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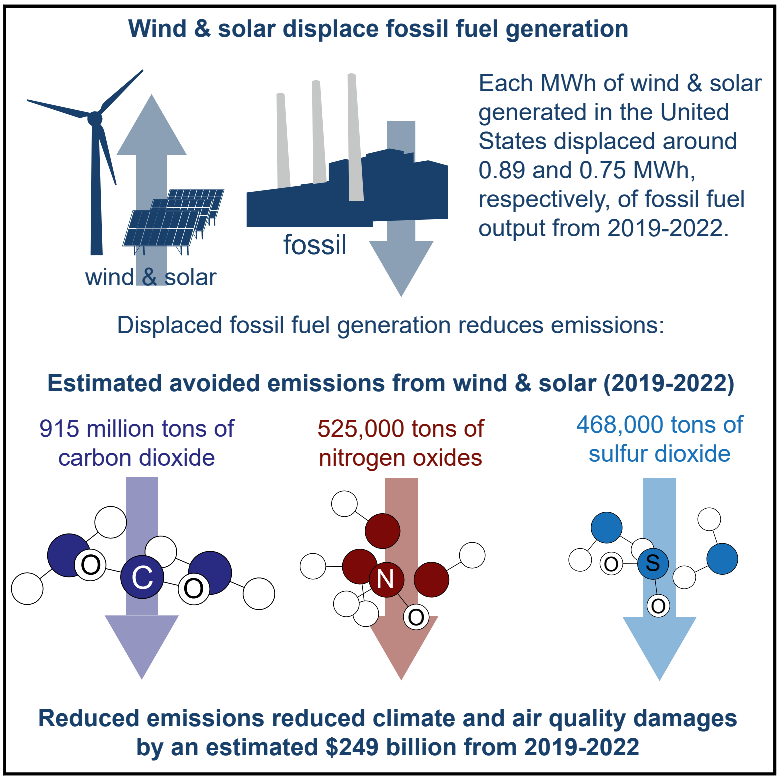
Climate and air quality benefits of wind and solar generation in the United States from 2019 to 2022

Graphical abstract



Highlights

- United States wind and solar power cut CO_2 emissions by 900 million metric tons from 2019–2022
- This wind and solar power cut SO_2 and NO_x emissions by 1 million metric tons
- These emission reductions provided $249 billion of climate and health benefits
- The average 2022 climate and health benefits were $143/MWh (wind) and $100/MWh (solar)

Authors

Dev Millstein, Eric O'Shaughnessy, Ryan Wiser

Correspondence

dmillstein@lbl.gov

In brief

Millstein et al. present new estimates of the climate and air quality benefits for wind and solar generation that occurred in the United States from 2019 to 2022. The new approach leverages public data, allows for uncertainty quantification and annual updates, and can possibly be ported to other regions.

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Climate and air quality benefits of wind and solar generation in the United States from 2019 to 2022

Dev Millstein,[1,2,*] Eric O'Shaughnessy,[1] and Ryan Wiser[1]
[1]Lawrence Berkeley National Laboratory, Berkeley, CA, USA
[2]Lead contact
*Correspondence: dmillstein@lbl.gov
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SCIENCE FOR SOCIETY Wind and solar electricity generation are critical for global decarbonization. Government support for wind and solar generators is often compared with their climate and air quality benefits. To accurately assess these benefits, assessments must be updated to reflect changes to the electricity system and to incorporate the newest research assessing the costs of emissions. For example, recent research finds much higher (>3×) societal costs to carbon emissions compared with commonly used metrics even just a few years ago, and important advances within air pollution epidemiology research have occurred in that time frame as well.

We develop a new and reproducible approach to estimate wind and solar climate and air quality benefits in the US using relatively simple and publicly available data and incorporating the recent advances described above. We find benefits are larger than most prior estimates, and they are larger than generation costs, subsidies, and electricity market value.

SUMMARY

Wind and solar generation reduce electric sector pollutant emissions and associated climate-related damages and air quality-related health damages. Here, we assess these emission reductions, focusing on carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x), and incorporate recent estimates of global warming costs and pollution health costs to estimate the dollar value of the associated climate and air quality benefits. From 2019 through 2022, wind and solar generation in the United States provided $249 billion of climate and air quality benefits based on central estimates. In 2022, the normalized benefits were $143/MWh and $100/MWh for wind and solar, respectively, or $36/MWh and $17/MWh when only including air quality benefits. Combined, wind and solar generation led to 1,200 to 1,600 fewer premature mortalities in 2022 (based on a 5^{th}–95^{th} percentile range). Our approach is based on simple, publicly available data, and it includes a sophisticated treatment of uncertainty.

INTRODUCTION

Expansion of renewable electricity generation, and particularly wind and solar generation, is a key pillar in many projected paths for global decarbonization.[1–5] Additionally, global decarbonization scenarios centered on wind and solar electricity generation are particularly effective in providing health co-benefits.[6] In the United States, regulatory or government support is needed to reach decarbonization goals.[7] Given the potential magnitude of new wind and solar generation required to meet decarbonization goals, it is critical to be able to compare the costs of support (often subsidies) for these technologies with the benefits received. This paper addresses a portion of that comparison, by providing a new estimate of the air quality and climate benefits of wind and solar generation in the United States in years 2019 through 2022.

There are two types of approaches to estimate wind and solar emission benefits. In one approach, an electric system model is used to simulate scenarios with different amounts of wind and solar energy generation and to quantify the difference in modeled emissions between scenarios. A second approach is to analyze patterns in recorded generation and recorded emissions to statistically assess the emission benefits of wind and solar generation. We discuss examples of both approaches in the "comparison to other benefit estimates" section. Our approach falls in the second category, and it offers an advantage over past work in that our approach uniquely utilizes easily accessible and publicly available data, allowing for annual updates (at least in the United States). Specifically, we offer an approach that relies on hourly generation records but not hourly emission records, removing dependence on a data source that can delay analysis by more than a year (see experimental procedures). Finally, the relatively simple data needed for our approach increases the possibility that it could be adapted to other regions around the world.

The air quality and climate benefits from wind and solar generation derive from displacing fossil generation and associated emissions. The value of displacing emissions is equal to the damages that would have occurred without displacement. The social cost of carbon (SCC) provides an estimate of the global monetary damage per incremental metric ton of carbon dioxide (CO_2) released. Estimates of the SCC have increased over time with methodological improvements. Rennert et al.[8] find a central-value SCC of \$185/tCO_2, 3.6 times larger than prior estimates used by the United States government. Similarly, new epidemiological research has led to updated damage estimates for emissions of nitrogen oxides (NO_x) and sulfur dioxide (SO_2) from the power sector.[9,10] These recent updates to the SCC and the NO_x and SO_2 damage estimates have profound implications for the social value of wind and solar generation.

In designing our approach to estimating fossil generation displacement, we have balanced ease of replication with the complexity required to capture important dynamics. For example, our analysis is based only on free and publicly available data but can capture the impact of hourly output profiles of wind and solar, interregional trade, and the interplay between wind and solar generation and hydropower. Our approach builds on and extends past work[11,12]—but is also designed for ease of replication over time and in other regions. It allows us to estimate the operational benefits of wind and solar generation, meaning we calculate the immediate response of fossil plant operations to changes in wind or solar generation. An additional important contribution of this work is the quantitative analysis of uncertainty. A limitation is that we do not address the structural benefits of wind and solar generation. We define "structural change" as a change of infrastructure rather than a change to the operations of existing infrastructure. This work therefore examines the impact of wind and solar on grid operations but not the longer-term impacts on fossil fuel plant construction or retirement decisions.[13]

RESULTS AND DISCUSSION

Before we calculate wind and solar air quality and climate benefits, we address two important intermediate steps: (1) assessing the monetary value of avoiding emissions of a particular pollutant and (2) calculating the quantity of emissions avoided from wind and solar generation.

Quantifying the value of avoided emissions

We focus on three important power sector air pollutants, CO_2, SO_2, and NO_x. Power plants release other pollutants that are not included in the scope of our research because they are either released at relatively low rates from United States power plants (e.g., volatile organic compounds [VOCs], directly emitted particulate matter, and mercury), and/or it is challenging to quantifiably assess their risk (e.g., mercury and other toxic metals). Mercury, while currently limited through effective control technology in the United States, can be an important pollutant to consider in other regions or time periods.[14] The full set of power sector pollutants is discussed in depth in an impact analysis by the US Environmental Protection Agency (EPA).[9] CO_2 is of concern as it is a greenhouse gas; SO_2 and NO_x emissions are of concern as they can serve as precursors to particulate and ozone pollution.

To value avoided CO_2, we follow Rennert et al.'s[8] guidance on SCC (i.e., a central value of \$185/metric ton of CO_2). Importantly, this value is at least 3× larger than prior commonly used SCC estimates,[11,15–20] suggesting that all else equal, new value estimates should be considerably larger than past estimates. That said, some past studies, for example, Millstein et al.[11] and Brown and O'Sullivan,[21] did explore the implications of higher SCC estimates as a sort of upper bound.

Rennert et al.[8] highlight two primary reasons for the large increase: first, the use of a discount rate of 2% versus 3%; and second, increased estimates of the global cost of climate damage as new science and more information are included. Rennert et al.[8] also highlight the contributions of four key areas of the SCC: reduced agriculture productivity, increased mortality risk, increased cost of energy generation, and sea level rise. The agricultural and mortality categories are dominant over the other two categories. The mortality category itself is of interest here, because increased mortality risk is also the primary driver of the value of reducing the other pollutants of interest (SO_2 and NO_x). In the case of climate impacts, however, the mortality risk is not a function of exposure to air pollution but is based on a large body of research linking an increase in all-cause mortality (including cardiovascular, respiratory, and infectious disease categories) to increased outdoor air temperature.[8,22] Although this is an area of active research, the SCC does not currently include the costs of feedback effects between temperature and air quality, such as increased surface-level ozone production or increased wildfire activity and associated air pollution. Finally, we note that the global costs of carbon are considered here, see US Environmental Protection Agency[23] and Interagency Working Group[24] for further discussion.

To assess the avoided damages from reduced SO_2 and NO_x emissions, we rely on four air quality models: EPA sectoral damage estimates,[9,10] the Estimating Air Pollution Social Impact Using Regression (EASIUR) model,[25] the Intervention Model for Air Pollution (InMAP),[26] and the Air Pollution Emission Experiments and Policy analysis model (AP2).[27] These models use data on population density, epidemiological information, and varying air quality modeling strategies to estimate the health impacts of emissions. Each of these models provides "benefit per ton" estimates of reducing emissions by location, which are incorporated into our approach. Benefit estimates primarily reflect the value of reducing mortality risk across the population.[10] Further description and comparison of these models can be found in the experimental procedures section and Gilmore et al.[28]

Of particular note is that the EPA benefit per ton estimates include relatively new epidemiological research for particulate matter (PM2.5)[29,30] and ozone impacts,[31] compared with the other models used here. Turner et al.[31] describes the increase to mortality due to long-term exposure to elevated ozone levels, which is in contrast to prior ozone exposure impact estimates[32,33] based on short-term exposure metrics. The consequence of including long-term ozone mortality impacts in the

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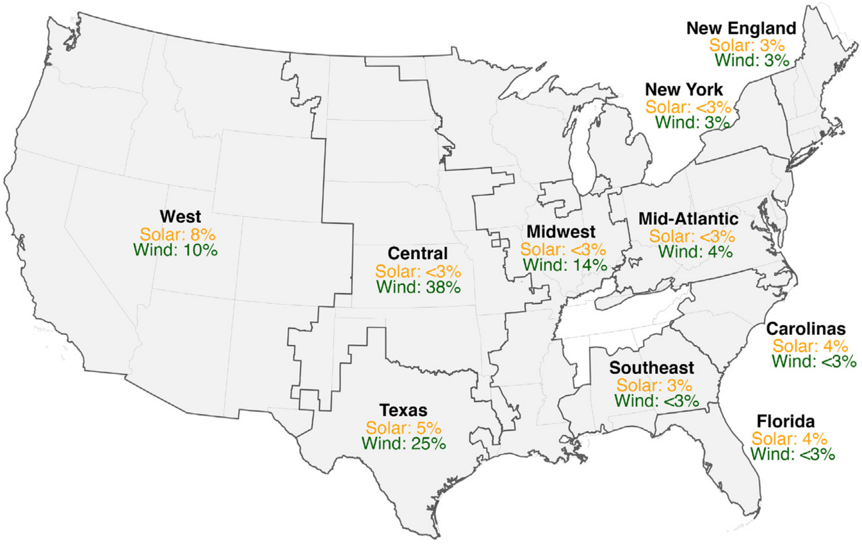

Figure 1. Wind and solar benefits are calculated across the 10 regions shown

Benefits were calculated for regions in which penetration of wind or solar supplied at least 3% of electricity demand. Wind benefits were calculated for the West, central, Texas, Midwest, mid-Atlantic, New York, and New England regions. Solar benefits were calculated for the West, Texas, Southeast, Florida, Carolina, and New England regions. The region centered around Tennessee is not currently included because penetration of both wind and solar was below the cutoff threshold, although it could be added in the future if wind or solar deployment increased.

value estimates is that NO_x emissions become relatively more important, compared with prior value estimates (for example, the US Environmental Protection Agency[10] finds regional average NO_x ozone benefits that are three to over five times larger than past estimates,[34] depending on which locations are compared).

An important context exists for health impacts of power sector pollution: after SO_2 and NO_x are emitted to the atmosphere, there is a delay before they contribute to PM2.5 and ozone impacts, owing to the time needed for atmospheric chemistry to proceed. The pollutants can therefore be transported for long distances, such that in the United States, a majority of early deaths due to power plant air pollution occur after the pollution has crossed state lines.[35,36] Partly due to this widespread dispersion, power sector pollution health impacts are not locally concentrated in vulnerable populations but spread widely across the population, a contrast to sources from other industries.[37] Therefore, avoided power sector emissions help reduce the air pollution health burden across a wide range of populations. This study does not investigate the impacts on equity of avoided pollution emissions.

Electric sector emission reductions due to wind and solar generation

One mechanism through which wind and solar generation reduce emissions is through impacting dispatch decisions. All else equal, wind and solar generation displace fossil fuel output and thus reduces emissions. Which fossil plants reduce generation and by how much are key questions to understanding the operational impact of wind and solar. An important context for the United States is that in 2022, natural gas, coal, and nuclear accounted for 39%, 19%, and 18% of total electricity, respectively, with wind and solar combined providing 15%, hydropower 6%, and other sources providing the remaining 4%.[38] Because nuclear is held constant in most hours, the generators that typically respond to varying wind and solar output are natural gas, coal, and, to a lesser extent, hydropower generators (although wind and solar may simply shift hydropower generation in time rather than reduce it on an annual basis). Thus, our analysis focuses on wind and solar impacts on gas, coal, and hydropower plants (other forms of energy storage are also discussed). Coal power plants generally have much higher emission rates than natural gas plants. In 2021, for example, the United States coal fleet released 95×, 3×, and 2× more SO_2, NO_x, and CO_2 than natural gas plants, respectively, per MWh of electricity produced.[39] Therefore, a key sensitivity to the emission benefits of wind and solar generation is their relative impact on coal versus natural gas generation.

We used a two-step approach to calculate wind and solar emission benefits: first, we used a regression to calculate wind or solar impacts on coal and natural gas generation; and second, we used recorded emission rates to estimate avoided emissions by multiplying those emission rates by the displaced coal and gas generation. This approach is implemented separately in each region. A map of the regions is shown in Figure 1, with wind and solar penetration, or share of total load provided, shown for each region based on information about generation and load derived from the US Energy Information Administration.[40] Regions were selected following those established by the US Energy Information Administration, with three western regions combined into a single region, as discussed in the experimental procedures section.

Our approach to calculate wind or solar impacts on coal and natural gas generation builds on Fell and Johnson.[12] Briefly, Fell and Johnson estimate wind and solar emission benefits by regressing regional hourly profiles of wind and solar generation versus hourly emissions (or hourly generation of coal and gas). An important aspect of their work was to treat cross-region impacts of wind and solar. Our approach deviates from Fell and Johnson[12] in a few key aspects, either to facilitate ease of replication or to address limitations related to collinearity between the variables. The primary simplification of our approach is to avoid the use of regional hourly emission profiles, and instead, we make use of generation profiles for gas and coal combined with regional average emission rates from gas and coal plants. This is an important simplification that facilitates replication. However, the simplification does obscure variation in emission rates across plants within a generator type. Importantly,

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Table 1. Rate of avoided coal and natural gas generation per MWh generated in 2022

	(Penetration)	(MWh-avoided/MWh-wind)		(Penetration)	(MWh-avoided/MWh-solar)	
Region	Wind/load	Coal	Gas	Solar/load	Coal	Gas
National	0.11	0.29 (±0.02)	0.60 (±0.04)	0.03	0.14 (±0.02)	0.62 (±0.04)
West	0.10	0.20 (±0.02)	0.69 (±0.05)	0.08	0.09 (±0.02)	0.68 (±0.04)
Central	0.38	0.53 (±0.04)	0.46 (±0.04)	<0.03	–	–
Texas	0.25	0.12 (±0.01)	0.85 (±0.01)	0.05	0.17 (±0.03)	0.79 (±0.03)
Midwest	0.14	0.32 (±0.08)	0.49 (±0.09)	<0.03	–	–
New England	0.03	0.00 (±0)	0.97 (±0.22)	0.03	0.00 (±0)	0.18 (±0.13)
New York	0.03	0.09 (±0.07)	0.37 (±0.15)	<0.03	–	–
Mid-Atlantic	0.04	0.19 (±0.18)	0.40 (±0.34)	<0.03	–	–
Carolinas	<0.03	–	–	0.04	0.35 (±0.09)	0.47 (±0.08)
Southeast	<0.03	–	–	0.03	0.17 (±0.14)	0.82 (±0.15)
Florida	<0.03	–	–	0.04	0.16 (±0.04)	0.02 (±0.31)

Solar penetration excludes distributed, behind-the-meter solar (e.g., roof-top solar). The ± ranges reflect 95th percentile bounds based on bootstrapped confidence intervals.

however, we quantify the uncertainty added due to this simplification. The context justifying this simplification is that in most cases, emission rates vary more across generation type than within generation type (as described in the first paragraph of this section). Additional discussion on our approach can be found in the experimental procedures section.

Taking the generation-weighted average across all regions in 2022, we find that 1.0 MWh of wind generation offsets 0.89 MWh of fossil generation (0.29 MWh of coal generation and 0.60 MWh of gas generation). We find that 1.0 MWh of solar generation offsets 0.76 MWh of fossil generation (0.14 MWh of coal generation and 0.62 MWh of gas generation). Table 1 shows national and regional details, and Tables S1 and S2 contain further details. There are several reasons why wind or solar would offset fossil generation at below a one-to-one rate. For example, if wind or solar plants are on average located further from load than fossil plants, we would expect that transmission losses would lead to a fossil offset rate below 1.0. In the western region specifically, net exports of electricity between California and its neighboring states correlate with hourly solar generation, indicating that solar is transferred across large distances in that region. Another possible reason is related to curtailment of solar or wind output—additional solar or wind output during hours and locations in which curtailment occurs would not lead to further reductions in fossil fuel generation (but simply further curtailment of wind and solar output). During the study period, wind and solar curtailment ranged from 0% to 10% of total potential energy output, depending on the year and region.[41,42] Additionally, battery storage absorbs wind and solar energy and is not explicitly accounted for in this analysis (see the discussion section for further explanation). Overall, the question of what explains the partial displacement effects of wind and solar on fossil fuel is one to be addressed in future research. Addressing this question may lead to mild increases in the estimates of benefits from wind and especially solar.

In a limited number of low-penetration regions (where 3% or 4% of the load is produced by wind or solar), e.g., wind in New York and the mid-Atlantic and solar in New England and Florida, we find a surprisingly low fossil response to wind or solar generation. The relatively small response likely reflects limitations in using our regression approach in low-penetration regions. Accordingly, we exclude all regions in which penetration is below 3% from our analysis, and one might argue that the threshold should be set slightly higher. However, the national results we report are not sensitive to regions with low levels of wind and solar as by definition there is relatively little wind and solar generation in these regions relative to national totals. Thus, we are willing to accept uncertainty in our results around low-penetration regions. An additional reason to include rather than exclude these low-penetration region results is that there are potentially other factors in some of these regions that could reduce the fossil response to wind or solar generation, such as interactions with hydropower, or for New York and New England, trade with Canada. For those interested specifically in low-penetration regions, a tool such as the Avoided Emissions and Geneation Tool (AVERT)[43] might provide an appropriate alternative to our approach for calculating the impacts of a marginal wind or solar plant.

Climate and air quality benefits of wind and solar

We calculated benefits as the product of three factors: (1) the change to generation of gas or coal, (2) the emission rate of that generator type, and (3) the damage caused by emission changes. We calculated benefits separately for wind and solar in each region, with national benefits representing a summation of the regional benefits. In 2022, wind and solar provided \$62 and \$12 billion in combined climate and air quality benefits, respectively, equivalent to \$143/MWh and \$100/MWh, all based on central estimates (Table 2). A Monte Carlo analysis was run to represent the uncertainty of all key input factors. The values across the 25th–75th percentile outputs from the Monte Carlo analysis ranged from \$91/MWh to \$183/MWh for wind and \$61/MWh to \$129/MWh for solar (see Figure 2, which also contains a 5th–95th percentile range).

Wind benefits derived primarily from the Central US, Midwest, and Texas regions, while solar benefits derived primarily from the

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Table 2. Avoided emissions and total benefits from wind and solar power (point estimates)

		(TWh)	Avoided emissions (thousands tonnes)			(Billion $)
Year	Type	Generation	CO_2	SO_2	NO_x	Total benefits
2019	wind	295.6	155,589	96	87	43.8
2020	wind	333.3	185,008	101	104	50.8
2021	wind	380.9	207,717	108	120	56.6
2022	wind	435.6	228,798	116	129	62.4
2019	solar	61.3	20,569	8	13	5.3
2020	solar	74.6	29,337	10	18	7.4
2021	solar	93.6	42,689	14	26	10.7
2022	solar	116.1	45,729	15	28	11.6

Western US, Texas, Southeast, and Carolina regions (see Figure 2). The Central US and Midwest regions have a relatively high amount of coal generation, while the opposite is true in the Western US region. Consistent with this, Figure 2 shows that while most wind emission benefits derive from offsetting coal power, most solar benefits derive from offsetting gas generation.

Most of the difference between the type of generation offset by wind or solar is because of the different regional distribution of the two technologies. To demonstrate this, we weighted coal and gas shares of generation by solar and wind output across hours and across regions. When weighted across hours, coal and gas shares are essentially the same across solar and wind (see Figure S5). That is, at a national level, hours with lots of solar have similar fossil fuel shares as hours with lots of wind. However, regions with relatively more wind tend to also rely more heavily on coal, particularly the central region. As a result, the per MWh emission impacts of wind output tend to be greater than the per MWh impacts of solar at a national level. Nonetheless, there are some intraregional differences. For example, the per MWh wind benefit was 30% larger than solar in the western US region (see Table 3 and Figure S6).

Finally, most of the value of both wind and solar benefits derives from reducing CO_2 emissions (74% for wind and 82% for solar) with the remainder due to avoided SO_2 and NO_x emissions. Note that for regions that maintain looser NO_x, SO_x, and PM control requirements for power plants than the United States or for regions with higher population density, the relative value of avoided SO_2 and NO_x emissions (as well as other non-greenhouse gas pollutants not quantified here) may be larger. The above considerations are especially important in low-income regions or emerging economies where the majority of global mortalities due to power sector emissions are concentrated.[44]

Uncertainty in total benefits for both wind and solar is almost entirely dependent on the uncertainty in the SCC (Figure 3). Rennert et al.[8] present a 5%–95% range for the SCC that spans an order of magnitude ($44–$413 per tCO_2). Further, the distribution implied by Rennert et al.[8] is right skewed, with a long tail of high-end estimates, which is why the point estimates depicted in Figure 2 are higher than the median estimates. By contrast, other factors are much less uncertain. For example, Pope et al.[29] and Wu et al.,[30] both seminal epidemiological studies of the mortality impacts of PM2.5 exposure, find results roughly within a factor of 2× of each other, representing an uncertainty that is large but much smaller than the uncertainty associated with the SCC.

Uncertainty in the fuel displacement estimates (i.e., MWh-coal-or-gas avoided per MWh-RE generated) plays a minor role in driving national uncertainty. The uncertainty of the fuel displacement estimates is based on standard errors from the regressions used to generate these estimates (see experimental procedures). Those standard errors are anti-correlated with penetration level—higher penetration regions have lower uncertainty (Figure S1). Yet relatively high uncertainty in low-penetration regions has little impact on the national totals shown in Figure 3 (in the generation category). Instead, the national totals depend mostly on high penetration regions with relatively small standard errors, explaining the relatively small contribution of the fuel estimates to overall uncertainty.

Over the study period, 2019–2022, wind and solar generation provided $249 billion dollars of climate and air quality benefits, based on central estimates. Central estimates of per MWh benefits varied mildly by year, with solar ranging from $86/MWh to $115/MWh and wind ranging from $143/MWh to $152/MWh. The range of inter-annual variation is much smaller than even the 25^{th}–75^{th} percentile range of benefits found in 2022 (Figure 2). Although per MWh benefits both increased and decreased over time, total annual benefits grew year over year with capacity growth for both wind and solar through the study period (Table 2).

Detailed discussion of air quality benefits

The large magnitude of the climate benefits can serve to obscure the important, but smaller, air quality benefits provided by wind and solar. In 2022, the 131 and 157 thousand metric tons of SO_2 and NO_x emissions avoided due to wind and solar generation were substantial, compared with total power sector emissions (roughly 770 and 680 thousand metric tons of SO_2 and NO_x).[45] These emission improvements continue a long-term trend of emission reductions in the power sector[45] and observed improvements in air quality metrics due to improvements across multiple sectors.[46] In 2022, wind and solar provided $16 and $2.2 billion worth of air quality health benefits, respectively, at a rate of $36/MWh and $17/MWh. These air quality benefits are almost entirely derived from reducing the risk of premature mortality across the US population—in

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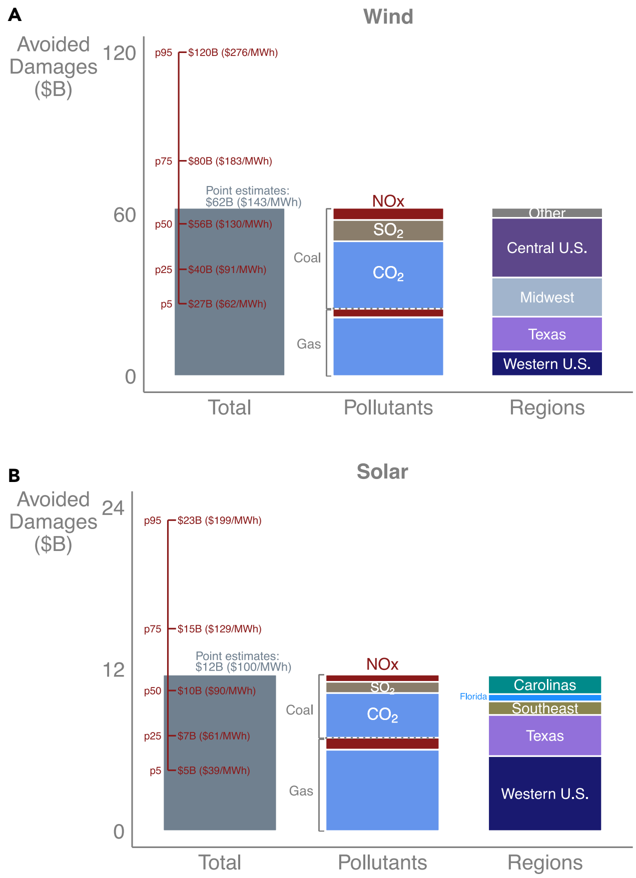

Figure 2. Total benefit estimates for year 2022

(A and B) Wind (A) and (B) solar benefits are shown separately; note the different y axis scales. The Monte Carlo 5th–95th percentile range is shown. The totals shown are the product of total generation by wind or solar and the per MWh benefit (shown parenthetically in the "total" column); therefore, wind benefits are larger due to both greater total generation and higher per MWh benefits. The "pollutants" and "regions" columns offer some insight into why per MWh benefits differ between wind and solar. The topic is further discussed in the text.

2022, wind and solar generation served to avoid roughly 1,400 premature mortalities based on central benefit estimates (see experimental procedures).

Focusing solely on air quality, the 5th–95th percentile ranges for the benefit estimates are relatively tight, compared with our total benefit ranges (since we are not including the SCC here). In 2022, air quality benefits range from $30/MWh to $41/MWh for wind and from $15/MWh to $20/MWh for solar. Or, in 2022, 1,200–1,600 (5th–95th percentile ranges) premature mortalities were avoided due to the combination of wind and solar generation. For context, improvements in prevention and treatment of cancer and heart disease are forecast to reduce ~21,000 premature deaths per year in the United States between 2017 and 2030.[47] In comparison, wind and solar benefits are small but not negligible.

The drivers of uncertainty in the air quality benefit estimates are spread across multiple factors and are different for wind compared with solar (see Figure 4). For both wind and solar, uncertainty is primarily caused by the variability in power plant emission rates within each region and by the uncertainty in the per ton damage rates. The rate of avoided coal or gas generation (i.e., MWh-coal-or-gas avoided per MWh-wind-or-solar generated) is not an important source of uncertainty nationally, for reasons already discussed. Wind benefits, being more dependent on avoided coal generation than are solar benefits, are particularly sensitive to the variability in SO_2 emission rates across coal plants in each region. Uncertainty in solar benefits is sensitive to both emission rates of NO_x and SO_2, as well as the uncertainty in the damage factor estimate of NO_x.

Benefits in comparison to market value, costs, and subsidies

To give a sense of scale for the benefits, unsubsidized levelized cost estimates for wind and solar generation in different regions in the United States range from $20/MWh to $60/MWh,[41,42] which in some cases is below the 5th percentile benefit estimate. The central benefit estimates for both wind and solar are much larger than average cost estimates for these technologies (as well as market value estimates and recently signed contracts for generation from these sources, i.e., power purchase agreements[41,42]). In other words, these out-of-market societal benefits are much larger than costs and revenues.

The air quality and climate benefits are also much larger than the subsidies made available to wind and solar through the production tax credit (PTC), investment tax credit, or the technology-neutral tax credits established by the Inflation Reduction Act (IRA). During the study period, wind PTCs ranged from $10/MWh to $26/MWh,[48] and utility-scale solar investment tax credits usually provided a slightly lower level of support, depending on project costs and performance.[41] Under the IRA, new wind and utility-scale solar projects are now eligible for a production credit of as much as $26/MWh–$34/MWh, depending on domestic content, labor, and location requirements.[48] However, these subsidies are smaller than our benefit estimates—below our 5th percentile estimate of wind benefits and similar to the 5th percentile estimate of solar benefits (or fractions, ~1/4th and ~2/5th, respectively, of our central wind and solar benefit estimates). Of course, a direct comparison between per MWh subsidies and per MWh benefits provides only rough intuition about a policy's relative fiscal cost versus benefits. That said, our results suggest that likely benefits outweigh the fiscal costs of this program. Bistline et al.[49,50] provide additional discussion on this topic.

Comparison to other benefit estimates

First, we compared our estimates of avoided emissions (e.g., kg/MWh) with other related approaches. For brevity, we compared national average rates here, but note that regional rates exhibit larger variation between approaches, especially in low-penetration regions.

As expected, we find broadly similar results at the national level to Fell and Johnson[12] (see Figure 5) but would not expect an exact match owing to methodological differences. The rough match with Fell and Johnson[12] shows that estimating benefits using our simpler set of input data can achieve similar outcomes to an approach with more complicated input data.

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Table 3. Climate and air quality benefit per MWh generated in 2022

	Wind ($/MWh)		Solar ($/MWh)	
Region	Point estimate	5th–95th range	Point estimate	5th–95th range
National	143	61–276	100	39–199
West	118	34–225	91	26–173
Central	205	74–367	–	–
Texas	120	36–226	129	39–241
Midwest	142	48–262	–	–
New England	90	24–177	17	3–38
New York	62	15–125	–	–
Mid-Atlantic	96	17–207	–	–
Carolinas	–	–	151	51–280
Southeast	–	–	127	32–253
Florida	–	–	51	12–103

Our avoided emission rates are also somewhat similar to those from AVERT,[43] although in some cases AVERT provides avoided emission rates 15%–35% greater than our estimates (Figure 5). The rough similarity with AVERT was not expected a priori as there are substantial methodological differences between our approach and AVERT. Most importantly, AVERT is designed to estimate the operational impact of a small change to a region's generation or load profile. In our case, with wind and solar penetration above 20% in many regions, the results from AVERT would not necessarily be applicable to such large changes. Finally, we note that our per MWh avoided emission rates differ from simple regional average emission rates, as shown in Figure S2 and discussed more generally in Holland et al.[51]

Prior research efforts have estimated total dollar air quality health and climate benefits from deployment of wind and solar. Silva et al.[52] review this literature and suggest that there is overall a dearth of research focusing on health co-benefits and that the rate of publications on this topic has stagnated. They find that most studies on these topics are based on forward-looking simulations, with fewer studies examining historical benefits (such as the focus here). We do not attempt to replicate a comprehensive review of prior work here, but we do highlight a limited number of key comparisons.

Compared with our analysis, prior efforts such as those of Millstein et al.,[11] Siler-Evans et al.,[15] Barbose et al.,[16] Buonocore et al.,[17] and Qiu et al.[53] find a similar, or even higher, magnitude of air quality health benefits but much lower climate benefits (comparing per MWh benefit estimates). The driver of increased climate benefits is the increase in the estimated SCC. On the air quality side, benefit estimates have remained relatively steady due to counteracting trends—tighter emission control requirements for United States coal plants, on the one hand, reduce per MWh benefits, but on the other hand, population and economic growth increase the per MWh benefit values. Additionally, epidemiology studies assessing the impacts of long-term exposure to elevated ozone pollution indicate larger than previously estimated health impacts from NO_x emissions (a pollutant that increases ozone formation).

Forward-looking electric sector simulations provide an alternate approach to assessing wind[54] and solar[18] benefits. Recently, Sergi et al.[20] simulated the future electricity system and found that a 30% reduction to electric sector CO_2 emissions yields annual health co-benefits of $21–$68 billion. Interestingly, our analysis shows that the ~550 TWh of wind and solar generation produced in 2022 provided a 15% reduction to CO_2 emissions from the electricity sector and $18 billion in health co-benefits, indicating that approximately half the generation and half the benefits found in Sergi et al.[20] have already been realized.

Discussion of key limitations and areas for future research

Structural impacts

Our approach does not capture the effects of wind and solar generation on fossil plant new build and retirement decisions (i.e., structural emission impacts). Structural emission impacts are generally important,[13] and indeed the United States electricity grid has undergone large structural changes over the last decade. For example, between 2010 and 2020, United States coal capacity fell from 313 to 214 GW while gas capacity grew from 390 to 468 GW.[55] Wind and solar capacity also grew during that time period from a combined 40 to 166 GW.[55] Had wind and solar not been available, there would now be a different relative mix of gas and coal plants available, possibly leading to higher emissions generally (coal plants have higher emission rates than gas plants). Electric system models can be used to assess structural emission impacts.[56] Alternatively, a semi-empirical approach can be used to fairly attribute past emission benefits, including structural impacts, across multiple causes.[57]

Intermittency effects

Our approach does not explicitly address the impacts of intermittency on generation. One concern is that variable renewable energy will lead to greater use of less efficient, but fast-responding, gas combustion turbines at the expense of very efficient combined cycle gas plants. Our approach does not capture differences between types of gas plants. It is worth noting, however, that nationally, and from 2010 through 2017 (2017 was the most recent year with available data), the share of total gas generation met by combined cycle gas generators increased with increased renewable penetration.[58,59]

Intermittency in renewable generation on the scale of multiple hours can lead to enhanced emission benefits through a shift

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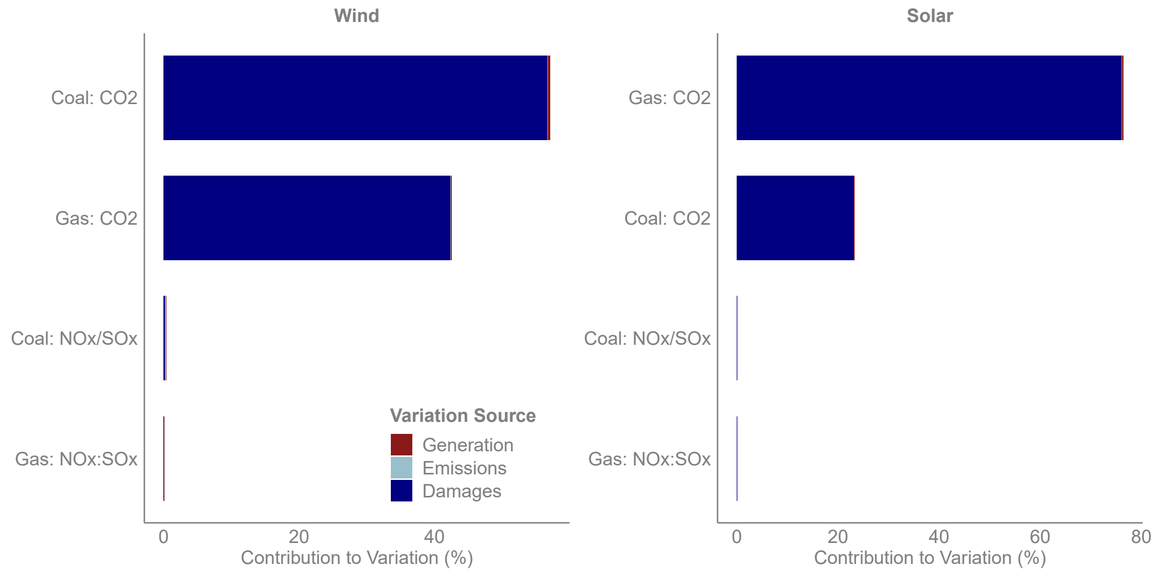

Figure 3. The fractional contribution to total uncertainty for climate and air quality benefits

The contribution toward the total uncertainty of individual input factors is calculated based on our inputs into the Monte Carlo simulation (see experimental procedures). All inputs for the Monte Carlo simulation have been grouped into one of 12 categories, 3 "source" categories for each of the 4 pollutant/generator-type groupings. The sum across all 12 categories is 100%. "Damages" refers to uncertainty in the per ton of emission cost estimates for either CO_2 or NO_x and SO_2. "Emissions" refers to the uncertainty caused by the within-type and within-region variation in emission rates across power plants. "Generation" refers to the uncertainty found in the quantity of gas or coal generation reduced by wind or solar (e.g., MWh-gas/MWh-solar).

toward gas over coal generation, for example, as shown in Texas.[60] The reason this second type of intermittency is not captured in our approach is that expected renewable generation in a subsequent hour may impact immediate generation choices, but our approach assesses the displacement only in concurrent hours. Intermittency on sub-hourly time frames has been shown to increase emissions, but the effect was small, reducing emission benefits by 6.5%, at least at modest penetration levels.[61] This topic deserves further research as wind and solar penetration levels deepen. Additionally, the rise of energy storage may impact how wind and solar intermittency interact with the fleet of dispatchable fossil generators.

Energy storage

Although we explicitly account for wind and solar interactions with hydropower, we have not incorporated a similar approach for battery storage. During the study period, battery storage provided a negligible fraction of energy storage, compared with hydropower, at the national scale. In California, however, battery storage capacity is now larger than 5 GW, and battery operators tend to charge during peak solar production hours (which are low-priced hours).[62] If we accounted for the solar energy shifted in time through storage, our estimates of solar emission benefits would be larger. In 2022, we could calculate an upper bound of this effect by assuming all early-evening (4 pm through 9 pm,

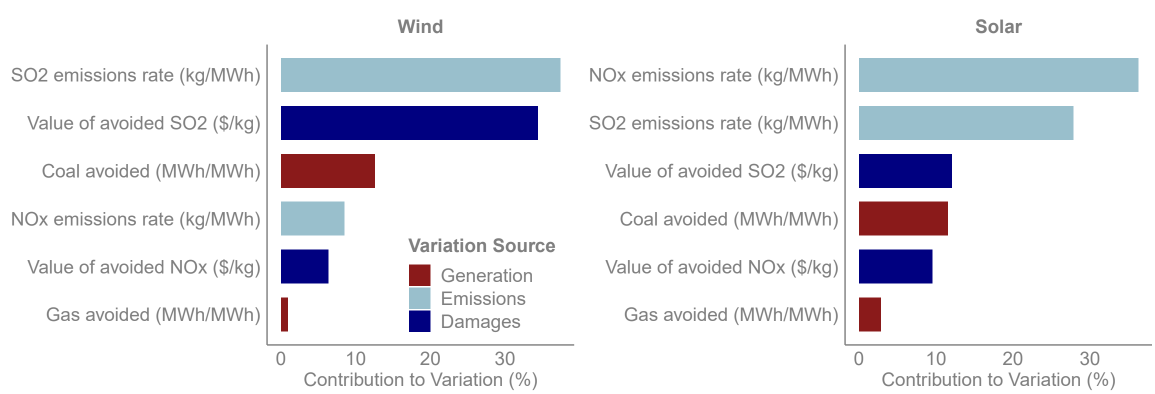

Figure 4. The fractional contribution to total uncertainty for air quality benefits (excludes climate benefits)

This figure is similar to Figure 3, but in this case, all inputs to the Monte Carlo simulation have been grouped into one of six categories (the sum across all categories is 100%). The contribution to uncertainty from emission rates sums the variability of emission rates across coal plants and across gas plants, although in the case of SO_2, essentially all the variability derives from coal plants.

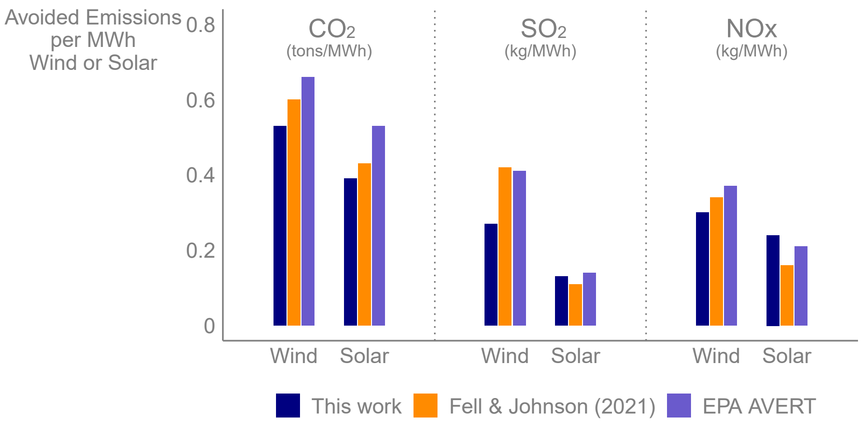

Figure 5. At the national scale the avoided emission rates calculated in this work are relatively similar to those from Fell and Johnson but in some cases smaller than those from AVERT

For the purpose of comparison to Fell and Johnson,[12] this figure shows emission rates from year 2020 from our work and AVERT, roughly matching Fell and Johnson's time frame, and all three national rates are based on weighting regional rates based on regional wind and solar generation records.

Pacific Standard Time) battery discharge derived from stored solar energy. Battery discharge during this time period amounted to 5% of total solar output in 2022, indicating that batteries still have a minimal impact on total solar emission impacts. With continued storage deployment, this issue is likely to become more prominent in future years. More generally, storage emission impacts deserve more study as storage interactions with dispatch and profitability of existing plants are complex and vary by region.[63]

Cap-and-trade programs

Depending on the situation, cap-and-trade programs can have different effects on the operational benefits of wind and solar generation. In some cases, total emissions of a region fall below the program cap. In these cases, emission allowance prices typically fall close to the market floor, and the existence of the cap-and-trade program has little effect on the wind and solar benefits as calculated here. In other cases, an emissions cap may be the dominant factor limiting further fossil generation in a region (called a strictly binding emissions cap). In this case, additional wind and solar generation may reduce emissions in a single hour only to see them rebound in other hours, maintaining total annual emission levels at the set cap (for example, additional solar in 1 h could free emission allowances to be used in other hours). Our approach does not capture the effects of *binding* cap-and-trade programs on emission reductions. An alternative valuation approach under a binding cap-and-trade system would be to value the emission reductions calculated here at the allowance price.[15]

In the United States, there are two prominent carbon cap-and-trade programs: the Regional Greenhouse Gas Initiative (RGGI), located in eastern states of the United States, and the California Cap-And-Trade Program. RGGI allowance auctions have indicated that the program has been non-binding during the study period as almost no auctions triggered the release of "Cost Containment Reserve" allowances.[64] In other words, had demand for allowances increased (putting upward pressure on prices), supply would have also increased with additional allowances made available, meaning the market was non-binding. Whether California's program is non-binding is less clear. From 2014 through 2020, auction prices essentially matched the price floor, providing evidence that the cap was not strictly binding. However, beginning in 2021, carbon prices rose mildly above the floor, suggesting the possibility of a more binding condition. Of note, prices (at ~$30/ton) remain well below the SCC used within our analysis, and some argue that even with the recent increases in price, California's carbon market is not binding.[65] Finally, there are markets for SO_2 and NO_x emissions in the United States, but all these markets have sizable and growing banked allowances for use in future control periods, indicating the markets are non-binding. To conclude, it is unlikely that our results were impacted by RGGI, SO_2, or NO_x markets, but it is possible that our results do not account for some of the recent effects of the California carbon market.

Methane leakage, life-cycle emissions, and land-use and infrastructure impacts

An additional benefit not calculated in this research is the avoidance of leaked methane from the production and transportation of natural gas. National estimates of leakage from the natural gas supply chain range from 1.5% to 2.3%.[66] With a leakage of 2.3%, for each metric ton of CO_2 emissions avoided, 0.0084 metric tons of leaked methane would be avoided (after accounting for the differences in molecular weight between CO_2 and methane). Assuming the social cost of methane is 8.4 times larger than the SCC,[23] the value of the leaked methane would be 0.07 times that of the avoided CO_2 (i.e., 8.4×0.0084). In other words, including methane leakage could increase the climate benefits of avoiding natural gas generation by ~7%. However, if leakage is much larger than commonly assumed, for example, Chen et al.[67] and Sherwin et al.[68] found a variety of leakage rates, including that of >9% in the New Mexico Permian Basin, then including the value of avoided methane leakage could substantially increase overall benefit estimates. Methane leakage is an important area for further study.

An additional cost not calculated in this research is the life-cycle emissions associated with wind and solar plants. Life-cycle emissions are generally low for wind and solar plants, compared with other generator types.[69] This research focused on operational emissions, not life-cycle emissions, a reasonable focus given that capacity additions were much smaller than the installed base of wind and solar—there were 232 GW of wind and solar capacity operating by the end of 2022 of which only 19 GW had been commissioned that year. Further, we note that 2/3 of new wind and solar capacity in 2022 consisted of thin-film solar or wind, which have manufacturing energy payback periods measured in months (often 2–6 months).[70,71] The remainder of new capacity was silicon-based solar, which has longer energy payback periods.[71] Additional information about upstream emissions, including construction emissions, can be found in Dolan and Heath[72] and Nicholson et al.[73] Given the above information, life-cycle emissions likely have a marginal impact on the results presented here.

Finally, we note that renewable generators cause other environmental and infrastructure impacts not discussed here, including impacts on property values, revenue sources for school funding, and other related externalities; see Bessette et al.,[74] Brunner et al.,[75,76] and O'Shaughnessy et al.[77] for further discussion.

Conclusions

We have newly assessed the climate and air quality benefits of recent wind and solar generation in the United States electricity system. Our updated assessment reflects recent changes within the electricity sector, such as the strict SO_2 emission controls that came into force in the last decade, the long-term shift toward natural gas generation and away from coal generation, and the large increase in wind and solar power plants. We also account for recently published science related to the global damages caused by CO_2 emissions and the domestic health and mortality impacts caused by emissions of NO_x and SO_2. Total benefits were found to be large, compared with levelized costs, energy market value, long-term contract prices, and direct subsidies. Although most of the value of benefits was due to avoided climate damages, even isolating the value of air quality health benefits alone was similar in magnitude to levelized cost estimates.

Compared with past benefit estimates, our approach depends on a relatively simple set of publicly available data, facilitating annual update and replication in other regions. The quantitative treatment of uncertainty provides insight into the sensitivity of our assessment to the various input data and methodological choices. Uncertainty in total benefit estimates was almost completely dependent on uncertainty within the SCC. When focusing on air quality health benefits alone, the uncertainty range was driven by variation in the emission rates of individual coal and gas power plants as well as by variation in estimates of the health impacts associated with NO_x and SO_2 emissions (i.e., benefit per ton estimates). The national average benefit estimates were not sensitive to uncertainty in the rate of avoided coal and gas generation associated with wind and solar generation, although some individual regions, especially low-penetration regions, did have substantial uncertainty associated with the rate of avoided generation. Finally, we highlight that total benefits were larger than or at least similar in magnitude to cost, value, and subsidy metrics, even when compared with the 5th percentile outcome based on our uncertainty analysis.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources and materials should be directed to and will be fulfilled by the lead contact, Dev Millstein (dmillstein@lbl.gov).

Materials availability

This study did not generate new unique materials.

Data and code availability

All analyses are based on publicly available data. Hourly generation and load data are published by the US Energy Information Administration, and the sources for all emission and damage estimates are explained in the text. An aggregated, cleaned version of the data used in this study and all scripts used for this analysis are available at https://github.com/eoshaugh2/solar_wind_aq_benefits.

Overview of our basic approach

Benefits, B, are calculated in units of \$/MWh-Wind or \$/MWh-Solar. Benefits are estimated as the product of three terms (Equation 1): avoided generation, G; an emissions rate, E; and a damage rate, D.

$$B_{ws,p,cg,r} = G_{ws,cg,r,nr} \times E_{p,cg,i} \times D_{p,i} \quad \text{(Equation 1)}$$

Benefits are calculated independently for wind or solar (subscript ws), by region (subscript r, referring to the regions shown in Figure 1), by fuel-type avoided (subscript cg, either coal or natural gas), and by pollutant (subscript p, CO_2, SO_2, and NO_x). On the right-hand side of the equation, G, in units MWh/MWh, represents the coal or natural gas generation displaced by wind or solar. The subscripts r and nr indicate that G represents avoided generation from within the region from which the wind or solar generation originated (r) and avoided generation from neighboring regions (nr). The emission rate term (E, in units of kg/MWh) is calculated separately for pollutant, fuel-type avoided, and also by interconnection region (subscript i). There are three interconnection regions: the Western Interconnect, matching the western region; the Texas Interconnect, matching the Texas region (which does not follow the Texas state boundary but corresponds to the Electric Reliability Council of Texas, ERCOT, boundary); and the Eastern Interconnect, which contains the remainder of the regions. Similarly, a damage rate (D, in units of \$/kg) is applied separately for each pollutant and each interconnect region.

G, E, and D are calculated with different approaches, which are detailed below. We note that we calculate "point" estimates as well as confidence intervals. The approach for calculating the point estimates is described below and then followed by a description of how uncertainty bounds are calculated.

Regression-based estimate of avoided natural gas and coal generation (G)

Our objective here is to estimate the impacts of wind and solar output on fossil fuel output. Conceptually, those impacts can be modeled as the sum of a series of partial impacts (Equation 2):

$$G_{ws,cg,r,nr} = \frac{\Delta f_{cg}}{\Delta RE_{ws,r}} = \underset{(a)}{\frac{\partial f_{cg,r}}{\partial RE_{ws,r}}} + \underset{(b)}{\frac{\partial f_{cg,r}}{\partial h_r}\frac{\partial h_r}{\partial RE_{ws,r}}} + \underset{(c)}{\frac{\partial f_{cg,nr}}{\partial RE_{ws,r}}} + \underset{(d)}{\frac{\partial f_{cg,nr}}{\partial h_{nr}}\frac{\partial h_{nr}}{\partial RE_{ws,r}}} \quad \text{(Equation 2)}$$

where f_{cg} is coal or natural gas output, RE_{ws} is wind or solar output, and h is hydropower output. And, as in Equation 1, the subscripts r and nr denote region and neighboring region, respectively. Each factor on the right-hand side of the equation is a component of the total impact of renewable energy on fossil fuel output (Figure 6):

(a) the direct intraregional impact (i.e., impacts on fossil fuel generators in the same region r) of renewable energy on fossil fuel output;
(b) the indirect intraregional impact of renewable energy via displaced hydropower output;
(c) the direct interregional impact (i.e., impacts on fossil fuel generators in neighboring regions nr) of renewable energy on fossil fuel; and
(d) the indirect interregional impact of renewable energy via displaced hydropower output.

We build a model to estimate the four component parts based largely on a previous model developed by Fell and Johnson (F&J).[12] The F&J approach is a reduced-form equation regressing either emissions or fossil fuel output on strictly exogenous regressors for renewable energy output and load. We adapt the F&J approach in four ways. First, we expand the model to estimate indirect impacts via hydropower (components (b) and (d) in Equation 2),

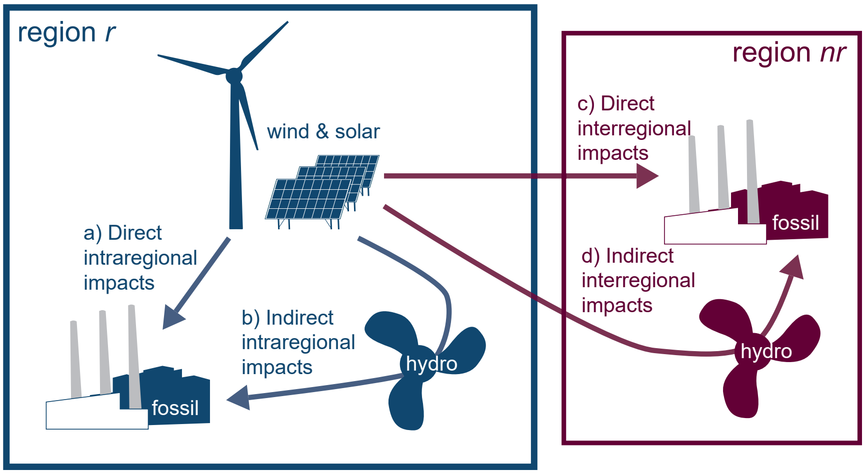

Figure 6. Illustrative schematic of pathways for renewable energy impacts on fossil fuel output

adjusting the model estimates' impacts stemming from regional trade (components (c) and (d)). Second, we translate fuel impacts (Equation 2) to emission impacts by multiplying displaced fuel by average emission rates. By contrast, F&J estimated emission impacts by regressing hourly emissions on wind and solar generation. This is an important simplification designed to facilitate easier replication of this work with up-to-date data in future years and possibly other regions. This simplification is needed because hourly emissions data are cumbersome to work with. For example, the Open Grid Emissions Initiative, which does provide publicly available hourly emissions data at sufficient geographic resolution, includes a delay of 11–23 months before data are able to be processed and released.[78] Third, we assess benefits across the Western Interconnect as a single region (rather than splitting the West into three separate regions). The reason for this choice was because of trading patterns throughout the interconnect: not only was intra-interconnect trading volume relatively high, but it was also extremely correlated with solar generation and, to a lesser extent, with wind generation. Treating this region as a single region helped avoid issues of strong collinearity in our analysis. Fourth, the F&J model directly regressed fossil fuel output in region r on renewable energy output in neighboring regions. The regressors for renewable energy tend to be highly collinear across regions. For instance, solar output in Florida tends to strongly correlate with solar output in the Carolinas. That multicollinearity could drive spuriously estimated impacts of wind and solar across regions. We develop an alternative approach that reflects the indirect nature of regional impacts and accounts for the regional multicollinearity. Our solution is to isolate regional impacts by first regressing net imports in region r on wind, solar, and load in neighboring regions. The predicted values for net imports from that regression are linear combinations of exogenous wind, solar, and load in neighboring regions but are not a function of wind and solar in region r. Those predicted values are thus exogenous but mitigate the problematic collinearity. We then use those predicted values as an exogenous control for the impacts of net imports.

Modeling intraregional impacts

We estimate direct intraregional impacts (component (a)) through the following model:

$$f_{r,t} = \alpha + X_{r,t}\beta + \eta h_{r,t} + \gamma \widehat{ix}_{r,t} + \zeta_t + \varepsilon \qquad \text{(Equation 3)}$$

where ζ_t is a set of fixed effects for hour–weekday and month–year, consistent with F&J. β provides the estimated direct intraregional impact, η provides the impact of hydropower on fossil fuel, and γ is the estimated coefficient for the import control variable. For simplicity, the symbols α and ε are used throughout to refer to model intercepts and error terms. Intraregional indirect impacts are estimated through the following model:

$$h_{r,t} = \alpha + X_{r,t}\beta_h + \gamma \widehat{ix}_{r,t} + \zeta_t + \varepsilon \qquad \text{(Equation 4)}$$

The indirect impacts (component (b)) are the product of the coefficients η and β_h.

Modeling interregional impacts

We estimate direct interregional (component (c)) through two models:

$$ix_{r,t} = \alpha + X_{r,t}\beta_{ix} + X_{nr,t}\gamma + \zeta_t + \varepsilon \qquad \text{(Equation 5)}$$

$$f_{nr,t} = \alpha + X_{nr,t}\beta + \gamma_{ix} ix_{nr,t} + \eta_{ix} h_{nr,t} + \zeta_t + \varepsilon \qquad \text{(Equation 6)}$$

The coefficient γ_{ix} is the average impact of net imports on generation. However, we are specifically interested in the impact of net imports during hours of solar and wind generation. We therefore estimate γ_{ix} in Equation 6 separately for each hour then take the solar- or wind-output-weighted average of γ_{ix} as a measure of the average impact of net imports on generation during solar- and wind-generating hours. The direct interregional impact is then the product of the output-weighted γ_{ix} and β_{ix} from Equation 5.

We estimate indirect interregional impacts following the same approach defined in Equations 3 and 4, using η_{ix} from Equation 6 and the following model:

$$h_{nr,t} = \alpha + X_{nr,t}\beta_h + \gamma_{h,ix} ix_{nr,t} + \zeta_t + \varepsilon \qquad \text{(Equation 7)}$$

The indirect interregional impact (component (d)) on exporting regions is the product of β_{ix}, $\gamma_{h,ix}$, and η_{ix} from Equation 6. Note that while we estimate γ_{ix} in Equation 6 at every hour, we only estimate a single η_{ix} for the model with all hours.

Note that Newey-West standard errors are reported for Equations 3, 4, 5, 6, and 7.

Total impacts

To summarize, the total impacts of renewable energy output are estimated as follows:

(a) Direct intraregional impacts: β (Equation 3)
(b) Indirect intraregional impacts: η (Equation 3) $\times \beta_h$ (Equation 4)
(c) Direct interregional impacts: β_{ix} (Equation 5) $\times \gamma_{ix}$ (Equation 6)
(d) Indirect interregional impacts: β_{ix} (Equation 5) $\times \eta_{ix}$ (Equation 7) $\times \gamma_{h,ix}$ (Equation 8)

The total impact of wind and solar on fossil fuel output is the sum of components a-d:

$$\frac{\Delta f_{r+nr}}{\Delta re_r} = \beta + \eta\beta_h + \beta_{ix}\gamma_{ix} + \beta_{ix}\eta_{ix}\gamma_{h,ix} \qquad \text{(Equation 8)}$$

Data used to estimate avoided natural gas and coal generation

The US Energy Information Administration compiles hourly electricity generation, demand, and regional trade data under form EIA-930.[40] We supplemented the EIA-930 data with solar generation data for the New England region from the New England ISO.[79] Given substantial electricity flows between New York and Canada, we also pulled data from the Ontario ISO.[80] We aggregated all EIA data from the balancing authority level to the regional level. Like F&J, we remove outliers that are less than half the first percentile value or more than 10 times the 99th percentile value relative to each region.

Observed emission rates for coal and natural gas plants (*E*)

Emission intensities (kg/MWh) are based on data from estimates reported in the US Environmental Protective Agency's Emissions & Generation Resource Integrated Database (eGRID).[39] The eGRID data reports emissions intensity estimates by plant. We aggregated those data to an interconnection level (East, Texas, and West) using generation-weighted averages across generators, developing, for each interconnection, one average emission rate for coal plants and one average emission rate for natural gas plants. We use plant-level emission rates from year 2021 (the most recent available) for the full study period. Although total emissions and emission rates have declined dramatically over the past two decades, average emission rates have been stable during the study period (2019–2022).

Avoided damages from emissions (*D*)

As discussed in detail in the main text, marginal damages for CO_2 in all regions are based on the mean estimate from Rennert et al.[8] of \$185/tCO_2 but are updated (by a factor of 1.015) to account for inflation between 2020 (the dollar year used by Rennert et al.[8]) and 2022, the dollar year used in this analysis. This and all dollar year conversions in this analysis are based on the personal consumption expenditures index from the US Bureau of Economic Analysis.[81]

To estimate damages from NO_x and SO_2 emissions, we focus on the health impacts caused by increased human exposure to particulate matter (or PM2.5) and ground-level ozone. Exposure to higher levels of either PM2.5 or ozone can increase the risk of premature mortality. Both SO_2 and NO_x are emitted in a gaseous form, but they can be transformed through atmospheric chemistry into particulate matter. Furthermore, NO_x can also contribute to ozone production through a catalytic process, allowing NO_x to contribute to both increased ozone and increased PM2.5 levels. We note that while organic aerosols generally comprise an important portion of particulate matter, organic aerosols are not discussed in this analysis. The reasons for not explicitly discussing organic aerosols are that NO_x and SO_2 are not precursors to organic aerosols, and power plants are not heavy emitters of VOCs, a key precursor to organic aerosols.

To understand how pollutant emissions impact human health, meteorological and chemistry models must be used to track where pollutants are transported and how they are transformed through atmospheric chemistry.[82–84] Meteorological and chemistry models are necessary because field experiments that track pollutant changes are infeasible. However, running a full meteorological and air quality model for each possible scenario of emission change is also not feasible owing to computational expense. To address this limitation, "reduced-complexity air quality models" use different strategies to capture the key capabilities, while minimizing the computations required.

We compiled marginal NO_x/SO_2 damage estimates from four sources, including from the EPA, and three research-based reduced-complexity air quality models,[25–27] compiled from the CACES. Gilmore et al.[28] provide an analysis comparing three of these models. In total, these sources provide eight distinct point estimates for NO_x and SO_2 damages based on low- and high-end estimates associated with each model. We aggregated results from all eight models into interconnection-level estimates using state generation-weighted averages (the EPA estimates are reported at the state level, and the models from CACES are reported at the county level). The aggregation of damage factors to the interconnect level simplifies our overall approach and does represent the damage rates found at the location of actual generators (through our weighting-by-generation approach), but a limitation is that detailed local assessment of impacts cannot be achieved using our approach.

The EPA data include separate estimates for damages related to short- and long-term exposure to ozone produced from NO_x emissions. The ozone-related NO_x damages are in units of \$/kg of NO_x emitted during ozone season, occurring from May through September. Our estimates of NO_x ozone benefits initially reflect annual totals, but ozone benefits are based on emissions only during the ozone season. To adjust for the ozone season, we calculated the percentage of NO_x emitted in the ozone season in each state, using eGRID data, and multiplied those percentages by the seasonal ozone-based NO_x damages. Very roughly, this can be approximated as multiplying initial annual ozone damages by 5/12 to reflect that NO_x emissions only contribute to ozone health damages during ozone season (5 months of the year). To ensure that ozone-related damages were reflected across all inputs, we added the long-term exposure estimate to the NO_x damage estimates from CACES models. Our point estimate represents the average value across the eight models in each interconnect.

Bootstrapped confidence intervals

We used a bootstrapping approach to estimate confidence intervals for benefit estimates. We constructed probability distributions for all of the inputs in Equation 10 as well as for *E* and *D* terms in Equation 1. The averages of those distributions are equal to the point estimates from the regressions (generation inputs) or the point estimates for emission intensities and marginal damages, as described above. We assumed the remaining parameters as follows.

Generation

We assumed that all the generation impacts are distributed normally with standard deviations represented by the standard errors of the coefficients in Equation 10.

Emission intensity

We assumed that emission intensities are distributed normally with standard deviations based on generation-weighted standard errors estimated from the eGRID data.

Marginal damages

Based on estimates provided by Rennert et al.,[8] we assume that marginal CO_2 damages exhibit a skewed normal distribution with an average of \$185/MWh, a 5th percentile value of \$44/MWh, and a 95th percentile value of \$413/MWh. For the NO_x and SO_2 estimates, we estimated standard errors across the estimates from the four models described above.

We generated 10,000 random distributions, using the parameters described above. All percentile range estimates are based on the outputs from those 10,000 simulations. The probability distributions for emissions intensity and marginal damages are depicted in Figures S3 and S4. One drawback of this approach is that different approaches are used to characterize uncertainty for each of the major steps. Specifically, the generation uncertainty is based on variation within our regression model, the emissions intensity uncertainty is based on variation in emissions across generators, the CO_2 damages uncertainty is based on the range provided by Rennert et al.,[8] and the air quality damages uncertainty is based on variation across models. As a result, the relative uncertainty contributions of each factor cannot be directly compared on an apples-to-apples basis. For instance, one reason why the generation estimates contribute less to overall uncertainty than air quality damage estimates (see Figure 4) is because the former is based on variation within a single model specification, whereas the latter is based on variation across specifications. On the other hand, the state of the science is such that alternative approaches to capture uncertainty are limited, and our approach represents an important step forward by making use of available science across a wide range of disciplines. Further, even without modeling, a heuristic assessment suggests an uncertainty profile consistent with Figure 3, namely more certain estimation of generation impacts and emission intensities but greater uncertainty of damage estimates. For generation impacts, the physics of the grid dictate that an additional MWh of wind or solar must displace a MWh from some other plant. Generation impacts are thus inherently bounded between 0 and 1. With some basic knowledge of marginal generation profiles, one could arrive at a reasonable heuristic for generation impacts with uncertainty bounds that span a factor of 1 or 2, e.g., that 1 MWh wind or solar displaces 0.4–0.9 MWh of natural gas in a given region where gas is usually the marginal generator (our regressions further reduce these uncertainty bounds to something like 10%). Similarly, the emissions intensity estimates are dictated by fuel chemistries and generator physics. These chemical and physical constraints mean that emission intensities are also bounded. Again, with basic knowledge of the emission intensities of fossil fuel plants, one could arrive at a heuristic estimate with uncertainty bounds that span a factor of 1 or 2 (e.g., the difference in emission intensities between the 5th and 95th percentile fossil fuel plant in eGRID is roughly a factor of 2). By contrast, damage estimates are highly uncertain and lack clear bounds. Damage estimation relies on numerous uncertain and potentially subjective assumptions about the social, economic, and public health consequences of emissions. These assumptions have shifted over time, and the ranges of damage estimates supported by these assumptions are far larger than the same ranges for generation impacts and emission intensities. The 5th–95th percentile range of SCC estimates from Rennert et al.,[8] for instance, spans roughly a factor of 9. Only further research to hone damage estimation can reduce those ranges and increase the precision of the climate and air quality benefits of wind and solar.

Fractional contribution to total uncertainty

We calculated the fractional contribution to uncertainty, shown in Figures 3 and 4, based on observed variation in the Monte Carlo outputs. Our total benefit estimates can be decomposed into the sum of six independent estimates:

$$B = B_{GasNox} + B_{GasSO2} + B_{GasCO2} + B_{CoalNox} + B_{CoalSO2} + B_{CoalCO2} \quad \text{(Equation 9)}$$

The properties of variance show that the variance of the total benefits is the sum of the individual variances, so:

$$V(B) = V(B_{GasNox}) + V(B_{GasSO2}) + V(B_{GasCO2}) + V(B_{CoalNox}) + V(B_{CoalSO2}) + V(B_{CoalCO2}) \quad \text{(Equation 10)}$$

In turn, each individual benefit B is the product of the three factors G, E, and D, as defined in Equation 1. The variance of the product is not the product of the variances of factors G, E, and D. However, the fractional variance of the product (i.e., the ratio of the variance to the mean) is the sum of the fractional variances of the individual factors, as expressed in standard deviations in the following formula:

$$\frac{V(B_X)}{B_X^2} = \frac{V(G)}{G^2} + \frac{V(E)}{E^2} + \frac{V(D)}{D^2} \quad \text{(Equation 11)}$$

where B_X is one of the six benefit components of Equation 10, and the terms in the denominators are all means (e.g., $\overline{G}$ is the average impact on generation). Through some algebra, the fractional contribution of each factor to each component can be expressed as follows, using G as an example:

$$\textit{contribution of G to variation of } B_X = \frac{V(G)\overline{B_X}^2}{\overline{G}^2 V(B_X)} \quad \text{(Equation 12)}$$

Equation 12 is the basis for estimating the contributions of each factor to variation. We estimate the variances and means based on the outputs of the Monte Carlo simulations.

Calculation of avoided mortalities

In the section "detailed discussion of air quality benefits", we reported total avoided mortalities. As mentioned, the health benefits are primarily based on the value of reducing mortality risk across the population. Roughly 98% of the EPA benefit estimates reflect reduced mortality risk, with the remaining 2% reflecting other health outcomes, including hospital admissions, asthma attacks, and other morbidities. The other reduced-complexity models only include the value of reduced mortality risk. The total avoided mortalities can be calculated from the benefit estimates through the value of statistical life (VSL), which is closely related to the value of avoided mortality risk but provides a ratio of value per avoided premature mortality. We follow EPA's guidance on the value of avoided mortality risk, as described in the US Environmental Protection Agency.[10,85] We use a VSL of 12.63 million dollars (this has been converted to 2022 dollar year), which is the 2025 estimate for VSL from EPA.[10] This VSL was maintained constant across all the reduced-complexity air quality and health models.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.crsus.2024.100105.

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AUTHOR CONTRIBUTIONS

Conceptualization, D.M., E.O., and R.W.; methodology, D.M. and E.O.; investigation, D.M. and E.O.; writing - original draft, D.M.; writing - review and editing, D.M., E.O., and R.W.; funding, R.W. and D.M.; supervision, R.W. and D.M.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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