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

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Abstract

Renewable energy development can reduce carbon emissions but can also harm wildlife, posing a tradeoff between local conservation and global climate goals. This paper estimates the effect of protections for golden eagles on wind energy development in the central United States. Federal enforcement of the Bald and Golden Eagle Protection Act sharply increased after a key court decision in 2013, increasing potential liability for wind developers in regions where golden eagles are common. We find that counties with high exposure to golden eagles slowed their wind energy development after 2013 relative to counties with few to no golden eagles. The forgone wind energy would have brought either $140 million in new electricity or $57 million in climate benefits. The quantifiable benefits from avoided eagle fatalities appear considerably lower. Our results suggest that current policy, at least at the margin, overvalues wildlife protection and undervalues 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 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. The golden eagle is an example of a species that, while not formally classified as endangered, is federally protected under the Bald and Golden Protection Act of 1940 (BGEPA). 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 policies to protect golden eagles on wind turbine development in the United States. To do so, we exploit both geographic variation in exposure to 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 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 shift in the potential liability of wind development. This potential liability, however, is likely greater in counties with high exposure to golden eagle range than in counties with little to no golden 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 golden eagles. Specifically, counties with high golden eagle exposure increased their average annual new wind energy capacity by 3.8 megawatts (MW) less than counties with little to no golden eagle exposure. (Importantly, we study the rate of *additions* to wind capacity, requiring only that wind energy growth rates – not trajectories of cumulative wind capacity – would have moved in parallel across treatment and control counties absent the policy shift.) This effect persists through a battery of alternative sample restrictions, covariates, fixed effects, and other sensitivity tests, lending support to a causal interpretation. 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.

Combining this estimated effect with USGS estimates of wind turbine output per MW (USGS, 2020) suggest that golden eagle protections prevented 426 MW of installed wind energy capacity. This amount of new electricity generation would have been capable of powering 140,000 homes per month and worth roughly $144 million per year. Alternatively, the new clean energy could have displaced carbon emissions, meaning golden eagle protections prevented climate benefits of up to $57 million per year.

The welfare implications of BGEPA enforcement require weighing these costs against the benefits of golden eagle protections. Using available valuation methods for golden eagle fatalities, we estimate that BGEPA protections resulted in benefits valued at $0.1 to $1.3 million per year. Even allowing for substantial error in our estimates, the costs of forgone wind capacity appear to considerably outweigh the benefits of golden eagle conservation. Our results suggest that, at least at the margin, current policy overvalues wildlife and undervalues 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 U.S. 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 Golden Eagles in the U.S.

Golden eagles are a raptor species found throughout the North American continent. The species' habitat is characterized by access to both elevated areas for nesting and open, undeveloped areas for hunting prey (Crandall et al., 2015). These habitat requirements draw golden eagles toward the Rocky Mountain region and the neighboring portions of the Great

Plains. 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 golden eagle habitats with potential wind development sites poses significant future risks for golden eagle population stability.

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). Golden eagles are currently classified as a species of least concern, but ongoing threats such as wind turbine development and climate change-related habitat destruction threaten the future stability of the species (Thompson, 2021). While golden eagles are not 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 golden eagles (defined as an unauthorized capture or killing). The BGEPA therefore serves as the primary legal basis for golden eagle protections and criminal prosecutions of individuals or corporations who injure golden eagle populations.

2.3 Golden 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 golden 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 golden 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 impacts to golden eagle species. 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 golden eagle 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 golden eagle 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 golden 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 golden eagle populations in a ratio of 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).

3 Data

3.1 Data Sources and Aggregation

Range of golden eagles. Data on golden eagles comes from the Cornell Lab of Ornithology's EBird project and dataset (Sullivan et al., 2009). The EBird project collects citizen-science observations of various bird species, including golden eagles. These raw observations are converted to geospatial distribution and abundance estimates through a machine learning process employed by 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. We employ these geospatial relative abundance values from high-resolution EBird data to estimate county-level golden eagle exposure. A national map of county average golden eagle relative abundance is shown in Figure 2. We use abundance estimates for 2021 as a time-invariant measure of exposure to the policy change. Although 2021 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).

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

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

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.

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.[2] 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. Maps of these factors are shown in Figures A.2, A.3, and A.4, respectively.

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.

3.2 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 golden eagles to similar counties without golden 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.

[2] 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.

4 Empirical Methods

4.1 Main Specification

To identify the impacts of golden 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 greater abundance of golden eagles than similar counties with lesser golden eagle abundance.

To estimate the difference-in-difference effects of BGEPA enforcement, we use a standard two-way fixed effects regression. Our basic regression specification is:

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

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. Treatment variable $GoldenEagleExposed_i$ equals 1 for treated counties with high exposure to golden eagles and 0 for control counties with little to no exposure to golden eagles; we define these categories below. 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 start with a binary treatment variable for ease of interpretation. Our data provides a continuous measure of golden eagle exposure, which we discretize. In our base specification, a county is defined as treated if its average value of golden eagle relative abundance is 0.025 or greater: $GoldenEagleExposed_i := I(RelativeAbundance > 0.025)_i$. Only a small portion of the sample has an average relative abundance above this value, so while the specific cutoff is arbitrary, it divides the sample into a high-exposure treated group and a little-to-no exposure control group. A map of the final sample, featuring 111 treated counties alongside control countiesl, is shown in Figure 3. Later, we relax this parameterization and show results using (a) different bin thresholds, (b) a discretized treatment variable of more than two bins, and (c) the continuous treatment variable in a linear specification.

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

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

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 illustrate the intensity of treatment effects over time. Negative θ_τ for $\tau > 0$ are evidence of negative impacts of BGEPA enforcement on wind capacity additions.

Identification Identification of β as the causal impact of BGEPA enforcement in high-golden eagle areas relies on a standard parallel trends assumption. Parallel trends requires that wind capacity additions in areas with high golden eagle exposure would have followed the same evolution over time as additions in areas with no golden 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 golden 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 rate 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 *growth rate* of 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 golden 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 golden 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.

4.2 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.2), potential capacity (Figure A.3), and distance to transmission networks (Figure A.4). 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. Second, we interact these three covariates with year fixed effects. These two specifications allow the likely most important determinants of wind development, and anything correlated with them, to affect the treatment and control groups differently at different times.

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.

Alternative definitions of the treatment variable We relax our specific parameterization of the treatment variable in three ways. We estimate regression using (1) different bin thresholds, (2) the continuous treatment variable entering the regression linearly, and (3) the treatment variable discretized into more than two bins. These three approaches allow us to relax parameteric assumptions, explore sensitivity of the results, and investigate potentially non-linear treatment effects by exposure group.

The third approach involves discretizing the relative abundance variable by conditional quartiles of its empirical probability distribution. We first separate the cross-sectional, county-level relative abundance distribution into two groups. The larger group, counties with a relative abundance value less than 0.001, constitute a set of "pure" control counties. Each conditional quartile group is then assigned as a treatment group. Figure A.5 shows the resulting division of the distribution, and Figure A.6 shows the geographic distribution of counties in the each quartile treatment group. We estimate effects separately for each of these four quartile groups, relative to the omitted group of control group counties with relative abundance values below 0.001.

5 Results

5.1 Main Results

Results for our base models, with binary treatment defined as average relative abundance greater than 0.025, are shown in Table 2. Counties with high exposure to golden eagles added 3.8 MW less wind turbine capacity per year, and 1.6 fewer turbines per year, after 2013, when BGEPA enforcement began – relative to counties with little to no exposure to golden eagles. Both estimates are statistically significant at a 99 percent level. Multiplying these coefficients by the 111 in-sample treated counties implies a total estimated loss of 426 MW of wind capacity, or 176 turbines, per year.

Event studies are presented in Figures 4 and 5. Prior to 2013, estimated coefficients are flat and near zero, suggesting that treatment and control counties were following differential trajectories prior to BGEPA enforcement. 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: Several estimates have confidence intervals that exclude zero, and those that are small or positive also have larger confidence intervals.

5.2 Robustness checks

Covariates Table 3 shows the results of the base specification plus covariates.[3] Column 2 shows the results of a regression that includes terms for mean wind speeds, potential capacities, and distances to transmission, each interacted with linear time trends. Treated counties experienced a significant decline in expected capacity additions of 4.5 megawatts. Column 3 shows the results of an even more flexible regression, in which these three key covariates are interacted with year fixed effects. In this specification, treated counties experienced

[3]Due to the high correlation between added capacity and added turbines, we show robustness check results for the added capacity specifications only. Robustness checks for added turbines are shown in Appendix B.

a significant 5.1 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.

Within-state variation Table 4 shows the results of the base specification plus state-by-year fixed effects. In this model, the treatment group experienced a significant 3.5 MW decline in expected capacity additions. Similarity with the base specification suggest that results are not driven by state-level policy variation over time.

Sample restrictions In Section 3, we formed our sample by restricting raw 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.

5.3 Alternative definitions of the treatment variable

Sensitivity of cutoff in binary treatment variable To show that the choice of cutoff for the binary treatment variable does not drive the main results, we perform sensitivity analysis on the 0.025 treatment cutoff value. Appendix D shows the results of estimates using alternate cutoff values of relative abundance. Results are broadly similar to the base specification.

Continuous treatment variable Results of a continuous treatment model that does not rely on arbitrary treatment cutoffs are shown in Appendix E. Again, results are very similar to the base specification.

Quantiles of treatment Results from the conditional quartile treatment group model are shown in Table 5. BGEPA enforcement is associated with statistically significant impacts only for the most-exposed quartile, where capacity additions fell relative to counties with no golden eagle exposure by 4.0 MW or 1.6 turbines per county per year on average. These results suggest that BGEPA enforcement only affects counties with the greatest exposure to golden eagles.

6 Cost-benefit analysis

Our empirical estimates suggest that BGEPA enforcement reduced wind turbine capacity additions in counties with high golden eagle exposure by an average of 3.8 MW per county per year. This implies a total wind capacity loss of 426 MW per year.

To understand the welfare implications of BGEPA enforcement, we need to weigh the benefits from golden 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 to golden eagles.

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 \$144 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 \$56.7 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 at least \$57 and \$144 million per year. These figures are economically meaningful, suggesting that the impacts of species protections on renewable development are substantial.

The costs of forgone wind capacity must be paired with valuations of averted wildlife damages. To estimate the gains of BGEPA enforcement to golden eagles, 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 golden 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 8 golden eagle deaths per year.

Second, we apply existing valuation methods to value golden eagle lives. One approach 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.

An alternative approach is specific to wind turbine development: levels of fines from recent prosecutions. Arguably, fines imposed by the justice system can be roughly interpreted as a revealed-preference method of the value society places on the golden eagles. Using fines from 2022 recent conviction of the electric utility ESI, we calculate a $169,000 value per golden eagle, placing the total annual value of preserved eagle lives as a result of this policy at $1.3 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.)

Comparing benefits and costs, we find that BGEPA enforcement prevents golden eagle fatalities valued at $1.3 million per year, while also preventing wind energy valued at $57 to $144 million per year. This suggests the costs of BGEPA enforcement are 43 to 110 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 golden 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 golden eagle ranges.

7 Discussion and Conclusion

Using a difference-in-differences approach, we find evidence that enforcement of the BGEPA reduced wind turbine capacity additions in counties with high golden eagle exposure by an average of 3.8 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 50 to 100 times greater than the benefits of avoided golden eagle fatalities. At least in the narrow trade-off of wind energy development versus golden eagle preservation, current policy appears to overvalue wildlife and undervalue new renewable energy.

A positive takeaway from these results is that BGEPA enforcement appears to be effectively targeted in that only high-exposure counties experience significant wind development losses. Although large, the effect of wildlife protections on wind development is restricted to specific geographic areas. While the tradeoffs in terms of wind development may be large in such areas, these results do not suggest that spillover effects of policy enforcement on marginal-exposure areas are a systemic concern.

One limitation of our analysis is the possibility of substitution across regions. If wind turbine developers substitute toward low-exposure areas as a response to BGEPA enforcement, our results and valuations might be overstated. However, even in the scenario where wind turbine developers extensively substituted towards low-exposure areas, our results still imply that wildlife protections have nontrivial impacts on wind turbine development in high-exposure regions. As wind turbine development is projected to expand, land availability will likely decrease, and it might not always be possible to offset wind capacity losses through substitution into densely-developed low-exposure areas. Therefore, land availability and renewable energy demand projections remain important considerations for wildlife protection policy design.

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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Figures

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

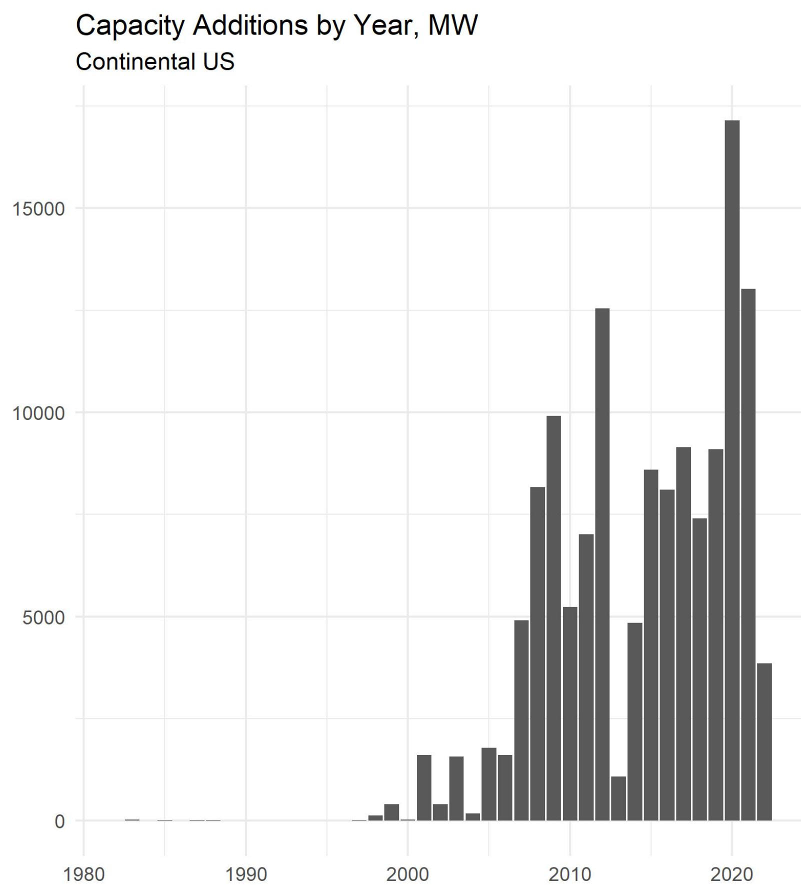


Figure 2: Golden Eagle Relative Abundance Map, EBird (Sullivan et al., 2009)

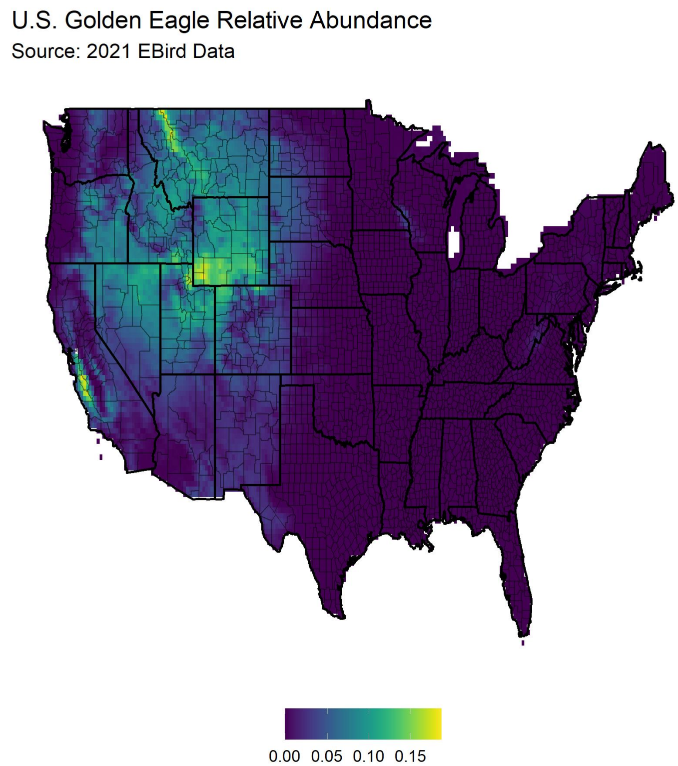


Figure 3: Main Sample Map by Treatment Status

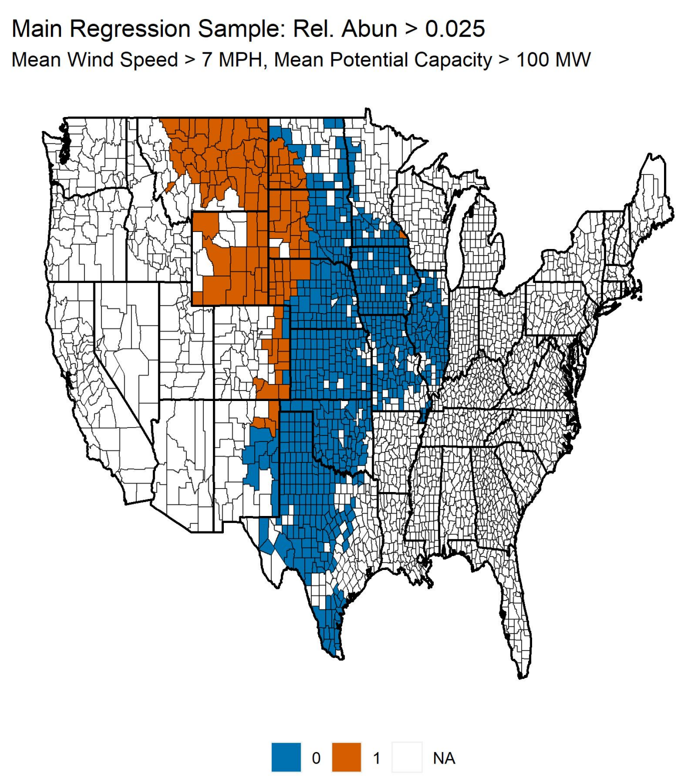
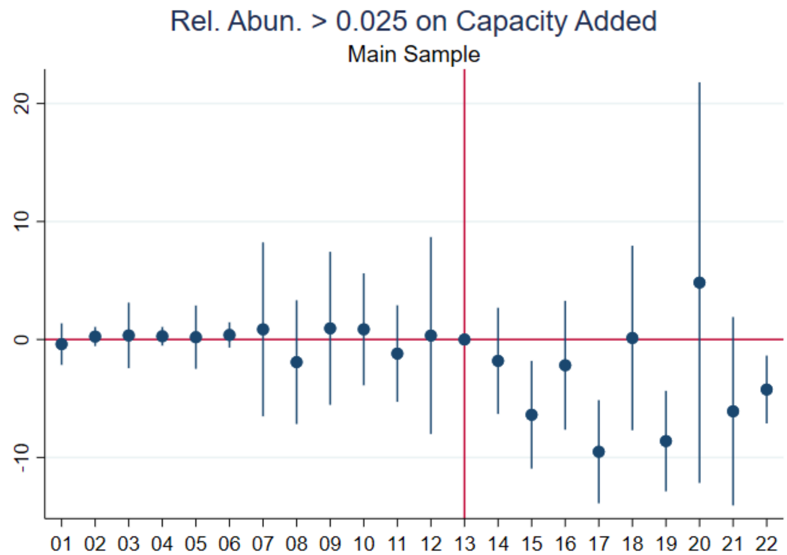
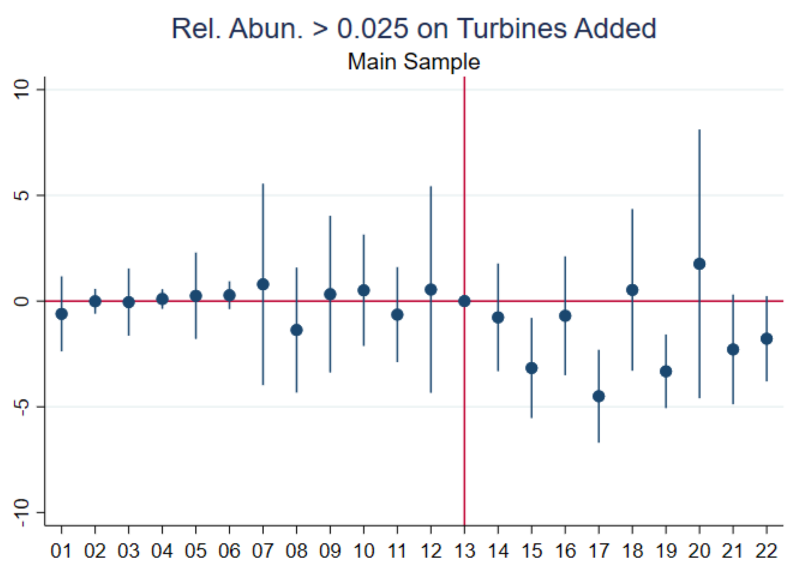


Figure 4: Event study: Effects of BGEPA enforcement on new wind capacity added per year



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 has a relative golden eagle abundance of 0.025 or greater. 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 5: 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 has a relative golden eagle abundance of 0.025 or greater. 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.

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
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. Rows (5)-(7) 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 development

	(1) Added Capacity	(2) Added Turbines
Post * I(Rel. Abun. > 0.025)	-3.835***	-1.590**
	(1.370)	(0.619)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	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 a relative golden eagle abundance of 0.025 or greater.

Table 3: Robustness checks: Covariates

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
Post * I(Rel. Abun. > 0.025)	-3.835***	-4.456**	-5.138***
	(1.370)	(1.772)	(1.949)
Wind Speed * t		0.412***	
		(0.119)	
Potential Cap. * t		0.00655***	
		(0.00192)	
Transmission Dist. * t		-0.00678***	
		(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 4: Robustness checks: Within-state variation

	(1) Added Capacity	(2) Added Capacity
Post * I(Rel. Abun. > 0.025)	-3.835***	-3.529*
	(1.370)	(1.978)
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 5: Alternative treatment definitions: Conditional quartiles

	(1) Added Capacity	(2) Added Turbines
Quartile 1 * post	3.088	1.908
	(2.760)	(1.238)
Quartile 2 * post	3.030	2.161
	(2.657)	(1.333)
Quartile 3 * post	-0.158	0.203
	(2.551)	(1.123)
Quartile 4 * post	-3.999***	-1.590***
	(1.390)	(0.572)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	18722	18722

Standard errors in parentheses

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

Notes: This table shows the results of a model in which the treatment variable is discretized into five groups, in which quartiles of mean relative abundance (conditional on a value greater than 0.001) are compared against counties with a mean relative abundance value below 0.001.

A Additional Figures

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

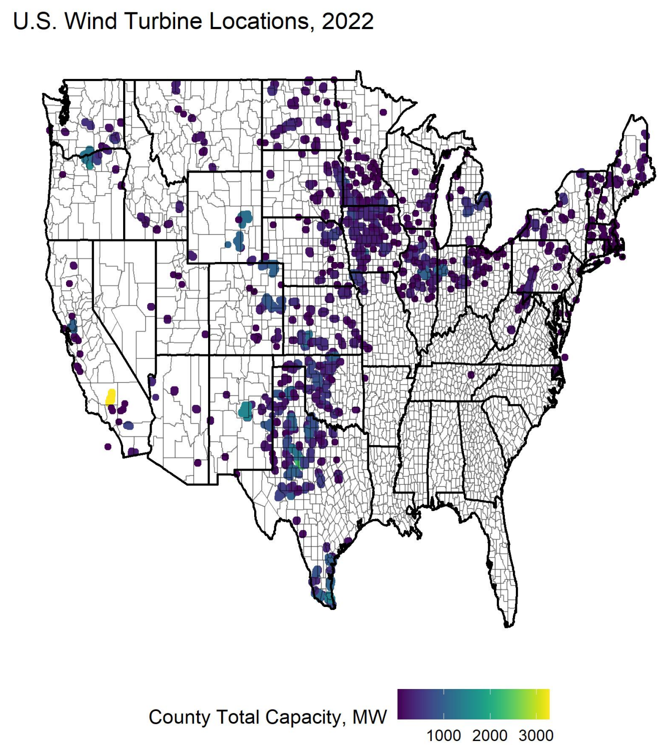


Figure A.2: Wind Speeds (MPH), NREL Wind Supply Curve Data (Lopez et al., 2021)

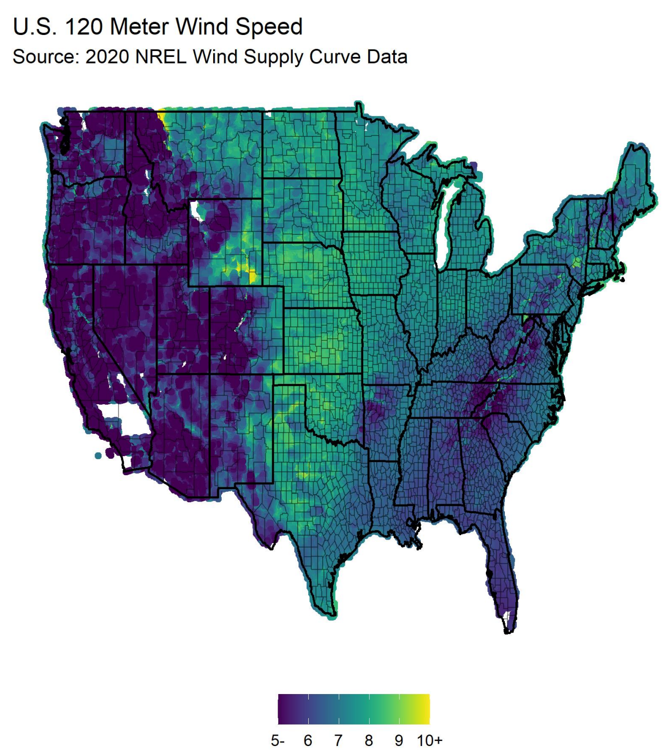


Figure A.3: Potential Capacity (MW), NREL Wind Supply Curve Data (Lopez et al., 2021)

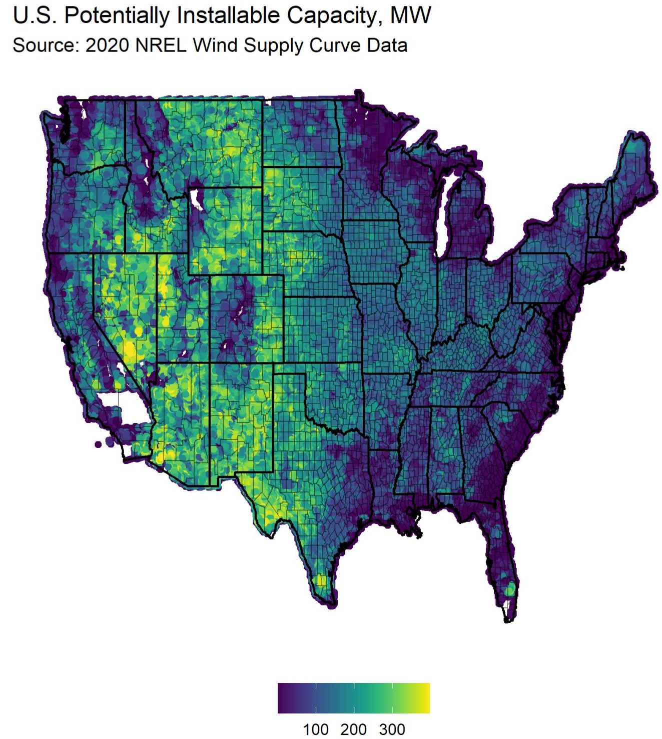


Figure A.4: Transmission Dist. (KM), NREL Wind Supply Curve Data (Lopez et al., 2021)

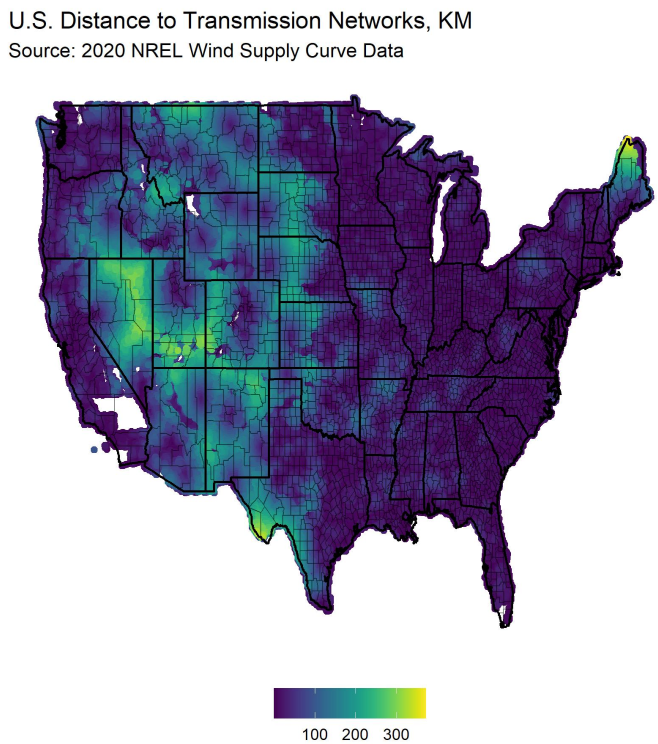


Figure A.5: Conditional Quartiles of Golden Eagle Relative Abundance Distribution: Relative Abundance > 0.001

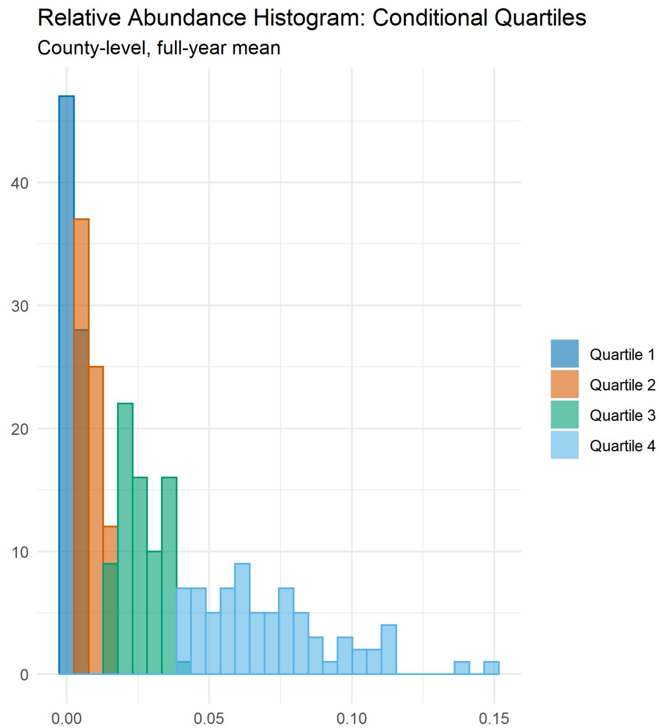
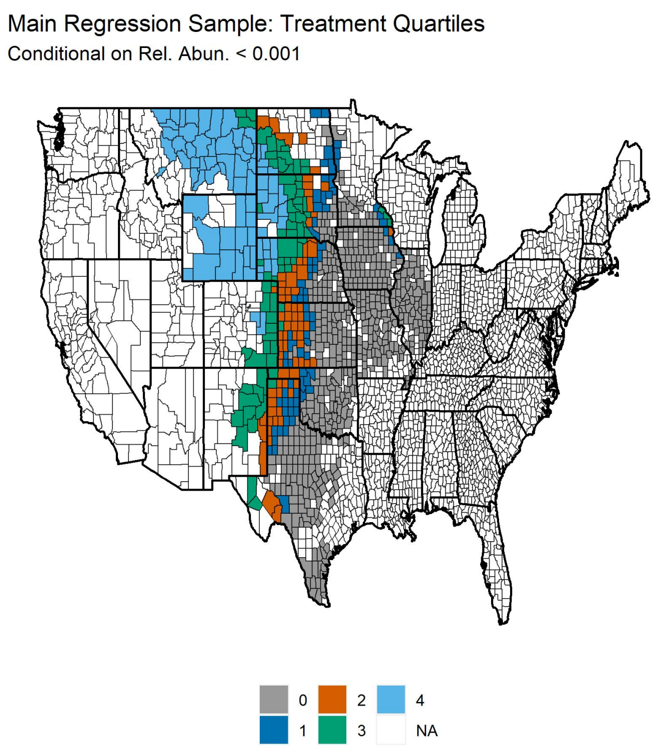


Figure A.6: Conditional Quartile Treatment Group Map



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
Post * I(Rel. Abun. > 0.025)	-1.590**	-1.748**	-2.157**
	(0.619)	(0.858)	(0.894)
Wind Speed * t		0.170***	
		(0.0525)	
Potential Cap. * t		0.00242***	
		(0.000911)	
Transmission Dist. * t		-0.00260***	
		(0.000724)	
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
Post * I(Rel. Abun. > 0.025)	-1.590**	-1.102
	(0.619)	(0.848)
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)

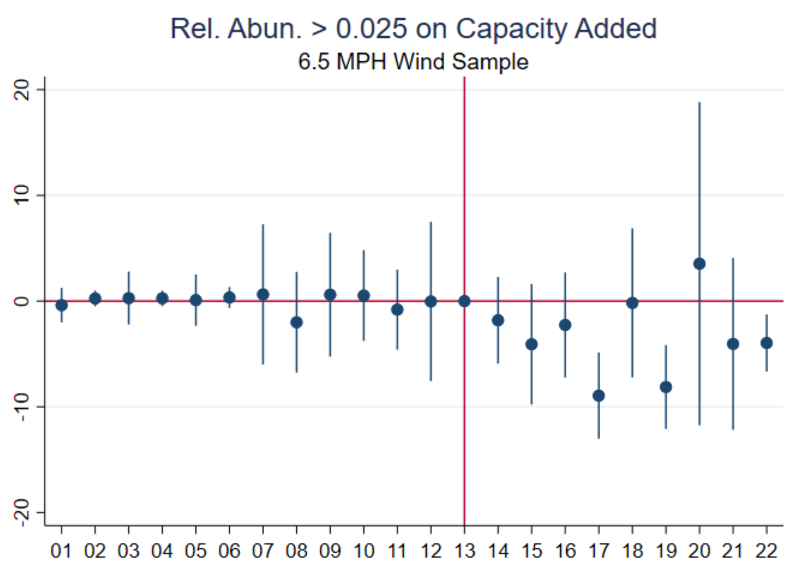
	(1) Added Capacity	(2) Added Turbines
Post * I(Rel. Abun. > 0.025)	-3.300***	-1.300**
	(1.276)	(0.584)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	20086	20086

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 has a relative golden eagle abundance of 0.025 or greater. 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 has a relative golden eagle abundance of 0.025 or greater. 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)

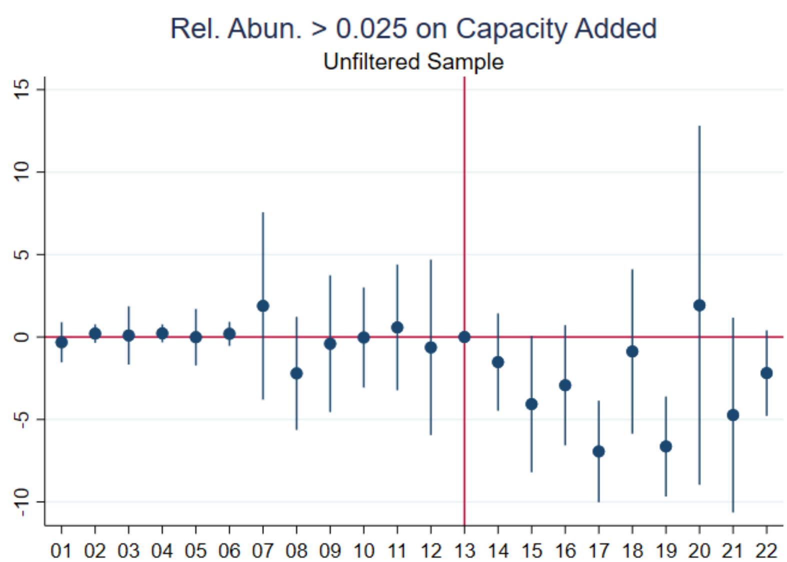
	(1) Added Capacity	(2) Added Turbines
Post * I(Rel. Abun. > 0.025)	-3.075***	-1.256***
	(0.927)	(0.431)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	26730	26730

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 has a relative golden eagle abundance of 0.025 or greater. 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 has a relative golden eagle abundance of 0.025 or greater. 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 Alternate Binary Treatment Definitions

Our baseline results use a binary discretization of the treatment variable, relative abundance of golden eagles, with a threshold value of 0.025. Here, we present results with alternative definitions of this binary treatment variable.

Specifically, we use 0.02 and 0.03 as alternate cutoff values of relative abundance. Combined regression results are shown in Table D.1, and event studies are shown in Figures D.1 and D.2.

Results for the model with a cutoff of 0.02 show reduced precision, but the point estimate remains similar to the baseline results. The event study remains consistent with negative effects in the years following 2014, and some individual yearly estimates are still statistically significant. Results for the model with a cutoff of 0.03 are more precise, with a point estimate that is larger in magnitude than the baseline model. The event study is stimilar to the baseline results.

Together, the results of these models and the baseline model suggest that the policy primarily affected relatively high-exposure counties. This is consistent with the findings of the quartile treatment model.

Table D.1: Effects of BGEPA enforcement (alternative binary treatment definitions)

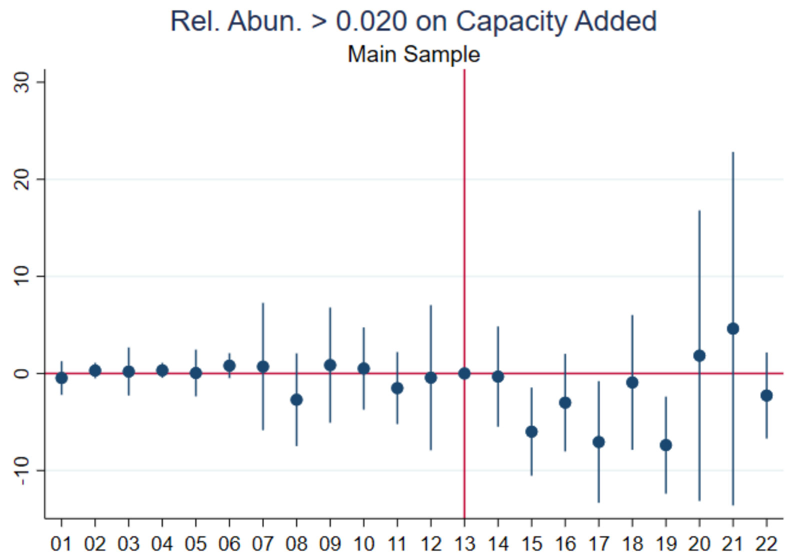
	(1) Added Capacity	(2) Added Capacity
Post * I(Rel. Abun. > 0.020)	-2.173	
	(1.700)	
Post * I(Rel. Abun. > 0.030)		-4.427***
		(1.272)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	18722	18722

Standard errors in parentheses

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

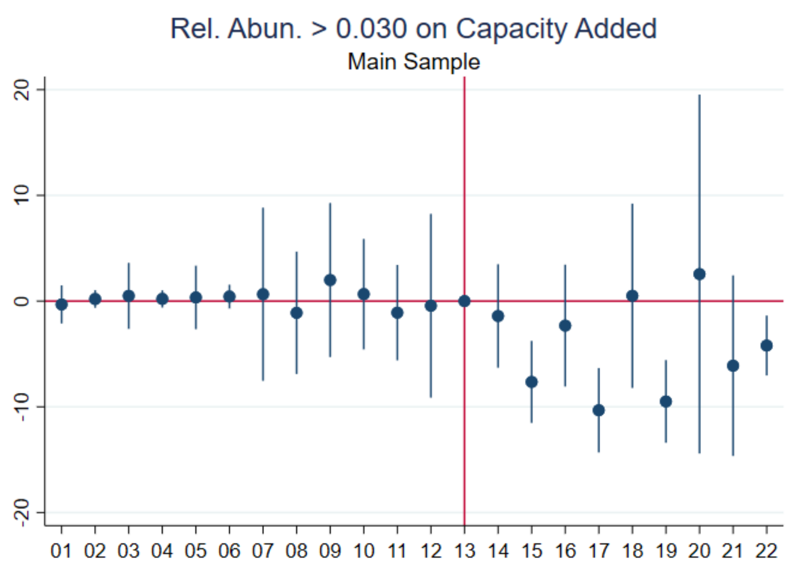
Notes: Table reports estimates from regressions of the form in Equation 1, using a binary treatment variable that equals 1 if a county has a relative golden eagle abundance of 0.02 or greater in column (1), and 0.03 or greater in column (2). Here, the sample is restricted to counties with a mean wind speed above 6.5 MPH and potential capacity above 100 MW.

Figure D.1: Event study: Effects of BGEPA enforcement (treatment threshold of 0.02)



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 has a relative golden eagle abundance of 0.02 or greater. 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 (treatment threshold of 0.03)



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 has a relative golden eagle abundance of 0.03 or greater. 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 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 arbitrary 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: $GoldenEagleExposed_i := RelativeAbundance_i$. The coefficient β then captures an average marginal impact of unit increases in relative abundance on the outcome variable y_{it}.

Regression results are shown in Table E.1. In this 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. 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 1.04 MW per year. Event study figures using the continuous treatment variable are shown in Figures E.1 and E.2. 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 E.1: Effects of BGEPA enforcement (continuous treatment)

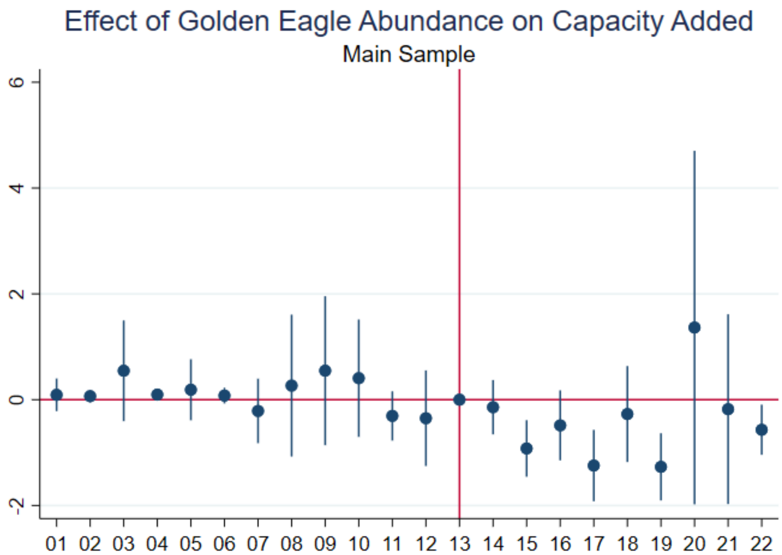
	(1) Added Capacity	(2) Added Turbines
Post * Rel. Abun. * 100	-0.523**	-0.242***
	(0.228)	(0.0838)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	18722	18722

Standard errors in parentheses

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

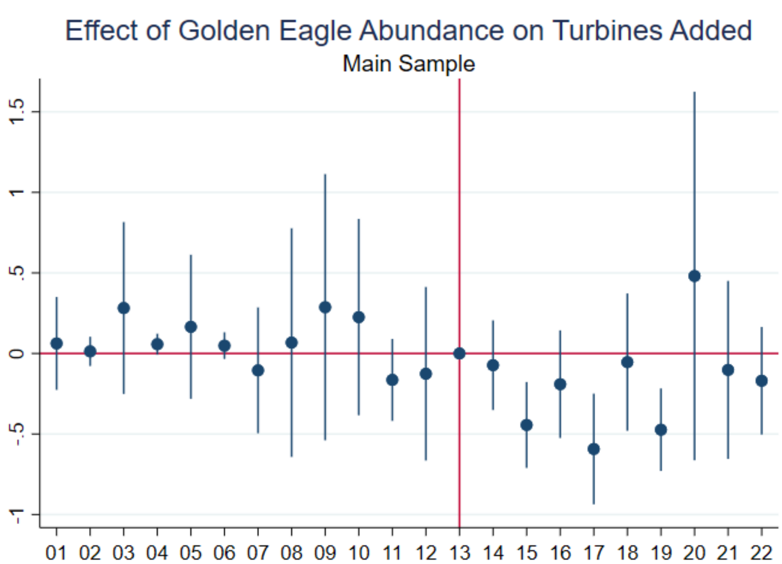
Notes: Table reports estimates from regressions of the form in Equation 1, using relative abundance as a continuous treatment variable.

Figure E.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 relative abundance as a continuous treatment 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 E.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 relative abundance as a continuous treatment 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.

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 420 MW. Using a 843 MWH/month output estimate for 2.75 MW of capacity (USGS, 2020), we estimate that 426 MW of capacity would have output $130,588$ MWH/month.

To value this level of output, we obtained electricity price information from publically-available EIA datasets. We used average total electricity prices across the states in-sample for the period after 2013 to represent the average post-period electricity value in-sample. This yielded an average electricity price of 9.218 c/KWH, which is equivalent to 92.18 $/MWH.

The final valuation is the product of $130,588$ MWH/month $*$ 12 months/year $*$ \$92.18/MWH, which is equal to \$144 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 $130,588$ MWH/month of electricity generation. Multiplying this by 12 yields a result of $1,567,056$ MWH/year, or equivalently, $1,567,056,000$ KWH/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. We then multiply this by the $1,567,056,000$ MWH/year displaced generation estimate for a total of $1,111,042$ tons of CO2/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 \$56.7 million per year.

F.3 Golden 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 golden 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).

Estimated golden eagle mortality is defined as the following:

$$F = C\lambda\epsilon \tag{3}$$

Where C represents collision probability, λ represents golden eagle exposure, and ϵ represents the cumulative annual hazardous footprint across turbines in a unit.

Golden eagle-specific collision probability C has the following distribution:

$$C \sim \beta(1.29, 227.6) \tag{4}$$

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

In the priors-only model, golden eagle exposure λ has the following distribution:

$$\lambda \sim \Gamma(0.287, 0.237) \tag{5}$$

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

Finally, hazardous footprint ϵ is defined as follows:

$$\epsilon = \tau n h \pi r^2 \tag{6}$$

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,[4] 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 golden eagle exposure and collision probability to an annual estimate based on the annual hours during which golden eagles are active.

We choose values for the parameters of ϵ to represent the average annual count of 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 -1.59 from the baseline binary treatment model with turbine additions as the outcome variable. We multiply this by the 111 treated counties to obtain a total of 176 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:

$$\tau = 4380 \tag{7}$$

$$n = 168 \tag{8}$$

$$h = 0.14km \tag{9}$$

$$r = 0.06km \tag{10}$$

We run $100,000$ repetitions of simulations of C and λ, calculating the estimated mortality F for each set of values. The resulting distribution of F has a mean of 8 golden eagle fatalities per year.

[4]To estimate this value from USWTDB data, we add hub height (distance from ground to the center of the blades) to the blade length radius.

F.4 Eagle Valuation: ESI Energy Case Method

To obtain the implicit eagle life valuation from the ESI energy case, we combin 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 12.6 golden eagles per year.

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

$$\$1,861,600 \text{ Fine} \tag{11}$$

$$+\$6,210,991 \text{ Restitutions} \tag{12}$$

$$+\$27,000,000 \text{ Compensatory Mitigation} \tag{13}$$

$$= \$35,072,591 \text{ Total Fixed Cost} \tag{14}$$

The fines against ESI also contain a variable cost component of $\$29,623$ per golden eagle. We expand this to an annual cost using the 12.6 golden eagles/year mortality rate:

$$\$29,623/\text{Golden Eagle} \tag{15}$$

$$*12.6 \text{ Golden Eagles/Year} \tag{16}$$

$$= \$355,476 \text{ /Year} \tag{17}$$

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:

$$(FC + VC_{\text{Annual}} * 20 \text{ Years})/(20 \text{ Years} * 12.6 \text{ Golden Eagles/Year}) \tag{18}$$

This implies a total cost per eagle of $167,000.