The Tradeoff Between Wildlife Conservation and Renewable Energy: Evidence from Eagles and Wind Turbines

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Abstract

This paper estimates the effect of wildlife protection on wind energy development in the central United States. Federal enforcement of the Bald and Golden Eagle Protection Act increased after a court decision in 2013, raising potential liability for wind developers in regions where eagles are common. We find that counties where eagles are common slowed their wind energy development after 2013 relative to counties with fewer eagles. The costs of forgone wind energy appear considerably greater than the quantifiable benefits from avoided eagle fatalities, suggesting that current policy overvalues wildlife protection relative to green energy.

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1 Introduction

The transition away from traditional fossil-fuel electricity generation toward renewable resources has been a key component of the United States' response to climate change. While the clean energy transition includes a variety of established and emerging technologies, wind turbines make up a significant portion of the U.S. renewable portfolio, with new wind capacity accounting for 32% of all new electricity capacity additions in 2021 (Gordon, 2022). Along with solar energy, an estimated tripling of current U.S. total wind capacity is projected to meet 100% renewable energy targets for 2035 (Denholm et al., 2022; Trabish, 2022). These ambitious renewable energy goals are projected to drive increased renewable investment and density.

While renewable energy installations can reduce carbon emissions and air pollution, they also require large amounts of land, potentially harming species conservation and biodiversity goals. Wind turbines in particular can have acute negative externalities for certain wildlife species. Birds, including federally-protected bald and golden eagles, frequently suffer habitat destruction and collision-based mortality due to wind turbine developments (Miao et al., 2019; Erickson et al., 2014; Loss et al., 2013; Smallwood, 2007). Many localities have adopted land-use restrictions to limit wind turbine development and mitigate negative impacts on humans and wildlife. These restrictions are projected to clash with ambitious renewable expansion goals (Denholm et al., 2022; Gross, 2020).

Species protections might constitute a land-use restriction against wind energy development if developers are held liable for damages to a particular species. While neither bald nor golden eagles are classified as endangered, both are federally protected under the Bald and Golden Eagle Protection Act of 1940 (BGEPA). Bald and golden eagle ranges overlap wind resource-rich areas of the United States (Pagel et al., 2013). Therefore, legal restrictions and conservation obligations might negatively impact wind turbine development in resource-rich areas. The existence and potential scope of these impacts may have important implications for future species protection policies under an expanding renewable sector.

This paper estimates the effects of eagle protection policies on wind turbine development in the United States. To do so, we exploit both geographic variation in exposure to bald and golden eagles and variation in BGEPA enforcement over time. Although the BGEPA predates large-scale wind turbine development, the U.S. Fish and Wildlife Service (USFWS) did not enforce BGEPA against wind turbine developers until a landmark case against Duke Energy Inc. in November 2013. Enforcement became common after this court decision, creating a sharp rise in the potential liability of wind development. The heightened potential liability, however, is likely greater in counties with high exposure to eagles than in counties with little to no eagle exposure. We compare these trajectories in a difference-in-difference analysis to estimate the amount of wind capacity forgone as a result of BGEPA enforcement.

We find that after the 2013 increase in BGEPA enforcement, wind energy development accelerated more slowly in counties with high exposure to protected eagles. Specifically, counties with high exposure to either bald or golden eagles increased their average annual new wind energy capacity by 4.8 megawatts (MW) less than did counties with little to no eagle exposure. Importantly, we study annual *additions* to wind capacity, requiring only that the pace of new wind energy installations – not trajectories of cumulative wind capacity – would have moved in parallel across treatment and control counties absent the policy shift. Quantitatively, the effect is more than half of all capacity additions in high-exposure counties over the sample period, suggesting the effects are economically large.

A causal interpretation of our results is supported by several lines of evidence. First, bald and golden eagles separately generate similar results, despite having very different geographical patterns of abundance. This suggests that our results are not driven by spurious spatial correlation. Second, the effect persists through a battery of covariates, fixed effects, alternative sample restrictions, and other sensitivity tests. Third, we find no evidence of spatial spillovers, either when excluding the low-exposure counties nearest to high-exposure counties, or when leveraging boundaries between electricity grid regions. This suggests that the effect represents a true reduction in national wind capacity, rather than merely a spatial reallocation of wind development across geography.

Combining our estimated effect with USGS estimates of wind turbine output per MW (USGS, 2020) suggest that eagle protections prevented 605 MW of installed wind energy capacity. This amount of new electricity generation would have been capable of powering 206,800 homes per month and worth roughly $111 million per year. Alternatively, the new clean energy could have displaced carbon emissions, meaning eagle protections prevented climate benefits of up to $80.5 million per year.

The welfare implications of BGEPA enforcement require weighing these costs against the benefits of eagle protections. Using two valuation methods for eagle fatalities, we estimate that BGEPA protections resulted in benefits valued at $6.1 million per year. Even allowing for substantial error in our estimates, the costs of forgone wind capacity appear to considerably outweigh the benefits of eagle conservation. Our results suggest that, at least at the margin, current policy overvalues wildlife relative to new renewable energy.

In studying the costs of regulating renewable energy development, this paper provides a counterweight to a literature in economics and conservation biology on the negative externalities of wind and solar energy facilities. Several studies have documented negative effects of wind turbines and solar farms on local housing prices (Dröes and Koster, 2016; Maddison et al., 2023), on temporary household well-being (Krekel and Zerrahn, 2017), and even suggested that noise from wind turbines may increase deaths by suicide (Zou, 2020). In wildlife impacts, Miao et al. (2019) find that each new wind turbine kills about 3 birds per year, while Hunt et al. (1999) and Pagel et al. (2013) implicate wind turbines in the deaths of golden eagles specifically.

We analyze the other side of this tradeoff. Instead of asking how renewable energy development harms wildlife, we turn the question around to ask whether wildlife protection policies end up obstructing renewable energy. Renewable energy itself also brings a range of environmental benefits – including to wildlife, which will otherwise be harmed by climate change. Policymakers need to understand both sides of the ledger in order to balance the benefits of species protections against the benefits of renewable energy, as direct conflicts between these goals become more common.

This paper also adds evidence on the costs and benefits of wildlife conservation policies more generally. Several recent papers document the tradeoffs associated with specific protection policies. For example, Auffhammer et al. (2020) show that critical habitat designation for endangered species reduce land values in California, Boskovic and Nostbakken (2017) show that Canadian oil leases exposed to protected caribou species drop in value, and Melstrom (2021) finds that Endangered Species Act restrictions decrease dryland value and profitability. We broaden the set of outcomes known to be affected by conservation policies to include renewable energy development.

Finally, we contribute to a broader literature on the regulation of renewable energy development. Species protections can be seen as a disincentive for renewable development. Estimated energy losses under such a policy can be compared to the energy gains under traditional pro-renewable policies. Du and Takeuchi (2020) find that feed-in tariff policies encourage both wind and solar development in regions of China. Similarly, Shrimali et al. (2015) find that renewable portfolio standards lead to increases in state-level capacity growth for renewable technologies. This study complements this literature by examining policies that prohibit or disincentivise renewable energy development, providing a fuller picture of the incentives guiding renewable development.

2 Background

2.1 Wind Energy Development in the U.S.

The rate of utility-scale wind turbine adoption in the United States has increased over time. As shown in Figure 1, U.S. wind turbine development accelerated in the early 2000s. Despite a variety of land-use restrictions, wind turbine development has grown considerably in recent years. This increase is likely driven both by federal and local renewable energy goals, and improvements in wind turbine output efficiency over time (Wiser et al., 2022).

The central U.S. region features relatively rich wind resources to support renewable development. Wind turbines require high wind speeds for output efficiency, land availability and suitable terrain for construction, and connections to electricity networks to transmit output. The Great Plains offers both high wind speeds (Brown et al., 2012) and strong land availability for development (Lopez et al., 2021). This area therefore supports much of the existing and potential wind energy in the U.S., and any restrictions on wind development in this region have potentially significant impacts on the nations' wind energy supply.

2.2 Bald and Golden Eagles in the U.S.

Bald and golden eagles are found throughout the North American continent, and both species are increasingly exposed to wind energy development. Bald eagles are frequently found near bodies of water, but they are exposed to wind turbines when migrating over upland areas (Pagel et al., 2013; Schmuecker et al., 2020). Golden eagles' habitat is characterized by access to both elevated areas for nesting and open, undeveloped areas for hunting prey (Crandall et al., 2015). While access to elevated areas for nesting is necessary for golden eagles, their additional requirement of open, undeveloped areas for hunting causes their habitat to overlap with areas of high wind development potential (Allison et al., 2017; Thompson, 2021). This overlap of both bald and golden eagle habitats with potential wind development sites poses significant future risks for native populations. Bald eagle populations have increased significantly since 2009 (Zimmerman et al., 2022), while golden eagle populations within the U.S. have remained stable at both the national and regional levels for roughly the past 20 years (Sauer et al., 2019; Millsap et al., 2013).

While neither bald nor golden eagles are protected under the Endangered Species Act, they are separately protected by the Bald and Golden Eagle Protection Act (BGEPA). This act prohibits any "take" of bald or golden eagles (defined as an unauthorized capture or killing). The BGEPA therefore serves as the primary legal basis in the U.S. for eagle protections and criminal prosecutions of individuals or corporations who injure eagle populations.

2.3 Eagle Protections and Wind Energy

The BGEPA has been active for the entire duration of U.S. wind turbine development. Although studies going back decades have noted the potential and realized impacts of wind turbines on eagles (Hunt et al., 1999), no wind developers were prosecuted for BGEPA violations prior to 2013. While the BGEPA enables the USFWS to sell eagle take permits, no wind turbine developers sought a permit in this time period (Opar, 2013). Under growing concerns for eagle populations, the USFWS signalled their intentions to begin BGEPA enforcement through new wind turbine development guidelines in 2012 (USFWS, 2012). These guidelines call for extensive pre- and post- construction site monitoring to mitigate species impacts. Furthermore, the guidelines require wind turbine developers to enact compensatory mitigation efforts to offset their impacts to eagle species. The USFWS enforced these guidelines for the first time in November 2013 against the utility Duke Energy Inc. The utility was found guilty of violating the BGEPA for the take of 14 golden eagles among other protected birds and was made to pay $1 million in direct fines and approximately $8 million in compensatory protection measures (Opar, 2013). This case plausibly represents a turning point after which costs associated with BGEPA compliance became a significant factor for wind turbine siting decisions.

Since the landmark Duke Energy case in late 2013, the USFWS has enforced the BGEPA against additional wind turbine developers. PacificCorp Energy paid $2.5 million in various fines and penalties after pleading guilty to BGEPA violations for the deaths of 38 golden eagles and other protected bird species (DOJ, 2014). Recently in 2022, electric utility ESI was sued for over 150 bald and golden eagle deaths, resulting in $8 million in direct fines, $27 million in mandatory compensatory mitigation, and charges of $29,623 per eagle killed for future instances of eagle take (Bever, 2022; DOJ, 2022). These cases illustrate the USFWS' proactive stance in enforcing the BGEPA against wind turbine developers following their

2012 guidelines and legal precedent established in the Duke Energy Inc. case.

Costs of eagle protections to wind developers includes not only the threat of prosecution but also new requirements to perform compensatory mitigation. The USFWS requires that any wind project developer applying for a permit perform compensatory mitigation by offsetting their damages to local eagle populations in a ratio of 1 bald eagle death prevented for every death caused and 1.2 golden eagle deaths prevented for every death caused (USFWS, 2012; USFWS, 2016; Mojica et al., 2021).[1] The estimated eagles saved by compensatory mitigation are weighed against the estimated eagles killed (USFWS, 2012; New et al., 2015; New et al., 2018). Expenses associated with compensatory mitigation are substantial; for example, compensatory mitigation costs make up the largest share of the fines levied against ESI in the recent 2022 prosecution (Bever, 2022; DOJ, 2022).

Back-of-the-envelope calculations suggest that the potential costs of fines and compensatory mitigation are large enough to plausibly affect whether developers expect a wind project to be profitable. Construction costs are around $4 million per turbine using U.S. Energy Information Administration data.[2] Calculations presented in Section 7 and detailed in Appendix F suggest that costs associated with eagle liability could be as high as $480,000 per turbine in present discounted value, or more than 10 percent of construction costs.[3]

3 Data

3.1 Abundance of bald and golden eagles

For data on eagle abundance across geography, we use the Cornell Lab of Ornithology's eBird project and dataset (Sullivan et al., 2009). The eBird project collects citizen-science observations of many bird species, including bald and golden eagles. While other sources offer range maps (i.e., a binary measure), no others provide continuous population estimates at high resolution across the country. eBird data is also used by USFWS itself since 2022 for evaluating wind turbine siting (USFWS, 2022).

Raw observations are converted to geospatial distributions and abundance estimates through a machine learning process described in Fink et al. (2020). The primary measure in the dataset is relative abundance. Relative abundance is a standardized measure based on field observations that reflects the expected count of a species seen in a 1-hour, 1-kilometer observation period. This captures the relative population intensity of a species in an area. Maps of relative abundance are provided in Figure 2 for bald eagles and Figure 3 for golden eagles.

We form county-level estimates of relative abundance by taking means across pixels within counties and across hours within years. We use abundance estimates for 2022 as our measure of exposure to the policy change. The year is chosen for convenience; although it comes after the initial policy change, scientific research has found golden eagle populations to be stable over the past 20 years (Millsap et al., 2013; Sauer et al., 2019), while bald eagle populations have increased since 2009 (Millsap et al., 2016; USFWS, 2020).

3.2 Wind energy installation

Outcome data on wind turbine development comes from the U.S. Wind Turbine Database (Hoen et al., 2022). The USWTDB records the universe of wind turbine installations in the United States. We use two outcome variables: the count of new turbines, and the total capacity of new wind energy. Turbine capacity is a measure of potential wind turbine output under ideal environmental conditions in megawatts (MW). This reflects the amount of developed wind energy in terms of output potential. A map of wind turbines by capacity in the U.S. is shown in Figure A.1.[4]

3.3 Covariates

To control for other determinants of potential wind energy development, we draw on the NREL Wind Supply Curve dataset (Lopez et al., 2021). This geospatial dataset is intended for use by wind developers when siting turbines. We use the reference wind supply curve dataset, which is estimated based on a moderate set of land restrictions. The data includes three key measures. One, wind speed, a primary determinant of output per unit capacity. Two, potential capacity, an estimate of how much wind capacity can developed on a unit of land, including terrain and land-use constraints.[5] Three, distance to transmission networks, which likely affects wind development because greater distances to pre-existing transmission networks translate to greater costs of creating new transmission infrastructure. These variables are essentially time-invariant; we use cross-sectional estimates from 2020.[6] Maps of these factors are shown in Figures A.3, A.4, and A.5, respectively.

3.4 Aggregation

We aggregate all datasets to the level of county (or county by year) for analytical convenience. For eBird and NREL wind supply curve data, we take county-level means across geospatial observations that fall within each county. For USWTDB outcome variables, we sum to county-year totals based on locations provided.

3.5 Sample selection

Temporally, our sample runs from 2001-2022, following the period of rapid wind energy growth as shown in Figure 1.

Our empirical strategy compares counties with both high wind potential and exposure to eagles to similar counties without eagle exposure. To make comparisons between similar counties, we focus our analysis to states in the central U.S., where wind speed and other resources are abundant. Following Brown et al. (2012), we restrict the sample to the following states: NM, CO, WY, MT, ND, SD, NE, KS, OK, TX, MN, IA, MO, IL. Because not all counties within these states are suitable to wind turbine development, we further restrict the same to counties with (a) average wind speeds of 7 miles per hour or greater, and (b) average potentially installable capacities of 100 MW or greater. (In sensitivity analyses we show that the particular method of sample selection does not drive baseline results.)

Summary statistics within this sample are shown in Table 1.

4 Empirical Methods

To identify the impacts of eagle protection policy on wind development, we leverage two sources of variation. First, temporal variation arises from the sudden increase in BGEPA enforcement surrounding the Duke Energy case in 2013. Second, geographical variation arises from the fact that this enforcement is likely to have a greater impact in counties with high exposure to bald or golden eagles than similar counties with lower exposure.

4.1 Treatment definition

To define our "high exposure" treatment variable, we follow thresholds set by USFWS for their wind energy permitting decisions (USFWS, 2022). These thresholds are the levels of relative abundance (in EBird data) below which wind turbine facilities are eligible for general eagle take permits and are not required to undergo site-specific review for specialized permits. The thresholds were published in 2022, as a clarification of pre-existing enforcement that began in 2013. Since they were set after the timespan of our data, we use them not as a measure of specific regulatory requirements, but rather as a measure of what values of relative abundance the regulator considers high for each species. Otherwise, without information on the regulator's objective function, relative abundance values are difficult to interpret, to compare within species, or especially to compare across species. These thresholds let us discretize and combine two continuous variables in a way that forms the best available proxy for regulatory liability.

We define $HighExposure_i$ to equal 1 if county i contains any area in which the relative abundance of either bald or golden eagles exceeds USFWS general permitting thresholds for any season, and 0 otherwise.[7] Figure 4 maps this treatment variable. Classification into treatment is primarily driven by golden eagles in the western part of the sample (in the Great Plains) and bald eagles in the eastern part of the sample (along the Mississippi River).

As a first cut of the data, we plot county means of our two outcome variables for treated (high-exposure) and control (low-exposure) counties in Figures 5 and 6. Up through 2013, treated and control counties track each other closely in both outcomes, including through large year-specific shocks, suggesting that the two groups represent reasonable counterfactuals for each other. After 2013, they diverge, with notably fewer additions in treated counties, suggesting a negative effect of BGEPA enforcement.

4.2 Regressions

To quantify and conduct statistical inference for the effect already seen in raw data, we use standard two-way fixed effect regressions.[8] Our basic regression specification is:

$$y_{it} = \beta(Post2013_t * HighExposure_i) + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

Outcome variable y_{it} denotes either MW of new capacity constructed in county i and year t, or new turbines constructed in county i and year t. $Post2013_t$ equals 0 in years up to and including 2013, and 1 in years 2014 and afterward to reflect the late-2013 timing of the Duke Energy case. County fixed effects γ_i account for county-specific time-invariant factors that influence wind turbine construction, such as terrain and wind speed. Year fixed effects δ_t account for year-specific factors, such as wind industry trends and increasingly efficient wind turbine technology over time. In all specifications, standard errors are clustered at the county level.

We also estimate event study regressions, to show the evolution of treatment effects over time and evaluate pre-trends:

$$y_{it} = \sum_{\tau=-12}^{9} \theta_\tau HighExposure_i + \gamma_i + \delta_t + \varepsilon_{it} \tag{2}$$

Here, treatment year τ is centered at 0 in 2013 as the year before treatment; it extends from 2001 through 2022. Coefficients θ_τ capture the average differences in trend between the treated and control groups for year τ. These visualizations support the parallel trends requirement if θ_τ is not significantly different from 0 when $\tau < 0$. For $\tau > 0$, θ_τ represent year-specific treatment effects over time. Negative θ_τ for $\tau > 0$ are evidence of negative impacts of BGEPA enforcement on wind capacity additions.

4.3 Identification assumptions

Interpretation of β as the causal impact of BGEPA enforcement in high-eagle areas relies on a standard parallel trends assumption. Parallel trends requires that wind capacity additions in areas with high eagle exposure would have followed the same evolution over time as additions in areas with no eagle exposure in the absence of BGEPA enforcement. We believe parallel trends is a reasonable starting point. Our sample is limited to high-wind counties, so identification comes from comparisons between otherwise similar counties with and without eagle exposure. Factors that influence wind turbine development such as wind speed, favorable terrain, and remoteness do not vary systematically over time, and county fixed effects absorb time-invariant differences in outcomes.

Importantly, our outcome variables measure not the stock of existing capacity but rather the flow of *new* capacity per year. It seems highly likely that the growth of wind development would vary across geography absent the shift in BGEPA enforcement, so an assumption of parallel trends in *cumulative* installed capacity would strain plausibility. Because we use measures of new capacity each year, we only need to assume that the annual *increase* in wind capacity would have followed parallel trends over time absent the policy shift. In other words, the potential trajectories of wind development may be different in different counties, so long as the slope of those trajectories did not change differentially in counties with high exposure to eagles post-2013 for reasons unrelated to BGEPA enforcement.

One potential challenge to the parallel trends assumption is the possibility that wind turbine developers might have substituted toward construction in low-exposure areas as a response to BGEPA enforcement. This spillover effect would violate the stable unit treatment value assumption (SUTVA), leading the control group to be a poor counterfactual for the treated group, and resulting in estimates that are biased away from 0. While substitution effects would lead to an overstated interpretation of β, significant values of β still provide evidence that wind turbine siting decisions are influenced by wildlife protection policies.

Under parallel trends, β has a causal interpretation as the treatment effect of BGEPA enforcement on wind capacity additions for high-exposure counties over the 2014-2022 period. A significant negative value of β is evidence of nontrivial negative impacts of BGEPA enforcement on wind turbine development. The size of β will shed light on the degree to which wind development may have been affected by the policy change, and the total impact of the policy can be estimated by multiplying β by the number of counties with eagle exposure. The significance and sign of β therefore show important information on the existence and intensity of tradeoffs between BGEPA enforcement and wind development.

5 Results

5.1 Main results

Our main results are shown in Table 2 for wind energy capacity additions and Table 3 for the count of turbine additions. First, we study the effects of high exposure to each species at a time, defining the treatment variable as whether a county exceeds USFWS thresholds for only bald eagles or only golden eagles. After BGEPA enforcement began in 2013, counties with high exposure to golden eagles added 4.5 MW less wind turbine capacity per year, and 1.9 fewer turbines per year, relative to counties with little to no exposure. Counties with high exposure to bald eagles added 5.5 MW less capacity and 2.0 fewer turbines per year than counties with little to no exposure. These estimates are statistically significant at a 99 percent level.

The fact that the results are so similar for both species – despite extremely different geographical distributions of where they are highly abundant – strengthens the evidence that we are indeed measuring a causal effect of BGEPA enforcement and not simply picking up spurious spatial correlation. We therefore pool the two species for the remainder of our analysis, defining the treatment variable as whether a county exceeds thresholds for either species.

Pooled results for our main specification are in column (3) of each table. Counties with high eagle exposure added 4.8 MW less in wind capacity or 2.0 fewer turbines than counties without high eagle exposure. Both estimates are statistically significant at a 99 percent level.[9] Multiplying these coefficients by the 126 in-sample treated counties implies a total estimated loss of roughly 605 MW of wind capacity, or 246 turbines, per year.

Event studies are shown in Figure 7 for capacity additions and 8 for turbine additions. Prior to 2013, estimated coefficients are flat and near zero, supporting the parallel trends assumption: Treatment and control counties followed similar trajectories prior to BGEPA enforcement, even in years of significant wind energy development. Within the first few years after the Duke Energy case, estimates turn negative. Individual yearly estimates are noisy but generally support the conclusion of a negative effect: Many estimates have confidence intervals that exclude zero, and those that are small or slightly positive also have larger confidence intervals.

5.2 Robustness checks

Covariates Many factors not captured in our model influence the location and extent of wind turbine development. Covariate imbalance alone does not invalidate our identification assumption, since county fixed effects absorb all time-invariant determinants of wind turbine development, observed and unobserved. However, one possible concern is that these factors, though time-invariant themselves, could have time-varying effects on wind development in response to the rising boom in wind energy over time. In that case, unbalanced covariates could violate the parallel trends assumption.

To check whether other factors are balanced across our treatment and control groups, we map the value of three particularly important determinants of wind development: wind speed (Figure A.3), potential capacity (Figure A.4), and distance to transmission networks (Figure A.5). Wind speed is balanced across treatment and control groups, but counties with greater golden eagle exposure have both greater potential capacity and greater distance to transmission networks.

To control for the possibility of time-varying effects of these key covariates, we estimate two additional regression models. First, we interact cross-sectional wind speed, potential capacity, and distance to transmission with linear time trends. This interaction allows the likely most important determinants of wind development, and anything correlated with them, to affect the treatment and control groups differently at different times. Results for added capacity are shown in column 2 of Table 4, with the main specification repeated in column 1 for comparison. Results are virtually unchanged: Treated counties experienced a significant decline in expected capacity additions of 4.9 megawatts.

Second, we estimate an even more flexible regression, interacting these three key covariates with year fixed effects. Column 3 shows that treated counties experienced a significant 5.3 MW decline in expected capacity additions. If anything, the negative effect of BGEPA enforcement on wind development becomes larger in magnitude, suggesting the baseline results are not driven by pre-existing differences between treated and control groups.

Results for added turbines are similar and shown in Appendix B.

Within-state variation State-level differences over time might also pose concerns for the parallel trends assumption. These identification challenges take two forms. One, some states in sample might experience higher or lower economic growth than others, leading to systematic differences in within-state renewable development that might differ between treated and control groups. Two, much renewable development is driven by state-level policies and subsidy programs (Shrimali et al., 2015). These issues might also systematically differ between treated and control groups, particularly because of the states that make up the control group. Texas and Iowa fall in the control group across specifications, and are the top two wind energy states due to natural resources and state policies. Furthermore, Texas experiences economic growth over time that is unlike other states.

To flexibly account for these issues, we estimate a specification that includes state-by-year fixed effects. Table 5 shows the results. In column 2, the treatment group experienced a significant 2.7 MW decline in expected capacity additions. The smaller effect is consistent with the idea that much of the useful variation is across states; highly restrictive fixed effects can increase attenuation bias by reducing the signal-to-noise ratio. Still, it is reassuring that the effect is on the same order of magnitude and remains statistically significant, suggesting that results are not driven by state-level policy variation over time.

Sample restrictions In Section 3, we formed our sample by restricting data to counties in the central U.S. with (a) average wind speeds of 7 miles per hour or greater, and (b) average potentially installable capacities of 100 MW or greater. Appendix C uses both intensified and relaxed sample restrictions to show that baseline results are robust to the specific values of sample restriction thresholds.

Continuous treatment variable In Appendix D, we use relative abundance directly as a continuous treatment variable. Because units of relative abundance may have different economic meaning for different species, we estimate results separately by species. Results are qualitatively similar to the specification with a binary treatment variable.

6 Ruling out spatial substitution

One potential threat to identification is that wind turbine developers may have responded to BGEPA enforcement by substituting development toward counties with low exposure to eagles. In this case, the negative effects we estimate might simply represent a spatial reallocation of wind development rather than an overall national reduction. We use two strategies to test for, and ultimately rule out, substitution effects. The strategies (1) exclude control-group counties near treated counties, and (2) leverage geographic differences in electricity grid regions.

6.1 Excluding nearby control counties

Our first approach relies on the idea that spatial substitution is more likely to occur over shorter distances. If wind developers respond to BGEPA enforcement by shifting wind projects away from otherwise optimal development locations, the new locations are unlikely to be thousands of miles away. Instead, they are likely to shift only as far away as necessary to equalize the marginal benefit of reduced liability with the marginal cost of the less-suitable location. This line of reasoning suggests that the greatest substitution is likely to be found just outside of the high-exposure treatment counties. Therefore, if we exclude these areas from the control group, we can estimate treatment effects that are less affected by substitution.

Table 6 shows results from regressions in which counties in the control group are omitted from the sample based on proximity to the nearest treated county. The regression in column (1) excludes control counties that lie within 50 kilometers of the nearest treated county, while columns (2) and (3) show the same specification with 100 km and 200 km radii. The effects appear to increase in magnitude as larger swaths of nearby control counties are excluded.

This is the opposite pattern from what we would expect to see if the treatment effects in the main specification were driven by substitution: If reduced wind development in high-exposure counties were balanced by increased development in nearby low-exposure counties, then excluding those counties would reduce the average difference between treatment and control counties remaining in the sample, shrinking estimated treatment effects toward zero. The fact we do not see this pattern suggests that our main results are not driven by nearby spillover effects.

Why would the treatment effects increase with the exclusion radius, rather than remain flat? The most likely explanation is that although we use a discretized treatment variable, underlying eagle abundance, and therefore potential liability, varies continuously across space. When we exclude the control counties closest to the treatment counties, we are excluding many of the counties with the greatest potential eagle liability among the control group. The resulting sample compares treatment and control counties with greater differences in potential liability as we increase the exclusion radius.

6.2 Comparing across grid regions

Our second approach relies on the idea that wind development is unlikely to be substituted across electricity grid regions. The continental U.S. is split into three grid regions – Western, Eastern, and Texas – with limited transmission capability between them. Grid regions act as separate markets: Developers are mostly unable to generate electricity in the Eastern grid and sell it in the Western grid. As a result, wind developers cannot easily substitute development towards one grid region in response to increased BGEPA enforcement and eagle exposure in another.

Interestingly, the boundary between the western and eastern grid regions coincides closely with the geographic division between high- and low-exposure counties for golden eagles; see Figure E.1 for grid region boundaries. Golden eagle liability primarily affects areas in the Western grid, and within the Western grid, few areas well-suited to wind development are *not* affected by golden eagles. Therefore, there is limited scope for spatial substitution in response to liability to golden eagles – certainly less than for liability to bald eagles, whose abundance patterns do not align with grid region boundaries in the same way. The fact that our main results show similar effects for golden eagles as for bald eagles already suggests that spatial substitution is not driving the results.

We can carry this logic further by restricting the sample. We estimate our main regression in a sample that includes only (a) high-exposure counties that lie strictly within the Western grid region, and (b) low-exposure counties that lie strictly within the Eastern or Texas grid regions. This comparison, mapped in Figure E.2, excludes the counties likely to experience the most substitution: the small number of low-exposure counties in the Western grid region that would receive the brunt of any substitution from all the high-exposure counties in the same region, and the small number of high-exposure counties in the Eastern grid region that would be most elastic to BGEPA enforcement if spillovers are important, since there are so many low-exposure counties in the same region. This approach is only able to use geographic variation based on exposure to golden eagles, not bald eagles, so we exclude counties in the Eastern grid region that are classified into treatment due to bald eagle exposure.

Results are shown in Table E.1. The estimates are extremely similar to the main specification, again suggesting that our main results are not driven by spatial substitution.

7 Benefit-cost analysis

Our empirical estimates suggest that BGEPA enforcement reduced wind turbine capacity additions in counties with high eagle exposure by an average of 4.8 MW per county per year. This implies a total wind capacity loss of 605 MW per year.

To understand the welfare implications of BGEPA enforcement, we need to weigh the benefits from eagle protections against the costs of preventing wind energy development. We perform back-of-the-envelope calculations to value both the losses to wind energy capacity and the gains from averted wildlife damages.

Costs of forgone wind energy capacity. We value the costs of forgone wind energy capacity in two ways. The benefits of new wind energy depend on the extent to which it supplements or displaces existing electricity supply. If new wind energy adds to existing electricity supply, it will generate benefits in the form of consumer surplus. If it displaces existing fossil fuel energy, it will generate benefits in the form of reduced carbon emissions and air pollution. Because estimating energy substitution patterns is beyond the scope of this paper, we alternate each of the two extreme assumptions to bracket the actual costs of forgone wind capacity.

First, we assume that wind energy only adds new electricity. Using market valuation methods, we find that the electricity prevented by BGEPA enforcement would have been worth \$111 million per year. Second, we assume that wind energy displaces an equal amount of electricity generated from fossil fuels. Using the U.S. federal government's estimate of the social cost of carbon, we find that the carbon emissions retained due to BGEPA enforcement result in social costs of \$80.5 million per year. (See Appendix F for details on both calculations.) Note this figure is an underestimate of the full environmental benefits of wind energy, since it considers only carbon emissions and ignores criteria air pollutants.

Because these two estimates bracket two opposite extreme possibilities, we can say that the costs of forgone wind energy capacity due to BGEPA enforcement are between \$80 and \$111 million per year. These figures are economically meaningful, suggesting that the impacts of species protections on renewable development are substantial.

Benefits of averted eagle fatalities. To estimate the benefits of BGEPA enforcement, we estimate mortality effects of the forgone wind installations, and then value the costs of eagle mortality. First, to estimate effects of wind turbines on eagle mortality, we follow a Bayesian simulation process employed by USFWS (2012), New et al. (2015), and New et al. (2018). We find that the wind installations prevented by BGEPA enforcement would have been responsible for an average of approximately 37 bald eagle deaths and 11 golden eagle deaths per year.

Second, we need to value eagle lives. In the absence of relevant revealed-preference estimates in the literature, we use two alternative valuation methods. One method uses the costs of compensatory mitigation, yielding an estimate of $\$15,200$ to $\$38,000$ per eagle (Millsap et al., 2022; Hosterman and Lane, 2017). This would place the total annual value of protected eagle lives at $\$121,600$ to $\$304,000$. A potential limitation of this approach is that it assumes that all eagle deaths are perfectly replaceable. Therefore, while it is potentially applicable for limited amounts of eagle deaths, it might undervalue specific individuals in the case of larger-scale impacts.

Another method is specific to wind turbine development: fines from recent prosecutions. We argue that fines imposed by the justice system can be interpreted as a revealed-preference method of the value society places on the eagles. Using fines from 2022 recent conviction of the electric utility ESI, we calculate a $127,000 value per eagle, placing the total annual value of preserved eagle lives as a result of this policy at $6.1 million. We carry forward this estimate since it is larger and therefore more conservative, erring on the side of greater benefits to wildlife. (Again, see Appendix F for details on these calculations.)

Both these methods result in greater eagle valuations than the available evidence from contingent valuation approaches. A handful of studies have used stated preference methods to value specific wildlife species, including eagles. A summary of this evidence by Richardson and Loomis (2009) suggests an average annual willingness-to-pay of $39 per household per year for bald eagles, which is $55 in 2022 dollars.[10] These estimates represent willingness-to-pay for the existence of an entire species, not marginal changes in the number of individuals. Still, we can attempt to estimate the value of an individual eagle, following Eagle and Betters (1998), by multiplying by the Census Bureau count of 127 million U.S. households and dividing by the USFWS estimate of 316,700 eagles. This results in an average value of only $22,100 per eagle.

Comparison. Comparing benefits and costs, we find that BGEPA enforcement prevents eagle fatalities valued at $6 million per year, while also preventing wind energy valued at $80 to $111 million per year. This suggests the costs of BGEPA enforcement are 13 to 18 times greater than its benefits.

These figures are relatively rough calculations. One especially important limitation is that they may not hold for large, non-marginal changes in wind energy supply or eagle fatalities. But even if our calculations of either costs or benefits are off by an order of magnitude, they still imply that there are significant economic gains to allowing at least marginally more wind development in high-potential areas that overlap eagle ranges.

8 Conclusion

Using a difference-in-differences approach, we find evidence that enforcement of the BGEPA reduced wind turbine capacity additions in counties with high eagle exposure by an average of 4.8 MW per county per year. Rough welfare calculations suggest that the costs of forgone wind capacity, in terms of either lost electricity value or retained carbon emissions, are on the order of 13 to 18 times greater than the benefits of avoided eagle fatalities. At least in the narrow trade-off of wind energy development versus eagle preservation, current policy appears to overvalue wildlife and undervalue new renewable energy.

Moving forward, conservation policies should be carefully evaluated to efficiently meet wildlife preservation objectives while limiting potential impacts on renewable energy development as much as reasonably possible. Conservation objectives should focus on effective mitigation procedures to limit effects and ensure that local species impacts do not affect overall species stability. This is the philosophy behind the USFWS' current compensatory mitigation procedure, alongside recent USFWS efforts to streamline the permit application process for wind turbine developers (USFWS, 2022). This streamlined process might reduce costs of wind turbine development while still maintaining conservation objectives.

In addition to streamlining, compensatory mitigation programs could improve welfare through reducing the liability of wind turbine developers and ratepayers, potentially driving more wind development. Some authors have suggested market-based mechanisms for compensatory mitigation credits to distribute mitigation resources more efficiently (Espey and Espey, 2022). Increased funding for wildlife conservation measures might improve species' stability and enable more renewable development, such as in the case of successful bald eagle conservation efforts (USFWS, 2016). Overall, this study suggests that the impacts of species protections on renewable potential are substantial, and that efficiently-designed mitigation practices might ease burdens on renewable electricity demands while limiting wildlife impacts throughout the renewable transition.

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Tables

Table 1: Summary Statistics, Main Sample

	Mean	SD	Min	Max	N
Added Capacity, MW	5.31	35.35	0.00	1106.00	18722
Added Capacity, > 0	116.22	120.23	0.10	1106.00	856
Added Turbines	2.62	17.10	0.00	455.00	18722
Golden Eagle Rel. Abun.	0.01	0.02	0.00	0.15	851
Bald Eagle Rel. Abun.	0.08	0.09	0.00	0.57	851
Mean Wind Speed, MPH	7.89	0.39	7.00	9.29	851
Potential Capacity, MW	172.33	51.47	100.24	338.63	851
Mean Dist. to Transmission, KM	39.01	43.72	2.89	221.14	851

Notes: Row (1) shows the regression sample summary statistics for the county-year level added capacity outcome variable. Since this variable is skewed with a value of 0 for many county-years, row (2) shows summary statistics for the variable conditional on it being greater than 0. Row (3) shows summary statistics for the county-year level added turbines variable. Rows (4)-(7) contain a smaller number of observations due to their nature as cross-sectional data. Row (4) shows county mean golden eagle relative abundance, while row (5) shows county mean bald eagle relative abundance. Rows (6)-(8) show county mean wind speed (MPH), potential capacity (MW), and distance to transmission networks (KM) from the NREL wind supply curve data, respectively.

Table 2: Main effects of BGEPA enforcement on wind capacity additions

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
County exceeds golden eagle cutoffs * Post	-4.466***		
	(1.201)		
County exceeds bald eagle cutoffs * Post		-5.550***	
		(0.674)	
County exceeds cutoffs * Post			-4.812***
			(1.108)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cluster	County	County	County
N	18722	18722	18722

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Table reports estimates from regressions of the form in Equation 1, using a binary treatment variable that equals 1 if a county has any area with seasonal golden eagle relative abundance above USFWS general permit cutoffs, bald eagle relative abundance above USFWS general permit cutoffs, or either species above general permit cutoffs, respectively.

Table 3: Main effects of BGEPA enforcement on wind turbine additions

	(1) Added Turbines	(2) Added Turbines	(3) Added Turbines
County exceeds golden eagle cutoffs * Post	-1.856*** (0.554)		
County exceeds bald eagle cutoffs * Post		-1.981*** (0.301)	
County exceeds cutoffs * Post			-1.950*** (0.510)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cluster	County	County	County
N	18722	18722	18722

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Table reports estimates from regressions of the form in Equation 1, using a binary treatment variable that equals 1 if a county has any area with seasonal golden eagle relative abundance above USFWS general permit cutoffs, bald eagle relative abundance above USFWS general permit cutoffs, or either species above general permit cutoffs, respectively.

Table 4: Robustness checks: Covariates

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
County exceeds cutoffs * Post	-4.812***	-4.924***	-5.297***
	(1.108)	(1.398)	(1.489)
Wind Speed * t		0.399***	
		(0.119)	
Potential Cap. * t		0.00650***	
		(0.00189)	
Transmission Dist. * t		-0.00677***	
		(0.00160)	
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Characteristics * Year FE	No	No	Yes
Cluster	County	County	County
N	18722	18722	18722

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Column (1) reiterates the baseline results for added capacity from table 2. Column (2) shows results from a model that includes three key covariates – wind speed, potential capacity, and transmission distance – interacted with a linear time trend. Column (3) shows results from a model that includes the same three covariates interacted with year fixed effects.

Table 5: Robustness checks: Within-state variation

	(1) Added Capacity	(2) Added Capacity
County exceeds cutoffs * Post	-4.812***	-2.654**
	(1.108)	(1.344)
County FE	Yes	Yes
Year FE	Yes	Yes
State-Year FE	No	Yes
Cluster	County	County
N	18722	18722

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Column (1) reiterates the baseline results for added capacity from table 2. Column (2) shows results from a model that includes state-by-year fixed effects.

Table 6: Robustness Check: Control Counties Omitted by Distance to Treated Counties

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
County exceeds USFWS cutoffs * Post	-5.834***	-6.475***	-8.489***
	(1.217)	(1.301)	(1.615)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Distance from Treated, KM	50	100	200
Cluster	County	County	County
N	15070	13178	9130

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Column (1) shows the results of the baseline model where control counties closer than 50 km to the nearest treated county are excluded from the sample. Columns (2) and (3) show the results of the baseline model where control counties closer than 100 km and 200 km to the nearest treatment county are excluded from the sample, respectively.

Figure Titles

Figure 1: Capacity Additions by Year, from USWTDB (Hoen et al., 2022)

Figure 2: Bald Eagle Relative Abundance Map, EBird (Sullivan et al., 2009)

Figure 3: Golden Eagle Relative Abundance Map, EBird (Sullivan et al., 2009)

Figure 4: Main Sample Map by Treatment Status

Figure 5: Mean Capacity Additions by Treated Status

Figure 6: Mean Turbine Additions by Treated Status

Figure 7: Event study: Effects of BGEPA enforcement on new wind capacity added per year

Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using a binary treatment variable that equals 1 if a county contains any area exceeding USFWS seasonal general permit relative abundance cutoffs for either golden or bald eagles. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The x-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

Figure 8: Event study: Effects of BGEPA enforcement on new wind turbines added per year

Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using a binary treatment variable that equals 1 if a county contains any area exceeding USFWS seasonal general permit relative abundance cutoffs for either golden or bald eagles. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The x-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

Notes

[1]Currently, the only official channel of compensatory mitigation recognized by the USFWS is power line retrofitting (Mojica et al., 2021).

[2]Onshore construction costs in 2021 were $1,428 per kW, and a typical turbine capacity is 3 MW.

[3]Appendix F estimates that settlement costs in the ESI case were $127,000 per eagle fatality, and the expected number of eagle fatalities per turbine is about 0.2 per year. A perpetual stream of these costs at a 7 percent discount rate has a present value of $480,000.

[4]A map of wind turbine development through 2012 before BGEPA enforcement began is shown in Figure A.2.

[5]This measure does consider habitat of protected species, but only based on discretized boundaries rather than the richer, continuous measure of relative abundance we use, avoiding concerns of collinearity with our treatment variable.

[6]Time-invariant variables could still have time-varying effects, which we allow for in robustness checks.

[7]The 2022 USFWS general permitting cutoffs are based on seasonal relative abundance values. For bald eagles, these values are 0.821 for the pre-breeding migration season from February-May, 0.686 for the breeding season from May-July, 0.705 for the post-breeding migration season from July-December, and 1.357 for the non-breeding season from December-February. For golden eagles, these values are 0.081 for the pre-breeding season from February-June, 0.065 for the breeding season from June-August, 0.091 for the post-breeding season from August-December, and 0.091 for the non-breeding season from December-February.

[8]Since the timing of our treatment is simultaneous across units rather than staggered, we avoid the negative-weight problems identified in the recent literature on differences-in-differences. When treatment is simultaneous in balanced panel data, a two-way fixed effects regression identifies an average treatment effect on the treated even under heterogeneous effects (Roth et al., 2023).

[9]The remaining tables in this section display results for the treatment definition using either species unless otherwise noted.

[10]Golden eagles are omitted from Richardson and Loomis (2009), and we did not find relevant evidence elsewhere.

Figures

Figure 1: Capacity Additions by Year, from USWTDB (Hoen et al., 2022)

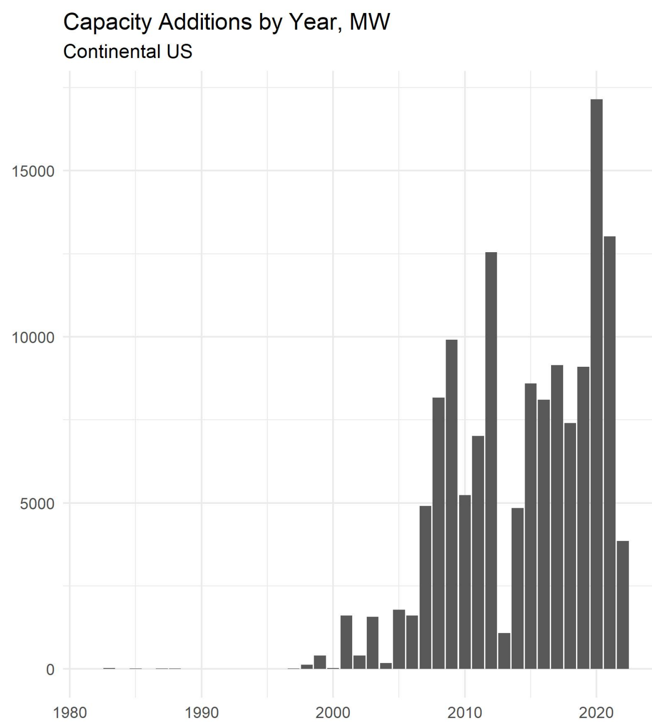


Figure 2: Bald Eagle Relative Abundance Map, EBird (Sullivan et al., 2009)

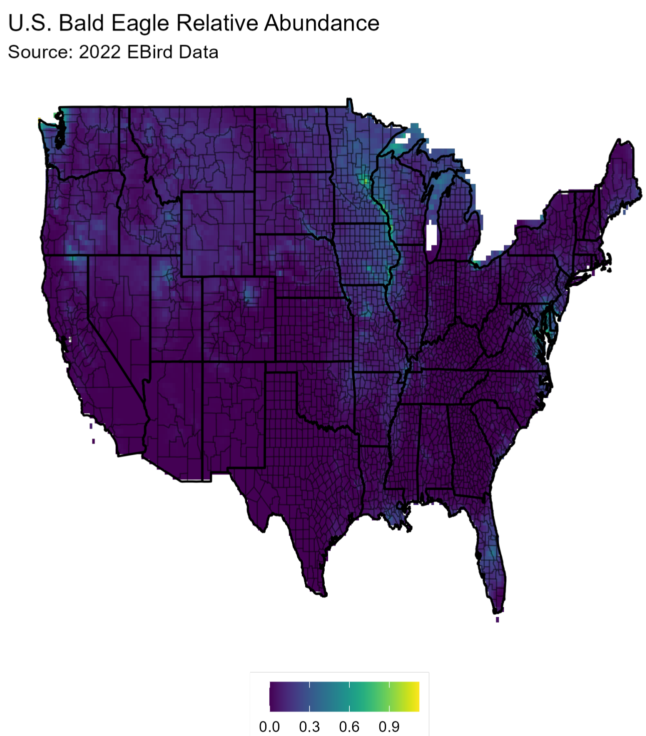


Figure 3: Golden Eagle Relative Abundance Map, EBird (Sullivan et al., 2009)

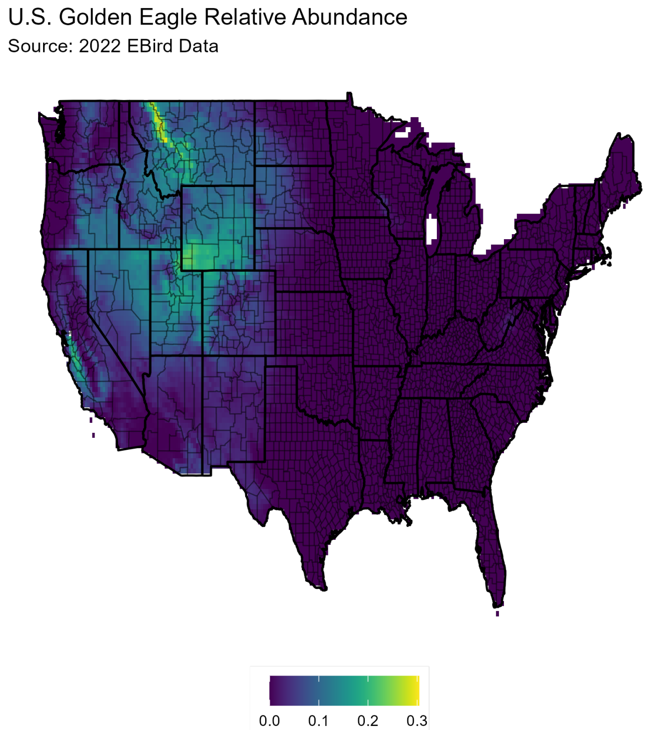


Figure 4: Main Sample Map by Treatment Status

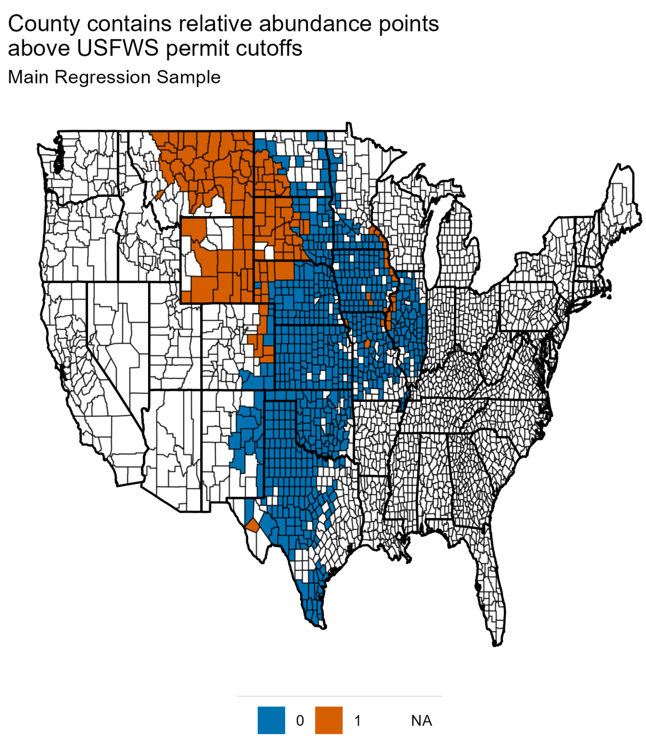


Figure 5: Mean Capacity Additions by Treated Status

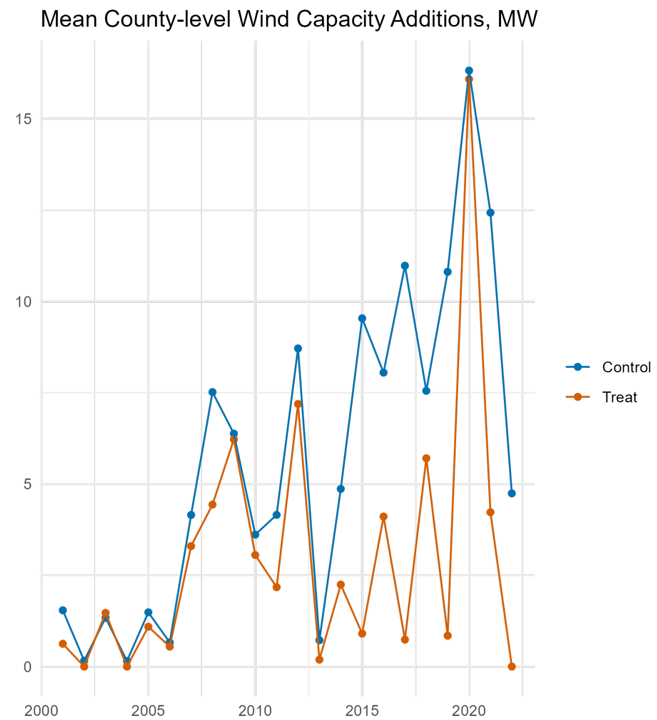


Figure 6: Mean Turbine Additions by Treated Status

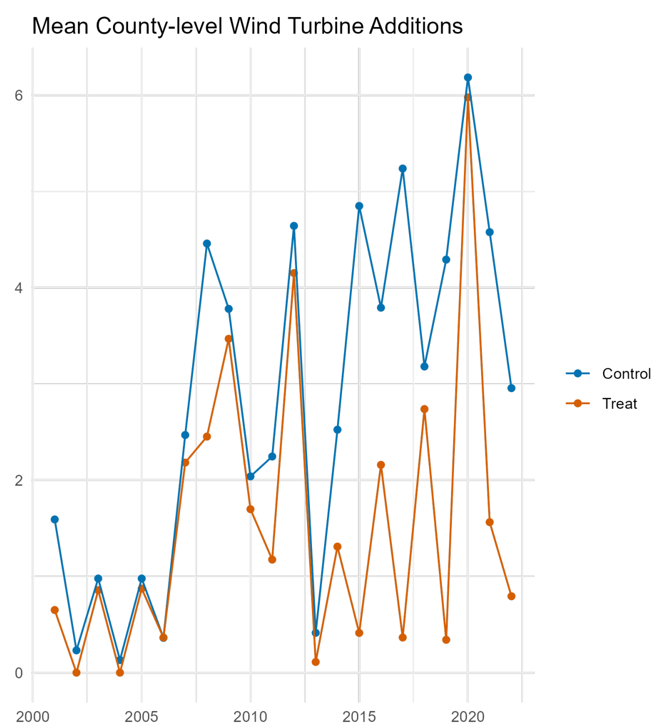
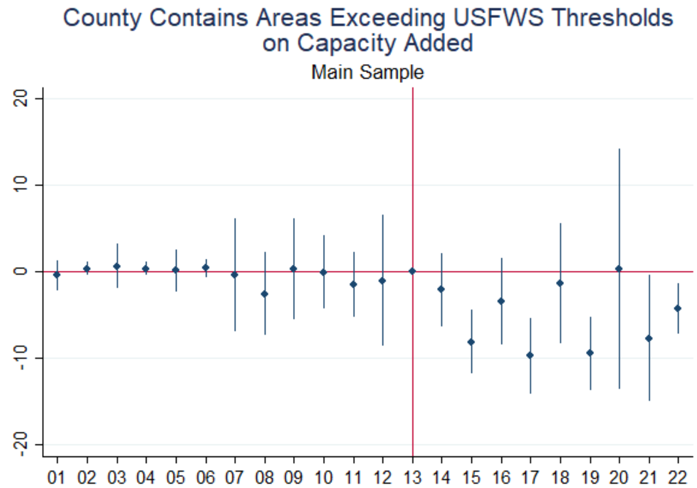
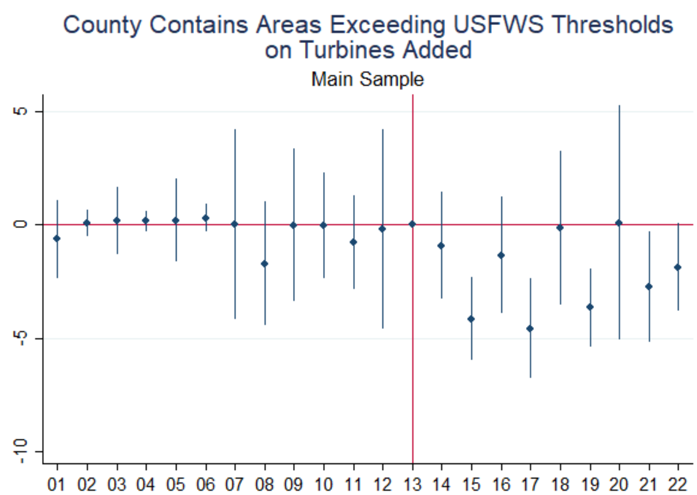


Figure 7: Event study: Effects of BGEPA enforcement on new wind capacity added per year



Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using a binary treatment variable that equals 1 if a county contains any area exceeding USFWS seasonal general permit relative abundance cutoffs for either golden or bald eagles. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

Figure 8: Event study: Effects of BGEPA enforcement on new wind turbines added per year



Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using a binary treatment variable that equals 1 if a county contains any area exceeding USFWS seasonal general permit relative abundance cutoffs for either golden or bald eagles. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

A Additional Figures

Figure A.1: Wind Turbine Locations, USWTDB (Hoen et al., 2022)

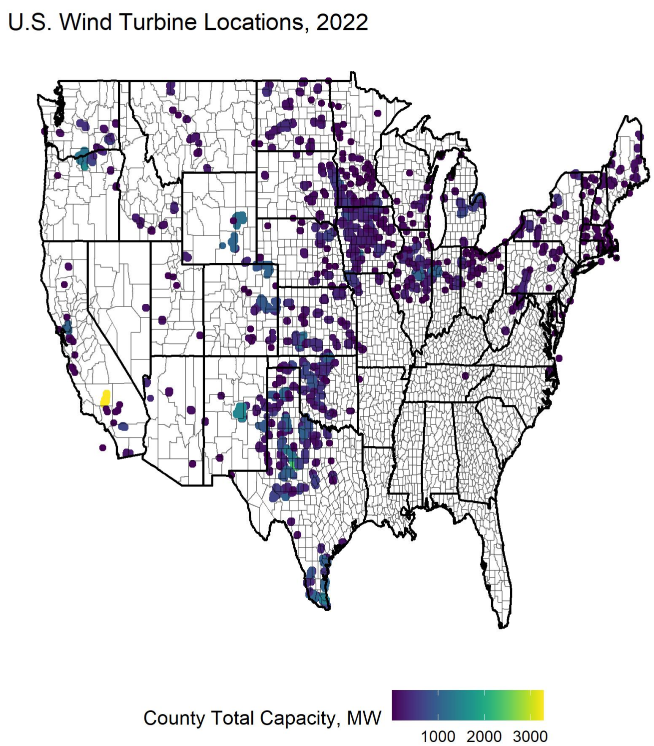


Figure A.2: Wind Turbine Locations through 2012, USWTDB (Hoen et al., 2022)

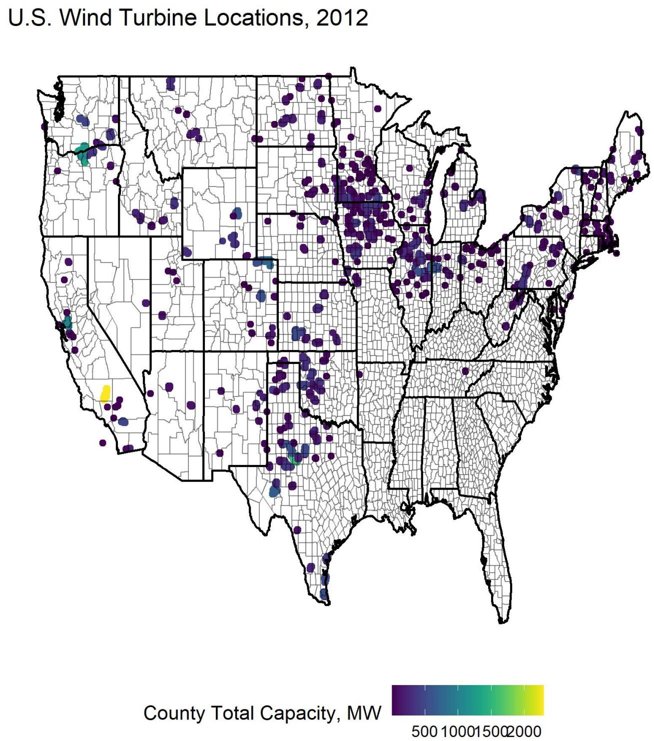


Figure A.3: Wind Speeds (MPH), NREL Wind Supply Curve Data (Lopez et al., 2021)

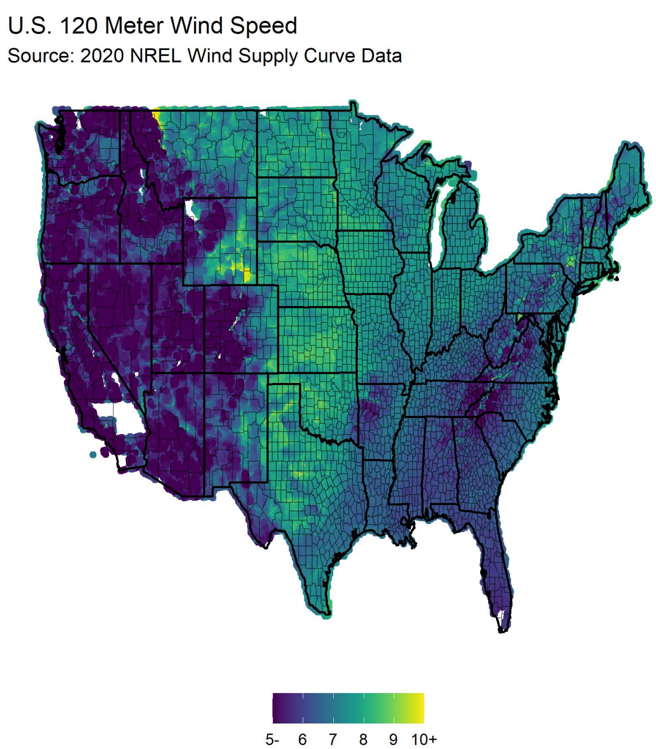


Figure A.4: Potential Capacity (MW), NREL Wind Supply Curve Data (Lopez et al., 2021)

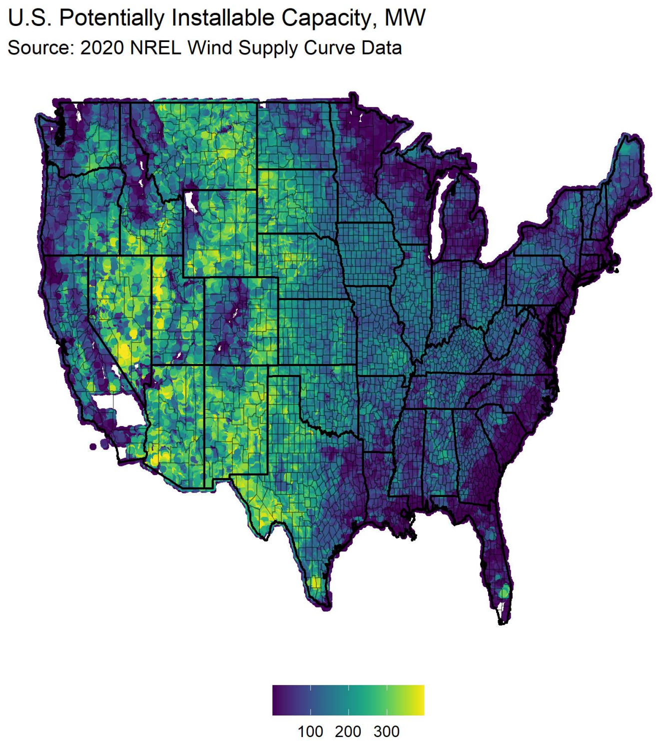
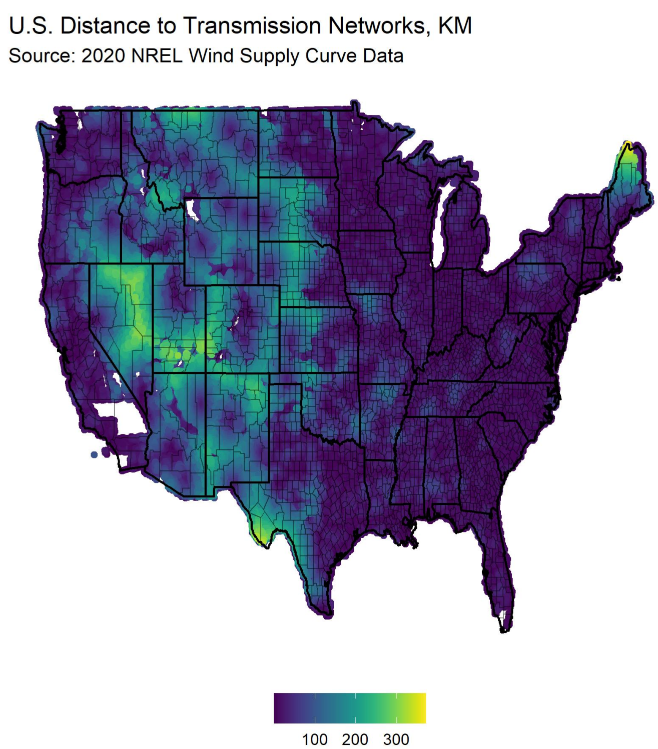


Figure A.5: Transmission Dist. (KM), NREL Wind Supply Curve Data (Lopez et al., 2021)



B Robustness Checks for Added Turbines

This appendix presents the results of robustness checks for specifications in which the outcome variable is the count of added turbines. Results are very similar to those using added capacity as the outcome variable.

Table B.1: Robustness checks: Covariates

	(1) Added Turbines	(2) Added Turbines	(3) Added Turbines
County exceeds cutoffs * Post	-1.950***	-1.922***	-2.158***
	(0.510)	(0.671)	(0.679)
Wind Speed * t		0.165***	
		(0.0525)	
Potential Cap. * t		0.00240***	
		(0.000892)	
Transmission Dist. * t		-0.00260***	
		(0.000725)	
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Characteristics * Year FE	No	No	Yes
Cluster	County	County	County
N	18722	18722	18722

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Column (1) reiterates the baseline results for the count of added turbines from Table 2. Column (2) shows results from a model that includes three key covariates – wind speed, potential capacity, and transmission distance – interacted with a linear time trend. Column (3) shows results from a model that includes the same three covariates interacted with year fixed effects.

Table B.2: Robustness checks: Within-state variation

	(1) Added Turbines	(2) Added Turbines
County exceeds cutoffs * Post	-1.950***	-0.713
	(0.510)	(0.638)
County FE	Yes	Yes
Year FE	Yes	Yes
State-Year FE	No	Yes
Cluster	County	County
N	18722	18722

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Column (1) reiterates the baseline results for the count of added turbines from Table 2. Column (2) shows results from a model that includes state-by-year fixed effects.

C Sensitivity to Sample Selection

Our baseline results are derived from a sample of only counties in central US states with average wind speeds above 7 MPH and average potentially installable capacities above 100 MW. The purpose of these sample restrictions is to limit identification to comparisons within a group of counties with similar wind energy potential at the outset. However, the precise choices of thresholds are arbitrary.

In this appendix, we show evidence that our main results are not sensitive to these specific sample restrictions. We do so in two ways. First, we reduce the wind speed minimum to 6.5 MPH, while keeping the 100 MW potential capacity minimum; results are shown in Table C.1 and Figure C.1. Second, we impose no sample restrictions on counties within the sample states; results are shown in Table C.2 and Figure C.2. In both specifications, results are qualitatively similar to the baseline results.

Table C.1: Effects of BGEPA enforcement (alternative sample restrictions)

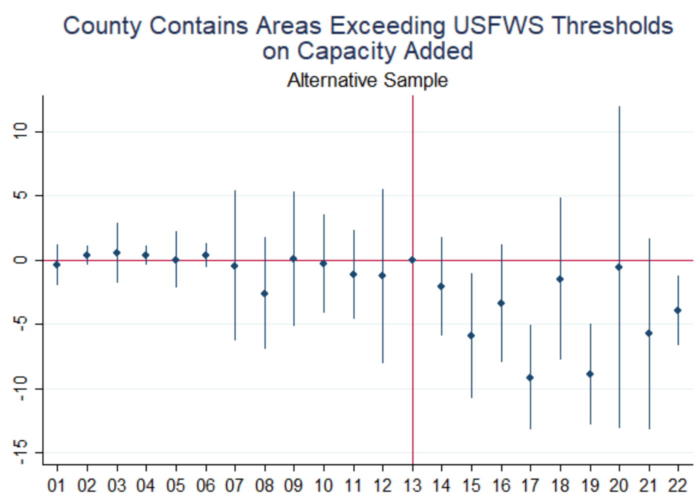
	(1) Added Capacity	(2) Added Turbines
County has area exceeding USFWS cutoffs * Post	-4.242***	-1.654***
	(1.046)	(0.487)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	20086	20086

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Table reports estimates from regressions of the form in Equation 1, using a binary treatment variable that equals 1 if a county contains area that exceeds seasonal USFWS general permit thresholds for either golden or bald eagles. Here, the sample is restricted to counties with a mean wind speed above 6.5 MPH and potential capacity above 100 MW.

Figure C.1: Event study: Effects of BGEPA enforcement (alternative sample restrictions)



Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using a binary treatment variable that equals 1 if a county contains area that exceeds seasonal USFWS general permit thresholds for either golden or bald eagles. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county. Here, the sample is restricted to counties with a mean wind speed above 6.5 MPH and potential capacity above 100 MW.

Table C.2: Effects of BGEPA enforcement (unrestricted sample)

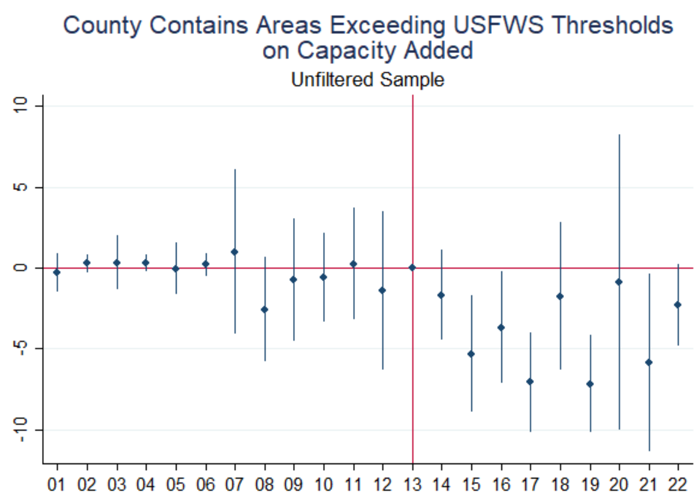
	(1) Added Capacity	(2) Added Turbines
County has area exceeding USFWS cutoffs * Post	-3.715***	-1.490***
	(0.782)	(0.370)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	26730	26730

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Table reports estimates from regressions of the form in Equation 1, using a binary treatment variable that equals 1 if a county contains area that exceeds seasonal USFWS general permit thresholds for either golden or bald eagles. Here, the sample is unrestricted beyond selecting states located within the wind-rich Great Plains region.

Figure C.2: Event study: Effects of BGEPA enforcement (unrestricted sample)



Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using a binary treatment variable that equals 1 if a county contains area that exceeds seasonal USFWS general permit thresholds for either golden or bald eagles. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county. Here, the sample is unrestricted beyond selecting states located within the wind-rich Great Plains region.

D Continuous Treatment Specifications

In this appendix, we use a continuous treatment model to supplement the baseline binary treatment results. This method potentially avoids the issue of ambiguous treatment definitions and may gain statistical power by leveraging all differences in relative abundance across counties. Instead of defining the treatment variable as a binary discretization of relative abundance, we simply use the raw values of relative abundance as treatment variable: $EagleExposed_i := RelativeAbundance_i$. The coefficient β then captures an average marginal impact of unit increases in relative abundance on the outcome variable y_{it}. Since relative abundance values are not comparable across species, we perform this specification separately with bald and golden eagle relative abundance.

Regression results are shown in Table D.1. In the golden eagle model, a one-percentage-point increase in golden eagle relative abundance is significantly associated with a decline in capacity additions of 0.52 MW and 0.24 turbines per year. In the bald eagle model, a one-percentage-point increase in bald eagle relative abundance is significantly associated with a decline in in capacity additions of 0.33 MW and 0.14 turbines per year. To put these results in perspective, the standard deviation of golden eagle relative abundance is 0.02, so a one-standard-deviation increase in golden eagle abundance reduces capacity additions by 1.05 MW per year. Similarly, a standard deviation of bald eagle relative abundance is 0.09, so a standard deviation increase in bald eagle relative abundance reduces capacity additions by 3.0 MW per year. Event study figures using the continuous treatment variable are shown in Figures D.1 and D.2 for golden eagles, and Figures D.3 and D.4 for bald eagles. Overall, results are qualitatively similar to the baseline binary treatment results.

The reason we prefer a binary treatment variable in the main body of this paper is that continuous treatment models feature unique challenges for causal inference under heterogeneous effects, as shown in recent work by Callaway et al. (2021). Continuous treatment models feature different treatment groups with potentially different treatment effects; if there exists systematic differences in treatment effects between realized treated outcomes and unrealized untreated outcomes by treatment group, these differences confound the identification of the marginal impact of a unit increase in treatment intensity. Therefore, continuous treatment models require a strong parallel trends assumption. This requires that each treatment group's unrealized outcomes at all different treatment intensities be parallel to all corresponding groups with those realized treatment intensities. This condition allows for different treatment groups to serve as valid counterfactuals for each other, allowing the identification of the marginal impacts of treatment intensity.

The strong parallel trends assumption is defensible for this study. Differences in unrealized treatment effects between treatment groups are a particular concern when observing agents optimizing their treatment intensity choices based on unobserved factors. This is why Callaway et al. (2021) frame this issue as "selection bias." In this application, observation units are counties. Treatment depends on plausibly exogenous golden eagle distributions, and units have no way to select into different exposures based on their unobserved wind turbine potential. Furthermore, just as in the basic difference-in-differences case, county fixed effects absorb potentially confounding differences such as wind speed and terrain. Finally, transmission networks grant developers some flexibility in wind turbine siting, diminishing variation in potential treatment effects across space.

Table D.1: Effects of BGEPA enforcement (continuous treatment)

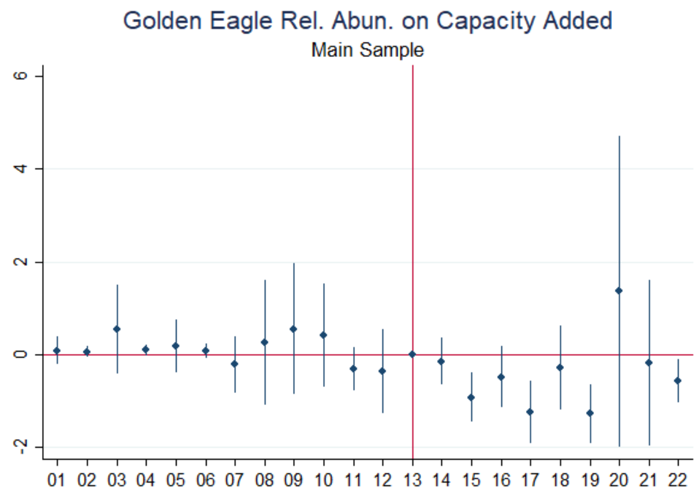
	(1) Added Capacity	(2) Added Turbines	(3) Added Capacity	(4) Added Turbines
Post * Golden Eagle Rel. Abun. * 100	-0.523**	-0.242***		
	(0.228)	(0.0838)		
Post * Bald Eagle Rel. Abun. * 100			-0.328***	-0.136***
			(0.0581)	(0.0264)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	County	County	County	County
N	18722	18722	18722	18722

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

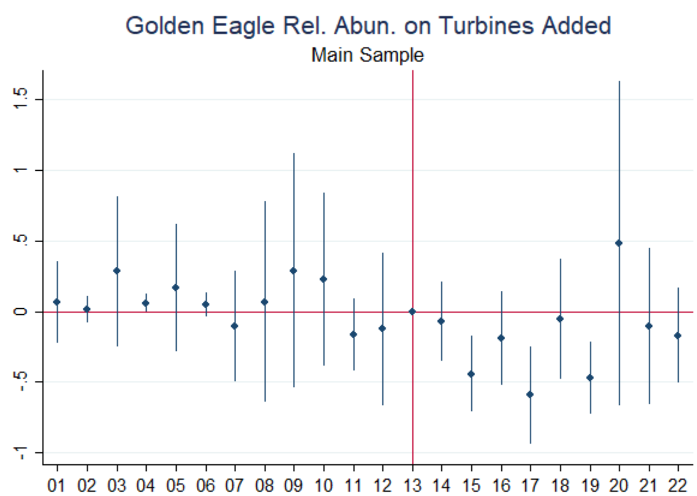
Notes: Table reports estimates from regressions of the form in Equation 1, using relative abundance as a continuous treatment variable. Results are displayed separately for golden and bald eagles, respectively.

Figure D.1: Event study: Effects of BGEPA enforcement (continuous treatment)



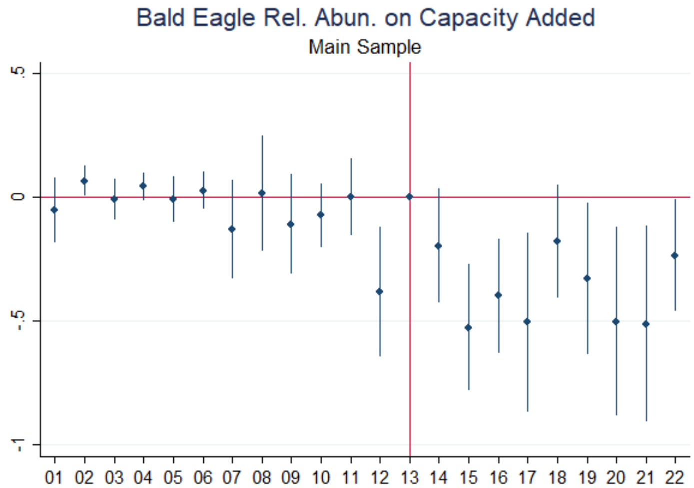
Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using golden eagle relative abundance as a continuous treatment variable and added capacity as an outcome variable. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

Figure D.2: Event study: Effects of BGEPA enforcement (continuous treatment)



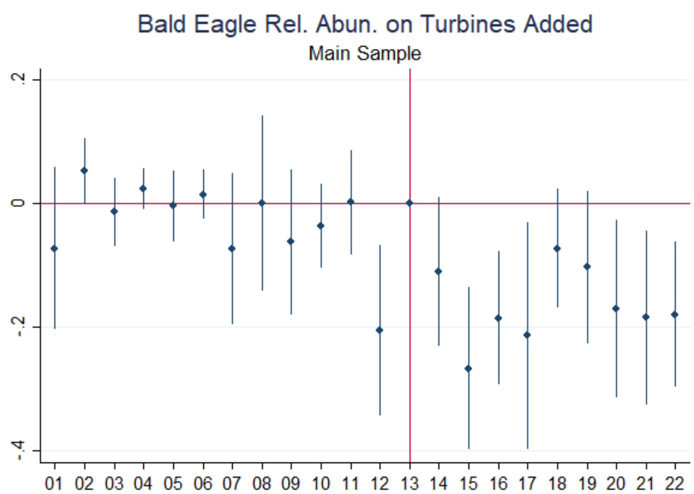
Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using golden eagle relative abundance as a continuous treatment variable and added turbines as an outcome variable. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

Figure D.3: Event study: Effects of BGEPA enforcement (continuous treatment)



Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using bald eagle relative abundance as a continuous treatment variable and added capacity as an outcome variable. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

Figure D.4: Event study: Effects of BGEPA enforcement (continuous treatment)



Notes: Graph plots point estimates and 95% confidence intervals from an event study regression of the form in Equation 2, using bald eagle relative abundance as a continuous treatment variable and added turbines as an outcome variable. The outcome is regressed on binary indicators for years 2001 through 2022, each interacted with the treatment variable, along with county and year fixed effects. The *x*-axis labels years since 2000; enforcement begins after 2013. Standard errors are clustered by county.

E Treatment Within Separate Grid Regions

Figure E.1: Grid Regions Map

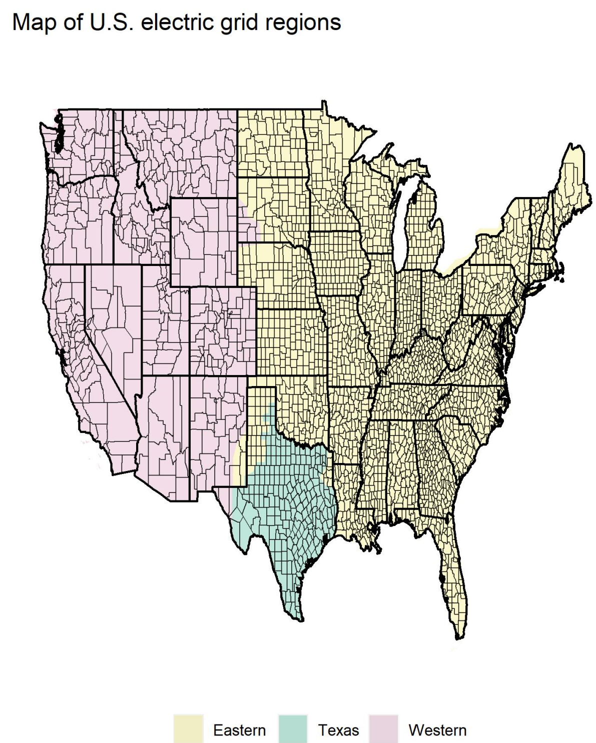


Figure E.2: Baseline Treatment Sample bounded within Grid Regions

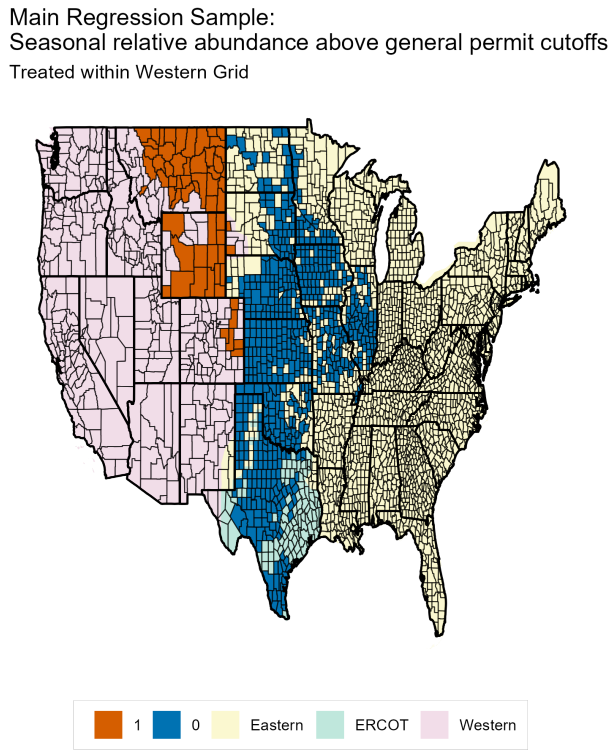


Table E.1: Main effects of BGEPA enforcement on wind capacity additions

	(1) Added Capacity	(2) Added Turbines
County exceeds USFWS cutoffs * Post	-4.223**	-2.029**
	(1.767)	(0.818)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	15466	15466

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: Table reports estimates from regressions of the form in Equation 1, using a binary treatment variable that equals 1 if a county has any area with seasonal golden eagle relative abundance above USFWS general permit cutoffs, bald eagle relative abundance above USFWS general permit cutoffs, or either species above general permit cutoffs, respectively. In these specifications, the sample is restricted to include only eagle-exposed counties in the Western grid and unexposed counties outside of the Western grid.

F Details of Valuation Methods

F.1 Valuation of Foregone Electricity: Electricity Added Method

To value the electricity generation foregone as a result of BGEPA enforcement, we first apply USGS wind turbine output estimates to the total loss of 605 MW. Using a 843 MWh/-month output estimate for 2.75 MW of capacity (USGS, 2020), we estimate that 605 MW of capacity would have output $185,460$ MWh/month. Using the USGS estimate that 843 MWh/month could power 940 average U.S. homes, we calculate that $185,460$ MWh/month could have powered 206,800 homes.

To value this level of output, we obtained electricity price information from publicly-available EIA datasets. We chose wholesale electricity prices from the Southwest Power Pool (SPP) for their geographical overlap with the eagle-exposed counties in our sample. We take the annual average of 2022-2023 SPP North Hub LMPs due to data availability. This yields an average electricity price of \$49.68/MWh.

The final valuation is the product of $185,460$ MWh/month, 12 months/year, and \$49.68 per MWh, which equals \$111 million per year.

F.2 Valuation of Foregone Electricity: Emissions Displaced Method

As an alternative to the above method, we value the foregone wind turbines through assuming that the generation from these turbines would have completely displaced an equal amount of generation from fossil-fuel generators. The wind turbines can then be valued using the social cost of carbon of the averted fossil-fuel emissions.

To estimate this at an annual level, we first use the same steps shown in the previous method to arrive at an estimate of $185,460$ MWh/month of electricity generation. Multiplying this by 12 yields a result of $2,225,520$ MWh/year.

We combine this estimate with EPA greenhouse gas equivalence estimates from EPA AVERT data (EPA, 2023). AVERT data gives an average of $7.09 * 10^{-4}$ tons of CO2 per KWh of generation. Multiplying by the displaced generation above, we obtain a total of $1,577,894$ tons of CO2 per year.

Finally, we apply the U.S. federal government's current estimate of the social cost of carbon, which is \$51 per ton of CO2 (Hersher et al., 2023). Multiplying this by the annual CO2 estimate yields a total valuation of approximately \$80.5 million per year.

F.3 Eagle Fatalities

We estimate the number of fatalities of golden eagles from forgone wind turbines using a process employed in USFWS (2012), New et al. (2015), and New et al. (2018). The estimation procedure involves a Bayesian process, in which site-specific eagle observations are used to update golden eagle exposure priors. Given a lack of site-specific observations, we employ the priors-only model using the most recent available priors from New et al. (2018). We perform this process separately for both species.

Estimated eagle mortality is defined as the following:

$$F_s = C_s \lambda_s \varepsilon \tag{3}$$

Where C_s represents collision probability for species s, λ_s represents exposure for species s, and ε represents the cumulative annual hazardous footprint across turbines in a unit.

Species-specific collision probability C has the following distributions:

$$C_{BaldEagle} \sim \beta(1.61, 228.2) \tag{4}$$

$$C_{GoldenEagle} \sim \beta(1.29, 227.6) \tag{5}$$

The parameters for this distribution are taken from realized eagle collision data detailed in New et al. (2018).

In the priors-only model, eagle exposure λ_s has the following distributions:

$$\lambda_{BaldEagle} \sim \Gamma(0.077, 0.024) \tag{6}$$

$$\lambda_{GoldenEagle} \sim \Gamma(0.287, 0.237) \tag{7}$$

These parameters are similarly taken from New et al. (2018).

Finally, hazardous footprint ε is defined as follows:

$$\varepsilon = \tau n h \pi r^2 \tag{8}$$

Where τ represents annual daylight hours, n represents the number of turbines, h represents turbine hazardous space defined as the maximum vertical height from blade tip to ground,[11] and r represents the radius of the circular area of a wind turbine's blades. The geometric components of ε represent a cylindrical space centered at the base of each turbine with height h and radius r, while τ scales the estimated eagle exposure and collision probability to an annual estimate based on the annual hours during which eagles are active.

We choose values for the parameters of ε to represent the average annual count of bald and golden eagles that would have been killed by wind developments in the treated group in the absence of treatment. We first assume 12 daylight hours per day, for a total of 4380 daylight hours per year for τ. To estimate the number of turbines, we take the coefficient -1.95 from the baseline binary treatment model with turbine additions as the outcome variable. We multiply this by the 126 treated counties to obtain a total of 246 foregone turbines. For the remaining variables, we take averages of turbine specifications found in USTWDB data. To represent average wind turbines constructed in the post-BGEPA enforcement period, we filter USWTDB data to years after 2013. This resulted in the following parameters:

$$\tau = 4380 \tag{9}$$

$$n = 168 \tag{10}$$

$$h = 0.14km \tag{11}$$

$$r = 0.06km \tag{12}$$

We run $100,000$ repetitions of simulations of C_s and λ_s, calculating the estimated mortality F_s for each set of values per species. The resulting distribution of $F_{BaldEagle}$ has a mean of 37 fatalities per year, while $F_{GoldenEagle}$ has a mean of 11 golden eagle fatalities per year.

F.4 Eagle Valuation: ESI Energy Case Method

To obtain the implicit eagle life valuation from the ESI energy case, we combine USFWS predicted mortality measures with costs levied against ESI as a result of the case. We employ predicted mortality measures rather than the observed measures shown in the case to avoid the possibility that the number of eagles cited in the case underestimates the true number of eagles killed due to imperfect detection. A summary of the case, including the dollar value of all costs and USFWS predicted mortality, can be found at DOJ (2022).

Using the 5-year eagle mortality estimates across all ESI wind facilities mentioned in the case, we obtain a predicted mortality value of 5.4 bald eagles per year and 12.6 golden eagles per year.

The one-time fixed costs imposed against ESI are as follows:

$$\$1,861,600 \text{ Fine} \tag{13}$$

$$+\$6,210,991 \text{ Restitutions} \tag{14}$$

$$+\$27,000,000 \text{ Compensatory Mitigation} \tag{15}$$

$$= \ \$35,072,591 \text{ Total Fixed Cost} \tag{16}$$

The fines against ESI also contain a variable cost component of $\$29,623$ per bald or golden eagle. We expand this to an annual cost using the 18 eagles/year mortality rate:

$$\$29,623/ \text{ Eagle} \tag{17}$$

$$*18 \text{ Eagles/Year} \tag{18}$$

$$= \$533,214 \text{ /Year} \tag{19}$$

To calculate the total per-eagle cost across the lifetime of the wind facility, we use a standard 20-year lifetime assumption for the wind facilities. Abstracting from time preferences, the calculation becomes the following:

$$(FC + VC_{\text{Annual}} * 20 \text{ Years})/(20 \text{ Years} * 18 \text{ Golden Eagles/Year}) \tag{20}$$

This implies a total cost per eagle of $127,000.