-use efficiency improvements in sector X (constant for all years and states) (years) (discussed below)

$fr_{PB,X}$ = the simple payback period expressed as a fraction of the lifetime $L_{el,eff,X}$

Combining the foregoing equations and re-arranging into the most useful forms gives

$$\begin{aligned} \Delta TC_{el,S,Y,BAU-WWS} &= E_{el,S,Y,BAU} \cdot AC_{el,S,Y,BAU} - E_{el,S,Y,WWS} \cdot AC_{el,S,Y,WWS} \\ &- \Delta E_{el,eff,S,Y,BAU-WWS} \cdot \sum_X C_{el,eff(am),X,S,Y,WWS} \cdot \frac{\Delta E_{el,eff,X,S,Y,BAU-WWS}}{\Delta E_{el,eff,S,Y,BAU-WWS}} \\ &= E_{el,S,Y,BAU} \cdot AC_{el,S,Y,BAU} - E_{el,S,Y,WWS} \cdot AC_{el,S,Y,WWS} - \sum_X C_{el,eff(am),X,S,Y,WWS} \cdot \Delta E_{el,eff,X,S,Y,BAU-WWS} \end{aligned}$$

$$= E_{el,S,Y,BAU} \cdot AC_{el,S,Y,BAU} - E_{el,S,Y,WWS} \cdot AC_{el,S,Y,WWS} - \sum_X \frac{r \cdot IC_{el,eff,X}}{1 - e^{-r \cdot L_{el,eff,X}}} \cdot \Delta E_{el,eff,X,S,Y,BAU-WWS}$$

Data

Here we need to specify two parameters, the lifetime $L_{el,eff,X}$ and the simple payback

period as fraction $fr_{PB,X}$ of the lifetime. On the basis of our review of a detailed analysis of energy efficiency measures for the residential, commercial, and industrial sectors of the U.S. economy (Granade et al., 2009), we assume the values shown in Table S2.

Note again that we have estimated here differences in energy expenditures only in the EIA's electricity end-use category, and have not estimated differences in all energy-related expenditures in the WWS vs. the BAU scenario.

Table S2. Assumed payback-time fractions (payback period as fraction of lifetime) and lifetimes (years) of efficiency measures, in the retail electricity sector

Energy-use sector	Payback time fraction (a)		Lifetime (years) (b)	
	<i>Low</i>	<i>High</i>	<i>Low</i>	<i>High</i>
Residential electricity	0.10	0.30	20.0	14.0
Commercial electricity	0.10	0.25	18.0	12.0
Industrial electricity	0.15	0.25	25.0	18.0
Transportation electricity	0.20	0.40	25.0	20.0

Notes.

Our assumptions based on Granade et al. (2009), who analyze a comprehensive range of efficiency measures, including improvements to building shells, heating and cooling systems, refrigeration, lighting, small and large appliances, office equipment, motors, pumps, compressors, industrial processes, and more.

"Low" and "high" mean low and high annualized initial costs.

(a) Time for energy savings to pay back initial investment, based on the US-average BAU electricity cost with no discounting, expressed as a fraction of the investment lifetime.

(b) Lifetime of energy efficiency improvements (until failure).

3) THE TOTAL DAMAGE COST OF AIR POLLUTION FROM CONVENTIONAL FUELS

The total damage cost of air pollution from fossil-fuel and biofuel combustion and evaporative emissions comprises mortality costs, morbidity costs, and non-health costs such as lost visibility and agricultural output. We estimate this total damage cost of air pollution in each state S in a target year Y as the product of an estimate of the number of premature deaths due to air pollution, which is determined from pollution exposure levels, relative risks, and population, and the total cost of air pollution per death as follows:

$$APcost_{S,Y} = N_{D,S,Y} \cdot V_{P/D,Y}$$

where

$APcost_{S,Y}$ = the damage cost of air pollution in state S year Y

$N_{D,S,Y}$ = the number of deaths D due to air pollution in state S in year Y

$V_{P/D,Y}$ = the total cost of pollution per death in year Y (includes mortality, morbidity, and non-health costs; assumed to be the same for all states)

The number of deaths due to air pollution

To estimate the number of premature deaths D due to air pollution in state S in year Y , we start with a detailed estimate of the average number of premature deaths per year in

each state from 2010 to 2012. We then scale this to account for changes in population, exposure, and air pollution between ca. 2011 and the target year Y as follows:

$$N_{D,S,Y} = N_{D,S,2010-12} \cdot \frac{A_Y}{A_{2011}} \cdot \frac{E_{S,Y}}{E_{S,2010}}$$

$$\frac{A_Y}{A_{2011}} = \exp^{\Delta A(Y-2011)}$$

$$\frac{E_{S,Y}}{E_{S,2010}} = \exp^{g_S \cdot x_S (Y-2011)} = \left(\exp^{g_S (Y-2011)} \right)^{x_S} = \left(\frac{P_{S,Y}}{P_{S,2011}} \right)^{x_S}$$

where

$N_{D,S,Y}$ = the number of premature deaths D due to air pollution in state S in year Y

$N_{D,S,2010-12}$ = the number of premature deaths in state S over the period 2010-2012 (see discussion in the main text)

A_Y = the ambient pollution level, as determined from all air quality monitoring stations in each county of each state, in target year Y .

$E_{S,Y}$ = the exposed population in state S in target year Y .

ΔA = the annual rate of change in the damage-weighted ambient pollution levels, in the future (see discussion below in this section)

g_S = the rate of population growth in state S (see section "Projection of State Population and GDP")

x_S = the change in exposed population per change in population in state S

$P_{S,Y}$ = the population in state S in year Y (see section "Projection of State Population and GDP")

The number of premature deaths in each state for the period 2010-2012 is determined by considering data from all air quality monitoring stations in each county of each state. For each county in each state, mortality rates are averaged over the three-year period for each station to determine the station with the maximum average mortality rate in the county. Daily air-quality data from that station are then used with the 2012 county population and the relative risk in the health effects equation described in the footnote to Table 7 of the main text to determine the premature mortality in the county. County numbers are then summed over all counties in a state to obtain state numbers.

Annual rate of change in damage-weighted ambient pollution. We estimate the annual rate of change in damage-weighted ambient pollution levels in the future by first examining historical trends and then considering how the future might be different from the past. The EPA provides historical time series data for ambient levels of fine particulate matter (PM2.5), ozone (O3), sulfur dioxide (SO2), and carbon monoxide (CO) (<http://www.epa.gov/airtrends/aqtrends.html>). We use these data to estimate rates of change in the concentration of each pollutant over several past time periods. We then estimate the rate of change of a damage-weighted combination of the pollutants,

where the weights are our judgment based on estimates of damages by pollutant in Delucchi (2000). The resulting rate-of-change values are

<i>Period</i>	<i>PM2.5</i>	<i>O3</i>	<i>SO2</i>	<i>CO</i>	<i>Damage weighted</i>
2012-2013	-2.0%	-11.0%	-17.3%	-5.1%	-3.1%
2009-2013	-2.1%	-0.8%	-12.2%	-3.6%	-2.5%
2004-2013	-3.2%	-1.2%	-9.8%	-5.8%	-3.4%
2000-2013	-3.1%	-1.5%	-7.5%	-6.5%	-3.2%
Damage weights	90%	5%	4%	1%	

Next we consider that for several reasons, in the future the *rate* of decline in damage-weighted ambient pollution is likely to be less, and perhaps much less, than the historic rates shown above. First, while emission levels will decline as stock turnover results in new, low-emission equipment (e.g., vehicles, power plants) replacing old, high-emission equipment, activity levels (e.g., driving, electricity use) will also increase, and the net effect of these opposing factors on emissions is unclear. Second, although government will continue to implement new emission-control regulations, the marginal costs of abating pollution tend to increase while the marginal emission reductions tend to decrease, which means that future policies will likely result in lower emission reductions than have past policies. Third, a warming climate in a non-WWS world will exacerbate the levels and impacts of air pollution (Madaniyazi et al., 2015).

With these considerations, we assume that in the future the effective damage-weighted ambient pollution levels decline at annual rates lower than the historical rate of approximately -3% / year estimated above. Specifically, we assume declines of -1.0%, -1.5%, and -2.0% in the LCHB, medium, and HCLB cases, respectively. (A lower rate leads to higher benefits of pollution reduction in the 100% WWS scenario.) We assume that the same rates apply in all states.

Change in exposed population. As discussed in the “Projection of state population and GDP” section below, we use U.S. Census projections of state population and other

assumptions to estimate $\frac{P_{s,y}}{P_{s,2011}}$. In order to calculate the rate of change of exposure with

population change (x_s), we assume that the exposed population is predominantly in urban areas, and use Census data to calculate the ratio of the change in urban population to the change in total population. Presently we do not have data to distinguish this ratio for each state, so for now we use a single set of low-medium-high values for all states. According to the U.S. Census Bureau (2012), from 2000 to 2010 the population of the U. S. changed by 9.7%, and the population of Metropolitan Statistical Areas changed by 10.8%, a ratio of 1.11. Given this, we assume values for x_s of 1.14, 1.11, and 1.08 in the LCHB, medium, and HCLB cases. (A high value of exposed population leads to higher benefits of pollution reduction in the 100% WWS scenario.)

The total cost of pollution per premature death

We estimate the total pollution cost per premature death as the product of (i) the mortality value per premature death *per se* and (ii) two adjustment factors, one that accounts for non-mortality (i.e., morbidity) health impacts and a second that accounts for health impacts. The calculation is as follows:

$$V_{P/D,Y} = V_{D,Y} \cdot F_1 \cdot F_2$$

where

$V_{D,Y}$ = the value per death *per se* (known as the value of a statistical life, VOSL) year Y

F_1 = adjustment factor that accounts for morbidity effects of air pollution, relative to the mortality effect

F_2 = adjustment factor that accounts for the non-health effects of air pollution, relative to the mortality effect

The VOSL is calculated by scaling an estimate for a base year to a value for the target year Y , accounting for the effects on the VOSL of increases in real per-capita income over time with

$$V_{D,Y} = V_{D,Y^*} \cdot \exp^{(r \cdot e)(Y - Y^*)}$$

where

V_{D,Y^*} = the VOSL in base year Y^*

r = the annual rate of change in income per capita

e = the income elasticity of the VOSL

VOSL in base year. Viscusi and Aldy (2003) and The National Center for Environmental Economics (NCEE) (2014) provide comprehensive reviews of estimates of the VOSL. Viscusi and Aldy's (2003) meta-analysis of US studies indicates a mean VOSL of \$6.1 million, with a 95% confidence interval of \$4.6 to \$8.2 million, in year-2000 dollars, for the robust regression with an income elasticity of 0.48. The NCEE (2014) gives a mean estimate of \$7.4 million with a standard deviation of \$4.7 million, in year-2006 dollars (mean of \$6.4 million in year-2000 dollars, for comparison with Viscusi and Aldy). We start with values of \$9, \$7, and \$5 million (LCHB, medium, and HCLB cases) in year-2006 dollars, and at year-2006 levels of wealth, and then update to year-2013 dollars using GDP implicit price deflators.

Income growth and the income elasticity of VOSL. At this point we have the VOSL in year-2013 dollars and, by assumption, at year-2006 levels of wealth or income. To estimate the VOSL in future years, we need projections of changes in income and a relationship between changes in income and changes in the VOSL. Projections of changes in income are discussed in the section "State GDP". The income elasticity of the VOSL typically is assumed to be 0.4 to 0.6 (Hammitt and Robinson, 2011), and the NCEE (2014) recommends values of 0.08, 0.40, and 1.0.

Given this, our assumptions are

	<i>LCHB</i>	<i>Medium</i>	<i>HCLB</i>
Input VOSL (million year-2006 dollars)	5.00	7.00	9.00
Annual change in real GDP per capita	See "State GDP"		
Income elasticity of VOSL	0.75	0.50	0.50

A higher VOSL results in higher benefits for the 100% WWS scenario.

Adjustment factors for morbidity and non-health impacts. Rather than perform detailed, original estimates of morbidity and non-health costs, we take a simpler approach and use other studies to scale up our VOSL to account for morbidity and non-health costs. Our method for this scaling is as follows.

First we define total air-pollution costs as the sum of premature mortality, morbidity, and non-health costs, where each is the product of a quantity and a value per unit quantity (here omitting the subscripts for states *S* and year *Y*):

$$APcost = N_D \cdot V_D + N_M \cdot V_M + N_O \cdot V_O$$

where

APcost = the total damage cost of air pollution

N_j = the quantity of impact *j*

V_j = the value per unit of *j*

j = premature mortality (D), morbidity (M), and other non-health impacts (O)

Next we expand the APcost term into a form that will allow us to scale-up our detailed estimates of deaths from air pollution. Specifically, we want to develop scaling factors related to mortality costs V_D .

$$\begin{aligned}
 APcost &= N_D \cdot V_D \cdot \left(\frac{N_D \cdot V_D + N_M \cdot V_M}{N_D \cdot V_D} \right) \cdot \left(\frac{N_D \cdot V_D + N_M \cdot V_M + N_O \cdot V_O}{N_D \cdot V_D + N_M \cdot V_M} \right) \\
 &= N_D \cdot V_D \cdot \left(\frac{N_D \cdot V_D}{N_D \cdot V_D} + \frac{N_M \cdot V_M}{N_D \cdot V_D} \right) \cdot \left(\frac{N_D \cdot V_D + N_M \cdot V_M}{N_D \cdot V_D + N_M \cdot V_M} + \frac{N_O \cdot V_O}{N_D \cdot V_D + N_M \cdot V_M} \right)
 \end{aligned}$$

$$\begin{aligned}
&= N_D \cdot V_D \cdot \left(1 + \frac{N_M \cdot V_M}{N_D \cdot V_D}\right) \cdot \left(1 + \frac{N_O \cdot V_O}{N_D \cdot V_D + N_M \cdot V_M}\right) \\
&= N_D \cdot V_D \cdot \left(1 + \frac{N_M \cdot V_M}{N_D \cdot V_D}\right) \cdot \left(1 + \frac{\frac{N_O \cdot V_O}{N_D \cdot V_D}}{1 + \frac{N_M \cdot V_M}{N_D \cdot V_D}}\right)
\end{aligned}$$

For simplicity, we designate

$$B_1 \equiv \frac{N_M \cdot V_M}{N_D \cdot V_D} \quad \text{and} \quad B_2 \equiv \frac{N_O \cdot V_O}{N_D \cdot V_D}$$

$$\text{giving } APcost = N_D \cdot V_D \cdot (1 + B_1) \cdot \left(1 + \frac{B_2}{1 + B_1}\right)$$

At this point we can create our adjustment factors, $F_1 \equiv 1 + B_1$ and $F_2 \equiv 1 + \frac{B_2}{F_1}$. Now we have

$$APcost = N_D \cdot (V_D \cdot F_1 \cdot F_2)$$

The next task is to find the adjustment factors F_1 and F_2 by referring to other studies of morbidity and non-health costs. Designating these other studies with an asterisk, we have

$$B_1 = B_1^* \cdot \frac{B_1}{B_1^*} = B_1^* \cdot \frac{\frac{N_M \cdot V_M}{N_D \cdot V_D}}{\frac{N_M^* \cdot V_M^*}{N_D^* \cdot V_D^*}} = B_1^* \cdot \left(\frac{\frac{N_M}{N_D}}{\frac{N_M^*}{N_D^*}}\right) \cdot \left(\frac{\frac{V_M}{V_D}}{\frac{V_M^*}{V_D^*}}\right)$$

Given that the impact functions that generate the values of N in B_1 are the same as the functions in B_1^* , and knowing that generally health effects N are linear functions of population and air pollution, then to a first approximation the ratio of premature deaths to morbidity impacts is constant; i.e., $\frac{N_M}{N_M^*} \approx \frac{N_D}{N_D^*}$. However, this relationship does not hold in the case of valuation, so instead we establish a more generation relationship,

$$\frac{V_M}{V_M^*} = \left(\frac{V_D}{V_D^*}\right)^K$$

Defining $\frac{V_D}{V_D^*} \equiv V_D^\wedge$ (where the values are expressed in the same year dollars), we now have

$$B_1 = B_1^* \cdot \left(\frac{\frac{V_M}{V_M^*}}{\frac{V_D}{V_D^*}} \right) = B_1^* \cdot \frac{(V_D^\wedge)^K}{V_D^\wedge} = B_1^* \cdot (V_D^\wedge)^{K-1}$$

With similar reasoning and algebra for B_2 we have $\frac{V_O}{V_O^*} = (V_D^\wedge)^L$ and $B_2 = B_2^* \cdot (V_D^\wedge)^{L-1}$.

The final adjustment factors thus are

$$F_1 = 1 + B_1^* \cdot (V_D^\wedge)^{K-1} \quad \text{and} \quad F_2 = 1 + \frac{B_2^* \cdot (V_D^\wedge)^{L-1}}{F_1}$$

Morbidity and non-health impacts in other studies. Using results in McCubbin and Delucchi (1999), we calculate LCHB and HCLB values for B_1^* (the reference ratio of morbidity to mortality costs) and V_D^* (the reference value of a statistical life). Using results in Delucchi (2000), we calculate LCHB and HCLB values for B_2^* (the reference ratio of non-health to health costs). (The EPA [2011] estimates much lower values for B_1^* and B_2^* , but the analyses summarized in Delucchi and McCubbin (2011) are much more comprehensive.) McCubbin and Delucchi (1999) and Delucchi (2000) do not report middle or mid-point estimates, so we calculate a “medium” case here based on the geometric mean of the LCHB and HCLB estimates. (This gives more reasonable results than does using the arithmetic average.)

The calculation of the morbidity multiplier (B_1^*) is as follows:

<i>All anthropogenic pollution, 1990 (McCubbin and Delucchi, 1999)</i>	<i>Medium LCHB (geo. mean)</i>	<i>HCLB</i>
Number of premature deaths (thousands)	138.5	80.5
Mortality costs (billion 1991 \$)	475.5	40.6
Other health costs	196.8	14.1
Value of life (V_D^*) (million 1991 \$)	3.43	0.50
Ratio of morbidity to mortality costs (B_1^*)	0.41	0.35

The calculation of the non-health damage multiplier (B_2^*) is as follows:

<i>Motor-vehicle air-pollution costs, excluding upstream emissions and road dust, 1990-91 (Delucchi, 2000)</i>	<i>LCHB</i>	<i>Medium (geo. mean)</i>	<i>HCLB</i>
Health costs (billion 1991 \$)	283.5	73.4	19.0
Non-health costs (billion 1991 \$)	43.1	18.7	8.1
Ratio of non-health to health costs (B_2^*)	0.15	0.25	0.43

Exponents K and L . The exponents K and L relate changes in morbidity valuation or non-health-impact valuation to changes in the VOSL. If the exponent is 0.0, then changes in the VOSL do not affect the other values; if the exponent is 1.0, then changes in the VSL affect the other valuations proportionately. We believe that intermediate values are more reasonable, and use 0.7, 0.5, and 0.3 in our LCHB, medium, and HCLB cases. (High values of the exponent result in high benefits of air pollution reduction in the 100% WWS scenario.)

Results

The main text shows the calculated values of $N_{D,S,Y}$, the number of deaths due to air pollution in state S in year Y , adjusting for changes in exposure and ambient air quality to year Y . These are multiplied by the calculated values of $V_{P/D,Y}$, the total cost of pollution per death in year Y (230, 13.1, 7.3 million \$; LCHB, medium, and HCLB), to produce $APcost_{S,Y}$, the damage cost of air pollution in state S year Y .

4) THE COST OF CLIMATE CHANGE FROM FOSSIL-FUEL USE: DAMAGES ATTRIBUTABLE TO AND BORNE BY EACH STATE

Overview

We estimate two kinds of climate-change costs of fossil-fuel use:

- 1) The cost of climate-change impacts in the U.S. and in the world *attributable to* emissions of greenhouse gases (GHGs) from the use of fossil fuels in each of the 50 states, and
- 2) The cost of climate-change impacts in the U.S., due to fossil-fuel use in the U.S., *borne* by each state.

We estimate damages borne by each state because this represents the monetary value of the benefits of converting to WWS in each state and hence is an appropriate alternative metric to add to the other state-specific monetary benefits of converting to WWS (electricity-cost savings and reduced air-pollution damages). The portion of damages

borne by each state is equal to total climate-change damages in the U.S. from total U.S. emissions multiplied by each state's share of total damages.

The cost of climate-change impacts attributable to each state's GHG emissions is the product of three factors, 1) estimated CO2 combustion emissions from energy use; 2) the ratio of total CO2-equivalent (CO2e) lifecycle GHG emissions to lifecycle CO2 combustion emissions; and 3) the damage cost per unit of CO2e emission. All three factors can vary over time.

The main work here is in calculating climate-change damage costs attributable to each state's GHG emissions. Formally,

$$CC_{A,GHG,S,Y} = E_{GHG,S,Y} \cdot D_{GHG,A,Y}$$

$$E_{GHG,S,Y} = E_{CO2,S,Y^*} \cdot \frac{E_{GHG,R:S \in R,Y^*}}{E_{CO2,R:S \in R,Y^*}} \cdot \exp^{w_{GHG,R:S \in R}(Y-Y^*)}$$

$$E_{CO2,R:S \in R,Y^*} = \sum_{S \in R} E_{CO2,S,Y^*}$$

$$w_{GHG,R:S \in R} = \frac{\ln \left(\frac{E_{GHG,R:S \in R,Y_e}}{E_{GHG,R:S \in R,Y_s}} \right)}{Y_e - Y_s}$$

$$E_{GHG,R:S \in R,Y^*} = \sum_i E_{i,CO2,R:S \in R,Y^*} \cdot \frac{E_{i,LC-CO2e,Y^*}}{E_{i,LC-CO2-EN,Y^*}}$$

$$D_{GHG,A,Y} = D^{\wedge}_{GHG,A,Y^*} \cdot \exp^{d(Y-Y^*)} \cdot \frac{p_{GDP-IPD,Y^*}}{p_{GDP-IPD,Y\#}}$$

where

$CC_{A,GHG,S,Y}$ = climate-change damages in area A (U.S. or world) attributable to energy-related, lifecycle, CO2-equivalent GHG emissions from state S in year Y (\$)

$E_{GHG,S,Y}$ = emissions of GHGs from state S in year Y (metric-tons)

$D_{GHG,A,Y}$ = the present worth of climate change damages in area A in year Y per unit of GHG emission in year Y (\$/metric-ton)

E_{CO2,S,Y^*} = emissions of CO2 from energy use (fuel combustion) in state S in base year Y^* (metric tons) (EIA estimates for 2011;

http://www.eia.gov/environment/emissions/state/state_emissions.cfm)

$E_{GHG,R:S \in R,Y^*}$ = lifecycle CO₂e GHG emissions from U.S. region R (containing state S) in base year Y^* (metric-tons)

$E_{CO_2,R:S \in R,Y^*}$ = emissions of CO₂ from energy use (fuel combustion) in region R in base year Y^* (metric-tons)

$w_{GHG,R:S \in R}$ = the rate of growth over time of GHG emissions in region R (see discussion below)

Y = technology or impact target year of the analysis (2050 here, but can be any year from 2015 to about 2075)

Y^* = the base year of EIA CO₂ emissions data (2011)

Y_s and Y_e = the start year and the end year of the time range over which the rate of growth in emissions is calculated (2011 and 2040)

$E_{i,CO_2,R:S \in R,Y^*}$ = emissions of CO₂ from combustion of fuel i in region R in base year Y^* (metric-tons) (EIA, 2014c)

$\frac{E_{i,LC-CO_2e,Y^*}}{E_{i,LC-CO_2-EN,Y^*}}$ = the ratio of lifecycle, CO₂-equivalent GHG emissions from fuel i to lifecycle combustion emissions of CO₂ from fuel i , in base year Y^* (see discussion below)

$D^{\wedge}_{GHG,A,Y^{\wedge}}$ = reference climate-change damages in area A in year Y^{\wedge} per unit of GHG emission in year Y^{\wedge} (\$/metric-ton) (see discussion below)

d = the rate of growth over time of damages per unit of GHG emissions (see discussion below)

Y^{\wedge} = the reference year of estimates of damages per unit of CO₂e emission (see discussion below)

Y' = designated price year (2013 here, but can be any date for which the GDP implicit price deflator is known)

$\frac{p_{GDP-IPD,Y'}}{p_{GDP-IPD,Y\#}}$ = the ratio of prices in our designated price year Y' to prices in the price-year $Y\#$ of the reference CO₂ damage-cost analysis (calculated using GDP implicit price deflators)

For $E_{GHG,R:S \in R,Y_e}$ and $E_{GHG,R:S \in R,Y_s}$, substitute Y_e or Y_s for Y^* in the equation for $E_{GHG,R:S \in R,Y^*}$.

Subscripts:

A = relevant area for which damages are estimated (U.S. or world)

S = state in the U.S.

GHG = lifecycle CO₂-equivalent emissions of all greenhouse gases

CO_2 = carbon dioxide per se (as distinguished from other GHGs, or the CO₂-equivalent of GHGs)

R = region of the U.S. in the EIA's estimates of energy-related CO₂ emissions (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific)

LC = lifecycle of a fuel from feedstock production through end use

i = fuels for which the EIA estimates CO₂ emissions (oil, natural gas, coal, other natural gas, other)

$GDP-IPD = GDP \text{ implicit price deflator}$

Important reminder: when we say “climate change damages in year Y,” we mean “the year-Y present worth of the future stream of damages from emissions in year Y.”

Lifecycle CO_{2e} emissions of all GHGs from all sources relative to lifecycle CO₂ emissions from energy use

As mentioned above, the EIA projects CO₂ emissions from the combustion of coal, oil, natural gas, and other fuels in 9 regions of the U.S. from 2011 to 2040. However, the use of fossil-fuels also produces a range of GHGs other than CO₂ and also a small amount of CO₂ from non-combustion processes. To fully account for the climate impact of all GHG emissions associated with fossil-fuel energy use, we use the Lifecycle Emissions Model (LEM) (Delucchi et al., 2003, unpublished updates; Delucchi, 2005) to estimate the ratio of lifecycle CO_{2e} GHG emissions to lifecycle combustion-CO₂ emissions for coal, oil, and natural gas. The LEM estimates emissions of greenhouse gases and urban air pollutants over the complete lifecycle of fuels, materials, vehicles, and infrastructure for the use of transportation fuels and electricity, as follows:

Lifecycle stages: electricity end use; electricity transmission and distribution; electricity generation; transportation of electricity-generation feedstocks (e.g., coal); and production of electricity generation feedstocks.

Sources of emissions: combustion of fuels; evaporation or leakage of energy feedstocks or finished fuels; venting, leaking or flaring of gas mixtures (e.g., venting of coal bed gas from coal mines); fugitive dust emissions; and chemical transformations that are not associated with burning process fuels (for example, the scrubbing of sulfur oxides from the flue gas of coal-fired power plants).

Pollutants/GHGs

carbon dioxide (CO ₂)	particulate-matter (PM) combustion, black carbon (BC)
carbon in (in NMOC, CO, CH ₄ , soil)	PM combustion, organic matter (OM)
nonmethane organic compounds (NMOCs) (weighted by O ₃ potential)	PM combustion, dust-like
methane (CH ₄)	PM all else
carbon monoxide (CO)	PM non-combustion, dust
nitrous oxide (N ₂ O)	hydrogen (H ₂)
nitrogen oxides (NO ₂)	sodium hexafluoride (SF ₆)
sulfur oxides (SO ₂)	chlorofluorocarbons (CFC-12)
ammonia (NH ₃)	hydrofluorocarbons (HFC-134a)

The LEM estimates emissions of each pollutant individually, and also converts all of the pollutants into CO₂-equivalent greenhouse-gas emissions. To calculate total CO₂-

equivalent emissions, the model uses internally developed CO₂-equivalency factors (CEFs) that convert mass emissions of all of the non- CO₂ gases into the mass amount of CO₂ with the equivalent present worth of damages from climate change.

The LEM projects energy use, emissions, and other factors out to the year 2050.

For this project, we used the LEM to calculate two quantities for each year from 2011 to 2050: #1) total lifecycle CO₂e emissions of GHGs from generic coal, oil, natural-gas, and other-fuel use; and #2) lifecycle combustion emissions of CO₂ from generic coal, oil, natural-gas, and other-fuel use. For generic coal we use the lifecycle of coal for electricity generation; for generic oil we used the average of the lifecycle of oil for gasoline and oil for distillate fuel; for generic natural gas we use the lifecycle of natural gas for commercial heating; and for generic other-fuel (a trivial fraction of the total) we assume the values for natural gas. The ratio of quantity #1 to quantity #2 is the

parameter $\frac{E_{i,LC-CO2e,Y}}{E_{i,LC-CO2-EN,Y}}$. The resultant LEM-calculated ratios for 5-year intervals from 2011 to 2050 are

	2011	2015	2020	2025	2030	2035	2040	2045	2050
Petroleum	1.21	1.11	1.11	1.11	1.11	1.09	1.09	1.09	1.09
Natural Gas	1.43	1.44	1.44	1.43	1.43	1.42	1.41	1.40	1.39
Coal	0.81	0.88	0.94	0.97	1.00	1.01	1.02	1.02	1.02
Other	1.43	1.44	1.44	1.43	1.43	1.42	1.41	1.40	1.39

The ratio for petroleum decreases as black-carbon emissions from vehicles and fuel-cycle methane emissions decrease over time. The ratio for coal is less than one until the year 2030 because of the negative forcing caused by sulfur oxide and nitrogen oxide emissions from coal power plants. As these emissions decline with improved emission controls over time, the negative forcing decreases and the ratio increases.

The damage cost per unit of CO₂e GHG emission

Several studies, including some important recent meta-analyses, estimate the damage cost of CO₂e GHG emissions, often referred to as the Social Cost of Carbon (SCC) (Table S3). Most studies recognize, even if only informally or qualitatively, that there is some non-trivial possibility of severe impacts of climate change and a correspondingly very high SCC. The main point of contention is the plausible lower bound on the SCC.

As shown in Table S3, the widely referenced FUND and DICE models estimate very small lower-bound estimates under some sets of assumptions regarding discount rates, risk aversion, equity weighting, extreme impacts, uncertainty, and other factors. However, in a recent review and meta-analysis, van den Bergh and Botzen’s (2014) argue against the assumptions that lead to the lowest estimates of SCC, and make a persuasive case that the *lower* bound of the SCC should not be less than \$125/tonne-CO₂. They conclude that “the lower bound...of US 125 per tCO₂ is far below various

estimates found in the literature that attribute a high weight to potentially large climate change impacts...[and} therefore can be considered a realistic and conservative value” (p. 256). (See also Pindyck, 2013, and Stern, 2013). In support of this, Moore and Diaz (2015), in another recent re-analysis of the SCC, find that incorporating the effect of climate change on the rate of economic growth – a feedback typically not included in standard low-end estimates of the SCC – can dramatically increase the SCC to hundreds of dollars per ton and higher (Table S3).

The SCC of emissions in a given year is also likely to increase over time as GDP, atmospheric GHG levels, and average temperatures increase (Ackerman and Stanton, 2012; Moore and Diaz, 2015). The Ackerman and Stanton (2012) estimates shown in Table S3 increase from 2010 to 2050 at 2.0% / year in the low-SCC case, 1.6% / year in the mid-case, and 1.4% / year in the high-SCC case.

On the basis of the estimates of Table S3 and the discussion above, we assume the following:

	<i>LCHB</i>	<i>Medium</i>	<i>HCLB</i>
Global SCC in 2010 (2007-\$)	600	250	125
Annual change in SCC	1.2%	1.5%	1.8%
U.S. share of global damages	10%	8%	5%

A high value of the SCC results in higher benefits for the 100% WWS scenario. However, if the SCC is at its high value in 2010, then a numerically high annual rate of change results in unreasonably high values in the future. Hence the high starting value of the SCC is paired with the low rate of change.

The incidence of climate-change impacts across U.S. states

Recently Houser et al. (2014) analyzed in detail the per-capita damage costs of climate change in every state in the U.S. They calculate the annual costs of coastal damages, increased energy expenditures, crop loss, reduced labor productivity, increased crime, and increased mortality, in the periods 2020-2039, 2040-2059, and 2080-2099, for three emissions scenarios: RCP 8.5 (relatively high emissions, CO2 at 940 ppm by 2100; “business as usual,”), RCP 4.5 (moderate emissions growth, CO2 at 550 ppm by 2100), and RCP 2.6 (aggressive emission reduction; CO2 below 450 ppm by 2100). (They also present another mid-range scenario, RCP 6.0, but do not provide estimates of coastal damages – one of the larger categories – for this scenario.) For each type of damage, period, and emissions scenario, they report the 5th, 17th, 50th, 83rd, and 95th percentiles of the range of damage estimates.

Table S3. Studies of the Social Cost of Carbon (SCC)

Authors	Moore and Diaz (2015)			Ackerman and Stanton (2012)			van den Bergh and Botzen (2014)			Johnson and Hope (2012)			Howarth et al. (2014)			Antoff et al. (2011)			Tol (2010)		
Model	gro-DICE			DICE			meta-analysis			DICE			IAM using DICE			FUND			FUND		
Emission year	2015-2100			2010, 2050			near term?			2010			2010			2010-2019			2010?		
Dollar year	2005			2007			2010?			2007			2005			1995			1995		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
World SCC (\$/tonne-CO2)	~200		1000+	~45, ~100	~230, ~430	~890, ~1520	125	--	--	-1	145	--	10	--	>500	0.5	10	~180	~0	1.3	11
Discount rate (DR)	n.r.	n.r.	n.r.	3%	1.5% or 3%	1.5%	avg.	--	--	5%	2.5%	--	n.r.	--	n.r.	n.r.	n.r.	n.r.	n.r.	n.r.	n.r.
Pure rate of time preference	3%	1.5%	0.1%	n.r.	n.r.	n.r.	n.r.	--	--	3.2%	1.1%	--	1.5%	--	1.5%	3%	1%	0.1%	3%	1%	0%
Equity weighting?	no	no	no	n.r.	n.r.	n.r.	no?	--	--	no	yes	--	no?	--	no?	no	no	ave.*	no	no	yes
Risk aversion rate	no?	no?	no?	n.r.	n.r.	n.r.	n.r.	--	--	no	no	--	2.0	--	5.6	no	no	no	1.5	1.5	15
Extreme climate impacts?	part.			no	part.	yes	part.	--	--	no	no	--	no (thin tail)	--	yes (fat tail)	no	no	no	no	no	no
U.S. % of world SCC	n.r.			n.r.			n.r.			n.r.			n.r.			33%	13%	< 10%	n.r.	8.5%	n.r.
Remarks	Authors did not estimate explicit low, mid, and high values, but rather estimated the importance of including feedbacks between climate change and the rate of economic growth.			SCC estimated as a function of the DR, climate sensitivity (CS), and form of damage function (DF). Our mid case includes all combos of DR, CS, and DF except low-low (our low) and high-high (our high).			SCC is equal to \$41/tonne – the average reported in a meta-analysis – plus the average of separate “surcharges” for uncertainty, extreme damages, and risk aversion.			Authors did not analyze what would be a “high” cost case (a low rate of time preference with equity weights).			With high risk aversion rate, SCC decreases with increasing emission control rate (ECR): when ECR > 40%, SCC <10.			SCC is higher with U.S.-based equity weights than with global equity weights. (* = global equity weights)			High estimates are based on “illustrative” parameter values.		

For each state we sum the Houser et al. (2014) per-capita damages for all six impacts and then multiply the resultant per-capita total damage by the state population (as in the Houser et al., [2014] analysis) to produce an estimate of total \$ damages in the state, for each emission scenario, period, and percentile. With these total \$ damages by state we then calculate each state's share of the total 50-state damages.

Figure S1 shows each state's share of the 50th percentile damages, by period and emission scenario. Because coastal damage is one of the largest categories in the Houser et al. (2014) analysis, states with high coastal damages have relatively high shares of total damages. For our purpose of estimating the incidence of damages across the U.S., we use the calculated state shares of total damages for the RCP 8.5 scenario for the period 2040-2059, with the calculated 17th-percentile shares as our "low" case, the 50th-percentile shares as our "middle" case, and the 83rd-percentile shares as our "high" case (Table S4).

There are two minor caveats and one major caveat to our use of the Houser et al. (2014) results. The first minor caveat is that the distribution of damage costs for each state (on the basis of the 5th, 17th, 50th, 83rd, and 95th percentile results) is calculated independently for each state, such that the set of conditions that produces, say, the 17th percentile results in state *A* is not necessarily the set that produces the 17th percentile results in state *B*. This means that, technically, adding up the *X*th percentile results for each state is inconsistent. However, it appears that this inconsistency is of minor consequence. In most cases, for the 17th, 50th, and 83rd percentiles, the sum of individual state damages at each percentile is not drastically different from the Houser-et al. (2014) reported total national damages at the same percentile.

The second minor caveat is that we estimate the distribution of damages across states based on the Houser et al. (2014) estimates for the period 2040-2059, whereas the unit damage-cost parameter (to which we apply the state-distribution shares) estimates the present worth of damages over a much longer period. However, we believe that if we were to estimate a present-worth weighted distribution of damages for, say, the period 2015 to 2100, it would not differ dramatically from the 2040-2059 distribution from Houser et al. (2014).

The major caveat is that we multiply the Houser et al. (2014)-based state shares of total climate-change costs in the U.S. by *other* estimates of climate-change costs for the U.S., and it is likely that methods and assumptions used to estimate damages in the other studies are different from those in the Houser et al. (2014) study.

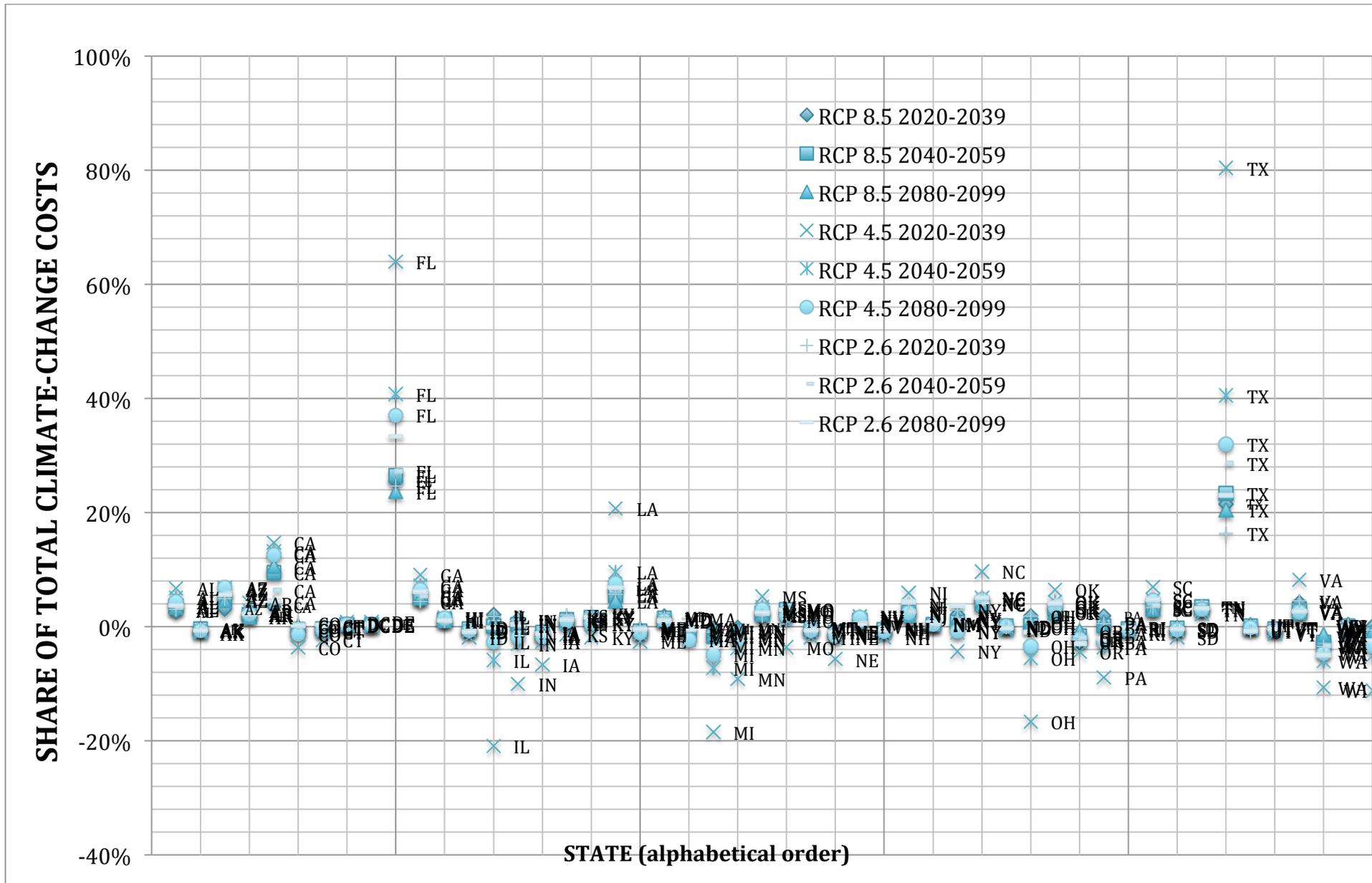


Table S4. Climate-change benefits received by each state as a result of switching WWS in the U.S., business-as-usual emissions scenario, 2040-2059 (% of total average damages in U.S.)

	Low damages	Middle damages	High damages		Low damages	Middle damages	High damages
AL	1%	1%	1%	MT	-1%	0%	0%
AK	0%	0%	0%	NE	-2%	0%	0%
AZ	1%	1%	2%	NV	0%	0%	0%
AR	0%	1%	1%	NH	-1%	0%	0%
CA	4%	7%	6%	NJ	13%	8%	0%
CO	-1%	0%	0%	NM	0%	0%	0%
CT	-1%	0%	0%	NY	13%	9%	0%
DC	0%	0%	0%	NC	2%	2%	0%
DE	1%	0%	0%	ND	0%	0%	0%
FL	60%	36%	28%	OH	-3%	0%	0%
GA	3%	3%	3%	OK	0%	1%	0%
HI	0%	0%	0%	OR	-2%	0%	0%
ID	-1%	0%	0%	PA	-3%	0%	0%
IL	-4%	0%	2%	RI	0%	0%	0%
IN	-2%	0%	1%	SC	0%	1%	0%
IA	-3%	0%	0%	SD	-1%	0%	0%
KS	0%	0%	1%	TN	0%	1%	0%
KY	0%	0%	1%	TX	15%	11%	1%
LA	18%	11%	9%	UT	-1%	0%	0%
ME	-1%	0%	0%	VT	0%	0%	0%
MD	0%	1%	1%	VA	7%	4%	0%
MA	3%	2%	2%	WA	-3%	-1%	0%
MI	-4%	0%	1%	WV	0%	0%	0%
MN	-3%	0%	0%	WI	-3%	0%	0%
MS	0%	1%	1%	WY	0%	0%	0%
MO	-1%	1%	1%	ALL	100%	100%	100%

Source: Our assumptions and calculations based on Houser et al. (2014). See the discussion in the text.

5) EARNINGS FROM NEW CONSTRUCTION AND OPERATION JOBS IN A 100% WWS WORLD

Calculation of earnings

Annual earnings from new construction and operation jobs are the product of the number of jobs and the annual earnings per job. The number of jobs is the product of a jobs/installed-MW factor, from the National Renewable Energy Laboratory (NREL) Jobs and Economic Development Impact (JEDI) models (Table S5), and the total installed MW assumed here.

Table S5. Jobs per MW of installed power for WWS technologies

Technology	Jobs/MW from JEDI model					
	Construction			Operation		
	CA	WA	Average	CA	WA	Average
Onshore wind	0.10	0.10	0.10	0.15	0.15	0.15
Offshore wind	0.18	0.16	0.17	0.66	0.60	0.63
Wave device	0.35	0.33	0.34	2.42	2.31	2.37
Geothermal plant	0.48	0.22	0.35	0.07	0.16	0.12
Hydroelectric plant	0.30	0.30	0.30	0.30	0.30	0.30
Tidal turbine	0.30	0.29	0.30	2.32	2.22	2.27
Res. roof PV system	1.61	1.37	1.49	0.48	0.44	0.46
Com. roof PV system	1.77	1.41	1.59	0.33	0.32	0.32
Solar PV plant	0.98	0.81	0.90	0.30	0.28	0.29
CSP plant	0.26	0.26	0.26	0.19	0.19	0.19

Source: JEDI models (<http://www.nrel.gov/analysis/jedi/>). CSP = concentrated solar power (solar thermal).

Earnings per year are calculated by scaling up JEDI earnings figures to our price (dollar) year and to account for effects of changes in wages and labor-hours/MW over time as follows:

$$E_J = E_{JEDI,J} \cdot \frac{P_{GDP-IPD,Y_B}}{P_{GDP-IPD,JEDI}} \cdot \exp^{w \cdot h \cdot Y}$$

where

E_J = Annual earnings for job type J (\$/year)

$E_{JEDI,J}$ = Annual earnings in the JEDI model (\$/year; shown below)

$\frac{P_{GDP-IPD,Y'}}{P_{GDP-IPD,JEDI}}$ = the ratio of our designated price-year basis Y' to the JEDI price-year basis (2010) (calculated using GDP Implicit Price Deflators)

w = rate of change in real wages, over time (we assume wages grow with our mid-range estimate of real GDP/capita; see discussion in section "State GDP" below)

h = rate of change in hours per MW, to account for improvements in production efficiency (we assume -1.0%/year)

Y = the period of time over which the changes in wages and hours/MW occur (we assume the midpoint of the entire 40-year phase-in period; i.e., 20 years)

The raw, unscaled earnings values ($E_{JEDI,J}$) from JEDI and the final scaled values (E_J) are shown in Table S6.

Table S6. Earnings in construction and operation jobs for WWS technologies

	Earnings (\$1000)/year							
	Construction				Operation			
	Unscaled, from JEDI			Scaled	Unscaled, from JEDI			Scaled
	CA	WA	Average	Average	CA	WA	Average	Average
Onshore wind	66.79	59.61	63.20	66.44	110.60	58.19	84.40	88.72
Offshore wind	73.68	71.73	72.71	76.44	67.28	64.10	65.69	69.06
Wave device	67.63	64.42	66.02	69.41	67.59	65.80	66.70	70.12
Geothermal plant	64.03	46.49	55.26	58.10	104.48	105.99	105.23	110.63
Hydroelectric plant	65.09	61.91	63.50	66.76	72.60	66.46	69.53	73.10
Tidal turbine	67.56	64.28	65.92	69.30	67.69	65.96	66.83	70.26
Res. roof PV system	50.86	52.23	51.54	54.19	56.74	58.42	57.58	60.53
Com. roof PV system	52.65	54.46	53.55	56.30	59.20	58.42	58.81	61.83
Solar PV plant	50.76	52.07	51.42	54.05	56.79	58.25	57.52	60.47
CSP plant	91.87	91.87	91.87	96.59	63.05	63.05	63.05	66.29

Source: JEDI models (<http://www.nrel.gov/analysis/jedi/>).

Check on consistency of labor costs implied by our earnings estimates with our estimated capital costs and O&M costs

Because the cost of labor is a component of estimates of capital costs and O&M costs, one ideally would use a single set of labor costs to estimate capital costs, O&M costs, and earnings from job creation. However, because our estimates of capital costs and O&M costs are not disaggregated into labor and materials components, we instead will check whether the labor-cost figures used in our earnings estimates are consistent with our overall capital cost and O&M cost estimates. We expect labor costs to be a small fraction of capital costs and a large or very large fraction of O&M costs for WWS technologies. As shown in Table S7, this indeed is what we find.

Table S7. Estimated construction costs and labor costs for WWS technologies

Technology	Construction cost		Operating cost					
	Labor (\$/kW)	Labor / total	Labor (\$/kW/yr)			Labor/total		
	Average	Avg/avg	Low	Average	High	Low/high	Avg/avg	High/low
Onshore wind	9.8	1%	8.9	13.1	17.4	22%	35%	50%
Offshore wind	26.0	1%	40.1	43.0	46.0	25%	32%	43%
Wave device	52.1	1%	158.3	164.0	169.9	32%	51%	121%
Geothermal plant	70.4	2%	8.0	13.0	18.0	3%	6%	8%
Hydroelectric plant	59.4	2%	20.7	21.7	22.6	57%	69%	87%
Tidal turbine	45.5	1%	152.1	157.5	162.9	76%	126%	326%
Res. roof PV system	14.0	0%	25.9	27.4	28.9	86%	100%	116%
Com. roof PV system	33.2	1%	19.1	19.6	20.1	96%	119%	155%
Solar PV plant	71.8	4%	16.6	17.5	18.3	66%	78%	92%
CSP plant	62.4	1%	12.3	12.3	12.3	10%	11%	11%

Solar PV plant uses values for crystalline tracking. CSP = concentrated solar power (solar thermal).
 "Labor (\$/kW)" is based on the average unscaled JEDI earnings (updated to the appropriate price year) over the average construction time for the technology.
 "Labor/total" is equal the Labor \$/kW divided by our estimated base-year capital cost in \$/kW.
 "Labor (\$/kW/yr)" is based on the min, average, or max unscaled JEDI earnings (updated to the appropriate price year).
 "Labor/total" is equal to Labor \$/kW/yr divided by total O&M costs expressed in \$/kW/yr. We have converted variable O&M, original in \$/kWh, to \$/kW/yr. Here, Low/high is low labor costs divided by high total O&M, and High/low is high labor costs divided by low O&M.

As indicated here, the labor costs used in the earnings analysis are less than 5% of capital costs. Labor costs typically are a much larger fraction of O&M costs, and account for the bulk of O&M costs for PV plants, which we expect.

There are a few combinations where the labor costs from our earnings analysis in this section constitute more than 100% of O&M costs as estimated in our “cost of delivered electricity section, but with one exception, this generally does not concern us. In one case for wave devices and two cases for tidal turbines, the labor cost exceeds 100% of the O&M cost, but this is not surprising given the enormous uncertainty in estimates of O&M costs for this non-commercial technology. In one case for residential rooftop PV – high labor costs and low O&M costs – labor costs exceed O&M costs, but only by a small amount, and in the other two (more likely) cases labor costs do not exceed 100%.

The only case of modest concern is for commercial rooftop PV, where even the average labor cost estimated here exceeds average O&M cost. Closer examination of the underlying data reveals that this is because our O&M cost estimates for commercial rooftop PV are low relative to the estimates for residential rooftop PV and utility-scale PV.

6) PROJECTION OF STATE POPULATION AND GDP

State population

We use state population estimates for 2000, 2005, 2010, 2011-2014, and 2015 to 2075 in 5 year increments. The sources of our estimates are

2000 and 2005: population estimates by the U. S. Bureau of the Census (<http://www.census.gov/popest/data/intercensal/state/state2010.html>).

2010-2014: population estimates by the U. S. Bureau of the Census (<http://www.census.gov/popest/data/state/totals/2014/index.html>).

2015: extrapolate from 2011-2014 trend.

2020 to 2075 in five year increments: see discussion in the next section.

Projection of state population to 2075. In 2006, the U. S. Bureau of the Census projected state populations from 2010 to 2030 (US Census, Table 6 Interim Projections: Total Population for Regions, Divisions, and States: 2000 to 2030.

<http://www.census.gov/population/projections/data/state/projectionsagesex.html>.)

With those Census projections, we calculate the annual rate of change over each five-year period from 2010 to 2030, for each state. We then fit a trend line to the series of five-year annual rates. Assuming that the annual rate of population growth actually changes nonlinearly rather than linearly with time, we multiply the slope of the trend line by an exponential decay function. We then use this decayed trend line to project each state’s population from 2020 to 2075. We pick the value of the decay-exponent so that our resultant projections of U.S. total population match the population projections of the EIA (2014c). Formally,

$$P_{S,Y_t} = P_{S,Y_{t-1}} \cdot \exp^{g_{Y_t,Y_{t-1}}(Y_t - Y_{t-1})}$$

$$g_{Y_t,Y_{t-1}} = (b_{2010-2030} + m_{2010-2030} \cdot Y_t) \cdot \exp^{h(Y_t - 2015)}$$

$$m_{2010-2030} = \frac{\sum_{2010}^{2030} (Y_t - \bar{Y}_{2010-2030}) \cdot (g_t - \bar{g}_{2010-2030})}{\sum_{2010}^{2030} (Y_t - \bar{Y}_{2010-2030})^2}$$

$$b_{2010-2030} = \bar{Y}_{2010-2030} - m_{2010-2030} \cdot \bar{Y}_{2010-2030}$$

where

P_{S,Y_t} = the population in state S in year Y_t

$t-1$ = the period prior to t

$g_{Y_t,Y_{t-1}}$ = the annual rate of change in population between year Y_t and year Y_{t-1} , calculated as a linear extrapolation based on the growth rates between 2010 and 2030, multiplied by an exponential decay (non-linearizing) factor.

$\bar{Y}_{2010-2030}$ = the average years between 2010 and 2030 (the period over which the Census projected each state's population)

$\bar{g}_{2010-2030}$ = the average of the five-year projected population growth rates between 2010 and 2030.

h = exponent determining the rate of decay of the population growth rate, away from the linear trend derived from the Census projections, after 2015 (we assume a value of -0.0095 resulting in modest decay that makes the resultant projected population of the U.S. close to the values projected by the EIA [2014c]).

State GDP

State GDP is calculated as the product of GDP per capita and state population. The state population is discussed above. The International Monetary Fund (World Economic Outlook Data Base,

<http://www.imf.org/external/pubs/ft/weo/2014/02/weodata/index.aspx>),

CitiGroup Global Markets (Buiter and Rahbari, 2011), and the EIA (2014c) project GDP/capita, and HSBC Global Research (Ward, 2012) projects income per capita. The projections range from between 0.6%/year to 2.1%/year, depending on the projection period, with an average of around 1.6%/year. We believe however that lower values are more realistic. We assume the following values for all states:

	<i>LCHB</i>	<i>Medium</i>	<i>HCLB</i>
Annual change in real GDP per capita	1.50%	1.25%	1.00%

A higher rate of change in GDP per capita results in a higher value of life, which results in higher benefits for the 100% WWS scenario.

7) THE NATIONAL-AVERAGE LEVELIZED COST OF ELECTRICITY BY TYPE OF GENERATOR

To estimate the national-average levelized cost of electricity by type of generator we expand and update the calculation documented in Delucchi and Jacobson (2011). Table S13 shows our complete set of assumptions and intermediate calculated values. In this section we document our assumptions and tabulate and annotate the main literature used in our analysis (Table S14).

Overview of the method

We estimate the fully annualized cost per delivered kWh from new capacity put in place in a near-term base year and a long-term target year, for the BAU scenario and the 100% WWS scenario. For the near-term base year, we estimate the costs of conventional (mainly coal, gas, and nuclear) and wind, water, and solar (WWS) technologies as part of present-day electricity systems. For the long-term target year, we estimate the costs of conventional, non-WWS technologies in the context of the U. S. Energy Information Administration's (EIA) *Annual Energy Outlook 2014* (EIA, 2014a, 2014c, 2014e) reference-case projections (our BAU), and estimate the costs of WWS technologies for both the BAU and the 100% WWS scenario. (The costs of WWS technologies in a 100% WWS system will be different from the costs of WWS technologies in a conventional, EIA-reference-case system because the 100% WWS system will require different measures for balancing supply and demand but also will have different costs due to economies of scale and learning associated with greater development and use of technology.) We assume that the benefit stream – the provision of electricity services – is the same in the EIA reference case (BAU) and the 100% WWS scenario, and hence the same for any particular plant/ technology type within the electricity-generation scenarios.

We first estimate national-average costs by technology, as described in this section, and then in a subsequent section adjust these to estimate regional and state-level costs by accounting for regional differences in initial costs, fuel costs and capacity factors. We calculate regional adjustments for gas, coal, oil, wind, and solar plants. For the fossil-fuel plants, hydropower, and geothermal plants, the regional adjustment accounts for differences in initial costs and fuel costs, and for the wind and solar plants the regional adjustment accounts for differences in initial costs and capacity factors. We do not account for regional differences in the cost of nuclear power.

The annualized cost per kWh is equal to the annualized initial cost plus annualized periodic costs and transmission and distribution-system costs, divided by annual kWh output. The annualized initial cost is based on the actual physical depreciation (loss of capacity) over time, accounting for construction interest cost prior to operation, major

capital expenditures to extend the life of the plant, and salvage value and decommissioning cost at end of life. Annual periodic costs are calculated as the present worth of the actual periodic cost stream, annualized over the operating life. Transmission and distribution system costs include the costs of measures needed to balance supply and demand in 100% WWS systems.

The annual kWh output is calculated by multiplying the rated kW capacity by the fraction of the 8760 hours in a year that the plant operates at capacity (the capacity factor). The capacity factor is estimated by considering the characteristics of the entire electricity generating system and, in the case of wind and solar power, the characteristics of the wind and solar resources and the performance of the technology. For the EIA reference-case (the basis of our BAU), we assume that the entire electricity generation system operates as projected in the EIA's *Annual Energy Outlook 2014* (EIA, 2014a, 2014c, 2014e). For the 100% WWS case, we assume what we believe is a plausible, reliable, electricity generation system, based partly on analyses by others and partly by our own analysis in Jacobson et. al (2015). (Note though that we have not done a least-cost optimization.)

Weighted LCOE vs. costs actually incurred in a particular year. Note that we estimate the levelized costs (going forward) of new systems put in place in the target year, and then estimate national or regional system-wide average costs by weighting each generator's LCOE by its assumed share of generation in the target year. This method, which we will call LCOE-TY (for "levelized cost of energy in the target year") facilitates comparison of the costs of different combinations of technology choices in the future. However, for two reasons, this method generally will not give the same relative overall system-average cost results as will an analysis of the *actual* system-wide costs incurred in the target year (ASC-TY) given a particular plan for phasing in various technologies over time, even when the target-year generation shares and capacity factors are the same in both cases (LCOE-TY and ASC-TY) The two reasons are

- 1) The in-place capacity of each technology can rise or fall over time, meaning that the actual total capital costs incurred in the ASC-TY case will be different from the total capital costs implied by the capacity factors and unit capital costs in the LCOE-TY case.
- 2) Capital costs, maintenance costs, and performance change over time, due to learning and scale economies, with the result that the actual costs and performance of the system in place in TY will not be the same as the going-forward costs and performance of new systems installed in TY.

Put another way, the two methods (LCOE-TY and ASC-TY) will give the same relative overall costs only in the case where the total installed capacity, performance, and costs of each technology are constant over time.

In our case, the LCOE-TY method differs from ASC-TY method on account of both reasons mentioned above. For example, the EIA (2014c) projects that over time natural-gas fired capacity increases substantially and coal-fired capacity decreases. This means that our LCOE-TY method, relative to the ASC-TY method

- overestimates the capital-cost component of coal-fired generation but underestimates the capital-cost component of gas-fired generation;
- underestimates the maintenance-cost component of coal-fired generation but overestimates the maintenance-cost component of gas-fired generation (because maintenance costs increase with age); and
- overestimates the fuel efficiency and hence underestimates the fuel cost of gas and coal-fired generation (because efficiency improves over time, with the result that efficiency of new plants built in TY will be higher than the efficiency of the fleet in TY).

Sources of data used in our analysis

With four exceptions, our analysis of national-average costs by technology type, shown in Table S13, is based on the data summarized in Table S14 and the information discussed in the following sections here. The four exceptions are: we estimate costs for i) “combined-cycle conventional” and ii) “combined-cycle advanced with carbon capture” relative to costs for “combined-cycle advanced,” using relative costs from the EIA (2014a, Table 8.2) and our judgment; and we estimate costs for iii) “municipal solid waste” and iv) “distributed generation” based on the EIA (2014a, Table 8.2) and our judgment. However, for these four we do estimate capacity factors as described below, using EIA AEO projections. We also assume that municipal solid waste feedstock is 40% of the cost of biomass feedstock.

Note also that we treat the Table S14 estimates for diesel generators as proxies for diesel steam turbines.

Important parts of our method

We calculate the levelized cost of electricity as the sum of the annualized initial costs, annualized fixed operating and maintenance (FOM) costs, variable O&M costs, fuel costs, and transmission and distribution costs, using (as we derive in the next subsection) a continuous rather than a discrete-interval annualization,

$$C_{j,US,Y,W} = \frac{C_{AI,j,US,Y,W} + C_{FOM,j,US,Y,W}}{CF_{j,US,Y,W} \cdot 8760} + C_{VOM,j,US,Y} + C_{FUEL,j,US,Y} + C_{TD,j,US,Y,W}$$

$$C_{AI,j,US,Y,W} = \frac{r \cdot C_{I,j,US,Y,W}}{1 - e^{-rt}}$$

$$C_{FUEL,j,US,Y} = \frac{C_{FUEL^*,j,US,Y}}{eff_{j,US,Y}}$$

where

$C_{j,US,Y,W}$ = the levelized cost of delivered electricity from technology j in the United States in year Y in scenario W (\$/kWh) (Table S13)

$C_{AI,j,US,Y,W}$ = the annualized initial cost of technology j in the U.S. in year Y in scenario W (\$/kW_{P-NM}/year) (Table S13)

$C_{FOM,j,US,Y,W}$ = the fixed operating and maintenance (OM) cost of technology j in the U.S. in year Y in scenario W (\$/kW_{P-NM}/year) (Table S13; discussed below)

$C_{VOM,j,US,Y,W}$ = the variable operating and maintenance (OM) cost of technology j in the U.S. in year Y in scenario W (\$/kWh) (Table S13; discussed below)

$C_{FUEL,j,US,Y}$ = the cost of fuel for technology j in the U.S. in year Y (\$/kWh) (Table S13)

$C_{TD,j,US,Y,W}$ = the transmission and distribution-system (TD) cost of technology j in the U.S. in year Y in scenario W (\$/kWh) (Table S13; discussed below)

$CF_{j,US,Y,W}$ = the capacity factor for technology j in the U.S. in year Y in scenario W
 $\left(\frac{\text{kWh}_{\text{ac-grid}}/\text{year}}{\text{kW}_{\text{P-NM}} \cdot 8760} \right)$ (discussed below)

$\text{kWh}_{\text{ac-grid}}/\text{year}$ = kWh of ac electrical energy delivered to the grid per year

$\text{kW}_{\text{P-NM}}$ = kW of rated “name-plate” peak power (see discussion immediately below)

8760 = hours per year

$C_{I,j,US,Y,W}$ = the initial cost of technology j in the U.S. in year Y in scenario W (\$/kW_{P-NM}) (discussed below)

r = the annual discount rate (discussed below)

t = the lifetime of the technology before replacement (years) (Table S13; discussed below)

$C_{FUEL^*,j,US,Y}$ = the cost of fuel for technology j in the U.S. in year Y (\$/million-BTU [HHV]) (Table S13; discussed below)

$eff_{j,US,Y}$ = the efficiency of fuel-use for technology j in the U.S. in year Y (kWh/million-BTU [HHV]) (Table S13; discussed below)

subscript j = technology types (Table S13) (note that the EIA’s AEO reference projections, used in our BAU scenario, include only fixed-tilt PV, of unspecified technology [EIA, 2014a]; therefore, for utility PV in our BAU we use the average of thin-film and crystalline fixed-tilt)

subscript W = 100% WWS or BAU scenario

HHV = higher heating value

The use of the rated or “nameplate” peak power. The peak rated or “name-plate” power, $\text{kW}_{\text{P-NM}}$, is part of the capital-cost parameter and part of the capacity-factor parameter, so it is important, of course, that estimates of the capital cost and the capacity factor are in fact based on the same definition of $\text{kW}_{\text{P-NM}}$. This definitional consistency mainly is an issue for photovoltaics (PVs) and wind turbines, because the

peak power of these depends on the intensity of solar radiation or the wind speed. PV manufacturers rate panels under “Standard Test Conditions” (STC; irradiance of 1,000 W m², solar spectrum of AM 1.5 and module temperature at 25 °C.) (http://en.wikipedia.org/wiki/Solar_panel), and generally analyses of the cost and performance of PVs use this standard convention (e.g., <http://rredc.nrel.gov/solar/calculators/pvwatts/version1/change.html>; U.S. DOE, 2012). It appears that wind turbines generally are rated at a wind speed of 11 m/s (http://distributedwind.org/wp-content/uploads/2012/08/Certified_Ratings.pdf), but that this standard is not as universally accepted as the STCs are for PVs. It therefore is possible that in the case of wind power cost figures from one source are not consistent with capacity figures from another source.

Derivation of the formula for a continuous annuity, for levelizing (annualizing) costs

A “levelized” cost per unit, such as the \$/kWh levelized cost of electricity, is equal to annualized initial costs plus periodic annual costs (such as fuel and operating and maintenance) divided by annual output. Typically, annualized initial costs are calculated using the formula for an annuity “paid” in a lump sum at the end of a discrete time interval,

$$C_{AI} = \frac{r \cdot C_I}{1 - (1 + r)^{-t}}$$

where r is the annual interest rate, t is the life of the technology in years, and annuity payments are made at a discrete point in time, the end of the year. This method is exactly correct for calculating a payment that actually is made at discrete intervals, but it is *not* technically correct for annualizing (or “levelizing”) energy-service costs, because the purpose of the annualization is to produce a cost stream with a time-flow characteristic that matches the time flow of the energy output (e.g., in the levelized \$/kWh cost calculation, the output is the continuous flow of kWh). Because energy production and use actually is continuous, the annualization of the initial cost of energy generators also should be based on a continuous time stream of “payments” rather than discrete-interval payments.

To derive a *continuous* annuity formula from the standard discrete-interval formula, we first introduce a variable n that represents the number of payments per year, with the ultimate aim of solving for C_{AI} when n approaches infinity (and hence the time interval approaches zero),

$$C_{AI(n)} = \frac{\frac{r}{n} \cdot C_I}{1 - \left(1 + \frac{r}{n}\right)^{-nt}}$$

Here r remains the *annual* discount rate, and t still is denominated in years, but n is denominated in 1/years. If for example $n = 12$ (months)/year, then r/n is effectively the

monthly interest rate ($\%$ / year \times years / month), $t \cdot n$ is the lifetime in months (months / year \times years), and $C_{AI(n)}$ is the “payment” made every $1/n$ th of a year; i.e., in every month for this example.

If we multiply both sides by n , then we have

$$C_{AI(n)} \cdot n = \frac{r \cdot C_I}{1 - \left(1 + \frac{r}{n}\right)^{-nt}}$$

where the quantity $C_{AI(n)} \cdot n$ is the total amount paid over the year (the $1/n$ th-year payment multiplied by n payments per year). Note that $C_{AI(n)} \cdot n$ is *not* the same as C_{AI} ; the latter is the single year-end payment made every year, whereas the former is the *sum*, over a year, of the n payments made every $1/n$ th of a year. No matter what the value of n , the quantity $C_{AI(n)} \cdot n$ always equals the total payments over a year. And as n approaches infinity, $C_{AI(n)} \cdot n$ becomes the total over a year of a *continuous payment rate*, which is just what we want, because it corresponds with the total over a year of the continuous annual energy (electricity) generation rate. We will designate this continuous payment rate C_{AI^*} , to distinguish it from the discrete lump-sum end-of-year payment C_{AI} .

Finally, we want to find

$$\lim_{n \rightarrow \infty} \left(1 + \frac{r}{n}\right)^{-nt}$$

Let us define $n \equiv m \cdot r$. Thus we have

$$\lim_{n \rightarrow \infty} \left(1 + \frac{r}{n}\right)^{-nt} \equiv \lim_{m \rightarrow \infty} \left(1 + \frac{r}{m \cdot r}\right)^{-m \cdot r \cdot t} = \lim_{m \rightarrow \infty} \left(1 + \frac{1}{m}\right)^{-m \cdot r \cdot t} = \left(\lim_{m \rightarrow \infty} \left(1 + \frac{1}{m}\right)^m\right)^{-r \cdot t}$$

The quantity in the outer parentheses is defined to be the constant e . Thus we have

$$\lim_{n \rightarrow \infty} \left(1 + \frac{r}{n}\right)^{-nt} = e^{-r \cdot t}$$

and

$$C_{AI^*} = \frac{r \cdot C_I}{1 - e^{-r \cdot t}}$$

where r remains the annual discount rate and t is the lifetime in years.

We apply this continuous annuity formula to the annualization of all initial costs, to the annualization of the present worth of capacity-factor-years, and to the annualization of the present worth of the operations and maintenance cost stream.

The cost of WWS technologies in the BAU in year Y

For three reasons, the cost of WWS technologies in year Y in the BAU differs from the cost of WWS in year Y in the 100% WWS scenario:

1) The transmission and distribution (T&D) system in the 100% WWS scenario is different from the system in the BAU. The cost of the T&D system in the BAU is based on the EIA's AEO cost projections; the cost of T&D in the 100% WWS scenario starts with the EIA's AEO cost projections and then incorporates the costs of modifications to the T&D system due to more decentralized generation and additional supply-and-demand balancing measures in the 100% WWS scenario. See the discussion of T&D system costs below.

2) The installed capacity of WWS is much less in the BAU than in the 100% WWS scenario, and as a result the initial cost of WWS technology, which on account of learning and economy-of-scale effects is a function of installed capacity, is higher in the BAU than in the 100% WWS scenario. We assume that the initial cost of WWS in the BAU declines over time (from year Y^* to year Y) by only a (small) fraction of the decline in the 100% WWS scenario. We estimate this fraction as a nonlinear function of the difference between Y^* and Y . See the discussion of the parameter $C_{wvs,Y,BAU}$.

3) Capacity factors for WWS technologies in the BAU are different from the capacity factor in the 100% WWS scenario, on account of differences in the installed capacity (which can entail differences in the average quality of the wind or solar resources used) and differences in system operation in order to ensure reliably matching of supply and demand. Capacity factors in the BAU are estimated based on the EIA's AEO projections; capacity factors in the 100% WWS scenario start with actual current-year factors and then account for assumed changes over time in resource quality, technological performance, and system operation. See the discussion of the capacity factor in the subsections below.

To ensure consistency between our estimates of WWS technology costs in the BAU and the 100% WWS scenario, we estimate BAU costs relative to 100% WWS costs where appropriate. Formally,

$$C_{wvs,Y,BAU} = C_{AI,wvs,Y,BAU} + C_{VOM,wvs,Y} + C_{FOM,wvs,Y,BAU} + C_{TD,Y,BAU}$$

$$C_{FOM,wvs,Y,BAU} = C_{FOM,wvs,Y,100\%WWS} \cdot \frac{CF_{wvs,Y,100\%WWS}}{CF_{wvs,Y,BAU}}$$

$$C_{AI,wvs,Y,BAU} = \frac{C_{AI,wvs,Y^*} \cdot CF_{wvs,Y^*} - K_1 \cdot (C_{AI,wvs,Y^*} \cdot CF_{wvs,Y^*} - C_{AI,wvs,Y,100\%WWS} \cdot CF_{wvs,Y,100\%WWS})}{CF_{wvs,Y,BAU}}$$

$$K_1 = \left(1 - \frac{Y - Y^*}{100}\right)^{K_2}$$

where

$C_{wvs,Y,BAU}$ = the levelized cost of WWS technologies in year Y in the BAU (\$/kWh)

$C_{AI,wvs,Y,BAU}$ = the annualized initial cost of WWS technologies in the BAU in year Y (\$/kWh)

$C_{VOM,wvs,Y}$ = the variable O&M costs of WWS technologies in year Y (\$/kWh) (assumed to be the same for the BAU and the 100% WWS scenario)

$C_{FOM,wvs,Y,BAU}$ = the fixed O&M costs of WWS technologies in year Y in the BAU (\$/kWh)

$C_{TD,Y,BAU}$ = the cost of the transmission and distribution system in year Y in the BAU (\$/kWh) (based on the EIA's AEO; see discussion below)

$C_{FOM,wvs,Y,100\%WWS}$ = the fixed O&M costs of WWS technologies in the 100% WWS scenario in year Y (\$/kWh) (see discussion of O&M costs in regards to Table S13)

$CF_{wvs,Y,100\%WWS}$ = the capacity factor for WWS technologies in year Y in the 100% WWS scenario (see discussion below)

$CF_{wvs,Y,BAU}$ = the capacity factor for WWS technologies in year Y in the BAU (see discussion below)

C_{AI,wvs,Y^*} = the annualized initial (AI) cost of WWS technologies in the base year Y^* (\$/kWh)

$C_{AI,wvs,Y,100\%WWS}$ = the annualized initial cost of WWS technologies in the target year Y in the 100% WWS scenario (\$/kWh)

K_1 = the decline in the annualized initial cost of WWS (in the BAU) as a fraction of the difference between the base-year Y^* and the target-year Y^* cost in the 100%WWS scenario

K_2 = exponent determining the rate of decline in the annualized initial cost of WWS technologies as a function of time (higher values result in smaller fractions) (see discussion below). Its values are as follows:

Geothermal	Hydropower	Wind	Solar thermal	Utility PV	Rooftop PV
0.00	0.00	2.50	0.50	3.50	3.00

Table S13 shows intermediate calculated values and results.

Annual discount rate

The U.S. Office of Management and Budget (OMB) (2003) recommends that cost-benefit analysis of public investments and regulatory impacts use two discount rates: one that reflects the opportunity cost of capital in the private sector, and one that reflects the time value of private consumption. In 2003, the OMB (2003) estimated that the former was 7% (based on the real before-tax rate of return on private investment) and that the latter was 3% (based on the real rate of return on long-term government debt, such as 10-year treasury notes). However, from 2003 to 2013 the real rate of return on 10-year treasury notes has averaged only 1.4%

(<http://www.federalreserve.gov/releases/h15/data.htm>; “Market yield on U.S. Treasury securities at 10-year constant maturity, quoted on investment basis, inflation-indexed”). In line with this, the OMB (2013) now recommends using a real discount rate of 1.9% for cost-effectiveness analysis (which the OMB treats differently from cost-benefit and regulatory-impact analysis). Moreover, the OMB (2003) adds that “if your rule will have important intergenerational benefits or costs you might consider a further sensitivity analysis using a lower but positive discount rate,” and suggests a range of 1-3%.

Other analyses, more comprehensive than the OMB's, indicate that for two reasons, the OMB's upper-range value of 7% is too high. First, the real pre-tax rate of return on private investment likely is less than 7% -- Moore et al. (2004) estimate that it is about 4.5%. Second, the pre-tax rate of return to private investment is the appropriate discount rate only for relatively short-term public projects that dollar-for-dollar crowd out private investment; for projects that have a longer time horizon or that affect consumption as well private investment, a lower discount rate is appropriate (Moore et al., 2004; National Center for Environmental Economics, 2014). Moore et al. (2004) review the accepted methods for estimating the social discount rate (SDR), and conclude that “no matter which method one chooses, the estimates for the SDR vary between 1.5 and 4.5 percent for intragenerational projects, and between 0 and 3.5 percent for projects with intergenerational impacts” (p. 809). The National Center for Environmental Economics (2014) has a similar discussion and indicates (without explicitly recommending) that a reasonable range is 2% to 5%.

With these considerations, we use a rate of 1.5% in our “low” cost (LCHB) scenarios and a rate of 4.5% in our “high” cost (HCLB) scenarios.

Year of prices

We use GDP implicit price deflators to convert all costs except electricity-power-plant capital costs from the price-year basis in the original source to our designated price-year basis (2013). (The designated price-year basis can be any user-specified year up to the year for which the most current GDP implicit price deflator is available.)

For electricity-plant capital costs, we follow the EIA (2014a, 2014c) and develop an adjustment that accounts for trends in prices relevant specifically to the construction of power plants *relative* to trends in the general price level embodied in the GDP implicit price deflator. The EIA (2014a) applies “a cost adjustment factor, based on the producer price index for metals and metal products, [which] allows the overnight costs to fall in the future if this index drops, or rise further if it increases” (p. 96). More precisely, the EIA projects the metals and metal- product producer price index (MMP-PPI) – a proxy for electricity-plant prices – *relative* to its projection of GDP chain-type price indices (GDP-CTPI), for each year of its projection, and then multiplies power-plant capital costs by the relative adjustment factor for each projection year.

We start with the EIA’s projection of the GDP-CTPI and the MMP-PPI from 2012 to 2040. We use historical data to fill in the series back to 1990 (to enable the use of a designated price year as early as 1990), and extend the series to 2075 using a ten-year moving linear extrapolation. To get from the starting estimate of capital costs in the original price year of the source material to capital costs in the designated price year of our analysis, we multiply the original estimate by the appropriate MMP-PPI ratio, which converts the capital-cost estimate to what it would be were it estimated in designated-year prices specifically for capital costs. To capture the effect of changes over time in real power-plant capital costs relative to changes in general prices, we then multiply by the ratio of the MMP-PPI to the GDP-CTPI for the target year vs. the designated price year.

Formally,

$$CC_{El,Y,Y} = CC_{El,Y_0} \cdot ADJ_{El,p}$$

$$ADJ_{El,p} = \frac{P_{MMP-PPI,Y}}{P_{MMP-PPI,Y_0}} \cdot \frac{P_{MMP-PPI,Y'}}{P_{GDP-CTPI,Y'}} \cdot \frac{P_{GDP-CTPI,Y}}{P_{GDP-CTPI,Y'}}$$

where

CC_{El} = the capital cost of electricity power plants (\$/kW)

$ADJ_{El,p}$ = the adjustment factor for changes in the price of electric power plants

p = price index

Subscripts:

MMP-PPI = metals and metal products producer price index
GDP-CTPI = gross domestic product chain-type price index
Y = target year of the analysis (for impacts or technology status)
Y' = the designated price-year of the analysis
Y_o = the price year of the original cost estimates in the source documents (2012 for power-plant cost data used here)

Because the EIA projects that the MMP-PPI will rise more slowly than the GDP-CTPI, the adjustment factor $ADJ_{El,p}$ is less than 1.0. Because WWS technologies are more capital intensive than conventional technologies, this has the effect of slightly reducing the levelized cost of electricity from WWS technologies relative to the levelized cost of conventional technologies.

Interest charges during construction

We assume that 1/2 to 2/3 of the total capital is required at the start of construction, and the remainder is required 1/2 or 2/3 of the way through the construction period. In comparison, Lazard (Jalan, 2014) estimates interest charges on construction capital assuming effectively that 1/2 of the capital is required at the beginning of construction and 1/2 is required at the end of construction. Lazard also ignores interest costs on projects less than 24 months.

Overnight capital cost (national average) (year-2012 dollars): technology base year 2013 (new capacity) (\$/kW)

These are complete system installed costs including engineering, other owner costs, and connection to the transmission system, but excluding borrowing costs during the construction period (which we treat separately). We estimate capital cost, lifetime, efficiency, capacity factors, and O&M costs to be mutually consistent. Our estimates are based on a review of the literature (Table S14) with extra weight given in some cases to the data from Lazard (2014), because those data are the most up-to-date and transparent. For hydropower we give more weight to EIA's estimates from our literature review. We assume that nuclear power costs are 10% to 35% higher than reported in the literature because nuclear power plants have tended to have particularly high cost over-runs (as much as 100%; Sovacool et al., 2014a, b, c), and as Hultman et al. (2007, p. 2088) note, for nuclear power "past experience suggests that high-cost surprises should be included in the planning process." (The discussion in Sovacool et al. supports the notion that even though recent estimates of the capital cost of nuclear power are higher than past estimates, the recent increases do not account for the factors that lead to cost overruns in the past.) We assume that coal-plant costs are 5% to 10% higher than reported in the studies consulted here because thermal plants also tend to have cost overruns (about 10%; Sovacool et al., 2014b). For PV systems the capital cost here includes the inverter; however, in the intermediate calculated results the total capital cost is broken into an inverter component and an all other components, and the annualized cost for each of these is estimated. Solar thermal costs are based on Lazard's (2014) estimates with 18-hour storage.

As mentioned above, here we estimate national-average costs. In the next main section we estimate state or region-specific cost adjustments.

Note: see the discussion in the section “Year of prices”.

Overnight capital cost (year-2012 dollars): long-run limit cost w.r.t. base cost

Our estimates of long-run costs relative to current costs are based on a review of the literature (Table S14 and other sources). We focus in particular on the long-run costs of wind and solar, because these are more uncertain.

PVs: Barbose et al. (2014a) show that PV capital costs in the US have declined rapidly in the last several years, and are expected to continue to decline. In the US there appears to be considerable opportunity to reduce system costs not related to the cost of the modules, as evidenced by the much lower system costs today in other developed countries (e.g., in Germany in 2014 residential systems cost \$2100/kW and commercial systems cost \$1900/kW, excluding taxes -- much lower than in the US). (See also Goodrich et al., 2012, 2013.)

For the residential and commercial PV markets, installed prices depend on the type of inverter (standard vs. micro-inverter) and the efficiency of the module (higher efficiency modules cost more) (Barbose et al., 2014), but we do not consider these differences here.

Wind: Capital costs have declined in recent years in part because of economies of scale from building larger projects and higher-capacity turbines (Barbose et al., 2014b).

Note: see the discussion in the section “Year of prices”.

Overnight capital cost (year-2012 dollars): decline rate towards limit

This is the continuous annual rate of approach to the long-run lower-limit cost from the base cost. We assume this is higher (i.e., that there are faster cost reductions) for technologies such as PVs for which there is significant potential for continued learning and relatively rapid cost reduction. In general we assume slower rates of decline in costs for conventional technologies than does the EIA (2014b) in its projections of the change in the levelized capital cost of generation technologies from 2019 to 2040.

Capital expenditure to extend life (% of overnight capital)

We assume that after at least 40 years of operating life, large coal, gas, and nuclear power plants either are allowed to age and retire or are refurbished for significant life extension (see e.g. EIA, 2010, 2014c; ICF Incorporated, 2013). We assume that operators will extend life only when it is economically advantageous, which we assume pertains to our low-cost (LCHB) (longest-potential-life) but **not** our high-cost (HCLB) case. Estimates of the expenditure for coal and nuclear are based on our judgment. Byrne (2013) indicates that capital costs to extend the life of wind turbines are a very small fraction of overnight capital costs.

Note that in principle we should have in internally consistent estimation of facility life, capital expenditure to extend life, initial capital cost, capacity factor, and O&M expenditure. Here we assume that if there is no capital expenditure to extend life, then O&M costs increase in the later years of the life of the facility.

Here we use ICF Incorporated (2013) estimates of the life extension cost as a percentage of new unit cost,

Coal steam	7.0%
Combined cycle	9.3%
Combustion turbine and internal-combustion engine	4.2%
Oil/gas steam	3.4%
IGCC	7.4%
Nuclear	9.0%

Timing of capital expenditure (% of facility life)

For most technologies, we assume that in the low-cost (LCHB), long-life case, the life-extension expenditure is made after about 65% of the ultimate *extended* life. For wind, we assume the expenditure is made after 60% of the ultimate extended life (Byrne, 2013). In the high-cost (HCLB), short-life case there is no life-extension expenditure, but the timing variable is relevant nevertheless because as discussed elsewhere it determines a break point between two rates of changes in O&M expenditures. We assume that this break point occurs at 70% of the life time in the HCLB case. The timing here is defined to be the time when the funds for the life-extension work are secured, which will be months and in some cases year before the life-extension work is completed.

Decommission/salvage cost (% of overnight capital)

This is the complete cost of decommissioning (scrapping) a power plant, as a fraction of its initial cost. Ideally the cost here is the total cost to return the site to the original condition, after any salvage value of material sold or left in place. Our estimates for nuclear and coal plants are based on site-specific cost estimates and other sources (Nuclear Regulatory Commission, 2013; Electric Power Research Institute, 2004; Nuclear Energy Agency, 2003). Our estimates for nuclear are consistent with World Nuclear Association's (2014) remark that decommissioning costs are 9-15% of initial capital cost. Our estimates of nuclear power-plant decommissioning cost are meant to include long-term waste disposal, but it is not clear if the estimates in the literature include this fully. For nuclear SMR, we scale decommissioning factor for APWRs by the APWR/SMR capital cost ratio. Our estimates for on-shore wind are based on Byrne (2013). Our estimates for solar are based on our consideration of the plant complexity, mass of materials, toxicity and hazardousness, recyclability, and salvageability. Note that in some cases the percentages are higher in the "low-cost" (LCHB) case because decommissioning costs tend to be constant rather than an actual percentage of the initial

cost, which means that if the initial cost is lower the decommissioning cost as a percentage is higher.

Build time (years)

Our estimates are based on a review of the literature (Table S14). For nuclear APWR we use estimates at the high end of the reported ranges because the construction time for nuclear power plants typically is substantially underestimated (Sovacool et al., 2014a). For nuclear SMR we assume significantly less time than for APWRs. We assume that future hydropower projects will be modest in size and hence not take up to a decade to build. We assume that CSP without storage takes 5% less time to build than does CSP with storage.

Facility life (years)

The facility life is the period of operation before the facility either is decommissioned or is so extensively rebuilt that it effectively is new construction. (Note that the facility life is not necessarily the same as the “cost recovery” period used in some financial analyses.) Our estimates are based partly on a review of the literature (Table S14) and partly on data on actual retirement ages, discussed below (Table S8).

Assumptions about the facility life must be consistent with assumptions regarding initial capital cost, capital expenditure to increase life, the capacity factor, and O&M expenditures. For example, the long lifetimes typically assumed for nuclear power presume major additional capital expenditures in mid-life, which we do account for here.

Similarly, Peltier (2011) analyzed a similar database of U.S. power plants and found that the capacity factor and energy efficiency of coal-fired plants decrease with the age of the units. He suggests that old, inefficient, infrequently used plants that are costly to upgrade are the most likely to be retired in the coming years. The EIA’s National Energy Modeling System (NEMS), used to produce its *Annual Energy Outlook*, has an “Electricity Capacity Planning” Submodule that will retire older fossil-fuel plants if the costs of continuing to run them (including expected capital / upgrade expenditures) is greater than the cost of building new capacity (EIA, 2014e).

The EIA’s Form 860 collects generator-specific data on capacity, power plant equipment, fuels used, date of operation, and planned and actual retirement dates (<http://www.eia.gov/electricity/data/eia860/>). Based on these data, an online “Today in Energy” brief from the EIA (<http://www.eia.gov/todayinenergy/detail.cfm?id=15031>) reports the following for retired coal-fired generating units:

	2010	2011	2012
total net summer capacity (MW)	1,418	2,456	10,214
number of units	29	31	85
average net summer capacity (MW)	49	79	123
average age at retirement	58	63	51
average tested heat rate (Btu/kWh)	11,094	10,638	10,353
capacity factor	36%	33%	35%

An earlier brief (<http://www.eia.gov/todayinenergy/detail.cfm?id=7290>) shows that units planned for retirement from 2012 to 2015 have an average age of about 56 years.

For this project we used the complete EIA-Form 860 database to calculate the capacity-weighted average actual or planned retirement age for plants using different fuels (Table S8).

Table S8. Summer-capacity-weighted average of retirement for generators using different energy sources (years)

Fuel or plant type	Plants retired 2001 to 2013			Planned for retirement 2014-		
	<i>All sectors</i>	<i>Electric Utility</i>	<i>IPP Non-CHP</i>	<i>All sectors</i>	<i>Electric Utility</i>	<i>IPP Non-CHP</i>
Nuclear	32.5	31.3	38.9	46.0	NA	46.0
Bituminous coal	51.5	52.9	49.7	53.2	53.8	53.6
Subbituminous coal	48.7	45.9	51.9	50.4	49.0	54.3
Lignite	52.8	NA	52.8	NA	NA	NA
Anthracite	NA	NA	NA	NA	NA	NA
Natural gas	41.8	48.7	39.2	49.7	53.8	46.3
Gas turbine	32.8	37.5	32.4	43.3	42.8	43.7
Distillate fuel oil	40.5	41.1	40.4	44.3	44.1	44.7
Residual fuel oil	46.9	44.2	51.6	47.2	59.6	42.0
Hydropower	62.4	57.5	79.7	53.2	53.4	30.2
Geothermal	17.3	NA	16.6	NA	NA	NA

Source: Data from EIA Form-860 (<http://www.eia.gov/electricity/data/eia860/>). IPP-Non-CHP = independent power producer, non-combined heat and power.

Our assumptions for the main BAU technologies (Table S13) are based in part on the results shown in Table S8. For nuclear SMR, we assume a slightly shorter life time than for APWRs. Our estimates for wind farms assume that longer-life wind farms have higher O&M costs and reduced availability (i.e., a lower capacity factor) (Byrne, 2013).

Capacity factors (national average): overview

The capacity factor is equal to [actual ac-electricity output to the grid over a year] divided by [potential energy output at maximum rated (“nameplate”) power for all 8760 hours in a year].

Actual output is less than maximum potential continuous output because of planned and un-planned outages and downtime, degradation of mechanical performance due to wear and tear, intentional idling or curtailing to meet system loads, and, in the case of solar or wind power, fluctuations in the primary energy inputs (wind speed and solar insolation) that result in the annual average input being less than the maximum potential.

Our objective here is to estimate the discounted lifetime average capacity factor for each technology, for the near-term base year and the BAU scenario and the 100% WWS scenario for the long-term target year. For most in-use technologies in the near-term base year, and for most technologies in the BAU scenario in the long-term target year, we start with the EIA’s (2014c, 2014f) AEO projections of fleet-average capacity factors. To estimate capacity factors in the 100% WWS scenario for the long-term target year, we start with estimates for the near-term base year, and then project future changes in four parameters that affect the capacity factor,

- degradation,
- resource availability (e.g., average wind speed or solar intensity),
- technological performance, and
- system operation to ensure balancing of supply and demand.

Note that the EIA estimates we start with are of the capacity factor of an in-use fleet, whereas we ultimately wish to estimate the discounted lifetime capacity factor for each technology. The two are not the same because the average age of the fleet is not necessarily the same as the effective average age of an individual technology over its life. Our method, therefore, is first to back out from the EIA’s fleet-average estimates what we assume are the effects of age-related degradation, to get the capacity factor for a brand-new fleet of a particular technology, and then to account for the effects of degradation over the entire life of the plant, with discounting (as discussed next), to arrive at our objective, the discounted lifetime average capacity factor.

As just mentioned, we estimate a *discounted* lifetime average capacity factor, in order to account for the effect, on the present worth of lifetime electricity generation, of changes in the capacity factor over time. For all technologies except wind we assume that the capacity factor changes over time due only to performance degradation; i.e., we assume that plant *availability*, already included in our estimates of the year-zero capacity factor, is constant over time, except in the case of wind power. For wind, we correct for the

difference between the present worth of the actual availability schedule (Byrne, 2013) and a constant availability schedule.

Capacity factor: fleet average capacity factors

The EIA's (2014c, 2014f) *AEO* projects national fleet-average capacity factors for all of the major generation technologies considered here. As mentioned above and shown below (Table S9), we use the EIA's estimates for our near-term, base-year case and for our target-year BAU scenario. In most cases, the EIA's *AEO* capacity factors are the same as, or very close to, the capacity factors we estimate for the year 2014 based on data reported for the first several months of 2014 (EIA, 2014d).

The EIA's *AEO* projects through the year 2040. We extend the projection to the year 2075 using a 10-year moving linear extrapolation, but with the resultant trend slope dampened by the 0.35 power. This prevents the capacity factor beyond 2040 from deviating much from the year-2040 value.

For any technologies not included in the EIA's *AEO*, our estimates are based on a review of the literature (Table S14). Capacity factors for solar vary greatly by solar or wind resource class; we have assumed national-average values typical for the year 2014.

Capacity factor: fleet average age (% of life)

This is the average age of the fleet to which the technology base year fleet-average capacity factor applies. We use this to back-out the effects of aging embedded in the fleet-average capacity factors, in order to obtain the capacity factors for new systems.

Capacity factor: annual degradation of capacity factor (base-year tech.) (+)

The degradation factor is meant to capture the effects of gradual, low-level, irreversible wear and tear as a system ages, resulting in, for example, increased mechanical friction, increased electrical resistance, and reduced combustion efficiency. This degradation factor does not incorporate loss of output due to planned or un-planned downtime for repairs and maintenance or the impacts of weather or other external conditions on output, effects that we include in the technology base-year capacity factors. The discounted lifetime degradation factor is calculated by taking the present worth of the actual series of degraded life-years and annualizing that into equal payments. The formula for a continuous annuity is discussed above. The present worth of degraded life-years is calculated as

$$DG_{PW} = -\frac{e^{-(d+r)L} - 1}{d + r}$$

where

DG_{PW} = the present worth of degraded life-years (years)

d = the annual rate of degradation of the capacity factor (discussed below)

r = the annual discount rate

L = the lifetime of the facility (years)

Staffell and Green (2014) cite studies that estimate or assume that conventional fossil-fuel technologies degrade at 0.2% to 0.7% per year. For wind assume that degradation is a minor component of the combined availability+degradation+turbine-death factor of 1.6%/year estimated by Staffell and Green (2014). Our assumptions for PV are based on the analysis in Jacobson et al. (2014) and Bolinger and Weaver's (2014) suggestion that 0.50%/year is a "standard" assumption.

Capacity factor: annual change in degradation rate (-)

We assume that over time the degradation factor decreases, at 0.1% per year for relatively mature technologies (all conventional generation) and 0.5% for year for relatively new technologies (e.g., wind and solar).

Capacity factor: resource availability long-run limit w.r.t. base (100% WWS scenario only) (<100%)

Resource availability refers to available energy from wind, solar, and water resources, with respect to the availability in the base year. Although one might expect that in general, at a national level, wind and solar would be developed in the best sites first, with the result that over time progressively worse sites would be developed leading to lower national-average capacity factors, this is not necessarily the case, because other forces are at work. Indeed, it appears that most high-wind and high-solar sites have yet to be developed. Bolinger and Weaver (2014) report that "the quality of the solar resource in which PV projects are being built in the United States has increased on average over time" (p. i), and Barbose et al. (2014b) state that "the United States still has an abundance of undeveloped high-quality wind resource areas" (p. 42).

These considerations suggest that effect on capacity factors of variation in solar intensity and wind speed over time is not well captured by a single national-average adjustment. Therefore, we account for the effect of variations in solar and wind resource availability at the state level (see discussion in a later subsection).

We do however assume that nationally most good hydropower sites already have been developed.

In the case of wind power, another factor affects the amount of energy available from wind resources in a target year with respect to the amount available in the base year. As the number of wind farms increases, the extraction of kinetic energy from the wind by the turbines decreases the average wind speeds, which in turn reduces the potential power output from the wind farms (Jacobson and Archer, 2012). We account for this at the state level (see discussion in a later subsection).

Table S9. Source of fleet-average capacity-factor estimates

Technology	Source of estimate of capacity factor
Advanced pulverized coal	EIA (2014f) Coal
Advanced pulverized coal w/CC	Assume same as “Advanced pulverized coal”
IGCC coal	EIA (2014f) IGCC without sequestration
IGCC coal w/CC	EIA (2014f) IGCC with sequestration
Gas combustion turbine	EIA (2014f) Combustion turbine/diesel
Combined cycle advanced	EIA (2014f) Combined cycle advanced without sequestration
Combined cycle conventional	EIA (2014f) Combined cycle conventional
Combined cycle advanced w/CC	EIA (2014f) Combined cycle advanced with sequestration
Diesel generator (for steam turbine)	EIA (2014f) Oil and natural gas steam
Nuclear, APWR	EIA (2014f) Nuclear power
Nuclear, SMR	Assume same “Nuclear APWR”
Fuel cell	EIA (2014f) Fuel Cells
Microturbine	Table S14
Distributed generation	EIA (2014c, 2014f) Distributed generation
Municipal solid waste	EIA (2014c) Municipal waste (electric power sector)
Biomass direct	EIA (2014c) Wood & other biomass (electric power sector) (because the EIA’s projections of capacity for the “wood and other biomass” category do not include plants that co-fire biomass and coal, we do not include generation from co-firing plants; i.e., we include generation from “dedicated plants” only)
Geothermal	EIA (2014c) Geothermal (electric power sector)
Hydropower	EIA (2014c) Conventional hydropower (electric power sector; we ignore hydro power in the “end-use” sector because it accounts for less than 1% of hydro generation)
On-shore wind	EIA (2014c) Wind
Off-shore wind	Table S14
CSP no storage	EIA (2014c) Solar thermal (electric power sector)
CSP w/ storage	Table S14
PV utility crystalline tracking	Table S14; literature review
PV utility crystalline fixed	EIA (2014c) Solar photovoltaic (electric power sector)
PV utility thin-film tracking	Table S14; literature review
PV utility thin-film fixed	EIA (2014c) Solar photovoltaic (electric power sector)
PV commercial rooftop	EIA (2014c) Solar photovoltaic (end-use sector)
PV residential rooftop	EIA (2014c) Solar photovoltaic (end-use sector)
Wave power	Table S14
Tidal power	Table S14
Solar thermal (water or glycol solution)	Table S14

Capacity factor: resource availability change rate (-)

See the discussion regarding the resource availability, above. We assume that the modest long-run lower limits of WWS resource availability are approached relatively modestly (Table S13).

Capacity factor: technology performance, long-run limit w.r.t. base (100% WWS scenario only) (>100%)

Technological performance refers to technological changes to WWS technologies that affect the capacity factor, holding resource availability and all other factors constant. Black and Veatch (2012) project that the capacity factor for class 3 onshore-wind resources increases from 32% in 2010 to 35% in 2050. Barbose et al. (2014b) report that rotor diameter, hub height, and swept area of wind turbines increased from 1999 to 2013. Bolinger and Weaver (2014) show that in recent years utility-scale PV projects have increased the "inverter loading ratio" (the ratio of array capacity to inverter capacity), with a resultant increase in capacity factor, although it does not seem that this trend can continue indefinitely. Our estimates (Table S13) are based on our judgment that the potential to increase the capacity factor for on-shore wind is greater than the potential to increase it for PVs.

Capacity factor: technology performance change rate (+)

See discussion of technological performance.

Capacity factor: multiplier to account for changes in system operation in the long-run (100% WWS scenario only) (<>100%)

This is a multiplier on the capacity factor that accounts for changes in the capacity factor in the long run in the 100% WWS scenario, with respect to the factor in the base year, due to changes in the operation of the entire electricity system for the purpose of matching supply with demand, holding constant the other determinants of the capacity factor (changes in degradation, resource availability, and technology). For example, one way to address the mismatch between the pattern of demand and the pattern of wind and solar power availability is to increase the installed capacity of wind and solar to minimize the greatest difference between demand and available wind and solar power. However, this increase in capacity will result in times in which the available wind and solar power exceeds demand. If it is not possible to shift demand or store the immediate "excess" generation, then the excess generation will be unused ("spilled"), which reduces the capacity factor.

Ideally the use of over-capacity, long-distance transmission, decentralized storage, and other means of matching supply and demand would be estimated jointly as part of an overall, comprehensive analysis of the least-cost methods of balancing supply and demand. Although we have not done such a comprehensive least-cost optimization analysis here, and have not formally modeled how selectively building over-capacity can help balance WWS supply with demand, we have estimated the cost of decentralized storage in a system that formally balances supply and demand (Jacobson et al., 2015). In the section "Transmission, distribution, storage, gap filling : other long-

term (2050) storage and related costs (100% WWS scenario only),” we estimate the amount of over-capacity (represented by a decrease in the capacity-factor multiplier) that increases the system-wide average delivered cost of electricity by the same amount as does the use of decentralized storage. In this section we briefly discuss considerations that affect the application of the capacity factor multiplier and the interpretation of the levels of over-capacity and excess generation that give the same cost increase as does decentralized storage.

Wind and solar power. For wind and solar systems, the capacity-factor multiplier represents the extent to which a system is built and operated to have "excess" or reserve renewable generation capacity, resulting in excess, unused ("spilled" or "curtailed") generation. Recent studies of the least-cost configuration of 100% renewable energy systems indicate that systems taking advantage of a relatively limited array of techniques to match supply and demand will spill 10% to 30% of total generation (Solomon et al., 2014; Rodriguez et al., 2014; Elliston et al., 2013). However, no study to date takes advantage of the full array of optimization techniques; for example, none consider aggressive demand management and decentralized storage. We therefore conclude that optimized systems taking advantage of the full array of balancing techniques will spill less than 30% of total generation from all sources (not just wind and solar), and perhaps substantially less.

In the case of wind and solar, it is most economical and practical to "overbuild" and curtail generation from technologies that are relatively inexpensive, relatively easy to control, relatively variable, and relatively abundant. We assume therefore that any overcapacity for the entire system is built into onshore wind and utility-scale solar PV plants. We do not assume any over-capacity for offshore wind because it is more expensive and less variable than is onshore wind, and we do not assume any over-capacity for rooftop PV because it is more expensive and more difficult to manage than is utility scale PV. We also assume that solar thermal with storage is not overbuilt on account of it having its own storage capacity.

With the cost estimates developed here (Table S13), it generally is less costly to build all of the over-capacity into onshore wind farms. Therefore, in the comparison, discussed below, of the cost of over-capacity with the cost of decentralized storage, we vary the capacity-factor multiplier for onshore wind.

Geothermal and hydropower. For geothermal and hydropower, which are less variable on short time scales than wind and solar, the capacity-factor multipliers in our analysis are slightly *greater* than 100% on account of these being used more steadily in a 100% WWS system than in the base year.

Capacity factor: long-run change rate (+)

For coal, oil, gas, nuclear, biomass, geothermal, and hydropower plants, we base our estimates on the rate of change in the capacity factor from 2014 to 2040, as estimated in the EIA's (2014f) *AEO 2014*. For wind and solar systems we use our judgment.

Capacity factor: final value

The maximum allowable capacity factor is 94%.

Variable and fixed operating and maintenance (O&M) costs (unadjusted average)

Most analyses distinguish “variable” from “fixed” O&M costs. Variable O&M costs generally are proportional to power output and hence typically are expressed in terms of cost per unit of generation (\$/kWh). Fixed O&M costs include periodic capital and other expenditures that generally are related to the capacity rather than the generation of the plant, and hence are expressed in \$/kW/year. We assume that fixed O&M costs do not include the cost of major refurbishment for the purpose of life extension, which we treat separately.

In this section we estimate “unadjusted average” costs, meaning that the estimates do not (yet) account for the effect on discounted present worth of the actual temporal variation in O&M costs, which we treat separately.

Our estimates of O&M costs are meant to include *all* the costs of operating and maintaining a power plant other than fuel costs and ongoing capital costs for the purpose of life extension. Thus, our estimates of O&M costs include administrative costs, insurance costs, plant overhead, and so on. However, O&M costs can be defined differently by different sources, and in some cases it is not clear what the reported estimates include.

Our estimates are based partly on a review of the literature (Table S14), and partly on actual O&M costs reported for electric utilities (Table S10). The actual reported costs are from the Federal Regulatory Energy Commission (FERC), which collects data on operating expenses of major investor-owned electric utilities in the U.S. (Table S10).

FERC Form 1 asks for operating expenses and maintenance expenses (separately) in 8 different categories (<http://www.ferc.gov/docs-filing/forms/form-1/form-1.pdf>),

- power production
- transmission
- regional market
- distribution
- customer accounts
- customer and service and informational
- sales
- administrative and general.

For nuclear SMR we assume the same O&M costs as for nuclear APWRs. We assume that CSP without storage has 90% of the fixed O&M cost of CSP with storage. For PVs, the fixed O&M cost here includes typical estimates of the cost of inverter replacement. However, as discussed under “capital costs,” we have estimated the annualized inverter cost separately. To avoid double counting, in the calculation of “periodic costs” we subtract from the input fixed O&M the fixed O&M charge implicit in our separately estimated inverter cost.

Table S10. Average reported power-plant operating expenses for major U.S. investor-owned electric utilities (year-2013 cents/kWh)

Year	Operation and maintenance				Fuel			
	<i>Nuclear</i>	<i>Fossil Steam</i>	<i>Hydro</i>	<i>Other</i>	<i>Nuclear</i>	<i>Fossil Steam</i>	<i>Hydro</i>	<i>Other</i>
2002	1.76	0.66	0.79	0.71	0.58	2.02	0.00	4.00
2003	1.77	0.67	0.71	0.71	0.57	2.13	0.00	5.40
2004	1.72	0.73	0.79	0.77	0.55	2.18	0.00	5.41
2005	1.57	0.72	0.78	0.65	0.54	2.52	0.00	6.44
2006	1.66	0.76	0.73	0.64	0.55	2.60	0.00	6.07
2007	1.68	0.77	1.02	0.62	0.55	2.62	0.00	6.44
2008	1.73	0.79	1.04	0.70	0.57	3.06	0.00	6.91
2009	1.74	0.87	0.89	0.60	0.57	3.45	0.00	5.54
2010	1.82	0.85	0.96	0.58	0.70	2.92	0.00	4.56
2011	1.83	0.83	0.92	0.59	0.72	2.80	0.00	4.01
2012	1.87	0.78	1.15	0.53	0.72	2.45	0.00	3.09
Average 2002-2012	1.74	0.77	0.89	0.65	0.60	2.61	0.00	5.26
Average 2008-2012	1.80	0.82	0.99	0.60	0.66	2.94	0.00	4.82

Source: Federal Energy Regulatory Commission, FERC Form 1, "Annual Report of Major Electric Utilities," as reported by the EIA for its *Electric Power Annual* (http://www.eia.gov/electricity/annual/html/epa_08_04.html). "Other" includes gas turbines, internal combustion engines, photovoltaics, and wind plants. FERC.

Annual rate of change in O&M costs (+/-)

We estimate two rates of change in O&M costs: one up to the L^* , which is the point at which any life-extension investment would occur, and one after L^* until the end of the facility life L . We take the present worth of the actual O&M stream, given the assumed rates of change, annualize the present worth, and divide the resultant annualized (discounted) cost by the present worth calculated with a zero discount rate. This ratio of the discounted to the undiscounted O&M stream then is multiplied by the unadjusted average O&M cost input. Note that we calculate the undiscounted present worth through a period of time between L^* and L because we assume that the average (undiscounted) cost estimates in the literature generally do not pertain to the entire life of a facility *after* life-extension measures.

We assume that the FERC Form 1 results shown in Table S10 include O&M expenses for the first category, “power production.” As shown on Form 1, the “power production” category includes supervision, engineering, rents, allowances, and miscellaneous, but not insurance, taxes, and general administration, which are included in the category “administrative and general.” It is not clear whether the results of Table S10 include any of these administrative and general expenses. If they do not, then they slightly underestimate O&M expenses as we define them.

In any event, the data in Table S10 are broadly similar to the estimates in the literature (Table S14), except that the Table S10 data for nuclear O&M costs are slightly higher than the estimates in Table S14. Our assumptions result in costs close to those reported in Table S10.

Data in Byrne (2013) and Barbose et al. (2014b) indicate that for wind, fixed O&M expenses are not constant but increase over the life of the project (6%/year according to Byrne et al., 2013). The EIA (1995) and the Nuclear Energy Institute (2014) show that O&M costs for nuclear power plants increase with age (2.5%/year according to the Nuclear Energy Institute, 2014). For other technologies our assumptions are based on our assessment of the technology. We assume that if the plant is refurbished and its life is extended, then O&M costs stop increasing, but that otherwise, they increase at a 10% to 40% higher rate than prior to L^* , depending on the technology.

Fuel cost: (national average): background

Throughout this cost analysis we wish to estimate the true economic cost, which is the area under the long-run supply curve. The per-unit economic cost (e.g., the cost of fuel in \$ per unit of energy) is equal to the area under this supply curve over some region of quantity divided by the quantity. This can be interpreted as the average long-run economic cost per unit.

This *average* long-run economic cost per unit generally is not the same as the *price*, which in a competitive market is based on the *marginal* cost. With supply curve rising due to increasing scarcity of labor and material inputs, the marginal cost and hence the price will be higher than the average cost. The difference between the price and the average cost is producer surplus (PS), which is *not* an economic cost but rather is a transfer of wealth from consumers to producers. In sectors of the economy that are non-competitive or have sharply rising cost curves – such as the oil industry – PS can be quite large.

Given this, there are in general two ways to estimate the economic cost of fuels, exclusive of PS: 1) build up an estimate of average cost from capital costs, feedstock costs, labor costs, and so on, or 2) start with known prices and subtract the portion that represents PS, which as just explained is the non-cost (pure transfer) component of price. For new, developing systems for which there are not good data on the price of the mature technologies, we must use method #1. However, for mature fuels, such as are considered here, it is easier to use method #2, which is to start with the price

and subtract an estimate of PS. This is what we do for coal, natural gas, oil, nuclear fuel, and biomass used by power plants.

As mentioned above, here we estimate national-average costs. In the next main section we estimate state or region-specific cost adjustments.

Fuel cost (year-2012 dollars): Starting estimates of fuel prices

The EIA (2014c) projects \$/million-BTU prices of coal, natural gas, distillate fuel, residual fuel oil, nuclear fuel, and biomass, to the electricity-generating sector, through the year 2040. (The values for nuclear fuel and biomass are not published but are available from the EIA on request.) We adopt their reference-case projections for the U.S. through the year 2040 and extend them to 2075 using a moving 10-year linear extrapolation. For our base-year analysis we use these EIA estimates as is; i.e., we have a single value, not a different “low” and “high” estimate. However for our target-year analysis we do estimate “low” and “high” values; we assume that the low-cost value is 10% below the (extended) EIA projection and that the high-cost value is 10% above.

We assume that microturbines and fuel cells use natural gas.

Fuel cost (year-2012 dollars): deducting producer surplus

Producer surplus in the oil industry can be substantial because oil is a worldwide commodity and a handful of countries own very low-cost reserves, resulting in a non-competitive global market with much of the supply curve far below the prevailing oil price. This is not the case for other fuels because most suppliers to a given national or regional market have access to resources of similar cost. Given this, we assume the following PS fractions of the prices estimated above:

Fuel	LCHB	HCLB	References and notes
Coal	0.06	0.04	Low because of competitive access to low-cost resources
Natural gas	0.10	0.06	Slightly higher than for coal because of presumably steeper supply curve
Oil	0.60	0.50	Based on Delucchi et al. (2015) estimates of the PS for gasoline made from U.S. crude oil given a 50%-100% reduction in fuel use.
Nuclear	0.06	0.04	Low because of competitive access to low-cost resources
Biomass	0.06	0.04	Low because of competitive access to low-cost resources

Combustion efficiency: technology base year, 2013

Our estimates are based on a review of the literature (Table S14 and other sources).

Combustion efficiency: long-run limit

Our estimates are based on a review of the literature (Table S14 and other sources).

Combustion efficiency: annual change rate (+)

Our assumptions.

Transmission, distribution, storage, gap filling: cost of the T&D system in the near-term base year and for the BAU in the target year

The EIA's (2014c) *AEO* projects the real (constant-dollar) cost of the U.S. transmission and distribution (T&D) system through the year 2040. We extend this projection to the year 2075 using a 10-year moving linear extrapolation. For our estimates of the cost of delivered electricity in (i) the near-term base year, and (ii) the long-term target year in the BAU scenario, we use the EIA's *AEO* estimates of the T&D cost, without any adjustments. For our estimates of the cost of delivered electricity in the long-term target year in the 100% WWS scenario, we start with the EIA's *AEO* cost projections and then incorporate the costs of modifications to the T&D system due to more decentralized generation and additional supply-and-demand balancing measures in the 100% WWS scenario. These modifications are discussed in the following subsections.

Transmission, distribution, storage, gap filling: % of plants distributed or on-site, long-run limit (100% WWS scenario only)

The 100% WWS scenario has more distributed and on-site generation than does the BAU scenario. Distributed and on-site generator plants do not require the use of the baseline (BAU) long-distance transmission system and may not require the same distribution system as in the BAU. Thus, as a 100% WWS system develops it will require less expansion of the transmission system, and possibly less expansion of the distribution system, than in the BAU scenario (IREC, 2014; Electricity Innovation Lab, 2013; Beach and McGuire, 2013). In addition, Repo et al. (2006) argue that distributed generation systems can reduce the energy-related and power-related variable costs of transmission and distribution systems.

To estimate the cost impacts of these potential changes in usage of the transmission or distribution system, we start with EIA (2014c) *AEO* reference-case projections of the costs of electricity transmission and distribution over time. We assume that these annualized costs are a function of the lifetime and the capacity of the transmission or distribution system. We make assumptions about how distributed and on-site systems change the throughput and capacity of transmission and distribution systems, and posit simple relationships between throughput and lifetime, and between capacity and cost, in the long-run limit. The estimated cost changes are relatively minor.

Transmission, distribution, storage, gap filling: change rate (+)

See discussion above. This refers to the rate of approach of the long-run limit of distributed-generation and on-site generation shares.

Transmission, distribution, storage, gap filling : additional long-term (2050) transmission costs (100% WWS scenario only)

These are costs for an upgraded, expanded, long-distance high-voltage DC transmission system that are i) not included in our estimates of capital costs for generation technologies, and ii) in addition to the cost of the baseline transmission system (the BAU system adjusted for increased distributed and on-site generation in the 100% WWS scenario). Given that most capital-cost estimates include all connections to the existing transmission and distribution network, the additional costs here generally comprise expansions to the transmission system for the purpose of integrating diverse sources of renewable energy. We assume that in the 100% WWS scenario, all WWS technologies are part of an integrated, balanced renewable energy system with an expanded transmission grid, and therefore we spread out the "additional (land-based) transmission" cost over *all* WWS generators in the 100% WWS scenario.

We calculate this additional transmission cost using Delucchi and Jacobson's (2011) detailed method, with new inputs as follows:

1) We distinguish between an expanded onshore land-based grid, the cost of which is assigned to all WWS generators including offshore wind, and an expanded offshore grid, the cost of which is assigned to offshore wind only. The expanded offshore grid here is sea-based transmission *in addition* to the generic windfarm-to-shore connections that already are included in our estimates of the capital cost of offshore wind farms.

We assign the cost of the additional long-distance onshore grid to all generators in the 100% WWS scenario, including on-site generators such as solar PV that do not transmit to the grid, because the long-distance grid, like system storage, in principle is part of a system-side supply-and-demand balancing that depends on the generation characteristics of all technologies.

2) Additional long-distance transmission costs apply only to the 100% WWS scenario in the long-term, target-year analysis, because there are no such additional costs in the near-term, base-year analysis.

3) The average length of additional transmission for the portion of the energy system that effectively sends all of its output through the new transmission is 750 to 1000 miles for onshore systems and 50 to 100 miles for offshore wind systems.

4) We assume that 30% to 45% of total WWS generation (all generators except offshore wind) is sent through the new onshore long-distance grid and that 15% to 25% of offshore wind generation is sent through the extended-transmission offshore grid.

Note that assumptions 3) and 4) are not the result of a comprehensive analysis of the least-cost combination of storage, long-distance transmission, and over-capacity in a 100% WWS system but rather represent our judgment of what is likely to be needed in a 100% WWS system.

5) The year-round average current capacity factor, as a fraction of the rated capacity, originally used to estimate transmission losses, now is used also as the overall energy (or power) capacity factor for calculating the transmission-system cost. (Given a constant voltage, the ratio of transmitted amp-hours to maximum amp-hours is the same as the ratio of transmitted energy to maximum energy.) The overall capacity factor for the transmission system depends on the capacity of the transmission system relative to the capacity of the connected generation centers, the extent to which individual generation centers have complementary generation profiles, and other factors, but it will be at least as great as the capacity factor for individual wind farms. We assume 35% to 45% for the onshore system, and 40% to 50% for the offshore system.

6) We estimate the cost per kWh delivered out of the transmission system into the distribution system, accounting for losses during transmission but not during distribution. (We assume that losses in distribution are accounted for in the estimates of the \$/kWh figures we use for distribution-system costs.)

Transmission, distribution, storage, gap filling : other long-term (2050) storage and related costs (100% WWS scenario only)

In the 100% WWS scenario, additional options for balancing supply and demand (beyond using an expanded long-distance transmission grid) include demand response, supply prediction, use of gas-fired back-up, energy storage, and over-building generation capacity (Jacobson and Delucchi, 2011). We assume that demand response and supply prediction cost very little, and that gas-fired back up will almost never be needed (e.g., Hart and Jacobson, 2011). Therefore, at this point in our analysis, we consider the cost of decentralized energy storage and the cost of over-building generation capacity.

We estimate the cost of several energy-storage options, including vehicle-to-grid (V2G), underground thermal-energy storage (UTES), pumped-hydro storage (PHS), sensible-heat thermal-energy storage (STES), and phase-change materials (PCM). For V2G, we update the calculations of the battery-degradation cost in Delucchi and Jacobson (2011), and estimate that cycling 10% to 15% of all delivered power through V2G would cost \$0.003 to \$0.006 (0.3 to 0.6 cents) per all-kWh delivered.

Our estimates of the costs of the other decentralized energy-storage options are from Jacobson et al. (2015), who develop cost estimates as part of a grid-integration model of a 100% WWS energy system for the U. S. In Jacobson et al. (2015), the storage systems are sized so that the entire set of storage technologies ensures that the grid matches WWS supply with all-sector end-use demand with zero loss of load over six years of simulation. Table S11 shows the estimated \$/kWh cost for each option, equal to the annualized capital cost plus O&M cost divided by total energy delivered for load.

Following Jacobson et al. (2015), we assume that energy-storage costs of Table S11 – 0.05 to 0.70 cents per all-kWh delivered – apply to the entire WWS system, and hence to every individual generating technology in the system, in the 100% WWS scenario.

How do the results of Table S11 compare with the approach of over-building generating capacity (and spilling unused generation) in order to balance supply and demand? Because we have not done a formal analysis of the amount of over-capacity needed to balance and demand, we answer this question by evaluating the level of over-capacity, represented by a reduction in the capacity factor and an increase in spillage, at which the resultant system-wide average costs equal the system-wide average costs in the case in which storage is used to balance supply and demand (Table S11). The cost of over-capacity is the increase in the annualized initial cost of generation due to the decrease in the capacity factor. We estimate this extra cost by reducing the capacity-factor multiplier for onshore wind and calculating the increased cost of wind power’s share of the WWS generation mix, using the generator costs of Table S13 and the generation shares by generator discussed earlier.

Table S11. Annualized cost of electricity storage technologies

Storage technology	Capital cost of storage beyond power generation (\$/maximum-deliverable-kWh-th)		Assumed energy storage capacity (maximum-deliverable TWh)	Operations and maintenance cost (% of capital cost per year)		Lifetime (years)		Annualized capital cost plus O&M cost (cents/all-kWh-delivered)	
	Low	High		Low	High	Low	High	LCHB	HCLB
Non-UTES									
PHS	12.00	16.00	0.808	1.0%	2.0%	35.0	25.0	0.003	0.008
STES	0.13	12.90	0.350	1.0%	2.0%	35.0	25.0	0.000	0.003
PCM-ice	12.90	64.50	0.525	1.0%	2.0%	35.0	25.0	0.002	0.020
PCM-CSP	10.00	20.00	11.60	1.0%	2.0%	35.0	25.0	0.037	0.136
Total/average	9.98	21.33	13.29					0.04	0.17
UTES	0.07	1.71	5.28	1.0%	2.0%	35.0	25.0	0.01	0.53
All storage	10.05	23.04	541.6					0.05	0.70

Source: Based on Jacobson et al. (2015).

UTES = Underground thermal energy storage. PHS = pumped hydro storage; STES = Sensible heat thermal energy storage; PCM = Phase-change materials; CSP=concentrated solar power. All storage is for 14 hours except UTES. CSP costs exclude the additional mirrors, which are included in the cost of a CSP plant with storage. UTES costs exclude the cost of the solar collectors, which are tracked separately.

Table S12 shows the wind capacity-factor multiplier and associated system-wide spillage (without any storage) that results in the same average overall system cost of

delivered electricity as in the case of using the storage-cost estimates of Table S11 with zero over-capacity and storage.

Table S12. Levels of over-capacity and spillage that result in the same system costs as does using decentralized storage

LCHB		HCLB	
Wind CF multiplier	System-wide spill	Wind CF multiplier	System-wide spill
90%	3.5%	57%	23.4%

The “Wind CF multiplier” applies to onshore wind only. The “system-wide spill” is equal to the amount of unused generation (due to excess capacity) divided by total delivered electricity for load.

Because system costs increase with decreasing CF multipliers and increasing spillage, the results in Table S12 indicate that in the LCHB case, decentralized energy storage is less costly than is over-capacity for any on-shore wind CF multiplier below and 90% and spillage above 3.5%. In the HCLB case, storage is less costly than is over-capacity for any CF multiplier below 57% and spillage above 23%.

As discussed earlier, analyses that explore a limited range of options for balancing supply and demand in an all-renewables energy system indicate that up to 30% of generation would end up being spilled. This means that it almost certainly will be impossible to balance supply and demand with only 3.5% spillage, but that it might well be possible to balance supply and demand with 23% spillage. Thus, in the LCHB case, decentralized storage that balances supply and demand almost certainly will be less costly than over-capacity that balances supply and demand. In the HCLB case, - capacity might be able to balance supply and demand at a cost similar to or even slightly lower than the cost of decentralized storage.

With these considerations, we assume, somewhat conservatively, that the cost of extra measures needed to balance supply and demand is given by the range of costs of decentralized storage estimated in Table S11. This is conservative because of the possibility that judicious use of over-capacity could result in lower total system costs, and because the grid-integration analysis that produced the results in Table S11 was itself not a least-cost optimization analysis.

Table S13. Cost and performance assumptions for electricity generating technologies

See accompanying spreadsheet (Delucchi et al., 2015).

Table S14. Tabulation of main literature used in our analysis of the LCEO

	Capital cost, near-term or high-cost case (2013-\$/kW)				
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Year of dollars in source ->	2012	2014	2009	2012	2013
GDP price deflator multiplier ->	1.015	0.984	1.067	1.015	1.000
Advanced pulv. coal	2969		3085		
Advanced pulv. coal w/CC		6687	7002		
IGCC coal	3827		4280		
IGCC coal w/CC	6665	6286	7044		
Gas peaking (turbine)	683	984	695		
Gas combined cycle	1036	1155	1313		
Diesel generator		787			
Nuclear, APWR	5583	6640	6511		
Nuclear, SMR					9000
Geothermal	2531	6529	6340		
Microturbine		3738			
Biomass direct	3977	3440	4088		
Hydropower	2471		3736		
On-shore wind	2238	1771	2113		1750
Off-shore wind	6284	5410	3533		
Fuel cell	7149	7378			
Solar thermal (CSP) without storage	5120				4000-4500
Solar thermal (CSP) with storage		6148	7535		6000-8500
PV utility crystalline tracking	3617	1722	2796		3200
PV utility crystalline fixed		1476	2708		L:1690 H:3000
PV utility thin film tracking	3617	1722			2700
PV utility thin film fixed		1476			2700
PV commercial rooftop		2951	5113		L:2390 H:3500
PV residential rooftop		4427	6351		L:3740 H:4500
Wave power			9965		
Tidal power			6340		

Capital cost, long-term or low-cost case (2013-\$/kW)						
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others	
Technology						
Advanced pulv. coal	2573	2472	3085			
Advanced pulv. coal w/CC			6020			
IGCC coal	3158	3204	4280			
IGCC coal w/CC	5261		7044			
Gas peaking (turbine)	545	787	695			
Gas combined cycle	858	884	1313			
Diesel generator		492				
Nuclear, APWR	4434	4279	6511			L:3800 H:6500
Nuclear, SMR						6000
Geothermal	3227	3956	6340			
Microturbine		2263				
Biomass direct	3340	2579	4088			
Hydropower	2444		3736			
On-shore wind	1976	1377	2113			
Off-shore wind	5077	3050	3191			
Fuel cell		3738				
Solar thermal (CSP) without storage	4101					
Solar thermal (CSP) with storage		8608	5016			3500-6000
PV utility crystalline tracking	3011		2167			1950
PV utility crystalline fixed			1814			1750
PV utility thin film tracking	3011					
PV utility thin film fixed						
PV commercial rooftop		2459	2796			1900
PV residential rooftop		3443	3127			2100
Wave power			2738			
Tidal power			1595			

Fixed O&M, near-term or high-cost case (2013-\$/kW/yr)					
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology					
Advanced pulv. coal	31.6		24.5		
Advanced pulv. coal w/CC		78.7	37.6		
IGCC coal	52.2		33.2		
IGCC coal w/CC	73.9	71.8	47.4		
Gas peaking (turbine)	7.1	24.6	5.6		
Gas combined cycle	15.6	5.4	6.7		
Diesel generator		14.8			
Nuclear, APWR	94.7	113.1	135.6		
Nuclear, SMR					
Geothermal	114.6	0.0	0.0		
Microturbine		0.0			
Biomass direct	107.2	93.5	101.4		
Hydropower	15.1		16.0		
On-shore wind	40.1	39.3	64.0		28.0
Off-shore wind	75.1	98.4	106.7		
Fuel cell	0.0	0.0			
Solar thermal (CSP) without storage	68.3				60
Solar thermal (CSP) with storage		78.7	53.4		60-70
PV utility crystalline tracking	25.1	19.7	51.2		30.0
PV utility crystalline fixed		12.8	51.2		25.0
PV utility thin film tracking	25.1	19.7			30.0
PV utility thin film fixed		12.8			25.0
PV commercial rooftop		19.7	53.4		
PV residential rooftop		29.5	53.4		
Wave power			505.9		
Tidal power			211.3		

Fixed O&M, long-term or low-cost case (2013-\$/kW/yr)					
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology					
Advanced pulv. coal	31.6	39.3	24.5		
Advanced pulv. coal w/CC			37.6		
IGCC coal	52.2	61.2	33.2		
IGCC coal w/CC	73.2		47.4		
Gas peaking (turbine)	7.1	4.9	5.6		
Gas combined cycle	15.6	6.1	6.7		
Diesel generator		15.0			
Nuclear, APWR	94.7	93.5	135.6		
Nuclear, SMR					
Geothermal	215.1	0.0	0.0		
Microturbine		0.0			
Biomass direct	107.2	93.5	101.4		
Hydropower	16.5		16.0		
On-shore wind	41.1	34.4	64.0		
Off-shore wind	75.1	59.0	106.7		
Fuel cell		0.0			
Solar thermal (CSP) without storage	68.3				
Solar thermal (CSP) with storage		113.1	53.4		40-50
PV utility crystalline tracking		19.7	35.2		
PV utility crystalline fixed			35.2		
PV utility thin film tracking		19.7			
PV utility thin film fixed					
PV commercial rooftop		12.8	35.2		
PV residential rooftop		24.6	35.2		
Wave power			138.8		
Tidal power			54.4		

Variable O&M, near-term or high-cost case (2013-\$/MWh)						
	Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology						
Advanced pulv. coal		4.5		4.0		
Advanced pulv. coal w/CC			4.9	6.4		
IGCC coal		7.3		7.0		
IGCC coal w/CC		8.6	8.4	11.3		
Gas peaking (turbine)		10.5	7.4	31.9		
Gas combined cycle		3.3	2.0	3.9		
Diesel generator			0.0			
Nuclear, APWR		2.2	0.8	n.r.		
Nuclear, SMR						
Geothermal		0.0	39.3	33.1		
Microturbine			21.6			
Biomass direct		5.3	14.8	16.0		
Hydropower		2.7		6.4		
On-shore wind		0.0	0.0	0.0		
Off-shore wind		0.0	17.7	0.0		
Fuel cell		43.6	49.2			
Solar thermal (CSP) without storage		0.0				
Solar thermal (CSP) with storage			0.0	0.0		
PV utility crystalline tracking		0.0	0.0	0.0		
PV utility crystalline fixed			0.0	0.0		
PV utility thin film tracking		0.0	0.0			
PV utility thin film fixed			0.0			
PV commercial rooftop		0.0	0.0	0.0		
PV residential rooftop			0.0	0.0		
Wave power			0.0	n.r.		
Tidal power			0.0	n.r.		

Variable O&M, long-term or low-cost case (2013-\$/MWh)						
	Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology						
Advanced pulv. coal			2.0	4.0		
Advanced pulv. coal w/CC				6.4		
IGCC coal			6.9	7.0		
IGCC coal w/CC				11.3		
Gas peaking (turbine)			4.6	31.9		
Gas combined cycle			3.4	3.9		
Diesel generator			0.0			
Nuclear, APWR			0.3	n.r.		
Nuclear, SMR						
Geothermal			29.5	33.1		
Microturbine			17.7			
Biomass direct			14.8	16.0		
Hydropower				6.4		
On-shore wind			0.0	0.0		
Off-shore wind			12.8	0.0		
Fuel cell			29.5			
Solar thermal (CSP) without storage	0.0					
Solar thermal (CSP) with storage			0.0	0.0		
PV utility crystalline tracking				0.0		
PV utility crystalline fixed				0.0		
PV utility thin film tracking						
PV utility thin film fixed						
PV commercial rooftop			0.0	0.0		
PV residential rooftop			0.0	0.0		
Wave power				n.r.		
Tidal power				n.r.		

Fuel cost, near-term or high-cost case (2013-\$/MBTU)						
	Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology						
Advanced pulv. coal		2.63		n.r.		
Advanced pulv. coal w/CC			1.96	n.r.		
IGCC coal		2.63		n.r.		
IGCC coal w/CC		2.63	1.96	n.r.		
Gas peaking (turbine)		5.26	4.43	n.r.		
Gas combined cycle		5.26	4.43	n.r.		
Diesel generator			28.29			
Nuclear, APWR		n.r.	0.69	n.r.		
Nuclear, SMR						
Geothermal		0.00	0.00	0.00		
Microturbine			4.43			
Biomass direct		n.r.	1.97	n.r.		
Hydropower		0.00		0.00		
On-shore wind		0.00	0.00	0.00		
Off-shore wind		0.00	0.00	0.00		
Fuel cell		n.r.	4.43			
Solar thermal (CSP) without storage		0.00				
Solar thermal (CSP) with storage			0.00	0.00		
PV utility crystalline tracking		0.00	0.00	0.00		
PV utility crystalline fixed			0.00	0.00		
PV utility thin film tracking		0.00	0.00			
PV utility thin film fixed			0.00			
PV commercial rooftop			0.00	0.00		
PV residential rooftop			0.00	0.00		
Wave power				0.00		
Tidal power				0.00		

Fuel cost, long-term or low-cost case (2013-\$/MBTU)						
	Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology						
Advanced pulv. coal		3.53	1.96	n.r.		
Advanced pulv. coal w/CC				n.r.		
IGCC coal		3.53	1.96	n.r.		
IGCC coal w/CC		3.53		n.r.		
Gas peaking (turbine)		10.40	4.43	n.r.		
Gas combined cycle		10.40	4.43	n.r.		
Diesel generator			28.29			
Nuclear, APWR		n.r.	0.69	n.r.		
Nuclear, SMR						
Geothermal		0.00	0.00	0.00		
Microturbine			4.43			
Biomass direct		n.r.	0.98	n.r.		
Hydropower		0.00		0.00		
On-shore wind		0.00	0.00	106.73		
Off-shore wind		0.00	0.00	106.73		
Fuel cell		n.r.	4.43			
Solar thermal (CSP) without storage		0.00				
Solar thermal (CSP) with storage			0.00	0.00		
PV utility crystalline tracking		0.00	0.00	0.00		
PV utility crystalline fixed			0.00	0.00		
PV utility thin film tracking		0.00	0.00			
PV utility thin film fixed			0.00			
PV commercial rooftop			0.00	0.00		
PV residential rooftop			0.00	0.00		
Wave power				0.00		
Tidal power				0.00		

Capacity factor, near-term or high-cost case (%)					
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology					
Advanced pulv. coal	85%		84%		
Advanced pulv. coal w/CC		93%	84%	95%	
IGCC coal	85%		80%		
IGCC coal w/CC	85%	75%	80%	89%	
Gas peaking (turbine)	30%	10%	92%	94%	
Gas combined cycle	87%	40%	90%	92%	
Diesel generator		30%			
Nuclear, APWR	90%	90%	90%	89%	80%
Nuclear, SMR					
Geothermal	92%	80%	97%		
Microturbine		95%			
Biomass direct	83%	85%	83%	65%	
Hydropower	53%		93%		
On-shore wind	35%	30%	32% to 46%	28%	20% to 50%
Off-shore wind	37%	37%	36% to 50%	38%	
Fuel cell	n.r.	95%			
Solar thermal (CSP) without storage	20%				20% to 28%
Solar thermal (CSP) with storage		52%	n.r.		40% to 50%
PV utility crystalline tracking	25%	30%	n.r.	11%	20% to 32%
PV utility crystalline fixed		21%	n.r.		18% to 30%
PV utility thin film tracking	25%	30%			33%
PV utility thin film fixed		21%			16% to 31%
PV commercial rooftop		20%	n.r.		
PV residential rooftop		20%	n.r.		
Wave power			25%		
Tidal power			28%		

Capacity factor, long-term or low-cost case (%)					
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology					
Advanced pulv. coal	85%	93%	84%		
Advanced pulv. coal w/CC			84%	97%	
IGCC coal	85%	75%	80%		
IGCC coal w/CC	85%		80%	91%	
Gas peaking (turbine)	30%	10%	92%	96%	
Gas combined cycle	87%	70%	90%	94%	
Diesel generator		95%			
Nuclear, APWR	90%	90%	90%	92%	90%
Nuclear, SMR					
Geothermal	94%	90%	97%		
Microturbine		95%			
Biomass direct	83%	85%	83%		
Hydropower	51%		93%		
On-shore wind	34%	52%	35% to 46%		
Off-shore wind	37%	43%	38% to 50%		
Fuel cell	n.r.	95%			
Solar thermal (CSP) without storage	20%				
Solar thermal (CSP) with storage		80%	n.r.		66%
PV utility crystalline tracking	25%		n.r.		
PV utility crystalline fixed			n.r.		
PV utility thin film tracking	25%				
PV utility thin film fixed					
PV commercial rooftop		23%	n.r.		
PV residential rooftop		23%	n.r.		
Wave power			20%		
Tidal power			22%		

Construction time, near-term or high-cost case (years)						
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others	
Technology						
Advanced pulv. coal	4.0		4.6		4.8, 6.0	
Advanced pulv. coal w/CC		5.5	5.5	5.0		
IGCC coal	4.0		4.8		6.0	
IGCC coal w/CC	4.0	5.3	4.9	6.0	6.0	
Gas peaking (turbine)	2.0	2.1	2.5	2.0	3.0	
Gas combined cycle	3.0	3.0	3.4	3.0	3.0	
Diesel generator		0.3				
Nuclear, APWR	6.0	5.8	5.0	8.0	7.5, 6.0	
Nuclear, SMR						
Geothermal	4.0	3.0	3.0		4.0	
Microturbine		0.3				
Biomass direct	4.0	3.0	3.0	1.0	4.0	
Hydropower	4.0		2.0		10.0, 3.0	
On-shore wind	3.0	1.0	1.0	2.0	1.0, 3.0	
Off-shore wind	4.0	1.0	1.0	3.0		
Fuel cell	3.0	0.3				
Solar thermal (CSP) without storage	3.0				3.0	
Solar thermal (CSP) with storage		2.5	2.0			
PV utility crystalline tracking	2.0	1.0	1.1	1.0	2.2, 3.0	
PV utility crystalline fixed		1.0	1.4		3.0	
PV utility thin film tracking	2.0	1.0			3.0	
PV utility thin film fixed		1.0			3.0	
PV commercial rooftop		0.3	0.5			
PV residential rooftop		0.3	0.2			
Wave power			2.0			
Tidal power			2.0			

Construction time, long-term or low-cost case (years)						
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others	
Technology						
Advanced pulv. coal		5.0	4.6			
Advanced pulv. coal w/CC				5.5	4.0	
IGCC coal		4.8	4.8			
IGCC coal w/CC				4.9	4.5	
Gas peaking (turbine)		2.1	2.5	1.5		
Gas combined cycle		3.0	3.4	2.0		
Diesel generator		0.3				
Nuclear, APWR		5.8	5.0	5.0	5.0	5.0
Nuclear, SMR						
Geothermal		3.0	3.0			
Microturbine		0.3				
Biomass direct		3.0	3.0			
Hydropower				2.0		
On-shore wind		1.0	1.0			
Off-shore wind		1.0	1.0			
Fuel cell		0.3				
Solar thermal (CSP) without storage						
Solar thermal (CSP) with storage		2.5	2.0			
PV utility crystalline tracking				0.8		
PV utility crystalline fixed				1.0		
PV utility thin film tracking						
PV utility thin film fixed						
PV commercial rooftop		0.3	0.3			
PV residential rooftop		0.3	0.1			
Wave power				2.0		
Tidal power				2.0		

Plant operating life, near-term or high-cost case (years)						
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others	
Technology						
Advanced pulv. coal	40		n.r.			65-75
Advanced pulv. coal w/CC		40	n.r.	20		65-75
IGCC coal	40		n.r.			65-75
IGCC coal w/CC	40	40	n.r.	20		65-75
Gas peaking (turbine)	30	20	n.r.	20		
Gas combined cycle	30	20	n.r.	20		55
Diesel generator		20				
Nuclear, APWR	60+	40	n.r.	60		60-80
Nuclear, SMR						
Geothermal	40	20	n.r.			
Microturbine		20				
Biomass direct		20	n.r.	22		
Hydropower	80		60			
On-shore wind	25	20	n.r.	24		
Off-shore wind	25	20	n.r.	23		
Fuel cell		20				
Solar thermal (CSP) without storage						
Solar thermal (CSP) with storage		40	n.r.			
PV utility crystalline tracking	25	20	n.r.	25		40
PV utility crystalline fixed		20	n.r.			
PV utility thin film tracking	25	20				40
PV utility thin film fixed		20				
PV commercial rooftop		20	n.r.			38
PV residential rooftop		20	n.r.			36
Wave power	20		20			
Tidal power	20		25			

Plant operating life, long-term or low-cost case (years)						
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others	
Technology						
Advanced pulv. coal		40	n.r.			
Advanced pulv. coal w/CC			n.r.	35		
IGCC coal		40	n.r.			
IGCC coal w/CC			n.r.	35		
Gas peaking (turbine)		20	n.r.	35		
Gas combined cycle		20	n.r.	35		
Diesel generator		20				
Nuclear, APWR		40	n.r.	60		
Nuclear, SMR						
Geothermal		20	n.r.			
Microturbine		20				
Biomass direct		20	n.r.			
Hydropower			60			
On-shore wind		20	n.r.		30 to 35	
Off-shore wind		20	n.r.			
Fuel cell		20				
Solar thermal (CSP) without storage						
Solar thermal (CSP) with storage		40	n.r.			
PV utility crystalline tracking			n.r.		50	
PV utility crystalline fixed			n.r.			
PV utility thin film tracking					50	
PV utility thin film fixed						
PV commercial rooftop		20	n.r.		48	
PV residential rooftop		20	n.r.		45	
Wave power			20			
Tidal power			25			

Fuel efficiency, near-term or high-cost case (%)					
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others
Technology					
Advanced pulv. coal	39%		36%		
Advanced pulv. coal w/CC		28%	27%	34%	
IGCC coal	39%		38%		
IGCC coal w/CC	32%	32%	29%	35%	
Gas peaking (turbine)	35%	38%	33%	37%	
Gas combined cycle	53%	49%	51%	57%	
Diesel generator		34%			
Nuclear, APWR	33%	33%	35%	100%	
Nuclear, SMR					
Geothermal	100%	100%	100%		
Microturbine		28%			
Biomass direct	25%	24%	24%		
Hydropower	100%		100%		
On-shore wind	100%	100%	100%	100%	
Off-shore wind	100%	100%	100%	100%	
Fuel cell	36%	52%			
Solar thermal (CSP) without storage					
Solar thermal (CSP) with storage		100%	100%		
PV utility crystalline tracking	100%	100%	100%	100%	
PV utility crystalline fixed		100%	100%		
PV utility thin film tracking	100%	100%			
PV utility thin film fixed		100%			
PV commercial rooftop		100%	100%		
PV residential rooftop		100%	100%		
Wave power			100%		
Tidal power			100%		

Fuel efficiency, long-term or low-cost case (%)						
Source ->	EIA	Lazard	Black & Veatch	Parsons; DECC	LBNL, others	
Technology						
Advanced pulv. coal	39%	39%	36%			
Advanced pulv. coal w/CC				28%	39%	
IGCC coal	46%	39%	43%			
IGCC coal w/CC	41%		33%	40%		
Gas peaking (turbine)	40%	33%	33%	39%		
Gas combined cycle	54%	51%	51%	60%		
Diesel generator		34%				
Nuclear, APWR	33%	33%	35%	100%		
Nuclear, SMR						
Geothermal	100%	100%	100%			
Microturbine		34%				
Biomass direct	25%	24%	27%			
Hydropower	100%		100%			
On-shore wind	100%	100%	100%			
Off-shore wind	100%	100%	100%			
Fuel cell	52%	47%				
Solar thermal (CSP) without storage						
Solar thermal (CSP) with storage		100%	100%			
PV utility crystalline tracking	100%		100%			
PV utility crystalline fixed				100%		
PV utility thin film tracking	100%					
PV utility thin film fixed						
PV commercial rooftop		100%	100%			
PV residential rooftop		100%	100%			
Wave power				100%		
Tidal power				100%		

ANNOTATION OF MAIN LITERATURE SOURCES USED IN OUR ANALYSIS OF THE NATIONAL-AVERAGE LCOE (TABLE S14)

EIA = Energy Information Administration; DECC = Department of Energy and Climate Change (United Kingdom); LBNL = Lawrence Berkeley National Laboratory; pulv. coal = pulverized coal; w/CC = with carbon capture; IGCC = integrated gasification combined cycle; APWR = advanced pressurized-water reactor; SMR = small modular reactor; CSP = concentrating solar power.

EIA

Near-term estimates are from Table 8.2 of EIA (2014a), except: near term fuel prices are 2019 prices to the electric power sector (EIA, 2014c), and capacity factors are from EIA (2014b).

Capital costs are "total overnight costs," for plants initiated in 2013, and include project contingency and "technological optimism" factors but exclude investment tax credits, learning effects, regional multipliers, and interest charges. Heat rate is higher-heating-value (HHV) basis (EIA, 2013). What we call "construction time" the EPA calls "lead time," which is the time from project initiation to the plant coming on line.

In the case of geothermal and hydro the values shown in Table S14 are the EIA's estimates for "the least expensive plant that could be built in the Northwest Power Pool region, where most of the proposed sites are located" (EIA, 2014a, p. 97). (In its NEMS runs the EIA estimates site-specific marginal costs for geothermal and hydropower plants [EIA, 2014a, p. 97].)

EIA (2014a) reports estimates for "advanced" and "conventional" gas/oil combined cycle plants, and "advanced" and "conventional" combustion turbines; the estimates shown here are for the "advanced" plants. What we call "advanced coal" the EPA calls "conventional coal" or "new scrubbed coal."

PV is fixed-tilt, single-axis tracking, of unspecified cell technology.

O&M costs include administration expenses, taxes and insurance (EIA, 2013). However, the EIA estimates O&M costs for *new* plants only (Jones, 2014).

We estimate long-term capital cost and fixed O&M costs by multiplying EIA's near-term estimates by the 2040/2019 LCOE ratios from EIA (2014b). We estimate long-term (year-2050) fuel prices to the electric power sector by extrapolating EIA's 2040 price projections at the 2030-2040 rate of growth projected by EIA (2014c).

Other notes: The EIA notes that plant lifetimes depend in general on the economics of extending plant lifetime, which in turn depends on the cost of additional O&M, upgrades and refurbishing, regulatory requirements, competing alternatives, and so on. In the case of nuclear power, the EIA (2014c) notes that the Nuclear Regulatory Commission has approved 70% of US plants for a 20-year extension beyond the initial 40-year license, and that "the nuclear power industry currently is developing strategies to submit license applications for additional 20-year life extensions that would allow

plants to continue operating beyond 60 years" (p. IF-35). The EIA (2014c) *AEO* reference case assumes that nuclear plants operate beyond 60 years, but the "Accelerated Nuclear Retirements case assumes that O&M costs for nuclear power plants grow by 3% per year through 2040; [and] that all nuclear plants not retired for economic reasons are retired after 60 years of operation" (p. IF-35). (The EIA's [2010] *AEO 2010* assumed that O&M costs increased by \$30/kW after plants reached 30 years of age.) Similarly, the EIA (2014c) assumes that in the "Accelerated Coal Retirements" case real O&M costs increase at 3% annually.

The EIA (2014c) also projects fuel use and generation in the electric power sector, from which we can calculate fleet-average generation efficiency by fuel type. For coal-fired plants, the efficiency remains just below 33% throughout the projection period (to 2040), because virtually no new coal capacity is added. However, the efficiency of natural-gas fired generation increases from about 42% in 2013 to almost 48% in 2040, as the total installed capacity of combined-cycle plants increases 1.7% per year and the total installed capacity of conventional gas steam plants decreases at -1.2%/year over the projection period (EIA, 2014f). (Note again that these are averages across a fleet of plants of a mix of different technologies.)

Lazard

From Lazard (2014). Cost estimates exclude subsidies. Our capital-cost figures include their "EPC cost" (engineering, procurement, and construction) and "Other Owner Costs," but not their "capital costs during construction" because those are interest costs on capital during construction (Jalan, 2014), which most other studies exclude and which we estimate separately. Lazard's capital costs include generic costs to connect to regular transmission grid, including such costs for off-shore wind. Their "high" case figures for a diesel generator assumes intermittent usage. Solar thermal storage "low" has 18-hours of storage; "high" has 10 hours. Their estimates of O&M cover all operating expenditures including administration, insurance, and taxes (Jalan, 2014). Fixed O&M includes periodic capital expenditures (Jalan, 2014) but not decommissioning and waste disposal costs.

Black & Veatch

From Black and Veatch (2012). Technology ca. late 2009, early 2010. Costs in 2009 USD. Costs exclude electric switchyard, transmission tap-line, interconnection, and interest during construction. For non-commercial plants, they base their estimates on engineering studies of "nth plant costs." "Near term" is their estimate for 2010 (2020 with carbon capture and sequestration); "long term" is their estimate for 2050. For thermal plants, the capacity factor we show here is equal to 100% minus their reported forced and planned outage rates. We assume that their heat rates are based on higher heating values. Geothermal is conventional hydrothermal. Wave and tidal estimates are based on their optimistic scenario, with the middle resource-availability band. For wave and tidal, "near term" is their estimates for 2015. In Black and Veatch hydropower life is "at least 50 years" (p. 106). PV utility estimates are for 100-MW systems; the technology is unspecified, so we assume crystalline-silicon. Their solar thermal has 6-hour storage. Wind capacity-factor range is for Class 3 to Class 7 resources. Offshore wind is fixed-bottom technology.

Parsons; DECC

Wind, solar, biomass estimates from U. K. Department of Energy and Climate Change (2013). Coal, gas, nuclear are low or high estimates for *n*th of a kind plant, from Parsons Binckerhoff (2013). Efficiency is based on lower heating values (LHVs). The capacity factor shown here is their “average lifetime load factor” for wind, solar, and biomass, and their “average availability” for coal, gas, and nuclear.

LBNL, others

Wind: Estimates of capacity factors, capital costs, and O&M costs are from Barbose et al. (2014b). Their capacity-factor range covers all individual project sites in 2012, and their fixed O&M estimates are for projects installed since 2000. Their estimates of O&M costs exclude administration, lease, insurance, and related costs.

Photovoltaics (PVs): Near-term, installed capital-cost estimates (except lower-end, near-term cost estimates) are based on installation prices (in \$/kW-dc) are from Barbose et al. (2014a), as follows: *Utility PV*: capacity-weighted average installed price in 2013. Note that these are utility PV prices contracted several years prior to installation, and hence do not reflect recent price declines. *Residential PV*: price for systems <10 kW installed in 2014. *Commercial PV*: price for systems >100 kW installed in 2014. PV near-term lower-end prices are turnkey prices estimated for Q2 2014 from GTM Research (2014). PV commercial and residential long-term cost estimates shown here are Barbose et al. (2014a) reported prices in Germany, which Barbose et al. (2014a) state are indicative of the potential for further significant cost reductions in the U.S. Estimates for utility-PV capacity factors and utility-PV O&M costs are from Bolinger and Weaver (2014). (We use our judgment to interpret their O&M data.) Bolinger and Weaver (2014) note that utility-PV capacity factors depend primarily on the intensity of the solar resource, and secondarily on the inverter loading ratio.

Goodrich et al. (2012) estimate that “evolutionary” cost reductions for PVs will result in the following system prices in the year 2020 (year-2010 dollars per peak-watt dc): 2.29 residential rooftop, 1.99 commercial rooftop, 1.71 fixed-axis utility ground mount, 1.91 one-axis utility-scale ground mount.

PV system lifetime estimates are from Jacobson et al. (2014) and Bazilian et al. (2013). Wind lifetime estimate is based on Dvorak (2014) and Byrne (2013).

Solar thermal (or Concentrated Solar Power [CSP]): Bolinger and Weaver (2014) estimate \$6000/kW capital cost for a trough with 6-hours of storage. They suggest that the storage adds \$1500/kW. They also estimate \$60/kW/yr for O&M for Solar thermal (CSP) without storage. US DOE (2012) estimates current costs of \$4000-\$8500/kW (capital) and \$60-\$70/kW/yr (O&M), with the low end for plants without storage and the high end for plants with storage. Current plants without storage have a capacity factor of 20%-28%; current plants with 6-7.5 hours of storage have a capacity factor of 40%-50%.

DOE (2012) estimates “evolutionary” technology cost and performance in 2020: \$6070/kW (overnight capital cost), \$50kW/yr (O&M cost), 66.4% capacity factor, 14 hours storage. DOE (2012) also estimates more aggressive “Sunshot” cost and performance targets for 2020: \$3560/kW, \$40/kW/yr, 66.6% capacity factor, 14 hours storage (in year-2010-\$.)

By comparison, Nithyanandam and Pitchumani (2014) estimate that 14-hours storage in an optimal system costs less than \$300/kW, and that total capital costs could be under the DOE Sunshot target.

Nuclear: Linares and Conchado (2014) assume 5 to 9 years construction time, 6-12% weighted-average cost of capital, and a capacity factor of 80%-90% for APWRs. Anadon et al. (2013) report the range of expert estimates of the capital cost of APWR Gen III technology in year 2030; Table S14 “long-term” capital costs are based on the 10th and 90th percentiles of the expert range.

For nuclear SMRs, Table S14 capital cost estimates are “realistic” cost estimates from Cooper (2014) for 2020 (our near term) and 2030 (our long term).

Construction time and operating lifetime: Sovacool et al. (2014c) show construction times for generic categories thermal, hydro, nuclear, wind, and solar (see also Sovacool et al., 2014a, 2014b). NREL (Short et al., 2011) reports the scheduled lifetime for coal plants (65 years for units < 100 MW; 75 years for units > 100 MW), natural gas combined cycle and oil-gas-steam units (both 55 years), and nuclear plants (60-80 years). They also report construction times for a range of plant types, as shown in Table S14.

8) CALCULATION OF THE COST OF ELECTRICITY BY STATE, YEAR, AND SCENARIO

We calculate the average cost of electricity by state, year, and scenario (BAU or 100% WWS) as the sum of the product of the state’s fractional generation mix and the levelized cost of electricity (LCOE), by technology, as follows:

$$AC_{S,Y,W} = \sum_j S_{j,S,Y,W} C_{j,S,Y,W}$$

$$S_{j,S,Y,BAU} = S_{j,M:S \in M,Y,BAU}$$

$$C_{j,S,Y,W} = C_{j,US,Y,W} \cdot R_{ADJ,j,S,Y,W}$$

$$R_{ADJ,j,S,Y,BAU} = 1 + C\%_{AI+FOM,j,US,Y,BAU} \cdot \left(\frac{R_{IC-C,j,M:S \in M} \cdot R_{IC-A,j,M:S \in M}}{R_{CF,j,M:S \in M,BAU}} - 1 \right) + C\%_{FUEL,j,US,Y} \cdot (R_{FUEL,j,M:S \in M,Y} - 1)$$

$$R_{ADJ,j,S,Y,100\%WWS} = 1 + C\%_{AI+FOM,j,US,Y,100\%WWS} \cdot \left(\frac{R_{IC-C,j,M:S \in M}}{R_{CF,j,S,Y,100\%WWS}} - 1 \right)$$

where

$AC_{S,Y,W}$ = the average levelized cost of electricity from all technologies in state S in year Y in scenario W (\$/kWh)

$S_{j,S,Y,W}$ = the fraction of total generation provided by technology j in state S in year Y in scenario W (for 100% WWS scenario see discussion below; for BAU, see equation for parameter $S_{j,S,Y,BAU}$)

$C_{j,S,Y,W}$ = the levelized cost of electricity from technology j in state S year Y in scenario W (\$/kWh)

$S_{j,M:S \in M,Y,BAU}$ = the fraction of total electricity provided by technology j in EIA Electricity Market Module Region (EMMR) M (containing state S) in year Y in the BAU scenario (see discussion below)

$C_{j,US,Y,W}$ = the average levelized cost of electricity from technology j in the United States in year Y in scenario W (\$/kWh) (Table S13)

$R_{ADJ,j,S,Y,W}$ = regional adjustment factor for technology j in state S in year Y and scenario W (we calculate adjustment factors for fossil-fuel-power plants, wind power, and solar power)

$C\%_{AI+FOM,j,US,Y,W}$ = the annualized+fixed O&M cost for technology j in the U.S. in year Y in scenario W , as a fraction of the total levelized cost (calculated from the intermediate national-average results)

$C\%_{FUEL,j,US,Y}$ = the fuel cost for technology j in the U.S. in year Y , as a fraction of the total levelized cost (calculated from the intermediate national-average results)

$R_{IC-C,j,M:S \in M}$ = the ratio of initial costs for technology j in region M (containing state S) to the national-average costs assumed here, reflecting regional variability in construction costs (see the discussion below)

$R_{IC-A,j,M:S \in M}$ = the ratio of initial costs for technology j in region M (containing state S) to the national-average costs assumed here, reflecting regional variability in ambient conditions such as temperature (see discussion below)

$R_{FUEL,j,M:S \in M,Y}$ = the ratio of fuel costs for technology j in region M (containing state S) in year Y to the national-average costs assumed here (EIA's [2014c] AEO projections)

$R_{CF,j,M:S \in M,BAU}$ = the ratio of the capacity factor for technology j in region M (containing state S) to the national-average factors estimated here, in the BAU (assumed to be 1.0 for all technologies in the BAU scenario, for all years; see discussion below)

$R_{ADJ,j,S,Y,100\%WWS}$ = the adjustment factor for technology j in state S in year Y in the 100% WWS scenario to the national-average factors assumed here

$R_{CF,j,S,Y,100\%WWS}$ = the ratio of the capacity factor for technology j in state S in year Y to the national-average factors estimated here, in the 100% WWS scenario (see discussion below)

subscript j = technology types (Table S13)

subscript W = 100% WWS or BAU scenario

subscript M = Electricity Market Module Region (EIA 2014a, 2014e; there are no EMMs for Alaska and Hawaii, so as explained above we make separate assumptions for these two states)

Fraction of generation by technology in the 100% WWS scenario ($S_{j,S,Y,100\%WWS}$)

We constrain hydropower to existing capacity in each state except in the case of Alaska. We perform a detailed analysis of the potential generation from rooftop PV in each state (following the method of Jacobson et al., 2014) and then estimate the actual installed capacity for each state subject to a constraint that the installed capacity not exceed 93% (residential) or 95% (commercial) of the potential. (With our assumptions the installed capacity is about 60% of the potential for all 50 states.) We assume minor contributions from geothermal, wave, and tidal based on available resources in each state. For onshore wind, offshore wind, and solar thermal, we analyze the solar and wind resources available for each state and develop appropriate assumptions. Finally, we assume that utility solar PV provides the difference between demand and the supply from all other sources. We assume that 65% of utility PV is crystalline single-axis tracking technology, and 35% is thin-film single-axis tracking technology.

We also maintain an estimate of the LCOE in a 100% WWS scenario at base-year cost levels. For this base-year scenario we assume the same 100% WWS generation mix as in the target year.

Fraction of generation by technology and EMM in the BAU scenario ($S_{j,M:S \in M,Y,BAU}$)

As indicated above, in order to calculate the average LCOE for each state in the BAU we need to know $S_{j,M:S \in M,Y,BAU}$, the fraction of total electricity provided by technology j in EIA Electricity Market Module Region (EMMR) M (containing state S) in year Y in the BAU scenario. Our technology categories j are shown in Table S13. Now, the EIA does not project exactly what we want ($S_{j,M:S \in M,Y,BAU}$), but it does project something close (EIA, 2014c), which we will designate $S_{f,M:S \in M,Y[2040],BAU}$, where the subscript f is the type of generator fuel (see below) and the subscript $Y[2040]$ means that their projection extends only to 2040 (we go to 2075). We therefore have to extend the EIA's projections

to the year 2075, and map their fuel (f)-based projections to our technology-type (j)-based projections.

Extending the EIA's projections. We extend the EIA projections to 2075 using a ten-year moving trend line.

Mapping the EIA's fuel-based projections to our technology-type projections. The EIA (2014c) projects electricity generation by EMM and fuel type f , where the fuel types are Coal, Petroleum, Natural Gas, Nuclear, Pumped Storage, Conventional Hydropower, Geothermal, Biogenic Municipal Waste, Wood and Other Biomass, Solar Thermal, Solar Photovoltaic utility, Wind, Offshore Wind, Solar Photovoltaic end-use, and Distributed Generation. Our renewable technology categories are similar, but our fossil-fuel categories are more disaggregated. Fortunately, the EIA (2014f) also projects electricity generation for the whole U.S. (but not by EMM) by type of fossil-fuel technology, and we can use these national projections to break out into more specific technology types the EIA's projection of coal, natural gas, and petroleum generation by EMM.

Table S15 shows how we map the EIA's (2014c, 2014f) projections into our technology types. This mapping is straightforward except in the case of petroleum and natural gas fuels, because the EIA's (2014f) projections of generation by technology include several technology categories (e.g., steam turbine) that can use either petroleum or natural gas. Thus, in these cases, we must further disaggregate the EIA's (2014f) projections to be by fuel type as well as technology type. To do this, we extract and aggregate plant-level EIA data on generation by oil and gas, by plant type, for the lower 48 states, Alaska, Hawaii, and the whole U.S. (Table S16). We use the results of Table 16, for the lower 48 states, to distribute the EIA's (2014f) projections by technology type to our technology- and fuel-specific categories. (We use results for the lower 48 states because the EIA's [2014f] projections are for the lower 48 states only; we and the EIA treat Alaska and Hawaii separately.)

Table S15. Mapping EIA fuel-use categories to our technology types.

EIA (2014c) fuel category	2050 weight	Our technology category
Coal	99.1%	Advanced pulverized coal
<i>Distribution based on EIA (2014f).</i>	0.0%	Advanced pulverized coal w/CC
	0.5%	IGCC coal
	0.4%	IGCC coal w/CC
Petroleum		Diesel generator (for steam turbine)
Natural Gas	5.3%	Gas combustion turbine
<i>Distribution based on EIA (2014f) and Table S16 analysis; see discussion below.</i>	34.0%	Combined cycle conventional
	60.4%	Combined cycle advanced
	0.2%	Combined cycle advanced w/CC
	0.0%	Fuel cell (using natural gas)
	0.0%	Microturbine (using natural gas)
Nuclear	100.0%	Nuclear, APWR
<i>EIA (2014g) assumes no storage</i>	0.0%	Nuclear, SMR
Distributed generation		Distributed generation (using natural gas)
Biogenic Municipal Waste		Municipal solid waste
Wood and Other Biomass		Biomass direct
Geothermal		Geothermal
Pumped Storage, Conventional hydropower		Hydropower
Wind		On-shore wind
Offshore Wind		Off-shore wind
Solar Thermal	100.0%	CSP no storage
<i>EIA does not consider storage.</i>	0.0%	CSP with storage
Solar Photovoltaic utility	65.0%	PV utility crystalline tracking
<i>EIA's AEO includes only single-axis-tracking PV of unspecified technology (EIA, 2014g, p. 66; EIA, 2014a, p. 178)</i>	0.0%	PV utility crystalline fixed
	35.0%	PV utility thin-film tracking
	0.0%	PV utility thin-film fixed
Solar Photovoltaic end-use	35.0%	PV commercial rooftop
<i>Our assumption.</i>	65.0%	PV residential rooftop
<i>No EIA projections.</i>		Wave power
<i>No EIA projections.</i>		Tidal power
<i>No EIA projections.</i>		Solar thermal (water or glycol solution)

Note: Our category “gas combustion turbine” includes the “steam turbine” and “gas turbine” categories of Table S16.

Table S16. Generation from oil and natural gas, by plant type, all generators (electric utilities and co-generators), U. S., 2013 (MWh)

Plant type	Lower 48		Alaska		Hawaii		United states	
	Oil	NG	Oil	NG	Oil	NG	Oil	NG
ICE	155,853	10,450,007	403,883	60,945	347,303	0	907,039	10,510,952
Steam turbine	4,452,615	92,181,479	3,515	5,000	4,257,719	0	8,713,848	92,186,480
Combined cycle	635,860	951,534,387	364,625	2,774,980	2,474,139	0	3,474,624	954,309,367
Gas turbine	669,432	94,582,808	53,120	625,621	172,112	41,330	894,665	95,249,759
<i>Total</i>	<i>5,913,760</i>	<i>1,148,748,681</i>	<i>825,143</i>	<i>3,466,547</i>	<i>7,251,273</i>	<i>41,330</i>	<i>13,990,176</i>	<i>1,152,256,557</i>

ICE = internal combustion engine; NG = natural gas.

Source: Our analysis of EIA plant-level database: U.S. Department of Energy, The Energy Information Administration (EIA), EIA-923 Monthly Generation and Fuel Consumption Time Series File, 2013 Final Release, EIA-923 and EIA-860 Reports (<http://www.eia.gov/electricity/data/eia923/>).

Alaska and Hawaii. The EIA’s EMM regions do not cover Alaska and Hawaii. For these states we assume the actual generation shares in 2013 (<http://www.eia.gov/electricity/data/state/>) remain constant over time. (This in essence is what the EIA does in its *AEO* projections [Jones, 2015].)

Note that our method properly and consistently accounts for the effects on CO₂ emissions *and* generation costs of the use of carbon-capture and sequestration (CCS): we use the EIA’s projections of generation with CCS, the EIA’s projections of the associated economy-wide CO₂ emissions from fossil-fuel use, and the EIA’s assumptions on the cost of generation technology with CCS relative to the cost without.

Regional variation in initial capital costs

The EIA’s *AEO* accounts for two sources of regional variation in the capital cost of electricity generation technologies: variation in construction costs (primarily labor costs), and variations in ambient conditions, such as temperatures, that affect the power output of the turbine and hence the \$/kW capital cost of the technology. (For example, air temperature influences the air pressure into the turbines, which in turn determines the turbine power output.) We account for the same effects here, using the EIA’s multipliers.

The EIA commissioned a consultant to estimate variability in construction costs and ambient conditions for a representative city (or cities) in all 50 states in the U. S. (EIA, 2013). With these estimates, the EIA developed its own estimates of $R_{IC-C,j,M;S \in M}$ (the capital cost in each region, relative to the national-average cost, due to the construction cost in the region relative to the national average) and $R_{IC-A,j,M;S \in M}$ (the capital cost in

each region, relative to the national-average cost, due to the ambient conditions in the region relative to the national average) (EIA, 2014h; see also Table 4 of EIA, 2013, for a summary of the product of $R_{IC-C,j,M;S \in M}$ and $R_{IC-A,j,M;S \in M}$ by EMM). For the 22 EMMs in the lower 48 states, we use the EIA's (2014h) estimates. For Alaska and Hawaii we use the estimates developed in the EIA's consultant report (EIA, 2013), the average of Anchorage and Fairbanks for Alaska, and Honolulu for Hawaii.

The EIA does not apply these regional capital-cost adjustments to geothermal and hydropower. Instead, the EIA estimates geothermal and hydropower capital costs and capacity by EMM region including in this case Alaska and Hawaii (EIA, 2014i). We use these to calculate capacity-weighted average capital costs in each EMM region relative to the capacity-weighted national-average capital cost. If the EIA (2014h) did not estimate capital cost or capacity for a region, we assume a relative factor of 1.0., except in the case of geothermal for Hawaii, where we assume an adjustment factor based on the generally higher construction costs in Hawaii.

In the EIA's analysis the regional multipliers apply to "base-case" capital-cost estimates, which pertain to a "generic" facility built in an unspecified, "typical" location (EIA, 2014a, p. 96; EIA, 2013, p. 5, p.2-6). Here we apply the same regional multipliers to our own estimates of generic, nationally typical capital costs. On the reasonable assumption that our generic capital-cost estimates are conceptually similar to the EIA's generic "base-case" estimates, our use of the EIA's regional multipliers is valid.

The relative capacity factor for technology j in region M in the BAU scenario.

In this analysis we ignore regional variations in capacity factors in the BAU and instead assume that capacity factors in all regions for all technologies are equal to the national-average capacity factor for the technology as projected by the EIA. (However, as discussed below, we do adjust the EIA's projected BAU capacity factors for wind power to account for the reduction in wind speed due to increasing numbers of wind turbines.) If we were to estimate region-specific capacity factors and then weight these by regional generation, the resultant total U.S. average costs would be the same, but region-by-region costs would be slightly different from what we have estimated here.

The relative capacity factor for technology j in state S in year Y in the 100% WWS scenario.

We estimate capacity factors for onshore wind and all solar technologies, for each state, in target-year Y , relative to the estimated or assumed national-average capacity factor in Table S13. For all other technologies in the 100% WWS scenario (e.g., hydro and offshore wind), we assume that each state's capacity factor is the same as the national average factor, meaning that the adjustment term $R_{CF,j,S,Y,100\%WWS}$ is 1.0.

Onshore wind. For onshore wind, we first calculate the capacity factor for each state and for the nation as a whole in 2013 based on reported wind generation by state from the EIA's *Electric Power Monthly* (<http://www.eia.gov/electricity/monthly/>) and installed wind capacity by state in 2013 from the DOE

(http://apps2.eere.energy.gov/wind/windexchange/wind_installed_capacity.asp).

For states with either zero generation or capacity, we assume the regional-average capacity factor. We then calculate the ratio of each state's 2013 capacity factor to the national average capacity factor (calculated from the same state-level data) in the base year (2013 in the present analysis, but represented generally by the parameter Y_{CF}); we designate this ratio $R_{CF,wind,S,Y_{CF}}$. The overall target-year adjustment factor

$R_{CF,wind,S,Y,100\%WWS}$ is then the product of $R_{CF,wind,S,Y_{CF}}$, a multiplier that accounts for changes in resource availability due to the use of more or less windy sites than in the base year (subscript RA), and a multiplier that accounts for the reduction in wind speed as the number of turbines extracting energy from the wind increases (subscript WX):

$$R_{CF,wind,S,Y,100\%WWS} = R_{CF,wind,S,2013} \cdot \varphi_{RA,wind,S,Y,100\%WWS} \cdot \varphi_{WX,wind,S,Y,100\%WWS}$$

$$\varphi_{RA,wind,S,Y,100\%WWS} = \varphi_{RA,wind,S,Limit} + (1 - \varphi_{RA,wind,S,Limit}) \cdot e^{\gamma_{RA}(Y - Y_{CF})}$$

$$\varphi_{WX,wind,S,Y,100\%WWS} = \varphi_{WX,wind,S,Limit} + (1 - \varphi_{WX,wind,S,Limit}) \cdot e^{\gamma_{WX}(Y - Y_{CF})}$$

where

$\varphi_{...Y}$ = the ratio of the capacity factor in year Y to the capacity factor in year Y_{CF} on account of changes in the availability in wind resources (subscript RA) or wind-energy extraction (subscript WX)

$\varphi_{RA,wind,S,Limit}$ = the ratio of the capacity factor in the long-run limit to the capacity factor in year Y_{CF} on account of changes in the availability in wind resources (discussed below)

$\varphi_{WX,wind,S,Limit}$ = the ratio of the capacity factor in the long-run limit to the capacity factor in year Y_{CF} on account of increasing wind-energy extraction (discussed below)

γ = the rate of approach of the long-run limiting reduction factor due to resource availability or competition among turbines (discussed below)

Y = the target year of the analysis

Y_{CF} = the year of the baseline capacity-factor data (2013 in the present analysis)

As discussed in the section "Capacity factor: resource availability long-run limit w.r.t. base (100% WWS scenario only) (<100%)," in the U. S. most of the high-wind sites have yet to be developed. However, in order to get a more quantitative sense of the long-run availability of wind resources by state, we examine NREL's map of wind power classes throughout the U.S., with appropriate land-use restrictions applied (Figure S3). Based on this examination, and considering that in Jacobson et al. (2015) "wind turbines are placed near each of 42,000 existing U.S. turbines.," we assume that $\varphi_{RA,wind,S,Limit}$ is 96% to 100%, with higher values for the states with the best wind resources, and that this limit is approached at a rate of 4%/year.

As mentioned above, another factor affects the amount of energy available from wind resources in a target year with respect to the amount available in the base year. As the number of wind farms increases, the extraction of kinetic energy from the wind by the turbines decreases the average wind speeds, which in turn reduces the potential power output from the wind farms (Jacobson and Archer, 2012).

The magnitude of this reduction depends on several factors, including the size, location, and spacing of wind farms; the height of the turbines; and the extent to which the increased dissipation of kinetic energy as heat eventually increases the available potential energy of the atmosphere (Jacobson and Archer, 2012). Results from Jacobson et al. (2015) indicate that the reduction in wind speeds due to large-scale deployment of wind farms, on the scale assumed here, can reduce the average capacity factor by about 7%. At higher levels of deployment – at what might constitute our long-run limit – the reduction presumably would be slightly higher. On the other hand, the base-year capacity factors we start with already reflect the actual performance of existing wind farms, and therefore account for the real-world reduction in wind speed due to use of wind power at the relatively low levels of penetration in the base year.

With these considerations, we assume that at highest levels of deployment the reduction in wind speeds due to extraction of kinetic energy by turbines would (further) reduce the capacity factor for onshore wind by 5% to 7%; i.e., that $\phi_{WX,wind,S,Limit}$ is 93% to 95%, with higher values for the states with the best wind resources.

Offshore wind. For offshore wind we assume smaller effects because these farms generally are spaced relatively far from one-another and from onshore farms; thus, we assume a 4% reduction in the low-cost case and a 6% reduction in the high-cost case.

Note that, as discussed later, this effect applies also to wind power in the BAU scenario.

Solar power. For solar power, the adjustment factor $R_{CF,j,S,Y,100\%WWS}$ is the ratio of the average insolation in year Y for technology j in state S to the generation-weighted national average insolation for technology j in the base year Y_{CF} . The average insolation in year Y is equal to the average insolation in year Y_{CF} multiplied by an adjustment factor that accounts for changes in siting opportunities between the base year Y_{CF} and the target year Y . The average insolation in the base year Y_{CF} is the product of the three factors: i) the average insolation in a representative city in the state; ii) an adjustment for the general effect of the size of the state on the opportunity for siting in places with insolation different than in the representative city; and iii) an adjustment that accounts for the specific effect of areas in the state, such as deserts, with especially good insolation.

Formally for the case of CSP technology,

$$R_{CF,CSP,S,Y,100\%WWS} = \frac{U_{CSP,S,Y}}{U_{CSP,US,Y_{CF}}}$$

$$U_{CSP,S,Y} = U_{CSP,S,Y_{CF}} \cdot AF_{LOC-CSP,S,Y}$$

$$AF_{LOC-CSP,S,Y} = AF_{LOC-CSP,S,Y_{CF} \rightarrow Limit} + \left(1 - AF_{LOC-CSP,S,Y_{CF} \rightarrow Limit}\right) \cdot e^{\gamma_{U-CSP}(Y-Y_{CF})}$$

$$U_{CSP,S,Y_{CF}} = U_{City-S} \cdot AF_{AREA,S} \cdot AF_{LOC-CSP,S,Y_{CF}}$$

$$AF_{AREA,S} = \max\left(1, \left(\frac{A_S}{A_{GEOMEAN-US}}\right)^a\right)$$

$$U_{CSP,US,Y_{CF}} = \frac{1}{G_{CSP,US,Y_{CF}}} \cdot \sum_S U_{CSP,S,Y_{CF}} \cdot G_{CSP,S,Y_{CF}}$$

where

$R_{CF,CSP,S,Y,100\%WWS}$ = the capacity factor for technology CSP in state S in year Y in the 100% WWS scenario relative to the national-average capacity factor for CSP in year Y_{CF}

U_{CSP} = average insolation at CSP locations in (kWh/m²/d)

$U_{CSP,US,Y_{CF}}$ = generation weighed average insolation at CSP locations in the U.S. in the base year

$AF_{LOC-CSP,S,Y}$ = The ratio of average insolation at the CSP locations in state S in year Y to the average insolation at CSP locations in state S in year Y_{CF}

$AF_{LOC-CSP,S,Y_{CF} \rightarrow Limit}$ = the limit of $AF_{LOC-CSP,S}$ in the long run (see discussion below)

γ_{U-CSP} = the rate of approach of the long-run limit in the case of CSP (see discussion below)

U_{City-S} = average insolation in a representative city in state S (kWh/m²/d)

(<http://stalix.com/isolation.pdf>)

$AF_{AREA,S}$ = adjustment factor accounting for the fact that the larger the state, the more likely there are to be sites for utility PV and CSP plants that have better insolation than for the representative city

$AF_{LOC-CSP,S,Y_{CF}}$ = the ratio of average insolation at the location of CSP plants to the average insolation for the representative city, in the base year (see discussion below)

A_S = land area of state S (U. S. Census)

$A_{\text{GEOMEAN-US}}$ = the geometric mean state area in the U.S.

a = exponent (we specify this so that $AF_{\text{AREA},S}$ is less than 1.10 for all states except Alaska)

$G_{\text{CSP},S,Y_{\text{CF}}}$ = generation from CSP in state S in year Y_{CF} (sources for all WWS technologies: <http://www.eia.gov/electricity/data/browser>; Interstate Renewable Energy Council, 2014)

For states with PV and CSP plants in the base year, our assumptions for $AF_{\text{LOC-CSP},S,Y_{\text{CF}}}$ are based on our assessment of the insolation at their actual locations in 2012 with respect to the insolation for the representative city (Figure S2). Our estimates for $AF_{\text{LOC-CSP},S,Y_{\text{CF}} \rightarrow \text{Limit}}$ also are based on our assessment of the information shown in Figure S2, with consideration of two countervailing trends over time, i) the possibility of finding better (sunnier) locations within each state for certain types of technology, but also ii) the possibility of using up the sunniest spots first.

The relative capacity factor for WWS technologies in the BAU scenario.

We have assumed that the $R_{\text{CF},j,M:S \in M, \text{BAU}}$ is 1.00 for all technologies, including WWS technologies, in the BAU scenario. Why do we make state-specific adjustments for the capacity factor for WWS technologies in the 100% WWS scenario but do not make EMM-region-specific adjustments in the BAU scenario? In general, we estimate state-specific parameters, relative to national-average parameters, so that i) we can report state-level costs, and ii) we can estimate a national-average LCOE based on a different set of state weights than those used to calculate the state-specific relative adjustment parameters. As discussed above, in the 100% WWS scenario the national-average capacity factors we estimate are based *implicitly* upon state generation shares that are different than the shares that we actually assume; thus, in the 100% WWS scenario, we need to know individual state capacity factors in order to estimate a national-average LCOE consistent with the state generation mix we actually assume. However, in the BAU all national-average capacity factors are taken from the EIA's *AEO*, and presumably the EIA's national average estimate is built from EMM-level capacity factors. If so, then in the BAU, there is no need to estimate the relative regional capacity factors for WWS technologies, at least for the purpose of calculating the national-average LCOE. (The use of relative regional capacity factors would change the reported state-level costs ever so slightly, but this difference is minor.)

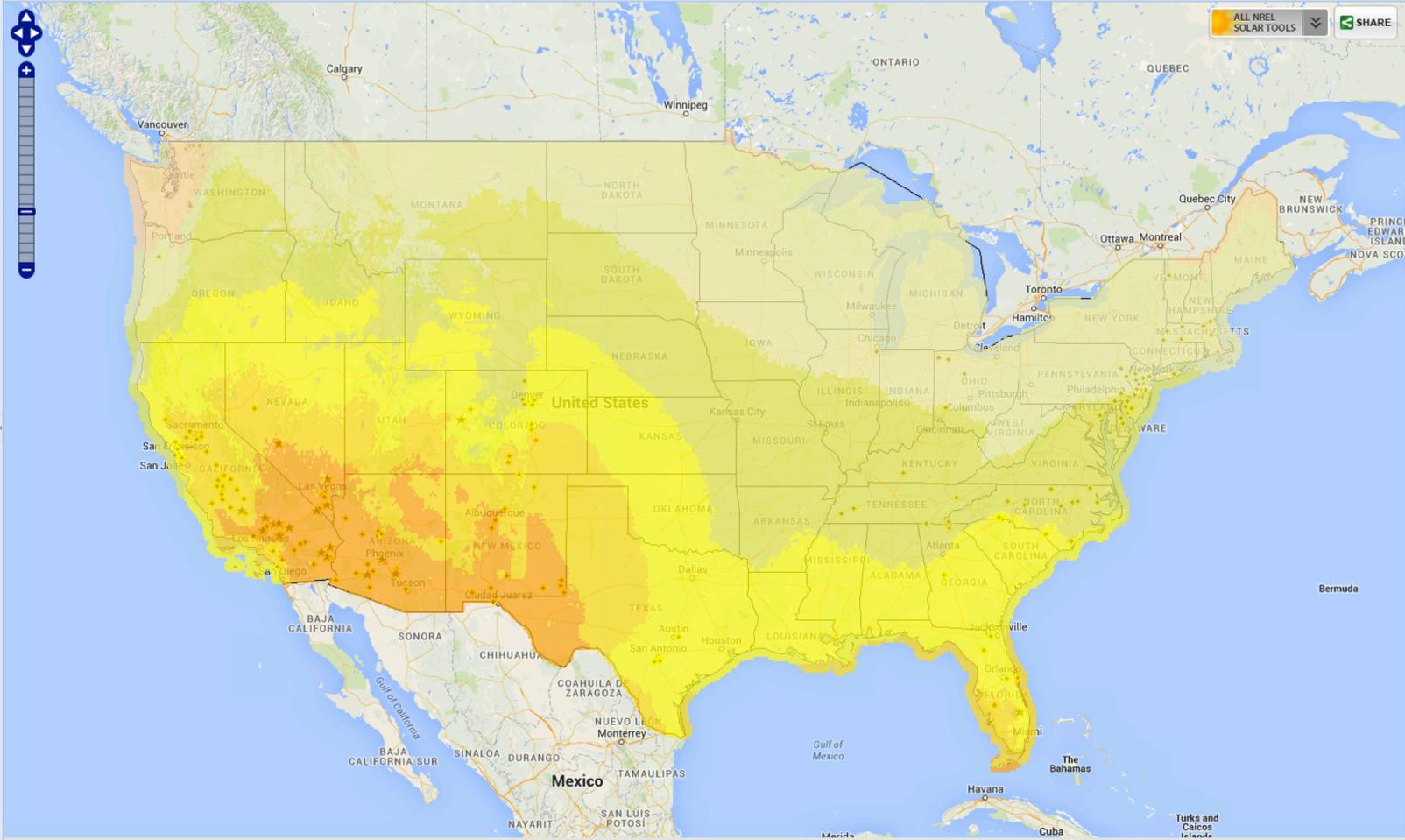
Layers Legend Data Sources

- Avg. Annual GHI (kWh/m2/day)**
- 2.0 to 2.5
 - 2.5 to 3.0
 - 3.0 to 3.5
 - 3.5 to 4.0
 - 4.0 to 4.5
 - 4.5 to 5.0
 - 5.0 to 5.5
 - 5.5 to 6.0
 - 6.0 to 6.5
 - 6.5 to 7.0
 - 7.0 to 7.5
 - 7.5 to 8.0
 - 8.0 to 8.5

- CSP Plant Locations**
- All Plants

- PV Plant Locations**
- All Plants

- State Borders**
- State Border



Apply Reset All Layers

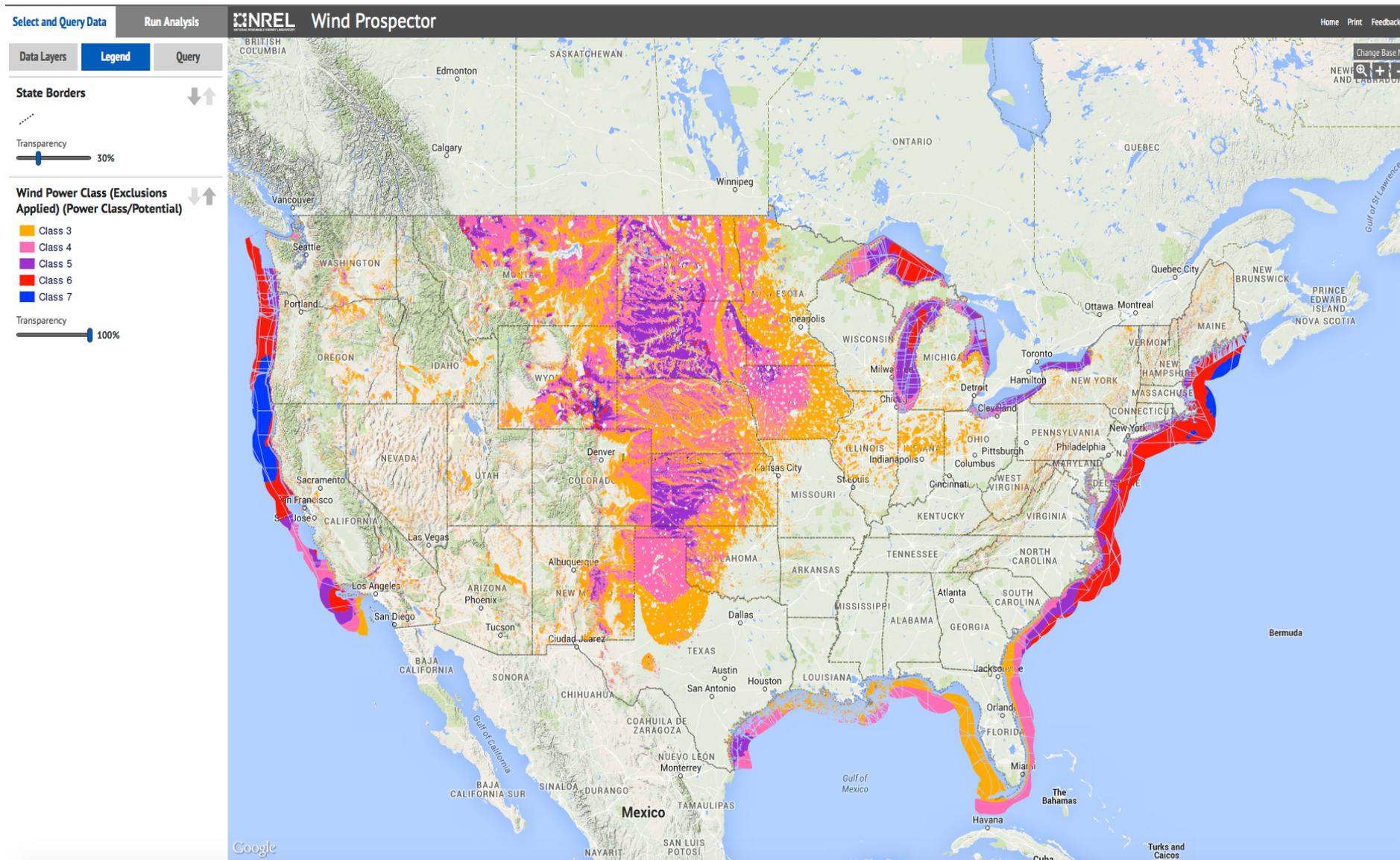


Figure S3. Wind power classes in the, U.S. (<https://mapsbeta.nrel.gov/wind-prospector/>).

Note that this reasoning also means that, for the purpose of accurately estimating national average costs, we did not have to estimate regional relative fuel costs, $R_{FUEL,j,M:S \in M,Y}$, because presently we use the EIA's AEO projections to estimate both relative regional costs and the national average cost used in the overall national LC calculation. Nonetheless, we have incorporated $R_{FUEL,j,M:S \in M,Y}$ into our model to accurately report state-specific costs and to allow for the possibility, in future analysis of calculating national-average costs with a different set of state-specific fuel-use weights than those used to calculate $sR_{FUEL,j,M:S \in M,Y}$.

However, even though we don't estimate region-specific capacity factor adjustments in the BAU, we do estimate a national-average adjustment to the wind capacity factor in the BAU in the TY to account for the effect, discussed in the previous section, of expanding the size of wind farms. The EIA's (2014c) reference-case projections of the capacity factor for wind power – the starting point of our estimates of energy use in the BAU – do not account for this effect of reduction in kinetic energy on the capacity factor for wind power, so for our BAU scenario we must adjust the EIA estimates accordingly. We use the method described for the 100% WWS scenario, except that we assume that in the BAU the state shares of onshore wind generation approach the long-run saturation limit at 20% of the rate in the 100% WWS scenario, and that each state's share of total national wind generation is equal to its share in the base year.

Note on the cost of installed WWS capacity by state

We use the same state/national capital-cost multipliers and capacity-factor multipliers to calculate the total installed capacity and the total cost of installed capacity by state. The total cost of installed capacity by state is used in the calculation of the amount of time it takes for energy-cost savings, air-pollution benefits, and climate-change benefits to payback the initial installed capacity cost.

REFERENCES

- F. Ackerman and E. A. Stanton, "Climate Risks and Carbon Prices: Revising the Social Cost of Carbon," *Economics* 2012-10 (2012). <http://www.economics-ejournal.org/economics/journalarticles/2012-10>.
- S. Alberici et al., Subsidies and Costs of EU Energy, interim report, by Ecofys, for the European Commission, Project number DESNL14583, October (2014). http://ec.europa.eu/energy/studies/energy_en.htm.
- L. D. Anadón, G. Nemet, and E. Verdolini, "The future costs of nuclear power using multiple expert elicitations: effects of RD&D and elicitation design," *Environmental Research Letters* 8, 03420 (2013). doi:10.1088/1748-9326/8/3/034020
- D. Antoff, S. Rose, R. S. J. Tol, and S. Waldhoff, "Regional and Sectoral Estimates of Social Cost of Carbon: An Application of Fund," *Economics*, No. 2011-18 (2011). <http://www.economics-ejournal.org/economics/discussionpapers/2011-18>.

M. M. A El Aziz, K. K. Ibrahim, and H. A. Kamel, "Estimation of the Lifetime of Electrical Components in Distribution Networks," *The Online Journal on Electronics and Electrical Engineering* 2(3): 269-273, W10-0002, July (2010).
<http://www.infomesr.org/en/scientific-research/journals/current-journals/43>.

G. L. Barbose, S. Weaver, and N. Darghouth, *Tracking the Sun VII: An Historical Summary of the Installed Price of Photovoltaics in the United States from 1998-2013*, Lawrence Berkeley Laboratory, Berkeley, California, September (2014a).
<http://emp.lbl.gov/reports/re>.

G. L. Barbose, N. Darghouth, B Hoen, A. D. Mills, S. Weaver, K. Porter, M. Buckley, F. Oteri, and S. Tegen, 2913 Wind Technologies Market Report, LBNL-6809E, Lawrence Berkeley National Laboratory, August (2014b). <http://emp.lbl.gov/publications/2013-wind-technologies-market-report>.

M. Bazilian, I. Onyeji, M. Liebreich, I. MacGill, J. Chase J. Shah, D. Gielen, D. Arent, D. Landfear, and S. Zhengrong, "Reconsidering the economics of photovoltaic power," *Renewable Energy* 53: 329-338 (2013).

R. T. Beach and P. G. McGuire, *Evaluating the Benefits and Costs of Net Energy Metering in California*, Crossborder Energy, January (2013). <http://votesolar.org/wp-content/uploads/2013/07/Crossborder-Energy-CA-Net-Metering-Cost-Benefit-Jan-2013-final.pdf>.

Black and Veatch, *Cost and Performance Data for Power Generation Technologies*, prepared for the National Renewable Energy Laboratory, February (2012).
<http://bv.com/docs/reports-studies/nrel-cost-report.pdf>.

M. Bolinger and S. Weaver, *Utility-Scale Solar 2013*, Lawrence Berkeley Laboratory, Berkeley, California, September (2014). <http://emp.lbl.gov/reports/re>.

W. Buitter and E. Rahbari, *Global Economics View*, CitiGroup Global Markets, February (2011). <http://www.willembuitter.com/Citi20.pdf>.

A. Byrne, "Life extension methodologies and economics," presentation handout, AWEA Windpower Conference, May 7 (2013).

M. Cooper, "Small modular reactors and the future of nuclear power in the United States," *Energy Research and Social Science* 3: 161-177 (2014).

M. A. Delucchi, Y. Sun, C.-Y. Lin, and J. M. Ogden, "The Producer Surplus Associated with Gasoline Fuel Use in the United States," to be submitted to *Journal of Transport Economics and Policy* (2015).

M. A. Delucchi and M. Z. Jacobson, "Providing All Global Energy Needs with Wind, Water, and Solar Power, Part II: Reliability, System and Transmission Costs, and Policies," *Energy Policy* 39: 1170-1190 (2011).

M. A. Delucchi et al., *A Lifecycle Emissions Model (LEM): Lifecycle Emissions from Transportation Fuels, Motor Vehicles, Transportation Modes, Electricity Use, Heating and Cooking Fuels, and Materials*, UCD-ITS-RR-03-17, Institute of Transportation Studies, University of California, Davis, December (2003). Main report and 13 appendices. www.its.ucdavis.edu/people/faculty/delucchi/.

M. A. Delucchi, *The Social-Cost Calculator (SCC): Documentation of Methods and Data, and Case Study of Sacramento*, for the Sacramento Area Council of Governments (SACOG) and the Northeast States for Coordinated Air-Use Management (NESCAUM), UCD-ITS-RR-05-18, Institute of Transportation Studies, University of California, Davis, September (2005). www.its.ucdavis.edu/people/faculty/delucchi/.

M. A. Delucchi, "Environmental Externalities of Motor-Vehicle Use in the U. S.," *Journal of Transport Economics and Policy* **34**: 135-168, May (2000).

M.A. Delucchi, M.Z. Jacobson, G. Bazouin, and Z.A.F. Bauer, 2015. Spreadsheets for 50-state 100% wind, water, and solar roadmaps, <http://web.stanford.edu/group/efmh/jacobson/Articles/I/WWS-50-USState-plans.html>, Accessed April 21, 2015.

Department of Energy and Climate Change, *Electricity Generation Costs*, London, England, December (2013). https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/269888/131217_Electricity_Generation_costs_report_December_2013_Final.pdf.

A. P. Dobos, *PVWatts Version 5 Manual*, NREL/TP-6A20-62641, National Renewable Energy Laboratory, Golden, Colorado, September (2014). <http://www.osti.gov/scitech/biblio/1158421>.

P. Dvorak, "Repower or retrofit, that is the question," *Wind Power Engineering and Development*, June, 39-43 (2014). http://www.windpowerengineering-digital.com/windpowerengineering/june_2014#pg2.

O. Edenhofer, L. Hirth, B. Knopf, M. Pahle, S. Schlömer, E. Schmid, and F. Ueckerdt, "On the economics of renewable energy sources," *Energy Economics* **40**: S14-S23 (2013).

Electric Power Research Institute, *Decommissioning Handbook for Coal-Fired Power Plants*, Technical Report 1011220, Palo Alto, California, November (2004). <http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=00000000001011220>.

B. Elliston, I. MacGill, and M. Diesendorf, "Least cost 100% renewable electricity scenarios in the Australian National Electricity Market," *Energy Policy* **59**: 270-282 (2013).

D. Feldman, G. Barbose, R. Margolis, T. James, S. Weaver, N. Darghouth, R. Fu, C. Davidson, S. Booth, and R. Wiser, *Photovoltaic System Pricing Trends*, NREL/PR-6A20-62588, National Renewable Energy Laboratory, Golden, Colorado, September (2014).

A. C. Goodrich, D. M. Powell, T. L. James, M. Woodhouse, and T. Buonassisi, "Assessing the drivers of regional trends in solar photovoltaic manufacturing," *Energy and Environmental Science* 6: 2811-2821 (2013).

A. Goodrich, T. James, and M. Woodhouse, *Residential, Commercial, and Utility-Scale Photovoltaic (PV) System Prices in the United States: Current Drivers and Cost-Reduction Opportunities*, Technical Report NREL/TP-6A20-53347, National Renewable Energy Laboratory, Golden, Colorado, February (2012).
<http://www.nrel.gov/docs/fy12osti/53347.pdf>.

H. C. Granade, J. Creyghts, A. Derkach, P. Farese, S. Nyquist and K. Ostrowski, *Unlocking Energy Efficiency in the U.S. Economy*, McKinsey Global Energy and Materials, McKinsey and Company, July (2009).
http://www.mckinsey.com/client_service/electric_power_and_natural_gas/latest_thinking/unlocking_energy_efficiency_in_the_us_economy.

GTM Research, September (2014). U.S. Solar Market Insight, Q2 2014, Executive summary, Solar Energy Industry Associates, September (2014).
<http://www.seia.org/sites/default/files/3RsOY33pQeSMI14Q2.pdf>.

J. K. Hammitt and L. A. Robinson, "The income elasticity of the value per statistical life: transferring estimates between high and low income populations," *Journal of Benefit-Cost Analysis* 2: 1-27 (2011).

E. K. Hart and M. Z. Jacobson, "A Monte Carlo approach to generator portfolio planning and carbon emissions assessments of systems with large penetrations of variable renewables," *Renewable Energy* 36: 2278-2286 (2011).
doi:10.1016/j.renene.2011.01.015.

O. H. Hohmeyer and S. Bohm, "Trends toward 100% renewable electricity supply in Germany and Europe: a paradigm shift in energy policies," *WIREs Energy and Environment*, doi: 10.1002/wene.128 (2014).

R. B. Howarth, M. D. Gerst, M. E. Borsuk, "Risk Mitigation and the Social Cost of Carbon," *Global Environmental Change* 24: 123-131 (2014).

T. Houser, R. Kopp, S. Hsiang, R. Muir-Wood, K. Larsen, M. Delgado, A. Jina, P. Wilson, S. Mohan, D. J. Rasmussen, M. Mastrandrea, and J. Rising, *American Climate Prospectus: Economic Risks in the United States*, Rhodium Group, New York, October (2014). http://rhg.com/wp-content/uploads/2014/10/AmericanClimateProspectus_v1.2.pdf.

N. E. Hultman, J. G. Koomey, and D. M. Kammen, "What history can teach us about the future costs of U.S. nuclear power," *Environmental Science and Technology*, April 1, pp. 2088-2093 (2007).

ICF Incorporated, *Current State and Future Direction of Coal-Fired Power in the Eastern Interconnection*, Final Study Report, for EISPC and NARUC, funded by the U.S.

Department of Energy, June (2013). <http://naruc.org/Grants/Documents/Final-ICF-Project-Report071213.pdf>.

International Energy Agency, Projected Costs of Generating Electricity, Organization for Economic Cooperation and Development, Paris, France (2010).
http://www.iea.org/publications/freepublications/publication/projected_costs.pdf.

Interstate Renewable Energy Council (IREC), *Annual U.S. Solar Market Trends Report*, July (2014). <http://www.irecusa.org/annual-u-s-solar-market-trends-report/>.

Interstate Renewable Energy Council (IREC), *A Regulator's Guidebook: Calculating the Benefits and Costs of Distributed Solar Generation*, October (2013).
<http://www.irecusa.org/a-regulators-guidebook-calculating-the-benefits-and-costs-of-distributed-solar-generation/>.

M. Z. Jacobson and C. L. Archer, "Saturation of Wind Power Potential and Its Implications for Wind Energy," *Proceedings of the National Academy of Sciences* **109** (39): 15679-15684 (2012).

M. Z. Jacobson, M. A. Delucchi, M. A. Cameron, and B. A. Few, "A Low-Cost Solution to the Grid Reliability Problem With 100% Penetration of Intermittent Wind, Water, and Solar for all Purposes," submitted to *Science* (2015).

M. Z. Jacobson and M. A. Delucchi, "Providing All Global Energy Needs with Wind, Water, and Solar Power, Part I: Technologies, Energy Resources, Quantities and Areas of Infrastructure, and Materials," *Energy Policy* **39**: 1154-1169 (2011).

M. Z. Jacobson, M. A. Delucchi, R. R. Ingraffea, R. W. Howarth, et al., "Evaluating the Technical and Economic Feasibility of Repowering California for all Purposes with Wind, Water, and Sunlight," *Energy* (2014).
<http://dx.doi.org/10.1016/j.energy.2014.06.099>

I. Jalan, Lazard Frères & Co. LLC, New York, New York, Personal communication via e-mail, November 6 (2014).

L. Johnson and C. hope, "The social cost of carbon in U.S. regulatory impact analyses: and introduction and critique," *Journal of Environmental Studies and Sciences* **2**:205-221(2012).

J. Jones, Office of Electricity, Coal, Nuclear, and Renewable Analysis, U. S. Energy Information Administration, personal communication by e-mail, November 21 (2014).

J. Jones, Office of Electricity, Coal, Nuclear, and Renewable Analysis, U. S. Energy Information Administration, personal communication by e-mail, November 21 (2015).

Lazard's Levelized Cost of Energy Analysis – Version 8, September (2014).
<http://www.lazard.com/PDF/Levelized%20Cost%20of%20Energy%20-%20Version%208.0.pdf>.

S. Larsson, D. Fantazzini, S. Davidsson, S. Kullander, M. Höök, "Reviewing electricity production cost assessments," *Renewable and Sustainable Energy Reviews* 30: 170-2013 (2014). <http://www.nrel.gov/docs/fy14osti/62558.pdf>.

P. Linares and A. Conchado, "The economics of new nuclear power plants in liberalized electricity markets," *Energy Economics*, in press, doi: 10.1016/j.eneco.2013.09.007 (2014).

L. Madaniyazi, Y. Guo, W. Yu, and S. Tong, "Projecting future air pollution-related mortality under a changing climate: progress, uncertainties and research needs," *Environment International* 75: 21-32 (2015).

F. C. Moore and D. B. Diaz, "Temperature impacts on economic growth warrant stringent mitigation policy," *Nature Climate Change*, DOI: 10.1038/NCLIMATE2481 (2015).

M. A. Moore, A. E. Boardman, A. R. Vining, D. L. Weimer, and D. H. Greenberg, "Just Give Me a Number! Practical Values for the Social Discount Rate," *Journal of Policy Analysis and Management* 23(4): 789-812 (2004).

National Center for Environmental Economics, Guidelines for Preparing Economic Analyses, U. S. Environmental Protection Agency, May (2014).
[http://yosemite.epa.gov/ee/epa/eerm.nsf/cf39f0d6770458fc8525769a006aba5a/0368dfba3b1f3d9f852578df004abf89/\\$FILE/EE-0568-50.pdf](http://yosemite.epa.gov/ee/epa/eerm.nsf/cf39f0d6770458fc8525769a006aba5a/0368dfba3b1f3d9f852578df004abf89/$FILE/EE-0568-50.pdf).

K. Nithyanandam and R. Pitchumani, "Cost and performance analysis of power systems with integrated latent thermal energy storage," *Energy* 64: 793-810 (2014).

Nuclear Energy Agency, *Decommissioning Nuclear Power Plants: Policies, Strategies, and Costs*, Organization for Economic Cooperation and Development, Paris, France (2003).
<http://www-ns.iaea.org/downloads/rw/projects/r2d2/workshop6/references/others/oecd-neadecom-npps-eng-2003.pdf>.

Nuclear Energy Institute, *Nuclear Energy 2014: Status and Outlook*, February (2014).
<http://www.nei.org/CorporateSite/media/filefolder/Policy/Wall%20Street/WallStreetBrief2014slides.pdf?ext=.pdf>.

Nuclear Regulatory Commission, 2013 Decommissioning Funding Status Reports (2013). <http://pbadupws.nrc.gov/docs/ML1326/ML13266A089.pdf>.

The Office of Management and Budget, Circular A-94, Appendix C, Discount rates for cost-effectiveness, lease purchase, and related analyses, The White House, Washington, D. C., December (2013). http://www.whitehouse.gov/omb/circulars_a094/a94_appx-c.

The Office of Management and Budget, Circular A-4, Regulatory Analysis, the White House, Washington, D. C., September 17 (2003).

http://www.whitehouse.gov/omb/circulars_a004_a-4.

Parsons Brinckerhoff, Electricity Generation Cost Model – 2013 Update of Non-Renewable Technologies, prepared for the Department of Energy and Climate Change, 3512649A, April (2013).

https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/223634/2013_Update_of_Non-Renewable_Technologies_FINAL.pdf.

R. Peltier, “Predicting U.S. Coal Plant Retirements,” *Power Magazine*, May 1 (2011).

<http://www.powermag.com/predicting-u-s-coal-plant-retirements/>.

R. S. Pindyck, “Climate Change Policy: What Do the Models Tell Us?,” *Journal of Economic Literature* **51**: 860-872 (2013).

S. Repo, A. Mäkinen, and P. Järvenausta, “Estimation of variable costs of electricity distribution company due to distributed generation,” *9th International Conference on Probabilistic Methods Applied to Power Systems*, KTH, Stockholm, Sweden, June 11-15 (2006).

Electricity Innovation Lab, Rocky Mountain Institute, *A Review of Solar PV Benefit and Cost Studies*, Rocky Mountain Institute, Boulder, Colorado, September (2013).

http://www.rmi.org/elab_empower.

R. A. Rodríguez, S. Becker, G. B. Andresen, D. Heide, and M. Greiner, “Transmission needs across a fully renewable European power system,” *Renewable Energy* **63**: 467-476 (2014).

F. Rong and D. G. Victor, What Does It Cost to Build a Power Plant, ILAR Working Paper #17, Laboratory on International Law and Regulation, School of International Relations and Pacific Studies, University of California, San Diego, September (2012).

<http://ilar.ucsd.edu/assets/001/503883.pdf>.

W. Short, P. Sullivan, T. Mai, M. Mowers, C. Uriarte, N. Blair, D. Heimiller, and A. Martinez, *Regional Energy Deployment Systems (ReEDS)*, NREL/TP-6A20-46534, National Renewable Energy Laboratory, Golden, Colorado, November (2011).

<http://www.nrel.gov/analysis/reeds/documentation.html>.

A. A. Solomon, D. M. Kammen, and D. Callaway, “The role of large-scale energy storage design and dispatch in the power grid: A study of very high grid penetration of variable renewable resources,” *Applied Energy* **134**: 75-89 (2014).

B. K. Sovacool, A. Gilbert, and D. Nugent, “An International Comparative Assessment of Construction Cost Overruns for Electricity Infrastructure,” *Energy Research & Social Science* **3**:152-160 (2014a.)

B. K. Sovacool, A. Gilbert, and D. Nugent, "Risk, Innovation, Electricity Infrastructure and Construction Cost Overruns: Testing Six Hypotheses," *Energy* 74: 906-917(2014b).

B. K. Sovacool, D. Nugent, and A. Gilbert, "Construction Cost Overruns and Electricity Infrastructure: An Unavoidable Risk?," *The Electricity Journal* 27 (4): 112-120 (2014c).

I. Staffell and R. Green, "How does wind farm performance decline with age?," *Renewable Energy* 66: 775-786 (2014).

N. Stern, "The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models," *Journal of Economic Literature* 51: 838-859 (2013).

R. S. J. Tol, "International Inequity Aversion and the Social Cost of Carbon," *Climate Change Economics* 1: 21-32 (2010).

U. S. Census Bureau, *Patterns of Metropolitan and Micropolitan Population Change 2000 to 2010*, C2010SR-01, U. S. Department of Commerce, Washington, D. C., September (2012). <http://www.census.gov/prod/cen2010/reports/c2010sr-01.pdf>.

U. S. Department of Energy, *Wind Vision: A New Era for Wind Power in the United States*, DOE/GO-102015-4557, March (2015). http://www.energy.gov/sites/prod/files/WindVision_Report_final.pdf.

U. S. Department of Energy, *SunShot Vision Study*, NREL Report No. BK5200e47927, DOE/GO-102012-3037, February (2012). <http://www.solar.energy.gov/pdfs/47927.pdf>.

U. S. Energy Information Administration, *An Analysis of Nuclear Power Plant Operating Costs: A 1995 Update*, SR/OIAF/95-01, U. S. Department of Energy, Washington, D. C., April (1995). <http://www.eia.gov/nuclear/archive/oiaf9501.pdf>.

U. S. Energy Information Administration, "When do commercial reactors permanently shut down? The recent record," May (2006). <http://www.eia.gov/nuclear/closures/closure16.pdf>.

U. S. Energy Information Administration, "U. S. nuclear power plants: Continued life or replacement after 60?," *Annual Energy Outlook 2010*, 0383(2010), U. S. Department of Energy, Washington, D. C., May (2010). http://www.eia.gov/oiaf/archive/aeo10/nuclear_power.html.

U. S. Energy Information Administration, "U. S. nuclear power plants: Continued life or replacement after 60?," *Annual Energy Outlook 2010*, 0383(2010), U. S. Department of Energy, Washington, D. C., May (2010).

U. S. Energy Information Administration, "Upgrades can increase U.S. nuclear capacity substantially without building new reactors," July (2012). <http://www.eia.gov/todayinenergy/detail.cfm?id=7130#>.

U. S. Energy Information Administration, Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants, U. S. Department of Energy, Washington, D. C., April (2013). <http://www.eia.gov/forecasts/capitalcost/>.

U. S. Energy Information Administration, Electric Power Annual 2012, U. S. Department of Energy, Washington, D. C., December (2013a).
<http://www.eia.gov/electricity/annual/>.

U. S. Energy Information Administration, Annual Energy Outlook 2013, 0383(2013), U. S. Department of Energy, Washington, D. C. (2013b).
<http://www.eia.gov/forecasts/aeo/>.

U. S. Energy Information Administration, Assumptions to the Annual Energy Outlook 2014, 0554(2014), U. S. Department of Energy, Washington, D. C., June (2014a).
<http://www.eia.gov/forecasts/aeo/assumptions/>.

U. S. Energy Information Administration, *Levelized Cost and Levelized Avoided Cost of Generation Resources in the Annual Energy Outlook 2014*, U. S. Department of Energy, Washington, D. C., June (2014b).
http://www.eia.gov/forecasts/aeo/electricity_generation.cfm.

U. S. Energy Information Administration, Annual Energy Outlook 2014, 0383(2014), U. S. Department of Energy, Washington, D. C., June (2014c)
<http://www.eia.gov/forecasts/aeo/>.

U. S. Energy Information Administration, *Electric Power Monthly, with Data for August 2014*, U. S. Department of Energy, Washington, D. C., October (2014d).
<http://www.eia.gov/electricity/monthly/>.

U. S. Energy Information Administration, *The Electricity Market Module of the National Energy Modeling System: Model Documentation 2014*, U. S. Department of Energy, Washington, D. C., August (2014e).
<http://www.eia.gov/forecasts/aeo/nems/documentation/>.

U. S. Energy Information Administration, *Annual Energy Outlook 2014*, Supplemental Reference-Case Table 59, "Electric Power Sector Generating Capacity and Generation by Plant Type and Technology," (available by e-mail) (2014f).

U. S. Energy Information Administration, Renewable Fuels Module of the National Energy Modeling System: Model Documentation 2014, U. S. Department of Energy, Washington, D. C., August (2014g).
<http://www.eia.gov/forecasts/aeo/nems/documentation/>.

U. S. Energy Information Administration, *Annual Energy Outlook 2014*, supplemental information, adjustments to capital costs used in the AEO (available by e-mail; L. Martin, Electricity Analysis Team) (2014h).

U. S. Energy Information Administration, *Annual Energy Outlook 2014*, supplemental information, supply curves for geothermal and hydropower production used in the

AEO (available by e-mail; D. Lowenthal-Savy, Renewable Electricity Analysis Team) (2014i).

J. C. J. M. van den Bergh and W. J. W. Botzen, "A lower bound the social cost of carbon emissions," *Nature Climate Change* 4: 253-258 (2014).

W. K. Viscusi and J. E. Aldy, "The value of a statistical life: a critical review of market estimates throughout the world," *The Journal of Risk and Uncertainty* 27:5-76 (2003).

K. Ward, *The World in 2050*, HSBC Global Research, January (2012).
[www.hsbc.com / ~ / media / HSBC-com / about-hsbc / advertising / pdfs / the-world-in-2050.pdf](http://www.hsbc.com/~ / media / HSBC-com / about-hsbc / advertising / pdfs / the-world-in-2050.pdf).

World Nuclear Association, "The economics of nuclear power," updated September (2014). <http://www.world-nuclear.org/info/Economic-Aspects/Economics-of-Nuclear-Power/>.