Chicken and Egg: Electricity Transmission and Investment in Renewable Energy*

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Abstract

I study the impact of grid expansion on long-run renewable investment spillovers in wholesale electricity markets. Using a discrete choice model of wind project location and a Difference-in-Difference design, I analyze a large-scale grid expansion project in Texas. Results show $1.71 billion per year in lower emissions and $11 million in increased annual payments to landowners due to wind investments in areas with grid infrastructure. However, localized wind investments coupled with limited transmission capacity have led to rising curtailments in recent years. This highlights the need for a long-term planning approach to transmission policy, which is essential for achieving decarbonization.

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1 Introduction

Massive investment in high-capacity electricity transmission lines is crucial for achieving rapid decarbonization (Larson et al. 2021). In the US, most renewable energy is generated far from the demand centers, necessitating high capacity transmission lines to connect supply with demand. Investments in grid expansion can also accelerate the energy transition. However, the important spillover effect of transmission expansion on renewable generation markets remains an understudied topic in economics (Davis, Hausman, and Rose 2023).

In this paper, I provide the first causal estimates of the effect of transmission expansion on long-term investment in renewable energy. However, a classic *chicken-and-egg* problem exists with transmission planning: building new transmission depends on generation, while new generation is dependent on the availability of transmission capacity (Renewable Energy World 2007). Texas addressed this problem in 2008 by announcing a massive grid expansion project aimed at integrating the growing wind generation in West Texas to the demand centers in the East (Lasher 2008). Thus, this context offers an excellent opportunity to study the research question.

I answer this question using a unique combination of model and design based approaches. I first use a discrete choice model to estimate the likelihood of siting a wind project in locations with grid expansion. Next, I use a Difference-in-Difference strategy to examine whether locations with grid expansion receive higher levels of wind investment than those without. I then use results from both approaches to quantify the social benefits due to lower emissions and the private benefits due to higher lease payments to landowners.

I leverage rich spatial and temporal data from the rollout of a large-scale transmission expansion project called Competitive Renewable Energy Zones (CREZ) in Texas. I combine spatial data from the Public Utilities Commission of Texas on locations announced to site grid infrastructure in 2008 with wind project data from EIA Form 860, detailed wind resource quality data from NREL, and land characteristics from USDA and the Real Estate Center at Texas A&M University.

I develop a model of location choice where a wind developer selects a project site to maximize profits. The model shows that, conditional on wind resource quality and site characteristics, locating near transmission infrastructure minimizes costs for the project. I take this model to the data and use a conditional logit model (McFadden 1974) to estimate the probability of locating in a county with CREZ transmission. This analysis uses data on all utility-scale wind projects in Texas that began operation from 2000 to 2020.

Results of the conditional logit model show that wind projects were 20 percentage points, or 46 percent, more likely to locate in a CREZ county than in other locations. Coefficient estimates imply a willingness to pay (WTP) of $1,137 per acre or $2,808 per MW of wind capacity to locate in these areas. This WTP is almost twice the annual average lease payment that wind projects pay to landowners for a MW of wind capacity in the US (Center for Sustainable Systems 2023). For an average wind project of 146 MW, these results translate to approximately $12.3 million in higher payments to landowners over the 30-year lifespan of the project.

I conduct a variety of heterogeneity analyses. The results show a positive relationship between project size and the likelihood of choosing a CREZ county. Interestingly, wind projects have become less likely to site in CREZ locations in recent years due to increasing congestion in these regions. In 2020, projects were 12 percentage points less likely to select CREZ locations compared to other areas. Finally, I find that the baseline results are robust to changes in choice set construction in the logit model.

Next, I use a difference-in-differences analysis in an event study framework to estimate whether counties announced for transmission infrastructure siting see higher wind investments over time. I employ the Callaway and Sant'Anna (2021) estimator to account for potential bias in the Two Way Fixed Effects estimator in cases of treatment effect heterogeneity and staggered treatment adoption. I use Coarsened Exact Matching to address the lack of common support in conditioning covariates in the regression specification. This matching step creates a set of counties that are comparable across a wide range of characteristics: wind resource quality, terrain characteristics, and land value

The event study indicates that locations with CREZ infrastructure saw higher levels of wind investment compared to other locations. Results also suggest a lagged effect in the materialization of wind investments post transmission announcement. The aggregate treatment effect using the Callaway and Sant'Anna (2021) estimator is about 100 MW of greater annual wind investment. This effect is 1.08 standard deviations of the wind capacity in control counties. This result is robust to several threats to identification and specification checks. This include selection into treatment due to lobbying efforts for or against siting CREZ transmission, investment spillovers to control counties, anticipation of CREZ announcement, and placebo test using canceled CREZ locations as treatment.

The wind investment driven by transmission expansion in Texas resulted in significant public benefits from lower emissions and private benefits to landowners through higher lease payments. A back of the envelope calculation shows that this wind investment prevented approximately $1.71 billion worth of emissions annually. Combining the willingness to pay estimates from the conditional logit model with the aggregate treatment effects from the event study analysis, I find that annual payments to landowners in the CREZ counties are approximately $11 million higher than in other locations.

The findings from this paper offer insights into renewable generation investments due to transmission expansion in other wholesale markets, such as the Southwest Power Pool and Midwest ISO. Recently, an increasing number of renewable projects have been dropping out of development due to inadequate transmission capacity and long interconnection wait times in these markets (Penrod 2022). Investing in high capacity transmission lines could address some of these issues. However, grid expansion projects are large capital investments, paid ultimately by the ratepayers. The CREZ project cost about

$6.8 billion and generated over $1.72 billion in annual public and private benefits, translating to a payback period as short as four years. Ignoring these long-run benefits can vastly understate the true benefits of transmission expansion.

One consequence of localized wind investment and limited transmission capacity is the increasing wind curtailments observed over the last few years. Regression estimates suggest average hourly curtailment of 120 MW during the periods of high wind generation in the West region of Texas in 2020. These curtailments translate to about $156 million in excess annual carbon and local emissions, partially offsetting some of the benefits. This finding underscores the importance of a long-term approach to transmission planning that considers these localized long-run investment responses.

Related Literature. Electricity grid expansions are major policy undertakings, often costing billions of dollars and several years of planning. This paper examines the impact of transmission projects on long-run renewable investment. Thus, more broadly this paper contributes to the extant literature focusing on the effects of energy policies on renewable investment (Metcalf 2010; Bento, Garg, and Kaffine 2018; Johnston 2019; Butters, Dorsey, and Gowrisankaran 2021; Holland, Mansur, and Yates 2022; Aldy, Gerarden, and Sweeney 2023; Feldman and Levinson 2023; Gonzales, Ito, and Reguant 2023; Fullerton and Ta, forthcoming).

This paper also builds upon the literature on the effects of market integration in wholesale electricity markets (Borenstein, Bushnell, and Stoft 2000; Joskow and Tirole 2000, 2005; Mansur 2007, 2008; Borenstein et al. 2008; Borenstein and Bushnell 2015). Previous studies have mainly focused on the fossil fuel sector without the entry of renewable firms over time. By examining investment spillovers in the increasingly significant renewable sector, I contribute to an area with relatively sparse economics research (Davis, Hausman, and Rose 2023).

A related strand of literature examines the interaction between transmission constraints and allocative efficiency in electricity markets due to changes in market structure (Bushnell, Mansur, and Saravia 2008; Woerman 2023; Cicala 2022). In contrast, I analyze the investment effects of electricity transmission expansion while keeping the market structure fixed. This allows me to isolate the impact of transmission expansion from changes due to changes in market structure or dispatch mechanism.

This paper also contributes to the nascent literature on the market and environmental impacts of transmission expansion. For instance, Ryan (2021) studies the impact of transmission expansion on market power in the Indian electricity market. My study uses the data and context of a large scale grid expansion in Texas. A number of recent papers have examined the impact of transmission expansion in the similar context. These studies examine the effect of transmission expansion on lower wholesale prices (LaRiviere and Lyu 2022), decline in emissions due to lower congestion (Fell, Kaffine, and Novan 2021), and reduction in fossil fuel market power due to integration of wind generation (Doshi 2024). While recent studies have primarily focused on short-run outcomes, I add to this literature by looking at investment decisions of wind developers.

Finally, my study is most closely related to Gonzales, Ito, and Reguant (2023). The authors look at the anticipatory investment in utility scale solar energy and wholesale prices in response to transmission line expansion in the Chilean electricity market. While I focus on investment in utility scale wind energy, my paper differs from theirs in two key aspects. Methodologically, I model the entry decision of wind projects using a discrete choice framework. Additionally, I use a Difference-in-Difference analysis which allows me to quantify both the public benefits due to lower emissions and private benefits to landowners, a novel contribution to the literature. Further, I also provide the first evidence of increasing curtailments due to localized wind investments and fixed transmission capacity.

The remainder of this paper is organized as follows. Section 2 describes the institutional context and Section 3 describes the data and shows some descriptive statistics. I present the theoretical model of wind project location choice in Section 4 and Section 5 takes this model to the data. Section 6 presents the event-study analysis of wind investment in response to transmission expansion. Section 7 provides evidence of rising wind curtailment and Section 8 concludes.

2 Institutional Details

2.1 The Texas Electricity Market

The Texas electricity market is one of the major deregulated wholesale electricity markets in the US, managed by the Electric Reliability Council of Texas (ERCOT) as its independent system operator. ERCOT operates separately from the Western and Eastern interconnections, the other two major interconnections in the US. Most of Texas's wind capacity is concentrated in the highly wind productive West and Panhandle regions, while the majority of fossil fuel power plants are situated in the East and South, near the major demand centers.

Due to the deregulated nature of the market, the generation/supply side comprises of a high proportion of independent power producers (IPPs). These are independent firms that build and operate their own power plants. In Texas, IPPs are responsible for building most of the wind projects, consistent with the pattern across the US (Doshi and Johnston 2024). Electricity transmission is owned and operated by non-profit public utilities known as Transmission Service Providers (TSPs), which are regulated by the Public Utilities Commission of Texas (PUCT). TSPs are responsible for the transmission and distribution of electricity from generation to demand centers. They also oversee maintenance and expansion of the electricity grid in coordination with ERCOT and PUCT.

2.2 Competitive Renewable Energy Zones

The Competitive Renewable Energy Zones (CREZ) was a large-scale transmission expansion project aimed at integrating electricity generation from wind farms in West Texas with the major demand centers in the East. The Public Utilities Commission of Texas (PUCT) announced CREZ in 2008 following a multi-year process to identify the locations and scale of the necessary transmission investments (NREL 2008). The project involved constructing approximately 3,600 miles of 345 kV transmission lines between new substations across the Panhandle, West, and East Texas, at a projected cost of $4.95 billion (PUCT 2009). The transmission lines were built over a period of 2011 through 2013 with a realized cost of approximately $6.8 billion (Lasher 2014).

ERCOT worked with several Transmission Service Providers to identify potential routes for the proposed transmission lines and associated infrastructure. ERCOT adopted an incremental approach to transmission planning, effectively overlaying the new CREZ lines on the existing grid in West Texas. In other words, the new system was not even indirectly connected to the existing grid in West Texas. This system was designed to prevent widespread congestion and overloads in the existing low-voltage system due to the increased wind generation in the West and Panhandle regions (ERCOT 2008). I exploit this feature of the CREZ project development to compare locations that received CREZ infrastructure investments (treatment group) with with other locations (control group) in the existing transmission network.

2.3 Wind Project Development

Developing a wind project is a multi-step process that typically takes about 3-4 years, depending on market conditions (AWEA 2019). The initial steps involve wind resource assessment and land permitting. Wind resource assessment is essential to determine the economic viability of a site. It is also informative about future decisions on the type of technology (such as turbine model) and project financing. Land permitting and acquisition involves acquiring the necessary rights and permits to build a project at a specific location. This includes getting permits from the respective local (e.g., county and municipality) and state authorities (WindExchange (DOE EERE), n.d.). In Texas, siting of wind projects is regulated at the county level and there are very few counties with restrictions on development of wind projects (Enterline, Valainis, and Hoen 2024).

After resource analysis and permitting, the next step is entering the interconnection queue. This entails conducting necessary interconnection studies to determine whether the grid can support the project and to identify the equipment needed to connect the project to the grid (Johnston, Liu, and Yang 2023). Often concurrently, projects seek financing and power purchasers or offtakers. Projects may choose to sell their power directly into the wholesale market or sign a long-term contract(s) with a potential buyer(s). Project financing is crucial for the subsequent procurement of wind turbines and construction, after which the project typically operates for about 25 to 30 years. A schematic of these steps with an approximate timeline is shown in Appendix Figure E1.

3 Data and Descriptive Statistics

3.1 Data

I use data on all utility-scale wind projects in Texas from 2001 to 2020 from the Energy Information Administration (EIA) Form 860. This data includes information on generator characteristics, such as nameplate capacity (MW), location, and year of operation for all generators greater than 1 MW in size. I combine this data with detailed information on wind resource quality at the project location from the National Renewable Energy Laboratory's Wind Integration National Dataset (Draxl et al. 2015). This dataset includes wind speed, capacity factor, and site-specific wind turbine class rating for 2 km x 2 km grid cells for all potential wind energy sites across the US.

To identify locations selected to site CREZ transmission lines and substations, I utilize ERCOT's Transmission Project and Information Tracking and supplement this with information from the Public Utilities Commission of Texas. The data only indicates the counties where these substations are located, so I refer to them as "CREZ counties."[1]

Local governments often enact regulations to restrict or regulate the siting of wind projects in their jurisdictions. These regulations, commonly known as setbacks or wind ordinances, specify limits on factors such as turbine size, height, noise, and maximum capacity. In Texas, all permitting and siting of wind projects occur at the local level (Enterline, Valainis, and Hoen 2024). I collect data on the presence of wind ordinances from the Department of Energy's WINDExchange Ordinance Database and hand-collect data for counties with missing information.[2]

Additionally, I collect various county-level data on land value and characteristics. This includes data on median and average farm value ($ per acre) and average farm size (acres) from the USDA Census of Agriculture for the years 2002, 2007, 2012, 2017, and 2022. I linearly interpolate to construct annual values from 2001 to 2020. As another measure of land value, I use data on average rural land prices ($ per acre) based on annual land transactions from the Real Estate Center at Texas A&M University.[3] Finally, using 30m $\times$ 30m grid data from the National Elevation Dataset, I construct measures of average elevation and terrain ruggedness, defined as the standard deviation of elevation for each county.

1. These substations serve as terminal points for high-voltage transmission lines and hubs for nearby generating plants to deliver power to the grid. Exact substation locations are restricted for national security reasons.

2. Most Texas counties do not have wind ordinances for wind projects. Out of 254 counties, I find that only five counties (Dallas, Ellis, Kleberg, Taylor, and Wichita) have enacted wind ordinances for both small and large wind projects. Land use restrictions in wind ordinances can affect investment in wind energy and may correlate with the siting of transmission infrastructure.

3. The average rural land price per acre is the four-quarter moving average of the median prices per acre. Regional prices per acre are weighted by markets segmented by property size. Figure E2 in Appendix shows the seven land market regions defined by the Real Estate Center at Texas A&M University (Texas Real Estate Research Center, n.d.).

3.2 Descriptive Statistics

Table 1 presents the summary statistics of key variables used in the empirical analysis, categorized by county type. On average, CREZ counties exhibit higher wind speeds and greater productivity. They are also situated at higher elevations but are slightly more rugged (measured by standard deviation of elevation) compared to non-CREZ counties. Land is cheaper in CREZ counties, as evident from lower farm values and land prices. The large standard deviation in farm variables in non-CREZ counties also indicates significant heterogeneity across counties in East and South Texas. Lastly, both types of counties have a low prevalence of wind ordinances.[4]

Table 1: Summary Statistics

	CREZ Counties		Other Counties	
	Mean	Std. Dev.	Mean	Std. Dev.
Wind Speed (m per s)	7.92	0.46	7.35	0.67
Capacity Factor	0.45	0.03	0.41	0.05
Site-Specific Turbine Class Rating	2.00	0.46	3.00	0.50
Average Elevation (m)	585.36	292.93	396.52	375.44
Terrain Ruggedness	22.24	7.98	20.01	19.13
Average Land Price ($ per acre)	1465.08	1036.57	2195.14	1477.15
Average Farm Size (acre)	1649.55	2203.05	1814.65	4574.89
Median Farm Size (acre)	373.46	424.12	461.12	2056.91
Average Farm Value ($ per acre)	1686.15	1737.74	1860.85	1303.24
Wind Ordinance (0/1)	0.03	0.16	0.01	0.08

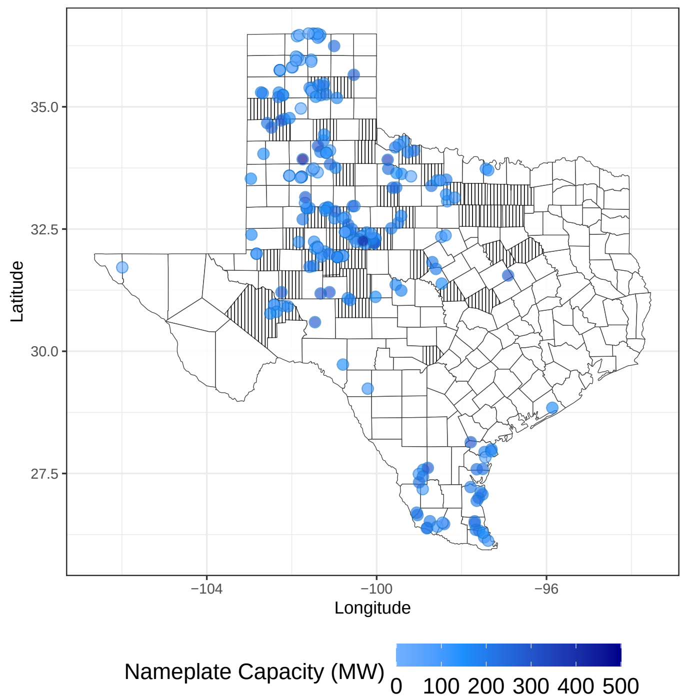
Notes: Sample is a balanced panel of all counties in Texas from 2001 to 2020, N = 5,313. CREZ Counties are the counties that had a substation as a part of CREZ Transmission Expansion.

Figure 1 shows a map of Texas with wind projects and the locations of CREZ substations. Two interesting observations emerge. First, there is a cluster of wind projects within and near CREZ counties, suggesting that the availability of transmission infras-

4. Table D1 in Appendix shows the summary statistics at the wind project level. Approximately 42 percent of projects are located in CREZ counties, with the average project size being 146 MW and a standard deviation of 90 MW.

tructure could have driven renewable energy growth in these areas. Second, there is another cluster of wind projects near the Texas Gulf Coastal region. These are some of the more recent wind projects, which may be indicative of developers shifting away from the West and Panhandle regions due to increasing congestion.

Figure 1: Wind Projects and CREZ Counties



Notes: This figure shows all wind projects in Texas greater than 1 MW in nameplate capacity (MW) that started operations in 2001 to 2020. Shaded counties are the counties with substations from CREZ expansion.

4 Theoretical Model of Wind Project Location Choice

In this section I develop a theoretical model of wind project location choice which serves as the microfoundation of the discrete choice model I estimate in Section 5. I make several assumptions in line with the institutional context to derive the location choice specification.

Wind developer i chooses location j to site its wind project in order to maximize the present value of annual profits. The static profits in year t of operations is given by:

$$\pi_{ijt} = p_{it}Q_{jt} - OM_{ijt} \tag{1}$$

where, p_{it} is the per MWh price for wind power received by project i in year t, Q_{jt} is the energy production from the project at location j in year t. Energy production is a function of wind resource quality, turbine technology, and the nameplate capacity of the project. OM_{ijt} is the annual operations and maintenance costs. Denoting r as the annual discount rate and T as the life of the project, the present value of expected profits is,

$$\Pi_{ij} = \sum_{t=1}^{T} \left(\frac{1}{1+r}\right)^{t} \mathbb{E}\Big[p_{it}Q_{ijt} - OM_{ijt}\Big] - F_{ij} \tag{2}$$

Equation 2 includes fixed costs incurred at the time of project siting st location j, denoted by F_{ij}. I make two simplifying assumptions to this microfoundation. First, I assume prices are location invariant. Developers often sign long-term contracts that fix the price per MWh of the output with pre-specified escalations to account for inflation. However, these off-take decisions and project financing occurs after site selection (AWEA 2019; Doshi and Johnston 2024). Second, I approximate the expected energy production as a flexible function of wind resource quality at site j. This resembles the resource assessment step of wind project development.[5]

Incorporating these approximations and dropping the time subscript, the profit function can be written as:

$$\Pi_{ij} = \gamma(r)\left[p_i f(wind_j) - \mathbb{E}[OM_{ij}]\right] - F_{ij} \tag{3}$$

5. In other words, I do not make any assumptions on the technology choice of the project. As outlined in Section 2.3, technology choice (turbine model) occurs after site selection and is often influenced by the chosen location, project size, and financing.

where $\gamma(r)$ is the geometric sum of discount rate i.e. $\gamma(r) = \frac{1}{r}\left(1 - \frac{1}{(1+r)^T}\right)$. OM_{ij} denotes the expected operations and maintenance (O&M) costs incurred in operating a wind project. Fixed costs F_{ij} includes site specific characteristics (e.g. local regulation, land value, terrain characteristics) that influence the costs of building a project.

4.1 Comparative Statics from the Model

The choice of optimal location l_j enters the profit function through wind resource quality and O&M costs at l_j. Access to transmission affects the location choice problem through its effect on fixed costs. The developer considers how far to locate from a substation and incurs cost as a function of the distance.[6] This can be shown by slightly modifying the profit function in Equation 3 as follows:

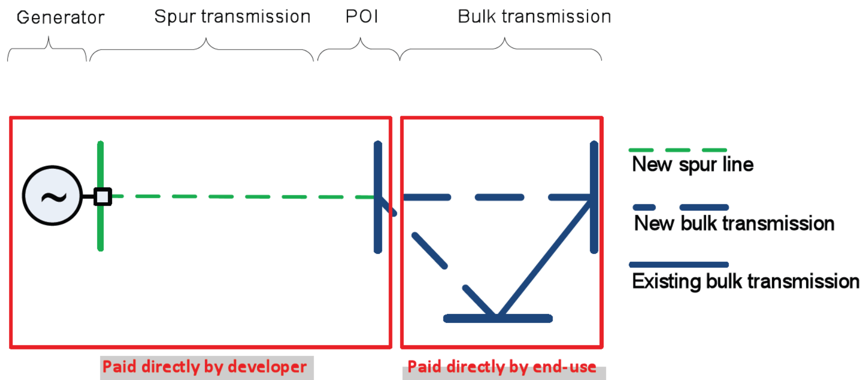
$$\Pi_i(l_j, \kappa) = \gamma(r)\left[p_i f(l_j) - \mathbb{E}[OM_i(l_j)]\right] - \underbrace{[C_i + \kappa \times l_j]}_{\text{fixed costs}} \tag{4}$$

where $f(l_j)$ is the wind resource quality at l_j and $OM_i(l_j)$ is the operations and maintenance costs at l_j. Fixed costs are combination of two main components. First is the cost incurred in purchasing wind turbines and building the wind project denoted by C_i. Second is the cost of constructing a spur transmission line at l_j, denoted by the product $\kappa \times l_j$ where κ is a positive cost multiplier.

Spur transmission line is a short transmission line that connects the generator to the bulk transmission grid (Andrade and Baldick 2016). The cost of building spur lines is borne by the developer of the project. The schematic in Figure 2 illustrates the cost allocation between spur transmission and bulk transmission between developer and end use consumers of electricity in Texas.

6. Electrical substations increase the voltage of electricity generated by power plants in order to make it efficient for transmission using long distance transmission lines. Therefore, these substations serve as the point of injection of electricity from the power plants into the grid.

Figure 2: Cost Allocation of Transmission Equipment in Texas Electricity Market



Notes: This figure illustrates cost allocation of transmission equipment in Texas for a new generation project. POI is the Point of Interconnection and typically comprises of connecting with a transmission substation which is part of the bulk transmission system. Source: Andrade and Baldick (2016)

The cost multiplier κ comprises of costs associated with building a unit length of spur line (of a specific voltage) at location j. These costs are mainly due to local land value and terrain features. In Texas, on average spur lines cost about \$1.114 million/mile for on-shore wind projects, borne entirely by the project developer (Andrade and Baldick 2016).

The indirect profit function corresponding to the optimal location l_j^* is,

$$\Pi_i^*(\kappa) = \Pi_i(l_j^*(\kappa)) = \gamma(r)\left[p_i f(l_j^*) - \mathbb{E}[OM_i(l_j^*)]\right] - \left[C_i + \kappa \times l_j^*\right] \tag{5}$$

Application of the envelope theorem on Equation 5 shows,

$$\frac{d\Pi_i^*(\kappa)}{d\kappa} = \frac{\partial \Pi_i^*(\kappa)}{\partial \kappa} \tag{6}$$

$$= -l_j^*(\kappa) \tag{7}$$

Equation 7 shows a negative relationship between the change in profit with respect to κ and the optimal location function $l_j^*(\kappa)$. In other words, everything else equal, increase in costs associated with building spur lines (κ) leads to a decline in optimal profits.

Thus, locating near the point of interconnection (substations) is cost minimizing for the developer.

4.2 Deriving the location choice problem

Denoting y as the year when the project makes the location choice, the utility specification for the choice problem corresponding to the profit function in Equation 4 is,

$$U_{ijy} = \beta \cdot f(wind_j) + \Lambda \mathbf{X}_{jy} + \epsilon_{ijy} \tag{8}$$

where $f(wind_j)$ is the flexible function of wind resource quality at site j. This function is an approximation of $\mathbb{E}(Q_j)$ during the site-selection process. The returns from location at a site with better wind quality is captured by the parameter β.

Vector $\mathbf{X}_{jy}$ includes for site-specific factors that affect project's O&M costs and fixed costs. This includes terrain characteristics and local regulations. Other than land lease and tax payments, most costs are project specific like purchasing turbines, costs of turbine operations and maintenance (Wiser, Bolinger, and Lantz 2019). These project specific costs are realized post site selection, and thus drop out from the location choice problem.

The location choice of a project is also dependent on the availability and access to transmission lines at site j. The final assumption in this microfoundation is that the local transmission network at any site j can accommodate the wind project in year y.[7] Since the CREZ transmission was overlaid on the existing transmission network (i.e. not directly connected with the existing network ERCOT (2008)), I use a binary indicator specifying whether location j received CREZ substation which serves as the point of

7. This assumption stems from ERCOT's interconnection policy of *connect and manage* which allows generators to connect to the grid by focusing on local upgrades instead of broader network upgrades. This has shown to accelerate the interconnection process in the Texas electricity market while connecting a large capacity of generation to the grid (Howland 2023).

interconnection for a project,

$$U_{ijy} = \underbrace{\alpha \cdot crez_{jy} + \beta \cdot f(wind_j) + \Lambda \mathbf{X}_{jy}}_{\delta_{jy}} + \epsilon_{ijy} \tag{9}$$

where $crez_{jy}$ is an indicator for the presence of a CREZ substation in location j and year y. Assuming errors follow Type 1 Extreme Value distribution, the probability of choosing location j from a choice set with J alternatives is:

$$\begin{aligned} Pr_{ij} &= \Pr(U_{ijy} \geq U_{ij'y},\ \forall\, j' \neq j) && (10) \\ &= \Pr(\epsilon_{ij'y} - \epsilon_{ijy} \leq \delta_{j'y} - \delta_{jy},\ \forall\, j' \neq j) && (11) \\ &= \frac{\exp(\delta_{jy})}{\sum_{j' \neq j} \exp(\delta_{j'y})} && (12) \end{aligned}$$

This is the model I estimate in Section 5.

5 Estimating the Location Choice Model

I estimate the utility model in Equation 9 using a conditional logit framework (McFadden 1974) and data on all utility scale wind projects in Texas from 2000 to 2020. Recall that the utility of a project i choosing location j in year y is,

$$U_{ijy} = \alpha \cdot crez_{jy} + \beta \cdot f(wind_j) + \Lambda \mathbf{X}_{jy} + \epsilon_{ijy} \tag{13}$$

where $crez_{jy}$ is an indicator for whether county j has a CREZ substation in year y when project i makes the location choice. $f(wind_j)$ flexibly controls for wind resource quality in county j (cubic spline of wind speed, capacity factor, and site specific turbine class rating).

Vector $\mathbf{X}_{jy}$ includes a wide variety of county and year of operation specific characteristics that can influence location choice. These variables include land price from housing market transactions ($ per acre), average and median farm size in a county (acre), average farm value in a county ($ per acre), local regulation (wind ordinance), terrain elevation, and terrain ruggedness measured by the standard deviation of terrain elevation.

In this model, a project's choice set consists of locations (counties) with similar wind resource quality and other site-specific characteristics. For each project, I use a K-Nearest Neighbor algorithm to construct a choice set of candidate counties with similar wind speeds, capacity factor, site specific turbine class rating, terrain ruggedness, terrain elevation, presence of local regulation (wind ordinance), average and median farm size, and average farm value.

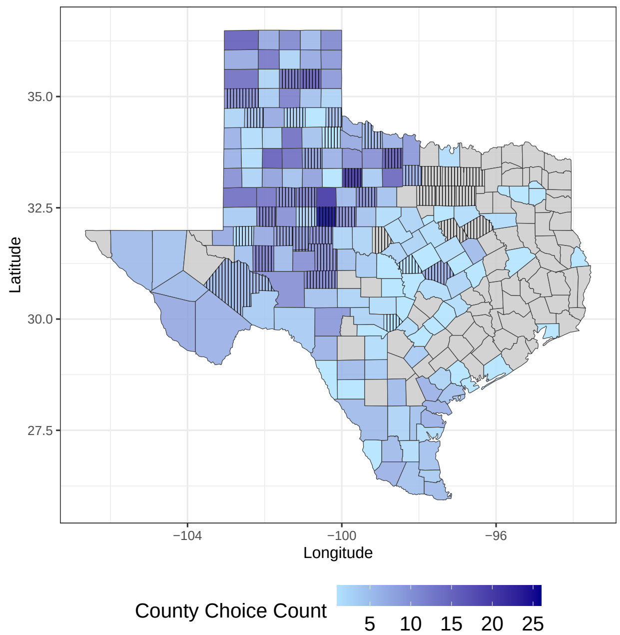
Figure 3 shows a heat map of counties across project choice sets when a project can choose from a set of 5 similar counties (i.e. setting K as 5 in the K-Nearest Neighbor Algorithm). While 168 distinct counties appear in the choice set across all the projects, counties in the Panhandle and the West appear most frequently across the choice sets.

5.1 Results

Table 2 shows the results of the conditional logit model of project location choice. Coefficient estimate of *crez* across all the specifications suggest that everything else equal, projects are more likely to select a CREZ county. This effect is robust across specifications that includes wide array of site-specific variables affecting project site selection.

The preferred specification in Column (4) suggests that a wind project is 20 percentage points more likely to site in a location with CREZ infrastructure. This specification includes the full set of controls accounting for variation affecting project site selection and CREZ transmission. This includes region fixed effects, variables measuring wind resource quality, land value, and regulations restricting development of wind projects.

Figure 3: Heat Map of Counties in Project Choice Sets



Notes: This figure shows a frequency map of counties appearing across wind project choice sets from K-Nearest Neighbor algorithm with K = 5 (i.e. a project can choose from a set of 5 counties). Darker shade indicates that a county appears in the choice set of multiple projects. Counties not part of any choice set are shown in grey. CREZ counties are shown in hash pattern.

Since the average probability of being located in a CREZ county is 0.42, this translates to a 47 percent effect.

Another way of interpreting these estimates is through the implied Willingness To Pay (WTP) to site a project in a CREZ county. A limitation in constructing WTP estimates in this setting is that I do not observe leasing prices or information on leasing contracts that wind projects sign with landowners. Instead, I use average farm value ($ per acre) from USDA as a proxy for value of land. The corresponding WTP is the ratio γ/α, where α is the coefficient of *crez* and γ is the coefficient for average farm value in Equation 13.

Using the coefficient estimates from Column (4) in Table 2, I find that compared to other locations, a wind project is willing to pay approximately $1,137 more per acre to site in a CREZ county. This WTP is about 60 percent of the average farm value ($1,952 per acre) over the period of the sample. Land use requirements for wind projects are project-

Table 2: Results of Conditional Logit Model of Wind Project Location Choice

	(1)	(2)	(3)	(4)
crez	0.866***	1.003***	1.068***	1.086***
	(0.178)	(0.186)	(0.212)	(0.212)
Wind Resource Controls	✓	✓	✓	✓
Region Fixed Effect		✓		✓
Site-specific Controls			✓	✓
Total Projects	206	206	206	206
Total Alternatives	168	168	168	168
Observations	1,030	1,030	1,030	1,030
Log Likelihood	-288.3	-272.5	-268	-262.1
Odds Ratio of *crez*	2.379	2.726	2.910	2.962
Average Marginal Effect	0.159	0.179	0.195	0.197

Notes: This table shows the coefficient estimates of conditional logit model of wind project location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. *crez* is an indicator for whether the chosen county has a CREZ substation. Wind Resource Controls include cubic spline of wind speed, capacity factor, and site-specific turbine class rating. Site-specific controls include average land prices, median farm acreage, average farm size (acre), median farm size (acre), average farm value ($ per acre), average and standard deviation of terrain elevation, and an indicator for presence of wind ordinance. Region Fixed Effect is a region specific indicator for West, Panhandle, East, and South regions. By design, each project faces a choice set of 5 distinct counties. Total Alternatives is the total number of distinct counties across all choice sets. Robust standard errors clustered at the project level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

and location-specific, with the exact area determined after site and turbine selection. With approximately 2.47 acres per MW required for siting wind turbines and other equipment (Department of Energy 2015), these estimates imply a WTP of approximately $2,808 per MW of wind capacity in CREZ locations.[8] Compared to the average annual lease payment of $3,000 per MW (Center for Sustainable Systems 2023), these results

8. Land area for wind projects is often difficult to predict beforehand and depends on various factors such as project size, land availability and cost, turbine size, and layout. There is also an important distinction between direct and indirect land use for wind projects. Direct use refers to land that is physically transformed for siting wind turbines and related infrastructure like access roads, turbine foundation, and tower. This area is permanently occupied for the life of a wind project and cannot be used for other purposes. According to (Department of Energy 2015), direct use area is estimated at 2.47 acres per MW, although this can vary by location and land-use definitions. Indirect use area refers to land not directly

suggest that wind developers are willing to pay almost double to site in CREZ locations. For an average project of about 146 MW in size and 30 years of operation, these estimates imply approximately $12.3 million in higher payments to the landowners.

5.2 Heterogeneity and Sensitivity Analysis

I conduct a variety of heterogeneity analyses along the dimensions of project size, time, phased extensions, and turbine model selections. I also test whether the baseline results are sensitive to changes in choice set construction.

The likelihood of choosing a location may vary by project size. To analyse this, I allow the utility specification in Equation 13 to vary by project size by including the interaction between *crez* and nameplate capacity. Larger wind projects also face higher costs of leasing land and other constraints to project development. Using nameplate capacity serves as a reasonable proxy because larger projects, on average, require more area. Therefore, I also include interactions of project capacity with farm value and farm size to account for variations in land cost by project area.

Table A1 in the Appendix shows the coefficient estimates of the corresponding conditional logit model, and Figure A1 shows the average marginal effect of *crez* by project capacity. Figure A1 indicates that larger projects are more likely to select locations with transmission expansion. For the preferred specification with full controls, the average marginal effect curve is an increasing function of nameplate capacity with a decreasing slope. This suggests that while larger projects are more likely to site in CREZ counties, they also face higher costs and siting restrictions. This finding could indicate that recent projects are moving away from CREZ counties due to increasing congestion.

Next, I analyze how the likelihood of choosing CREZ locations has evolved over time. Since I do not observe the exact year when a project makes the location choice,

impacted by the project and can be used for other purposes like farming or ranching. Utility-scale projects typically require 85.24 acres per MW of indirect use land (Denholm et al. 2009).

I use the year when the project begins operation as a proxy for the time of location choice. I estimate the utility specification in Equation 13 by allowing the coefficient on *crez* to vary with a quadratic polynomial of the linear time trend of operating year. The coefficient estimates are reported in Table A2, and Figure A2 shows the average marginal effect of *crez* over time.

The average marginal effect of choosing a CREZ county in Figure A2 follows an inverted U-shaped pattern. Interestingly, the marginal effect is negative post-2018, indicating that, on average, projects were less likely to site in a CREZ county compared to similar locations. For instance, in 2020, wind projects were approximately 12 percentage points less likely to site in a CREZ location than elsewhere.

Wind projects are often developed as phased expansions of existing projects in the same or nearby counties.[9] About 45 percent of projects, representing approximately 40 percent of the total wind capacity in the data, are expansions of existing projects. These expansions are often located in the same county as the other phase(s). The likelihood of choosing a location could be higher if the project is an expansion and the existing project is located in that county. To test if the siting of phased expansions can explain some of these findings, I estimate a utility model that includes the interaction of *crez* with an indicator for whether a project is part of a multi-phase expansion.

The coefficient estimates in Table A3 are similar in magnitude to the baseline estimates in Table 2. As expected, the interaction term is positive, suggesting that multi-phase projects are more likely to choose CREZ locations; however, this effect is not precisely estimated. Figure A3 shows the average marginal effect of selecting a CREZ location for single and multi-phase projects. Across specifications, multi-phase projects are approximately 5 to 7 percentage points more likely to locate in a CREZ county than single-phase projects.

9. Although each project has a unique EIA Plant Code and Generator ID combination, the expansions can share a common EIA Plant Code. In the EIA Form 860, projects part of a phased expansion often share a common name of a master project or phase name, even if they end up having different plant codes. I collect information by hand for projects with missing data on master project or phase name.

Next, I explore whether turbine model selection affects proejct site selection. While turbine models are chosen after site selection and are often conditional on project financing, preference for specific turbine technology might affect site selection (Doshi and Johnston 2024). I estimate the model in Equation 13 by allowing the coefficient on *crez* to vary by the square of the rotor diameter of the chosen turbine model. Table A4 reports the coefficient estimates for the conditional logit model.

Figure A4 shows a negative relationship between turbine size and the average marginal effect of choosing a CREZ county across all specifications. Projects with rotor diameters greater than 120 meters are less likely to locate in a CREZ county. The average turbine size was over 120 meters for projects that began operation post-2018, indicating that this effect could be driven by some of the recent projects locating outside of CREZ regions as shown in Figure A2.

These results could, in part, be driven by the choice structure of restricting the number of choices for each project to 5 counties. To address this, I estimate the conditional logit model by expanding the number of counties in the choice set for each project to 10. Table A5 in Appendix shows that the coefficient estimates for *crez* and the associated average marginal effects are similar to the baseline estimates.

As another test of sensitivity to the choice structure, I run the Nearest Neighbor algorithm at the individual site level, allowing each project a choice of 100 potential sites.[10] Since most of the variation across locations is at the county level, I then aggregate site-specific choices to the county level for the conditional logit estimation. Thus, the number of location choices varies from 2 to 22 counties, with the average choice set comprising of 5.5 counties. Table A6 in the Appendix shows that the coefficient estimate and the average marginal effect of *crez* are very similar to the baseline estimates.

10. Each *site* is a 2 km by 2 km grid of potential wind project locations from NREL's Wind Toolkit. For K = 100, each project faces a choice of 100 potential sites for the project location. Recall that the site specific wind resource data is also from NREL's Wind Toolkit. I combine data on other location specific characteristics like average farm size and value, and wind ordinance which is at the county level.

6 Wind Investment in CREZ Locations

In this section, I analyze whether locations with transmission investment also saw higher wind investment in the long run. The Competitive Renewable Energy Zones (CREZ) Transmission Optimization Study in 2008 provided the first comprehensive information on CREZ transmission expansion, connecting locations from West Texas to East Texas (ERCOT 2008). I use the announcement year of this study, 2008, as the treatment year and the CREZ locations as the treatment group.

Using a balanced panel of county-level data from 2000 through 2020 and a Differences-in-Differences design, I examine whether treated counties saw higher levels of wind investment post-treatment. I estimate the following event study specification:

$$y_{it} = \alpha_i + \delta_t + \sum_{k \neq -1} \beta_k \cdot crez_i \times \mathbb{1}\{K_t = k\} + \mathbf{X}_{it}'\Pi + \epsilon_{it} \tag{14}$$

where y_{it} is the outcome of interest. I use total wind capacity in county i in year t and average size of wind projects in a county (total nameplate capacity/total number of projects) as the dependent variables for this analysis. $\mathbb{1}\{K_t = k\}$ is the set of relative year indicators from 2000 to 2020, and $crez_i$ is a binary variable that specifies whether a substation for CREZ lines was sited in county i. α_i and δ_t are county and year fixed effects respectively, and ϵ_{it} is the random error term clustered at the county level.

The parameter of interest, β_k is identified from within county variation in wind investment in treated vs. control counties relative to the announcement year of 2008. The vector $\mathbf{X}_{it}$ includes an array of controls correlated with CREZ locations and wind investment. These variables include cubic polynomial of wind speed, site-specific capacity factor, terrain elevation and ruggedness, and average farm value and farm size to control for land value. County fixed effects account for unobserved and time-invariant county-specific factors. Year fixed effects control for common time specific shocks, for example, expiration of the Production Tax Credit in late 2012 and its subsequent extension in early 2013.

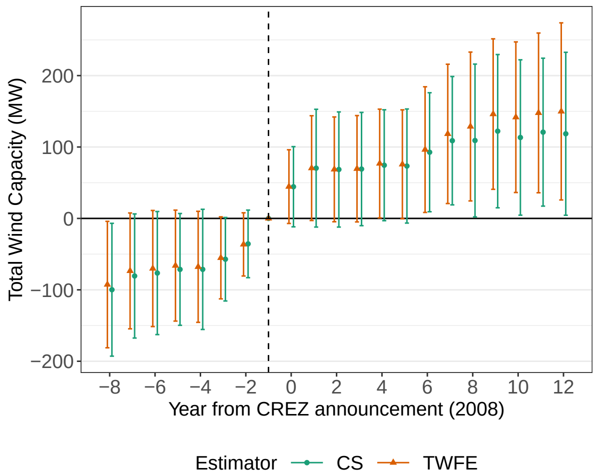
The main identification assumption in Equation 14 is that of parallel trends between the control and treated counties in the pre-announcement period conditional on the vector of controls in $\mathbf{X}_{it}$. These variables are a combination of pre-treatment characteristics like wind resource quality and time varying factors like land value are correlated with CREZ locations and control for differential trends in wind investment amongst treatment and control locations. Conditioning on these variables allows for a more robust inference (Roth et al. 2023).

Any unobserved factor that could differentially affect wind investment across locations and is correlated with $crez_i$ can bias the estimates of β_k. However, Texas did not see any transmission line expansions connecting West to the East beyond CREZ, ruling out this concern. Another violation of the identification assumption could be enactment of policies like the Renewable Portfolio Standard (RPS) that are aimed to promote renewable development. This could lead to biased estimates if the timing of policy changes in the RPS is correlated with CREZ expansion. Texas achieved its RPS goal of 10,000 MW of renewable capacity by 2025 in 2009 and the legislature did not make any further updates to this goal (ERCOT 2009), which effectively rules out this concern as well.

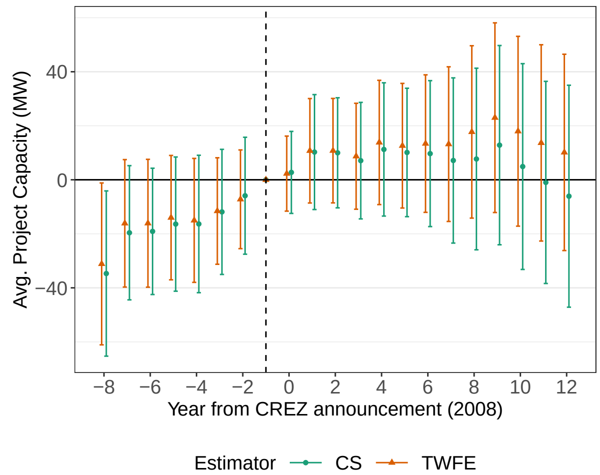
I implement Callaway and Sant'Anna (2021)'s (CS) group-time average treatment effects on the treated estimator as the estimator of choice. CS estimator corrects for the bias due to negative weights in the Two Way Fixed Effects (TWFE) estimator in event study frameworks with treatment heterogeneity (Goodman-Bacon 2021; Sun and Abraham 2021), while allowing for parallel pre-trends conditional on a set of covariates (Callaway and Sant'Anna 2021).

Figure 4 shows the CS and TWFE estimators (for reference) for the event study specification in Equation 14. Conditional on $\mathbf{X}_{it}$, parallel trends assumption holds for all

Figure 4: Effect of CREZ Announcement on Wind Investment



(a) Total Project Capacity (MW)



(b) Average Project Capcity (MW)

Notes: Figures 4a and 4b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 253 counties in Texas from 2000 to 2020 (N = 5,313). 95 percent confidence intervals are constructed using standard errors clustered at the county level.

pre-treatment periods except for the year 2000.[11] Figure 4a shows that counties with CREZ substations saw higher levels of wind investments post announcement in 2008, with an aggregate ATT of 91 MW (standard error of 34.4 MW). This effect is statistically significant at the 5 percent level for all the years beyond 2014. However, from Figure 4b, I do not find evidence for the hypothesis that CREZ counties saw larger wind projects.

One concern with the sample used in Figure 4 is the lack of a common support over the set of conditioning covariates. The balance between treated and control units is crucial for the problem of causal inference (Heckman, Ichimura, and Todd 1997; Khan and Tamer 2010; Roth et al. 2023). I use a matching strategy to address the issue of

11. The p-value for the pre-test for conditional parallel trends from the CS estimator is 0.124 when dependent variable is total capacity and 0.139 when dependent variable is average project capacity. Thus, for both the cases I fail to reject the null hypothesis of conditional parallel trends assumption in pre-treatment periods.

common support and obtain a comparable set of treated and control units, followed by estimating the event study specification in Equation 14 on the matched sample.

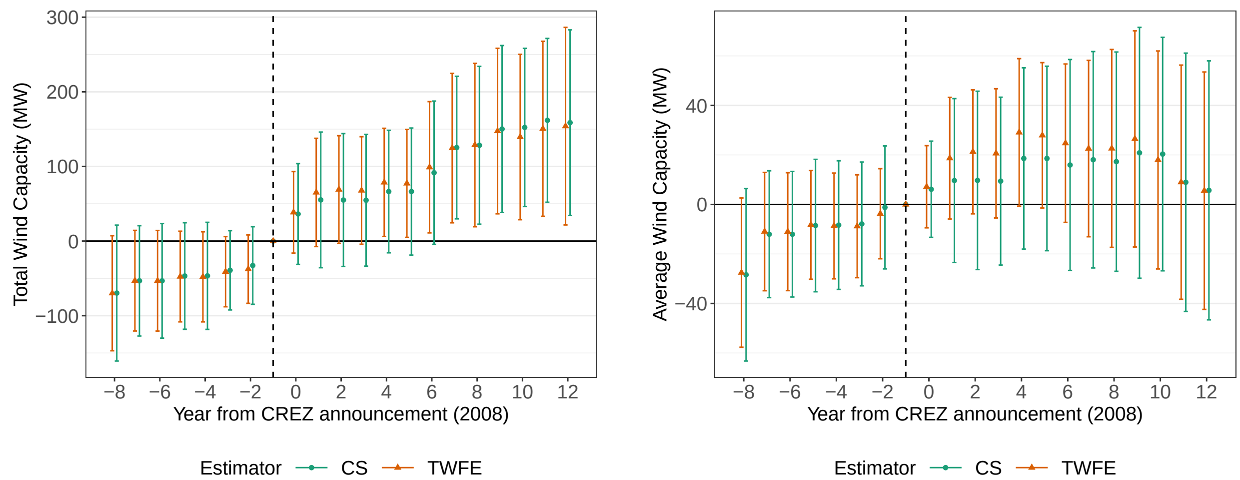
I implement Coarsened Exact Matching (Iacus, King, and Porro 2012) to address the issue of common support and obtain a set of counties comparable on observable dimensions that include both continuous and discrete variables. I use a wide variety of pre-treatment variables to account for factors that were correlated with CRE siting as well as investment in wind energy. These variables include wind resource quality (this includes wind speed, capacity factor, and site specific turbine wind class), average farm size and average farm value, terrain elevation and ruggedness, average population, and ERCOT zones.[12]

Next, I estimate the event study specification in Equation 14 using the sample of counties obtained from matching. Figure 5 shows the coefficient estimates and the associated 95 percent confidence interval for both CS and TWFE estimators, with total project capacity and average project capacity as dependent variables. For both the specifications coefficient estimates using the matched sample are similar to the estimates in Figure 4. Furthermore, the assumption of parallel trends holds for all the pre-treatment periods across both the estimators for specifications with total project capacity and average project capacity.

Counties with CREZ infrastructure see an increase in total wind investment post announcement in all the years following announcement in 2008. Similar to Figure 4a, the CS estimator shows this effect is statistically significant at the 5 percent level for the years after 2014. This suggests a lag between the transmission expansion announcement and the materialization of wind investments. Notably, the CREZ transmission expansion was completed by the end of 2013 as expected. The lagged effect indicates that developers

12. Table D2 in Appendix shows the balance table of control and treated counties before and after matching. Control counties obtained from matching look very similar to the treated counties. The matching step provides a better counterfactual group for the CREZ locations - counties that look identical on a wide variety of dimensions that affected selection of CREZ counties (RS&H 2010).

Figure 5: Effect of CREZ Announcement on Wind Investment



(a) Total Project Capacity (MW)

(b) Average Project Capcity (MW)

Notes: Figures 5a and 5b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 31 treated counties and 68 control counties obtained from Coarsened Exact Matching, from 2000 to 2020 (N = 2,079). 95 percent confidence intervals are constructed using standard errors clustered at the county level.

incorporate potential uncertainties in transmission expansion timelines, as well as the time required for wind project development and possible delays.

The aggregate Average Treatment on the Treated (ATT) estimate using the preferred CS estimator is about 100 MW per year with a standard error of 42 MW. The higher annual wind investment in CREZ counties is about 147 percent at the mean, or about 1.08 standard deviations higher than the wind capacity in control counties. Similarly, there is also a slight increase in average project size in a county post CREZ announcement, however, this effect is not precisely estimated.

To contextualize these estimates, I compute the value of carbon emissions avoided due to wind investment as a result CREZ expansion. I use an emissions rate of 0.601 tons of CO_2 avoided for each MWh of on-shore wind in Texas (EPA 2021). Assuming the capacity factor of wind in Texas to be 34.57 percent, wind capacity added due to CREZ avoided roughly 7.1 million tonnes of CO_2 emissions from the power sector in Texas annually. Using a social cost of carbon of \$185/ton-CO_2 (Rennert et al. 2022) the value of total reduction in carbon emissions is about \$1.31 billion per year.

The value of damages avoided is larger if I include local pollutants, namely, SO_2, NOx, and $PM_{2.5}$. Accurately calculating the value of these damages requires computing the amount of local pollutants offset by additional wind across location and time. As an approximation, I use the avoided emissions rate for SO_2, NOx, and $PM_{2.5}$ (EPA 2021) and weighted marginal damage valuations for these pollutants from the most recent Integrated Assessment Model, AP4T (Dennin et al. 2024). I find that the wind capacity led to an annual reduction of approximately \$288 million worth of SO_2, \$75 million worth of NOx, and \$34 million worth of $PM_{2.5}$. Thus, including local pollutants, the total value of reduction in emissions is about \$1.71 billion per year.[13]

Wind investment in these locations also generates private benefits in terms of higher annual payments to landowners. From the discrete choice model of project location choice, I estimate that the Willingness To Pay (WTP) to locate in CREZ counties is about \$2,808 per MW higher than other locations. Assuming that this WTP translates directly to higher lease payments, the aggregate treatment effect implies higher annual payments of approximately \$11 million per year to landowners. This extra payment is about 5 percent of total lease payments by wind projects to landowners in Texas in 2020 (AWEA 2019).

13. I use the avoided emissions rates associated with on-shore wind in 2020 in Texas. These are 0.63 lb per MWh for SO_2, 0.46 lb per MWh for NOx, and 0.06 lb per MWh for PM_2.5 (EPA 2021). The AP4T like its predecessors, AP4 and AP3, is an Integrated Assessment Models which is connects emissions to monetized damages in the US for the five criteria pollutants (Dennin et al. 2024). The marginal damage valuations associated with Electricity Generation Unit points sources are \$77.4 thousand per ton for SO_2, \$27.8 thousand per ton for NOx, and \$96.5 thousand per ton for $PM_{2.5}$.

6.1 Threats to Identification and Robustness Checks

6.1.1 Selection on unobservables - lobbying for or against CREZ:

The key threat to identification is the selection of counties on unobservable characteristics. This would violate the parallel trends assumption and the estimates would lose their causal interpretation. While the assumption of parallel trends seems to hold from Figure 5, I provide further institutional evidence and robustness checks to support its validity in this context.

One of the unobservable factors is whether certain counties lobbied for or against siting of the CREZ lines. While opposition is likely not a major concern in West Texas due to superior wind resources, low land value, and minimal community opposition, it is certainly a concern for East and South Texas, where some of the lines were closer to urban areas (Andrade and Baldick 2016). In contrast, certain counties in the Panhandle region expressed interest to the Public Utilities Commission of Texas (PUCT) for CREZ investment. This was in part due to an already declining population and economic losses in these counties in the years preceding CREZ expansion (Cohn and Jankovska 2020).

I construct a set of 'opposing' and 'enthusiastic' counties by reviewing individual cases filed by counties to PUCT.[14] These filings led to hearings and negotiations between county officials and PUCT regarding CREZ locations. I run the event study specification in Equation 14 for both total wind capacity and average project size on the matched sample obtained after excluding the three sets of counties (opposing, enthusiastic, and opposing and enthusiastic) separately from the original sample.

The event study results for the matched samples excluding opposing counties (Figure B1), favorable counties (Figure B2), and both (Figure B3) are similar to the baseline estimates in Figure 5 for both the specifications. The aggregate treatment effect using the preferred CS estimator for total wind capacity is 108 MW (standard error of 43 MW)

14. The 'opposing' counties are: Kendall, Gillespie, Newton, Kimble, Kerr, Mason, and Schleicher. The 'enthusiastic' counties are: Dallam, Sherman, Oldham, Swisher, Lipscomb, Parmer, Lamar, Hall, and Deaf Smith.

when excluding opposing counties, 96 MW (standard error of 46 MW) when excluding favoring counties, and 105 MW (standard error of 44 MW) when excluding either types.

6.1.2 SUTVA violations due investment spillover to neighboring control counties:

Figure E4 shows that several control counties selected by matching are adjacent to the treated counties. If these control counties saw higher or lower levels of wind investment as a consequence of their adjacency, it could potentially lead to violation of the Stable Unit Treatment Value Assumption (SUTVA). [15] To that end, I estimate the event study specification in Equation 14 on the matched sample excluding adjacent control counties. Thus, this specification compares wind investment between treated counties and non-adjacent control counties. A substantial deviation in the estimates from this exercise to the one in Figure 5 would suggest that the latter results are driven, by investments in adjacent control counties.

Figure B4 in Appendix shows the coefficient estimates for the post treatment period are slightly higher but qualitatively similar to the estimates in Figure 5. This suggests that the baseline results are not driven by deferentially higher investments in counties adjacent to CREZ than investments in other (non-adjacent) counties. [16] Further, because the share of wind added due to CREZ expansion is relatively smaller than the energy mix and overall wind capacity in Texas, any competitive effects on control counties are likely to be small.

15. A control unit located adjacent to a treated county could be more competitive in receiving higher wind investment than non-adjacent control county. However, such control counties could also see lower investments if developers instead shifted future investments from non-CREZ counties to CREZ counties. Therefore, grid expansion would have simply lead to a realignment of investments instead of overall greater investments. Both these cases would be instances of SUTVA violations and the assumption of parallel trends will no longer hold.

16. As an additional check, I estimate an event study specification excluding treated counties and assume adjacent control counties as the treated group and non-adjacent counties as the controls. This setup compares investment between adjacent and non-adjacent CREZ counties. While the point estimates are positive, this effect is small and statistically insignificant for all post-treatment periods for both the dependent variables.

6.1.3 Anticipation of CREZ announcement:

A source of bias in measuring the causal impact could be the anticipation amongst wind developers to the CREZ announcement in 2008. This would be reflected as a spike in investment in wind projects within CREZ counties in the years leading up to the transmission expansion announcement. While I do not see such a pattern in Figure 5, I examine the possibility of an anticipation effect in two ways.

First, I estimate the event study specification in Equation 14 while allowing for 2 and 4 years of anticipation. This involves estimating the event-study estimates by shifting the pre-treatment period to allow for the anticipation behavior δ years before the treatment (where δ takes the value 2 and 4). Figure C1 in Appendix C.1 shows that the coefficient estimates allowing for anticipation behavior are qualitatively similar to the baseline estimates in Figure 5.

Second, I use data on generator interconnection requests in Texas to check for changes in interconnection requests prior to CREZ announcement in 2008. Appendix C.2 provides further details of this data on generator interconnection and harmonization with the county-level wind dataset. The intuition is similar as before. An anticipation effect would be marked by an increase in interconnection requests in CREZ counties in the pre-treatment period. However, results from the event study analysis in Figure C2 on matched sample do not show any evidence of such an anticipation effect.

6.1.4 Placebo test using cancelled CREZ counties as the treatment group:

I conduct a placebo test using counties that were initially announced to site grid infrastructure, but the siting decision was later canceled prior to the development stage.[17] I estimate the event study specification using these counties as the *placebo* or *fake* treatment group instead of the original treatment group. This analysis acts as a placebo test because in the long-run, both the placebo treatment group and the control group should

17. These counties are: Gillespie, Lampasas, Mills, Brown, Eastland, Briscoe, Taylor.

exhibit similar levels of wind investment. Coefficient estimates in Figure B5 in Appendix confirm this hypothesis: the difference in wind investment between the placebo treatment group and the control counties is statistically insignificant.[18]

6.1.5 Impact of CREZ on output and input prices for wind power:

Impact on output prices (i.e. price of power from wind projects) or input prices (i.e. price of turbines and equipment) as a result of CREZ expansion could affect the competitiveness of control counties relative to treated counties. If projects in CREZ counties received higher prices for their power or faced lower prices for equipment, then control counties would be less competitive in receiving wind investment.

Recall, that Texas already achieved its Renewable Portfolio Standard (RPS) of 10,000 MW of new renewable generation by 2025 in 2009, making the RPS non-binding for the remaining periods of the sample (ERCOT 2009). Therefore, any output price spillovers due to CREZ are likely to be small, if any. Moreover, because the turbines for wind projects are purchased on a global market, grid expansion in Texas is unlikely to impact prices of wind turbines differentially across counties, ruling out this concern.

6.1.6 Sensitivity analysis with unconditional parallel trends:

A key assumption for the identification of ATTs in Equation 14 is that of parallel trends conditional on the set of covariates which includes variables measuring wind resource quality and land value. I relax this assumption and re-estimate the event study specification for the samples with and without matching as test for whether parallel trends still hold for the pre-treatment periods. Figure B6a in the Appendix shows that the parallel trends is violated for several pre-treatment periods for the specification estimated on full sample with Total Project Capacity as the dependent variable. This is mitigated in Fig-

18. A caveat to these results is a lack of variation in the number of placebo treatment counties. From the 6 counties that were cancelled, the matching algorithm only selects 4 of them and 44 control counties.

ure B6c which uses the matched sample for the event study and the resulting treatment effect estimates are very similar to Figure 5.

7 Localized Wind Investment and Rising Curtailments

Electricity market operators typically curtail renewable resources during periods of congestion to maintain grid stability. Wind curtailment refers to the reduction in electricity generated from a wind generator below the level it could have produced given available resources. For example, if a wind generator can produce 100 MW of electricity in a given period but is scheduled to produce only 80 MW, the wind curtailment is 20 MW. Curtailment is typically involuntary on the part of the generator. In Texas, ERCOT determines the extent of curtailments based on factors such as available transmission capacity, total demand, and total supply.

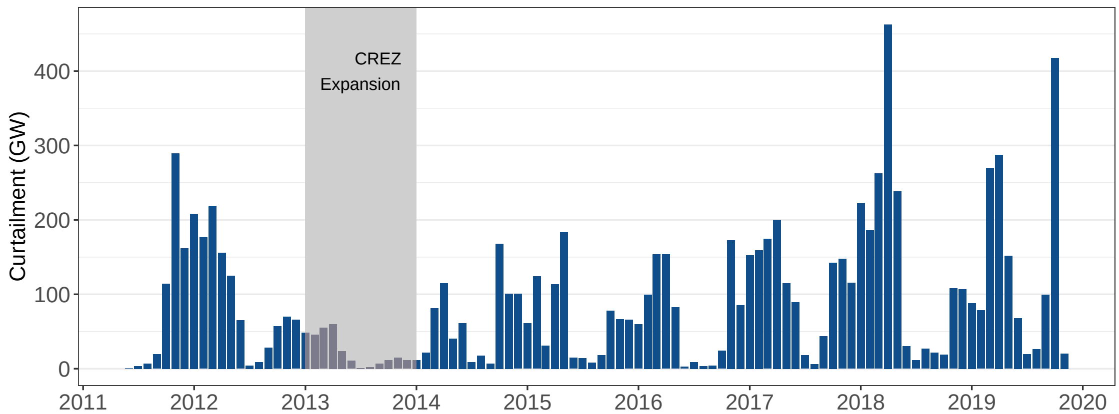
Electricity market operators typically curtail renewable resources during periods of congestion to maintain grid stability.[19] In Texas, the lack of adequate transmission capacity between West and the East has been the primary source of wind curtailment (Bird, Cochran, and Wang 2014). Figure 6 shows that CREZ expansion led to a significant decline in total wind curtailments post CREZ expansion, but have been steady rising since 2017.[20]

Analysis in Section 6 shows that locations with CREZ expansion saw higher levels of wind investments in the long-run. Although wind generation in Texas has been steadily increasing over the past couple of decades, there has not been any other significant

19. Wind curtailment is the reduction in electricity generated from a wind generator below the level it could have produced given available resources (Bird, Cochran, and Wang 2014). For example, suppose a wind generator can produce 100 MW of electricity in a given period but is finally scheduled to produce 80 MW, the wind curtailment is 20 MW. Curtailment is typically involuntary on the part of the generator. ERCOT determines the extent of curtailments based on a combination of factors like available transmission capacity, total demand and total supply.

20. Figure E5 in Appendix breaks down the average wind curtailment by hour for each year in 2011 to 2019, showing that curtailments in 2019 were higher than pre-grid expansion levels in 2011 and 2012, especially during Off-Peak hours.

Figure 6: Wind Curtailment in Texas



Notes: This figure shows total monthly curtailment from 2011 to 2019. Shaded area is the period of CREZ transmission expansion.

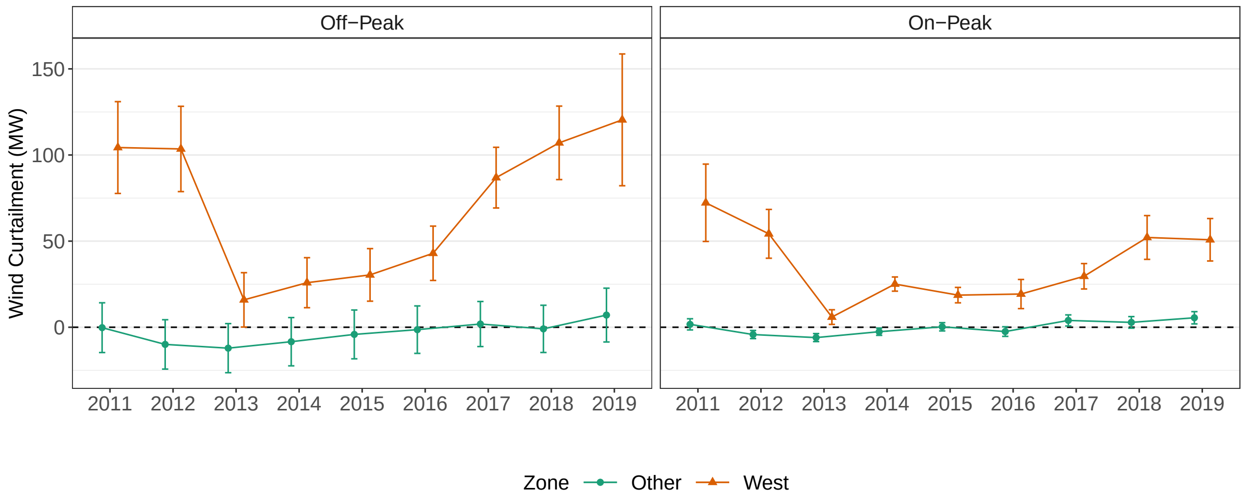
transmission expansion project. A potential consequence of this localized investment and limited transmission capacity is rise in curtailment of wind farms in the West. Using data on hourly wind curtailments at the ERCOT Zone level (West, North, South, and Houston) from August 2011 to December 2019, I explore this phenomenon by estimating the following specification:

$$y_{it} = \sum_{k=2011}^{2019} \alpha_k \cdot west_i + \sum_{k=2011}^{2019} \beta_k \cdot other_i + \gamma_{md} + \delta_{dh} + \epsilon_{it} \tag{15}$$

where y_{it} is total wind curtailment in zone i at hour t, $west_i$ is an indicator if the observation is in the West, and $other_i$ is an indicator if the observation is in one of the other zones (North, South, Houston). The parameters of interest α_k and β_k measure the mean hourly curtailment in west and other zones for the years 2011 to 2019. Random errors denoted by ϵ_{it} are clustered by the day-of-the-sample to account for serial correlation at the daily level.

I include month-of-year-by-day-of-month (γ_{md}) and day-of-month-by-hour-of-day (δ_{dh}) fixed effects to flexibly control for seasonal variation in wind patterns and wind generation at a high level of temporal granularity. In other words, α_k and β_k are identified from deviations from hourly averages of curtailments over each day and month of the sample for each years in 2011 to 2019. To explore heterogeneity by time of the day, I estimate the specification in Equation 15 separately for Off-Peak and On-Peak hours.[21]

Figure 7: Annual Curtailment in West v.s. Other Regions



Notes: This figure shows the coefficient estimates of α_k and β_k from Equation 15, estimated separately for the Off-Peak and On-Peak hours. *West* is an indicator for observations in West Zone, and *Other* is an indicator for observations in North, South, and Houston Zones. Sample is a balanced panel of hourly total wind curtailment at the zonal level from 2011 to 2019. 95 percent confidence intervals are constructed using standard errors clustered at the day of the sample.

Figure 7 shows the coefficient estimates from Equation 15 for Off-Peak and On-Peak hours. With the CREZ expansion underway in 2013, curtailments in the West saw a dramatic drop post 2012 across both Off-Peak and On-Peak hours. Average curtailments in the West remained below 50 MW during On-Peak hours through 2017 and about 50 MW during 2018 and 2019. Furthermore, curtailments in other zones remained almost zero throughout 2011 to 2019 for both Off-Peak and On-Peak hours. This result is expected since congestion and subsequent wind curtailment, particularly during Off-Peak hours is mainly an issue for wind generation in the West. Thus, this result also serves as an empirical check.

More interestingly, there has been an increase in hourly wind curtailments during Off-Peak hours in the West and Panhandle post-2016. Coefficient estimates show that

21. Peak period in Texas is defined as the hours ending in 7:00 a.m. to 10:00 p.m. CPT.

hourly curtailment in 2019 was about 120 MW, approximately 20 MW higher than the pre-transmission expansion estimates of 2011 and 2012. The rise in curtailments indicates a combination of higher wind generation and limited transmission capacity connecting the West to the demand centers in the East.

These curtailments translate to excess emissions that could be avoided with adequate transmission capacity. From Figure 7, the average hourly curtailment of 120 MW during Off-Peak hours in 2019 in the West implies $85 million in excess emissions. Similarly, an average curtailment of 51 MW during On-Peak hours in 2019 translates to $71 million in excess emissions. Taken together, these estimates imply $120 million in excess carbon emissions and $36 million in excess local emissions (SO_2, NOx, and $PM_{2.5}$) annually due to wind curtailment in the West.

8 Conclusion

This paper shows that large scale grid expansion projects can lead to long-run investment in renewable energy. These investments create significant public and private benefits. Using the context of CREZ expansion in Texas, I find that the benefits from lower emissions and higher lease payments to landowners is about $1.72 billion per year. These benefits are in conjunction with several short-run benefits like lower market power and emissions the fossil fuel sector (Fell, Kaffine, and Novan 2021; Doshi 2024). These benefits are in the order of hundreds of millions of dollars annually. Estimating these investment spillovers and accurately quantifying the associated benefits is essential to justify large capital costs associated with transmission expansions, a hurdle that these projects often face with the regulators.[22]

22. An example is the case of Grain Belt Express, a $7 billon, 780 mile transmission project proposed in 2014 aimed at connecting wind generation in Kansas to customers in Indiana, passing through Missouri and Illinois. While the regulators in Kansas, Illinois, and Indiana signed-off on the project, regulators in Missouri denied approval citing lack of benefits to justify the costs. Though the developers and regulators in Missouri eventually came to an agreement, the delay cost nearly 10 years of project development (Solomon 2023).

Localized renewable investment in response to transmission expansion can lead to higher curtailments if transmission capacity remains inadequate. In Texas, wind curtailments in recent years are equivalent to $156 million worth of excess emissions per year. These curtailments can also diminish the value of wind investment, reflected by the declining likelihood of siting projects in these locations over time. These results highlight the value of taking a long-term planning approach to transmission policy (FERC Order No. 1920).[23]

23. Recent research has suggested several reforms to mitigate these issues. This includes building or expanding high capacity transmission lines in existing Right-Of-Way and other public infrastructure corridors (Department of Energy 2024). Other reforms include increasing capacity of existing transmission lines by large scale reconductoring (Chojkiewicz et al. 2024), converting existing High Voltage Alternating Current (HVAC) into high-voltage direct current (HVDC) lines or hybrid AC/DC lines (Reed et al. 2019) within existing Right-Of-Way.

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Appendix

A Heterogeneity Analysis for Wind Project Location Choice

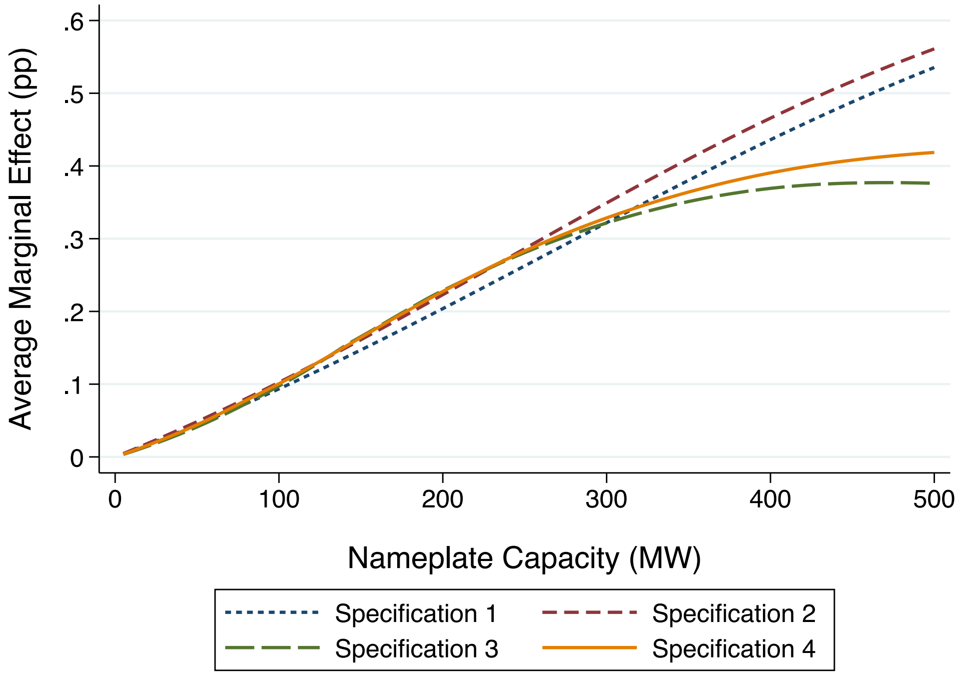
A.1 Results with nameplate capacity

Table A1: Conditional Logit Model of Wind Project Location Choice

	(1)	(2)	(3)	(4)
crez × *nameplate*	0.005***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
median farm size × *nameplate*			-1.25×10^{6}	-1.07×10^{6}
			(1.23×10^{6})	(1.23×10^{6})
average farm size × *nameplate*			4.13×10^{6}***	3.68×10^{6}***
			(1.28×10^{6})	(1.31×10^{6})
average farm value × *nameplate*			-9.85×10^{7}	-1.96×10^{6}
			(4.07×10^{6})	(4.31×10^{6})
Wind Resource Controls	✓	✓	✓	✓
Region Fixed Effect		✓		✓
Site-specific Controls			✓	✓
Total Projects	206	206	206	206
Total Alternatives	168	168	168	168
Observations	1,030	1,030	1,030	1,030
Log Likelihood	-287.5	-272	-271.2	-265.1
Odds Ratio of *crez*	1.005	1.006	1.006	1.006

Notes: This table shows the coefficient estimates of conditional logit model of wind project location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. *crez* is an indicator for whether the chosen county has a CREZ substation. *nameplate* is the project nameplate capacity (MW). Wind Resource Controls include cubic spline of wind speed, capacity factor, and site-specific turbine class rating. Site-specific controls include average land prices, average and standard deviation of terrain elevation, and an indicator for presence of wind ordinance. Region Fixed Effect is a region specific indicator for West, Panhandle, East, and South regions. By design, each project faces a choice set of 5 distinct counties. Total Alternatives is the total number of distinct counties across all choice sets. Robust standard errors clustered at the project level reported in parenthesis. Significance: ***$p<0.01$;**$p<0.05$;*$p<0.1$

Figure A1: Average Marginal Effect of CREZ by Project Nameplate Capacity



Note: This figure shows the average marginal effect (percentage point pp) of choosing a CREZ county by project nameplate capacity (MW), obtained from estimating conditional logit model of location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. Specification 1 includes Wind Resource Controls, Specification 2 includes Wind Resource Controls and Region Fixed Effects, Specification 3 includes Wind Resource Controls and Site-specific Controls, and Specification 4 includes Wind Resource Controls, Region Fixed Effects, and Site-specific Controls. All specifications include interaction of *crez* and project nameplate capacity. Specifications 3 and 4 include interactions of project capacity with variables measuring farm value and farm size.

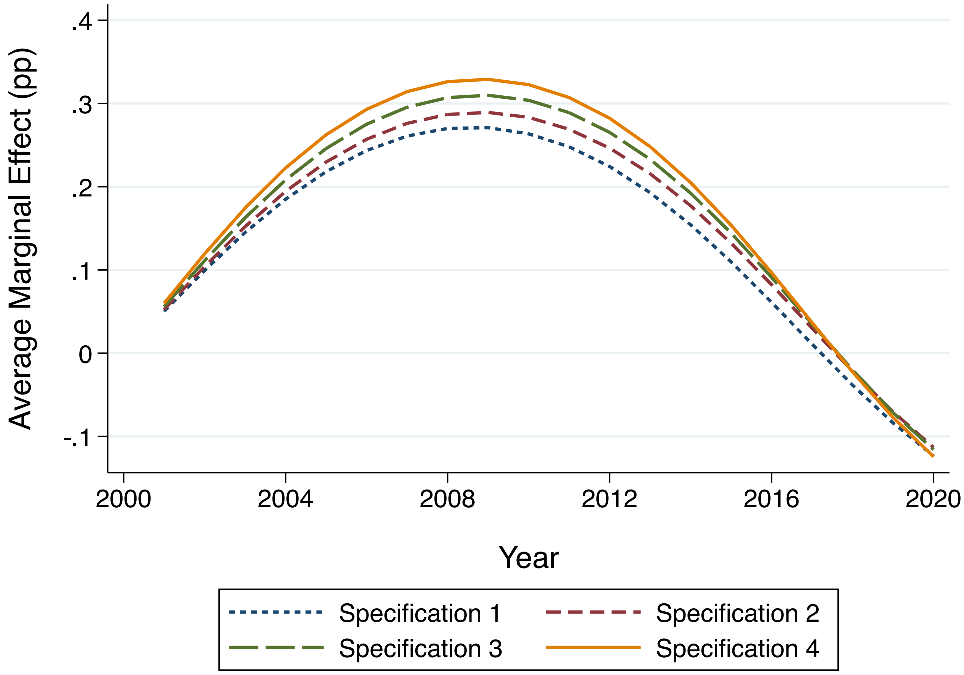
A.2 Results with project operation year

Table A2: Conditional Logit Model of Wind Project Location Choice

	(1)	(2)	(3)	(4)
crez $\times$ *trend*	0.321***	0.348***	0.364***	0.392***
	(0.061)	(0.062)	(0.066)	(0.069)
crez $\times$ *trend*^{2}	-0.019***	-0.020***	-0.021***	-0.022***
	(0.004)	(0.004)	(0.004)	(0.004)
Wind Resource Controls	✓	✓	✓	✓
Region Fixed Effect		✓		✓
Site-specific Controls			✓	✓
Total Projects	206	206	206	206
Total Alternatives	168	168	168	168
Observations	1,030	1,030	1,030	1,030
Log Likelihood	-284.5	-269.6	-264.4	-257.7

Notes: This table shows the coefficient estimates of conditional logit model of wind project location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. *crez* is an indicator for whether the chosen county has a CREZ substation. *trend* is a linear time trend for the year when project began operation. Wind Resource Controls include cubic spline of wind speed, capacity factor, and site-specific turbine class rating. Site-specific controls include average land prices, median farm acreage, average farm size (acre), median farm size (acre), average farm value ($ per acre), average and standard deviation of terrain elevation, and an indicator for presence of wind ordinance. Region Fixed Effect is a region specific indicator for West, Panhandle, East, and South regions. By design, each project faces a choice set of 5 distinct counties. Total Alternatives is the total number of distinct counties across all choice sets. Robust standard errors clustered at the project level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

Figure A2: Average Marginal Effect of CREZ by Project Operation Year



Note: This figure shows the average marginal effect (percentage point pp) of choosing a CREZ county over time (i.e. by project operation year), obtained from estimating conditional logit model of location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. Specification 1 includes Wind Resource Controls, Specification 2 includes Wind Resource Controls and Region Fixed Effects, Specification 3 includes Wind Resource Controls and Site-specific Controls, and Specification 4 includes Wind Resource Controls, Region Fixed Effects, and Site-specific Controls. All specifications include interaction of *crez* with a quadratic polynomial of time trend.

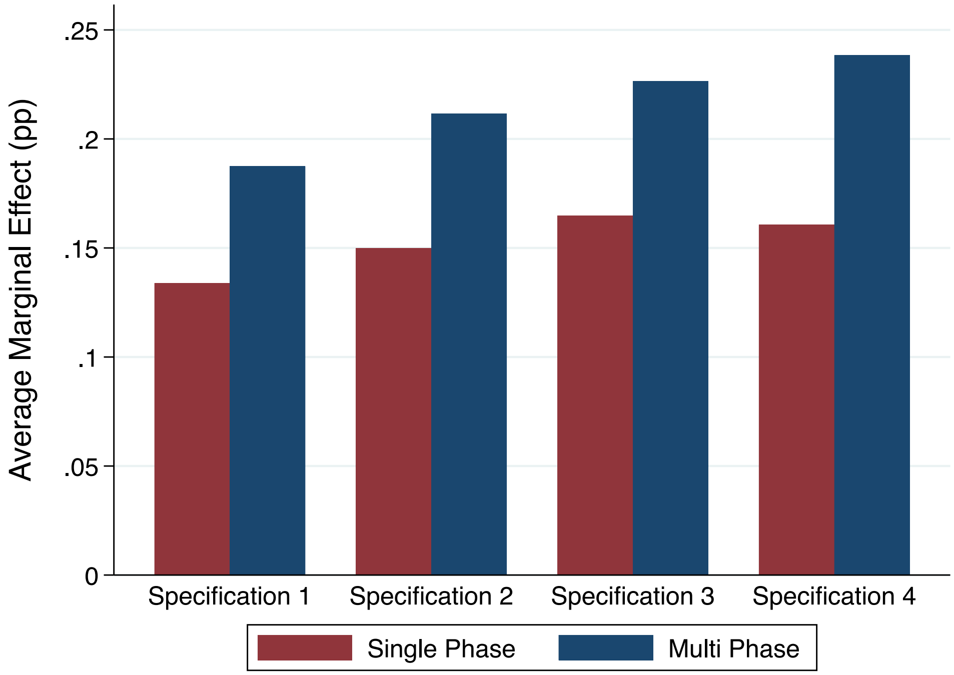
A.3 Results for project phase type

Table A3: Conditional Logit Model of Wind Project Location Choice

	(1)	(2)	(3)	(4)
crez	0.744***	0.861***	0.923***	0.906***
	(0.255)	(0.263)	(0.297)	(0.297)
crez × *multi-phase project*	0.256	0.304	0.295	0.378
	(0.342)	(0.343)	(0.377)	(0.383)
Wind Resource Controls	✓	✓	✓	✓
Region Fixed Effect		✓		✓
Site-specific Controls			✓	✓
Total Projects	206	206	206	206
Total Alternatives	168	168	168	168
Observations	1,030	1,030	1,030	1,030
Log Likelihood	-288	-272.2	-267.7	-261.6

Notes: This table shows the coefficient estimates of conditional logit model of wind project location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. *crez* is an indicator for whether the chosen county has a CREZ substation. *multi-phase project* is an indicator for whether the project is part of a multi-phase expansion. Wind Resource Controls include cubic spline of wind speed, capacity factor, and site-specific turbine class rating. Site-specific controls include average land prices, median farm acreage, average farm size (acre), median farm size (acre), average farm value ($ per acre), average and standard deviation of terrain elevation, and an indicator for presence of wind ordinance. Region Fixed Effect is a region specific indicator for West, Panhandle, East, and South regions. By design, each project faces a choice set of 5 distinct counties. Total Alternatives is the total number of distinct counties across all choice sets. Robust standard errors clustered at the project level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

Figure A3: Average Marginal Effect of CREZ by Project Phase



Note: This figure shows the average marginal effect (percentage point pp) of choosing a CREZ county for single phase and multi-phase projects, obtained from conditional logit model estimates in Table A3. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. Specification 1 includes Wind Resource Controls, Specification 2 includes Wind Resource Controls and Region Fixed Effects, Specification 3 includes Wind Resource Controls and Site-specific Controls, and Specification 4 includes Wind Resource Controls, Region Fixed Effects, and Site-specific Controls. All specifications include interaction of *crez* with a quadratic polynomial of time trend.

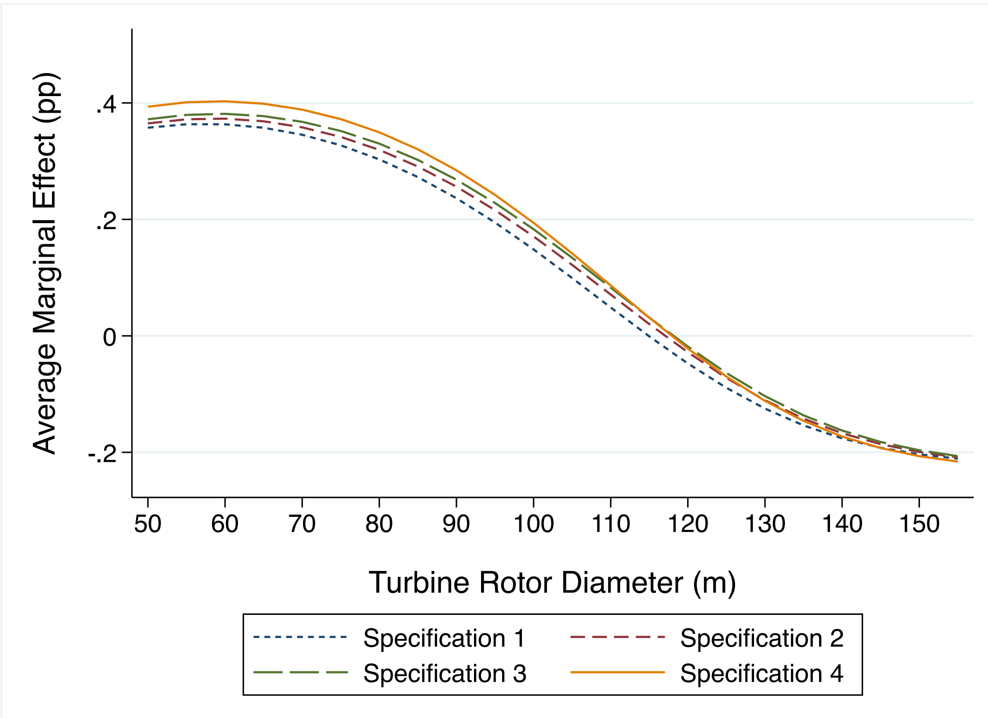
A.4 Results by turbine rotor diameter

Table A4: Conditional Logit Model of Wind Project Location Choice

	(1)	(2)	(3)	(4)
crez × *rotor diameter*	0.064***	0.067***	0.067***	0.072***
	(0.012)	(0.012)	(0.013)	(0.013)
crez × *rotor diameter*^{2}	-0.0006***	-0.0006***	-0.0006***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Wind Resource Controls	✓	✓	✓	✓
Region Fixed Effect		✓		✓
Site-specific Controls			✓	✓
Total Projects	206	206	206	206
Total Alternatives	168	168	168	168
Observations	1,030	1,030	1,030	1,030
Log Likelihood	-278.5	-263.5	-259.3	-252.7

Notes: This table shows the coefficient estimates of conditional logit model of wind project location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. *crez* is an indicator for whether the chosen county has a CREZ substation. *rotor diameter* is the rotor diameter in meters of the predominant wind turbine used in the wind project. Wind Resource Controls include cubic spline of wind speed, capacity factor, and site-specific turbine class rating. Site-specific controls include average land prices, median farm acreage, average farm size (acre), median farm size (acre), average farm value ($ per acre), average and standard deviation of terrain elevation, and an indicator for presence of wind ordinance. Region Fixed Effect is a region specific indicator for West, Panhandle, East, and South regions. By design, each project faces a choice set of 5 distinct counties. Total Alternatives is the total number of distinct counties across all choice sets. Robust standard errors clustered at the project level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

Figure A4: Average Marginal Effect of CREZ by Turbine Rotor Diameter



Note: This figure shows the average marginal effect (percentage point pp) of choosing a CREZ county by rotor diameter of the chosen wind turbine, obtained from estimating conditional logit model of location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. Specification 1 includes Wind Resource Controls, Specification 2 includes Wind Resource Controls and Region Fixed Effects, Specification 3 includes Wind Resource Controls and Site-specific Controls, and Specification 4 includes Wind Resource Controls, Region Fixed Effects, and Site-specific Controls. All specifications include interaction of *crez* with a quadratic polynomial of time trend.

A.5 Results with K = 10 in Nearest Neighbor Matching for Choice Set

Table A5: Conditional Logit Model of Wind Project Location Choice

	(1)	(2)	(3)	(4)
crez	0.724***	0.849***	0.876***	0.902***
	(0.169)	(0.184)	(0.196)	(0.210)
Wind Resource Controls	✓	✓	✓	✓
Region Fixed Effect		✓		✓
Site-specific Controls			✓	✓
Total Projects	206	206	206	206
Total Alternatives	202	202	202	202
Observations	2,060	2,060	2,060	2,060
Log Likelihood	-426	-402.6	-395.2	-384.9
Odds Ratio of *crez*	2.063	2.338	2.401	2.465
Average Marginal Effect	0.088	0.106	0.113	0.117

Notes: This table shows the coefficient estimates of conditional logit model of wind project location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. *crez* is an indicator for whether the chosen county has a CREZ substation. Wind Resource Controls include cubic spline of wind speed, capacity factor, and site-specific turbine class rating. Site-specific controls include average land prices, median farm acreage, average farm size (acre), median farm size (acre), average farm value ($ per acre), average and standard deviation of terrain elevation, and an indicator for presence of wind ordinance. Region Fixed Effect is a region specific indicator for West, Panhandle, East, and South regions. By design, each project faces a choice set of 10 distinct counties. Total Alternatives is the total number of distinct counties across all choice sets. Robust standard errors clustered at the project level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

A.6 Results with choice set at the site level

Table A6: Conditional Logit Model of Wind Project Location Choice

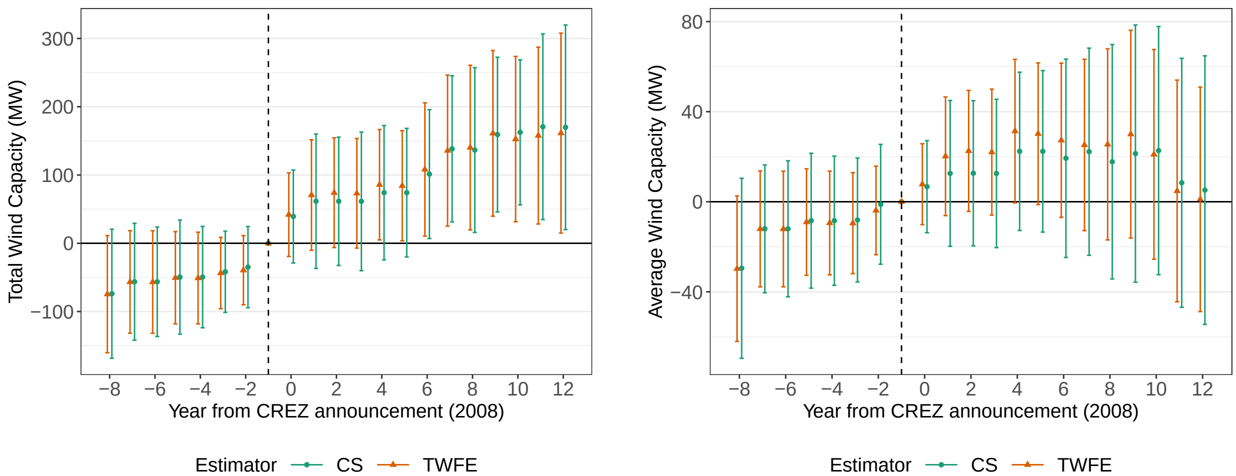
	(1)	(2)	(3)	(4)
crez	0.626***	0.758***	1.037***	0.982***
	(0.239)	(0.239)	(0.269)	(0.267)
Wind Resource Controls	✓	✓	✓	✓
Region Fixed Effect		✓		✓
Site-specific Controls			✓	✓
Total Projects	136	136	136	136
Total Alternatives	177	177	177	177
Observations	614	614	614	614
Log Likelihood	-171.8	-157	-155.9	-150.7
Odds Ratio of *crez*	1.871	2.133	2.819	2.669
Average Marginal Effect	0.088	0.106	0.113	0.117

Notes: This table shows the coefficient estimates of conditional logit model of wind project location choice. Sample is all wind projects in Texas, larger than 1 MW in size that began operation in 2001 to 2020. *crez* is an indicator for whether the chosen county has a CREZ substation. Wind Resource Controls include cubic spline of wind speed, capacity factor, and site-specific turbine class rating. Site-specific controls include average land prices, median farm acreage, average farm size (acre), median farm size (acre), average farm value ($ per acre), average and standard deviation of terrain elevation, and an indicator for presence of wind ordinance. Region Fixed Effect is a region specific indicator for West, Panhandle, East, and South regions. Total Alternatives is the total number of distinct counties across all choice sets. Choice set is constructed by running K-Nearest Neighbor Algorithm at the site level with K = 100, followed by aggregating choices at the county level. The average size of a choice set is about 5.5, whereas the minimum and maximum number of choices are 2 and 22 respectively. 70 projects only have one county in the choice set and are thus excluded from the conditional logit estimation. Robust standard errors clustered at the project level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

B Robustness Checks for Event Study Analysis

B.1 Matching on Unobservables - Results excluding Opposing Counties

Figure B1: Effect of CREZ Announcement on Wind Investment

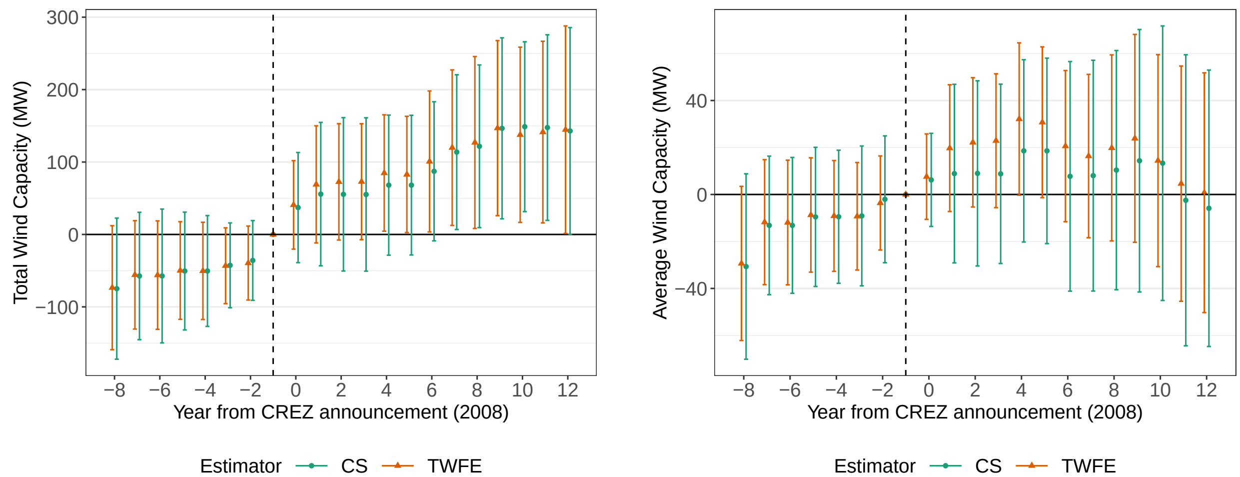


(a) Total Project Capacity (MW) (b) Average Project Capacity (MW)

Notes: Figures B1a and B1b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 29 treated counties and 65 control counties obtained using Coarsened Exact Matching, from 2000 to 2020 (N = 1,974) after excluding counties that formally opposed CREZ siting in legal filings to the Public Utilities Commission of Texas: Kendall, Gillespie, Newton, Kimble, Kerr, Mason, and Schleicher. 95 percent confidence intervals are constructed using standard errors clustered at the county level.

B.2 Matching on Unobservables - Results excluding Favorable Counties

Figure B2: Effect of CREZ Announcement on Wind Investment



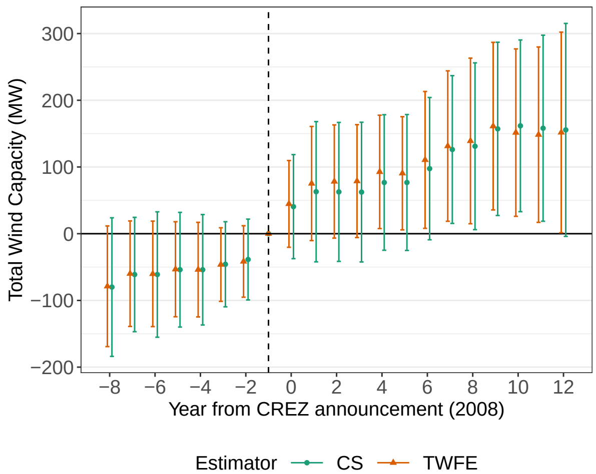
(a) Total Project Capacity (MW)

(b) Average Project Capcity (MW)

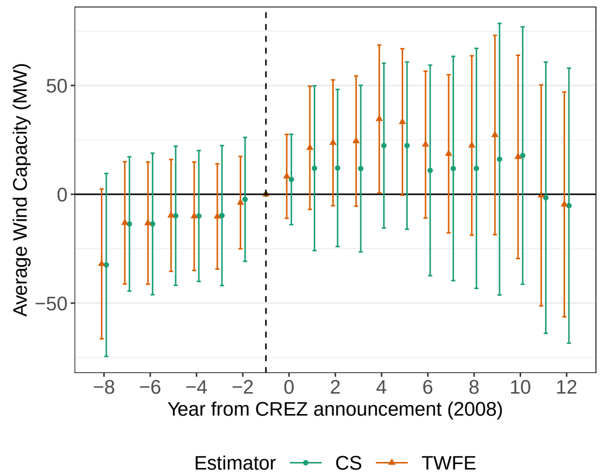
Notes: Figures B2a and B2b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 29 treated counties and 61 control counties obtained using Coarsened Exact Matching, from 2000 to 2020 (N = 1,890) after excluding counties that formally favored siting CREZ substations/lines in legal filings to the Public Utilities Commission of Texas: Dallam, Sherman, Oldham, Swisher, Lipscomb, Parmer, Lamar, Hall, Deaf Smith. 95 percent confidence intervals are constructed using standard errors clustered at the county level.

B.3 Matching on Unobservables - Results excluding Opposing and Favorable Counties

Figure B3: Effect of CREZ Announcement on Wind Investment



(a) Total Project Capacity (MW)

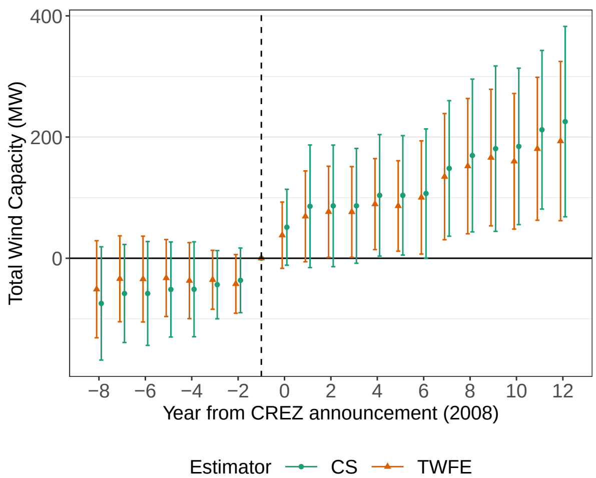


(b) Average Project Capcity (MW)

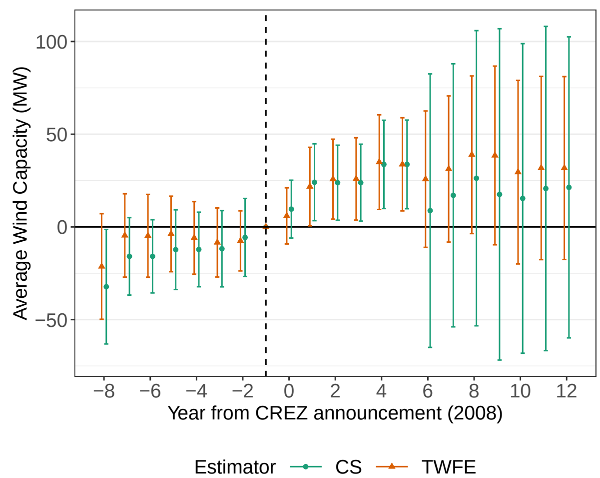
Notes: Figures B3a and B3b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 27 treated counties and 58 control counties obtained using Coarsened Exact Matching, from 2000 to 2020 (N = 1,785) after excluding counties that either opposed (Kendall, Gillespie, Newton, Kimble, Kerr, Mason, and Schleicher) or favored (Dallam, Sherman, Oldham, Swisher, Lipscomb, Parmer, Lamar, Hall, Deaf Smith) siting CREZ substations/lines in legal filings to the Public Utilities Commission of Texas. 95 percent confidence intervals are constructed using standard errors clustered at the county level.

B.4 Results for investment spillover to adjacent counties

Figure B4: Effect of CREZ Announcement on Wind Investment



(a) Total Project Capacity (MW)

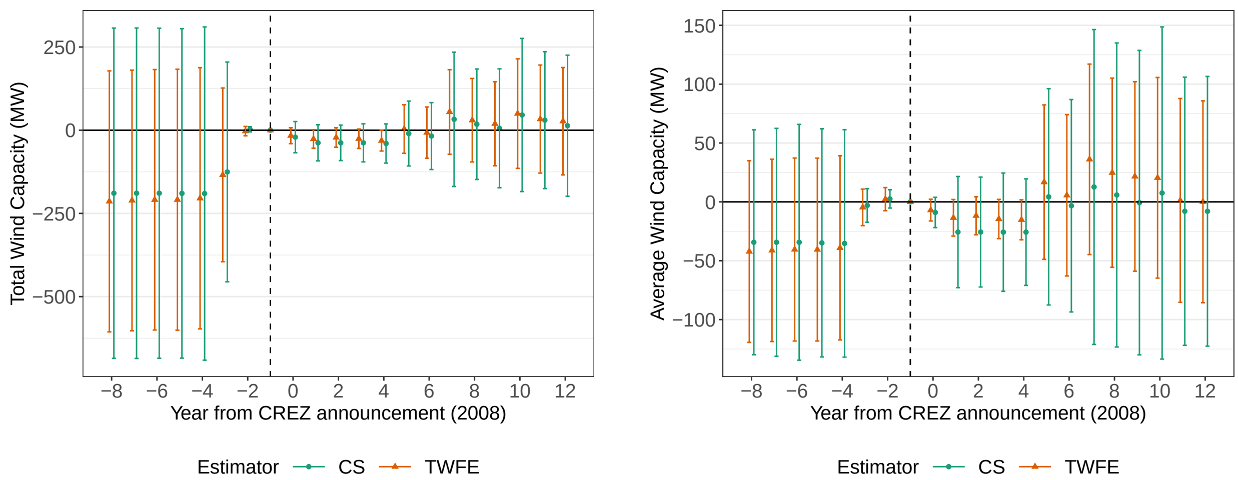


(b) Average Project Capcity (MW)

Notes: Figures B4a and B4b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 31 CREZ counties as the treatment group and 22 counties non-adjacent to CREZ locations as control counties obtained using Coarsened Exact Matching, from 2000 to 2020 (N = 1,113). 95 percent confidence intervals are constructed using standard errors clustered at the county level.

B.5 Results of Placebo test using cancelled CREZ counties

Figure B5: Effect of CREZ Announcement on Wind Investment: Excluding Opposing and Favorable Counties



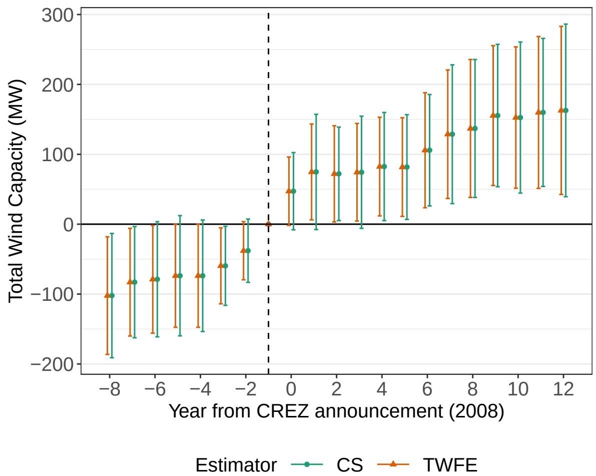
(a) Total Project Capacity (MW)

(b) Average Project Capcity (MW)

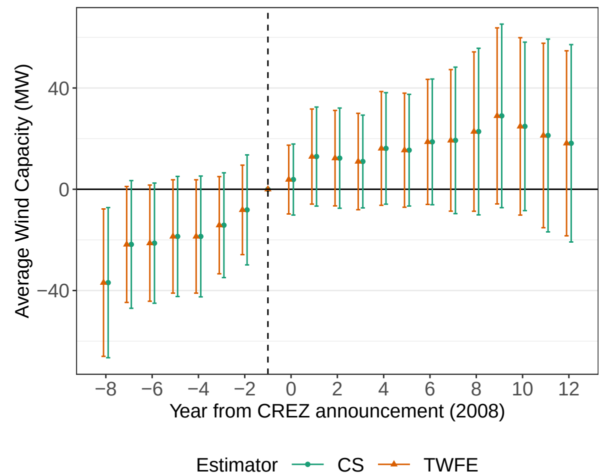
Notes: Figures B5a and B5b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 4 counties as the placebo treatment group and 44 counties as control counties obtained using Coarsened Exact Matching, from 2000 to 2020 (N = 1,008). The placebo treatment counties are the counties that were selected to site CREZ lines but the siting was canceled before the development- Gillespie, Lampasas, Mills, Brown, Eastland, Briscoe, Taylor. 95 percent confidence intervals are constructed using standard errors clustered at the county level.

B.6 Testing for Unconditional Parallel Trends

Figure B6: Effect of CREZ Announcement on Wind Investment

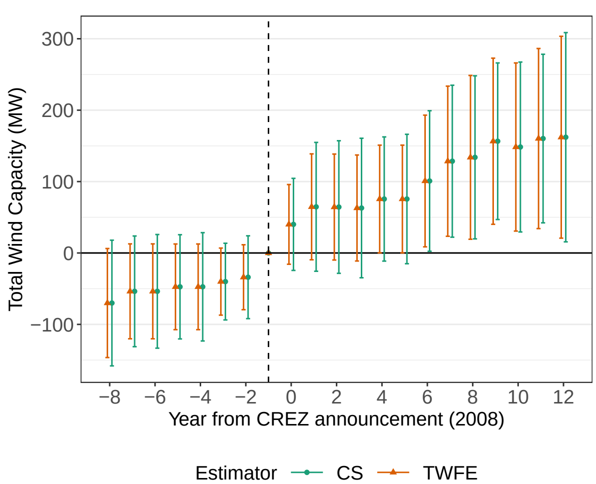


(a) Total Project Capacity (MW)

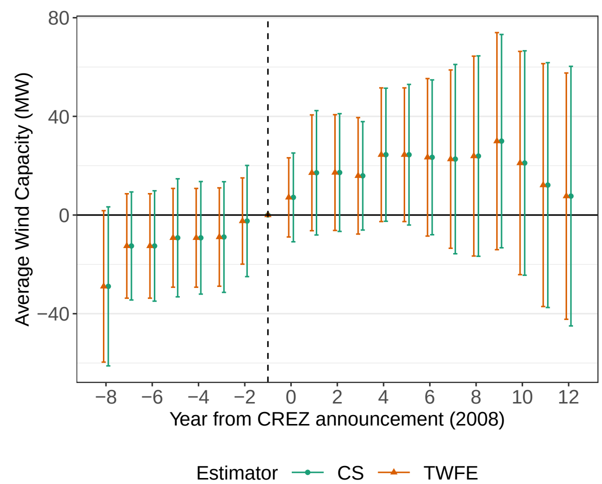


(b) Average Project Capacity (MW)

Notes: Figures B6a and B6b show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications allow for unconditional parallel trends. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 253 counties in Texas from 2000 to 2020 (N = 5,313). 95 percent confidence intervals are constructed using standard errors clustered at the county level.



(c) Total Project Capacity (MW)



(d) Average Project Capacity (MW)

Notes: Figures B6c and B6d show the coefficient estimates of the event study in Equation 14 with Total Wind Capacity and Average Wind Capacity in a county as dependent variables respectively. Both specifications allow for unconditional parallel trends. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 31 treated counties and 68 control counties obtained from Coarsened Exact Matching, from 2000 to 2020 (N = 2,079). 95 percent confidence intervals are constructed using standard errors clustered at the county level.

C Anticipation Behavior

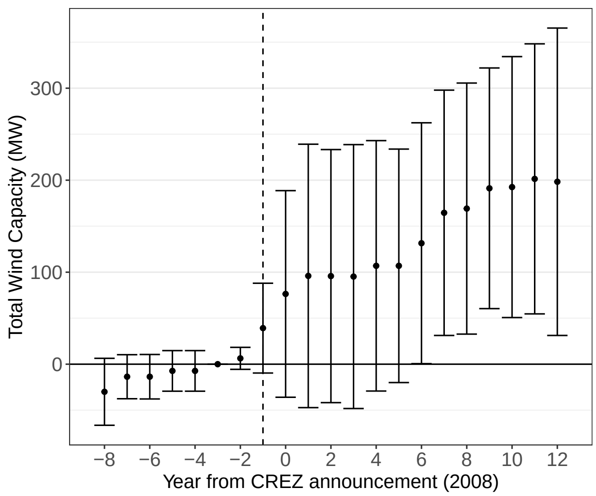
In this section, I examine whether there was an anticipation amongst wind developers to announcement of CREZ transmission expansion in late 2008. Existence of such an anticipation could lead to biased estimates of the impact on CREZ announcement on wind investment in Section 6. The direction of the bias is expected to be downwards since the coefficient estimate would not capture the wind investment in periods before the announcement.

C.1 Allowing for anticipation behavior in Callaway and Sant'Anna (2021) estimates

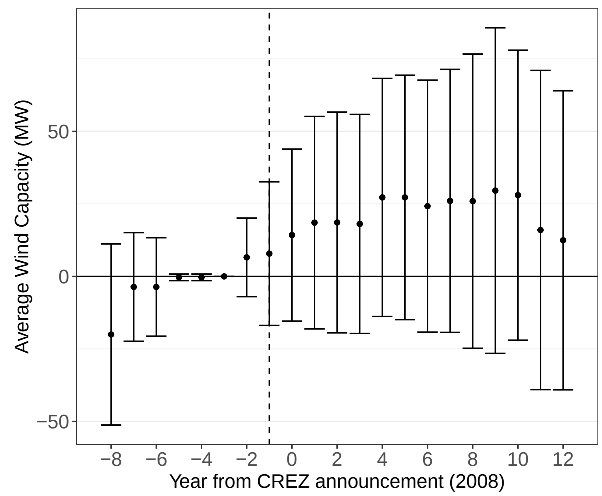
I first test for the anticipation behavior by allowing for anticipation periods in the preferred Callaway and Sant'Anna (2021) (CS) estimator for the event study specification in Equation 14. Allowing for δ anticipation periods involves estimating the event study with the pre-treatment window shifted by $\delta - 1$ periods. I estimate specifications with anticipation two and four years from CREZ announcement, i.e. 2006 and 2004 respectively. Allowing for earlier anticipation periods comes at the expense of the number of pre-treatment periods remaining (Callaway and Sant'Anna 2021).

Figure C1 shows the event study estimates allowing for anticipation behavior ($\delta = 2$ and $\delta = 4$) for total wind capacity and average project size as the dependent variable. While the coefficient estimates for both the dependent variables (Figures C1a and C1b) are positive for the two anticipation periods (i.e. periods -2 and -1), they are statistically indistinguishable from zero. Further, the estimates for the post treatment period are qualitatively similar to the no-anticipation behavior baseline estimates in Figure 5 for total capacity and average project size. In a similar vein, the coefficient estimates for post-treatment period when allowing for four periods of anticipation ($\delta = 4$) in Figures C1c and C1d are also similar to the baseline estimates.

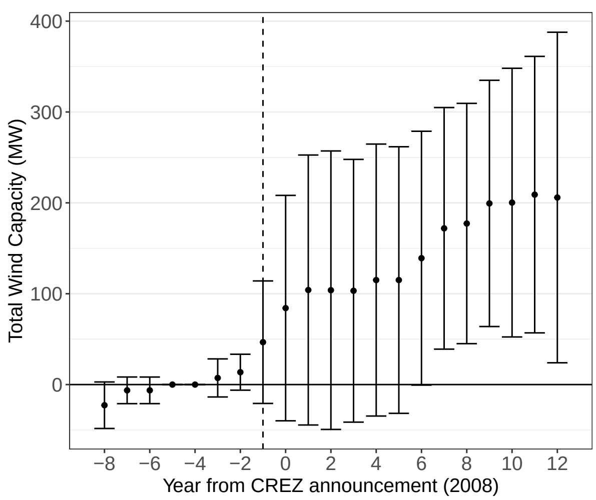
Figure C1: Effect of CREZ Announcement on Wind Investment - Anticipation Behavior



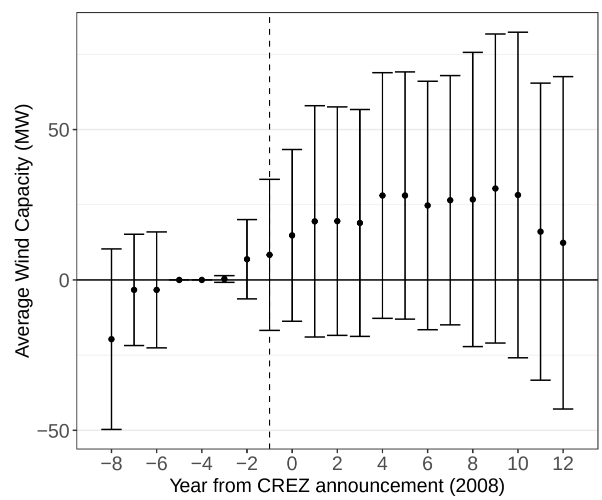
(a) Total Project Capacity (MW)



(b) Average Project Capacity (MW)



(c) Total Project Capacity (MW)



(d) Average Project Capacity (MW)

Notes: Figures C1a and C1c shows the coefficient estimates of the event study in Equation 14 with Total Wind Capacity in a county as the dependent variable. Figures C1b and C1d shows the coefficient estimates of the event study in Equation 14 with Average Wind Capacity in a county as the dependent variable. Figures C1a and C1b allow for two periods of anticipation behavior whereas Figures C1c and C1d allow for four periods of anticipation behavior. All of the specifications use Callaway and Sant'Anna (2021) estimator and include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. Sample is a balanced panel of 31 treated counties and 68 control counties obtained using Coarsened Exact Matching, from 2000 to 2020 (N = 2,079). 95 percent confidence intervals are constructed using standard errors clustered at the county level.

C.2 Testing for anticipation behavior using generator interconnection data

Next, I use the information on generator interconnection requests as another test for existence of anticipation behavior. An increase in generator interconnection requests or interconnection capacity can reflect anticipatory investment towards future transmission expansion at a location. Recall that signing the interconnection agreements and entering the queue is one of the first steps in the process of wind project developments and precedes financing and project construction (AWEA 2019).

I collect interconnection data from EIA Form 860 for the years 2004 to 2012 and combine this with Generator Interconnection Status (GIS) Reports from ERCOT for the years 2013 to 2019 to get the date when a wind project signed the interconnection agreement. I match these data with the wind project data from EIA Form 860 and American Clean Power Association (formerly AWEA). The matched dataset comprises of 147 projects that signed the interconnection agreement between 2004 and 2018. These projects represent about 87 percent of the existing wind projects in Texas during this period. Therefore, I restrict the sample to 2004 to 2018 for the analysis below.

I run several event study specifications, similar in spirit to Equation 14 to test whether CREZ locations saw significantly more interconnection requests than other locations, pre- and post-CREZ announcement. Specifically, I estimate versions of the following specification:

$$y_{it} = \alpha_i + \tau_t + \sum_{k=2004,\neq 2007}^{2018} \beta_k \cdot crez_i \times \mathbb{1}\{K_t = k\} + \mathbf{X}'_{it}\Pi + \epsilon_{it} \tag{16}$$

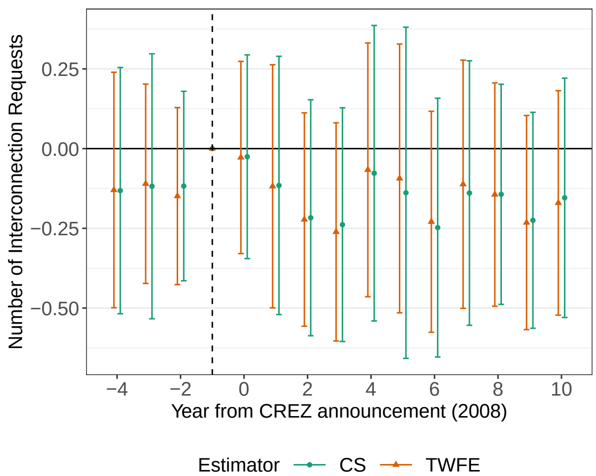
where y_{it} is the outcome of interest. I use number of interconnection requests in county i in year t and total capacity of projects that signed an interconnection request in county i in year t as the dependent variables. $\mathbb{1}\{K_t = k\}$ is the set of relative year indicators from 2004 to 2018 with 2007 as the base year, and $crez_i$ is a binary variable that specifies whether a substation for CREZ lines was announced to site in county i. α_i and τ_t are county and year fixed effects respectively, and ϵ_{it} is the random error term clustered at the county level.

The parameter of interest, β_k captures the average difference in the outcome variable in treated vs. control counties relative to the announcement year of 2008. I include a wide variety of control variables summarized in vector $\mathbf{X}_{it}$ which account for factors that could affect wind project siting and are correlated with CREZ locations. These variables include cubic polynomial of wind speed, capacity factor, terrain elevation and ruggedness, and farm value and size to control for land value. County fixed effects account for unobserved and time-invariant county-specific factors and year fixed effects account for common time specific shocks.

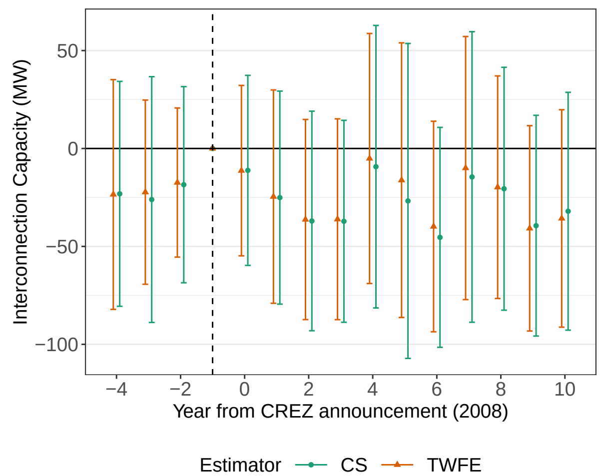
I implement a matching strategy to address the concern of a lack of common support in comparing treated and control counties in Equation 16. Similar to the empirical strategy in Section 6, I use Coarsened Exact Matching to obtain a set of counties that are identical on a wide array of characteristics that affected selection of CREZ locations and affect wind project site selection. Table D3 shows the balance table of counties pre- and post matching strategy. Finally, I implement the Callaway and Sant'Anna (2021) staggered treatment effects estimator for the event study specification in Equation 16 using the sample obtained from matching.

Figure C2 shows the coefficient estimates for Equation 16 with number of interconnection requests and interconnection request capacity as the dependent variables. I do not observe any discernible impact of CREZ announcement on generator interconnection requests, pre- or post-treatment period.

Figure C2: Effect of CREZ Announcement on Generator Interconnection



(a) Number of Interconnection Requests



(b) Total Interconnection Capacity (MW)

Notes: Figure C2a shows the coefficient estimates of the event study in Equation 16 with Number of Interconnection Requests in a county as the dependent variable. Figure C2b shows the coefficient estimates of the event study in Equation 16 with Interconnection Capacity in a county as the dependent variable. Both specifications include cubic polynomial of wind speed, capacity factor, average farm size, average farm value, terrain elevation, and terrain ruggedness as covariates. CS is Callaway and Sant'Anna (2021) estimator and TWFE is the Two Way Fixed Effects estimator. Sample is a balanced panel of 34 treated counties and 75 control counties obtained using Coarsened Exact Matching, from 2004 to 2018 (N = 1,635). 95 percent confidence intervals are constructed using standard errors clustered at the county level.

D Supplementary Tables

Table D1: Summary Statistics at the Project Level

	Mean	Std. Dev.	Min	Max
CREZ (0/1)	0.42	0.49	0	1
Nameplate Capacity (MW)	146.33	89.69	1.30	478.00
Wind Speed (m per s)	8.16	0.53	6.93	9.52
Capacity Factor	0.45	0.04	0.33	0.55
Elevation (m)	673.46	358.30	6.13	1,330.36
Terrain Ruggedness	20.04	9.49	1.51	66.17
Land Price ($ per acre)	1,494.85	1,087.37	104.00	6,478.33
Average Farm Size (acre)	2,931.57	5,392.27	176.60	35,635.20
Median Farm Size (acre)	517.00	490.15	12.00	2,218.80
Average Farm Value ($ per acre)	1,217.24	747.41	137.00	4,180.40
Wind Ordinance (0/1)	0.00	0.00	0	0

Notes: This table shows the summary statistics at the project level of key variables used in the wind project location choice estimation. Sample is all wind projects in Texas bigger than 1 MW in size that began operation from 2001 to 2020.

Table D2: Balance Table of Pre- and Post-Matching Sample

Variables	Pre-Matching				Post-Matching			
	Control Mean	Treated Mean	Difference (1) - (2)	p-val	Control Mean	Treated Mean	Difference (5) - (6)	p-val
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wind Speed (m/s)	7.350	7.920	0.570	0.000	7.870	8.000	0.130	0.190
Capacity Factor	0.410	0.450	0.040	0.000	0.440	0.450	0.010	0.070
Average Population (1000s)	75.510	155.540	80.030	0.140	32.590	29.570	-3.020	0.780
Average Farm Size (1000 acres)	1.810	1.660	-0.160	0.830	1.300	1.420	0.120	0.670
Median Farm Size (1000 acres)	0.430	0.370	-0.060	0.770	0.370	0.370	0.000	0.970
Average Farm Value (1000 $ per acre)	1.240	1.070	-0.170	0.200	0.930	0.820	-0.110	0.420
Average Elevation (m)	396.520	585.360	188.850	0.000	642.630	628.070	-14.550	0.850
Terrain Ruggedness	20.010	22.240	2.230	0.480	19.580	22.150	2.580	0.130
ERCOT Zone: Coastal	0.051	0.000	0.051	-	0.000	0.000	0.000	-
ERCOT Zone: Houston	0.028	0.000	0.028	-	0.000	0.000	0.000	-
ERCOT Zone: North	0.215	0.308	-0.093	-	0.263	0.263	0.000	-
ERCOT Zone: Panhandle	0.135	0.179	-0.044	-	0.380	0.217	0.162	-
ERCOT Zone: South	0.257	0.026	0.231	-	0.030	0.030	0.000	-
ERCOT Zone: West	0.206	0.487	-0.282	-	0.328	0.490	-0.162	-
Total Counties	214	39			68	31		

Notes: This table shows balance test of key variables at their pre-treatment values used in matching using Coarsened Exact Matching. Pre-treatment sample is constructed from wind project data from 2000 to 2007. Terrain ruggedness is the standard deviation of elevation in a county. Exact matching is implemented for ERCOT load zones.

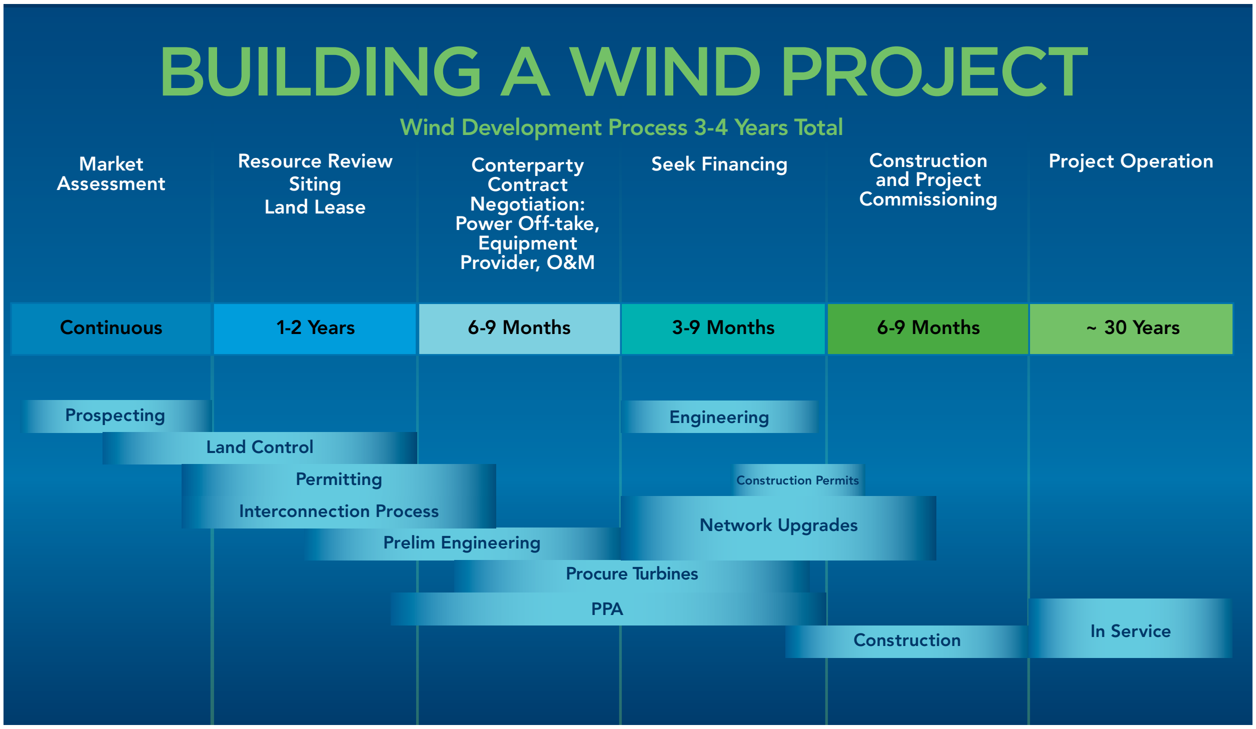
Table D3: Balance Table of Pre- and Post-Matching Sample: Anticipation Analysis

Variables	Pre-Matching				Post-Matching			
	Control Mean	Treated Mean	Difference (2) - (1)	p-val	Control Mean	Treated Mean	Difference (6) - (5)	p-val
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wind Speed (m/s)	7.350	7.920	0.570	0.000	7.880	7.950	0.060	0.480
Capacity Factor	0.410	0.450	0.040	0.000	0.440	0.450	0.000	0.560
Average Population (1000s)	78.280	161.080	82.800	0.140	31.150	48.940	17.790	0.270
Average Farm Size (1000 acre)	1.800	1.590	-0.210	0.780	1.340	1.490	0.160	0.630
Median Farm Size (1000 acre)	0.420	0.360	-0.060	0.770	0.390	0.370	-0.030	0.770
Average Farm Value (1000 $ per acre)	1.430	1.240	-0.200	0.170	1.110	1.090	-0.030	0.850
Average Elevation (m)	396.520	585.360	188.850	0.000	617.370	608.380	-8.990	0.900
Terrain Ruggedness	20.010	22.240	2.230	0.480	20.060	21.960	1.900	0.240
ERCOT Zone: Coastal	0.051	0.000	0.051	-	0.000	0.000	0.000	-
ERCOT Zone: Houston	0.028	0.000	0.028	-	0.000	0.000	0.000	-
ERCOT Zone: North	0.215	0.308	-0.093	-	0.295	0.266	-0.066	-
ERCOT Zone: Panhandle	0.135	0.179	-0.044	-	0.334	0.195	-0.382	-
ERCOT Zone: South	0.257	0.026	0.231	-	0.027	0.027	0.000	-
ERCOT Zone: West	0.206	0.487	-0.282	-	0.343	0.511	0.369	-
Total Counties	214	39			75	34		

Notes: This table shows balance test of key variables at their pre-treatment values used in matching using Coarsened Exact Matching for anticipation behavior analysis in **??**. Pre-treatment sample is constructed from wind project data from 2004 to 2007. Terrain ruggedness is the standard deviation of elevation (metres) in a county. Exact matching is implemented for ERCOT load zones.

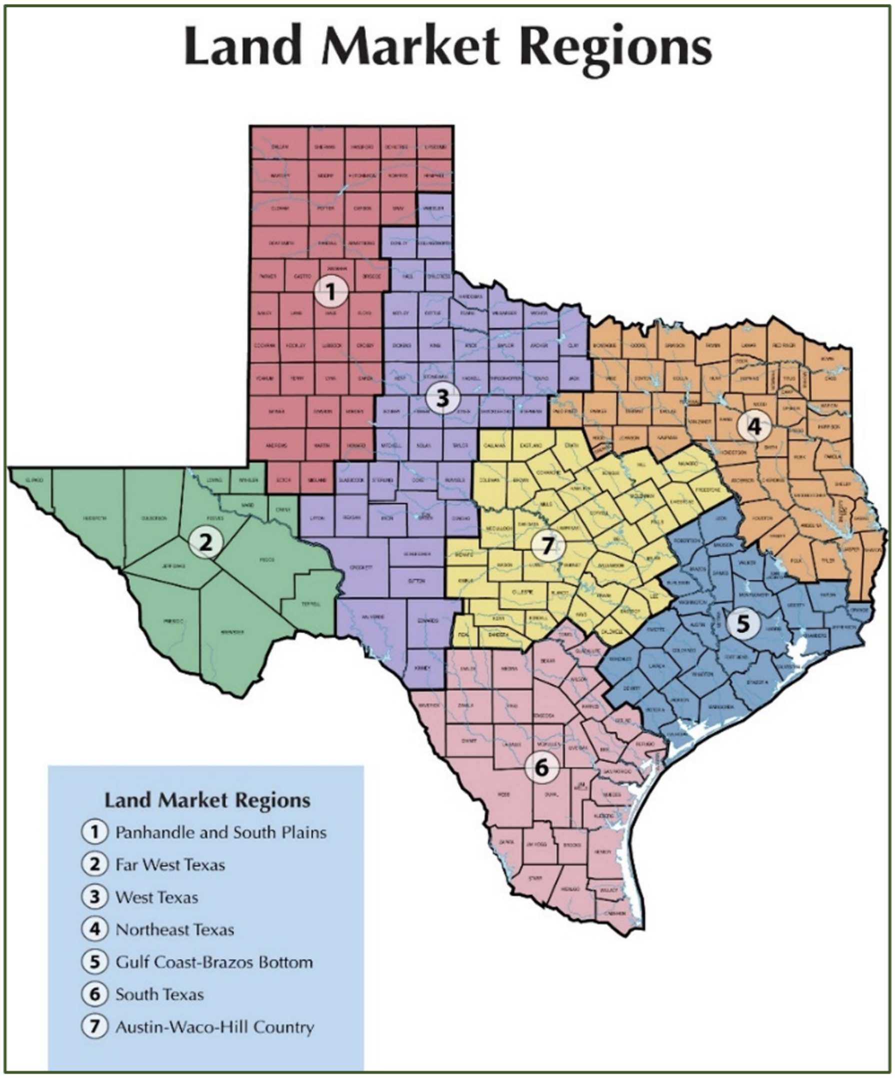
E Supplementary Figures

Figure E1: Wind Project Development Timeline



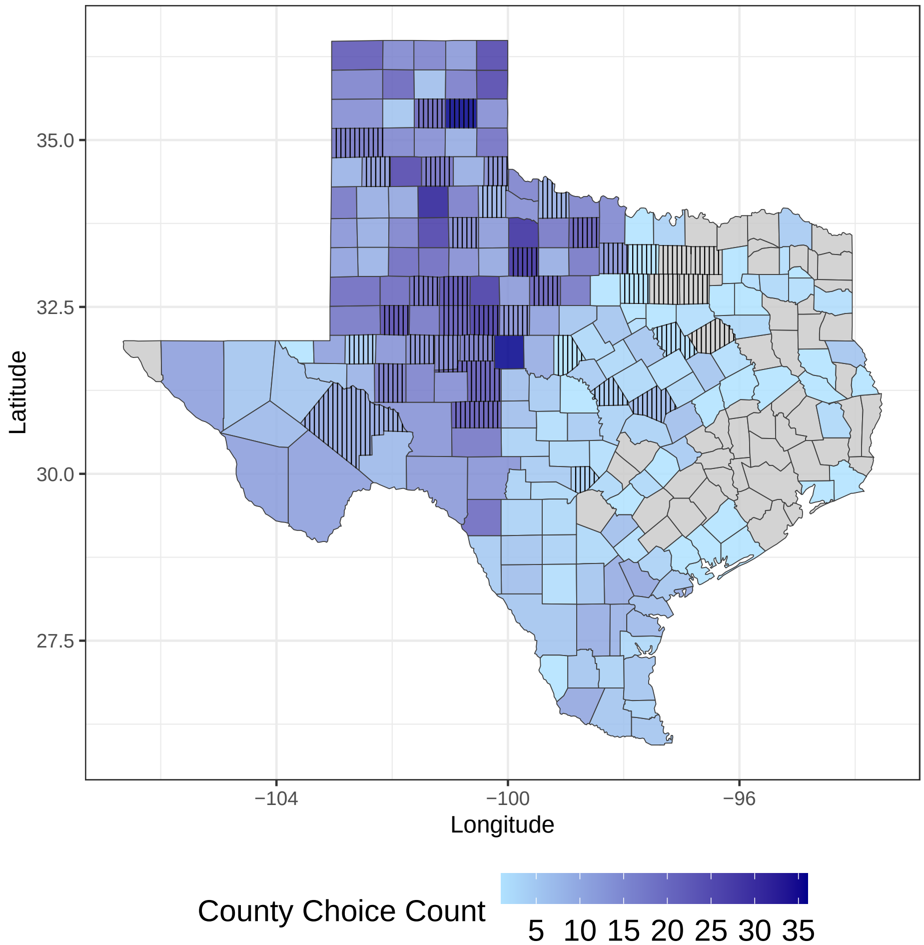
Source: American Wind Energy Association (AWEA) Wind Powers America Annual Report 2019

Figure E2: Land Market Regions



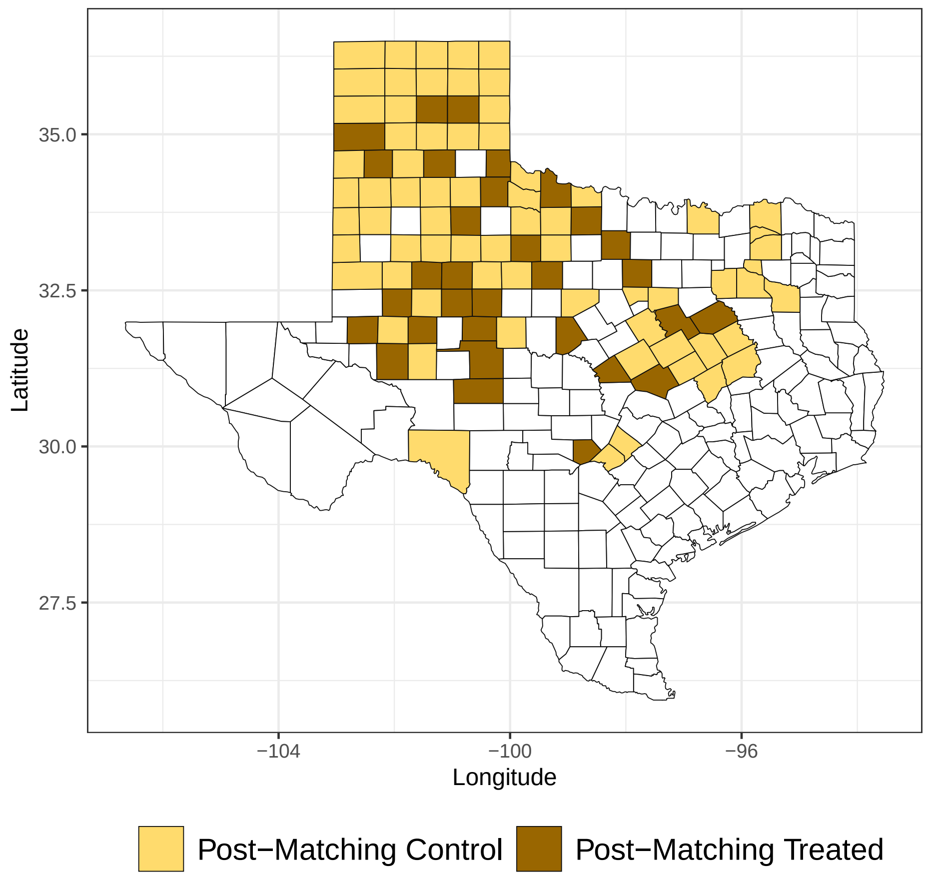
Source: Real Estate Center at Texas A&M University

Figure E3: Heat Map of Counties in Project Choice Sets



Note: This figure shows a frequency map of counties appearing across wind project choice sets from K-Nearest Neighbor algorithm with K = 10 (i.e. a project can choose from a set of 10 counties). Darker blue shade indicates that a county appears in the location choice set of multiple projects. Counties not part of any choice set are shown in grey. CREZ counties are shown in hash pattern.

Figure E4: Treated and control counties obtained using Coarsened Exact Matching



Notes: Total number of control counties are 30, total number of treated counties are 13. Unshaded counties are discarded from the sample used in the regression analysis because they lie outside of the common support of observable characteristics.

Figure E5: Average Hourly Wind Curtailment