Title: Burdened by renewable energy? A multi-scalar analysis of distributional justice and wind energy in the United States

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Abstract:
The transition towards renewable energy is likely to be uneven across social and spatial dimensions. To ensure this transition is equitable and just, energy injustice has become the key framework for analyzing and interpreting the distribution of energy infrastructure. Wind energy development has experienced a significant gap between broad public support for increased development but persistent localized opposition to proposed projects, indicating that wind represents a locally unwanted land use. We present the theoretical argument that although the negative impacts of wind energy infrastructure are less extreme than those posed by other, more toxic, unwanted land uses, their status as a locally unwanted land use will produce similar distributional injustices as have been found throughout the environmental injustice literature. Using data from both the American Community Survey, the U.S. Wind Turbine Database, and the National Renewable Energy Lab we use logistic and Poisson regressions, fixed effects, and temporal lags to evaluate the current landscape of wind energy injustice along the social dimensions of income, race and ethnicity, age, education, labor force participation, and rurality at three spatial scales: between all counties within the contiguous United States, between counties within states with wind energy, and between census tracts within counties with wind energy. We do not find strong evidence of distributional injustice along the lines of race, ethnicity, or low-income. However, we do find evidence of injustice for populations which are younger, less educated, have lower labor force participation, and are more rural.

Keywords: Environmental justice; Energy justice; Wind energy; Renewable energy; United States; Development

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Introduction

The expansion of, and transition to, renewable energy is essential if the world is to decrease reliance on fossil fuels and carbon emissions in the coming decades [1]. This need has been met with calls to ensure this transition does not create new social imbalances, nor exacerbate existing environmental and social inequalities [2]. Assessing and preventing inequality in the distribution of renewable energy infrastructure is necessary, not only to ensure these transitions to renewable energy are just, but also successful [1–4]. As hallmarked by the importance of the social license to operate in mining and energy development [4,5], community support and buy-in for development is crucial for the sustainability and efficacy of projects [6]. Further, as Walker, Mason, and Bednar [7], Walker and Baxter [8,9], and Zárate-Toledo et al. [6] have shown recently in the case of wind energy, this support ultimately hinges on public perceptions of fairness, equity, and power in the siting process. Thus, an uneven distribution of renewable energy infrastructure along social dimensions such as income, race, or ethnicity results in distributional injustices that not only further marginalize vulnerable populations, but also limit the success of renewable energy transitions.

These concerns over both social equity and the future of energy development have resulted in energy injustice emerging as the key framework for understanding these issues [10,11].[1] Distributional social injustices occur when the costs and benefits of an action are unevenly distributed throughout the population [10]. In the case of energy injustice, this means that the

[1] Throughout this manuscript, we adopt a somewhat unconventional approach and refer to the frameworks of environmental and energy justice as environmental and energy *in*justice. We adopt this approach, in-line with that of Walker, Mason, and Bednar [7], to distinguish our research—which focuses on identifying current injustice—from research which evaluates or delivers justice. While this distinction may seem trivial, or semantic, we believe it is an important distinction to make so that we preserve the term ‘energy justice research’ for those studies which either deliver, or assess the delivery of, energy justice to those who have previously been treated unjustly.

burden of energy production is felt disproportionately by one segment, or a few segments, of the population. Historically, injustices related to the siting of locally unwanted land uses, such as energy infrastructure and toxic waste facilities, have fallen along societal divisions of both class and race [12]. In this analysis we test these historic lines of division as they relate to the current landscape of wind energy development in the United States.

Wind energy, unlike many forms of non-renewable energy, has experienced a unique ‘social gap’ in public support for development [13,14]. This gap is marked by widespread public support for increased wind energy development, but considerable localized opposition to many proposed wind farms. Thus, although recent polls suggest that the vast majority of Americans support increased wind energy development in the United States [15], significant localized opposition to the actual siting of this infrastructure persists [16]. Based upon this persistent social gap characterized by local opposition to the majority of projects, we argue wind energy can be classified as a locally unwanted land use.

Localized resistance to any locally unwanted land use requires significant social and financial capital [17,18]. Therefore, we argue the spatial pattern of wind energy development can be expected to be similar to other locally unwanted land uses in the United States such as toxic waste dumps and power plants [19,20]. From this, we argue that environmental and energy injustice theory suggest wind energy will be disproportionately sited in areas where residents have lower social and financial capital, placing the cost and burden of wind energy development on groups historically marginalized in society. Indeed, recent research in Mexico suggests that the exclusion of local residents from the decision-making process surrounding wind energy bore a striking resemblance to the patterns of injustice surrounding the siting of toxic waste facilities in the United States [6].

We test this theoretical argument of uneven distribution with a multi-scalar sub-national approach. We view this approach as an answer to Lobao, Hooks, and Tickamyers's [21] call for more attention at the subnational scale, meaning the scale missing between nation-state focused and locally focused social science. The scale at which we assess issues of inequality, environmental or otherwise, can have a significant impact on results due to the smoothing effects of aggregation [22–24]. To avoid this pitfall, we draw our conclusions using models of energy injustice at three levels of geographic aggregation. In particular, we investigate distributional wind energy injustice associated with the social dimensions of age, income, ethnicity/race, education, labor force participation, and rurality at three spatial scales: counties across the nation, counties within states, and census tracts within counties.

Background

Energy and Environmental Injustice

Energy injustice emerged from environmental injustice, which developed out of the historical siting of environmental hazards, energy infrastructure, and other locally unwanted land uses in areas predominately inhabited by marginalized populations [11,12]. Environmental justice, the positive form of the term, is defined by Bullard and Johnson [25] as "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies (p.558)." From this, environmental injustice is then the absence of this fair treatment, meaningful involvement, or equitable distribution across all people. In short, environmental injustice occurs when a minority is forced to bear an unequal share of an environmental burden imposed by the majority [26].

There are three main theoretical explanations for the unjust siting of unwanted infrastructure: economic, social, and racial [18]. Although Mohai and Saha [18] discuss these perspectives in regard to environmental injustice, we believe they are equally valuable for understanding issues of distributional energy injustice. The economic perspective argues that the pattern of uneven infrastructure siting is largely the result of industries finding it cheaper to do business in geographic areas inhabited by those who are historically disadvantaged in American society, such as people of color and the poor. In this framework, societal discrimination may be a factor, but the direct cause of injustice remains economic. The sociopolitical perspective has to do with the 'path of least resistance.' This framework argues that those siting unwanted infrastructure will often choose areas where effective protest is unlikely [17,18]. This perspective acknowledges that industries siting locally unwanted land uses know they face costly opposition, and therefore choose to target areas with lower social and financial capital, where local opposition has historically been less effective.

The final explanation for the disparate siting of hazardous and unwanted land uses is racial discrimination. Environmental racism is the most prominent dimension of environmental injustice in the United States, remaining at the forefront of discussion since the start of the movement [20]. While there remains a debate as to whether intentional racial discrimination is the cause of disparate siting, the consistent findings of unjust distribution make structural environmental racism undeniable. Even if outright racial animus is not present, siting choices may still be made in communities of color due to the sociopolitical reasons described above [18]. This results in what Mohai and Saha [18] call side effect discrimination, or "discrimination in one area of institutional actions leading to discriminatory outcomes in another, even if there is not intent to discriminate in the other (p. 3)." Ultimately, it is not just one of these perspectives that is the cause of energy injustice, but rather a combination of these dimensions that leads to the persistent injustices faced by marginalized portions of society.

Forms of Energy Injustice. The framework of energy injustice is largely in keeping with that of environmental injustice, except that its focus is explicitly on energy development and energy supply [27]. Similar to environmental injustice, there are three main forms of energy injustice: distributional, procedural, and recognition [10,27,28]. Although this paper only directly considers distributional injustice, we briefly outline all three forms here. Distributional injustice refers to the unequal distribution of the costs and benefits of energy development [29], meaning the burdens of energy development are unfairly placed on one, often marginalized, segment of society.

The second prominent dimension of energy injustice is procedural injustice [10]. Procedural injustice represents unequal access to the process of decision-making that occurs concerning energy development. In addition to access to the decision-making process, procedural injustice also involves the incomplete disclosure of information on various forms of energy development, which forms of energy development receive subsidies, and any plans for future development [27]. Although procedural injustice is commonly invoked in the literature, it is important to note that ensuring involvement in the process of decision making does not necessarily equate to environmental justice. This is due to the fact that the very structure of decision making is often imposed by both the state and other actors in power [30].

A related, but alternative form of injustice is recognition injustice [31]. This is the failure of industry and society to treat local people with equal respect, thus not giving them recognition as full members of society and resulting in stigmatization, inequality, and injustice. Importantly, Schlosberg [28] notes that while preventing procedural injustice often amounts to a seat at the table and looks to the state for solutions or enforcement, the prevention of recognition injustice requires recognition not only by the state, but also by social, cultural, and symbolic realms. Thus, preventing recognition injustice requires recognition by the community and culture at large [28].

Wind Energy

Wind energy has experienced rapid growth throughout the United States from the early 2000s to today [32], with its contribution to meeting the total electricity demand growing from 1.5% to 4.5% in the period from 2008 to 2013 alone. The growth has continued, and the wind energy industry has built over 57,000 commercial wind turbines in 615 counties throughout the contiguous continental United States (Figure 1) [33].

[Figure 1]

The land required for wind energy can be significant. Under the current goal of wind energy meeting 20% of U.S. electrical demand, the estimated land area required for on-shore wind energy will reach 50,000 square kilometers, or 19,305 square miles, by 2030 [34]. However, in the case of wind it is important to distinguish between the total wind plant area, meaning the total area occupied by an entire wind farm, and the direct impact area, meaning the actual impact on the ground of individual turbines and support infrastructure [35]. Wind energy’s presence on the landscape can be diffuse, meaning that the entire square footage of an average 100 turbine wind power plant, or wind farm, occupies around 5,175 hectares, or 20 square miles. However, the direct impact of the wind turbines will only occupy about 150 hectares, or 0.57 square miles [34]. Thus, unlike some other forms of energy development, it is possible for activities such as farming, grazing, or other land uses to occur alongside wind energy development.

The negative impacts associated with wind energy remain contested. Opposition to proposed wind energy projects is multi-dimensional and stems from a number of concerns including annoyance and chronic stress due to noise [36], visual impacts caused by landscape change [36], perceived impacts to property values [37-39], wildlife impacts [36], and feelings of exclusion and powerlessness in the planning process [6,8,40]. While habitat and wildlife related impacts from wind turbines are smaller than impacts from other forms of energy such as coal and oil, a potentially more significant negative impact of wind turbine proximity is noise pollution [36,41]. The constant noise associated with wind turbine proximity has been linked to lower sleep quality [42] and annoyance [42–44]. While concerns of chronic stress due to wind turbine noise have been raised as a concern, no peer-reviewed literature has demonstrated this effect [45,46].

Wind turbines have commonly been associated with increased annoyance among nearby residents and a large portion of the variation in annoyance due to wind turbine noise has been attributed to visual impacts of wind turbines [44]. This visual impact, wherein the implementation of a wind farm disrupts the existing landscape, is a common complaint levied at wind energy development [13]. Public dissatisfaction with wind development is often deeper than simply 'Not in My Backyard' visual concerns [47,48]. The implementation of a large-scale landscape change can impact deep place attachments, which are tied to living in a specific place the way it has historically been known [13]. This landscape change may cause disruption and what Albrecht et al. [49] have termed 'solastalgia', the feeling of homesickness and distress caused by the radical change of the home environment. Overall, while 'by the numbers' wind energy development may have a smaller impact on both communities and the environment than other forms of energy development, its qualitative impacts to both sense of place and individual lives remain quite significant.

It should be noted that beyond the society-wide environmental positive impacts of wind energy, there are also local positive benefits in the form of both lease fees [50] and, increasingly, community benefit agreements [51,52]. A primary way that direct positive impacts of wind energy development accrue is through fees to the landowner where the turbine is sited. Although this does provide a benefit, the negative impacts of development accrue to both the landowner and surrounding residents who may or may not own land. This is similar to shale gas development, as both wind turbines and wells often pay lease fees to the landowner whose property they are placed upon [50,53]. Importantly, these benefits are generally enjoyed exclusively by those who already own land in an area. As demonstrated by Schafft et al. [53] in the case of Marcellus Shale, this has the possibility of exacerbating existing inequalities and generating resentment within a community, as those who do not own land suitable for development are left out of the benefit but still bear the burden of development and landscape change. This parallel suggests that research focusing on landowners, who are the most likely to benefit from development, may be missing important dimensions of injustice and concern.

To remedy this discrepancy between benefit and impact, as well as increase the community support necessary for successful project implementation, many development projects now provide community benefit agreements [51,54,55]. Community benefit agreements are arrangements between developers and communities where a financial package is conferred to the community impacted by development [55]. These benefits can either be direct, in-kind, or through the provision of local ownership or contracting [54]. In return for these benefits, the community agrees to support the project [52]. Although the primary discourse of these agreements as it relates to wind energy has been on engendering community support, others have argued these agreements can serve as a means of enacting environmental justice [56].

In the past several decades, community benefit agreements have become increasingly popular in wind energy development, particularly in the United Kingdom where the bulk of the research on this topic has been conducted. As the majority of this work has been in Europe, it is unclear the extent of these agreements in the United States. However, with the Nature Conservancy and the Alliance for Clean Energy New York advocating for their increased inclusion in renewable energy development [57], the Department of Energy publishing literature on their use [52], and the emergence of benefit agreements in off-shore wind development in New England [51], they are clearly of increasing importance in the United States context.

Although energy justice research on wind energy remains emergent, researchers have begun analyzing the phenomena and have found evidence, particularly as it relates to procedural injustice. Pedersen et al. [40] found that residents viewed wind energy development as an intrusion and expressed a sense of powerlessness surrounding development. Walker and Baxter [8] tested perceptions of procedural injustice and wind energy development in Canada and found evidence of procedural injustice in Ontario, which developed its wind energy using a top-down technocratic approach. Walker and Baxter [8] also found that perceptions of power in the planning process were the strongest predictors of wind energy approval. In a related study, Walker and Baxter [9] found perceptions of distributional fairness of the benefits from wind were the strongest predictor of project support.

As it relates to spatial inequality, Walker, Mason, and Bednar [7] investigated perceptions of injustice in rural Ontario with a focus on rural versus urban environmental injustice. They found rural residents felt they were bearing the majority of the burden for renewable energy development, while urban residents were able to benefit without experiencing any of the impacts. The residents felt development was out of their control and they were receiving little, if any, economic benefit [7]. Finally, in a recent study in Mexico, Zárate-Toledo et al. [6] found strong evidence of procedural energy injustice surrounding wind and concluded the wind energy development in Mexico used an extractive model of development, where indigenous communities were not considered, land was grabbed, and large companies were allowed to build with limited community engagement. This injustice sparked such fierce opposition that one of the largest projects was ultimately halted [6].

The impacts we have outlined contribute to what is known as the social gap in wind energy siting [13]. For example, in the United Kingdom over 80% of residents support increased wind energy development, but only 25%-50% of proposed projects are successfully implemented [13]. In the United States, the context of this study, as much as 85% of residents support increased wind energy development, but local opposition to specific projects persists [15,58]. In an analysis of 53 wind energy proposals in the western United States, Giordono et al. [16] found some form of local opposition occurred to 43 of the 53 proposals. While three or more forms of local opposition only occurred in 19 of the 53 proposals, it is unclear if that difference in the number of forms of opposition was due to a true lack of opposition or a simply a local inability to effectively mobilize, which the sociopolitical explanation for environmental injustice would suggest [18].

While there is documented opposition [16,39,60] and ambivalence [61] to proposed wind energy development, we must note that there is also research documenting local support for future and existing development [3,62–65]—particularly in the areas directly surrounding wind energy development [3,59]. Thus, not all wind energy projects are contested—many have been welcomed—but the issue appears divergent, context specific, and subject to the mechanisms of environmental injustice discussed above.

Theoretical Rationale and Hypotheses

Given the significant gap between overall support for wind energy and the frequent local opposition to wind turbine placement [13,14,16,60], it is clear wind represents a locally unwanted land use, much like the sources of toxic pollution identified by the environmental justice movement [12,20]. We posit that although the negative health impacts of wind energy are less direct than those of toxic waste dumps or other sources of point pollution, the landscape of wind energy will carry with it the same trends of distributional injustice found throughout the environmental and energy injustice literature [19,12,18]. Key to this framework are the economic, sociopolitical, and racial explanations for the unjust distribution of locally unwanted land uses described by Mohai and Saha [18]. We hypothesize wind energy infrastructure will be more common in areas with higher aggregate levels of societal disadvantage.

This unequal distribution will be due to the sociopolitical explanation, meaning the difficulties of organizing and effectively opposing locally unwanted land uses; the economic explanation, meaning the economic realities of where marginalized groups live and the capitalist orientation of developers; and the racial explanation, meaning the outright, as well as structural, discrimination of marginalized groups by corporations. Importantly, we *do not* argue that wind energy development is as detrimental as toxic waste dumps and other facilities to local health and the environment. Rather, we argue that due to its status as a locally unwanted land use, wind energy development can be expected to follow similar distributional patterns as these more harmful locally unwanted land uses across the United States. Through this perspective on the unjust siting of locally unwanted land uses, we test one overall theoretical hypothesis:

Hypothesis 1: Wind energy development is more likely in geographic areas with higher levels of societal disadvantage.

To test this larger hypothesis, we test six sub-hypotheses focused on dimensions of disadvantage found in the United States, and associated with historic distributional environmental injustices.

Income

The inequitable dumping of environmental harms on the poor is one of the most common injustices identified from the start of the environmental justice movement [12,19]. Research has consistently found that locally unwanted land uses are more frequent in areas inhabited by poorer segments of society [18]. In their review of socioeconomic status and health, Evans and Kantrowitz [66] identified that those with lower incomes have been found to be more proximate to hazardous waste, air pollution, water pollution, ambient noise, and residential crowding. While numerous studies have found relationships between injustice and income, it is important to note that the empirical support for this has been found to depend on the source of development [67]. In a meta-analysis of 34 studies using income measures, this variation caused Ringquist [67] to assert that, while there is evidence for income-based environmental inequality in the literature, the evidence is weak when considering all available studies.

Although the relationship has shown mixed results, the literature suggests that we should generally expect locally unwanted land uses to be more common in areas with lower economic advantage, leading us to propose the sub-hypothesis:

Hypothesis 1.1: Wind energy infrastructure is more likely in geographic areas with lower median income.

Race and Ethnicity

More consistent than the impacts of income on injustice is environmental racism [12,18,67,68]. In the same meta-analysis by Ringquist [67], significant and consistent evidence of racial inequity was found across 48 independent studies. Noxious pollutants and other facilities were disproportionately concentrated in communities where residents were more likely to be racial and ethnic minorities. While findings have varied between studies, with some even reporting no racial environmental injustice, Mohai and Saha [68] showed that many of the studies finding limited effects can be explained by the choice of method. When using explicitly spatial approaches, as opposed to traditional approaches using dichotomous classifications of either in proximity of a hazard or not, Mohai and Saha [68] showed that the estimates of racial environmental inequity become even larger. Given the historically racialized distribution of locally unwanted land uses similar to wind energy, we propose our second sub-hypothesis:

Hypothesis 1.2: Wind energy infrastructure is more likely in geographic areas with higher proportions of non-White and Hispanic residents.

Age

Our hypothesis regarding the relationship between age and the siting of wind energy infrastructure draws less on the environmental or energy justice literature, and more on the literature surrounding community participation in natural resource management [69,70]. Wind energy often faces public resistance from concerned local citizens. However, as discussed by Mohai and Saha [18] and Been [13], effective resistance requires significant time and capital. Research on the public attendance of community meetings for collaborative natural resource management has shown that attendance at meetings is not representative of the population, with attendees often being older and more affluent than the general population [69,70]. This attendance is reflective of the greater amounts of free time enjoyed by older adults due to both retirement and a lack of childcare responsibilities. Given this, we expect that areas with higher median ages will have been more effective at opposing wind energy development due to their increased level of time to engage in resistance. We formally state this as:

Hypothesis 1.3: Wind energy infrastructure is more likely in geographic areas with lower median ages.

Education and Labor Force Participation

Our hypotheses concerning education and labor force participation represent an extension of the findings of environmental justice scholarship surrounding income [18,67,68], as well the necessary conditions for successful opposition to an unwanted land use at the local level. While research has often shown that locally unwanted land uses are disproportionately sited in areas with lower median income, this income is likely to be a reflection of the labor conditions and human capital (e.g. education) in a region. Thus, we would expect wind energy development to be more likely in places with lower labor force participation and lower overall education. Further, research has shown a direct relationship between areas with both lower employment and education and proximity to environmental hazards [71,72]. Given this we propose two sub-hypotheses:

Hypothesis 1.4: Wind energy infrastructure is more likely in geographic areas with lower levels of education.

Hypothesis 1.5: Wind energy infrastructure is more likely in geographic areas with lower labor force participation.

Rurality

In step with the recent volume presented by Ashwood and MacTavish [26] and the work of Walker et al. [7], we propose rurality remains an under-explored dimension of both environmental and energy injustice. The spatial inequality faced between urban and rural areas in America has been long documented by researchers [73,74], with poverty rates consistently higher and economic development more stagnant in rural areas, relative to urban [73,75]. While many high-profile environmental justice studies have taken place in rural areas [30], the consideration of environmental and energy injustice between urban and rural areas remains underdeveloped [26,30].

Rural areas bear the large share of the burden when it comes to food, natural resource, and energy production [76] and face disproportionate environmental hazards relative to their urban counterparts [77]. Recent research has highlighted the important rural dimension of energy injustice as it relates to the burdens placed on rural Americans, and particularly poor rural Americans [76]. Research by Malin and Demaster [78] on unconventional natural gas extraction has shown that rural residents endure environmental and energy injustice in the form of procedural injustice due to forced lease terms and corporate bullying. Further, work by Kulcsar, Selfa, and Bain [79] showed how the bioenergy industry has used privileged access and privileged accounts to facilitate support for biofuels plants in the Midwest, even when local benefit was minimal and harms were noteworthy.

As stated earlier, wind energy, as currently constructed, does require a significant area of land [35]. However, it should be noted that while wind energy is unlikely to be feasible in dense urban areas due to setback requirements and noise ordinances, due to the diffuse nature of wind impacts and the varying scale at which wind farms can be constructed, wind energy development need not be in the *most* rural and remote areas. With the large amounts of heterogeneity present in counties and census tracts in many parts of the United States, the land area required may often be available in counties traditionally viewed as urban or suburban [80]. We propose that wind energy will be more likely in rural areas, which we operationalize as population density. This hypothesis draws on the arguments presented by Ashwood and MacTavish [26], as well as the economic and sociopolitical explanations discussed by Mohai and Saha [18]. In terms of economics, land in rural areas is generally cheaper, making investment more affordable. Related to the sociopolitical perspective, rural residents often live far apart and, by definition, there are fewer total residents. This makes it more difficult to organize and makes misinformation and the bullying by developers described by Malin and DeMaster [78] more likely. Given this, we propose one sub-hypothesis related to rurality:

Hypothesis 1.6: Wind energy siting is more likely geographic areas with lower population density.

Methods

Data Sources and Data Collation

For our analysis we collated data from three sources: the United States Census Bureau American Community Survey (ACS) five-year estimates for 2008-2012 and 2013-2017, the Wind Prospector from the National Renewable Energy Laboratory (NREL) [81] and the U.S. Wind Turbine Database [33]. We extracted our ACS estimates from the National Historical

Geographic Information Systems database hosted by the Integrated Public Use Microdata Series (IPUMS-NHGIS) [82]. The ACS five-year estimates were used to ensure complete data coverage due to the sampling scheme used by the Census Bureau. ACS estimates were extracted at both the county and census tract level for the contiguous United States. We use county-level data due to the county's dominance in the literature and governmental authority and census tract-level data due to its status as the smallest geographic area for which reliable and unsuppressed sociodemographic data is publicly available. Although a smaller unit of analysis at the local level would be desirable, the amount of suppression placed upon data at units smaller than the census tract, such as the census block or block group, would make analysis unreliable. Thus, for this paper, we use two operationalizations of 'local', the county and the census tract.

The Wind Prospector is an interactive spatial database of wind turbines and wind resource availability provided by NREL [81]. Certain elements of the database are available for download at a high degree of spatial precision. For this analysis, NREL provided us with our measure of wind resource availability—annual average wind speed (m/s) at 80 meters—for the contiguous United States at a cell size of 200 meters.

The U.S. Wind Turbine Database, released to the public in April of 2018, hosts a comprehensive set of information regarding the location of commercial wind turbines constructed throughout the United States. The dataset is a collaboration of the United States Geological Survey, Berkeley labs, and the American Wind Energy Association. Although the year of construction is not provided for every turbine, the oldest turbines in the dataset are reported as being built in 1981, and the newest were built in 2018. The dataset contains a total of 57,646 wind turbines across 41 states, as well as Guam and Puerto Rico [33].

To create our master datasets, we extracted the GIS shapefiles of all active wind turbine locations in the contiguous United States provided by the U.S. Wind Turbine Database. We then georeferenced each wind turbine to both its county and census tract using ArcGIS. As we were interested in exclusively active inland wind turbines, we excluded the few off-shore or under construction wind turbines reported in the dataset. Next, we overlaid the raster data of wind resource availability on the shapefiles of counties and tracts provided by NHGIS to calculate the average wind speed of each geographic area. We then merged our ACS, wind turbine, and wind resource data into two longform master datasets, one for counties nested within states and one for census tracts nested within counties. These datasets were created twice, once for the primary cross-sectional analysis of the present-day social landscape of wind energy in 2018, and once for the temporal sub-analysis of social dimensions in 2008-2012 with turbines in 2018.[2]

Variables of Interest

Independent Variables. The independent variables for this analysis were those sociodemographic characteristics associated with our hypotheses, as well as wind resource availability. We incorporated eleven independent variables representing the six sociodemographic dimensions: median income, race and ethnicity, median age, education, labor force, population density. A number of variables were recoded prior to model estimation. Median income was recoded into thousands to increase coefficient interpretation and result presentation. We included the quadratic of median income to account for the possibly non-linear association between median income and wind energy location. We view

[2] As the analysis using the 2012-2018 ACS five-year estimates was the temporal lag models, this dataset did not include the 117 turbines in the U.S. Wind Turbine Database without missing data on year of construction.

the inclusion of the quadratic as a solution to the issue of including poverty and income within the same model. Due to their high level of correlation, including both income and poverty would have introduced multi-collinearity into our model. However, given the possibility that the association between income and wind siting may vary at extremely high and low levels of income, we include the quadratic term.

We represented ethnicity and race with three percentage variables: percent Hispanic, percent non-Hispanic Black, and percent non-Hispanic other. Non-Hispanic other was created by adding together the categories of non-Hispanic American Indian or Alaska Native, Non-Hispanic Asian, non-Hispanic Native Hawaiian or other Pacific Islander, non-Hispanic Other, and non-Hispanic multiple racial groups. We did not include percent non-Hispanic white to avoid our percentage variables coming close to summing to one and introducing multi-collinearity into our model. For our education term we collapsed education into a single percentage variable, percent of the population with a bachelor's degree or higher. We included two measures of labor force participation: percent unemployed and percent not in the labor force. Finally, we also included population per square kilometer as a way to assess whether the burden of wind energy is disproportionately placed on those residing in more rural areas.[3]

To ensure our findings are over and above the availability of wind resources, we ran all models with a measure of wind resource availability, average annual wind speed (m/s) at 80 meters. Areas with an average annual wind speed greater than 6.5m/s are generally viewed as having wind resources suitable for development [81]. Wind speed estimates were provided in

[3] The census produced definition of rural/urban was not used, because we believe that the census definition for urban, which is determined at the census block level, does not properly define what makes some places more rural or urban than others [80]. Other available county level measures of rurality, such as the USDA's rural-urban continuum codes, were also not used because as county-level variables they would not be appropriate for inclusion in the tract level analysis.

raster (point) data format in 200m cells. Therefore, to calculate our variable we averaged across each geographic area to produce a single estimate of wind speed for each county or tract. Wind speed was included as a non-linear predictor. This is because we expected that higher average wind speeds have increasing impacts on the likelihood of wind energy development. To accomplish this the first order (linear) and second-order (quadratic) terms were included in the model.

Dependent Variable. The dependent variables for this analysis were a dichotomous classification of either being a wind county or a wind tract and a count variable of the total number of turbines. This classification, and therefore the terms 'wind county' or 'wind tract,' means that a county or census tract has at least one wind turbine within its geographic boundary. For the temporal sub-analysis discussed below, an additional dependent variable representing a count of the turbines constructed in a geographic area since 2012 was created.

Analytic Approach

For our primary analysis we estimated three binary logistic regressions and three Poisson regressions in Stata 15/IC, with each subsequent model focusing on a smaller spatial scale.[4] The issue of scale, although often ignored, is important for understanding the relationships between social phenomena [24]. Due to the unavoidable reality that the results of multiple regression analyses are a product of the chosen geographic unit [22,23], we tested our theoretical hypotheses at three narrowing scales to provide a more comprehensive analysis of the current social landscape of wind energy development in the United States. Importantly,

[4] We elected to not use a spatial-econometric model. Spatial logistic regression models generally do not account for fixed effects and remain underdeveloped. Meaning that if a separate spatial regression model was run, it would be using fundamentally different assumptions than the produced fixed effects models; likely producing very different results.

although we present each model separately in our results, when drawing our ultimate conclusions, we consider all models in tandem, as they all tell the story of wind energy development in the United States in a different, yet equally meaningful way. In our models, we evaluate the presence of distributional injustice via the significance ($p < .05$) and direction of model coefficients. Thus, if there is a significant effect suggesting an unequal distribution of wind energy in-line with one of our hypotheses, we conclude that there is a distributional injustice present.

Each of the logistic regression models can be viewed as a unit-hazard coincidence model, common to environmental injustice research. Using this approach, hazards are identified within geographic units and the demographic characteristics of the affected units are evaluated to determine if the coincidence of hazard is higher for certain segments of the population [68]. We follow each binary model with a Poisson model predicting the total number of turbines in an area. This approach allowed us to first assess which social dimensions are associated with moving from no development to any amount of development, and then assess which social dimensions are associated with the absolutely size of wind energy development.

First, we estimated a binary logistic model and a Poisson model at the national level. In these models we included all counties within the contiguous United States and did not include any further geographic constraints. We used robust standard errors to ensure conservative estimates of significance. Next, we estimated a conditional fixed effects logit and a fixed effects Poisson model to analyze the social dimensions of wind energy while using state-level fixed effects. Therefore, only the 41 contiguous states with wind energy development were included.[5] The use of state-level fixed effects allowed us to examine what county level sociodemographic characteristics were associated with a county having wind energy development, compared to other counties within the same state. For the Poisson model, cluster robust standard errors were used. As robust or clustered standard errors are not appropriate when using the conditional logit model, we bootstrapped our standard errors to ensure conservative estimates of significance; a total of 1000 bootstraps were performed.

We then estimated a second set of conditional fixed effects logit and fixed effects Poisson models using county level fixed effects on tract-level data. Similar to the state level analysis, the use of county-level fixed effects allowed us to investigate whether or not there were localized issues of energy injustice systemically occurring within counties in the contiguous United States, while controlling for unobserved county-level variables. Due to the chosen method of analysis, which restricted our analysis to variables that varied within county, counties with wind farms in all census tracts, a total of 27, were excluded from the logit analysis due to its dichotomous nature, but were included in the Poisson model. Additionally, a number of tracts had missing data on demographic characteristics due to it not being reported (i.e. suppressed), in these instances we elected to use listwise deletion due to many of the excluded tracts being atypical (e.g. comprised solely of prisons or hospitals). This resulted in one county with only one tract with a single wind turbine, Kings County, NY, being removed from the primary analysis. Finally, the 65 wind counties with only one census tract were also not included in model estimation due to the variation required by this analytic

[5] Because it uses each unit (e.g. state, county) as its own control, a requirement of conditional logit fixed effects modeling is that there must be variation in the independent and dependent variables within units. If all subunits (e.g. counties, tracts) do not have wind energy, then there is no way to assess how demographic characteristics are associated with wind energy within that unit.

approach. As with the state-level analysis, cluster robust standard errors were used for the Poisson model and 1000 bootstraps were performed on standard errors in the logit model.

To compare our findings across spatial scales we compared the significance, direction, and magnitude of odds ratios and incidence rate ratios among our predictor variables, as well as which hypotheses were supported at each spatial scale. While the practice of direct comparisons between logit coefficients across groups has received negative attention in the literature [83,84], and at times been deemed a methodological error due to unobserved heterogeneity, for our analysis the practice is appropriate [85].[6]

As a final step we investigated the issue of Tiebout sorting using a series of temporally lagged models. A common concern within environmental injustice scholarship is whether development was sited in marginalized communities, or whether marginalized populations moved into a community after development occurred [18,86]. Indeed, recent work by Hoen et al. [36] found attitudes towards wind projects improved as people self-selected into wind energy communities, highlighting the importance of considering changing populations. Although our primary analysis was not causal, but descriptive, this analysis represents an initial investigation into one possible mechanism driving the patterns in the primary models. For this sub-analysis, we focused only on the within-county models. We estimated two county-level fixed effect Poisson regressions. Unlike the primary models, we use sociodemographic data from the 2008-2012 ACS five-year estimates, meaning our

[6] The reason for this is that the substantive outcome of interest in our models is the dichotomous outcome of whether or not a geographic unit has wind energy development, and not an underlying latent variable (see Kuha and Mills [85]). An example of when comparisons would be inappropriate is if the variable of interest was toxicity of a chemical and the outcome used to represent the latent construct was death [85]. Further, the use of a consistent model across each level of scale avoids further difficulties of comparisons between binary logit models [85].

independent variables are temporally lagged to be before the dependent variable. The first model predicts the total count of turbines while controlling for the level of development in 2012, the final year of data collection for the ACS estimates. The second model is restricted to counties where new turbines were sited after 2012 and predicts the total number of new turbines, while still controlling for the level of development in 2012. Cluster-robust standard errors were used in both cases. These temporally lagged models are then presented along-side models estimated using the present-day sociodemographic data (i.e. 2013-2017 ACS five-year estimates) and same dependent variables to compare the associations before and after development.[7]

Results

Descriptive Statistics

Summary statistics, divided by places with and without wind energy, for the variables included in the primary models are presented in Tables 1 and 2 at the county and census tract level, respectively. Summary statistics for census tracts for 2008-2012 are presented in Table 4. There were a total of 57,316 active inland wind turbines located within the contiguous United States. They were located within 41 states, 615 counties, and 1,035 census tracts. Nationally speaking, 19.7% of counties and 1.4% of tracts had wind turbines. The highest number of wind turbines in one county was 4,564, and the largest number of wind turbines in one census tract was 3,525. The average number of turbines within counties with wind energy was 93.2 (SD = 240.7), with a median of 34. The average number within tracts with wind

[7] Although a more precise single-year estimate would be desirable in this instance (e.g. 2017 as opposed to 2013-2017), the use of five-year estimates from the ACS is the only way to ensure full data coverage and reasonable predictions for all census tracts in the United States. This is particularly relevant for the comparison of the 2008-2012 models of post-2012 development with the 'present day' models, as a turbine built in 2015 in the 2013-2017 models could have been built just before, or just after, data collection depending on census sampling phase. Thus, results should be interpreted with this limitation in mind.

energy was 52.2 (SD = 149.551), with a median of 14. As may be expected, the average wind speed was higher in wind counties and tracts than areas without wind energy development.

[Table 1]

[Table 2]

National Level Model

The national county-level analyses demonstrated a number of significant ($p < .05$) associations (Table 3). In the logistic model—which assessed whether or not there is *any* wind energy development—median income (odds ratio = 1.167), percent Hispanic (odds ratio = 1.022), percent out of the labor force (odds ratio = 1.025), and percent with a Bachelor's degree (odds ratio = 1.020) had a significant positive association with increased odds of being a wind county. Three variables had significant negative associations with the odds of being a wind county: median age, median income squared, and percent non-Hispanic Black. The independent variable with the largest association with decreased odds of being a wind county was percent non-Hispanic Black (odds ratio = 0.915).

At the national level, the relationships were similar in significance and direction between the Poisson model—which assessed the absolute size and scale of the wind energy development—and the binary logit model. The variable with notably a different relationship was education. In the logit model, percent with a Bachelor's degree had a positive association with the odds of being a wind county, but in the Poisson model this effect was not significant.

Results of the national county-level did not fully support any hypotheses. The results provided mixed support for hypotheses regarding income, labor force participation, and race and ethnicity, and refuted our hypothesis concerning education. While the linear term for income is the opposite of the hypothesized direction, the significant quadratic effect shows that at a certain level of median income the likelihood of wind energy development decreases. Regarding race and ethnicity, we see the opposite of our hypothesized effect for percent Black, but the expected effect for percent Hispanic. Further, the effect of education was the opposite direction hypothesized in the logit model. Finally, percent not in the labor force had a relationship supporting our hypothesis in both models, but percent unemployed had no effect.

[Table 3]

State Level Fixed Effects Model

Both of the state-level fixed effects models had fewer significant associations than the geographically unconstrained national model (Table 3). When looking at counties within states, only median age had a significant negative association with wind energy development in both the logit and Poisson models. The only other significant associations were the negative effect of education in the Poisson model and the positive effect of percent Hispanic in the logit. The state level model supported our hypothesis regarding age in both models, provided some support for race and ethnicity hypothesis, and supported our education hypothesis.

County Level Fixed Effects Model

In the within-county models, many of the significant relationships were similar between the logit and the Poisson models. Six independent variables in the county level model had significant relationships with the odds of being a wind tract (Table 3). When looking at tracts within counties with wind energy we see that, relative to other tracts in their county, tracts with a lower percentage of residents with at least a bachelor's degree (odds ratio = 0.970), more people out of the labor force (odd ratio = 1.023), lower population density (odds ratio = 0.998), and lower median age (odds ratio = 0.978) were more likely to be a wind tract. Additionally, both the linear and quadratic terms for median income were significant. This suggests that while the likelihood of being a wind tract increases with median income, there is a point where this effect tapers and eventually reverses direction. Notably, the odds ratios for the linear term of wind speed were large in both models, suggesting that wind speed is a crucial determinant of wind energy development at the within-county level.

The Poisson model had a similar number of significant associations. In this model, areas with a lower median age (IRR = 0.978), a lower percentage of Black residents (IRR = 0.892), more education (IRR = 0.942), and lower population density (IRR = 0.977) were associated with higher levels of wind energy development. Ultimately, we see the most support for our proposed hypotheses in the within-county models. The logit model supported hypotheses associated with age, education, and rurality, while providing mixed support for our labor force and income hypotheses. The Poisson model supported the age, education, and rurality hypotheses, provided mixed support for income, and partially refuted our hypothesis regarding race and ethnicity.

Comparison of Models

When considering all models together, three hypotheses—age, education, and rurality—received full support by at least one set of models. Three hypotheses, those related to income, labor force participation, and race and ethnicity, received mixed support in at least two models. While we do not see that wind energy is systemically sited within poorer tracts or counties, in both national and county level models the curvilinear relationship shows that wind energy is systemically *not* sited in areas with very high relative median income. The effect of education was refuted in the national model but supported at the within-state and within-county level. The association between percent Hispanic was significant in the coarse national and state models but not at the within-county level. Further, when looking across scales we see that population density was not associated with wind energy development until we look at the within-county scale.

Sub-Analysis of Temporal Lag Models

In the interest of exploring whether or not these associations were present before or after development, a series of temporally lagged models were estimated (Table 5). In the first set of models, we compare models using the 2008-2012 ACS five-year estimates and the 2013-2017 ACS five-year estimates to predict the total number of turbines using fixed effect Poisson models. Although the p-values are large, indicating noisy estimates, three variables are significant in the 2013-2017 models as opposed to the 2008-2012 models: age, income, and percent non-Hispanic Black. This suggests that these associations are not necessarily due to demographic make-up pre-siting, but due to changing population demographics. Oppositely, percent Hispanic had a significant negative relationship in the 2008-2012 model but not in the 2013-2017 model. Finally, two highly significant relationships ($p<.001$) were present in both periods—education and population density. This suggests these effects are more persistent and have been less subject to changing population characteristics.

The second set of temporal lag models focus only on counties which experienced increases in wind energy development between 2012 and 2018. As with the other within-county models, rurality played a strong and significant role in both periods. Two variables were significant in the earlier period, but not in the latter: education and percent Hispanic. When looking within counties, we see that higher levels of wind energy development post-2012 were associated with less Hispanic and less educated tracts in 2008-2012. However, by 2013-2017 these relationships are no longer significant. Suggesting that these effects were associated with siting of additional turbines and not the in-migration of new residents.

[Table 4 here]

[Table 5 here]

Discussion

Taken together, our models suggest there is distributional injustice in the case of wind energy, at least at one spatial scale, across the contiguous United States along the dimensions of ethnicity, age, education, labor force participation, and rurality. We do not find evidence of distributional injustice related to race, and find a nuanced relationship for median income. This work adds to the recent work on wind energy injustice of Walker and Baxter [8,9] and Walker et al. [7] in Canada and Zárate-Toledo et al. [6] in Mexico documenting the evidence of wind energy injustice in North America. However, while we do find evidence of distributional injustice, the findings do not offer full support, and at times refuted, our theoretical hypotheses.

We find the signals of distributional wind energy injustice in the contiguous United States vary by scale. The finding of scalar differences is unsurprising given the issues of scale that have been raised by many researchers, particularly as it relates to the human-environment relationship [85]. Our comparison of national, state, and local models highlights key statistical differences, and how scale—as defined by administrative boundaries—can hide, or alter, results. This is particularly clear in the case of education. At the scale of the nation, education refuted our hypotheses, however, once we focused at the within-state and within-county models education had the expected relationship with wind energy development indicative of injustice.

While there appears to be some evidence of a trend toward distributional energy injustice when considering all scales and models in tandem, we must note that coefficients were generally small and no hypotheses were fully supported. However, this is not necessarily out of step with environmental injustice research broadly. In his meta-analysis of 49 studies on environmental inequity, Ringquist [67] found consistent racial injustices, but a far more context specific relationship for the social dimensions of income and poverty. Meaning that while injustices occur, finding evidence of injustice at a systemic level across the entire landscape of wind energy in the United States represents a statistically high bar. Thus, it is likely our analysis represents a lower-bound estimate of the current distributional injustices related to age, education, labor force participation, and rurality across the wind energy landscape. That said, given the generally small coefficients, we do not view the injustice as severe, but it does warrant further attention.

In our theoretical framework we have positioned wind energy development as a locally unwanted land use. However, the material impact of wind energy infrastructure on populations is likely to be far less than other forms of energy development common to energy injustice research. In fact, wind energy can easily be argued to be a net positive for society and renewable energy transitions are viewed by many as essential for slowing global climatic change. By showing that energy injustice theory can be applied to more environmentally benign forms of energy development, and that distributional injustices can occur along the same social dimensions, we have shown that the power of certain segments of society to distance themselves from undesirable local land uses translates to renewable energy development. This highlights the power that change to local areas, such as brought on by wind energy, may have in mobilizing resistance, even absent of negative health impacts.

In line with Ashwood and MacTavish [26], Malin and DeMaster [78], Walker et al. [7], and Kelly-Reif and Wing [76], we consider rurality as an under-explored dimension of environmental and energy injustice. Rurality, due to the availability of suitable land for development, may be expected to be a strong predictor of wind due to its nature as a siting characteristic. However, at the national and state level we, somewhat surprisingly, do not see a significant relationship between aggregate population density and wind energy infrastructure. However, at the within-county level the relationship is significant. This shows that, within counties with wind energy, the tracts with the lowest population density are the most likely to bear the burden of wind energy development as it relates to both the existence of wind energy and the size and scope of that wind energy development. While the theoretical framework of this study suggests this can be interpreted as a distributional injustice, determining the extent of injustice requires further information about land-ownership, compensation, and intersectionality. If this localized trend continues, then rural people may experience land-use change well beyond what other segments of society are forced to face when it comes to the transition to renewable energy.

Limitations and Future Work

Any attempt to analyze something as local as energy injustice at a national scale has its limitations, our study is no exception. First, while our analysis is concerned with the location of energy infrastructure, the framework of energy injustice is also about access to the power that is created by that infrastructure. For this analysis we treated access to the power provided by wind turbines as invariant based upon proximity and we viewed proximity as a cost. If proximity to turbines was associated with cheaper electricity, increased local tax revenue, or the previously discussed community benefit agreements [55], then research would require balancing that benefit, with the cost of the energy infrastructure development. As highlighted in our introduction, community benefit agreements have become increasingly common in the

United Kingdom and appear to be growing in the United States [51,52]. These types of agreements impact the calculus of injustice, as the benefits may be shared throughout the community. Including this dimension in our analysis was infeasible due to data availability, however future research should explore their occurrence and efficacy in the United States in detail.

Second, it is important to acknowledge that any injustice from wind energy siting is likely felt strongest at the intersection of the social dimensions examined here. While we did not explore the intersectional nature of distributional injustice in this analysis, future research should explore how the distribution of wind infrastructure may systemically operate across multiple marginalized identities. As with all forms of intersectionality, the experience of injustice across multiple identities is unlikely to simply be additive, but rather multiplicative in nature [88].

Third, this analysis, while multi-scalar, is still at a larger scale than the majority of environmental or energy injustice research. Census tracts vary in size and do not perfectly map onto the geographies of communities. Similarly, counties vary in size across the United States and are imperfect geographic units for research [80]. The goal of this paper was to generate a national understanding of the social dimensions of wind energy for the United States. To do this, we were required to use the data available and this resulted in tradeoffs. Any data at the scale lower than the census tract (e.g. census block or block group) is unreliable and heavily suppressed by the census for privacy reasons. Thus, this analysis represents the finest grain of detail possible given the data provided by the United States Census Bureau. That said, the use of this scale may have resulted in smoothing effects across the landscape. Future research should explore other data sources to incorporate parcel level data or clearer community geographies. However, as discussed by Bristow et al. [89], it is important to remember that any attempt to identify the specific community impacted by a development project carries its own risks including top-down exclusion, difficult benefit calculations, and conceptual murkiness.

Finally, in our analysis we only evaluated distributional injustice, while this form of injustice is certainly related to other forms of injustice, we have not evaluated the entire picture. The data available to us, and used in this study, cannot analyze procedural or recognition injustice. Future research, in line with the work of Zárate-Toledo et al. [6], should gain access to data and communities in a way that understands energy injustice as it relates to procedure and recognition. In-depth qualitative analyses are needed to add context to the observational models we present here. In step with this, we did not evaluate how land ownership patterns influence wind energy siting. While the impacts of wind energy development are likely to be felt by all in a community, not just those who have wind turbines on their land, future research should attempt to understand the role of land ownership and lease fees in this issue. Additionally, future research may attempt to use the parcel as the unit of analysis to look at this issue from a different perspective.

Conclusion

Although we do not find evidence of distributional wind energy injustice related to race, and find a nuanced relationship in the case of ethnicity and income, we do find the signs of distributional injustice along the dimensions of age, education, labor force participation, and rurality. However, these findings varied significantly by scale and the type of model. When looking within counties in the contiguous United States we saw that wind turbines are more likely to be sited in areas with lower median ages, lower education, lower labor force participation, and lower population density. Additionally, areas of high relative median income were less likely to have wind energy development than areas with low to medium levels of relative median income in our national and within-county models. While the injustice does not appear to be extreme, researchers should continue to monitor the distribution of wind energy as it continues to boom throughout the continental United States. As indicated by recent research on procedural injustice [6,8], if the public perceives these inequities or feels left out of the process, opposition toward for current and future development may mount.

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TABLES

Table 1: Summary Statistics for Counties

	Mean	SD	Min	Max
Wind Counties (n = 615)				
Median Income (Thousands)	52.960	11.061	24.800	104.703
Hispanic (%)	13.993	19.045	0.139	99.185
Non-Hispanic Black (%)	2.869	4.620	0.000	41.777
Non-Hispanic Other (%)	5.047	7.928	0.000	86.971
Median Age	40.462	5.434	24.400	58.000
At Least a Bachelor's Degree (%)	22.652	8.500	6.452	57.510
Unemployed (%)	3.100	1.393	0.000	10.832
Not in Labor Force (%)	38.339	6.902	23.695	69.794
Population Density (Thousands per km)	100.510	674.724	0.152	14523.010
Wind Speed (m/s)	6.874	0.630	3.906	8.723
Number of Turbines	93.197	240.704	1.000	4564.000
Turbines Per Square km	0.0362	0.0625	.00005	0.581
Non-Wind Counties (n = 2493)				
Median Income (Thousands)	48.732	13.346	19.264	129.588
Hispanic (%)	7.964	11.836	0.000	95.295
Non-Hispanic Black (%)	10.489	15.664	0.000	86.921
Non-Hispanic Other (%)	4.685	7.128	0.000	92.030
Median Age	41.368	5.315	21.600	66.400
At Least a Bachelor's Degree (%)	20.825	9.431	4.688	78.133
Unemployed (%)	3.702	1.539	0.000	17.990
Not in Labor Force (%)	42.210	8.026	17.489	88.407
Population Density (Thousands per km)	103.468	704.429	0.042	27916.510
Wind Speed (m/s)	6.128	0.699	3.265	9.182

Table 2: Summary Statistics for Tracts in Wind Counties

	Mean	SD	Min	Max
Wind Tracts (n = 961)				
Median Income (Thousands)	57.253	17.106	14.559	166.771
Hispanic (%)	11.307	19.081	0.000	98.844
Non-Hispanic Black (%)	2.329	7.301	0.000	96.356
Non-Hispanic Other (%)	4.336	8.158	0.000	97.833
Median Age	42.119	6.621	19.600	64.800
At Least a Bachelor's Degree (%)	21.880	11.015	3.041	77.628
Unemployed (%)	3.044	1.897	0.000	20.844
Not in Labor Force (%)	38.786	8.973	14.347	89.309
Population Density (Thousands per km)	99.130	343.541	0.105	5588.649
Wind Speed (m/s)	6.929	0.641	3.102	9.769
Number of Turbines	52.211	149.551	1.000	3525.000
Turbines Per Square km	0.142	0.683	0.0001	19.025
Non-Wind Tracts (n = 19382)				
Median Income (Thousands)	63.309	30.592	3.709	250.001
Hispanic (%)	24.128	26.800	0.000	100.000
Non-Hispanic Black (%)	10.168	18.528	0.000	100.000
Non-Hispanic Other (%)	9.474	11.368	0.000	99.910
Median Age	38.030	7.566	7.700	84.500
At Least a Bachelor's Degree (%)	30.358	19.712	0.000	100.000
Unemployed (%)	4.533	2.910	0.000	29.528
Not in Labor Force (%)	35.482	9.026	0.000	98.973
Population Density (Thousands per km)	2403.191	3394.602	0.061	118333.700
Wind Speed (m/s)	5.536	1.420	2.273	9.442

Note: Only tracts included in Poisson model estimation included in summary statistics

Table 3. Models predicting the prevalence of wind turbines

	National Model		Within-State Model		Within-County Model	
	Logit	Poisson	Logit	Poisson	Logit	Poisson
Median Age	0.959***	0.951*	0.937***	0.935***	0.978*	0.951*
	(0.0110)	(0.0189)	(0.0157)	(0.0150)	(0.0102)	(0.0205)
Median Income (Thousands)	1.167***	1.248*	1.033	1.023	1.038**	1.144*
	(0.0350)	(0.110)	(0.0434)	(0.0299)	(0.0121)	(0.0653)
Median Income Squared	0.999***	0.998*	1.000	1.000	1.000*	0.999*
	(0.000249)	(0.000787)	(0.000351)	(0.000239)	(0.0000747)	(0.000337)
Hispanic (%)	1.022***	1.025***	1.019*	1.008	0.990	0.991
	(0.00385)	(0.00506)	(0.00885)	(0.00637)	(0.00615)	(0.00905)
Black (%)	0.947***	0.943***	1.008	1.010	1.000	0.892*
	(0.00920)	(0.0136)	(0.0192)	(0.0407)	(0.0108)	(0.0424)
Non-Hispanic Other (%)	0.993	1.001	0.991	0.969	0.997	0.958
	(0.00820)	(0.0119)	(0.0106)	(0.0171)	(0.00894)	(0.0219)
Bachelor's Degree (%)	1.020**	0.986	1.002	0.960*	0.970***	0.942**
	(0.00786)	(0.00971)	(0.0114)	(0.0175)	(0.00656)	(0.0203)
Unemployed (%)	1.067	1.084	0.909	0.965	0.962	1.022
	(0.0477)	(0.0698)	(0.0513)	(0.0338)	(0.0298)	(0.0595)
Not in Labor Force (%)	1.025*	1.053***	0.997	1.006	1.023**	1.026
	(0.0112)	(0.0130)	(0.0152)	(0.0217)	(0.00715)	(0.0156)
Population Density (km)	1.000	1.000	1.000	1.000	0.998***	0.977***
	(0.0000975)	(0.000358)	(0.000407)	(0.0000741)	(0.000397)	(0.00382)
Wind Speed (m/s)	1.664	0.0259*	1.862	1.009	11.09*	16.14*
	(3.049)	(0.0427)	(7.399)	(1.774)	(12.81)	(22.72)
Wind Speed (m/s) Squared	1.076	1.399**	1.138	1.113	0.930	0.962
	(0.152)	(0.162)	(0.347)	(0.149)	(0.0807)	(0.100)
Constant	0.959***	0.951*	0.937***	0.935***	0.978*	0.951*
	(0.0110)	(0.0189)	(0.0157)	(0.0150)	(0.0102)	(0.0205)
Log Likelihood/Pseudolikelihood	-1193.42	-115726.58	-937.65	-90244.39	-1520.17	-35369.77
Wald Chi-square (df=12)	518.69***	630.93***	121.69***	1352.61***	268.66	446.69***
Observations	3108	3108	2436	2436	20280	20343
Groups	NA	NA	41	41	521	549

Odds ratios reproted for logit models, incidence rate ratios reported for Poisson models; Standard errors in parentheses.
For the national models robust standard errors were used. For the within-state and within-county models, 1,000 bootstraps were performed for logit models and cluster-robust standard errors were used for Poisson.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 4: Summary Statistics for Temporal Analysis

	Mean	SD	Min	Max
Tracts in counties with new turbines since 2012 (n = 8770)				
Median Income (Thousands)	55.863	26.040	5.198	250.001
Hispanic (%)	24.981	27.940	0.000	100.000
Non-Hispanic Black (%)	10.699	20.720	0.000	100.000
Non-Hispanic Other (%)	7.728	10.234	0.000	99.002
Median Age	37.054	7.847	15.400	85.100
At Least a Bachelor's Degree (%)	26.548	18.514	0.000	96.908
Unemployed (%)	6.230	3.626	0.000	34.962
Not in Labor Force (%)	35.253	9.476	0.949	99.213
Population Density (Thousands per km)	2069.857	3374.585	0.085	187261.200
Wind Speed (m/s)	5.694	1.337	2.38	9.769
Number of Turbines	4.149	50.039	0.000	3525.000
Turbines Per Square km	0.0106	0.226	0.000	19.025
Tracts included in model of total turbines in 2018 (n = 20215)				
Median Income (Thousands)	57.814	27.290	2.499	250.001
Hispanic (%)	22.313	26.406	0.000	100.000
Non-Hispanic Black (%)	9.816	18.842	0.000	100.000
Non-Hispanic Other (%)	8.412	10.911	0.000	100.000
Median Age	37.282	7.459	13.000	85.100
At Least a Bachelor's Degree (%)	27.763	18.893	0.000	100.000
Unemployed (%)	6.297	3.628	0.000	57.895
Not in Labor Force (%)	34.450	9.234	0.000	99.896
Population Density (Thousands per km)	2238.862	3413.289	0.067	187261.200
Wind Speed (m/s)	5.595	1.428	2.273	10.379
Number of Turbines	2.482	34.433	0	3525
Turbines Per Square km	0.00675	0.152	0	19.025

Table 5. Temporal Poisson models of wind energy development

	Total Turbines Built post-2012		Total Turbines	
	2008-2012[a]	2013-2017[b]	2008-2012[a]	2013-2017[b]
Median Age	1.016	0.950*	1.014	0.988
	(0.0150)	(0.0205)	(0.0237)	(0.0243)
Median Income (Thousands)	1.047	1.145*	1.034	1.027
	(0.0258)	(0.0654)	(0.0473)	(0.0367)
Median Income Squared	1.000	0.999*	1.000	1.000
	(0.000182)	(0.000337)	(0.000412)	(0.000233)
Hispanic (%)	0.976**	0.991	0.967**	0.990
	(0.00810)	(0.00905)	(0.0120)	(0.0165)
Black (%)	1.002	0.893*	1.001	0.998
	(0.0157)	(0.0426)	(0.0185)	(0.0222)
Non-Hispanic Other (%)	1.002	0.958	0.982	0.991
	(0.0115)	(0.0219)	(0.0156)	(0.0174)
Bachelor's Degree (%)	0.945***	0.942**	0.939*	0.985
	(0.0126)	(0.0203)	(0.0230)	(0.0203)
Unemployed (%)	0.937	1.022	0.977	1.006
	(0.0450)	(0.0592)	(0.0475)	(0.0578)
Not in Labor Force (%)	0.998	1.027	0.984	0.991
	(0.0113)	(0.0156)	(0.0203)	(0.0162)
Population Density (km)	0.982***	0.977***	0.952***	0.941***
	(0.00311)	(0.00389)	(0.00850)	(0.00951)
Wind Speed (m/s)	58.97**	16.60*	6.014	11.19
	(91.10)	(23.50)	(22.19)	(29.65)
Wind Speed (m/s) Squared	0.875	0.961	1.028	0.968
	(0.0932)	(0.101)	(0.290)	(0.201)
Turbine Count in 2012	1.002***		1.002**	
	(0.000300)		(0.000806)	
Log Pseudolikelihood	-27735.23	-35208.33	-8999.62	-9816.302
Wald Chi-square (df=12)	370.82***	452.35***	132.66***	115.77***
Observations	20215	20200	8770	8762
Groups	545	545	269	269

[a]Model estimated using sociodemographic data from 2008-2012 ACS five-year estimates
[b]Model estimated using sociodemographic data from 2013-2017 ACS five-year estimates
Coefficients are incidence rate ratios; Cluster-robust standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

FIGURES

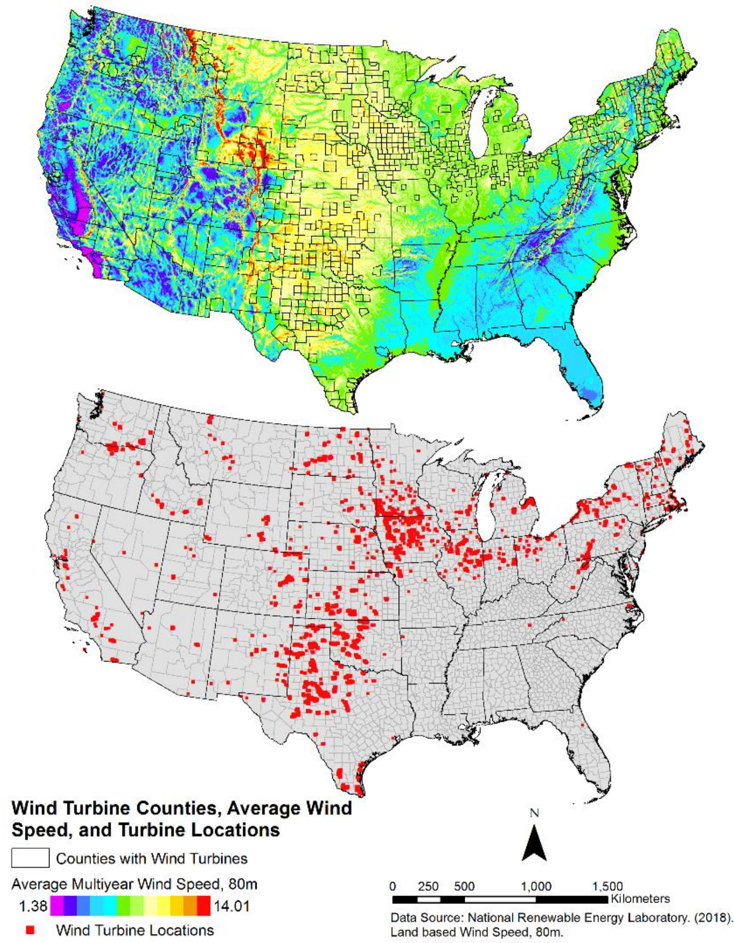

Figure 1: Wind Resource Availability and Wind Turbine Counties and Locations in the United States, 201