ENVIRONMENTAL STUDIES

Impacts of wind power on air quality, premature mortality, and exposure disparities in the United States

Minghao Qiu[1]*†, Corwin M. Zigler[2], Noelle E. Selin[1,3]*

Understanding impacts of renewable energy on air quality and associated human exposures is essential for informing future policy. We estimate the impacts of U.S. wind power on air quality and pollution exposure disparities using hourly data from 2011 to 2017 and detailed atmospheric chemistry modeling. Wind power associated with renewable portfolio standards in 2014 resulted in $2.0 billion in health benefits from improved air quality. A total of 29% and 32% of these health benefits accrued to racial/ethnic minority and low-income populations respectively, below a 2021 target by the Biden administration that 40% of the overall benefits of future federal investments flow to disadvantaged communities. Wind power worsened exposure disparities among racial and income groups in some states but improved them in others. Health benefits could be up to $8.4 billion if displacement of fossil fuel generators prioritized those with higher health damages. However, strategies that maximize total health benefits would not mitigate pollution disparities, suggesting that more targeted measures are needed.

INTRODUCTION

Wind power provides climate, air quality, and health benefits by displacing the emissions of both greenhouse gases and air pollutants such as SO_2 and NO_x from fossil fuel electricity generating units (EGUs). Compared with longer-term and globally distributed climate benefits, the immediate and local air quality benefits of wind power development have the potential to incentivize policy-makers to take measures to address global energy and climate challenges. In the United States, much wind power development has historically been driven by the state-level renewable energy policies [such as a renewable portfolio standard (RPS)] (*1*–*8*). An RPS mandates electric utilities to deliver a certain fraction of their electricity sales from eligible renewable energy producers. The air quality benefits from renewable energy depend on the specific fossil fuel EGUs displaced and their emission profiles; the distribution of this displacement also affects the magnitude of air quality benefits that accrue to different population groups. Future policy-making on renewable energy can thus be informed by detailed understanding of the air quality benefits of the existing wind power implementation at the local and regional levels, including identifying specific fossil fuel EGUs associated with air quality improvements and implications for different population groups. In the U.S. context, this is relevant to the recent Inflation Reduction Act that focuses on decarbonizing the electricity sector through development of renewable energy (among many other targets).

Previous studies have used empirical data to evaluate the impacts of historical wind power development on emissions from fossil fuel EGUs. One approach is to use statistical models to directly link the short-term variability of wind power to fossil fuel plant generation and emissions (*9*–*12*). These analyses directly exploit the exogenous variation in wind power production to establish a causal relationship between emissions and wind power. Cullen (*10*) and Novan (*11*) both evaluated emission reductions due to wind power development in Texas using hourly data. Another common approach is to use marginal emission factors (MEFs), the emission factors associated with the last EGU needed to meet power demand, to estimate the impacts of renewable energy. MEFs are often derived from regressions of emissions on electricity generation (*13*) or from dispatch models with historical data as inputs (*14*). Millstein *et al.* (*15*) used the Avoided Emissions and geneRation Tool (AVERT) model developed by U.S. Environmental Protection Agency (EPA), which calculates avoided emissions from historical generation patterns, to estimate emission changes due to U.S. solar and wind energy development between 2007 and 2015.

Studies that project the impacts of wind power and/or other types of renewable energy on air quality and health often rely on reduced-complexity air quality approaches that simplify the relationship between emissions and the formation of atmospheric fine particulate matters ($PM_{2.5}$) and ozone (O_3). Millstein *et al.* (*15*) used reduced-complexity atmospheric chemistry models to estimate cumulative air quality benefits of 28 to 108 billion dollars associated with the emission changes that they calculated with AVERT. Many other studies project the potential impacts of future wind power and renewable energy development on air quality and health (*15*–*19*). Sergi *et al.* (*20*) used a capacity expansion model and three reduced-form atmospheric models to estimate the air quality and climate benefits of replacing existing fossil fuel power plants with wind, solar, or new natural gas plants to reduce the CO_2 emissions in the United States, estimating an additional 7 to 14 billion dollars in net benefits by including air pollution–related health benefits as a co-objective along with climate benefits. However, the simplified air quality models used in these studies cannot account for some important factors in calculating the impacts of wind power on air quality, such as the seasonal and regional heterogeneous responses of $PM_{2.5}$ and O_3 to precursor emissions.

Air pollution affects different populations unequally and is an important focus of environmental justice efforts. As defined by Bullard (*21*), "Environmental justice embraces the principle that all people and communities are entitled to equal protection of environmental and public health laws and regulations." The concept of environmental justice is multifaceted and involves a variety of considerations.

[1]Institute for Data, Systems, and Society, Massachusetts Institute of Technology, Cambridge, MA, USA. [2]Department of Statistics and Data Sciences, University of Texas, Austin, TX, USA. [3]Department of Earth, Atmospheric, and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA.
*Corresponding author. Email: mhqiu@stanford.edu (M.Q.); selin@mit.edu (N.E.S.)
†Present address: Department of Earth System Science, Stanford University, Stanford, CA, USA.

A substantial body of work relevant to environmental justice has documented existing inequities in air pollution exposure among racial/ethnic and income groups (*22*–*26*). These disparities are associated with a variety of emission activities (*27*) and, in part, reflect systemic environmental racism such as long-lasting consequences of discriminatory practices such as redlining (*28*). Research to better understand the disparities of exposure to environmental risks (e.g., air pollution) among different population groups, the causes of these disparities, and the potential solutions to reducing the exposure disparities can help further inform environmental justice efforts (*29*).

There are few existing studies that address the impacts of policies that could improve air quality (including renewable energy development) on air pollution exposure disparities despite emerging interest from policy-makers. In January 2021, the U.S. government announced a target that 40% of the overall benefits of certain federal investments, including investments in the areas of clean energy, should flow to disadvantaged communities (*30*). As air quality benefits of U.S. renewable energy deployment comprise a large fraction of their total benefits (*15*, *18*, *19*, *31*, *32*), it is thus important to quantify the distributions of air quality benefits of renewable energy over different communities. Understanding the degree to which changes in energy production have influenced exposure disparities can inform efforts to mitigate them. Previous research has not explicitly assessed the distributional impacts of renewable energy on air quality for different population groups. Zhu *et al.* (*33*) projected that the $PM_{2.5}$ disparities in California will generally reduce under decarbonization scenarios in 2050, with important heterogeneity across regions and scenarios. Retrospectively, a limited number of studies used econometric methods to assess the implications of a subset of climate mitigation strategies (including emission trading or electric vehicle deployment) on inequities related to air pollutant emissions (*34*–*37*). However, these studies often do not account for the full complexity in the formation and transport of air pollution. To our knowledge, there has not been a comprehensive study that evaluates the impacts of renewable energy development on air quality and the exposure disparities while accounting for the detailed atmospheric processes and the empirical responses at the plant level.

Here, we estimate the air pollution and health impacts of wind power using EGU-level hourly data and detailed atmospheric chemistry modeling, for the seven independent system operator (ISO) regions in the United States. We then use these EGU-level impact estimates to assess the implications of wind power development on disparities in exposure to $PM_{2.5}$ and O_3. To do this, we first establish a statistical relationship between hourly wind power and unit-level electricity generation and emissions (CO_2, SO_2, and NO_x) for each fossil fuel EGU from 2011 to 2017. We combine these unit-level emission changes for SO_2 and NO_x with source-receptor information from the GEOS-Chem adjoint model (*38*) to estimate their impacts on $PM_{2.5}$, O_3 concentrations, and associated premature mortality in all 48 states in the contiguous United States. We further simulate the air quality impacts of the wind power used to meet RPS targets in 2014 under existing dispatch decisions and compare these results to idealized theoretical scenarios that identify the potential for increased air quality and health benefits. Last, we estimate the fraction of air quality benefits flowing to low-income and racial/ethnic minority populations and examine the impacts of wind power on existing air pollution disparities among population groups, under current practice, and for our idealized scenarios.

RESULTS

In this section, we first present marginal impacts of wind power on unit-level emissions calculated using hourly data and statistical models. These emission effects are then used to calculate the associated premature mortality for each fossil fuel EGU, determined by the adjoint of GEOS-Chem, a global three-dimensional chemical transport model, combined with epidemiological concentration response functions (CRFs). Using our unit-level estimates, we then calculate the benefits of wind power used to meet RPS targets in 2014, under current practices (ex post scenario), and idealized theoretical scenarios in which fossil fuel EGU displacements are prioritized on the basis of EGU's emission intensity (emission-minimizing scenarios) or its contribution to overall premature mortality (health damage–minimizing scenario). Last, we present the distributional impacts of air quality changes under these scenarios and show the fraction of total benefits that accrues to disadvantaged communities.

Marginal impacts of wind power on unit-level emissions and associated premature mortality

Figure 1 (A to C) shows the changes in electricity generation, SO_2, and NO_x emission associated with a marginal increase (1 MWh) in wind power for fossil fuel EGUs in each of the ISO regions. Marginal increases in wind power have different impacts on fossil fuel EGUs with different fuel types in different regions. Most generation displaced by wind power comes from sources using natural gas and subbituminous coal, except for in the PJM interconnection (PJM) where 56% of the displaced generation comes from sources using bituminous coal. As a result of the displacement patterns, the emission change due to 1 MWh wind power differs markedly between different regions. The largest emission reduction due to wind power is seen in PJM, where 1 MWh wind power, on average, reduces SO_2 emissions by 2.2 kg and NO_x emissions by 0.85 kg. The marginal emission impacts calculated using the data here are largely consistent with previous estimates using other methods (see fig. S1) (*12*, *14*, *15*). The estimated marginal effects on electricity generation and emissions are consistent across different statistical model specifications that include additional control variables and different time fixed effects (see tables S1 to S3).

The avoided emissions associated with marginal increases in wind power deviate markedly from the emission reductions estimated using the ISO-wide average emission factors in our dataset (indicated by the black dots in Fig. 1, B and C). Our estimated SO_2 emission reduction associated with wind power is 74% larger for PJM but 43% smaller for Electric Reliability Council of Texas (ERCOT) than the ISO-wide average emission factors. This is consistent with a previous analysis of the differences between average emission factors and MEFs (*13*). Our main statistical model only estimates the impacts of wind power on fossil fuel EGUs in the same ISO region; however, increases in wind power in one ISO region can likely displace generation from fossil power plants in the neighboring regions due to interregional exchange of electricity (*12*). We further estimate the effects of wind power on electricity export (shown as the shaded areas in Fig. 1A) using a separate dataset from Energy Information Agency (*39*) (method detailed in the Supplementary Materials). We focus on the impacts of wind power on fossil fuel EGUs within each region in the subsequent analysis due to the uncertainty in quantifying the effects of export on each individual power plant; the implications of interregional export of electricity for our air quality analysis are discussed below.

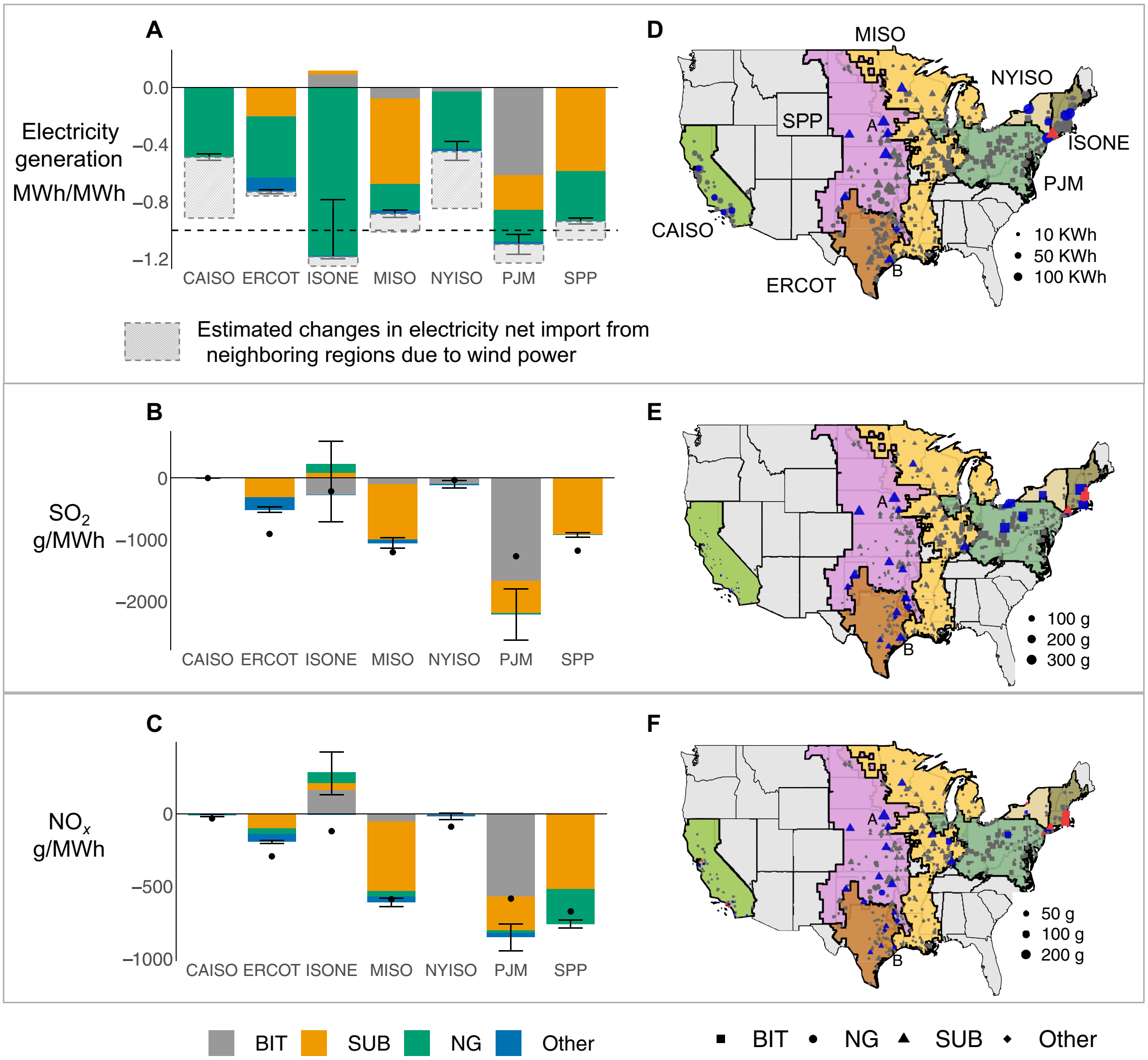

Fig. 1. Estimated changes in electricity generation, SO_2, and NO_x emissions from fossil fuel EGUs due to 1 MWh increase in wind power in each ISO region. (**A** to **C**) The aggregated changes by different ISO regions. Dashed line in (A) represents the 1-MWh threshold. Dots in (B) and (C) represent the ISO-wide average emission factors during 2011 to 2017. The error bar indicates the 95% confidence interval of the aggregated estimates. EGUs are classified by their primary fuel types (BIT, bituminous coal; NG, natural gas; SUB, subbituminous coal). The shaded bars in (A) indicate the estimated changes in electricity net import from neighboring regions due to wind power. (**D** to **F**) Changes for each fossil fuel power plant. Plants in blue and red on the map are those for which generation or emission changes account for >5% of the total displacement of generation or emissions within each ISO region (plants with >10% of the total ISO impacts are colored in the ISONE and NYISO region). Blue indicates a decrease in generation or emissions due to increased wind power, and red indicates an increase. Points A and B on the maps show two power plants as illustrations (discussed in the results section "Marginal impacts of wind power on unit-level emissions and associated premature mortality").

Emission reductions due to marginal increases in wind power mostly come from a small number of fossil fuel EGUs in each ISO region, while the generation and emissions of most other units change only a small amount (see Fig. 1, D to F; see also fig. S2 for box plots of the EGU-level sensitivity). For example, 9.6% of the displaced generation, 11% of the CO_2, 15% of the SO_2, and 18% of the NO_x reductions from a marginal increase of wind power in Midcontinent ISO (MISO) are associated with two adjacent powerplants in West Iowa (point A, including four EGUs). Similarly, 6.0% of the displaced generation, 8.1% of the CO_2, 18% of the SO_2, and 5.0% of the NO_x reductions from a marginal increase of wind power in ERCOT are associated with a single subbituminous coal power plant in southeast Texas (point B, including four EGUs). Within each ISO region, 10% of EGUs are responsible for 28 to 52% of the total displacement of electricity generation, more than 64% of the total avoided SO_2 emissions, and 42% of the avoided NO_x emissions. We focus on the long-term average emission response to wind power for each EGU and thus do not explicitly account for the potentially different marginal impacts of wind power on emissions during different seasons, times of the day, gas price level (*40*), or congestion status (*41*). Differences in the emission impacts of wind power across different seasons and time of the day are limited (see figs. S3 and S4), and seasonal variations are dominated by the variability in wind power production (see the Supplementary Materials for further discussion).

Similarly, displacement of emissions from a small number of fossil fuel EGUs contributes the majority of avoided premature mortality and monetized health benefits that result from marginal increases in wind power (shown in fig. S5). The unit-level health benefits are characterized as the monetized benefits of avoided premature mortality (in the entire United States) attributed to the EGU's emission changes due to an increase of 1-MWh wind power in the corresponding ISO region. Impacts on premature mortality are calculated with CRFs from (*42*) and (*43*) and then monetized using a value of statistical life (VSL) of 7.4 million dollars (year 2006 dollars) recommended by the U.S. EPA (*44*). Fossil fuel EGUs located upwind of populous regions show higher health impacts relative to their emission impacts. For example, 21% of the $PM_{2.5}$-related health benefits and 11% of the O_3-related benefits attributable to wind power and fossil fuel EGUs in the ERCOT region can be attributed to a single coal power plant near the Houston metropolitan area (point B). On average, 10% of the fossil fuel EGUs are responsible for 57% of the $PM_{2.5}$-related health benefits and 71% of the O_3-related health benefits from all fossil fuel EGUs within each ISO region. O_3-related health benefits are approximately 10% of the $PM_{2.5}$-related health benefits. The spatial pattern of O_3-related health benefits is slightly different from that of $PM_{2.5}$-related benefits, mainly because of the different O_3 chemistry regimes at different locations.

Responses to a marginal increase of wind power vary markedly across fossil fuel EGUs within each ISO region. On average, larger EGUs that use natural gas or subbituminous coal have larger (more negative) sensitivities to wind power within each ISO region. Controlling for the size and the fuel type of the units, fossil fuel plants that are older and have pollution control technologies have larger (more negative) sensitivities to wind power (see table S4). We also observe some electricity generation and emission increases due to wind power: We find statistically significant ($P < 0.05$, adjusting for multiple comparisons; see Materials and Methods) positive associations between wind power and unit-level generation and emissions for six EGUs in our sample, including one coal-fired EGU in ISO New England (ISONE) and five gas-fired EGUs in Southwest Power Pool (SPP) and California ISO (CAISO). This may be because these EGUs were ramped up and down frequently to compensate for the variability of wind power, resulting in more frequent start-up, lower operating efficiency, and higher emissions (*45*, *46*). For these six EGUs, we observe that their NO_x emission factors (per unit heat input) increase with wind power production.

Marginal benefits of wind power development

In addition to the air quality benefits, we also estimate the benefits of wind power related to two other factors: reduced cost of fossil fuel generation (including the variable cost of fuel use, operations, and management) and monetized climate benefits from avoided CO_2 emissions. The climate benefits are calculated using a social cost of carbon (SCC) of 35 dollars (year 2007 dollars) as recommended by the U.S. EPA (*47*). All monetary impacts presented in this paper are expressed in 2014 dollars adjusting for inflation. Figure 2 shows these three categories of benefits of wind power development at the ISO level. Consistent with the previous analyses (*15*, *48*), we find the largest benefits of wind power development in the PJM, SPP, and MISO region where the air quality benefits account for 42, 26, and 35% of the total benefits, respectively. The air quality impacts are dominated by the $PM_{2.5}$-related health impacts (>93% of the total health impacts) in most ISO regions, while the O_3-related health benefits account for 22 and 17% of the total air quality benefits in the ERCOT and SPP region, respectively. Benefits of wind power in CAISO, New York ISO (NYISO), and ISONE are dominated by the cost savings of fossil fuel generation, as the predominant natural gas units in these regions generally have higher costs but lower emission intensity (the marginal cost of electricity generation is \$23 for sub-bituminous coal, \$29 for bituminous coal, and \$51 natural gas plants in our sample). Marginal benefits of wind power largely exceed the cost of wind power development [e.g., the levelized cost of wind energy estimates from (*49*)] in MISO, SPP, and PJM, where air quality benefits contribute a large margin to the total benefits (see fig. S6).

Wind power development in one ISO region can also lead to health benefits in neighboring ISO regions through pollution transport, which account for 40 to 78% of the total air quality benefits (see the light blue and light green bars in Fig. 2). For example, every kilowatt-hour wind power increase in PJM leads to a total monetized health benefit of 4.4 cents, with 2.3 cents (52%) accruing to other

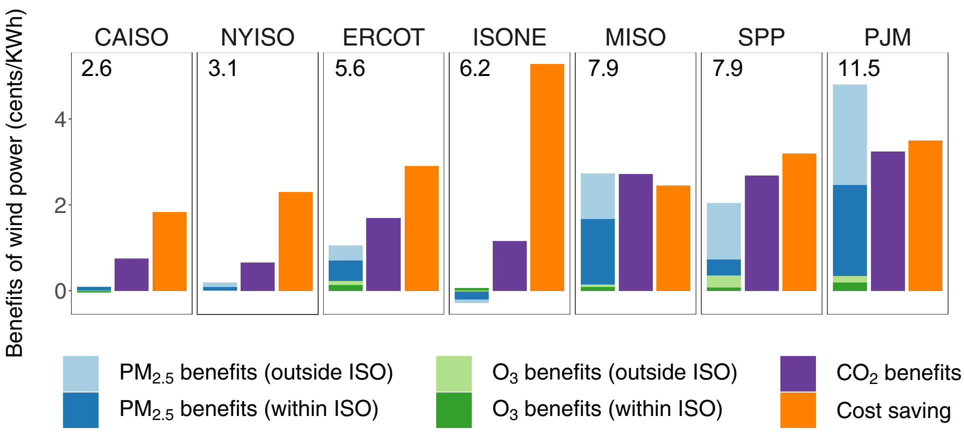

Fig. 2. Benefits of wind power from air quality improvements, cost saving, and CO_2 reductions at the ISO level. The sum of calculated marginal benefits for each ISO region is shown. For a given ISO region, $PM_{2.5}$ or O_3 benefits outside the ISO represent the reductions of air pollution exposure in other ISO regions due to wind power–related emission changes of fossil fuel EGUs in that region. Health impacts are monetized using a value of statistical life (VSL) of 7.4 million dollars (year 2006 dollars) recommended by the U.S. EPA (*44*). Economic cost savings are estimated with the unit-level marginal cost of electricity generation including the marginal cost associated with fuel consumption, operation, and management of the pollution reduction equipment. CO_2 benefits are calculated using a social cost of carbon (SCC) of \$35 (year 2007 dollars). Benefits are expressed in 2014 dollars.

ISO regions and 2.1 cents (48%) retained within the PJM area. Another driver of the cross-border effects of wind power on air quality is due to the interregional export of electricity mentioned above. For NYISO and CAISO, we conduct a sensitivity analysis to calculate the emission and $PM_{2.5}$ impacts due to the increased net export of electricity. We find that the total air quality impacts of the increased export of electricity are quite small due to the small magnitude of absolute air quality benefits from wind power in these two regions (methods detailed in the Supplementary Materials).

Within each ISO region, the state-level benefits of wind power also vary markedly due to the heterogeneous responses of fossil fuel EGUs and regional atmospheric transport of air pollutants (see fig. S7). Impacts of wind power on air pollution exposure in one state (state A) can be attributed to emission changes from three types of fossil fuel EGUs: units in state A ("in state"), units in other states but in the same ISO region ("in ISO"), and units in other ISO regions ("outside ISO"). For most states, the air quality benefits of wind power are dominated by transboundary pollution reductions that cross the border of states and ISO regions. On average, only 35.4% of the air quality benefits at the state level are associated with the in state emission changes. A total of 21.2% of the air quality benefits are associated with in ISO emission changes, and 43.4% are associated with the outside ISO emissions.

Application to RPS: Comparing ex post with theoretical scenarios

Figure 3A shows the total benefits of the wind power used to meet RPS targets in 2014 under the ex post scenario. Estimated with our statistical model, wind power associated with RPS reduced CO_2 emissions by 32 million tons (1.6% of the total power sector emissions in the United States in 2014), SO_2 emissions by 51,000 tons (1.6% of U.S. total), and NO_x emissions by 25,000 tons (1.3% of U.S. total) from fossil fuel EGUs in our sample. These estimates, however, do not aim to represent the causal effects of RPS policy (i.e., we do not aim to assess whether the RPS policy itself was the mechanism that led to this wind power development). Here, we use RPS as a case to quantify effects of wind power development. When monetized, this wind power generated total benefits of 5.0 billion dollars, accounting for economic cost savings, CO_2 reductions, and air quality improvement in the contiguous United States. We estimate an annual reduction of 231 premature mortalities (95% confidence interval, 146 to 318) from decreased $PM_{2.5}$ concentrations due to wind power. The value of these mortalities accounts for 40% of the total benefits. Wind power has mixed impacts on O_3 concentrations, with seasons and areas of both positive and negative improvements (see fig. S10). Nationwide, there is a small decrease in the annual Maximum Daily Average 8-hour (MDA8) O_3 concentration that leads to net health benefits of 0.9 million dollars.

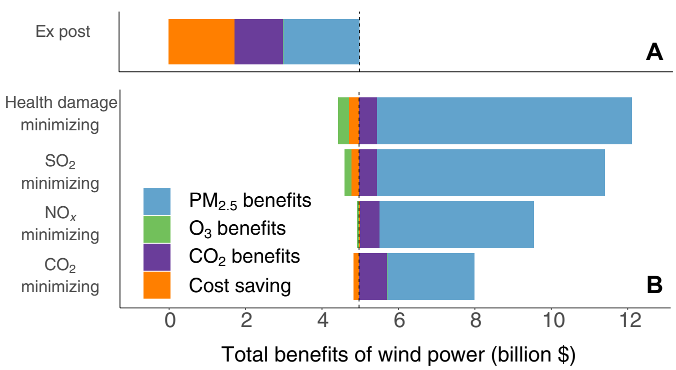

Fig. 3. Substantial extra environmental benefits under alternative theoretical scenarios compared to the expost scenario. Total benefits of wind power associated with RPS targets under the ex post scenario (**A**) and the additional benefits of wind power under theoretical scenarios compared to the ex post scenario (**B**). Benefits are expressed in 2014 dollars.

Figure 3B shows the relative benefits of wind power under the four theoretical scenarios compared with the ex post scenario. Our idealized scenarios are not intended to be realistic policy options but are intended to explore the theoretical maximum potential for alternative displacement strategies to lead to benefits. A smaller but different set of fossil fuel EGUs is displaced under the theoretical scenarios that maximize emission reductions or health benefits. For example, under the CO_2-minimizing scenario, only 228 fossil fuel EGUs reduce more than 1% of their annual generation as a result of wind power (compared to 952 fossil fuel EGUs in the ex post scenario), but the total avoided CO_2 emissions are 57% larger. As a result, the theoretical scenarios lead to larger environmental benefits despite smaller reductions in cost savings relative to the ex post scenario. Under the health damage–minimizing scenario, the same amount of wind power could deliver 11.6 billion dollars in total benefits (relative to 5.0 billion dollars under the ex post scenario). The additional benefits mostly come from health benefits associated with $PM_{2.5}$ reductions (6.7 billion dollars); additional climate benefits add another 0.47 billion dollars. Economic cost savings decreases by a small amount (0.26 billion dollars), because the theoretical scenarios do not minimize the economic cost of electricity generation. The O_3-associated damage also slightly increases (by 0.28 billion dollars) under the theoretical scenarios, due to higher NO_x emission reductions that lead to O_3 increases in certain seasons and regions (see fig. S11). Relative comparisons between these scenarios remain largely similar with alternative CRFs and values of VSL or SCC (see table S5 and fig. S12). We also show that these theoretical scenarios will generate smaller benefits if each state takes separate action to prioritize displacements (e.g., only 9.1 billion dollars under the health damage–minimizing scenario) relative to the case that prioritizes within each ISO region as shown above (see fig. S13).

Distributional effects of air quality benefits from wind power

The air quality benefits of wind power are distributed unequally across populations with different baseline exposure to air pollution, as well as across different income and racial/ethnic groups. For each subgroup, we calculate the differences between the impacts of wind power on the subgroup's mortality rates and the nationwide average impacts due to changes in $PM_{2.5}$ and O_3 (see Fig. 4, A and B). Positive differences indicate that mortality rates declined more due to wind power for the group compared to the nationwide average. People living in more polluted areas ("high-$PM_{2.5}$" group, defined as populations living in the 20% grid cells with the highest $PM_{2.5}$ in 2014) experienced 16% greater $PM_{2.5}$-related health benefits than average in the ex post scenario. Households with annual income less than or equal to twice the federal poverty level ["low-income" group in Fig. 4, defined by EPA's Environmental Justice Screening and Mapping Tool (*50*)] experienced a slightly larger benefit (+1.6%). Hispanic residents experienced substantially smaller-than-average $PM_{2.5}$ benefits (−43%), while Black populations experienced relatively larger benefits (+4.4%). Relative benefits for each income group, racial/ethnic group, and decile group of baseline $PM_{2.5}$ concentration are shown in figs. S14 and S16.

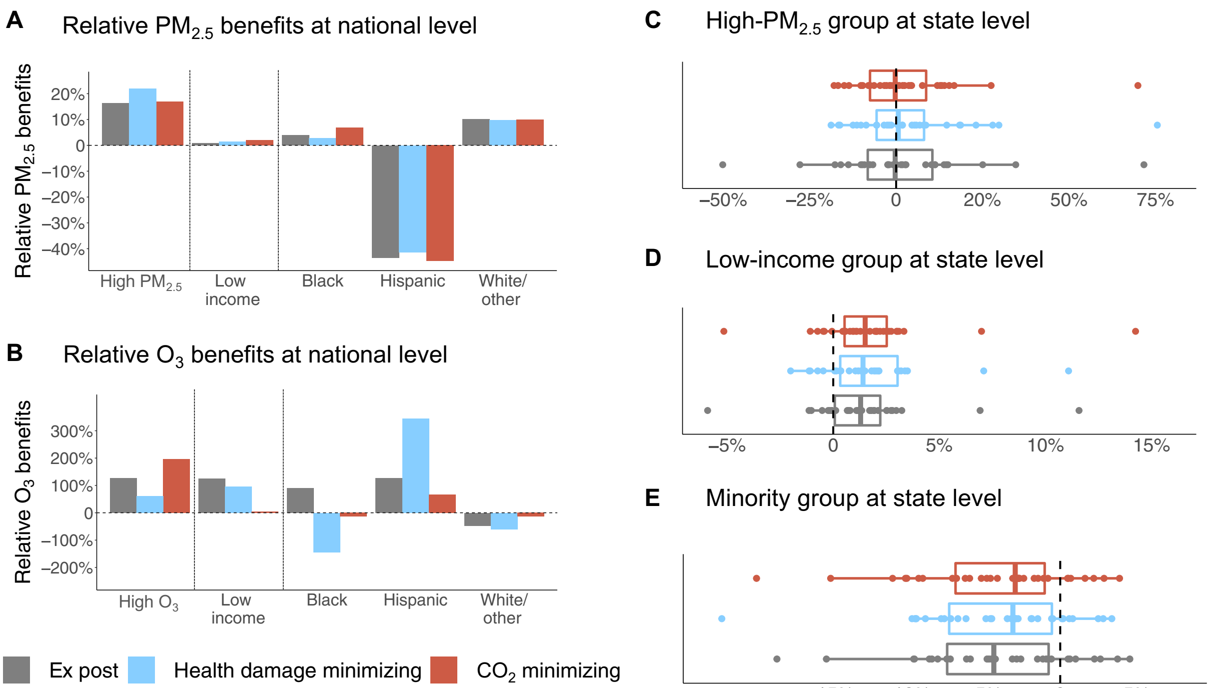

Fig. 4. Percentage difference in health benefits for different demographic groups relative to the nation-wide or state-level average. (**A** and **B**) Percentage difference in health benefits for different demographic groups at the national level compared with the nation-wide average. Positive relative benefits indicate that the specific population group experiences a larger reduction in premature mortality rate compared to the national average changes. (**C** to **E**) Results for different demographic groups at the state level compared with the state-wide average changes in premature mortality. Each dot in the box plots represents one state, and the box lines represent the 25th, 50th, and 75th percentile of the state-level results. Positive relative benefits indicate that the specific population group experiences a larger reduction in $PM_{2.5}$-related premature mortality rate compared with the state average. Negative benefits indicate smaller reductions in mortality rates. Only states that have fossil fuel EGUs in our original sample are plotted here. The three emissions scenarios are shown in different colors.

The distributional effect of wind power on air quality is highly variable at the state level. Figure 4 (C to E) shows the relative $PM_{2.5}$ health benefits experienced by different population groups relative to the state average. Populations living in the high-$PM_{2.5}$ locations within each state do not always experience greater health benefits compared to the state-level average (see Fig. 4C and fig. S18). In most states, low-income populations experienced a larger reduction in $PM_{2.5}$-related premature mortality relative to the state average (see Fig. 4D and fig. S17). On the other hand, wind power leads to larger $PM_{2.5}$ benefits for racial/ethnic minority groups relative to the state average in about a quarter of the states, as much as 4.5% greater, but is up to 22% less in the other three quarters. We find the relative impacts of wind power on $PM_{2.5}$ pollution experienced by the high-$PM_{2.5}$, low-income, and racial/ethnic minority groups remain largely consistent across different scenarios at the state level despite the differences in total avoided emissions and mortality (also see fig. S19). These patterns remain consistent across recent changes in demographic patterns (see fig. S21 for a sensitivity analysis using demographic data for different years between 2007 and 2019) and when accounting for changes in the underlying electricity systems (see fig. S22 for a separate analysis that only uses the more recent emissions and generation data of 2017).

Of the total air quality benefits from the wind power associated with the 2014 RPS targets, we estimate that 32% flows to the low-income populations and 29% flows to the racial/ethnic minority groups as defined by EPA's Environmental Justice Screening and Mapping Tool (*50*) (see fig. S15 for the fraction of the low-income and racial/ethnic minority populations living in each county). Fractions of benefits flowing to the low-income and racial/ethnic minority populations are similar in the two alternative scenarios that maximize total avoided mortality or CO_2 reductions. Across three emission scenarios, 32.5 to 32.7% of the benefits accrue to the low-income populations and 28.8 to 29.1% of the benefits accrue to the racial/ethnic minority groups (see fig. S23). Fractions of benefits flowing to each income and racial/ethnic group can be found in fig. S24.

We perform sensitivity analyses to explore the factors that influence distributional effects of wind power on air quality using alternative air quality modeling methods and demographic information at higher spatial resolution. Our main analysis calculates the impacts on exposure disparities using county-level demographic data, mainly due to the spatial resolution of GEOS-Chem (0.5° × 0.625°, approximately comparable to the sizes of typical U.S. counties). To assess the influence of spatial resolution of the air quality model and demographic information on the exposure disparities, we conduct a sensitivity analysis using the Intervention Model for Air Pollution (InMAP) model. InMAP is a reduced-form air quality model that simulates $PM_{2.5}$ concentrations at higher spatial resolution than GEOS-Chem (approximately at the census tract level) and has been previously used to evaluate the impacts of specific emission sources on $PM_{2.5}$ exposure disparities (*23*, *27*). We calculate the impacts on exposure disparities using InMAP and the census tract level demographic information to account for the demographic variability within counties. For another sensitivity analysis, we use a highly simplified approach that calculates the inverse distance-weighted emissions [IDWEs; used in (*51*)], which only considers the emission changes and the distance between EGUs and county centers, to quantify the influence of distance from sources relative to atmospheric chemistry and pollution transport (see fig. S25). Across these different approaches and emission scenarios, we estimate consistently that 31 to 33% of the air quality benefits accrue to low-income populations (see fig. S23). The alternative approaches estimate a slightly higher fraction of benefits accruing to the racial/ethnic minority populations (30 to 35% with InMAP and 33 to 35% with IDWE) under different emission scenarios, but none exceeds 40%, the target for overall policy benefits recently set at the national level. InMAP estimates at the census tract level are virtually identical to results from the same model aggregated at county scale, suggesting that the spatial resolution of air quality modeling and demographic information has little effect on estimated distributional impacts. This is consistent with a recent work showing that the exposure disparities among racial/ethnic groups are primarily driven by the regional (not local) variability in air quality (*24*) and the robustness of exposure disparity calculations at the census tract level compared with finer scale analyses (*52*). We observe similar variability and heterogeneity of wind power impacts on racial/ethnic minority and low-income populations across states between GEOS-Chem and InMAP (see fig. S26). However, numerical estimates for specific states vary, likely due to assumptions in InMAP that simplify chemistry and pollution transport.

DISCUSSION

Our analysis provides unit-level estimates of the impacts of wind power on emissions, air quality, premature mortality, and exposure disparities using high spatial and temporal resolution data and detailed atmospheric chemistry modeling. We identify a small set of fossil fuel EGUs that are responsible for large fractions of the air quality impacts of wind power within each region. The unit-level information is critical for correctly estimating the changes in air quality—for example, we find that heterogeneous impacts of wind power on O_3 concentrations are negligible when aggregated but are important for some neighborhoods and population groups at smaller scales.

We quantify a large gap between realized and the theoretical upper bound of air quality benefits of wind power. While our theoretical scenarios do not consider transmission constraints and detailed dispatch processes, they show that large gains in health benefits could be achieved by targeting a few high-damaging fossil fuel EGUs with only a modest increase in economic cost. Relative to the ex post scenario, we observe increased health benefits under health damage–minimizing scenarios in all states, suggesting that modified dispatch decisions could provide environmental benefits throughout the country by targeting only a few fossil fuel EGUs in a few states. Comparisons between different theoretical scenarios also demonstrate the relative impacts of using different environmental indicators as the criteria (e.g., carbon emissions or health benefits) and illustrate potential trade-offs between climate benefits and air quality benefits.

By combining empirical estimates at the unit level with a detailed chemical transport model, our analysis estimates the air quality effects of wind power at high spatial and temporal resolution that are important for understanding local impacts on health and air pollution exposure disparities. In particular, our analysis jointly considers the seasonal and diurnal variability of wind power production and atmospheric chemistry regimes, an important component for accurately modeling effects on $PM_{2.5}$ and O_3. Comparing to our InMAP simulations with identical emission changes, health benefits estimated by GEOS-Chem are 34 to 66% larger (across different scenarios). On the other hand, our aggregated estimates of impacts on air quality and human health are lower than the previous estimates reported by Millstein *et al.* (*15*) (see fig. S8). These differences are driven by the fact that EGUs associated with large emission reductions are often far away from population centers. Because we take into account the specific locations of these units, and previous studies were aggregated at regional scale, we calculate a smaller reduction in the population-weighted $PM_{2.5}$ concentrations. There is also considerable variability across different methods of translating emissions into air pollution damages. This highlights important differences between reduced-complexity models (RCMs) and full-chemistry transport models. Similar to most previous studies [e.g., (*15*, *23*, *38*)], our estimates of health benefits only consider the avoided mortality using CRFs derived from long-term exposure studies and thus do not consider the full impacts of air pollution on human health.

Our results suggest that a large fraction of the air quality impacts of state-level policy decisions to develop wind power will fall on other states or ISO regions. Therefore, although air quality benefits could substantially offset costs at a regional level, state-level air quality benefits alone may not provide enough incentive for many individual states to take actions [although adoption of RPS was not historically driven by quantifying such environmental benefits (*53*)]. We also directly quantify the theoretical maximum gains in air quality benefits that would be achieved if the states within each ISO region could cooperate to prioritize displacing the most health-damaging sources.

We find highly heterogeneous impacts of wind power on existing disparities in air pollution exposure in different U.S. states. Under the current practice (ex post scenario), wind power development can have larger benefits for demographic groups known to experience greater pollution burdens in some states but relatively smaller benefits in others. This could contribute to shrinking or enlarging the existing pollution disparities identified in prior work, depending on the location. Even for the same state, wind power development could reduce pollution disparities between different racial/ethnic groups but further enlarge disparities between low and high income households. The theoretical scenarios that minimize the total air pollution damages or CO_2 emissions do not increase their relative impacts for the high-$PM_{2.5}$, low-income, or racial/ethnic minority groups. This underscores the importance of explicitly incorporating distributional issues into policy design. We find that the accurate modeling of the pollutant transport and the absolute magnitude of $PM_{2.5}$ reductions at different locations are essential for assessing the differential impacts of wind power on racial/ethnic groups for $PM_{2.5}$. Under the health damage–minimizing scenario (see figs. S23 and S25), the fractions of benefits flowing to minority populations are slightly higher in IDWE estimates where the range of modeled pollution transport is shorter and the air quality impacts are much more localized than the GEOS-Chem model. InMAP estimates a larger reduction in $PM_{2.5}$ in Texas relative to other parts of the country and thus estimates a higher fraction of benefits flowing to the racial/ethnic minority population, as Texas has a higher fraction of the racial/ethnic minority population compared to the national average. Low computational cost and higher spatial resolution are often cited as reasons for using RCMs. Our results show that the benefit of the increased model resolution is quite limited in this case, as disparities in pollutant exposure from the power sector are driven by regional patterns. Distributional impacts from InMAP are similar to those from the GEOS-Chem simulation when aggregated at the national scale (despite differences in the estimated absolute mortality). However, the more accurate representation of varying chemistry and meteorological conditions in GEOS-Chem leads to very different calculated impacts for specific locations (see fig. S25).

Our data-driven approach identifies the impacts of wind power on air quality and human health for individual fossil fuel EGUs. Our approach can thus be easily extended to regions with available wind power and emission data and modified to investigate similar questions (e.g., the impacts of solar power). Detailed information for the energy system and accurate modeling of pollution transport can provide a key basis for designing complementary policies to existing renewable energy programs to maximize and distribute air quality benefits in an equitable way. The assessed impacts at the EGU level can provide important insights on the localized benefits of wind power and its distribution in different communities. In conclusion, we find that the overall benefits associated with increasing renewable energy capacity under the current market systems are substantial but achieve far less air quality benefit than they could if more damaging fossil fuel EGUs were displaced. However, even efforts that prioritize total health benefits do not increase the fraction of benefits accruing to the racial/ethnic minority groups and low-income groups. As air quality benefits comprise a large fraction of the overall benefits of similar policies, this informs analysis toward future policies that might meet recently set national goals to address environmental justice. More targeted policy design could achieve higher overall environmental benefits from renewable energy development and better address existing disparities in exposure to air pollution.

MATERIALS AND METHODS

Data

Our analysis focuses on the seven ISO regions in the United States: CAISO, ERCOT, ISONE, MISO, NYISO, PJM, and SPP. Hourly level electricity generation and emissions (CO_2, SO_2, and NO_x) of major fossil fuel EGUs (nameplate capacity > 25 MW) are obtained from the EPA Air Market Program Data for the years 2011 to 2017 (*54*). The hourly wind power production and the load demand of each ISO region are derived from each individual ISO website (for NYISO and ERCOT, 2015 to 2017; for the remaining ISOs, 2011 to 2017). We include only the fossil fuel EGUs that have at least 10% nonmissing values of observed generation and emissions during the period. Our final sample consists of 1264 EGUs: 744 EGUs that use natural gas, 248 EGUs that use subbituminous coal, 213 EGUs that use bituminous coal, and 59 EGUs of other types of fuel. The EGUs in our final sample covered 67% of electricity generation and more than 94% of the emissions in the seven ISO regions in 2014.

Unit-level and plant-level characteristics such as location, primary fuel type, age, and stack height are derived from the EPA Emissions & Generation Resource Integrated Database (*55*). Plant-level information on annual net generation, heat inputs used for electricity generation, and cost are derived from the U.S. Energy Information Administration (*56*). The marginal cost of fuel consumption for electricity generation is calculated using fuel cost per unit of heat input [dollar per metric million British thermal unit (MMBtu)] and average heat rate of the plant (MMBtu per megawatt-hour). The marginal operation and maintenance (O&M) cost is calculated as the total O&M cost of flue gas desulfurization, ash collection, and water abatement subtracting the revenues made from the byproducts of these processes, divided by the net generation.

Statistical models

Our statistical model follows the statistical model used by Cullen (*10*). For each EGU i in our sample, we estimate the marginal impacts of wind power on the unit-level electricity generation and emissions with the following equation

$$Y_{i,ymdh} = \alpha_i + \sum_{n=0}^{24}\left(\beta_{i1}^{n} W_{i,ymdh-n} + \beta_{i2}^{n} W_{i,ymdh-n}^{2} + \gamma_{in} X_{iymdh-n}\right) + \delta_{i,\text{ymh}} + \varepsilon_{i,ymdh} \tag{1}$$

where $Y_{i,ymdh}$ is the electricity generation or emissions (CO_2, SO_2, and NO_x) of unit i at year y, month of year m, day of month d, and hour of day h. $W_{i,ymdh}$ is the wind power production in the ISO region (which unit i belongs to). $X_{i,ymdh}$ is the set of control variables including the contemporary and lagged system demand (with both linear and quadratic forms) in the ISO region (which unit i belongs to). $\delta_{i,ymh}$ is the year-month-hour fixed effects that we use in the main specification. $\varepsilon_{i,ymdh}$ is the normally distributed error term. Our main model only estimates the impacts of wind power on the EGUs in the same ISO region.

The main parameters of interest are $\{\beta_{i1}^{n}, \beta_{i2}^{n}\}_{n=0,\ldots,24}$ that measure the impacts of wind power at hour t–n on the unit-level generation and emissions at some specific hour t. These parameters measure the causal impacts of wind power under the identifying assumption that the hourly wind power W is uncorrelated with the error term ε after controlling for the electricity demand and the time fixed effects. As suggested by previous literature, this assumption is likely to be satisfied as the hourly variation in wind power production can be viewed as exogenous (*10*, *11*). The exogeneity of wind power production comes from the facts that (i), in the short run, the wind power potential is almost entirely driven by exogenous meteorological variables (such as wind speed) and that (ii) real wind power production is very close to the wind power potential, as the marginal cost of wind power production is negligible. The quadratic form of W in the regression models allows us to partially capture the nonlinear impacts of wind power on unit-level emissions and generation at different levels of wind power. Our model also allows historical wind power and demand (up to 24 hours) to influence the current emissions, as previous study shows that accounting for dynamics in the power production could significantly influence the estimates of emission offsets of wind power (*10*). We aggregate the impacts of current and lagged wind power into the coefficients β_{i1} and β_{i2} ($\beta_{i1} = \sum_{n=0}^{24}\beta_{i1}^{n}$, $\beta_{i2} = \sum_{n=0}^{24}\beta_{i2}^{n}$).

We calculate the partial derivative of Y_i due to a unit change of W_i, $\partial Y_i/\partial W_i$ (denoted as the marginal impacts of wind power on unit i) as

$$\frac{\partial Y_i}{\partial W_i} = \beta_{i1} + 2\,\beta_{i2} \times \overline{W}_i \tag{2}$$

where $\overline{W_i}$ denotes the average value of wind power production in the ISO region (which unit i belongs to) across all hours. $\partial Y_i/\partial W_i$ thus quantifies the marginal impact of wind power on unit i at the average wind power production level.

We use the heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimator (the Newey-West estimator) to estimate the standard error (SE) (*57*). The maximum lag with positive weight for the Newey-West estimator is 24 hours. We also adjust the *P* values of the estimates to adjust for multiple comparisons with the procedure from Benjamini and Hochberg (*58*). This procedure adjusts the test statistic and *P* value of the estimated sensitivity for each EGU and controls the expected portion of "false discoveries" (falsely rejected null hypothesis) below a certain threshold.

Alternative specifications of the statistical model

We use several alternative specifications of the statistical model to understand the influence of potential confounders and model specifications on the estimated wind power effects. Tables S1 to S3 show the estimated changes in electricity generation, SO_2, and NO_x emissions from fossil fuel EGUs due to marginal increases in wind power in each ISO region, under different statistical models. In addition to our main specification (column 1 in the tables), we also construct two alternative specifications of the time fixed effects and quantify the influences of gas prices, zero values (thus testing the effects of wind power on operating fossil fuel EGUs alone), missing values, and the congestion status. Sources of the underlying variables and regression specifications are detailed in the Supplementary Materials.

Air quality modeling

We use GEOS-Chem to estimate the impacts of wind power on $PM_{2.5}$ and O_3 concentrations. GEOS-Chem is a global three-dimensional chemical transport model driven by meteorological input from the Goddard Earth Observing System (GEOS) of the NASA Global Modeling and Assimilation Office (www.geos-chem.org/) (*59*).

We estimate the unit-level impacts of wind power production on air quality using the adjoint of the GEOS-Chem model. The GEOS-Chem adjoint model can calculate how model parameters (e.g., emissions in a single grid cell) influence model outputs (e.g., $PM_{2.5}$ concentrations in a single grid cell or over a larger spatial domain) (*60*). Here, we use archived model outputs from Dedoussi *et al.* (*38*) that calculate the sensitivities of the state-level population-weighted $PM_{2.5}$ and O_3 concentrations to the SO_2 and NO_x emission changes in each 0.5° × 0.666° grid cell in the contiguous United States. The adjoint model projects how emission changes in any location influence $PM_{2.5}$ concentrations with full spatial resolution and then aggregates these concentrations to calculate impacts on state-level population weighted concentrations. More details regarding the air quality sensitivities can be found in the Supplementary Materials and Dedoussi *et al.* (*38*).

We use the GEOS-Chem forward model to simulate the air quality impacts of the wind power used to meet RPS targets in 2014, under different scenarios, and for our analysis on exposure disparities. We use GEOS-Chem version 12.3.0 with a horizontal resolution of 0.5° × 0.625° in North America (*61*). More details on GEOS-Chem can be found in the Supplementary Materials.

Health impacts

The health impacts of wind power development are quantified in terms of the premature mortality associated with changes in exposure to $PM_{2.5}$ and O_3. For premature mortality associated with $PM_{2.5}$, we use the CRF from Krewski *et al.* (*42*). We estimate the premature mortality of all causes [hazard ratio (HR): 1.056 (95% confidence interval, 1.035 to 1.078)], cardiopulmonary diseases [HR: 1.129 (1.095 to 1.164)], and lung cancer [HR: 1.129 (1.056 to 1.225)]. Table S5 shows the avoided all-cause mortalities related to $PM_{2.5}$ changes estimated with alternative CRFs (*62*–*65*). For O_3, we estimate the premature mortality using the CRF from Turner *et al.* (*43*). We calculate the premature mortality for all causes [HR: 1.02 (1.01 to 1.04)] and for respiratory diseases [HR: 1.12 (1.08 to 1.16)].

All-cause and cause-specific baseline mortality rates of the 30-plus population in the United States in 2014 are derived from the 10th version of the International Classification of Diseases (*66*). For the analysis on the exposure disparities, we use county-specific baseline mortality rates from the U.S. Centers for Disease Control and Prevention (*67*). Gridded population data are obtained from the Columbia University Center for International Earth Science Information Network (*68*) for the year 2015 and scaled to match the state-level U.S. population in 2014. Population data and the fraction of adults over 30 years old in each state are obtained from the U.S. Census Bureau (*69*).

Distributional impacts

We calculate the impacts of wind power on population-weighted $PM_{2.5}$ and O_3 concentrations for different demographic groups. We combine simulated $PM_{2.5}$ and O_3 concentrations from GEOS-Chem with the county-level demographic information (i.e., population counts of different income and racial/ethnic groups in each county). We then estimate the premature mortality of each demographic group in each county due to changes in $PM_{2.5}$ and O_3 and further aggregate the results to the state and national levels. The main analysis uses the American Community Survey data from 2013 to 2017 (*70*), and we perform sensitivity analyses with demographic data in other years (2007 to 2011 and 2015 to 2019). We also match the GEOS-Chem outputs with the county-level population count of the racial/ethnic minority and low-income groups as defined in the Environmental Justice Screening and Mapping Tool developed by the U.S. EPA. We defined the high-$PM_{2.5}$ group as populations living in the 20% grid cells with the highest $PM_{2.5}$ in 2014. We use the estimates of ground-level $PM_{2.5}$ (annual average of 2014) from Hammer *et al.* (*71*), which uses satellite products as a data-informed baseline. We perform a sensitivity analysis using the simulated $PM_{2.5}$ concentration from GEOS-Chem to determine the high-$PM_{2.5}$ group and to find similar results.

To address whether our results were influenced by the spatial resolution of GEOS-Chem, we perform a sensitivity analysis with the InMAP at the census tract level (*72*). The spatial resolution of our GEOS-Chem simulation is 0.5° × 0.625°, approximately the size of typical U.S. counties (see fig. S20). InMAP is a reduced complexity model that simulates annual average $PM_{2.5}$ concentrations at finer resolution near urban areas and has been previously used at national scale to identify disparities in pollutants between different racial/ethnic groups (*23*, *27*). The grid cell size of InMAP varies dynamically on the basis of the population density (smaller cell size in the urban populous regions) but is generally comparable to the size of census tracts (see fig. S20).

We also perform a sensitivity analysis that accounts only for displaced emissions and the EGU locations (and thus ignores the role of atmospheric chemistry and meteorology). This approach calculates the IDWEs as a simplified way to assess the air pollution exposure. For each county i, IDWE is calculated as

$$\text{IDWE}_i = \sum_{j \in J} \text{emissions}_j \times \text{distance}_{i,j}^{-1} \tag{3}$$

where J is the set of all fossil fuel EGUs in our sample and $\text{distance}_{i,j}$ is the distance between the center of county i and EGU j. This approach has been previously applied as a simplified reduced-complexity approach for assessing pollution exposure (*51*).

Emission projections

We estimate the impacts of wind power associated with RPS targets in 2014 on emissions and air quality under current (ex post scenario) and idealized theoretical scenarios. In 2014, the total amount of renewable power generation associated with RPS (number of renewable energy credits) was 118.9 TWh in the 21 states that we studied, and 52.7% of the target was met by wind power produced in the seven ISO regions (62.6 TWh). RPS targets met by wind power in each state and the wind power production used to meet the RPS are shown in fig. S9. State-level RPS targets and the amount of wind power used for compliance are derived from the annual RPS compliance reports (*73*) and the website of each individual state. To derive an hourly estimate, the wind power used to meet RPS targets in 2014 is then aggregated to the ISO level and partitioned to each hour based on the observed temporal pattern of wind power production in 2014.

We use Eq.1 to estimate the ex post impacts of the wind power associated with RPS on unit-level emissions. We can use marginal effects (Eq. 1) to quantify nonmarginal emission changes because the amount of wind power associated with RPS targets is quite small (1.5% of the U.S. total generation in 2014) and comparable to the variability of observed wind power that is used to estimate the marginal effects. Impact of wind power on the emissions of unit i in a specific hour t can thus be calculated as

$$\Delta \text{Emission}_{it} = \beta_{i1} \times \Delta W_{\text{it}} + \beta_{i2} \times \left(W_{it}^2 - \left(W_{it} - \Delta W_{it}^2\right)\right) \tag{4}$$

where ΔW_{it} is the amount of wind power produced in the ISO region (which unit i belongs to) at hour t to meet RPS targets. This allows us to estimate what the emissions would have been for each fossil fuel EGU if the amount of wind power associated with RPS in 2014 was not produced.

Idealized theoretical scenarios

The impacts of wind power on unit-level electricity generation and emissions under the ex post scenario are the outcome of current dispatch decisions that the system operators decide dispatch schedules based on the marginal generating cost subject to dispatch constraints. We also construct theoretical scenarios to estimate theoretical maximum emission reductions and health impacts for hypothetical cases where dispatch decisions are made using other unit-level characteristics instead of the marginal cost. For each hour of 2014, each of the theoretical scenarios displaces the same amount of electricity generation from the fossil fuel EGUs in our sample as the ex post estimates. However, each theoretical scenario decides which unit to ramp down based on alternative criteria. This could be formulated as an optimization problem

$$\begin{gathered} \min_{g_{it}} \sum_{i \in I} g_{it} \times k_i \\ s.t. \sum_{i \in I} g_{it} = \text{G}_{It} \end{gathered} \tag{5}$$

where g_{it} represents the amount of electricity generation changes of unit i at hour t under the theoretical scenario. k_i is the unit-level characteristic that is used in the hypothetical dispatch decision. I is the set of fossil fuel EGUs within each ISO region. The objective is to minimize the emissions or pollution-related mortalities. The constraint condition of the optimization problem makes sure that the total displacement of electricity generation is the same as the displaced generation in the ex post scenario every hour for each ISO region (G_{It}).

We design four theoretical scenarios: three that use unit-level emission intensity (CO_2, SO_2, and NO_x) and one that uses unit-level impacts on premature mortality as the decision criteria. The three emission-minimizing scenarios minimize the total emissions from fossil fuel EGUs and thus maximize the avoided emissions due to wind power generation by displacing electricity generation from EGUs with higher emission intensity. The health damage–minimizing scenario minimizes the health damages from fossil fuel EGUs based on their impacts on premature mortality. Our main scenarios do not include any dispatch constraints on how much generation could be displaced for each unit. We perform sensitivity analyses that evaluate these four scenarios with some dispatch constraints that the electricity generation is only allowed to be displaced up to a certain fraction (detailed in the Supplementary Materials; see fig. S27). We also design four additional sensitivity scenarios that displace same amount of electricity generation as the ex post scenario for each state (instead of each ISO region), which simulate the impacts of a situation in which each state is only allowed to coordinate the dispatch schedule of EGUs within the state. More details on the theoretical scenarios can be found in the Supplementary Materials.

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at https://science.org/doi/10.1126/sciadv.abn8762

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