IMPACTS OF SPECIES PROTECTIONS ON WIND TURBINE DEVELOPMENT: EVIDENCE FROM GOLDEN EAGLE PROTECTION POLICIES

by

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ABSTRACT

As demand for wind energy grows, policymakers face tradeoffs between wind turbine development and wildlife species protections. This is particularly relevant for golden eagles, which have a habitat that overlaps areas of high wind energy development potential. Golden eagle protections, such as the Bald and Golden Eagle Protection Act (BGEPA), therefore potentially conflict with wind energy development goals. Policymakers face a lack of information regarding the existence and size of potential impacts of species protections on wind development. To approach this issue, I employ a difference-in-differences research design exploiting variation in BGEPA enforcement over time and geographic variation in golden eagle exposure to identify the impacts of species protections on wind development in resource-rich areas. I find that counties with high golden eagle exposure experienced declines in expected wind turbine capacity additions of 3.78 megawatts during the enforcement period, suggesting a total of 420 megawatts of foregone wind energy. This electricity generation loss has an estimated value of $56 to $142 million annually. Existing golden eagle valuation methods suggest significant economic gains from wind turbine expansion, although these estimations arguably apply only to marginal wildlife impacts and should be applied with caution. These results emphasize that the value of foregone renewable energy is an often-overlooked component of species protection policy discussions, and that effective conservation measures and funding are necessary both for the futures of many species and for renewable technology deployment.

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 wind power provides a generation source that is free of environmental damages from carbon emissions, wind turbines cause a variety of local negative externalities. In particular, wind turbines drive acute negative externalities to certain wildlife species. Birds, including federally-protected golden eagles, frequently suffer habitat destruction and collision-based mortality due to wind turbine developments (Miao, Ghosh, Khanna, Wang, and Rong, 2019; Erickson, Wolfe, Bay, Johnson, and Gehring, 2014; Loss, Will, and Marra, 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 aims to exploit both variation in geographic exposure to golden eagles and variation in BGEPA enforcement over time to identify the impacts of golden eagle protection on U.S. wind turbine development. While 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. This shift in USFWS enforcement and legal precedent provides a natural experiment through which to study the impacts of species protections on renewable resource development. This policy shift has potentially differential impacts on high-wind potential counties with high golden eagle exposure relative to similar counties with little to no golden eagle exposure. This natural experiment allows the estimation of the wind capacity that is foregone as a result of BGEPA enforcement. This estimate may advance policy discussions through illustrating the existence and magnitude of the potentially adverse effects of species protection policies on wind turbine development.

Under the post-2013 BGEPA enforcement period, counties with high golden eagle exposure experienced a 3.7 MW decrease in wind capacity additions relative to counties with no golden eagle exposure. This effect is greater than one half of the average county-level capacity addition over the 2001-2022 sample period, suggesting substantial impacts of BGEPA enforcement on wind development. Combining this estimated effect with the distribution of golden eagle exposure in-sample and USGS estimates of wind turbine output per MW (USGS, 2020) suggest that the golden eagle protections cost 420 MW of installed capacity potentially capable of powering roughly 140,000 homes per month. The significance of these costs underscores the need for clarity in species protection policy to minimize efficiency losses, and effective conservation and mitigation efforts to enable future renewable development.

BACKGROUND

U.S. Wind Turbine Development

The rate of utility-scale wind turbine adoption in the U.S. has increased over time. As shown in figure 2.1, 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, Pender, Wiser, Lantz, & Hoen, 2012) and strong land availability for development (Lopez et al., 2021). This area therefore supports much of the U.S.' existing and potential wind energy, and any restrictions on wind development in this region have potentially significant impacts on the nations' wind energy supply.

U.S. Golden Eagle Population

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, Bedrosian, & Craighead, 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, Cochrane, Lonsdorf, and Sanders-Reed, 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, Link, and Hines, 2019; Millsap et al., 2013). Golden eagles are currently classified as a species of least concern (Thompson, 2021). However, 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[1] of golden eagles. 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.

Golden Eagle Protections and Wind Development

In theory, the BGEPA strictly forgoes wind turbine development in favor of golden eagle preservation. The BGEPA has been active for the entire duration of U.S. wind turbine development. While concurrent studies did note the potential and realized impacts of wind turbines on golden eagles (Hunt, Jackman, Hunt, Driscoll, & Culp, 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

[1] In the Bald and Golden Eagle Protection Act, take is defined as any unauthorized capture or killing.

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.

While direct fines against BGEPA violators are one component of the mechanism through which the USFWS might restrict wind turbine development, the Duke Energy and ESI cases both show that the expenses associated with mandatory golden eagle compensatory mitigation make up most of the expenses levied against wind developers found guilty of BGEPA violations. Due to the USFWS' eagle take permitting requirements, these costs are not necessarily restricted to only prosecuted wind turbine developers. 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, Eccleston, and Harness, 2021)[2]. The estimated eagles saved by compensatory mitigation are weighed

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

against the estimated eagles killed based on a Bayesian process (USFWS, 2012; New, Bjerre, Millsap, Otto, and Runge, 2015; New, Simonis, Otto, Bjerre, and Millsap, 2018). The expenses associated with compensatory mitigation are likely substantial, as shown by the fact that compensatory mitigation costs make up the largest share of the fines levied against ESI in the recent 2022 prosecution (Bever, 2022; DOJ, 2022). This illustrates that compensatory mitigation costs might deter compliant wind turbine developers from selecting sites with high golden eagle exposure. Furthermore, these mechanisms raise the costs of development in proportion to golden eagle population damages. Therefore, high-exposure potential wind turbine sites are likely most impacted by the policy.

While BGEPA enforcement can improve welfare through protecting golden eagles, it potentially reduces welfare through trading off wind energy potential. Restricting development in high-wind areas due to golden eagle presence, and raising costs of development through compensatory mitigation requirements, eliminates the potential benefits of foregone wind development. These restrictions might effectively reduce the supply of renewable electricity to an area. Furthermore, developers might also pass compensatory mitigation costs onto electricity consumers. Restricting wind development also reduces the positive externalities associated with renewable energy, including the mitigation of negative environmental impacts of fossil-fuel energy generation. Finally, these impacts are likely to become more severe over time given the increasing efficiency of and demand for wind energy. The existence of these tradeoffs do not necessarily imply that BGEPA enforcement to protect golden eagles is welfare-reducing. However, they do motivate a closer inspection of the impacts of BGEPA enforcement to attempt to quantify these tradeoffs, both for guiding future BGEPA enforcement and for navigating future conflicts between species protection and renewable development as a whole.

Literature Review

This paper relates to existing literature on the relationship between wind energy and harms to bird populations, renewable energy policy, and costs of endangered species protection. Several empirical papers have estimated the effects of wind turbine development on local bird mortality. Notably, Miao et al. (2019) employ a two-way fixed effects approach and report that the construction of one wind turbine is associated with 3.1 breeding bird deaths annually within a 400 meter buffer zone. Hunt et al. (1999) provide one of the first examinations of wind-turbine related deaths on golden eagle populations. Through a case study stationed near wind facilities in the Altamont Pass region of California, the authors found that turbine collisions accounted for a 37% majority of recorded golden eagle deaths in the study period. Pagel et al. (2013) summarize publically-available eagle mortality reports, finding 79 recorded golden eagle deaths in a sample of wind facilities spanning 10 states from 1997-2012. Literature on wind turbine damages to general bird species such as Miao et al. (2019) and specific harms to golden eagles such as Hunt et al. (1999) and Pagel et al. (2013) provide empirical evidence of the negative impacts that wind turbines might have on local avian species. This paper aims to build on this literature through analyzing the other side of the tradeoff between wind turbines and golden eagles. A full picture of costs, including both eagle mortality estimates and energy capacity losses associated with eagle protections, are necessary to fully inform policymakers as such conflicts between renewable development and species conservation become more common.

This paper also complements research on renewable energy policies. Species protections can be seen as a disincentive for renewable development. Therefore, estimated energy losses under such 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 Chinese regions. Similarly, Shrimali, Chan, Jenner, Groba, and Indvik (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.

Finally, this paper aligns with recent research on the costs of species protections. Bošković and Nøstbakken (2017) employ a regression discontinuity design to show that Canadian oil leases exposed to protected Caribou species drop 24% in value. Melstrom (2021) finds that endangered species act restrictions decrease dryland value and profitability by 4%. Auffhammer, Duru, Rubin, and Sunding (2020) document that the valuations of California land parcels fall significantly after critical habitat designation for endangered species. While this literature does not necessarily argue that endangered species protections are a net loss, they do document the specific tradeoffs of certain protection policies. This paper similarly examines the costs of species protection tradeoffs in a renewable energy development context.

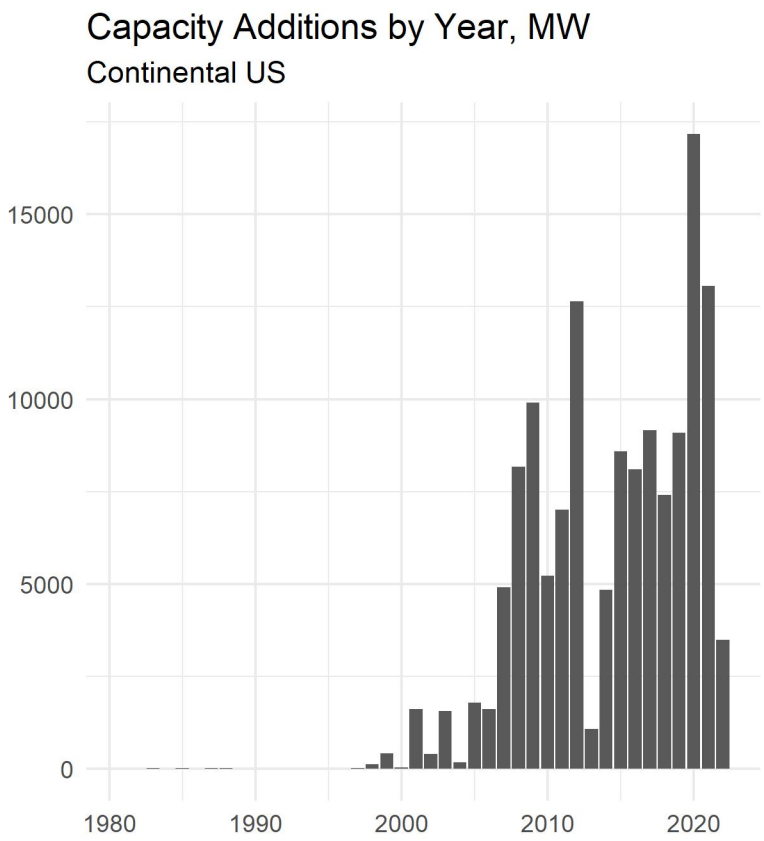

Figure 2.1: Capacity Additions by Year, from USWTDB (Hoen et al., 2022)

DATA

Data Sources and Aggregation

Data on golden eagle exposure 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. This paper employs these geospatial relative abundance values from low-resolution EBird data to estimate county-level golden eagle exposure. A national map of county average golden eagle relative abundance is shown in figure 3.1. This paper employs the 2021 EBird projection data. Therefore, results rely on the implicit assumption that 2021 golden eagle projections are representative for the entire sample period. This assumption is supported by findings of golden eagle population stability both at aggregate and regional levels over the past 20 years (Millsap et al., 2013; Sauer et al., 2019).

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. A key variable measuring wind turbine intensity in this dataset is turbine capacity. 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. The outcome variables employed in this paper include wind capacity additions and turbine additions at the county-year level. A map of wind turbines by capacity in the U.S. is shown in figure 3.2.

Finally, data on wind turbine natural resources are sourced from the NREL Wind

Supply Curve dataset (Lopez et al., 2021). This geospatial dataset is intended for use by wind developers when siting turbines. This paper employs the reference wind supply curve dataset, which is estimated based on a moderate set of land restrictions. The data includes three key measures. Wind speed is a primary determinant of output per unit of capacity. Potential capacity is an estimate of how much wind capacity might be developed on a unit of land, and reflects land availability for wind development given terrain and land-use constraints.[1] Finally, distance to transmission networks reflects a constraint on wind turbine development, because greater distances to pre-existing transmission networks translate to greater costs of creating new transmission infrastructure. This paper uses the 2020 cross-sectional wind supply curve data. The cross-sectional nature of this data reflects the relatively fixed nature of its key measures. While these factors can be thought of as roughly fixed over time, they are used to guide sample selection. Maps of county level averages of these factors are shown in figures 3.3, 3.4, and 3.5, respectively.

This paper employs county- and county-year aggregates of these datasets. County borders provide simple spatial units for analysis of average golden eagle exposure and wind turbine development. EBird data and the NREL wind supply curve data are aggregated to county-level means from geospatial data, while USWTDB outcome variables are aggregated to county-year totals based on locations provided in the underlying dataset. The sample runs from 2001-2022, following the period of rapid wind energy growth as shown in figure 2.1.

Sample Selection

Identification in this project will compare high wind-potential counties with golden eagle exposure to similar counties without golden eagle exposure. Following a similar approach to Brown et al. (2012), I restrict analysis to states in the central U.S., where wind speed and

[1] Importantly, while the wind supply curve dataset does calculate potential capacity based off of strict protected species boundaries among other factors, it does not include the flexible boundary of golden eagle exposure in its potential capacity calculations.

other resources are abundant.[2] This focuses the analysis on regions with high wind potential. States along the northwestern side of this region, such as Montana, Wyoming, and Colorado, contain counties with both high wind speeds and high golden eagle exposure as shown in figures 3.1, 3.3, 3.4, and 3.5. While the sample states all have some exposure to rich wind resources, not all counties within those states are suitable to wind turbine development. Average wind speeds and average potentially installable capacity decline sharply on the western sides of the mountain ranges featured in these states. To remove these low-potential areas, I filter the sample further to counties within these states with average wind speeds of 7 miles per hour or greater and average potentially installable capacities of 100 MW or greater.[3] The resulting sample, in which low-potential counties are excluded, is shown alongside golden eagle relative abundance in figure 3.6. The remaining sample consists of relatively high-potential counties with a range of average golden eagle relative abundance exposures.

Summary statistics within this sample are shown in figure 3.7. The distribution of relative abundance values for sample counties are shown in figure 3.8.

[2]States included: NM, CO, WY, MT, ND, SD, NE, KS, OK, TX, MN, IA, MO, IL

[3]Sensitivity analyses illustrating that this sample selection method does not drive baseline results are presented in appendix A.

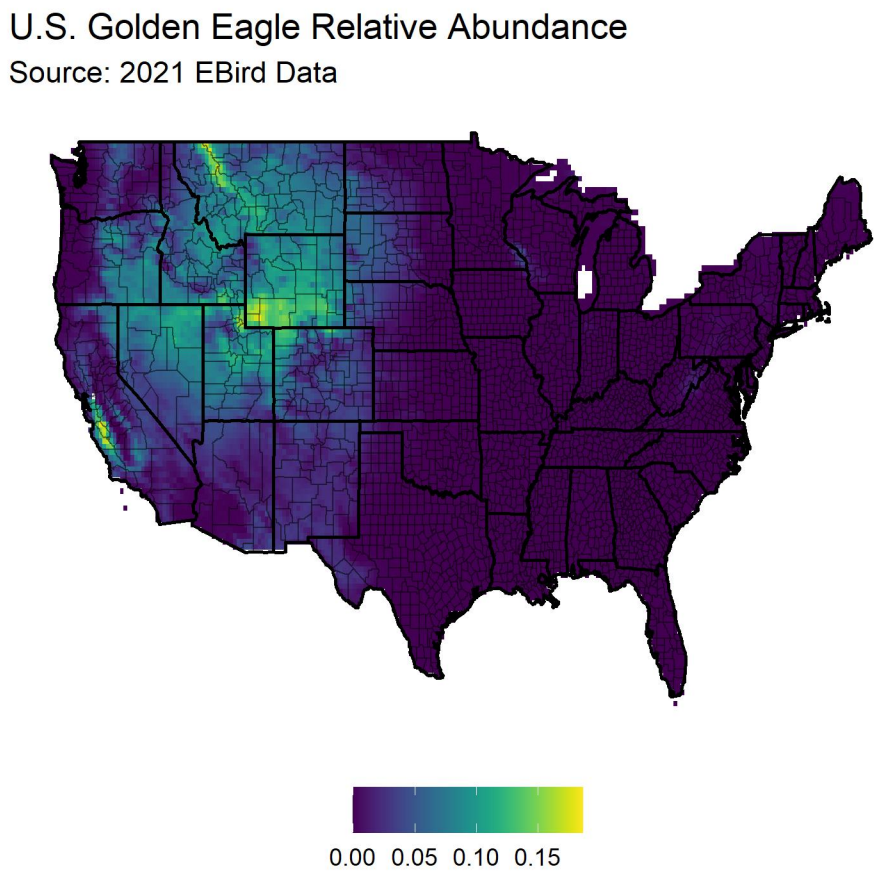

Figure 3.1: Golden Eagle Relative Abundance Map, EBird (Sullivan et al., 2009)

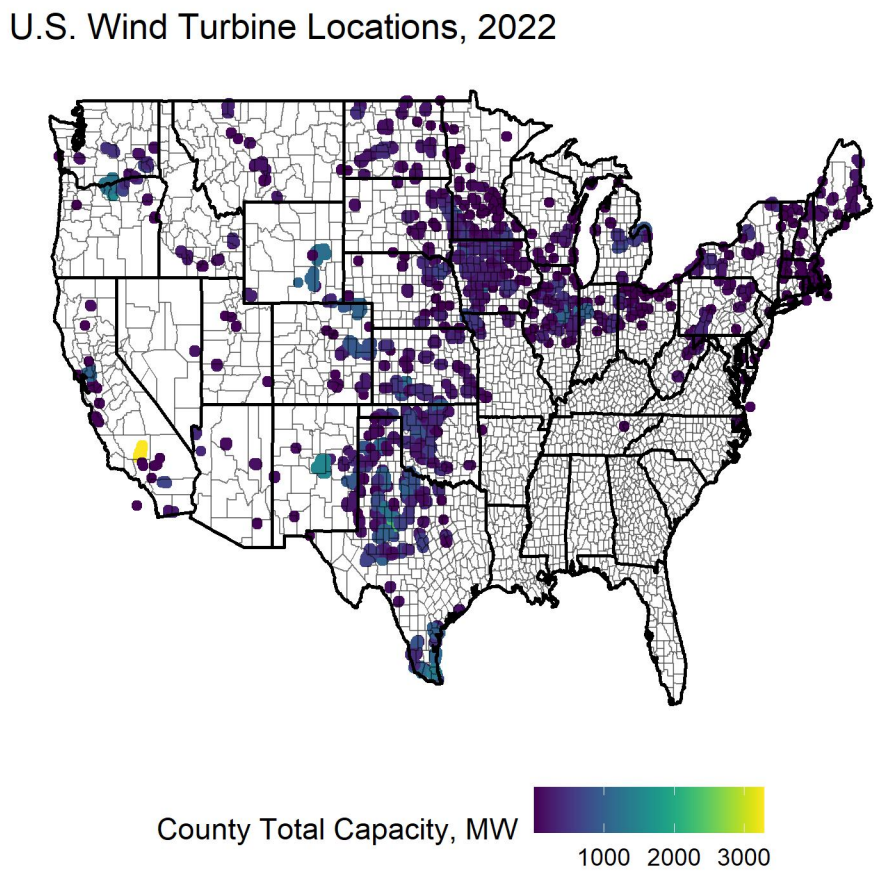

Figure 3.2: Wind Turbine Plant Locations, USWTDB (Hoen et al., 2022)

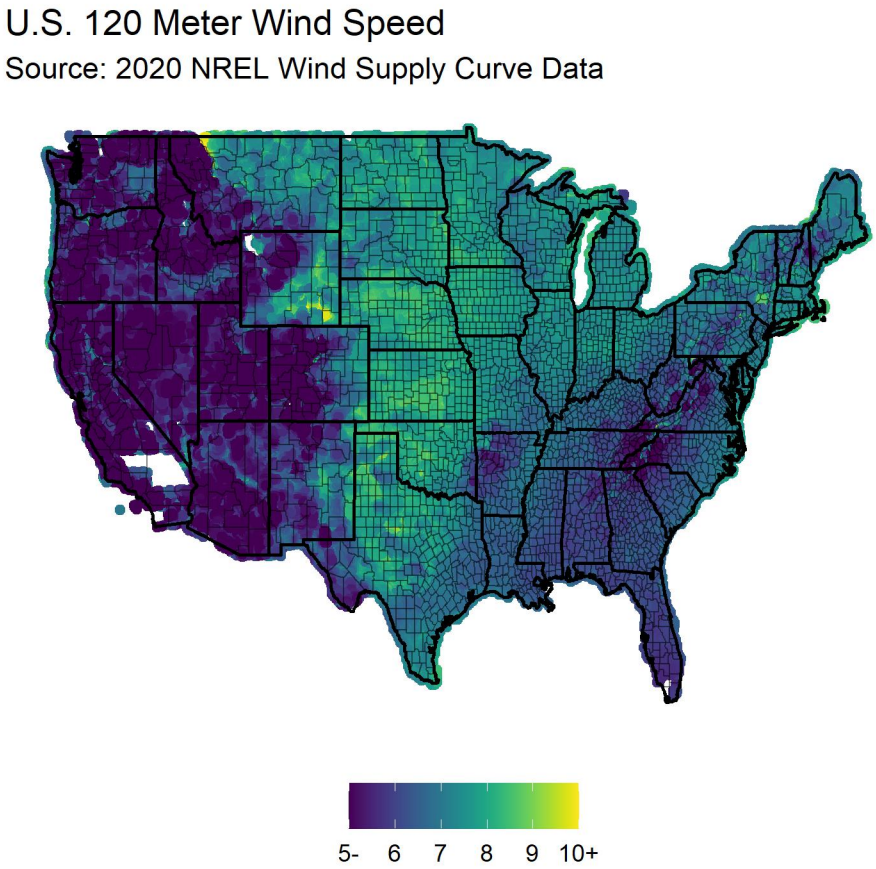

Figure 3.3: Wind Speeds (MPH), NREL Wind Supply Curve Data (Lopez et al., 2021)

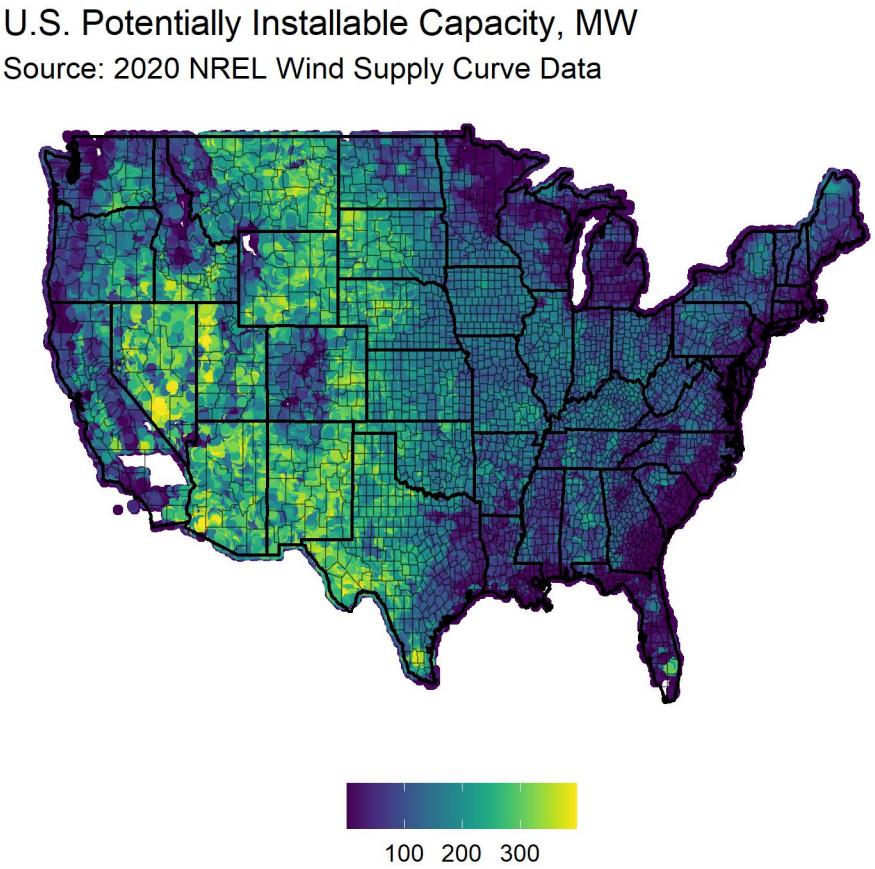

Figure 3.4: Potential Capacity (MW), NREL Wind Supply Curve Data (Lopez et al., 2021)

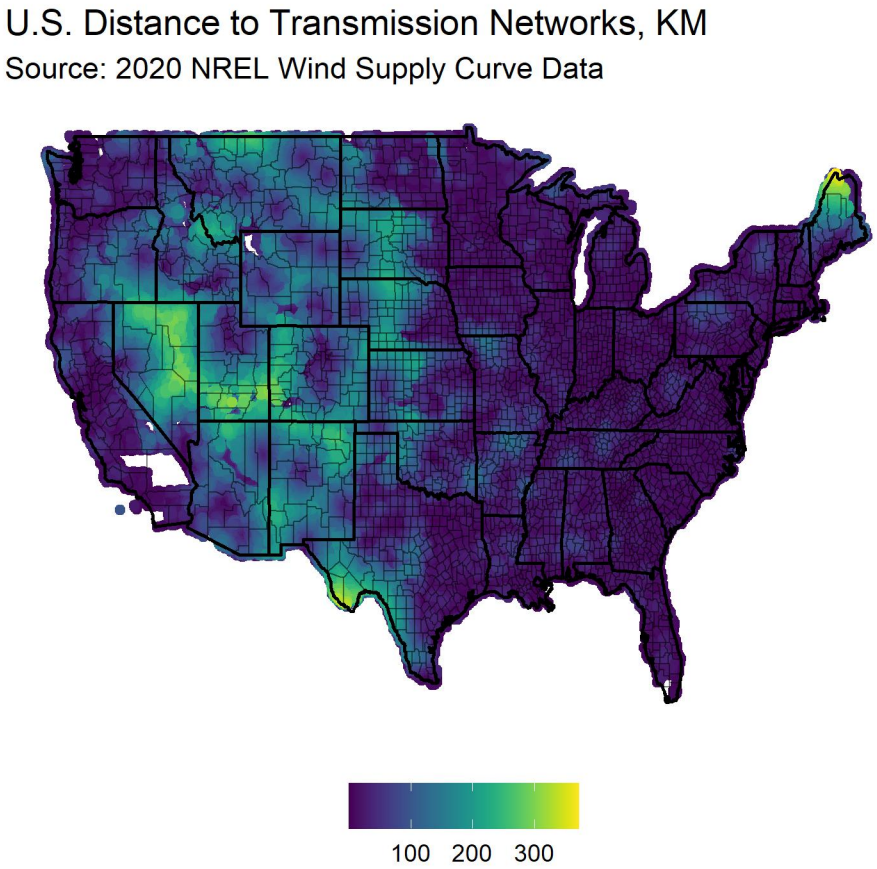

Figure 3.5: Transmission Dist. (KM), NREL Wind Supply Curve Data (Lopez et al., 2021)

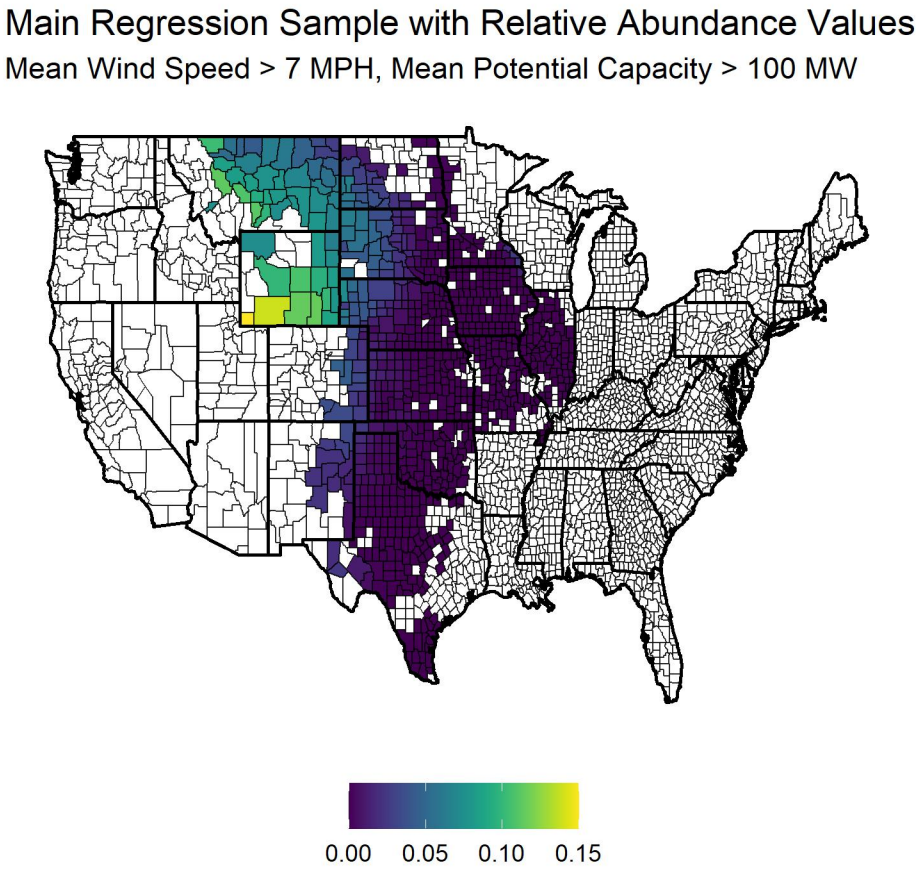

Figure 3.6: Main Sample with Relative Abundance Values

	Mean	SD	Min	Max	N
Added Capacity, MW	5.30	35.30	0.00	1106.00	18722
Added Capacity, > 0	115.96	120.16	0.10	1106.00	856
Added Turbines	2.60	17.02	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.

Figure 3.7: Summary Statistics, Main Sample

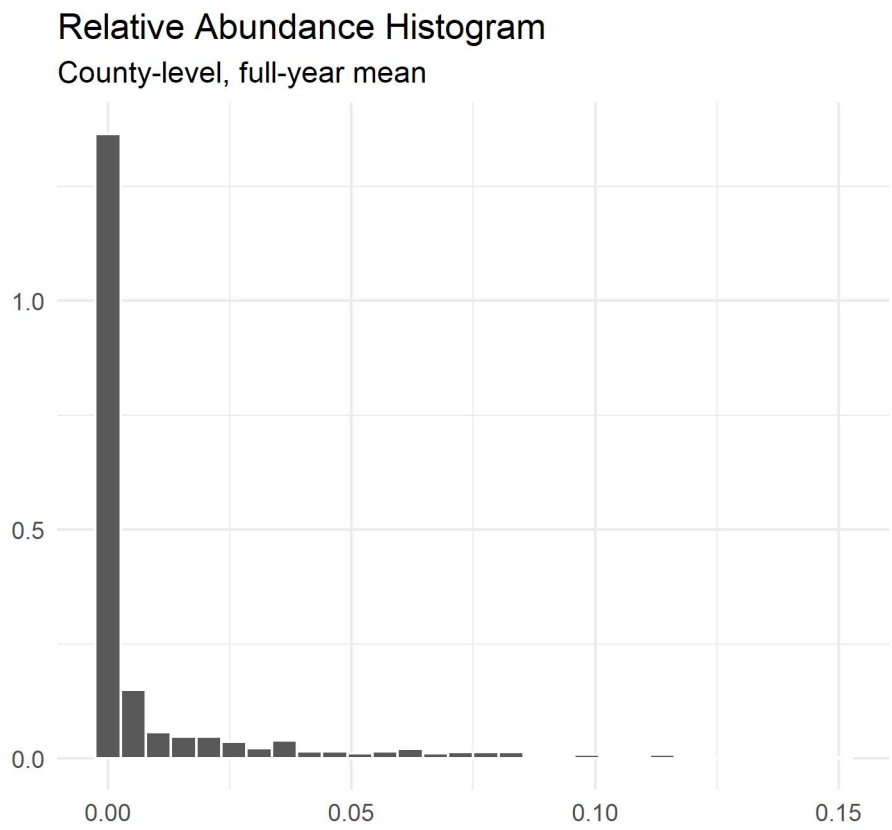

Figure 3.8: Distribution of Sample Relative Abundance

METHODOLOGY

Primary Specifications

This paper leverages two sources of variation to identify the impacts of golden eagle protection policy on wind development at the county level. First, geospatial variation in county exposure to golden eagles dictates that some counties will be exposed to BGEPA enforcement while others will not based solely on pre-existing golden eagle exposure. Second, the initial late-2013 Duke Energy case creates variation in BGEPA enforcement over time. This natural experiment setup suggests the use of a difference-in-differences model to identify the causal impacts of BGEPA enforcement. The basic difference-in-differences model specification is as follows:

$$y_{it} = \beta(Post2013_t * GolEagExposed_i) + \gamma_i + \delta_t + \epsilon_{it} \tag{4.1}$$

Where outcome variable y_{it} denotes MW of capacity constructed in county i and year t or turbines constructed in county i and year t. The time variable $Post2013_t$ 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. Binary treatment variable $GolEagExposed_i$ equals one for treated counties with high golden eagle exposure and zero for control counties with little to no golden eagle exposure. 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. Finally, ϵ_{it} represents the error term. In all specifications, standard errors are clustered at the county level.

Identification of β as the causal impact of BGEPA enforcement in high-golden eagle areas relies on a standard difference-in-differences 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. The difference-in-differences model leverages low

golden eagle areas as counterfactuals for high golden eagle areas, and the accuracy of this comparison relies on the parallel trends assumption.

Parallel trends is a reasonable assumption in this scenario. With the sample limited to high-wind counties, identification comes from comparisons between otherwise similar counties with and without golden eagle exposure. Furthermore, factors that influence wind turbine development such as wind speed, favorable terrain, and remoteness are not likely to vary significantly over time. County fixed effects likely absorb any of these sources of differential trends between the treated and untreated groups. However, if these differences in potential lead to different wind turbine development growth rates over time, fixed effects might fail to completely control for these differences, and differences in growth rates might confound the parallel trends assumption. Robustness checks that attempt to address this concern are discussed in the next section.

Another 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 contaminating spillover effect would cause the control group to be an invalid counterfactual for the treated group, and would result in estimates that are biased away from 0. While this possibility cannot be directly tested in this experimental framework, transmission cost and efficiency constraints might restrict developers' ability to substitute freely between different areas. 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.

A key challenge of this empirical strategy is that there is that golden eagle exposure at the county level occurs as a continuous variable. There is no a priori relative abundance value above which counties are obviously "treated" with golden eagle exposure. This challenges the validity of the basic DD approach because any imposed binary treatment definition is potentially arbitrary. In this scenario, different treatment definitions likely provide different results. A body of evidence is therefore necessary to show that the interpretation β is robust to alternative treatment definitions.

To address the ambiguous treatment definition issue, I employ a preferred specification along with a set of supporting specifications to demonstrate that the results are not driven by an arbitrary treatment definitions. In the preferred specification, counties are defined as treated if they have an average golden eagle relative abundance of 0.025 or greater. Only a small portion of the sample has an average relative abundance above this value, so while this cutoff is potentially arbitrary, it is designed to divide the sample into a high-exposure treated group and a little-to-no exposure control group. The baseline model then becomes the following:

$$y_{it} = \beta(Post2013_t * I(RelAbun > 0.025)_i) + \gamma_i + \delta_t + \epsilon_{it} \tag{4.2}$$

This model captures the effects of BGEPA enforcement on wind development for counties with relatively high golden eagle exposure. The same general DD assumptions are necessary for a causal interpretation of β; the parallel trends assumption requires that counties with a relative abundance greater than 0.025 would have experienced the same wind turbine development as counties with lower relative abundances in the absence of treatment. A map of the 111 treated counties alongside control counties in-sample are shown in figure 4.1.

In addition to the baseline results, I also present event study results with the following

model:

$$y_{it} = \sum_{j=-12}^{9} \beta_j (I(t = j) * I(RelAbun > 0.025)_i) + \gamma_i + \delta_t + \epsilon_{it} \tag{4.3}$$

Where treatment year index j is centered at 0 in 2013 as the year before treatment, and extends from 2001-2022. Coefficients β_j capture the average differences in trend between the treated and control groups for year j. These visualizations support the parallel trends requirement if β_j is not significantly different from 0 when $j < 0$. For $j > 0$, β_j illustrate the intensity of treatment effects over time. Negative β_j for $j > 0$ are evidence of negative impacts of BGEPA enforcement on wind capacity additions.

To show that this treatment definition does not drive the main results, I first perform sensitivity analysis on the 0.025 treatment cutoff value. I employ models with relative abundance treatment cutoffs of 0.02 and 0.03, respectively. These models show how much the arbitrary treatment cutoff influences the results. Unstable results indicate that primary model findings are potentially driven by noise; however, stable results across specifications lend credibility to baseline findings. The results of these models are detailed in appendix B. Furthermore, results of a continuous treatment model that does not rely on arbitrary treatment cutoffs are shown in appendix C.

In addition to sensitivity analyis on the simple difference-in-differences model, I employ a difference-in-differences model with multiple treatment definitions based on conditional quartiles of the relative abundance distribution. This approach avoids parametric assumptions on a binary low- and high- exposure cutoff, and allows investigation into potentially nonlinear treatment effects by exposure group. In this method, I 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 the set of control counties. Each conditional quartile group is then assigned as a treatment group. Figures 4.2 and 4.3 show this process for the entire distribution, including control counties with relative abundance values below 0.001 and for the conditional distribution with values above 0.001, respectively. Figure 4.4 shows the geographic distribution of counties in the each quartile

treatment group. The regression equation for this specification is the following:

$$y_{it} = \sum_{n=1}^{4}(\beta_n(Post2013_t * Quartile_{i,t})) + \gamma_i + \delta_t + \epsilon_{it} \tag{4.4}$$

In this specification, β_n represents the difference-in-differences estimate of the impact of BGEPA enforcement for counties in conditional quantile group n relative to control group counties with relative abundance values below 0.001. These specifications capture differential effects by different exposure groups, and rely on parallel trends assumptions between the each treatment group and the untreated group with low golden eagle exposure. Results for an additional specification where the distribution is split into deciles are shown in appendix D.

Robustness Checks

In addition to sensitivity analysis on the treatment cutoff value and the quartile treatment model, I include a variety of other controls in robustness check specifications. I apply these both to the primary specification and to the quartile treatment specification.

In the baseline model, the parallel trends assumption requires that counties with high golden eagle exposure would have experienced wind turbine growth parallel to the growth experienced in untreated counties in the absence of BGEPA enforcement. Therefore, any determinants of wind turbine development that are unbalanced between the treated and control groups pose concerns for the parallel trends assumption. In the primary sample, wind speed is balanced across both groups as shown in figure 4.5. However, the group with golden eagle exposure has systematically higher average potential capacity as shown in figure 4.6 and higher average distance to transmission networks as shown in figure 4.7. Both of these factors are likely attributable to the relatively remote nature of the treated counties. While potential capacity is likely a driver of wind turbine development, distance to transmission restricts development. Therefore, the overall difference between the two samples in terms of wind turbine growth potential is ambiguous. The baseline model imposes the assumption that these differences effect wind turbine capacity additions in a time-invariant manner. To relax this assumption, I add two specifications that interact these characteristics with time

variables to allow for parallel trends conditional on differential growth rates. First, I multiply the cross-sectional wind speed, potential capacity, and distance to transmission data with time trends and include them as controls. This accounts for the ways in which these factors might individually contribute to wind turbine development within counties over time.

$$\begin{aligned} y_{it} = \beta(Post2013_t * I(RelAbun > 0.025)_i) + WindSpeed_i * t \\ + PotentialCapacity_i * t + TransmissionDistance_i * t \\ + \gamma_i + \delta_t + \epsilon_{it} \end{aligned} \tag{4.5}$$

While the above specification reflects the intuition behind including these controls, it relies on inflexible linear time trends. I also include a specification where these characteristics are interacted with year fixed effects. This accounts for the impacts of wind speed, potential capacity, and transmission distance over time in a more flexible manner. Together, these specifications address concerns that the model results are driven by systematic differences in wind potential between treated and control groups.

$$\begin{aligned} y_{it} = \beta(Post2013_t * I(RelAbun > 0.025)_i) + WindDpeed_i * \delta_t \\ + PotentialCapacity_i * \delta_t + TransmissionDistance_i * \delta_t \\ + \gamma_i + \epsilon_{it} \end{aligned} \tag{4.6}$$

A further extension of this specification, where each factor is split into decile bins, is shown in appendix E.

State-level differences over time might also pose concerns for the parallel trends assumption. These identification challenges take two forms; first, 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. Next, 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, I include a specification with state-year fixed effects. These control for all state-year level variation, including state-specific growth and state-specific policies. This specification is intended to show whether the baseline results are robust to allowing for state-specific differences over time.

$$y_{ist} = \beta(Post2013_t * I(RelAbun > 0.025)_i) + \gamma_i + \tau_s * \delta_t + \epsilon_{ist} \tag{4.7}$$

Where i denotes county, s denotes state, and t denotes year.

Finally, results from Poisson regression specifications are discussed and shown in appendix F.

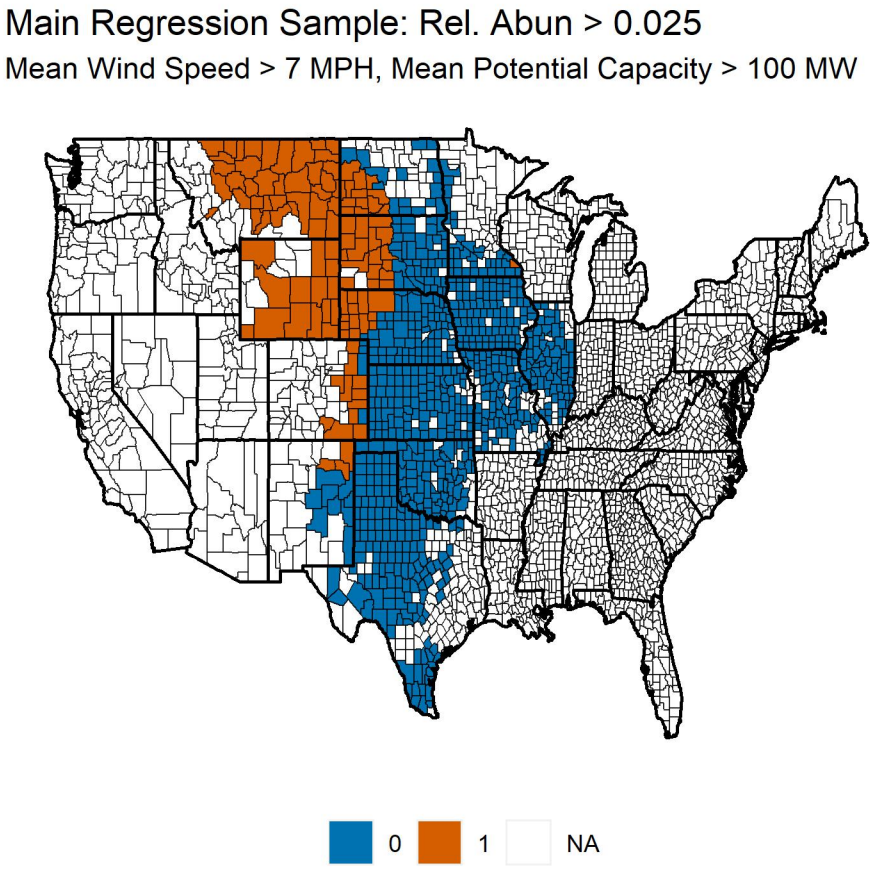

Figure 4.1: Main Sample Map by Treatment Status

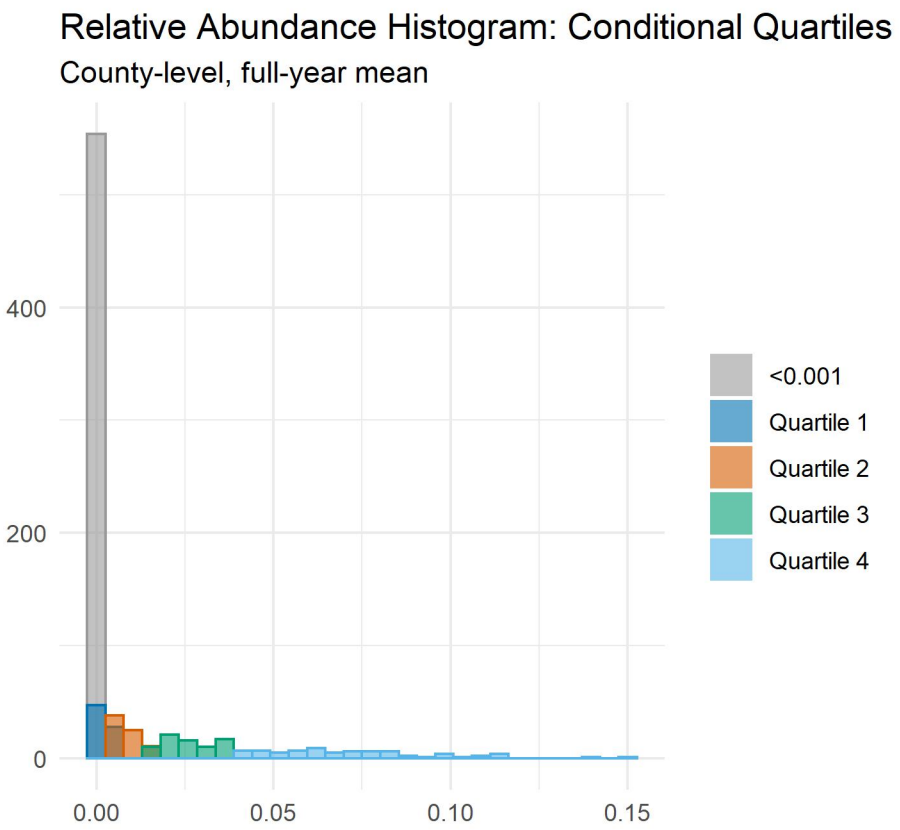

Figure 4.2: Conditional Quartiles of Golden Eagle Relative Abundance Distribution

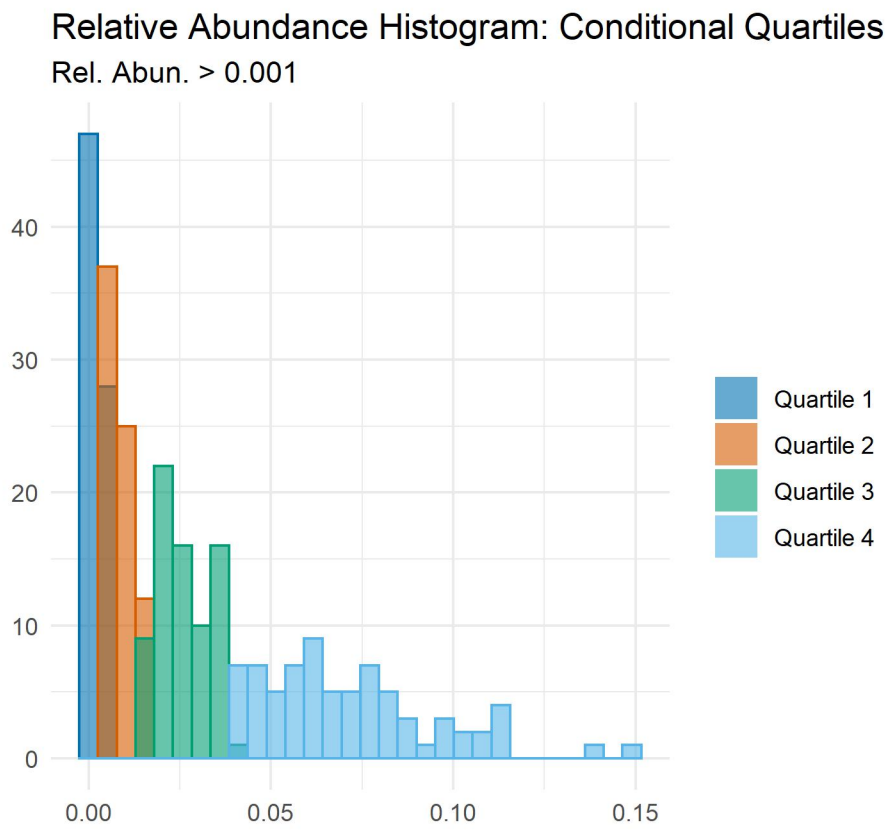

Figure 4.3: Conditional Quartiles of Golden Eagle Relative Abundance Distribution: Rel. Abun. > 0.001

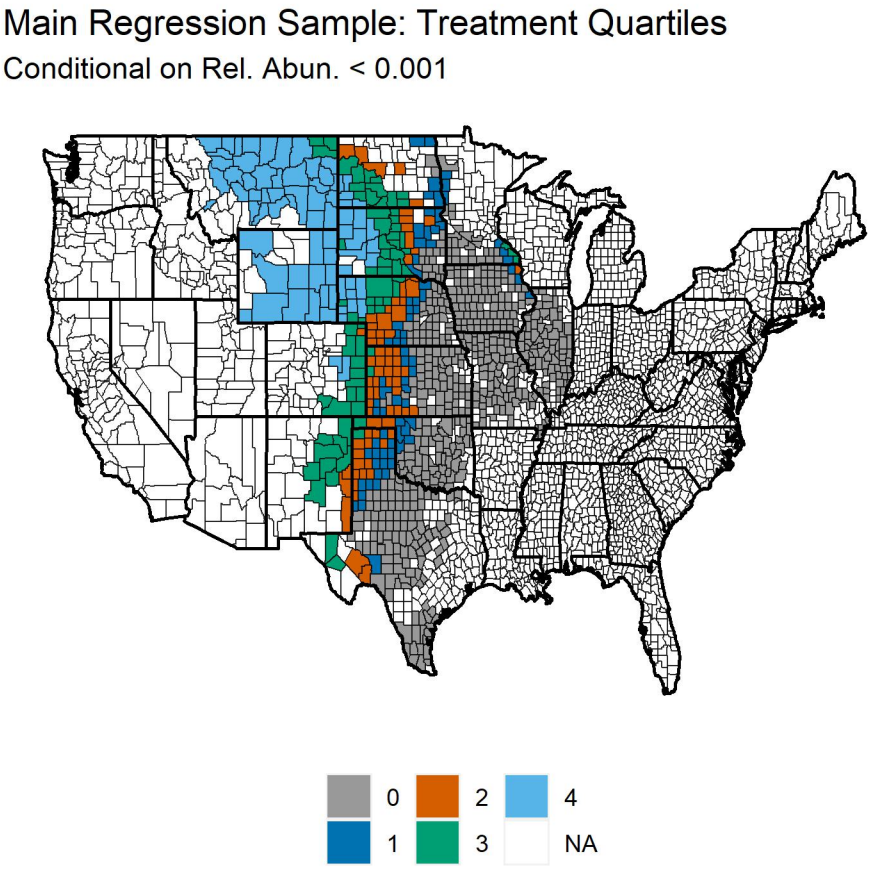

Figure 4.4: Conditional Quartile Treatment Group Map

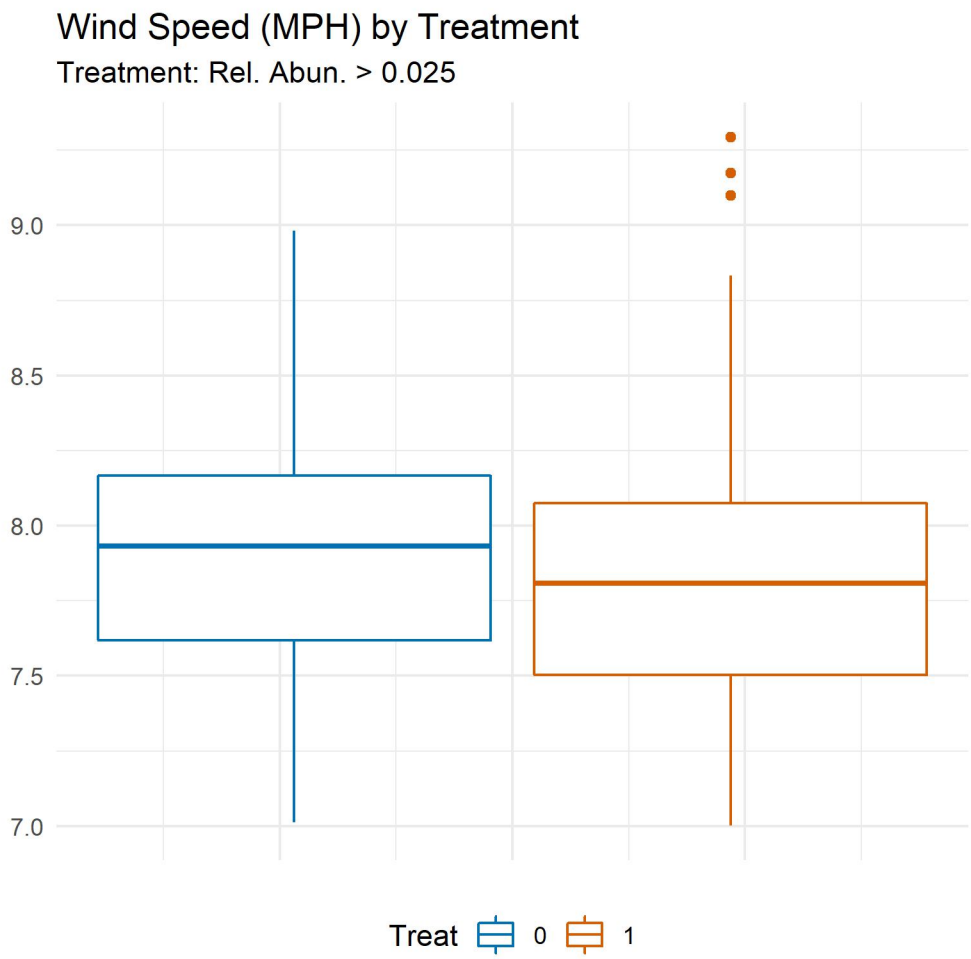

Figure 4.5: Wind Speed by Treatment Status

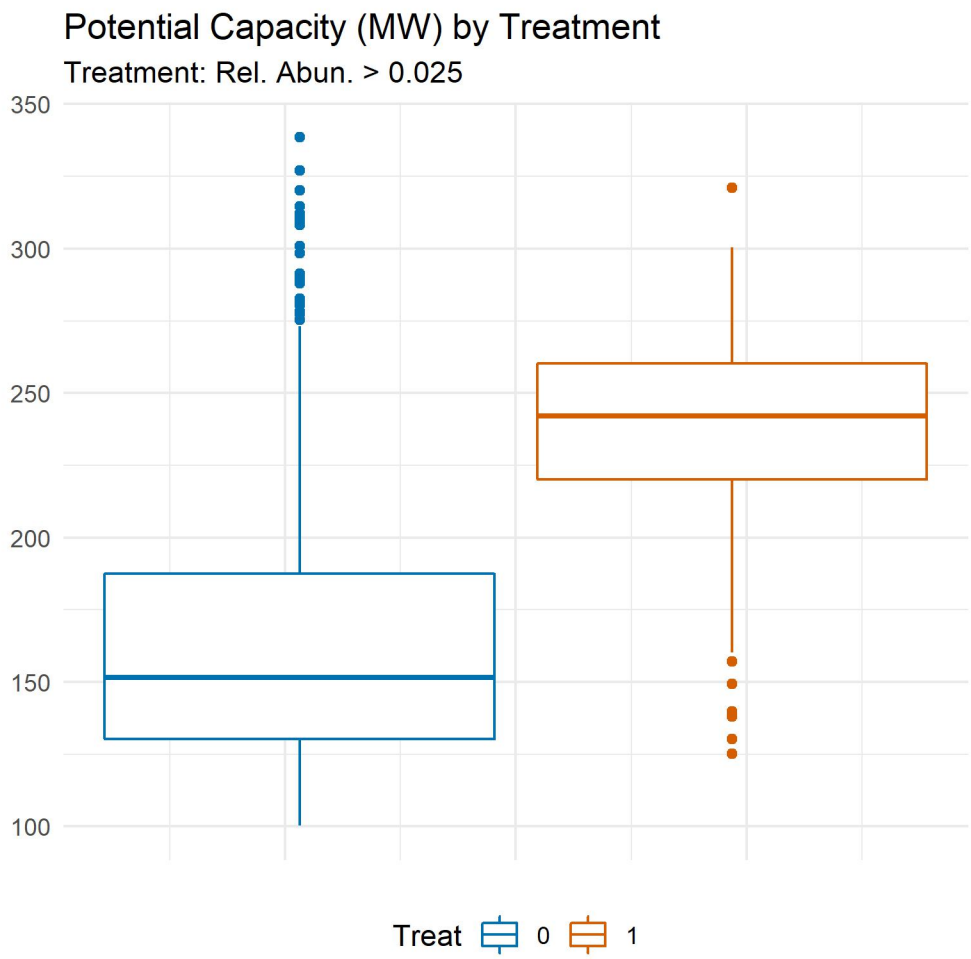

Figure 4.6: Potential Capacity by Treatment Status

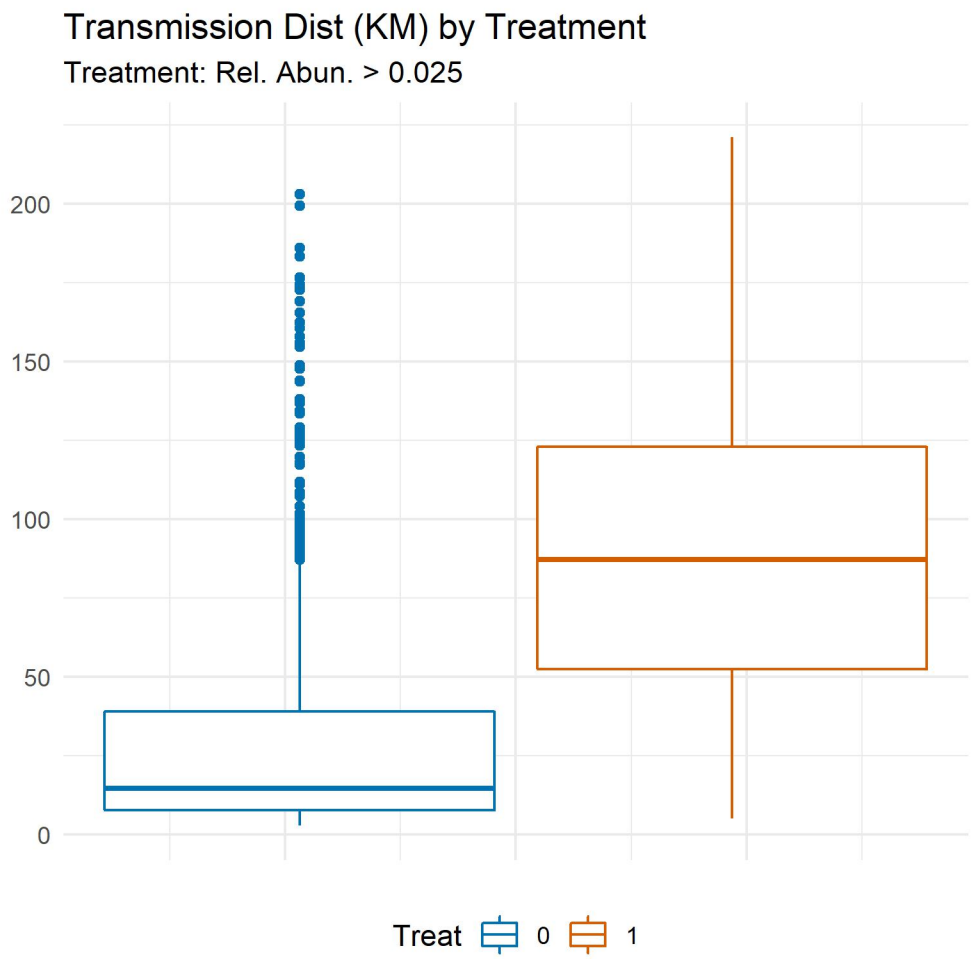

Figure 4.7: Distance to Transmission by Treatment Status

RESULTS

Baseline Results

Results for the baseline models with binary treatment defined as average relative abundance greater than 0.025 and continuous treatment are shown in table 5.1. For the binary treatment model, counties with a relative abundance of golden eagles above 0.025 experienced a significant decline in wind turbine capacity additions of 3.78 megawatts. In terms of turbine additions, treated counties experienced a 1.52 turbine decrease in average annual construction. Multiplying these coefficients by the 111 treated counties in-sample implies a total estimated loss of 420 MW of wind capacity or 168 turbines. Figures 5.2 and 5.3 present these results as an event study. This shows that there were not significant differences between treated and control counties prior to BGEPA enforcement, and that significant negative impacts occurred within the first few years after the Duke Energy case.

The quartile treatment group model results are shown in figure 5.6. BGEPA enforcement is associated with significant impacts only for the most-exposed quartile, where capacity additions fell relative to counties with no golden eagle exposure by 3.9 MW per county or 1.5 turbines per county on average. Taken as a whole, these results suggest that BGEPA enforcement only impacts counties with particularly high golden eagle exposure. Event study coefficients for the highest quartile are shown in figure 5.7.

Robustness Checks

Robustness Checks: Binary Treatment Model

Table 5.4 shows the results of the robustness check specifications for the binary treatment model where treatment is defined by average relative abundances greater than 0.025 with added capacity as the outcome variable.[1] Column 2 shows the results of estimating

[1]Due to the high correlation between added capacity and added turbines, I show robustness check results for the added capacity specifications only. Robustness checks for added turbines are shown in appendix G.

equation 4.5, where mean wind speeds, potential capacities, and distances to transmission are multiplied by linear trends. In this specification, treated counties experienced a significant decline in expected capacity additions of 4.43 megawatts. Column 3 shows the results of estimating equation 4.6, where the time trends of 4.5 are replaced with flexible year fixed effect interactions. In this specification, treated counties experienced a significant 5.1 MW decline in expected capacity additions. The significance of these results addresses concerns that the baseline results are driven by differences in treated and control groups.

Table 5.5 shows the results of state-year fixed effects specification 4.7. In this model, the treatment group experienced a significant 3.54 MW decline in expected capacity additions. The significance of this coefficient and its' similarity in magnitude to the baseline coefficient suggest that results are not driven by state-level policy variation over time.

Robustness Checks: Quartile Treatment Model

Table 5.8 shows the results of both specifications that control for wind speed, potential capacity, and distance to transmission interacted with time trends or year fixed effects for the quartile treatment model. The results for both of these specifications are qualitatively similar to the baseline results, suggesting that the main findings are not driven by how differences in endowments of wind resources might contribute to wind turbine development growth over time.

Table 5.9 shows the results for the quartile treatment model after controlling for state-year fixed effects. The coefficient for the highest quartile group retains its size but falls in statistical significance. This might be due to a lack of meaningful within- state-year variation due to the concentration of the highest exposure areas in Wyoming and Montana, as well as limited statistical power of the conditional quartiles model.

	(1) Added Capacity	(2) Added Turbines
Post * I(Rel. Abun. > 0.025)	-3.776***	-1.518**
	(1.369)	(0.618)
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: Column (1) shows the results of the baseline specification with added capacity as the outcome variable. Counties with an average relative abundance of golden eagles greater than 0.025 experienced a significant decline in expected capacity additions of 3.7 MW. Column (2) shows the baseline results with added turbines as the outcome variable. Counties with an average relative abundance of golden eagles greater than 0.025 experienced a significant decline in expected turbine additions of 1.5 turbines.

Figure 5.1: Baseline Results

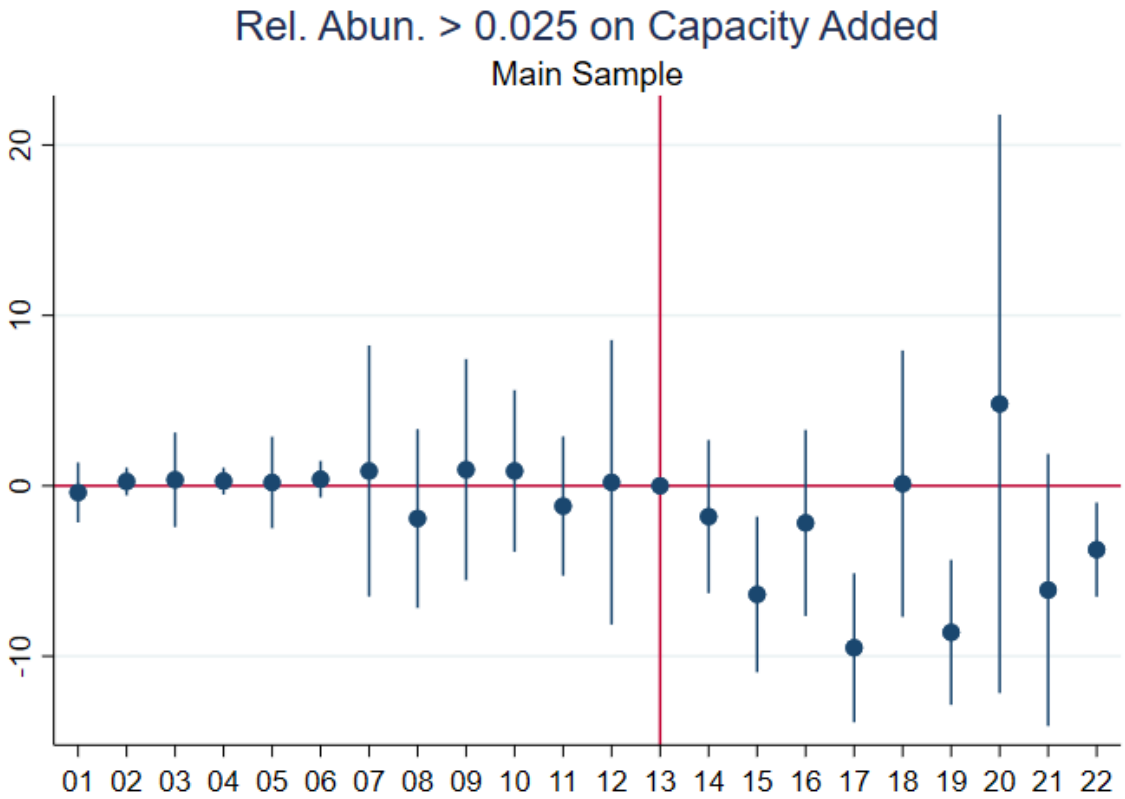

Figure 5.2: Binary Treatment Event Study, Capacity Added

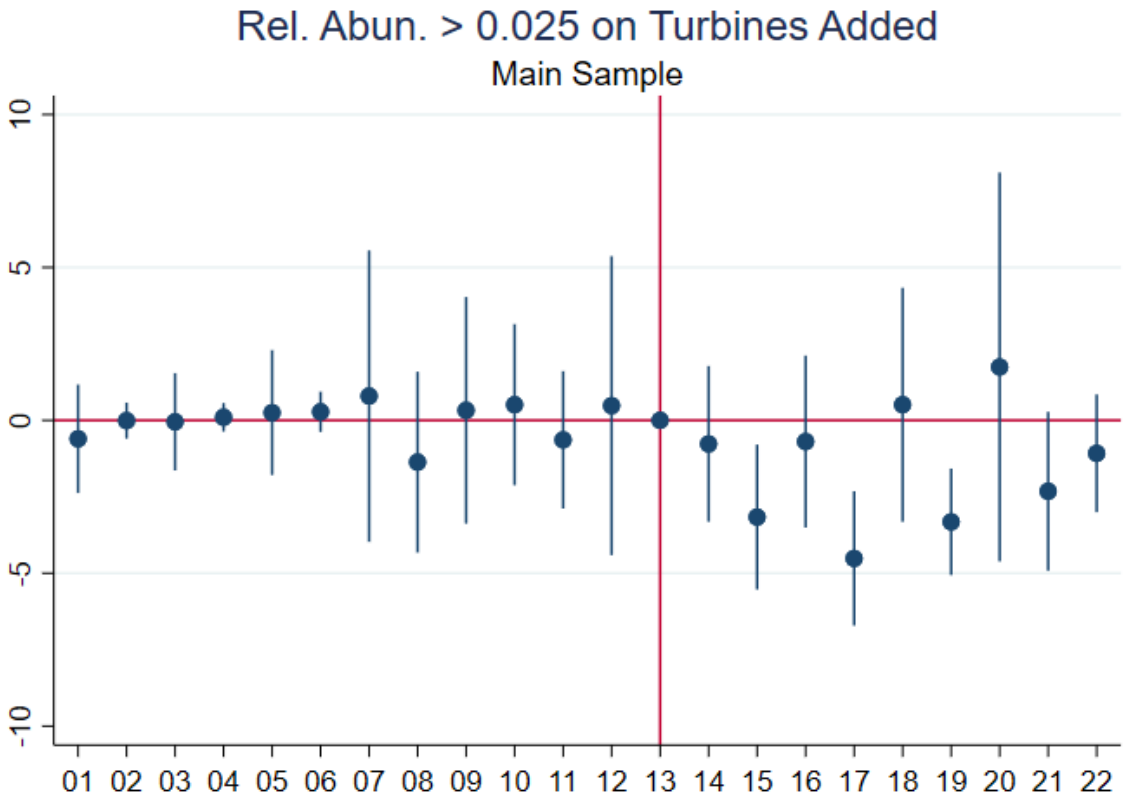

Figure 5.3: Binary Treatment Event Study, Turbines Added

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
Post * I(Rel. Abun. > 0.025)	-3.776***	-4.427**	-5.096***
	(1.369)	(1.772)	(1.949)
Wind Speed * t		0.431***	
		(0.117)	
Potential Cap. * t		0.00653***	
		(0.00192)	
Transmission Dist. * t		-0.00669***	
		(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 5.1. Column (2) shows the results from model 4.5, where counties with an average relative abundance greater than 0.025 experienced a significant decline in expected capacity additions of 4.4 MW relative to control counties. Column (3) shows the results from model 4.6, where counties with an average relative abundance greater than 0.025 experienced a significant decline of 5.1 MW of wind turbine capacity additions relative to control counties.

Figure 5.4: Robustness Checks: Characteristics Over Time

	(1) Added Capacity	(2) Added Capacity
Post * I(Rel. Abun. > 0.025)	-3.776***	-3.543*
	(1.369)	(1.979)
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 5.1. Column (2) shows the results from equation 4.7, with added capacity as the outcome variable and state-year fixed effects. In this model, counties with an average relative abundance greater than 0.025 experienced a decline in expected wind capacity additions of 3.5 MW.

Figure 5.5: Robustness Checks: State-Year Fixed Effects

	(1) Added Capacity	(2) Added Turbines
Quartile 1 * post	3.157	1.983
	(2.759)	(1.237)
Quartile 2 * post	2.991	2.066
	(2.652)	(1.316)
Quartile 3 * post	-0.0928	0.269
	(2.550)	(1.121)
Quartile 4 * post	-3.934***	-1.516***
	(1.389)	(0.569)
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 model 4.4. Column (1) shows the results for the added capacity specification. Counties in quartiles 1-3 did not experience any significant effects of BGEPA enforcement on wind turbine development. Counties in the highest exposure group, quartile 4, experienced a significant decline in expected capacity additions of 3.9 MW relative to counties with a mean relative abundance value below 0.001. Column (2) shows the results for the same model with added capacity as the outcome variable. Similarly, while there are no significant effects for quartiles 1-3, counties in the highest exposure conditional quartile experienced a significant decline in expected turbine additions of 1.5 turbines relative to control counties.

Figure 5.6: Conditional Quartile Specification Results

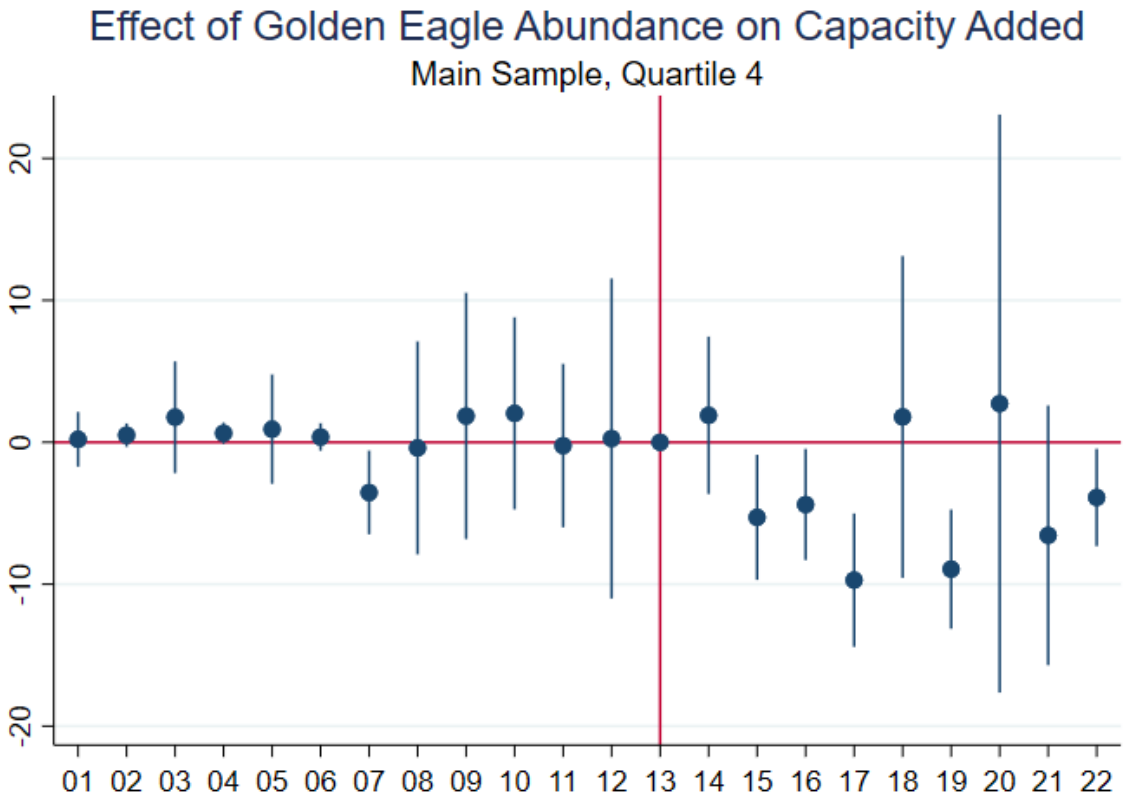

Figure 5.7: Conditional Quartile Specification: Quartile 4 Event Study

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
Quartile 1 * post	3.157	2.250	1.742
	(2.759)	(2.659)	(2.622)
Quartile 2 * post	2.991	2.316	1.455
	(2.652)	(2.802)	(2.986)
Quartile 3 * post	-0.0928	0.582	-0.220
	(2.550)	(2.696)	(3.098)
Quartile 4 * post	-3.934***	-4.995***	-6.009***
	(1.389)	(1.926)	(2.324)
Wind Speed * t		0.394***	
		(0.120)	
Potential Cap. * t		0.00657***	
		(0.00189)	
Transmission Dist. * t		-0.00741***	
		(0.00182)	
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

This table shows the results of robustness check specifications 4.5 and 4.6 in the conditional quartile treatment specification of 4.4. Column (1) reiterates the baseline conditional quartile treatment group specification. Column (2) shows the results of the specification where wind speed, potential capacity, and transmission distance are interacted with linear time trends. In this specification, quartile groups 1-3 experienced no significant effects, while quartile 4 experienced a decline in expected capacity additions of 5 MW relative to the control counties. Column (3) shows the results of the specification where the same characteristics are interacted with year fixed effects. Quartiles 1-3 experienced no effect, while quartile 4 experienced a decline in expected capacity additions of 6 MW.

Figure 5.8: Conditional Quartile Specification: Characteristics Over Time

	(1) Added Capacity	(2) Added Capacity
Quartile 1 * post	3.157	2.377
	(2.759)	(2.847)
Quartile 2 * post	2.991	1.619
	(2.652)	(2.764)
Quartile 3 * post	-0.0928	-3.375
	(2.550)	(2.130)
Quartile 4 * post	-3.934***	-2.507
	(1.389)	(2.120)
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

This table shows the results of the state-year fixed effect robustness check specification 4.7 applied to the conditional quartile treatment specification of 4.4. Column (1) reiterates the baseline conditional quartile treatment group specification. Column (2) shows the results of the state-year fixed effect specification. In this model, none of the quartile groups show significant results. However, the coefficient signs and size are roughly consistent for quartile 4.

Figure 5.9: Conditional Quartile Specification: State-Year FE

CONCLUSION

Using a difference-in-differences approach, I find evidence that BGEPA enforcement reduced wind turbine capacity additions in counties with high golden eagle exposure by roughly 3.78 MW per county. This implies a total wind capacity loss of 420 MW, or roughly 8% of the 5,015 MW total new capacity additions in the region in the 2014-2022 period. I estimate that this capacity loss would have produced an amount of electricity valued at $56 million to $142 million per year.[1] These figures represent an economically significant reduction in wind turbine capacity, illustrating that the impacts of species protections on renewable development are potentially substantial.

While the size of foregone capacity effects and their economic valuations are informative, they must be paired with valuations of wildlife damages for a complete welfare analysis. I estimate that the foregone wind installations would have been responsible for an average of 7.6 golden eagle deaths per year. A variety of methods have been used in the past to value golden eagle lives. One approach uses the costs of compensatory mitigation, yielding an estimate of $15.2 thousand to $38 thousand per eagle (Millsap et al., 2022; Hosterman and Lane, 2017). This would place the total annual value of protected eagle lives at $115.5 thousand to $288.8 thousand. 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 individuals in the case of large-scale impacts. As an alternative approach that is specific to wind turbine development, I use fines from the recent ESI prosecution to calculate a $169 thousand value per golden eagle, placing the total annual value of preserved eagle lives as a result of this policy at $1.3 million.

While further research is necessary to value the impacts of large-scale wind development on golden eagles, existing golden eagle valuation methods suggest that there are significant economic gains to allowing at least marginally more wind development in high-potential

[1] Details on this estimation and the following social cost of carbon estimation method, along with golden eagle mortality and valuation estimates, are provided in appendix H.

areas that might overlap golden eagle ranges. This result generally holds even admitting some imprecision in the estimated amount of eagle lives preserved. Beyond the direct effects of increased electricity supply, such development would reduce negative environmental externalities associated with fossil-fuel electricity generation. These findings suggest that the gains to renewable development are potentially large relative to their localized species damages in limited scenarios.

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.

The possibility that wind turbine developers substituted toward low-exposure areas as a response to BGEPA enforcement remains an identification challenge that might lead to overstated results and valuations. Investigating this possibility remains an area for future research. However, even in the scenario where wind turbine developers extensively substituted towards low-exposure areas, this study still contributes to the literature by providing evidence that such substitution might have occurred as a response to BGEPA enforcement. These 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 must 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, one could argue that government-subsidized compensatory mitigation efforts to protect golden eagles as a public good could improve welfare through reducing obligations 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 & 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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APPENDICES

APPENDIX A

SAMPLE SELECTION ROBUSTNESS

The 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. This sample selection is driven by the identification strategy, which compares counties with similar wind potential that do and do not have golden eagle exposure.

To show that this sample selection does not drive the results, I present two additional sample selection strategies. In the first, I filter to counties with wind speeds above 6.5 MPH and potential capacities above 100 MW. Results from this sample demonstrate that the baseline results are not driven by the particular value of the wind speed filter.

The second alternate sample takes all counties in the sample states with no filtering imposed. This sample now includes low-potential counties, primarily in the treated group. However, these counties are likely to have no wind turbine development at all during the sample period. Therefore, county fixed effects will likely absorb the variation in capacity additions attributable to these low-potential areas. This sample is intended to show that, while the filtering strategy results in a clearer identification strategy, general results hold even in the absence of filtering the dataset.

Maps of the counties in the 6.5 MPH sample and the unfiltered sample by baseline binary treatment status[1] are shown in tables A.1 and A.2. Results and binary treatment event studies for the 6.5 MPH sample are given in figures A.3 and A.4, while the same results are shown in the unfiltered sample in figures A.5 and A.6. In either specification, results are qualitatively similar to the baseline results, suggesting that the sample selection scheme does not drive this papers' findings.

[1] Relative abundance >= 0.025

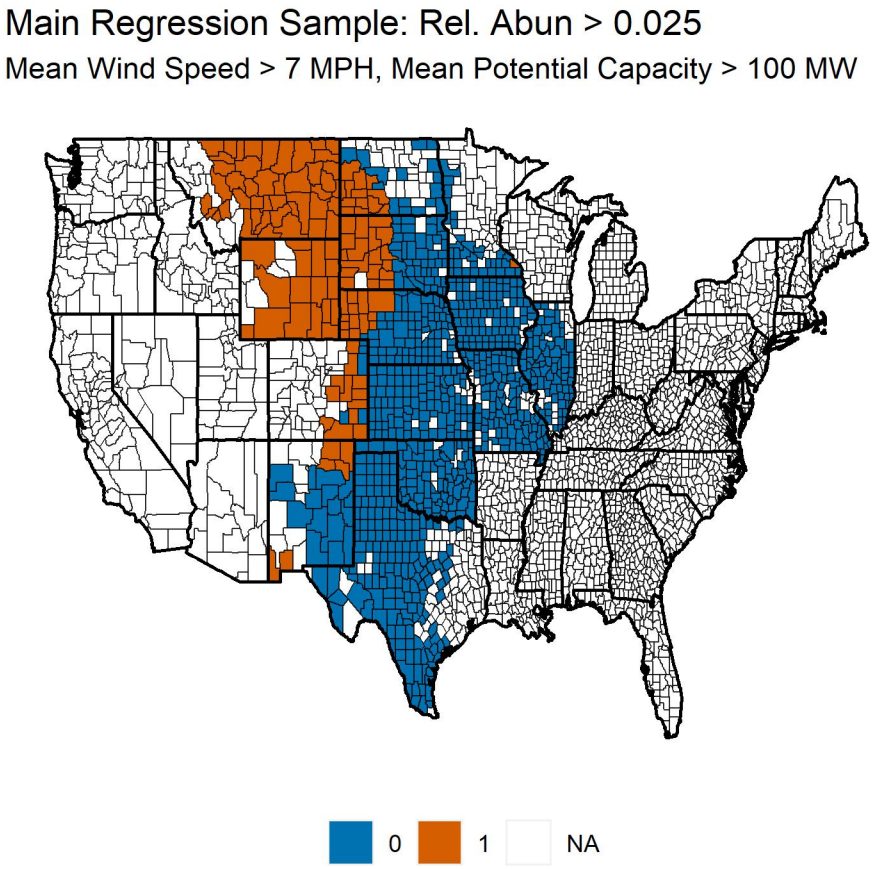

Figure A.1: Alternative Filter Sample: Binary Treatment

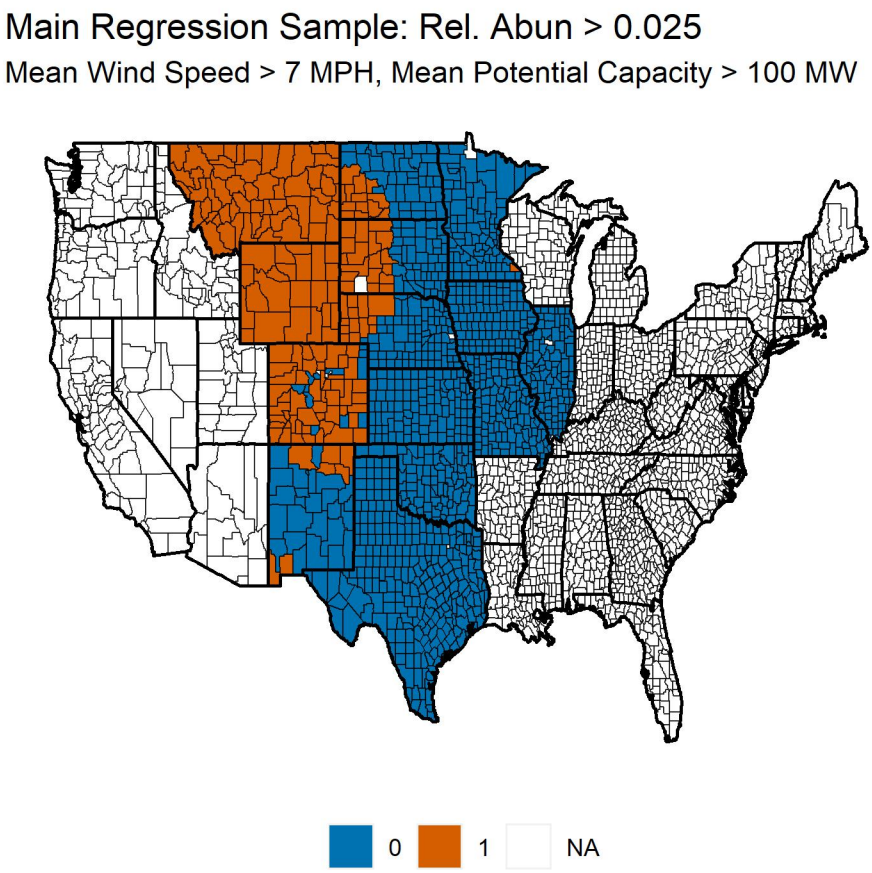

Figure A.2: Unfiltered Sample: Binary Treatment

	(1) Added Capacity	(2) Added Turbines
Post * I(Rel. Abun. > 0.025)	-3.245**	-1.232**
	(1.275)	(0.583)
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: This table shows the results of the baseline model 4.2 applied to the alternative sample shown in map A.1, where the sample is filtered to counties with a mean wind speed above 6.5 MPH and potential capacity above 100 MW. Column (1) shows baseline results for added turbine capacity, where counties with a relative abundance above 0.025 experienced a 3.2 MW decline in expected capacity additions over the BGEPA enforcement period. Column (2) shows the same results for the added turbines outcome variable, where counties with a relative abundance greater than 0.025 experienced a 1.2 turbine decrease in expected wind development relative to low-exposure counties over the sample period.

Figure A.3: Alternative Filter Sample: Baseline Results

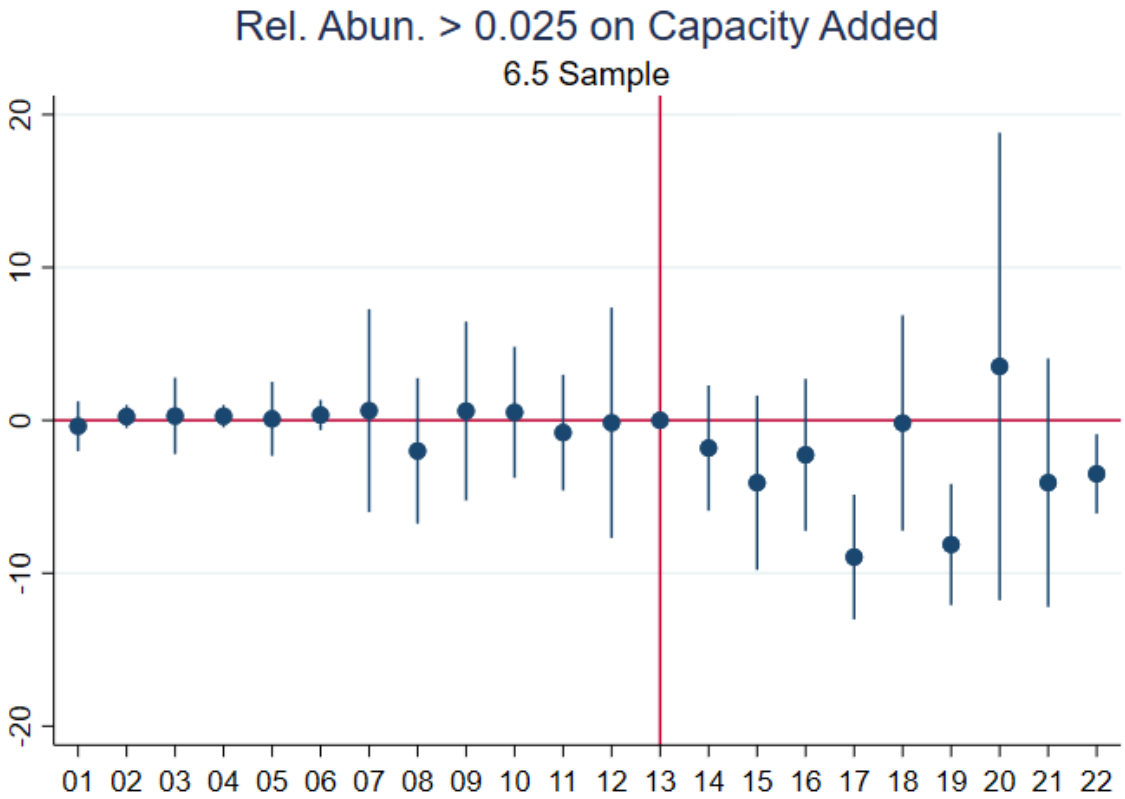

Figure A.4: Alternative Filter Sample: Binary Treatment Event Study

	(1) Added Capacity	(2) Added Turbines
Post * I(Rel. Abun. > 0.025)	-3.051***	-1.214***
	(0.919)	(0.428)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster	County	County
N	26796	26796

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: his table shows the results of the baseline model 4.2 applied to the alternative sample shown in map A.2, where the sample is not filtered beyond selecting states located along the Great Plains wind-rich region. Column (1) shows baseline results for added turbine capacity, where counties with a relative abundance above 0.025 experienced a 3 MW decline in expected capacity additions over the BGEPA enforcement period. Column (2) shows the same results for the added turbines outcome variable, where counties with a relative abundance greater than 0.025 experienced a 1.2 turbine decrease in expected wind development relative to low-exposure counties over the sample period.

Figure A.5: Unfiltered Sample: Baseline Results

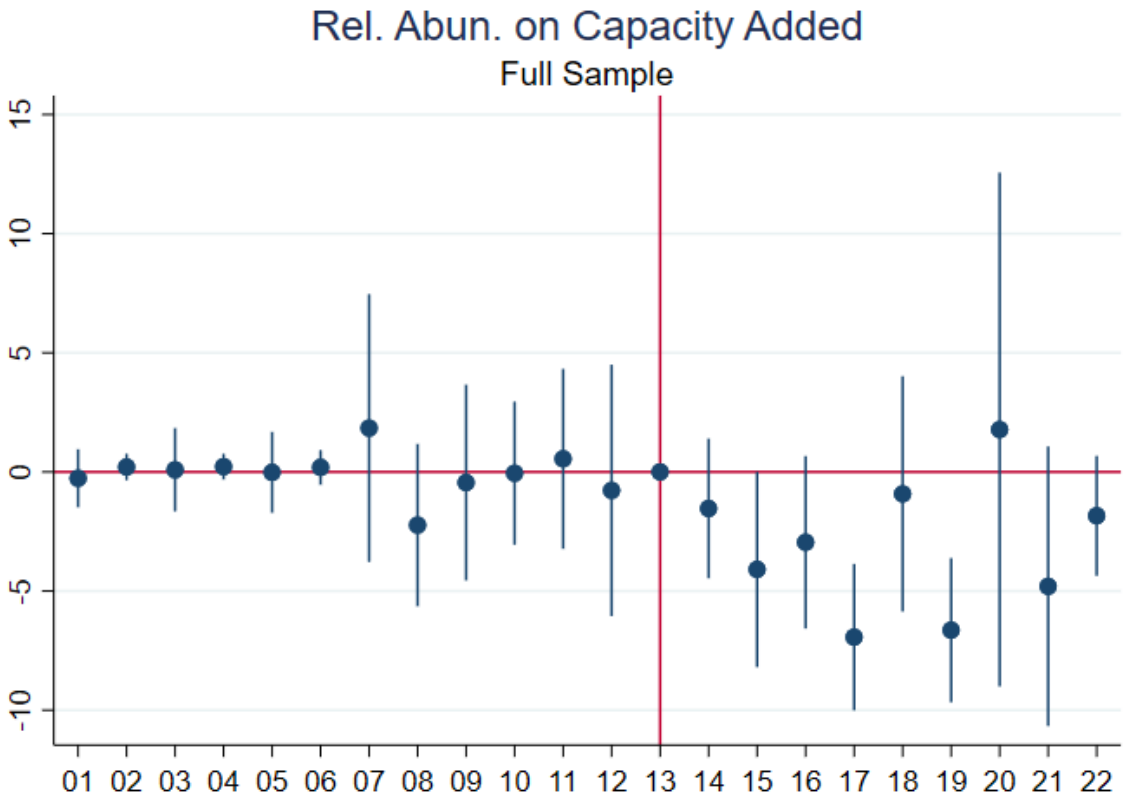

Figure A.6: Unfiltered Sample: Binary Treatment Event Study

APPENDIX B

ALTERNATE BINARY TREATMENT DEFINITIONS

Baseline binary treatment results are based on a relative abundance value cutoff of 0.025. While these results are supplemented with continuous treatment results that yield similar results, I also present results with alternative binary treatment definitions.

For these specifications, I change the 0.025 relative abundance cutoff value to 0.02 and 0.03, respectively. The estimating equations become the following:

$$y_{it} = \beta(Post2013_t * I(RelAbun > 0.020)_i) + \gamma_i + \delta_t + \epsilon_{it} \tag{B.1}$$

$$y_{it} = \beta(Post2013_t * I(RelAbun > 0.030)_i) + \gamma_i + \delta_t + \epsilon_{it} \tag{B.2}$$

Consistent results across these specifications might serve as evidence that the primary results are not driven by the specific treatment cutoff value.

Maps of treated and control counties are shown in figures B.1 and B.2. Results for both models are shown in figure B.3, while event studies for the 0.02 cutoff model and the 0.03 cutoff model with added capacity as the outcome variable are shown in figures B.4 and B.5, respectively.

Results for the model with a cutoff of 0.02 show a loss of statistical significance, although the coefficient remains similar to the baseline coefficient. The event study results show significant negative impacts in the years immediately following 2014. While the overall result is no longer statistically significant, these results are consistent with an interpretation of immediate impacts that faded over time.

Results for the 0.03 cutoff model retain statistical significance with a more negative coefficient than the baseline model, and the event study results show a similar pattern to the baseline results.

Taken altogether, 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.

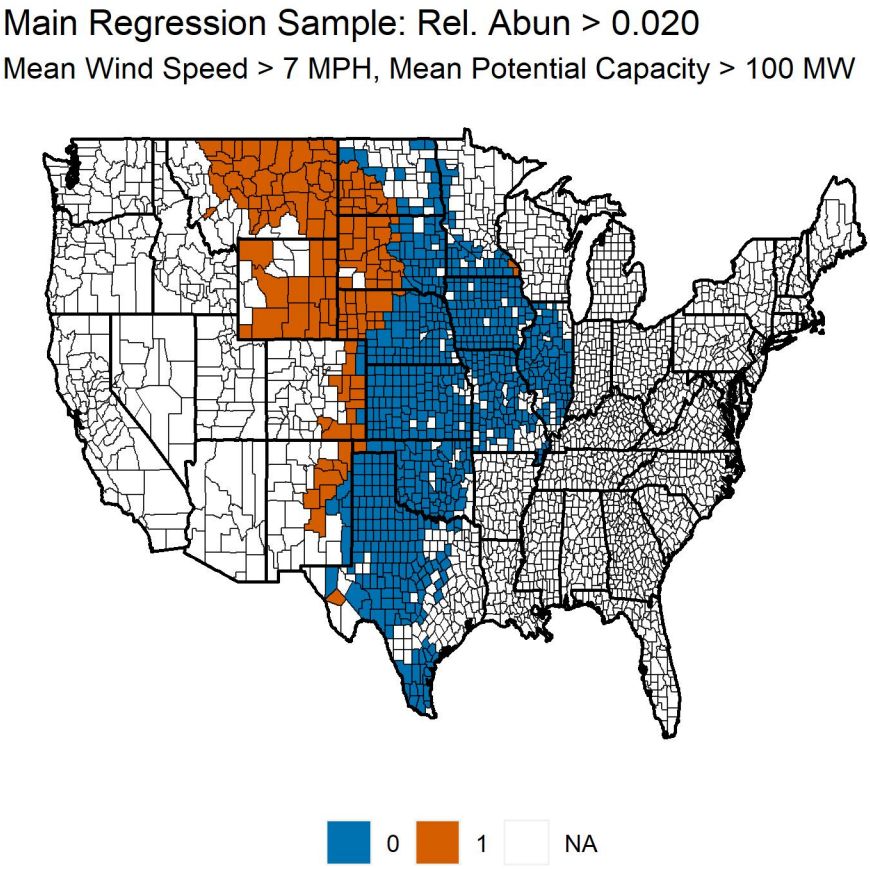

Figure B.1: Main Sample: Rel. Abun. > 0.02 Alternative Treatment

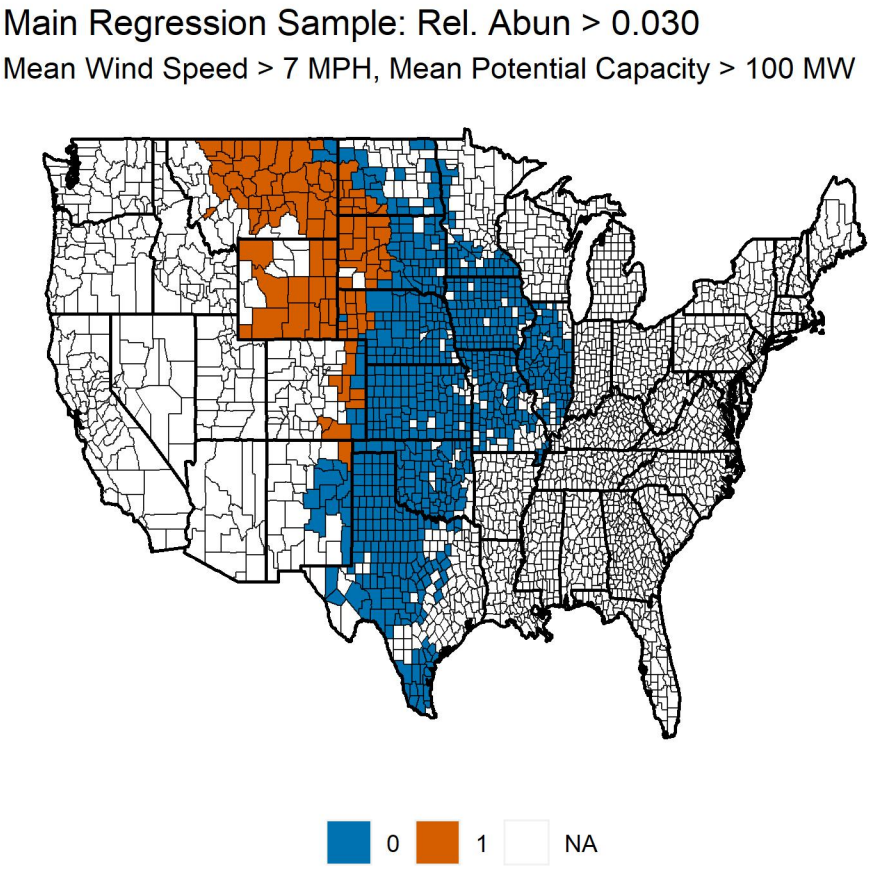

Figure B.2: Main Sample: Rel. Abun. > 0.03 Alternative Treatment

	(1) Added Capacity	(2) Added Capacity
I(RelAbun > 0.2) * Post	-2.113	
	(1.700)	
I(RelAbun > 0.3) * Post		-4.369***
		(1.271)
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 specifications B.1 and B.2, which slightly alter the primary treatment cutoff value. In column (1), counties with an average relative abundance above 0.02 experienced a decrease in expected capacity additions of 2.1 MW, although this effect is not statistically significant. In column (2), counties with an average relative abundance above 0.03 experienced a significant decrease in expected wind capacity additions of 4.4 MW.

Figure B.3: Alternative Treatment Values: Results

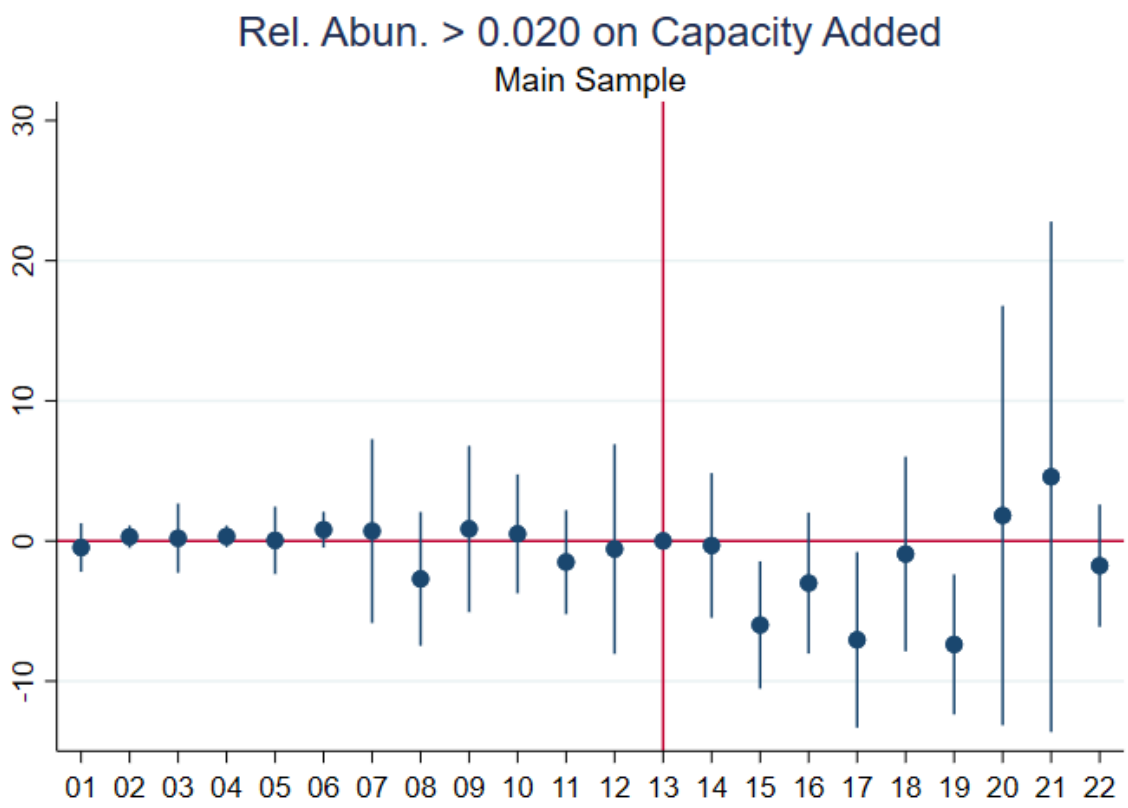

Figure B.4: Main Sample, Rel. Abun. > 0.02 Treatment: Event Study

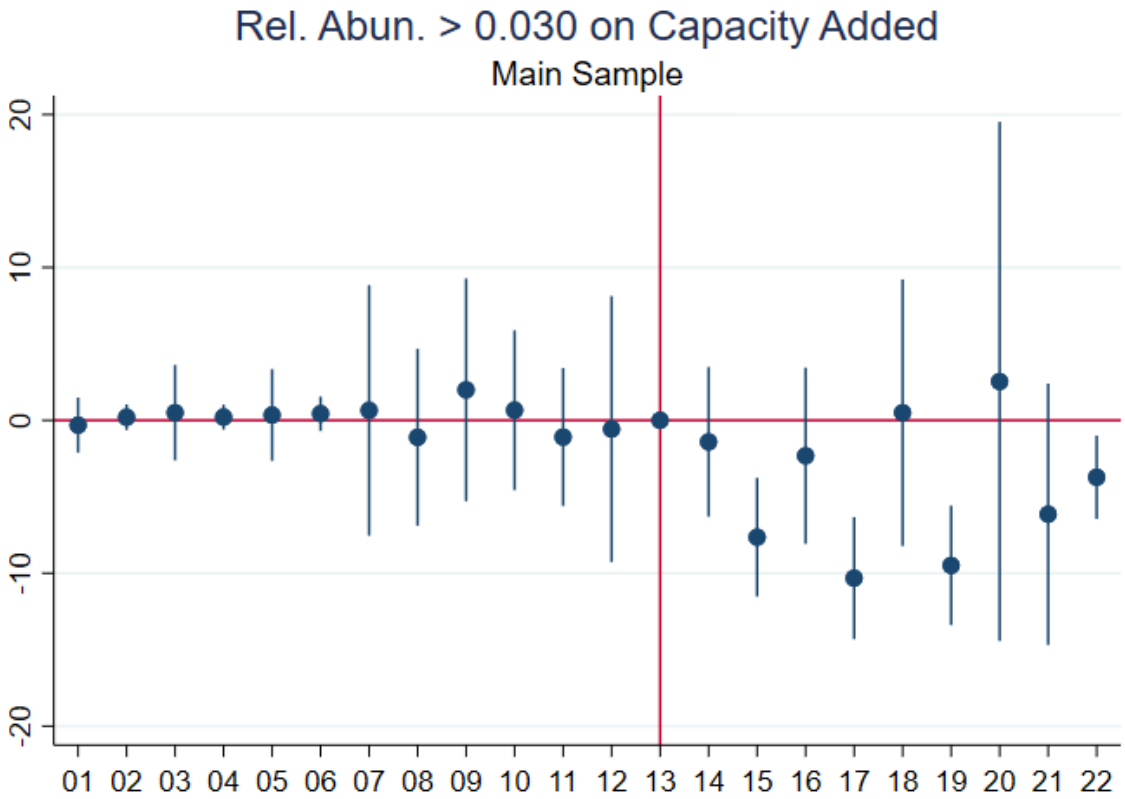

Figure B.5: Main Sample, Rel. Abun. > 0.03 Treatment: Event Study

APPENDIX C

CONTINUOUS TREATMENT SPECIFICATIONS

I employ a continuous treatment DD model to supplement the baseline binary treatment results. In this specification, no binary treatment value is imposed; rather, the naturally-occurring values of county-level mean relative abundance take the place of the treatment variable. Such non-binary treatment models are proposed by Wooldridge (2005). This method potentially avoids the issue of arbitrary treatment definitions. The specification becomes the following:

$$y_{it} = \beta_{CT}(Post2013_t * RelAbun_i) + \gamma_i + \delta_t + \epsilon_{it} \tag{C.1}$$

In this specification, β_{CT} captures the marginal impact of unit increases in relative abundance on outcome variable y_{it}. Given causal identification, significant negative values of β_{CT} support the hypothesis that BGEPA enforcement negatively impacts wind turbine development. An estimate of the full impact of the policy can be obtained by multiplying β_{CT} by the distribution of sample relative abundances.[1]

Just as in the simple DD model, I also show these results in an event study:

$$y_{it} = \sum_{j=-12}^{9} \beta_{CT,j}(I(t=j) * RelAbun_i) + \gamma_i + \delta_t + \epsilon_{it} \tag{C.2}$$

In this specification, $\beta_{CT,j}$ show the marginal effects of golden eagle relative abundance on wind turbine development by year. $\beta_{CT,j}$ that are not significantly different from 0 for $j < 0$ support parallel trends assumptions, and $\beta_{CT,j}$ for $j > 0$ show the marginal impacts of golden eagle exposure by year given BGEPA enforcement.

Recent work by Callaway, Goodman-Bacon, and Sant'Anna (2021) highlights unique identification challenges posed by continuous treatment models. The traditional DD parallel trends assumption, which requires that the unrealized untreated outcomes of treated groups would have been parallel with the realized untreated outcomes of the control groups, is inadequate for a causal identification of β_{CT}. 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

[1] An implicit assumption of both models, and particularly the continuous treatment model, is that the 2021 golden eagle relative abundance data is representative of golden eagle exposure for the entire time period. While prior-year relative abundance data are not available, this assumption is supported by findings of stable golden eagle populations at aggregate and regional levels from Sauer et al. (2019) and Millsap et al. (2013).

distributions, and units have no way to select into different exposures based on their unobserved wind turbine potential. Furthermore, just as in the basic DD 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.

Baseline regression results are shown in table C.1. In this model, a percentage point increase in golden eagle relative abundance is significantly associated with a decline in expected capacity additions of 0.51 MW or a decline in expected turbine additions of 0.23 turbines. To put this in perspective, a standard deviation increase in golden eagle relative abundance is 0.02; a standard deviation increase is associated with a decline in expected capacity additions of 1.02 MW. Multiplying this average coefficient by the distribution of golden eagle relative abundance in-sample yields a similar estimated total loss of 410 MW in capacity or 187 turbines. The event study results showing the marginal effects of golden eagle relative abundance by year are shown in figures C.2 and C.3. Robustness checks are shown in figures C.4 and C.5. Overall, results are qualitatively similar to the baseline binary treatment results.

	(1) Added Capacity	(2) Added Turbines
Post * Rel. Abun. * 100	-0.514**	-0.232***
	(0.228)	(0.0836)
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 baseline continuous treatment specifications from equations C.1 in the main sample. Since relative abundance has a range from roughly 0 to 0.15, the variable is multiplied by 100 to ease interpretation of the regression coefficents. In column (1), a 0.01 increase in average county golden eagle relative abundance is significantly associated with a 0.5 MW decline in expected wind turbine capacity additions over the BGEPA enforcement period. In column (2), a 0.01 increase in county average golden eagle relative abundance is significantly associated with a 0.2 turbine decrease in turbine additions over the BGEPA enforcement period.

Figure C.1: Continuous Treatment Model: Baseline Results

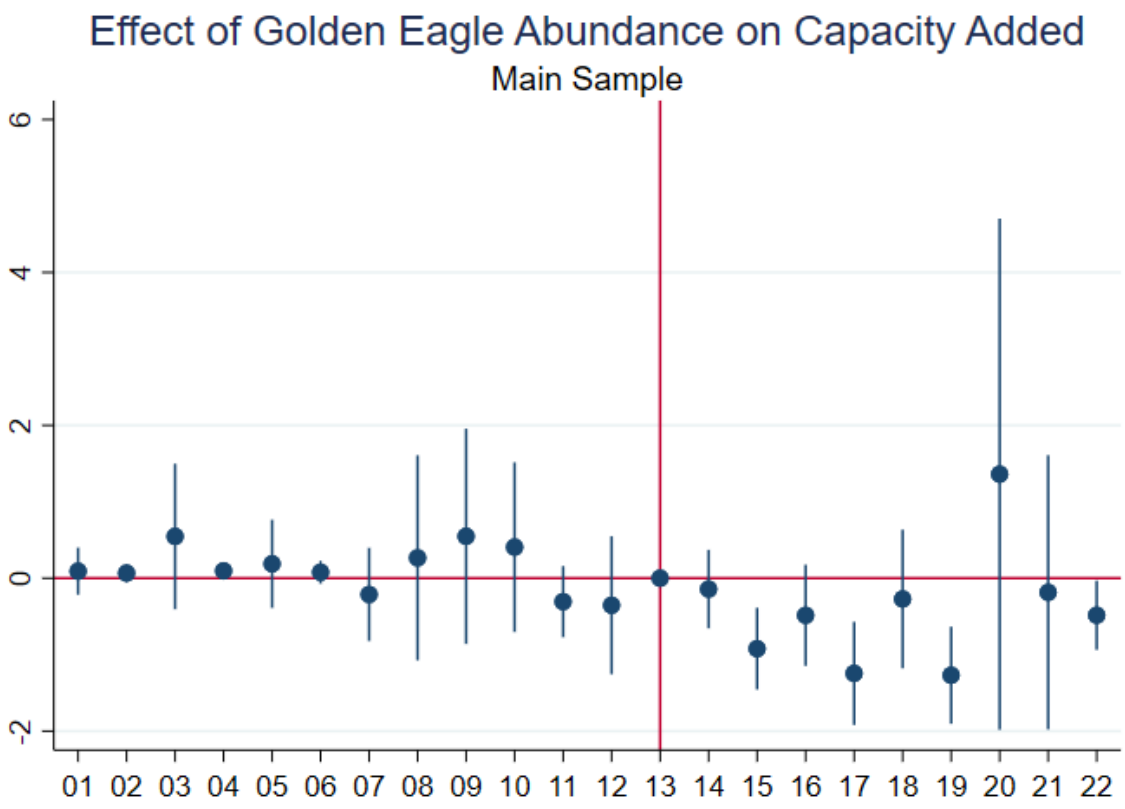

Figure C.2: Continuous Treatment Event Study, Capacity Added

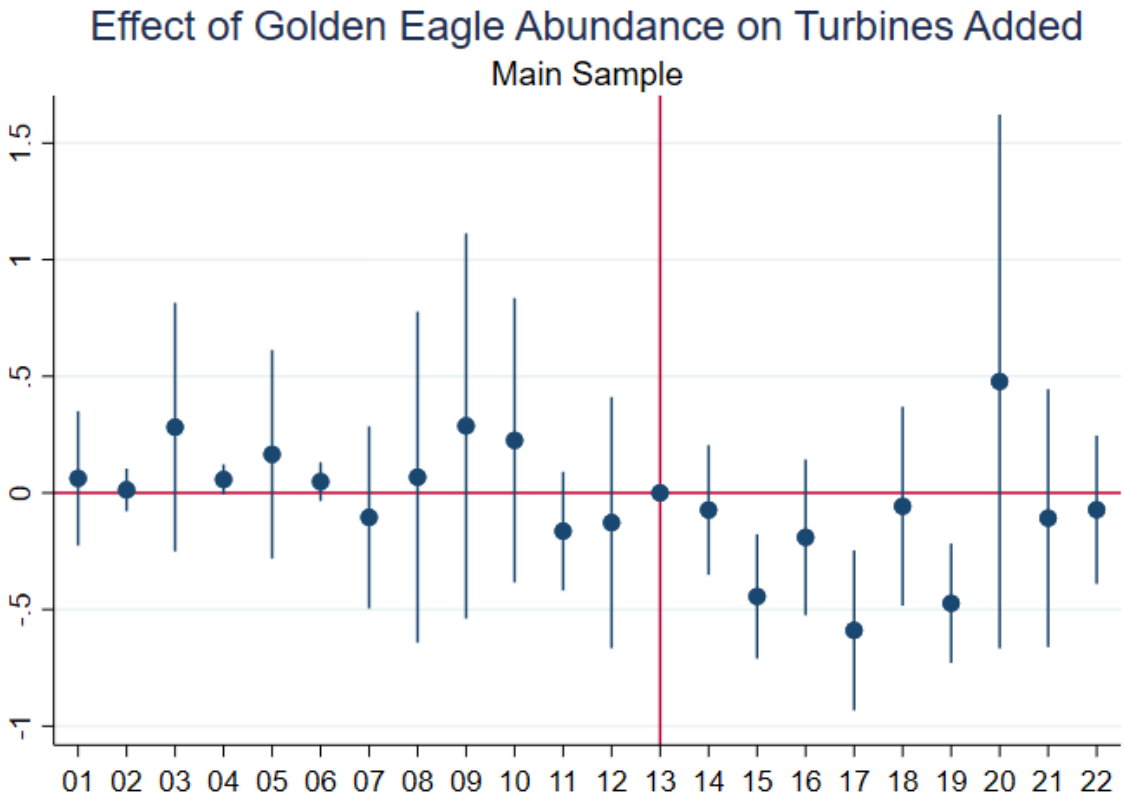

Figure C.3: Continuous Treatment Event Study, Turbines Added

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
Post * Rel. Abun. * 100	-0.514**	-0.702**	-0.836***
	(0.228)	(0.274)	(0.309)
Wind Speed * t		0.438***	
		(0.117)	
Potential Cap. * t		0.00665***	
		(0.00191)	
Transmission Dist. * t		-0.00676***	
		(0.00162)	
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: This table shows the results of the robustness check specifications demonstrated in 4.5 and 4.6 applied to the continuous treatment specification of C.1. Column (1) reiterates the baseline results for the added capacity specification from C.1. Column (2) shows the results from the model where wind speed, potential capacity, and distance to transmission networks are interacted with linear time trends. Here, a 0.01 increase in county average golden eagle relative abundance is significantly associated with a 0.7 MW decline in expected capacity additions. Column (3) shows the results from the model where these same characteristics are interacted with year fixed effects. In this specification, a 0.01 increase in county average relative abundance is significantly associated with a 0.8 MW decline in expected wind capacity additions.

Figure C.4: Robustness Checks: Characteristics Over Time, Continuous Treatment

	(1) Added Capacity	(2) Added Capacity
Post * Rel. Abun. * 100	-0.514**	-0.632*
	(0.228)	(0.333)
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: This table shows the results of the state-year fixed effects specification demonstrated in 4.7 applied to the continuous treatment model of C.1. Column (1) reiterates the baseline continuous treatment results for added capacity shown in table C.1. Column (2) includes state-year fixed effects. In this model, a 0.01 increase in county average golden eagle relative abundance is significantly associated with a 0.6 MW decline in expected wind capacity additions.

Figure C.5: Robustness Checks: State-Year Fixed Effects, Continuous Treatment

APPENDIX D

DECILE TREATMENT SPECIFICATION

In this specification, I follow the same procedure as the conditional quartile specification with ten treatment groups. While this analysis is limited by small sample sizes within decile treatment groups, it is useful for illustrating the distribution of the effects of the policy.

The regression specification is the following:

$$y_{it} = \sum_{n=1}^{10} (\beta_n (Post2013_t * Decile_{i,t})) + \gamma_i + \delta_t + \epsilon_{it} \tag{D.1}$$

Figure D.1 graphically shows the results of this specification. Only the highest exposure groups show a significant effect of the policy. These results are therefore significant with the interpretation that BGEPA enforcement significantly reduces wind turbine development, but only for high-exposure areas.

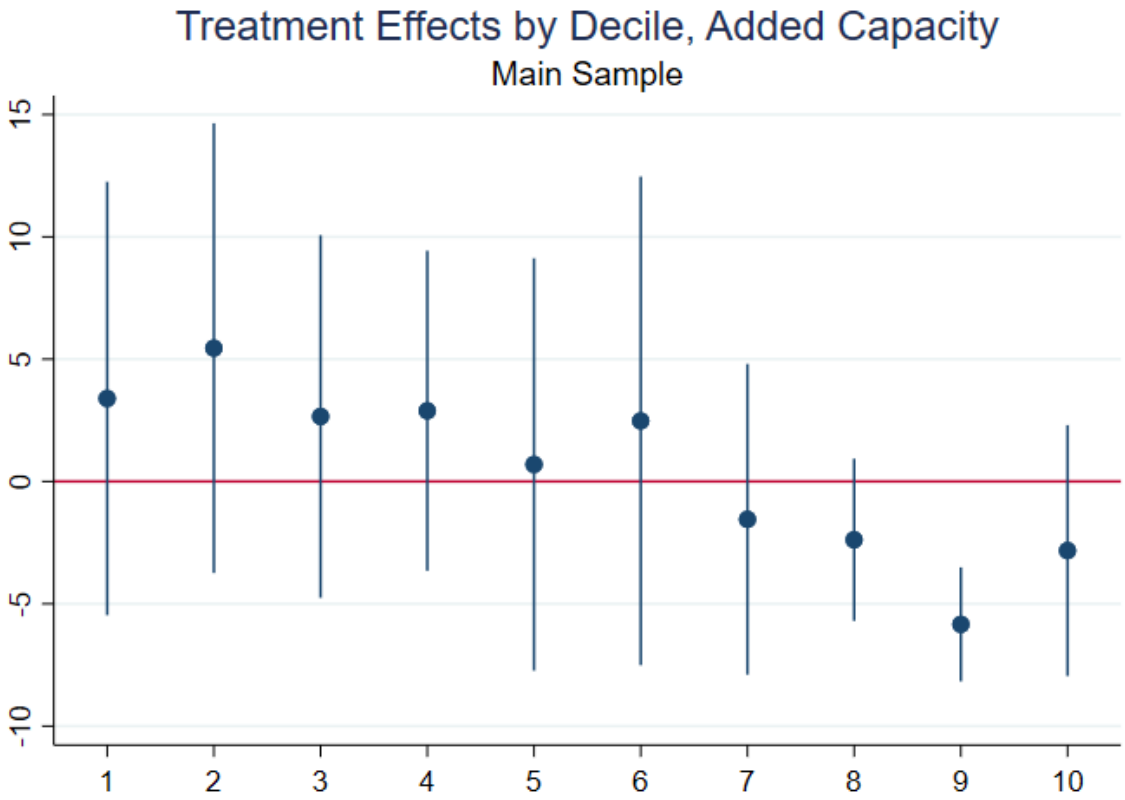

Figure D.1: Conditional Decile Treatment Results

APPENDIX E

FLEXIBLE CONTROLS SPECIFICATION

As an extension on specifications 4.5 and 4.6, I perform another specification that interacts binned wind speed, potential capacity, and distance to transmission characteristics with year fixed effects. This potentially improves on the previous specifications by relaxing the assumption that wind speed, potential capacity, and transmission distance have linear impacts by year on wind turbine development. Furthermore, with these fixed effects, the remaining identifying variation comes from county-years of counties in similar characteristic groups, mitigating concerns about the lack of balance in potential capacity and transmission distance in the sample.

The regression equation for the baseline binary treatment specification is the following:

$$\begin{aligned} y_{it} = \beta(Post2013_t * I(RelAbun > 0.025)_i) + \sum_{n=1}^{10} WindSpeedDecile_{i,n} * \delta_t \\ + \sum_{n=1}^{10} PotCapDecile_{i,n} * \delta_t \\ + \sum_{n=1}^{10} TransDistDecile_{i,n} * \delta_t \\ + \gamma_i + \epsilon_{it} \end{aligned} \tag{E.1}$$

Results for added capacity as the outcome variable are shown alongside baseline results in table E.1. The significance of the results is robust, and the size of the point estimates are larger in this specification. This specification suggests that the findings are not driven by differential wind capacity growth rates by cross-sectional characteristic group.

	(1) Added Capacity	(2) Added Capacity
Post * I(Rel. Abun. > 0.025)	-3.776***	-5.517***
	(1.369)	(2.136)
County FE	Yes	Yes
Year FE	Yes	Yes
Flexible Controls	No	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 flexible control specification E.1 in the main sample. Column (1) reiterates the baseline binary treatment results from table 5.1. Column (2) shows the results of model E.1. In this specification, counties with an average golden eagle relative abundance value above 0.025 experienced a significant decline in expected wind capacity additions of 5.5 MW.

Figure E.1: Flexible Control Specification Results

APPENDIX F

POISSON ROBUSTNESS CHECKS

The baseline linear regression models impose a parallel trends assumption. While there are reasons to accept this assumption and robustness checks that attempt to address potential imbalances between treated and control counties discussed in section 4, Poisson regression specifications may provide a reasonable, alternative set of assumptions. In a difference-in-differences setting, Poisson regressions impose a parallel proportional trends assumption. This imposes that the ratio of the mean outcomes between treated and control groups would have remained constant over time in absence of the treatment policy. This assumption is potentially more flexible than the linear parallel trend assumption in allowing for differential wind capacity growth trajectories, and for trends that may appear linearly parallel in early stages due to low development that might nevertheless have diverged regardless of BGEPA enforcement.

Poisson results for the baseline binary treatment specification shown in equation 4.2, the conditional quartile treatment model shown in equation 4.4, and the continuous treatment model shown in equation C.1 are given in table F.1. In the baseline model, counties with an average golden eagle relative abundance above 0.025 experienced a 38% decrease in capacity additions relative to counties with average golden eagle relative abundance below 0.025 over the BGEPA enforcement period, although this effect is not statistically significant. In the quartile model, counties in the highest exposure quartile experienced a significant 43% decrease in expected capacity additions over the BGEPA enforcement period relative to counties with a mean golden eagle relative abundance below 0.001. In the continuous treatment model, an increase of 0.01 in county average golden eagle relative abundance is significantly associated with a 6% decrease in expected wind capacity additions following 2014. While the baseline binary treatment model results lose statistical significance, the quartile and continuous treatment model results still support the interpretation that BGEPA enforcement reduced wind development for high-exposure counties.

	(1) Added Capacity	(2) Added Capacity	(3) Added Capacity
Post * I(Rel. Abun. > 0.025)	-0.479		
	(0.301)		
Quartile 1 * post		0.406	
		(0.339)	
Quartile 2 * post		0.488	
		(0.411)	
Quartile 3 * post		0.292	
		(0.485)	
Quartile 4 * post		-0.566*	
		(0.302)	
Post * Rel. Abun. * 100			-0.0611*
			(0.0354)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cluster	County	County	County
N	7854	7854	7854

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: This table shows the results of Poisson regression specifications for the baseline model 4.2, the conditional quartile treatment model 4.4, and the continuous treatment model C.1. Poisson regressions with fixed effects were implemented using the Stata ppmlhdfe package (Correia, Guimarães, & Zylkin, 2020). Column (1) shows the results of the baseline binary treatment model. Interpreting the Poisson coefficient, counties with an average golden eagle relative abundance greater than 0.025 experienced a $e^{-0.497} - 1 = 38\%$ decrease in capacity additions relative to counties with an average relative abundance below 0.025 over the BGEPA enforcement period, although this effect is not statistically significant. Column (2) shows the results of the quartile treatment specification. While quartiles 1-3 did not experience significant effects, counties in the highest exposure group experienced a significant $e^{-0.566} - 1 = 43\%$ decrease in wind capacity additions relative to counties with an average golden eagle relative abundance below 0.001. Column (3) shows the results of the continuous treatment specification. An increase in county average golden eagle relative abundance is significantly associated with a significant $e^{-0.061} - 1 = 6\%$ decrease in expected wind capacity additions in the BGEPA enforcement period. The number of observations per specification decreased relative to the baseline regression specifications due to counties with no wind turbine development in either period, which are separated by fixed effects and therefore excluded in the Poisson estimation.

Figure F.1: Robustness Checks: Poisson Specifications

APPENDIX G

TURBINE ROBUSTNESS CHECKS

In this appendix, I present the results of robustness check specifications 4.5, 4.6, and 4.7 with added turbines in the outcome variable. These are excluded from the main paper due to the similarities of the results. Table G.1 shows the results of equations 4.5 and 4.6 with binary treatment and added turbines as the outcome variable. Table G.2 shows the results of equation 4.7. Tables G.3 and G.4 show the results of the same robustness check specifications applied to the conditional quartile model, respectively.

	(1) Added Turbines	(2) Added Turbines	(3) Added Turbines
Post * I(Rel. Abun. > 0.025)	-1.518**	-1.656*	-2.057**
	(0.618)	(0.854)	(0.891)
Wind Speed * t		0.166***	
		(0.0521)	
Potential Cap. * t		0.00230**	
		(0.000901)	
Transmission Dist. * t		-0.00248***	
		(0.000712)	
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: This table shows the results of robustness check specifications 4.5 and 4.6 for the added turbines outcome variable. Column (1) reiterates the baseline results for added turbines shown in table 5.1. Column (2) shows the results of the specification where county average wind speed, potential capacity, and distance to transmission are interacted with linear time trends. In this model, counties with an average golden eagle relative abundance greater than 0.025 experienced a significant decline in expected wind turbine development of 1.6 turbines. Column (3) shows the results of the specification where these same county characteristics are interacted with year fixed effects. Here, counties with a golden eagle relative abundance greater than 0.025 experienced a significant decline in expected wind development of 2.1 turbines.

Figure G.1: Turbine Robustness Checks, Characteristics Over Time

	(1) Added Turbines	(2) Added Turbines
Post * I(Rel. Abun. > 0.025)	-1.518**	-1.110
	(0.618)	(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: This table shows the results of robustness check specification 4.7 for the turbines added outcome variable. Column (1) reiterates the baseline results from table 5.1. Column (2) shows the results when controlling for state-year fixed effects, where counties with a relative abundance above 0.025 experienced a decline in expected wind development of 1.1 turbines over the BGEPA enforcement period. While this effect is not significant, the sign and size remain similar to the baseline specification.

Figure G.2: Turbine Robustness Checks, State-Year FE

	(1) Added Turbines	(2) Added Turbines	(3) Added Turbines
Quartile 1 * post	1.983	1.789	1.549
	(1.237)	(1.210)	(1.182)
Quartile 2 * post	2.066	2.131	1.724
	(1.316)	(1.314)	(1.418)
Quartile 3 * post	0.269	0.918	0.538
	(1.121)	(1.231)	(1.376)
Quartile 4 * post	-1.516***	-1.526*	-1.999**
	(0.569)	(0.902)	(1.018)
Wind Speed * t		0.136**	
		(0.0540)	
Potential Cap. * t		0.00226**	
		(0.000897)	
Transmission Dist. * t		-0.00303***	
		(0.000787)	
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: This table shows the results of robustness check specifications 4.5 and 4.6 for the added turbines outcome variable in the conditional quartile treatment model. Column (1) reiterates the baseline results for added turbines shown in table 5.6. Column (2) shows the results of the specification where county average wind speed, potential capacity, and distance to transmission are interacted with linear time trends. In this model, counties in the lowest three quartile groups experienced no significant effects of BGEPA enforcement on turbine additions. Counties in the highest relative abundance quartile experienced a significant decline in expected turbine additions of 1.5 turbines. Column (3) shows the results of the specification where these same county characteristics are interacted with year fixed effects. Here, counties in the highest exposure quartile experienced a significant 2 turbine decline in expected turbine additions.

Figure G.3: Turbine Robustness Checks, Characteristics Over Time, Quartile Model

	(1) Added Turbines	(2) Added Turbines
Quartile 1 * post	1.983	1.819
	(1.237)	(1.272)
Quartile 2 * post	2.066	1.709
	(1.316)	(1.410)
Quartile 3 * post	0.269	-0.537
	(1.121)	(0.956)
Quartile 4 * post	-1.516***	-0.276
	(0.569)	(0.965)
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: This table shows the results of robustness check specification 4.7 for the turbines added outcome variable in the conditional quartiles treatment model. Column (1) reiterates the baseline results from table 5.6. Column (2) shows the results when controlling for state-year fixed effects. Here, no county groups show statistically significant effects, although quartiles 3 and 4 retain negative treatment effect point estimates.

Figure G.4: Turbine Robustness Checks, State-Year FE, Quartile Model

APPENDIX H

ESTIMATION PROCEDURES

Foregone Electricity Valuation: Electricity Added Method

To value the electricity generation foregone as a result of BGEPA enforcement, I 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), I estimate that 420 MW of capacity would have output 128,700 MWH/month.

To value this level of output, I obtained electricity price information from publically-available EIA datasets. I 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 $128,700$ MWH/month $*$ 12 months/year $*$ $92.18/MWH, which is equal to $142 million per year.

Foregone Electricity Valuation: Emissions Displaced Method

As an alternative to the above method, I 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, I first use the same steps shown in the previous method to arrive at an estimate of 128,700 MWH/month of electricity generation. Multiplying this by 12 yields a result of 1,544,400 MWH/year, or equivalently, 1,544,400,000 KWH/year.

I 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. I then multiply this by the 1,544,400,000 MWH/year displaced generation estimate for a total of 1,094,979 tons of Co2/year.

Finally, I apply the current social cost of carbon, which is $51 per ton of Co2 (Hersher, Scott, Ramirez, & Cirino, 2023). Multiplying this by the annual Co2 estimate yields a total valuation of approximately $56 million per year.

Eagle Valuation from ESI Energy Case

To obtain the implicit eagle life valuation from the ESI energy case, I combined USFWS predicted mortality measures with costs levied against ESI as a result of the case. I 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, I obtain a predicted mortality value of 12.6 golden eagles per year.

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

$$\$1,861,600 \text{ Fine} \tag{H.1}$$

$$+\$6,210,991 \text{ Restitutions} \tag{H.2}$$

$$+\$27,000,000 \text{ Compensatory Mitigation} \tag{H.3}$$

$$= \ \$35,072,591 \text{ Total Fixed Cost} \tag{H.4}$$

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

$$\$29,623/\text{Golden Eagle} \tag{H.5}$$

$$*12.6 \text{ Golden Eagles/Year} \tag{H.6}$$

$$= \$355,476 \ /\text{Year} \tag{H.7}$$

To calculate the total per-eagle cost across the lifetime of the wind facility, I use a standard 20-year lifetime assumption for the wind facilities. Without using present values, the simple calculation becomes the following:

$$(FC + VC_{\text{Annual}} * 20 \text{ Years})/(20 \text{ Years} * 12.6 \text{ Golden Eagles/Year}) \tag{H.8}$$

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

Eagle Mortality Estimation

Golden eagle wind turbine mortality can be estimated based on 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, I 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:

$$F = C\lambda\epsilon \tag{H.9}$$

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:

$$C \sim \beta(1.29, 227.6) \tag{H.10}$$

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:

$$\lambda \sim \Gamma(0.287, 0.237) \tag{H.11}$$

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

Finally, hazardous footprint ϵ is defined as follows:

$$\epsilon = \tau n h \pi r^2 \tag{H.12}$$

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,[1] and r represents the radius of the circular area of a wind turbine's blades. The

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

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.

I 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. I first assume 12 daylight hours per day, for a total of 4380 daylight hours per year for τ. To estimate the number of turbines, I take the coefficient -1.52 from the baseline binary treatment model with turbine additions as the outcome variable. I multiply this by the 111 treated counties to obtain a total of 168 foregone turbines. For the remaining variables, I take averages of turbine specifications found in USTWDB data. To represent average wind turbines constructed in the post-BGEPA enforcement period, I filtered USWTDB data to years after 2013. This resulted in the following parameters:

$$\tau = 4380 \tag{H.13}$$

$$n = 168 \tag{H.14}$$

$$h = 0.14km \tag{H.15}$$

$$r = 0.06km \tag{H.16}$$

I 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 7.6 golden eagle fatalities per year.