Learning By Regulating: The Evolution of Wind Energy Zoning Laws[*]

Justin B. Winikoff[†]

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Abstract

When new industries develop, governments face the challenge of creating effective regulations in the presence of uncertainty and limited expertise. I study the uptake and evolution of local zoning regulations in the emerging wind energy industry by assembling a novel database of county wind energy conversion system (WECS) ordinances. Using a duration analysis, I find counties adopt ordinances when potential benefits from regulation are high and regulatory costs are low. Although counties mimic the standards of their neighbors, regulations become spatially heterogeneous over time, presumably as governments better align policies with local preferences. The findings highlight the dynamic nature of regulation and contribute to an ongoing policy debate about which level of government should have the authority to regulate wind power. Current state proposals to reclaim centralized control will stunt the local adaptation observed in the data. States might more usefully focus on assisting those counties with limited regulatory capacity.

Keywords: Regulation, Wind Energy, Zoning, Environmental Federalism
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[*]The most recent draft of this paper can be found at www.justinwinikoff.com.

[†]Agricultural and Applied Economics, University of Wisconsin-Madison. *Email: jwinikoff@wisc.edu.* I thank Spencer Martin and Tyler Meulemans for assistance gathering data, as well as Dominic Parker, Dan Phaneuf, and Bill Provencher for helpful comments. Most importantly, I would like to acknowledge the hundreds of county officials who responded to emails and phone calls about their county's zoning regulations. Without them, this project would not have been possible. This material is based on work supported in part by the National Institute of Food and Agriculture, United States Department of Agriculture, AFRI project 1002303.

1 Introduction

According to seminal theories of institutional adaptation, informal rules governing natural resource use will dynamically evolve as efficient responses to changing costs and benefits (e.g., Demsetz, 1967; Ostrom, 1990). How well does this framework apply to formal regulation of emergent industries utilizing natural resources? Do regulators iteratively adjust standards as the net benefits of doing so change? How is regulatory adaptability impeded or hasted by decentralized (e.g., counties) or centralized (e.g., states) government control? This paper addresses these questions in the context of a novel industry: wind energy.

The most direct attempt to apply Demsetz and Ostrom's thesis to formal regulation is found in Mulligan and Shleifer (2005). They demonstrate that rules first appear in jurisdictions with lower legislative costs and those benefiting the most from regulation. Their analysis only examines the adoption and quantity of legislation, however, rather than the full regulatory history. To fully understand the regulatory process, it is important to examine not only the creation of new standards, but also how they change over time.

I study a nascent regulatory environment — wind energy zoning — and demonstrate empirically the determinants of local regulatory differences across time and space. I find evidence of learning and adaptation, suggesting local regulation is indeed an evolutionary process that may converge toward a level of stringency effectively balancing the costs and benefits of relevant stakeholders.

I analyze the dynamic regulatory process by examining the adoption, strictness, and evolution of wind energy zoning standards. Specifically, I study policies mandating how far turbines must be set back from neighboring property lines and residences. I do so by assembling a new database of county-level ordinances regulating commercial wind energy conversion systems (WECS) that documents the entire regulatory history of turbine setbacks in about 750 counties across ten states.

I first develop a three-stage theoretical model that assumes policymakers are incentivized to adopt wind energy zoning laws that are locally efficient, subject to the costs of implementation.[1] The regulator determines how much wind energy capacity is optimal, what policy achieves that level, and finally whether the expected gains from regulation exceed the legislative costs. Because the wind power industry is relatively young, regulators are uncertain about how much development results from a specific policy. The model produces three main predictions. First, as the benefits from wind energy increase and the potential harm decreases, counties encourage development through less restrictive regulations. Second, in the face of limited information and uncertainty, regulators copy standards from neighboring governments. Finally, only those for whom the benefits from regulation exceed the legislative fixed costs of implementing new rules will do so.

I test these predictions first with a duration (or survival) analysis of the decision to adopt a WECS ordinance. Counties create ordinances in response to factors reflecting both the costs and benefits of regulation. Specifically, counties with more wind potential adopt regulations earlier. Ordinances emerge sooner when neighboring counties have already adopted WECS standards, suggesting regulators adjust their perceptions about the demand for local wind power. On the other hand, counties lacking zoning regulations, which are themselves costly to provide, are less likely to enact ordinances.

I next examine the relative strictness of each county's regulations using a repeated cross-sectional analysis of property line and residential setbacks. Regulators mimic the standards in nearby counties: setbacks are stricter when neighboring setbacks are more restrictive. Regulations are also tailored specifically to the community, however, and respond to factors affecting the local demand for wind energy, including land ownership inequality, where farmers live, the seasonal population, and, in some specifications, income.

[1] I therefore assume regulators act in the public interest (Pigou, 1932) and are not "captured" (Stigler, 1971; Posner, 1974; Peltzman, 1976; Laffont and Tirole, 1991).

Finally, I document the ways in which the regulatory environment has evolved over time. Counties with greater wind energy potential, and therefore more to gain from optimal regulations, are more likely to update their WECS ordinances after initial adoption. Although turbine regulations are initially homogenous, they become increasingly varied, and "standard" setback levels that have been criticized as arbitrary become less common.[2]

This study is timely because state and local governments are currently grappling with how to most effectively zone wind power, and these determinations are politically contested and controversial.[3] While some states have handed regulatory authority to counties and townships, others have mandated statewide standards with which local jurisdictions must comply (Heibel and Durkay, 2015). The results suggest decentralization better enables adaptation over time by allowing regulators to learn and adapt rules based on the experiences of a larger sample of neighboring jurisdictions.[4]

In the context of wind power, county control also allows communities to better tailor regulation to local externalities from wind turbines that potentially reduce property values (Jensen et al., 2014; Gibbons, 2015) and adversely affect well-being (Krekel and Zerrahn, 2017). State control may be preferred if it can help internalize cross-county externalities by displacing carbon-intensive energy production (Cullen, 2013; Novan, 2015; Fell and Kaffine, 2018). The political arguments that state governments have advanced to justify centralized regulatory authority, however, have focused instead on concerns of underregulation of local turbine externalities with proposals that are substantially stricter than existing local stan-

[2]See *Wind ordinance debate: The 1,000-foot set-back standard (Are environmentalists underregulating themselves?)*: https://www.masterresource.org/wind-offset-distance/wind-ordinance-offset-debate/.

[3]One such example is the debate surrounding regulations in Ohio: *Lawsuit: Ohio wind setbacks were adopted in violation of state constitution,* https://energynews.us/2018/11/15/midwest/lawsuit-ohio-wind-setbacks-were-adopted-in-violation-of-state-constitution/.

[4]This work also relates to the literature describing "learning by doing," by which firm experience affects future productivity (Arrow, 1962).

dards.[5,6] One of the primary benefits of centralization — reductions in interjurisdictional pollution — would therefore not be realized, and wind power development would likely slow if these proposals were to become law.

States do have a role, however, assisting local communities reduce the otherwise large fixed costs of adopting and maintaining regulatory infrastructure (Oates, 1972; Adler, 2005).[7] Counties without zoning ordinances and those with limited administrative capacity may benefit from some state-level guidance. States can allow counties to opt into statewide regulations rather than form their own. Furthermore, they can enact model ordinances (as many already do) that low-capacity localities can adapt or modify as needed.

This work also contributes to the literature on policy diffusion (Gray, 1973; Berry and Berry, 1990; Volden, 2006; Shipan and Volden, 2008).[8] Policy researchers have long sought to understand the mechanisms by which laws and regulations spread from one government to its neighbors. I study not only the adoption and stringency of regulations, but also their evolution over time. Copying nearby standards may be optimal in the short run, but diverging may be preferred in the long run as regulators learn more about the targeted industry.

[5] *Kansas House Bill 2273,* http://www.kslegislature.org/li/b2019_20/measures/documents/hb2273_00_0000.pdf and *Nebraska Legislative Bill 373,* https://nebraskalegislature.gov/FloorDocs/106/PDF/Intro/LB373.pdf.

[6] This growing tension between state and local governments is not exclusive to wind energy. For example, the Oklahoma state legislature banned local ordinances outlawing fracking. See *Oklahoma blocks local fracking bans* https://thehill.com/policy/energy-environment/243645-oklahoma-blocks-local-fracking-bans. For other emerging industries in which similar debates are occurring, see Haddow et al. (2019).

[7] Other benefits of centralized control include the ability to limit competition and the influence of interest groups (Laffont and Pouyet, 2003).

[8] Chandler (2009), Alvesa et al. (2019) and Fadly and Fontes (2019), among others, examine how renewable energy policies diffuse over space. While most work focuses on incentives, this paper studies the spread of a restriction of renewable energy deployment. Similarly, Lyon and Yin (2010) explores how renewable energy portfolio standards evolve spread over time.

2 Wind Energy, Externalities, and WECS Ordinances

The wind energy industry is rapidly expanding. Environmentalists support its development because wind power helps reduce pollution from fossil fuel based electricity generation (Cullen, 2013; Novan, 2015; Fell and Kaffine, 2018). Rural communities have welcomed wind power because farmers are compensated for allowing turbines on their land, often between \$3,000 and \$6,000 per megawatt (MW) annually (AWEA, 2018).[9] Consequently, federal and state lawmakers have implemented tax credits, subsidies, and renewable portfolio standards to promote its development (Yin and Powers, 2010; Hitaj, 2013; Aldy et al., 2018; Johnston, 2019). The policies have been generally successful; wind energy capacity has increased from about 4,000 MW in 2001 to over 96,000 MW in 2018 (AWEA, 2019).

Although a positive global good, wind turbines may create negative local externalities by generating noise, shadow flicker (rotating shadows caused by spinning turbines), and obstructed viewsheds. Many express concern about the effect of proximity to wind turbines on property values, although the empirical evidence is mixed. Jensen et al. (2014) and Gibbons (2015) find turbines reduce property values, but Hoen et al. (2011) and Vyn and McCullough (2014) do not. Opponents of wind power also worry about potential adverse health effects of living near wind turbines. Krekel and Zerrahn (2017) use data in Germany to demonstrate that proximity to wind farms is associated with lower self-assessments of well-being.

These externalities (or at least, the perception thereof) have led regulators to adopt ordinances governing the placement of wind energy conversion systems (WECS).[10] In the United States, there are no federal laws governing how wind turbines are sited. The author-

[9] In 2017, the average turbine size was 2.32 MW, suggesting per-turbine payments between \$7,000 and \$14,000.

[10] I use "WECS" to refer to all utility-scale wind energy. Ordinances use a number of terms, including "wind energy systems (WES)", "wind energy facilities (WEF)", or simply "wind power."

ity to regulate WECS is therefore left to the states, among which legislative approaches are vary substantially. Some states, including Ohio and Oregon, take authority over larger wind farms. Others give control to localities, including Illinois, Indiana, and Kansas. States like Minnesota and South Dakota require joint approval from both state and local regulators (Heibel and Durkay, 2015).

WECS ordinances outline a variety of turbine standards including color, wiring, and decommissioning procedures. In this paper I focus on setback regulations mandating how far wind turbines must be from a given feature such as a property line, residence, or right of way. Most controversial are setbacks from property lines and residences that most directly correspond to human exposure to wind turbine externalities.

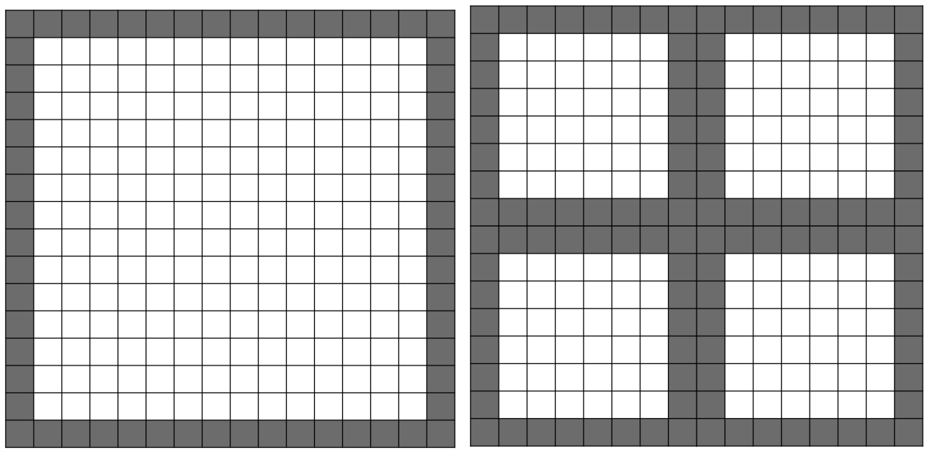
Setbacks are a common zoning tool used to regulate where businesses and residences can locate, and how or where industrial activities can take place. These standards may apply to every structure built in certain zoning district, or target very specific land uses.[11] The most similar analogue to wind energy is oil and gas development, where residential setbacks mandate how far drilling wells must be from homes (Ericson et al., 2019).

A minimum turbine setback from a property line, residence, or any other landmark necessarily reduces the available land for wind energy development. Figure 1a provides a simple illustration. Consider a property on which developers want to place a wind turbine. In the absence of setbacks, any "box" in the parcel can host the turbine. A setback of one box from property lines mandates that the surrounding rim of the property is no longer available for development. Setbacks may also have differential effects on varying levels of land ownership concentration by pushing development toward larger farms (Winikoff and Parker, 2019). Consider Figure 1b. If the same land is owned by four individuals, rather

[11] For discussions on the origins, implications, and history of setbacks, see Horne (1969), Pogodzinski and Sass (1991), Green (1999), and Jaeger (2006).

than one, the amount of unavailable land increases.[12]

Figure 1: Illustration of suitable (white) and unsuitable (gray) land for wind energy development with setback policy of one box



(a) One landowner **(b)** Four landowners

The origins of early turbine setback regulations in the United States is somewhat unclear. Large-scale wind energy development and zoning began in California in the 1980s, but there is little public information describing how regulators determined setback levels. Regulations were likely determined with input from industry interest groups (Larwood and van Dam, 2006). As the wind energy industry matured, setbacks became a popular tool for regulators across the country. Although local jurisdictions have control over zoning in many states, government officials lacking experience with wind energy were tasked with developing wind energy regulations. As a result, it became beneficial to borrow from others with more experience. Several states developed "model ordinances" for local governments to use as a template for their own regulations (Stanton, 2012).

Generally, minimum distances between turbines and property lines or residences are

[12]If all four of these landowners choose to"participate" in the wind farm, however, they may be able to waive the setback requirements. Nonetheless, if one of these landowners does not participate, the amount of unavailable land would increase.

calculated in three different ways: distances (e.g., 1,000 feet), turbine height multipliers (2.0 times the turbine height), or rotor diameter (the diameter created by the rotating turbine blades) multipliers (2.5 rotor diameters). Some ordinances combine some of these measurements by mandating setbacks be the minimum of one or the other (e.g., the greater of 3.0 times turbine height or 1,500 feet). Others sum multiple measures (e.g., half a rotor diameter plus 100 feet).

As local opposition to wind energy grew, setback policies have became more controversial. Public hearings began to last hours, and turbine setbacks became a pivotal factor in local county board elections.[13,14] Some states responded to opposition by passing (or proposing) stricter statewide setbacks. Since their passage in 2014, Ohio's turbine regulations have been widely debated among policymakers and stakeholders and led to lawsuits.[15]

Despite their emergence in the local public policy debate, very little is understood about how WECS regulations emerge and why they are stricter in certain communities.[16] Recognizing the motivating factors for ordinance adoption and stringency of these setback policies is essential for establishing best practices and advising policymakers. I try to bridge this gap, first with a theoretical model explaining the regulator's decision to establish zoning standards and then with an empirical analysis.

[13]See: *How a county election in rural Illinois became a referendum on wind energy,* Energy News Network, https://energynews.us/2018/11/05/midwest/how-a-county-election-in-rural-illinois-became-a-referendum-on-wind-energy/.

[14]In private conversations, zoning officials noted how heated arguments at public hearings occasionally resulted in threats of violence.

[15]See *Lawsuit: Ohio wind setbacks were adopted in violation of state constitution,* Energy News Network, https://energynews.us/2018/11/15/midwest/lawsuit-ohio-wind-setbacks-were-adopted-in-violation-of-state-constitution/.

[16]Several reports discuss wind energy zoning best practices, including Stanton (2012), Doerr (2014), and Baer et al. (2018).

3 Theory

I model the county regulator's decision to set zoning standards to achieve the ideal level of installed wind energy capacity. First, the regulator determines the optimal amount of wind energy capacity demanded. Next, it chooses the best policy to achieve this outcome. The county is uncertain about the exact mapping from policy to outcome and has three choices for its standards: (1) engage in costly research to obtain the optimal policy, (2) mimic the policy of a neighboring regulator, or (3) modify the nearby policy. This optimization problem borrows heavily from the work of Callander (2008, 2011a,b) and Glick (2012). Once it has determined the best policy, the county decides whether to regulate wind energy, given the county's wind energy potential and regulatory costs.

3.1 Optimal Amount of Wind Energy

Consider a county i where only a certain proportion of landowners, $p_i \epsilon (0, 1]$, benefit from wind energy. This can be thought of as the number of landowners who would receive royalty payments from a hypothetical wind farm. Scaling the benefits to one, the county gains from wind energy capacity level w_i can be written as $p_i w_i$. Wind energy also imposes dis-amenities on the local community such as noise and shadow flicker. The amount of damage $d_i \epsilon (0, 1]$ depends on county characteristics, such as the natural amenity value, population density, and how many landowners are exposed to dis-amenities. Costs from wind energy are represented by $C(w_i) = w_i^2$.[17] The overall damages from wind energy can therefore be written as $d_i w_i^2$. The regulator's utility maximization problem is

$$\max_{w_i} U_i = \ p_i w_i - d_i w_i^2, \tag{1}$$

[17]The quadratic function is convenient because it allows me to exploit the second moment generated from policy uncertainty. See Epstein and O'Halloran (1999) and Bendor and Meirowitz (2004) for a discussion of the quadratic loss function in similar models.

resulting in the optimal level of wind energy:

$$w_i^* = \frac{p_i}{2d_i}. \tag{2}$$

Equation 2 produces several intuitive predictions, demonstrating how counties demand more or less wind power in response to local characteristics. First, as the proportion of people who benefit from wind energy, p_i, increases, so too does the ideal amount of capacity. On the other hand, as the damage from turbines, d_i, rises, w_i^* falls.

3.2 Optimal Zoning Policy

Denote s_i as county i's turbine setback policy. A greater s_i increases the expected amount of wind energy w_i.[18,19] The setback policy maps to a level of wind energy via the policy mapping function $\psi(s_i)$. The county's utility can now be written as

$$U_i(\psi(s_i)) = p_i\psi(s_i) - d_i\psi(s_i)^2. \tag{3}$$

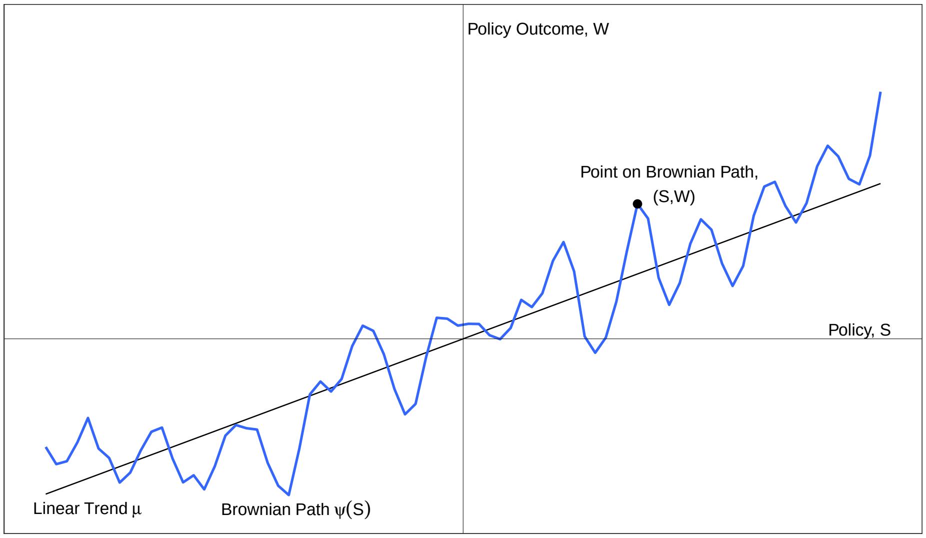
Due in part to the nascency of the industry, the exact mapping for any given policy s_i is unknown. I model this uncertainty using a *Brownian motion* (Callander, 2008), defined by an underlying linear trend with random fluctuations. The positive sloping trend μ and the variance of the fluctuations σ^2 are known by the regulator. After nature determines the Brownian path and one outcome is realized, the remainder of the path is still uncertain. Figure 2 illustrates an example of Brownian motion.[20]

[18] I model a positive relationship between setbacks and wind capacity for mathematical simplicity, and using a negative relationship would not change any conclusions.

[19] A key assumption here is that the setback policy affects only the amount of wind energy w_i, and not the share of people benefitting and harmed by development. This reduces the complexity of the maximization problem and avoids having to define statistical moments beyond the mean and variance.

[20] Brownian motion has a number of desirable attributes. Specifically, it allows for "partial invertibility." Knowing one outcome reduces uncertainty about other policies, but does not eliminate it. For a full discussion of its benefits, see Callander (2011a).

Figure 2: Illustration of Brownian motion



Uncertainty is formalized using the following moments. Consider some realized policy, s_j, resulting in $\psi(s_j) = w_j$. The expected capacity of setback level s can be written as $E(\psi(s)|s_j) = w_j + \mu(s - s_j)$. In the absence of uncertainty, this is how a regulator would decide its setback: add w_j and the difference between policies, multiplied by the linear slope, μ. The variance of this policy is $Var(\psi(s)|s_j) = |s - s_j|\sigma^2$. Intuitively, as the difference between the known and proposed policy increases, there is more uncertainty.

Under this uncertainty, the regulator has three options for determining its setback policy. Borrowing the notation of Glick (2012), the regulator can *tailor* the setback policy to get exactly w_i^* by engaging in costly research, *mimic* the regulations of a neighboring county, s_j, to achieve outcome w_j, or *modify* the existing policy of neighbor j.[21]

The regulator can obtain its ideal level of wind energy, w_i^*, and the corresponding setback by engaging in costly research, R_i. This research could represent the costs of talking to industry experts and detailed studies of the terrain of the county. If the regulator

[21] Of course, the first regulator would have no neighbors to mimic and would have to tailor its regulations.

chooses this option, the county can achieve exactly w_i^* and eliminate all uncertainty. The county's expected utility is therefore

$$EU_{tailor} = U_i(w_i^*) - R_i = \frac{p_i^2}{4d_i} - R_i. \tag{4}$$

If the regulator copies the policy of its neighbor j, it again eliminates all uncertainty and achieves the capacity level w_j. The expected utility is therefore

$$EU_{mimic} = U_i(w_j) = p_i w_j - d_i w_j^2. \tag{5}$$

If $w_j = w_i^*$, the expected utility from mimicking equals $U_i(w_i^*)$, the maximum utility. How much this utility deviates from the optimal outcome depends on the difference between the ideal and the neighboring outcome, $\Delta_{ij} = w_i^* - w_j$.

The final option for the regulator is to modify the policy of neighbor j. This strategy allows the regulator to attempt to reach a level of capacity nearer to w_i^* while simultaneously hedging against uncertainty by learning from the neighbor. Without loss of generality, assume that $w_i^* > w_j$.[22] Taking into consideration the mean and variance of the Brownian motion, $\psi(s)$, the regulator chooses the setback policy s_i to maximize the following expected utility function:

$$\begin{aligned} \max_{s_i} EU(\psi(s_i)|s_j) &= E[p_i\psi(s_i) - d_i(\psi(s_i))^2 \big| s_j] \\ &= p_i(w_j + \mu(s_i - s_j)) - d_i(s_i - s_j)\sigma^2 - d_i(w_j + \mu(s_i - s_j))^2. \end{aligned} \tag{6}$$

Solving for the optimal modified setback, $\hat{s}_i$, yields

$$\hat{s}_i = s_j + \frac{\Delta_{ij}}{\mu} - \frac{\sigma^2}{2\mu^2}. \tag{7}$$

[22] Some of the signs change, but the underlying conclusions reached do not when assuming $w_i^* < w_j$.

This is the identical result from Glick (2012). Moving from the neighbors' setback s_j, the regulator adjusts according to the difference between the two policies divided by the slope, $\frac{\Delta_{ij}}{\mu}$. The third term, $\frac{\sigma^2}{2\mu^2}$,represents a hedge against uncertainty in the policy mapping. The greater the variance, the less the regulator wants to deviate from the neighbor's outcome because the outcome is less certain. The expected utility of the optimal modified policy can be written as

$$EU_{modify} = U_i(w_i^*) - U_i(\frac{\sigma^2}{2\mu}) + \frac{d_i w_j \sigma^2}{\mu}. \quad (8)$$

In the absence of uncertainty, the regulator would achieve the exact utility from its optimal installed wind energy capacity, w_i^*. As w_j rises, there are utility gains because the reference policy is closer to the optimal policy. There are additional reductions to the expected utility, however, from the adjustments to mitigate uncertainty.

Which of the three strategies should the regulator choose? This decision is made by comparing the expected utilities. In the absence of any research costs, tailoring the setback policy will maximize utility. As it becomes more costly to research policies (R_i rises), creating one's own policy is more expensive, and borrowing regulations from a neighbor becomes optimal. This relationship is illustrated in Figure 3a. As research costs rise, tailoring becomes less beneficial, and is dominated by modifying when $R_i > U_i(\frac{\sigma^2}{2\mu}) - \frac{d_i w_j \sigma^2}{\mu}$.

When is modifying preferred to mimicking a neighboring policy? Looking at equation (7), the optimal modified policy equals the neighbor's policy, s_j, when $\Delta_{ij} = \frac{\sigma^2}{2\mu}$. The term $\frac{\sigma^2}{2\mu}$ can be thought of as an indicator of policy complexity (Callander, 2011a; Glick, 2012). As the variance rises, holding μ constant, the policy environment becomes more complex because there is more uncertainty about the outcome. As complexity increases, the regulator will want to stay closer to the neighboring regulations. When policy complexity falls, it is less costly to deviate from neighboring counties.

Figure 3b illustrates the utility from the optimal modified policy, $\hat{s}_i$, under increasing policy complexity. When there is little complexity and σ^2 is small, EU_{modify} approaches $U_i(w_i^*)$, the maximum possible utility. As policy uncertainty increases, the county's optimal modifying strategy, and therefore expected utility, approaches the value from mimicking the neighboring policy exactly.

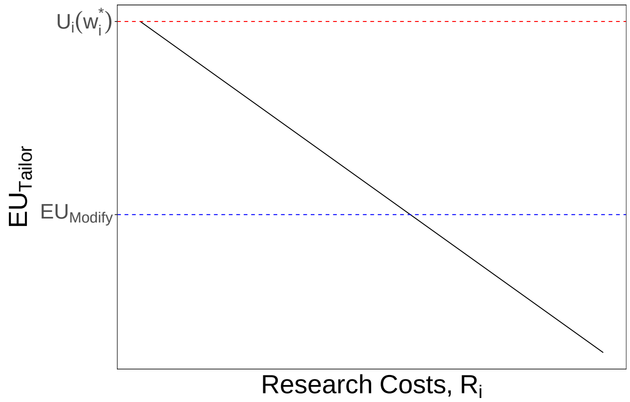
When the difference between the county's optimal wind energy capacity w_i^* and the neighbor's outcome w_j converge, Δ_{ij} approaches 0, and implementing policy s_j will maximize expected utility. As this gap grows, the benefits to modifying rise. This is illustrated in Figure 3c. The difference between EU_{modify} and EU_{mimic} falls as Δ_{ij} does.

Before moving on, it is useful to summarize the conditions from this stage of the optimization process that push regulators toward adopting regulations similar to nearby jurisdictions. First, when it is costly to learn the optimal policy, regulators are borrowing policies identical or similar to those of their neighbors. Second, as uncertainty about the outcomes of a given policy increases, it is best not to deviate too far from those known policies of the neighbor. Finally, if a county has similar preferences to its neighbors, it is less costly to adopt identical rules.

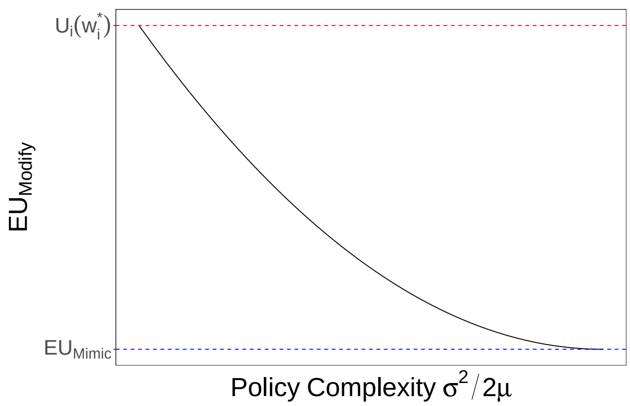
3.3 Whether to Regulate

New regulation requires public hearings and the time and effort of regulators at the expense of other policy issues. This cost of supplying regulation, denoted here as L_i, is realized only if wind regulations are implemented. Furthermore, let $\gamma_i \epsilon [0, 1]$ represent the wind energy potential of county i, and therefore the demand for regulation. If the county chooses to regulate wind energy, its expected utility can be written as $\gamma_i EU_i^*$, where EU_i^* denotes the expected utility from the optimal policy. If developers hope to site a wind farm in an unregulated county and there are no existing standards, the regulators bear a cost

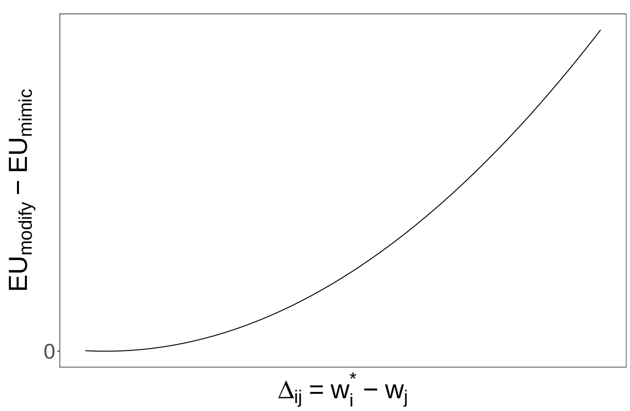
Figure 3: Theoretical predictions



(a) Expected utility from tailoring policy under increasing research costs



(b) Expected utility from modifying policy under policy complexity



(c) Gains from modifying policy as neighboring outcome W_j approaches ideal outcome W_i^*

β_i, reflecting the uncertain legal framework and public scrutiny. The decision to legislate is represented by

$$\max_{Legislate\ \epsilon\ \{0,1\}} \{Legislate = 1\}\big[\gamma_i EU_i^* - L_i\big] - \{Legislate = 0\}\gamma_i\beta_i. \tag{9}$$

As wind energy potential increases, the benefits of legislating rise. Conversely, when wind energy potential is limited, the benefits from regulating will be small relative to the legislative costs and the regulator could be better off taking no action. If legislative costs are not exorbitant, it may be safer to legislate than face legal uncertainty. These costs may be lower when there exists a full-time zoning officer who could help craft legislation.

4 Data

4.1 WECS Ordinance Database

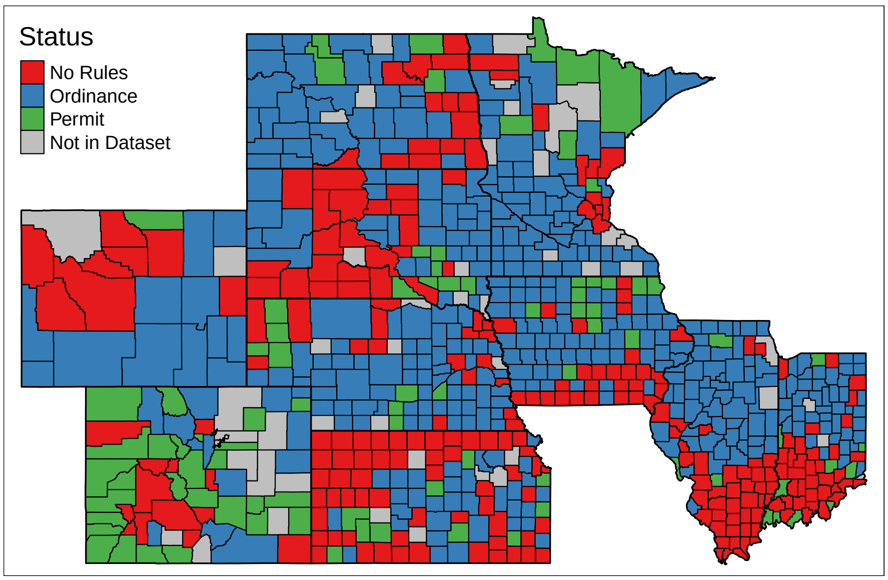
In order to analyze wind energy zoning regulations, I have assembled a database of county-level wind energy regulations and ordinances across ten midwestern states: Colorado, Illinois, Indiana, Iowa, Kansas, Minnesota, Nebraska, North Dakota, South Dakota, and Wyoming. These states generally grant authority to zone wind energy to county governments.[23] I created the dataset by utilizing a variety of publicly available resources, including county websites, internet searches, and periodical databases. I then contacted each county to confirm the information I had found. No counties were added to the dataset without first speaking with public officials. Full details of the data collection process appear in Appendix A.

I was able to incorporate 739 of 784 counties, or about 94 percent. Figure 4 displays

[23] The Minnesota Public Utilities Commission takes control of larger wind farms, although it defers to local regulations. It can override local regulations, however, and has done so (Doerr, 2014). Many counties have fully ceded the regulation of commercial WECS to the state. Wyoming enacted rules in 2010 establishing minimum setback regulations (Stanton, 2012). For some specifications, these states are excluded.

the counties in the database, including their regulatory status (no regulations, WECS regulations, or a permit process only). The counties that did not respond to emails or phone calls appear to be random, with a mix (from my own research) of loose and strict ordinances, and no apparent regulation. These counties are well distributed across all ten states, although the response rate was lower in Colorado.

Figure 4: Map of wind energy conversion system (WECS) regulatory status in 2019



The database reports several attributes of a county's wind energy regulations. First, it notes whether a county has enacted commercial WECS rules and the year in which they were first implemented. It also includes the type of permit required for wind turbines in each county, and when such requirements were added. I also record if a county is zoned and when its zoning regulations were first implemented.[24,25]

[24]Several counties, particularly those in Colorado, are not formally zoned but have land use codes regulating unincorporated areas in a similar way to a zoning ordinance. I consider these counties zoned.

[25]Many counties implemented zoning ordinances several decades ago, and administrators were uncertain of the exact year of the code's enactment. Approximate dates are recorded for some zoning ordinances. For example, an ordinance that an administrator said was enacted in the "1970's" is coded as 1975. Ordinance dates after 1997, the beginning of my sample period for this study, are correct to the year, or otherwise

The database documents the lengths of setbacks from nonparticipating property lines and residential structures.[26] Although there are additional setbacks (often from transmission lines, roads, churches, and schools), they tend to be homogenous, and according to conversations with industry experts, less consequential.[27] I also record the maximum turbine heights (if they exist) and years in which turbine bans are implemented. In several cases, strict height restrictions can effectively ban commercial wind energy from a county.

Many counties have made changes to their wind turbine setbacks or height restrictions since first implementing WECS regulations. I account for these changes by adding observations for each iteration of a county's ordinance in which these regulations change. If a county changes a setback, I record it as an new observation, including the year of the update, and note that this version of the ordinance is updated.[28]

One of my primary hypotheses is that regulators may adopt regulations similar to those of their neighbors. Because some counties do not appear in the database, and many do not have regulations, I expand the definition of neighbors beyond immediately adjacent counties to those within the same agricultural district as defined by the U.S. Department of Agriculture (USDA) in 2007. The districts are clusters of adjacent counties, usually in groups of five to fifteen, within the same state. Figure A1 shows a map of these districts.

I also create an inverse-distance-weighted measure in which each county within the state has an effect on a given county. The measure puts more emphasis on nearby counties and assigns less weight to those far away .Consider, for example, a state with three counties, A,B, and C. Suppose County A is 5 miles from County B and 10 miles from County C.

noted with a flag.

[26]"Nonparticipating" indicates that the setback applies to a property or residence that is not part of the wind farm. In other words, the landowners have not signed lease agreements with wind energy developers.

[27]I also do not record the maximum sound regulations for wind turbines. With a few notable exceptions, these restrictions are between 50 and 60 decibels and would be met by any reasonable property or structure setback.

[28]Updates to other aspects of the ordinance that do not relate to these setbacks or height restrictions are noted but not counted as different observations.

From the perspective of County A, the inverse distances are 1/5 and 1/10, respectively, which sum to 3/10. County B therefore receives 2/3 weight, and County C receives 1/3. Figure A2 presents an example for an Illinois county.

4.2 Other Sources

I include control variables from mostly publicly available sources to control for the other parameters of the model: wind potential α_i, the benefitting population p_i, and the potential damages from wind power, d_i. I use spatial data of the average 100-meter wind speed (in meters/second) in 2012 from the National Renewable Energy Laboratory (NREL) to calculate the mean wind speed across each county in my dataset. As an additional proxy for wind potential, I calculate the kilometers of transmission lines within a county from the Homeland Infrastructure Foundation.

The USDA Census of Agriculture occurs every five years and is intended to be a comprehensive survey of all American farm operators. I include statistics from the 2007 census, including the percentage of county land covered by farmland as an additional indicator for wind energy potential. I also control for the average farm size in each county. Smaller farms may be more exposed to wind turbine dis-amenities and therefore may want stricter regulations (Winikoff and Parker, 2019). The share of farm operators who live off-farm provides an additional measure of exposure to turbine externalities because living off-farm would yield less exposure to the noise and views from wind turbines. Finally, I include the ratio of median to average farm size within a county. When the median farm size rises relative to the average, land is more evenly distributed, and more individuals may benefit from wind power through royalty payments.

Additional covariates include population and the percentage of homes that are seasonally occupied from the 2010 U.S. Census. Population may proxy as a function of both legislative capacity, as in Mulligan and Shleifer (2005), and exposure to turbine dis-amenities. Seasonally occupied homes correlate with natural amenities through recreational uses (Marcouiller et al., 1996; Green, 2001) and therefore reflect potential losses from dis-amenities associated with wind energy. I additionally include 2007 per-capita income from the Bureau of Economic Analysis (BEA) and county-level vote shares for the Republican John McCain in the 2008 presidential election from the MIT Election Data and Science Lab (MEDSL) (MIT, 2017). Finally, I calculate the amount of installed wind energy capacity in a given county and agricultural district using the United States Wind Turbine Database (USWTDB).

5 Timing of Ordinance Adoption

5.1 Duration Model

I first analyze the timing of the decision to adopt wind energy regulations using a duration, or survival, analysis. Duration models originate from the medical literature and analyze the time until an "event" such as death.[29] I evaluate the number of years after 1997 until a county adopts an ordinance pertaining to the zoning of large or commercial WECS. I use 1997 as the base year because it is the first year in which multiple ordinances were enacted.

More formally, consider the probability that a county decides to enact a WECS ordinance in year t, defined by the probability density function $f(t)$. Defining 1997 as $t = 0$,

[29]Economists have used duration models in a wide variety of contexts, including the analysis of unemployment spells (Ham and Rea, 1987; Dawkins et al., 2005), bankruptcy (Shumway, 2001), investment (Gompers, 1995; Bulan et al., 2009), labor strikes (Kiefer, 1988), and regulatory action (Ando, 1999; Knittel, 2006). Duration models are popular for analyzing the uptake of Renewable Portfolio Standards (Lyon and Yin, 2010; Jenner et al., 2012).

the cumulative density function (CDF) for a random variable T is

$$F(t) = Prob(T \leq t) = \int_0^t f(s)ds, \tag{10}$$

which gives the probability of enacting regulations prior to year t. The survival function, or the probability of "surviving" until year t without enacting regulations, is therefore

$$S(t) = 1 - F(t) = Prob(T > t). \tag{11}$$

The hazard rate, or probability of enacting regulations in year t given having not enacted regulations prior, is

$$\lambda(t) = \frac{f(t)}{S(t)}. \tag{12}$$

I use the popular Cox (1972) proportional-hazards (Cox-PH) model for my estimation. The semiparametric model is beneficial because it does not make an explicit assumption about the baseline hazard rate. Instead, covariates proportionally shift the hazard rate in each time period. The hazard rate for county i in year (t) is

$$\lambda(t_i) = \lambda_0(t)exp(X'_{it}\beta), \tag{13}$$

where X'_{it} is a vector of covariates and $\lambda_0(t)$ is the baseline hazard function. I then estimate the parameters β using log-likelihood maximization.

The model described above works best when time is assumed to be continuous. As additional robustness checks, I run logistic (logit) and complementary log-log (clog-log) models that are more equipped to handle discrete duration models such as those using yearly data. The details of these models are presented in Appendix B.

Summary Statistics

Summary statistics appear in Table 1. After cleaning missing data, the sample consists of 700 counties and 12,436 observations. A total of 385 counties in the sample, 55 percent, ultimately adopt WECS ordinances during the sample period. A majority (94 percent) of counties adopted zoning ordinances at some point, while only about half of those that did not are zoned.

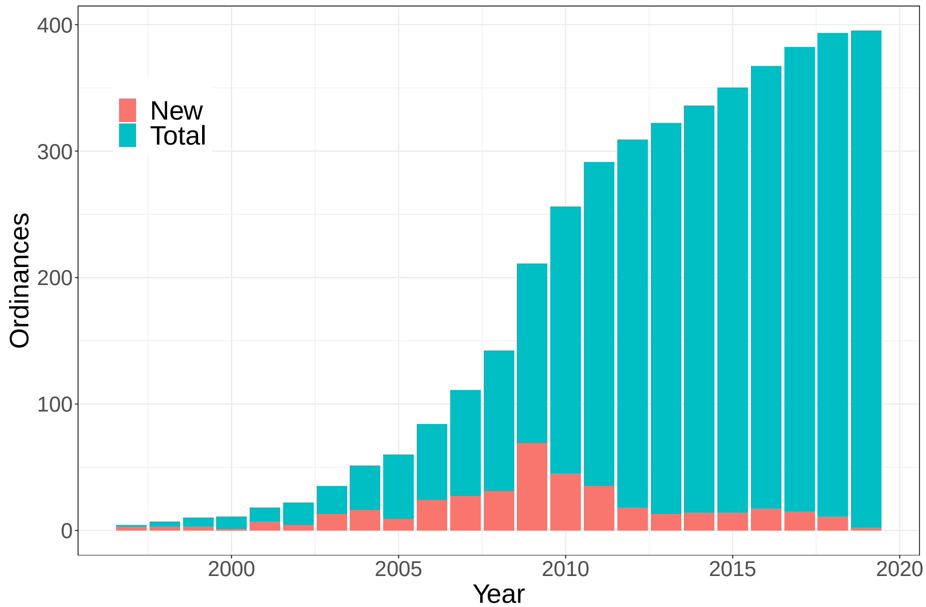
Table 1: Duration Model Summary Statistics

	Mean	SD	Min	Max	Mean (Ordinance=1)	Mean (Ordinance=0)
=1 if WECS Ordinance	0.03	0.17	0	1	0.07	0
=1 if Ever Zoned	0.71	0.45	0	1	0.94	0.54
Share of Neighbors with Ordinance, $t-1$	0.13	0.22	0	1	0.11	0.15
WECS Permit, $t-1$	0.04	0.20	0	1	0.01	0.06
MW Wind, $t-1$	7	38	0	843	4	9
Neighbors' MW Wind, $t-1$	74	232	0	2,030	55	88
Wind Speed	7.34	0.60	4.40	9.36	7.53	7.21
km Transmission Lines	182	189	0	1,605	197	171
Percent Farmland	0.75	0.25	0.003	1	0.82	0.70
Population (100s)	419	1,031	5	11,524	394	437
Republican Vote Share, 2008	0.57	0.13	0.16	0.86	0.57	0.57
Percent Public Land	0.13	0.23	0	1.00	0.08	0.16
Income Per Capita (100s)	342	91	144	1,567	346	339
Avg. Farm Size (Acres)	852	1,006	31	7,570	835	864
Median Farm Size/Avg. Farm Size	0.38	0.15	0.05	0.86	0.40	0.36
Percent Live Off-Farm	0.28	0.10	0.06	0.66	0.27	0.28
Percent Seasonal Homes	0.05	0.08	0	0.71	0.05	0.06

N = 12,436. 385 WECS ordinances adopted in 700 counties.

Figure 5 shows the number of WECS ordinances adopted each year from 1997 to 2019. Growth was relatively steady from 1997 through the mid-2000s. In 2009, the number of counties adopting ordinances increased dramatically and stayed relatively high through 2011. During this three year period, more than a third of all ordinances were adopted. From 2012 onwards about fifteen new ordinances were adopted per year. The nonlinearity of adoption justifies the choice of the Cox-PH model because it allows for year-specific baseline hazard rates, while parametric duration models such as a Weibull or gamma do not.

Figure 5: Number of counties adopting WECS ordinances each year



5.2 Results

Prior to presenting the proportional hazard results, I briefly discuss visual evidence for two variables of interest. Figure 6 shows Kaplan-Meier (KM) survival curves of the estimated probability of surviving (not adopting an ordinance) to a given time period t for two key variables (Kaplan and Meier, 1958).[30] Figure 6a breaks survival probability into counties with zoning ordinances and those without. Zoned counties appear substantially more likely to adopt WECS regulations than those without zoning ordinances. The KM estimated survival probability for a zoned county through 2019 is about 31 percent, while the probability for unzoned counties is about 87 percent.

Figure 6b shows survival probabilities based on how many neighbors (counties in the same agricultural district) have already adopted WECS regulations. KM estimates work only for discrete covariates, so I break the sample down into those counties for which 25

[30] In Appendix B I describe the process by which these estimates are calculated.

percent or more of neighbors have regulations in the prior year, and those for which fewer do.[31] The likelihood of adopting a WECS ordinance appears much higher in counties where more neighbors have adopted similar regulations. By 2019, the probability of a county in which a quarter or more of neighbors have adopted regulations surviving without one is about 23 percent. Those for which fewer than a quarter of neighbors have rules survive with an estimated probability of 64 percent.

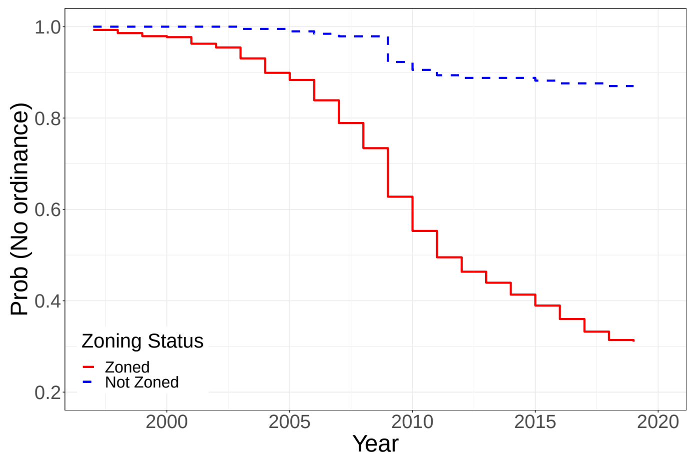
Table 2 shows regression coefficients from three proportional hazards models: Cox-PH in column (1), logistic regression in column (2), and complementary log-log (clog-log) in column (3). In this table neighboring ordinances using the share of counties within the same agricultural district with WECS ordinances in the previous period. As an additional robustness check, I show the statewide weighted ordinances measure in table A2. Results are qualitatively similar.

A positive coefficient corresponds with an increased likelihood of adopting a WECS ordinance in a given year, while a negative coefficient corresponds with a decrease in the probability. Standard errors are clustered at the county level. By taking the exponential of the coefficient, I obtain the hazard ratio, the relative increase in the likelihood of ordinance adoption from a unit increase in the variable. I focus on column (1), noting that results are consistent across specifications.

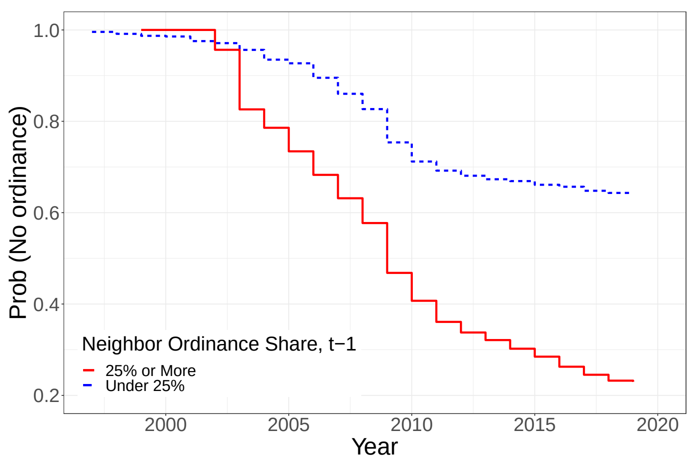
Consistent with the KM survival curve, zoned counties are substantially more likely to adopt wind energy regulations. The hazard ratio for a zoned county is $exp(2.045) = 7.73$, implying a zoned county is almost eight times more likely to adopt a WECS ordinances than one without zoning regulations. Counties without zoning laws may have a preference for a deregulatory government. However, they also lack officials devoted to and familiar with the procedures required to implement zoning regulations. The fact that several unzoned

[31] I choose 25 percent rather than a larger cutoff because it allows for more "treatment," particularly in early years. Nonetheless, the results are robust to higher cutoffs.

Figure 6: Kaplan-Meier probabilities of "surviving" without adopting a WECS ordinance



(a) Zoning status



(b) Neighbors' ordinance status

Table 2: Duration model: Probability of adopting WECS ordinance

	Model		
	Cox-PH	Logistic	Clog-Log
	(1)	(2)	(3)
Zoned	2.045*** (0.237)	2.102*** (0.238)	2.048*** (0.235)
Neighbor Ordinance Share, $t-1$	1.007*** (0.297)	1.100*** (0.319)	1.012*** (0.301)
WECS Permitting, $t-1$	−1.146*** (0.371)	−1.199*** (0.384)	−1.150*** (0.374)
IHS(MW Wind), $t-1$	−0.095** (0.042)	−0.093** (0.045)	−0.095** (0.042)
IHS(Neighbors' MW Wind), $t-1$	−0.007 (0.025)	−0.005 (0.027)	−0.007 (0.025)
Wind Speed	1.065*** (0.175)	1.104*** (0.185)	1.068*** (0.173)
IHS(km Transmission)	0.078 (0.059)	0.078 (0.062)	0.078 (0.059)
Percent Farmland	1.720*** (0.463)	1.834*** (0.490)	1.724*** (0.465)
Log(Population)	0.090 (0.087)	0.102 (0.093)	0.090 (0.088)
Republican Vote Share, 2008	−0.050 (0.717)	−0.009 (0.753)	−0.054 (0.714)
Percent Public Land	0.191 (0.513)	0.183 (0.537)	0.192 (0.514)
Log(Income Per Capita)	−0.141 (0.347)	−0.167 (0.364)	−0.143 (0.349)
Log(Avg. Farm Size)	−0.091 (0.144)	−0.102 (0.152)	−0.091 (0.145)
Median Farm Size/Avg. Farm Size	0.092 (0.569)	0.138 (0.608)	0.092 (0.578)
Percent Live Off-Farm	−0.267 (0.804)	−0.289 (0.850)	−0.263 (0.809)
Percent Seasonal Homes	2.286** (0.970)	2.497** (1.052)	2.298** (0.987)
Observations	12,436	12,436	12,436
Events	385	385	385

Notes: Standard errors (clustered by county) in parentheses. An "event" is defined as the adoption of the county's first WECS ordinance. All models include state FEs. *p<0.1; **p<0.05; ***p<0.01.

counties have enacted WECS ordinances suggests that there is some desire to mitigate turbine externalities in these communities. It is therefore likely that unzoned counties do not have the government infrastructures to pass wind energy regulations, consistent with Mulligan and Shleifer (2005). Many county officials will have no prior experience with wind energy and limited resources to create rules (Rosenberg, 2008; Stanton, 2012). Residents in these communities may be exposed to local harm from wind energy, but regulation is too costly to implement.

As neighboring governments adopt WECS regulations, a county becomes more likely to adopt rules of its own. The hazard ratio for a county going from 0 (no neighbors with rules) to 1 (all neighbors have rules) is $exp(1.007) = 2.74$, implying this county is almost three times more likely to adopt its own ordinance. Similarly, a one standard deviation increase in neighboring ordinance share yields a hazard rate of 1.247, implying a 25 percent increase in the likelihood of ordinance adoption. As more neighbors implement ordinances, regulators may anticipate wind power developers will soon target their own county. This spillover also relates to the policy diffusion literature, by which regulators learn from and emulate their neighbors (Gray, 1973; Berry and Berry, 1990; Volden, 2006; Shipan and Volden, 2008; Glick, 2012).[32]

Counties with wind energy permitting processes in the previous year appear less likely to adopt separate WECS regulations. Furthermore, counties with more wind energy installed a year earlier survive longer without an ordinance. This suggests some counties had already established systems that worked, and felt no need to create new rules. Conditional on ordinances in neighboring areas, counties do not respond to the stock of installed capacity

[32] The policy diffusion literature emphasizes three main motivating factors for policies to transfer from one government to the next: learning, emulation, and competition. Although the policy context does not allow me to conclusively determine the diffusion mechanism, conversations with regulators suggest the spread of WECS ordinances is not driven by competition. Because zoning officers communicate with each other, there is a culture of working together to establish best practices. For discussions on how to separately identify effects from each mechanism, see Shipan and Volden (2008) and Maggetti and Gilardi (2016).

surrounding them.

Wind speed and percent of land covered by farms increase the likelihood of ordinance adoption. This result, coupled with the response to neighbors, demonstrates how ordinances pass when there is increased demand for regulation. Windier counties with more farmland are more suitable for wind energy development and host substantially more wind farms (Hitaj, 2013; Winikoff and Parker, 2019). As the theoretical model predicts, areas benefitting more from the establishment of wind power regulations are among the first to regulate.

Several demographic variables and land characteristics have no impact on the adoption of WECS ordinances. One exception is the share of homes that is seasonally used within the county. Natural amenities are integral to the economy of communities with larger seasonal populations. These counties therefore have increased incentive to limit wind energy externalities.

5.3 Alternative Models, Robustness Checks, and Threats to Identification

Many counties elect to regulate wind energy only through a permitting process, rather than through a formal ordinance. In Table A1, I define an "event" as a county adopting either wind-energy-specific permits or an ordinance, rather than just an ordinance. All models and covariates are the same as in Table 2, with two exceptions. First, the share of counties with regulations now reflects both wind permits and WECS ordinances. Second, I control for whether a county had a permitting process that was not specific to wind in the previous period. Such permits may cover structures such as towers and power plants but do not specifically reference wind energy. Other than installed capacity, which does not appear to reduce the likelihood of adopting regulations, results are consistent with the main specification.

The proportional hazards (PH) assumption requires treatment variables to have time-invariant effects on the hazard rate. I assess the validity of this assumption by examining how the covariate-specific Schoenfeld (1982) residuals change over time (Grambsch and Therneau, 1994). If the residuals vary statistically over time, I would have to reject the PH assumption. Figure A3 plots the Schoenfeld residuals and estimated coefficient for the two key covariates, whether a county is zoned (Fig. A3a), and the share of neighbors with ordinances (Fig. A3b). The estimated coefficients seem relatively flat over time, and I fail to reject the PH assumption for each variable, with p-values of .84 and .27, respectively.[33]

It is possible that high-population, urban counties do not regulate wind power because there is little unincorporated farmland that could potentially host turbines. To see if rural counties differentially enact ordinances based on population, I eliminate counties with populations greater than 250,000. In Table A3, I show that population hastens ordinance adoption. One possible explanation is counties with higher populations have more individuals exposed to potential externalities, and therefore must regulate wind power sooner. Population may also function as an additional proxy for regulatory capacity. Higher-population counties may have greater infrastructure to regulate wind power. Mulligan and Shleifer (2005) makes a similar argument when analyzing determinants of regulation.

6 Strictness of Turbine Setbacks

I now turn to evaluating the relative strictness of WECS regulations. Evaluating the stringency of property and residential structure setbacks poses several empirical challenges due to the simultaneity of the two setbacks and the bunching and skewness observed in

[33]One state fixed effect fails the PH test. A solution is to include a time trend for this variable. Doing so does not change the key findings.

the data. As noted earlier, some setbacks are outlined in feet, some are defined multiples of the turbine height or rotor diameter, and others use a combination of both. In order to make regulations directly comparable, I convert each standard to a measurement of feet, using the mean size among turbines installed in 2018. The mean turbine height in 2018 was about 466.8 feet, and the average rotor diameter was 366.3 feet. A setback 1.1 times turbine height would therefore equal $1.1 * 466.8 = 513.48$ feet, and a setback of 2.5 times the rotor diameter equals $2.5 * 366.3 = 917.5$ feet. Some counties have more complex standards that mandate setbacks be the greater of multiple standards, such as the greater of 1.1 times turbine height or 500 feet. For such regulations, the greater setback is applied. In this case, it would be 1.1 times turbine height, because $513.48 > 500$.

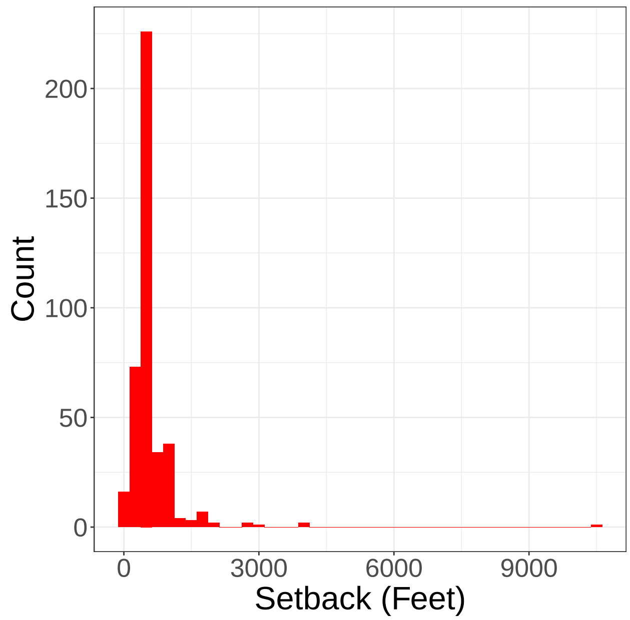
Property and residential setbacks are decided simultaneously and jointly affect development. A strict setback for one may not be necessary if there is a strict setback for the other.[34] Conversely, if a government wants to limit wind energy it may elect to strengthen setbacks for both properties and residences. Because standards have this joint relationship, it is useful to analyze the two setbacks together.

Figure 7 shows the distribution of property and residential structure setbacks appearing in the regressions. There is substantial clustering around certain distances for both setbacks. For the property line setbacks shown in Figure 7a, the cluster occurs at 1.1 times turbine height, or 513.48 feet. There is more variation in residential structure setbacks in Figure 7b, but there is still a large cluster at 1,000 feet. Furthermore, both setbacks have skewed right tails, with some setbacks more than an order of magnitude greater than the modes.

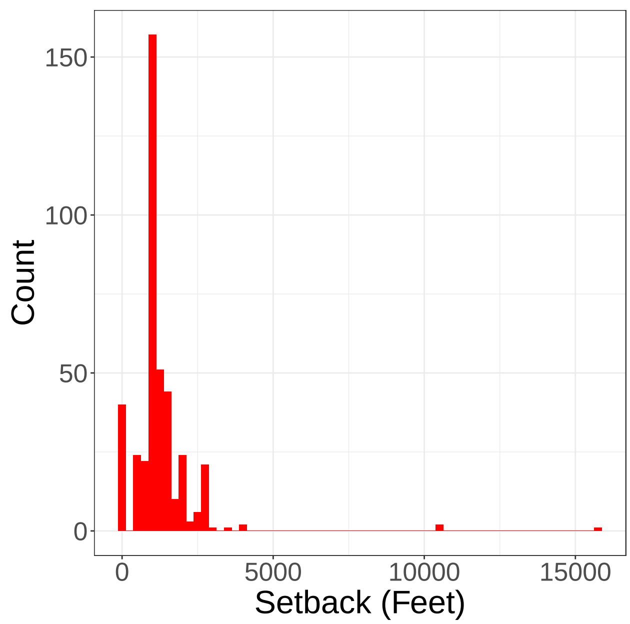
Because the challenges outlined above, I define strictness strictness as the greater de-

[34]Consider, for example, a county with a property line setback of 1,500 feet. This standard may be sufficiently strict to limit development, even if a residence is not located on this property. Therefore, a large residential structure setback may not be necessary to mitigate turbine externalities.

Figure 7: Distribution of property line and residential structure wind turbine setbacks



(a) Property line setbacks



(b) Residential structure setbacks

viation from the observed "standard" setbacks for property line and residential setbacks. More specifically, strictness is defined as

$$Strictness = max\Big(\frac{Property\, Setback}{513.48}, \frac{Residential\, Setback}{1,000}\Big). \tag{14}$$

A strictness measure of two can be interpreted as an ordinance twice as strict as the "standard" regulations. This measure has several advantages for evaluating the strictness of WECS standards. First, it allows the strictest of the two measures to determine how strict the standards are. If there is a sufficiently strict residential setback, then this will be captured. If both standards are strict, this will be captured as well. Second, the measure is normalized relative to observed modes, and is therefore not arbitrarily defined. Furthermore, this allows for the comparison of property and residential setbacks, which are often substantially different. The distribution of strictness measures appears in Figure 8. Because some outliers remain, I remove from my plot (and from my analysis) counties with strictness measures greater than six. A little less than half of the ordinances have a strictness measure of one, indicating the setbacks do not deviate from the typical ordinance.

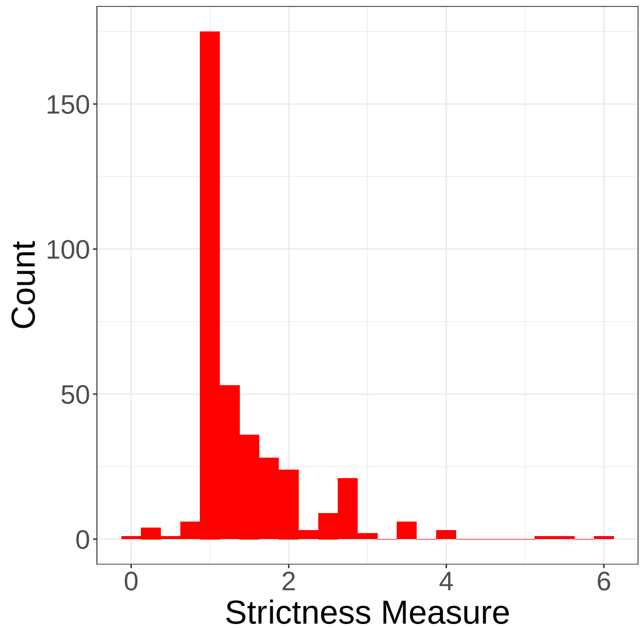
My empirical strategy for determining the causes of setback strictness is a simple, cross-sectional regression consisting of both current and historic ordinances. Specifically, I estimate

$$Strictness_{it} = \alpha + \beta_1 X_i + \beta_2 X_{it} + S_i + \epsilon_{it}, \tag{15}$$

where $Strictness_{it}$ is the level of stringency of a setback adopted by county i in year t, X_i is a vector of county-level characteristics, X_{it} is a vector of time-variant controls related to the ordinance and the wind energy activity in surrounding counties, S_i is a vector of state-level fixed effects, and ϵ_{it} is an error term clustered at the agricultural district level.[35]

[35] Because multiple counties have multiple observations, there is certainly correlation that would justify a

Figure 8: Distribution of setback strictness measures, as defined in Equation (14)



Of note, X_{it} includes the year the regulations were adopted, whether the ordinance is an updated version, whether a county was the first in its district to adopt WECS regulations, and the analogous the strictness measures for counties within the same district at the time of adoption.

My measures of neighboring strictness are the average strictness within the same agricultural district or the spatially-weighted average strictness in the state in the year of adoption. I use the current average, rather than a lag for two reasons. First, because of the small sample size, I gain substantial variation. It also allows for regulations to influence one another through the legislative process. Ordinances are not passed in secret, and regulators are likely aware of deliberations in neighboring counties. [36] It is therefore possible

county-level cluster. I follow the guidance of Abadie et al. (2017) and cluster at the district level because this is the level of treatment for one of the key covariates. Further, these errors are slightly more conservative.

[36]Some officials expressed to me that they were paying close attention to hearings and discussions in nearby communities.

for two counties to simultaneously influence one another. To ensure there is limited reverse causality, however, I instrument for neighboring strictness with the value from the previous year.

Summary Statistics

Summary statistics for the strictness regressions appear in Table 3. After cleaning the data and eliminating outliers, the sample consists of 375 individual WECS ordinances. I omit ordinances from Minnesota and post-2010 ordinances from Wyoming because these counties are limited in their ability to set their own setbacks. I also exclude counties with severe turbine height restrictions (< 300 ft) and bans. The average property line setback is 552 feet, while the average residential structure setback is 1,195 feet.[37] The mean year of ordinance adoption is about 2010, and about 19 percent of ordinances are updated regulations.

The spatial distribution of the (current) setback standards appears in Figure 9. There appears to be some geographic concentration of stricter setbacks. Property line setbacks in Figure 9a are generally stricter in northeastern Indiana, northeastern Illinois, and western North Dakota. They are less restrictive in much of Iowa, Nebraska and South Dakota. Residential structure setbacks in Figure 9b are generally greater in northern Indiana and Illinois, western North Dakota, and northern Nebraska. They are less restrictive in Colorado and Iowa.

6.1 Results

Regression results appear in Table 4. Columns (1) and (2) show results when neighboring strictness is defined relative to the agricultural district. In columns (3) and (4), strict-

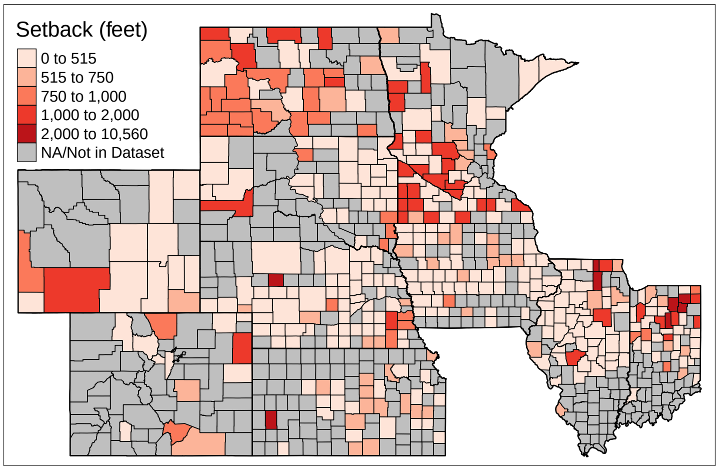
[37]These respective averages including the outliers and ordinances with height restrictions are 597 feet from property lines and 1,257 feet from residences.

Table 3: Strictness regression summary statistics

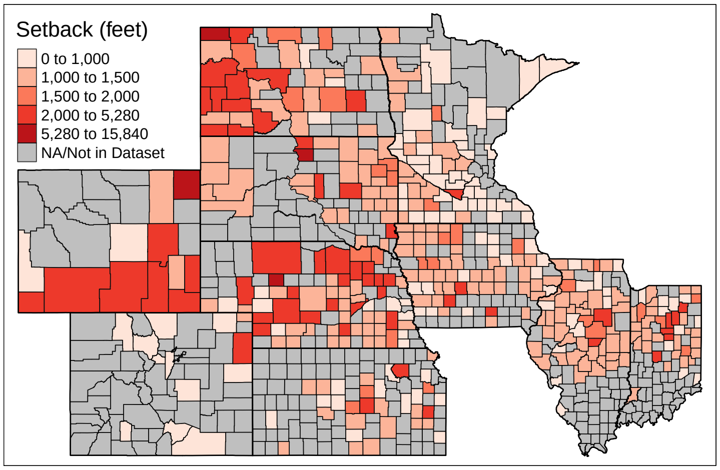
	Mean	SD	Min	Max
Property Line Setback (ft)	552	369	0	3,035
Residential Structure Setback (ft)	1,195	668	0	3,960
Strictness Measure [1]	1.44	0.73	0.10	5.91
Year of Ordinance	2,010.49	4.63	1997	2019
Updated	0.19	0.39	0	1
MW Wind, $t-1$	14	55	0	548
Neighbors' MW Wind, $t-1$	175	328	0	1,643
Neighbors With Ordinances	3.53	2.73	0	10
First Ordinance in District	0.14	0.35	0	1
Wind Speed	7.53	0.42	5.79	9.36
Kilometers Transmission Lines	201	197	0	1,376
Percent Farmland	84.21	15.10	1.60	100
Population (100s)	414	786	5	6,776
Republican Vote Share, 2008	0.57	0.11	0.28	0.83
Percent Public Land	6.15	12.76	0	93.65
Income Per Capita (100s)	345	53	225	601
Avg. Farm Size (acres)	749	789	107	6,714
Median Farm Size/Avg. Farm Size	0.39	0.14	0.05	0.77
Percent Live Off-Farm	0.28	0.08	0.10	0.57
Percent Seasonal Homes	0.04	0.07	0	0.66

N = 375 represents the number of observations excluding strictness measures greater than 6, as well as counties with bans or height restrictions. [1] Strictness defined as the maximum of the property line setback divided by 513.48 feet and the residential structure setback divided by 1,000 feet.

Figure 9: Spatial distribution of property and residential wind turbine setbacks



(a) Property line setbacks



(b) Residential structure setbacks

ness is defined using the spatially-weighted average of the state. Odd-numbered columns exclude strictness measure outliers greater than six, and even-numbered columns exclude counties with strictness measures greater than three.

Table 4: Turbine setback strictness regressions

	Setback Strictness [1]			
	(1)	(2)	(3)	(4)
Year	0.053*** (0.014)	0.030*** (0.009)	0.038* (0.021)	0.012 (0.012)
Updated	0.297** (0.117)	0.319*** (0.090)	0.245** (0.111)	0.285*** (0.088)
IHS(MW Wind), $t-1$	0.020 (0.028)	−0.005 (0.016)	0.015 (0.028)	−0.009 (0.017)
IHS(Neighbors' MW Wind), $t-1$	0.012 (0.014)	0.008 (0.010)	0.003 (0.014)	0.005 (0.010)
Neighbors With Ordinances	−0.021 (0.014)	0.002 (0.010)	0.001 (0.004)	0.005* (0.003)
First Ordinance in District	0.458*** (0.166)	0.430*** (0.152)	0.278** (0.109)	0.214*** (0.081)
Avg. Neighboring Strictness [2]	0.235** (0.093)	0.211** (0.105)	0.531** (0.224)	0.392** (0.152)
Wind Speed	0.090 (0.080)	0.123* (0.073)	0.125 (0.079)	0.152** (0.075)
IHS(km Transmission)	0.054 (0.034)	0.061** (0.029)	0.051 (0.033)	0.062** (0.026)
Percent Farmland	0.294 (0.293)	0.141 (0.205)	0.260 (0.292)	0.171 (0.219)
Log(Population)	−0.061 (0.051)	−0.065 (0.042)	−0.061 (0.052)	−0.064 (0.042)
Republican Vote Share, 2008	0.596 (0.419)	0.655** (0.305)	0.697* (0.397)	0.764** (0.305)
Percent Public Land	−0.727* (0.386)	−0.366 (0.254)	−0.889** (0.394)	−0.499* (0.296)
Log(Income Per Capita)	0.247 (0.214)	0.226 (0.147)	0.160 (0.205)	0.202 (0.143)
Log(Avg. Farm Size)	−0.120 (0.098)	−0.047 (0.084)	−0.109 (0.103)	−0.050 (0.092)
Median Farm Size/Avg. Farm Size	−0.915*** (0.280)	−0.874*** (0.243)	−0.792*** (0.293)	−0.790*** (0.256)
Percent Live Off-Farm	−1.247** (0.570)	−0.825*** (0.305)	−1.412** (0.617)	−0.912** (0.353)
Percent Seasonal Homes	1.042* (0.625)	0.207 (0.406)	0.991* (0.540)	0.345 (0.412)
Observations	375	363	375	363
Neighbor Definition	District	District	State	State
Strictness Outlier Cutoff	6	3	6	3
Adjusted R^2	0.317	0.384	0.312	0.372

Notes: [1] Strictness defined as the maximum of the property line setback divided by 513.48 feet and the residential structure setback divided by 1,000 feet. [2] The average neighboring setback strictness instrumented by the average in $t-1$. Standard errors (clustered by agricultural district) in parentheses. All models include state FEs. *p<0.1; **p<0.05 ***p<0.01.

Setbacks appear to follow similar patterns to those in neighboring counties. Focusing on column (1), if all setbacks in neighboring counties were to be one standard deviation (0.73) larger, the county's strictness by $0.235 * 0.73 = 0.172$, a 12 percent increase relative to the mean. Although somewhat small relative to the mean, the result suggests counties not only respond to neighbors when deciding to if they should regulate, but also respond when deciding *how* to regulate.[38] The finding aligns with the theoretical prediction that counties should borrow from neighboring governments in the wake of uncertainty about optimal regulation (Glick, 2012).[39] Neighbors with ordinances are the best source for a county lacking full information because the outcomes from regulation will likely be similar.

One of the strongest predictors of strict setbacks is when the regulations were enacted. Furthermore, updated ordinances are more restrictive. This finding has three potential explanations. First, setbacks are increasing strictly in response to turbines growing in size. Although this may be true to some extent, it does not appear to explain the full story. In 2009, the average structure setback was about 1,000 feet, about 2.5 times the average turbine height of 392 feet. In 2018, the average setback was about 1,630 feet, close to 3.5 times the average turbine height of 467 feet. This finding may also be explained by growing animosity toward wind energy. Conversations with regulators and public anecdotes suggest that opposition groups have gained momentum in recent years.[40]

Finally, it is possible initial setback values were too low, and counties have learned this and responded by creating more socially optimal regulations. Regulators would not bother updating ordinances unless they felt as though the current standards were insufficient. The updates reflect policy learning: more efficient regulations emerge over time with more experience. Additional evidence of learning can be seen in the coefficients for the first enacted ordinance within the district. When no neighbors have regulations, a county is more likely to implement strict setback policies. In the absence of neighbors from whom the regulator can learn, the theoretical model predicts the efficient policy can be achieved

[38]The finding is consistent with what regulators told me about how setbacks were established, noting that they "just copied our neighbors." This quote provides further evidence that this diffusion is driven by emulation and learning, rather than competition.

[39]Some officials said they use organizations such as the state associations of planners for additional guidance. South Dakota even compiled a list of county regulations to share among elected officials.

[40]See, for example, *How a county election in rural Illinois became a referendum on wind energy,* Energy News Network, https://energynews.us/2018/11/05/midwest/how-a-county-election-in-rural-illinois-became-a-referendum-on-wind-energy/.

through research. Given these regulations were enacted without a nearby reference policy, research likely played a role in their creation. The trajectory of updated ordinances aligns with the strictness of the researched regulations, suggesting a move toward socially optimal policies.

Although standards are similar to those in neighboring counties, they also respond to factors affecting local demand for wind power, consistent with the theory. Counties in which more farmers live off of their farm are less likely to increase their setback levels. Individuals who live on their farmland where turbines are sited will have spent more time encountering turbine dis-amenities. When they live elsewhere, this is less of a concern. Counties with a greater share of seasonal homes are (weakly) more likely to establish strict setbacks. Given that these counties depend more on the natural amenity value of the land, they will want to limit anything that may interfere with their local economies.[41]

Although the size of farms does not affect setback levels, the distribution of such land matters. Counties in which the ratio of the median to average farm size is greater adopt less restrictive regulations. As this ratio increases, land is more evenly distributed. If a county is dominated by just a few large farms, only a small number of landowners will receive royalties from hosting wind turbines, but others may still experience the turbine externalities. Existing research suggests landowners are more likely to support wind energy if they feel as though the development process was fair and benefits are evenly distributed (Gross, 2007; Wilson and Dyke, 2016; Walker and Baxter, 2017).[42]

These findings emphasize how regulators respond to local factors affecting both the potential benefits and harms from wind energy. If regulators were responding only to their

[41]One regulator told me that "how the land is used" is essential for how strict setbacks are. Regulators and industry experts said standards can be more stringent if the counties have a large number of seasonal ranch-style homes in which retired families spend their summers.

[42]This effect also aligns with what some county regulators told me, noting that for wind power to be successful in a community, everyone must benefit.

neighbors, there would be no need for decentralized control. Because standards are tailored to the characteristics of the county, it appears as though counties are acting in the public interest when regulating wind power.

Although the evidence supports public interest theory of regulation (Pigou, 1932), more Republican counties appear more likely to adopt strict setbacks. This finding may reflect partisan opinions regarding the threat of climate change and the benefits of wind energy. Climate change mitigation, however, has not been found to be a primary reason communities support local wind energy development (Mills et al., 2019). Although stricter regulation is generally associated with more liberal governments, local wind energy policies may prove to be an exception.

Alternative Models, Robustness Checks, and Threats to Identification

As an alternative to my strictness measure described above, Table A4 provides regression results in which I define strictness as a discrete indicator. The first indicator equals one if either setback exceeds the "standard" setback levels, 1.1 times turbine height (about 514 feet with 2018 turbine heights) from property lines and 1,000 feet from residences. The next three indicators work analogously, but increase the level that must be exceeded: 750 feet from property lines or 1,500 feet from residences; 750 feet from property lines or 2,000 feet from residences; and 1,000 feet from property lines or 2,500 feet from residences.[43] The final indicator includes those strict counties as defined in the previous specification, as well as those with height restrictions and bans.[44] Neighboring strictness is defined as the share of counties within the agricultural district with similarly strict standards, and is instrumented as described above.

[43] I include only three variations of the property line setback because there is substantially less variation, as Figure 7a suggests.

[44] Bans are particularly challenging to study because many bans are actually temporary moratoriums. Some last a short period of time while setbacks are updated, but others last semiindefinitely.

Results are generally consistent with those from the main specification. Counties respond to neighboring ordinances and factors affecting demand for setbacks. One exception is column (5), which includes the strictest setbacks, height restrictions, and bans. Although these strictest ordinances follow patterns similar to those in neighboring counties, they are less responsive to farm sizes, and off-farm and seasonal populations. This may be partially the result of statistical imprecision; only about 17 percent of ordinances are defined as "strict." I do find strong evidence that the strictest ordinances and bans are more common in higher-income counties, however. One of the primary benefits of wind energy is the income it brings to local communities. Wealthier counties therefore may be less willing to put up with turbine dis-amenities because the royalty payments are less important. suggesting the potential for an "environmental Kuznets curve" for wind power (Grossman and Krueger, 1991).

In Table A5, I show regression results in which strictness is defined based on 2009 turbine heights to ensure my findings are not driven by how setbacks are calculated. In 2009, the average turbine height was 392 feet. Correspondingly, I define the "standard" property line setback as 431.2 feet, 1.1 times the average turbine height. Results are generally consistent. Counties respond to how their neighbors regulate wind, as well as farm sizes and off-farm populations. I no longer find evidence, however that the seasonal population affects regulation. Overall, these regressions suggest findings are robust to how setbacks are defined.

Generally, results are consistent with findings from the main specification. Of note, the year of the ordinance enactment does not appear to affect setback strictness as strongly. This is likely because setbacks relative to turbine height do not become stricter over time as turbines grow larger. Although setbacks still respond to those in neighboring counties, the relationship is weaker at the lower levels of strictness. Most other coefficients are similar in size and generally in significance, with evidence that the share of seasonal homes, appears to only weakly affect stringency. Overall, however, the results are similar to those in the primary model.

7 Updates and the Dynamics of Regulation

Table 5 presents results from duration models in which an “event” is defined as an update to turbine setbacks in a preexisting ordinance. Because counties can update their ordinance more than once, these models incorporate the occurrence of repeat events. Columns (1) and (2) show results from stratified duration models incorporating the time since the previous event (conditional gap) or time since the first event (conditional time) (Prentice et al., 1981). Column (3) shows results in which event risk is assumed equal regardless of whether a previous event occurred (Anderson and Gill, 1982).

Most covariates do not appear to influence the decision to update setbacks. Counties with higher wind speeds and more farmland, however, are more likely to update their ordinances. These communities with higher wind potential, represented in the theoretical model by a larger γ_i, require more efficient policies. This finding therefore emphasizes how counties are not neglecting their duty to regulate wind energy. Those for whom the stakes are the highest update their regulations more frequently.

How are setbacks changing over time? In Figure 10, I provide visual evidence that they are becoming more heterogeneous, particularly for residential structure setbacks. The graphs plot the densities of new setbacks from 2006 to 2019.[45] Focusing on residential setbacks in Figure 10b, setbacks are becoming stricter, but also more variable, with a flatter distribution.

As additional evidence, Table 6 shows regression results in which the dependent variable

[45] I omit setbacks equal to zero or greater than 10,000 feet so that they do not distort the distributions.

Table 5: Duration models: Probability of updating WECS ordinance

	Model		
	Conditional Gap	Conditional Time	Anderson-Gill
	(1)	(2)	(3)
Setback Strictness $t-1$	-0.228 (0.313)	-0.349 (0.296)	-0.302 (0.278)
Zoned	-0.695 (0.726)	-0.297 (0.683)	-0.283 (0.678)
Neighbor Ordinance Share, $t-1$	-0.139 (0.072)	-0.055 (0.068)	-0.060 (0.066)
IHS(Installed MW), $t-1$	1.175 (0.819)	0.814 (0.763)	0.762 (0.755)
IHS(Neighbors' MW Wind), $t-1$	0.004 (0.062)	0.022 (0.060)	0.021 (0.059)
Wind Speed	2.643^{***} (0.739)	1.460^{**} (0.697)	1.454^{*} (0.693)
IHS(km Transmission)	0.220 (0.195)	0.205 (0.192)	0.171 (0.187)
Percent Farmland	4.274^{**} (1.618)	3.618^{***} (1.383)	3.407^{***} (1.367)
Log(Population)	0.486^{*} (0.251)	0.269 (0.232)	0.274 (0.230)
Republican Vote Share, 2008	1.429 (2.222)	0.437 (2.127)	0.670 (2.106)
Percent Public Land	8.996^{***} (2.094)	5.883^{***} (1.579)	5.738^{***} (1.588)
Log(Income Per Capita)	-1.736 (1.113)	-1.035 (1.043)	-0.924 (1.032)
Log(Avg. Farm Size)	-0.631 (0.498)	-0.592 (0.443)	-0.553 (0.436)
Median Farm Size/Avg. Farm Size	5.131^{***} (1.589)	2.577^{*} (1.538)	2.612^{*} (1.522)
Percent Live Off-Farm	-0.342 (2.946)	-0.673 (2.582)	-0.823 (2.574)
Percent Seasonal Homes	-6.861 (4.860)	-5.837 (4.275)	-5.889 (4.300)
Observations	2,919	2,919	2,919
Events	73	73	73

Notes: Standard errors (clustered by county) in parentheses. An "event" is defined as an update to a county's WECS ordinance. All models include state FEs. *p<0.1; **p<0.05; ***p<0.01.

is the share of new ordinances implementing "standard" setbacks. I define these standards based on the clusters in Figure 7: 1.1 times turbine height for property lines and 1,000 feet for residential structures. These setbacks, which have been criticized as arbitrary, insufficient regulation, are becoming less common over time.[46]

Table 6: "Standard" ordinance adoption over time

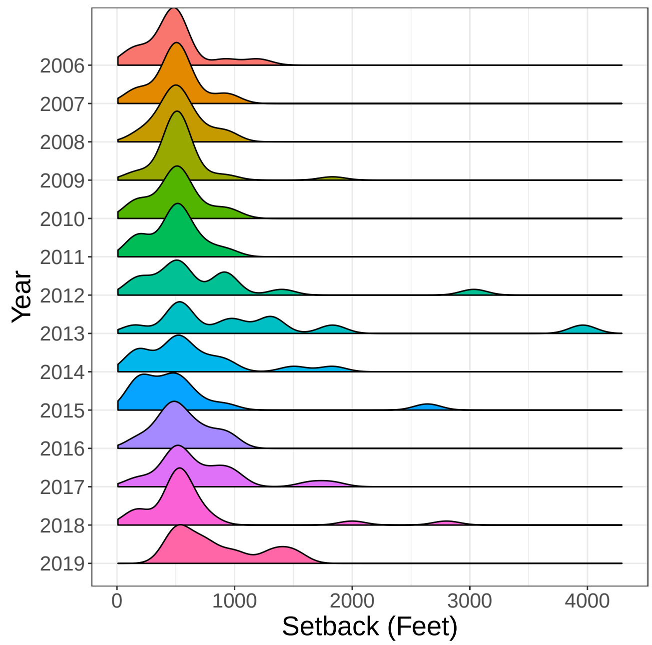
	Share of "Standard" Setbacks	
	Property Line	Residential Structure
	(1)	(2)
Year	-0.018^{**}	-0.022^{**}
	(0.008)	(0.008)
Observations	20	20
Adjusted R^2	0.126	0.221

Notes: "Standard" property line setback is 1.1 times turbine height. Standard residential structure setback is 1,000 feet. Models control for the number of ordinances adopted each year. Standard errors in parentheses. *p<0.1; **p<0.05 ***p<0.01.

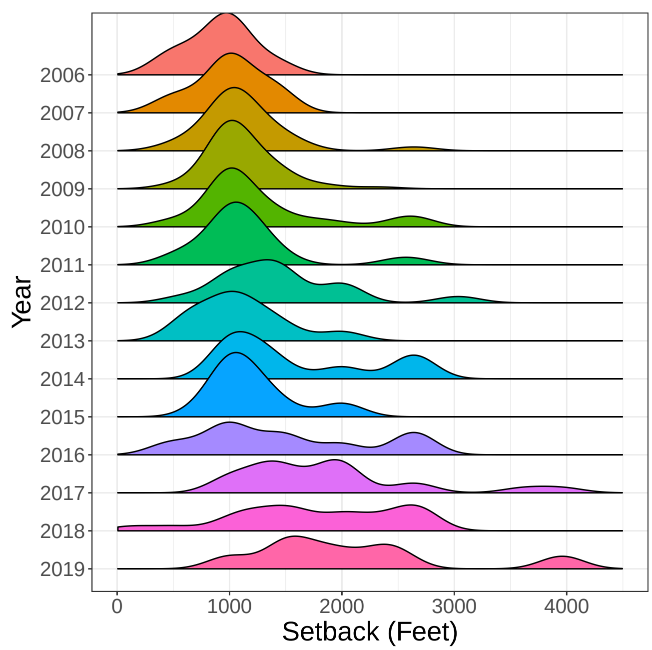
The increasing variation in standards reflects a growing reliance on factors other than the standards of neighboring counties, such as the distribution of land, where farmers live, and the seasonal population. This is consistent with theoretical predictions and suggests local policymakers are learning to create regulations that reflect local preferences. As wind energy expands, regulators cannot only observe WECS ordinances in other counties, but also development and the public response. This allows the county to update its preferences, and demand for wind energy may increase or decrease accordingly. The county can adjust its assumptions about whether wind energy is a good fit for the community. Some counties will determine it is, while others will not. Those that determine current regulations are

[46] A particular source of criticism has been 1,000 foot setbacks from residential structures. See *Wind Ordinance Debate: The 1,000-foot set-back standard (Are environmentalists underregulating themselves?)*: https://www.masterresource.org/wind-offset-distance/wind-ordinance-offset-debate/.

Figure 10: Density of property line and residential structure setbacks



(a) Property line setbacks



(b) Residential structure setbacks

Notes: Setbacks equal to 0 or greater than 10,000 feet are omitted.

too restrictive or too loose can respond by updating their ordinance.

8 Discussion and Concluding Remarks

Regulators are currently debating which level of government should have authority to zone wind energy. Should states reclaim this role from local regulators? The results from this paper suggest this would be a mistake. Using a duration analysis, I find counties with greater wind potential are among the first to adopt WECS ordinances, and are more likely to update their ordinances in the future. Furthermore, anticipating future demand for wind energy, counties are more likely to adopt rules when their neighbors have done so. When given the authority to regulate, regulators needing to address turbine externalities have generally done so.

In the absence of perfect information, regulators learned from the experiences of their neighbors by creating similar standards. My theoretical model demonstrates how this is optimal in the wake of uncertainty. Over time, however, as policymakers learn more about the regulatory environment of wind energy, setbacks become more location specific. Standards reflect local demand for wind energy, responding to land ownership inequality, where farmers live, and the county's seasonal population. The findings suggest county governments are learning and generally implementing policies that reflect the local community.

Economic theories of federalism suggest welfare will be at least as high with decentralized regulation as with uniform rules across all jurisdictions, unless there are jurisdictional spillovers or high regulatory fixed costs (Oates, 1972, 1999). One argument for state control of wind energy is therefore a coordinated regulatory environment that promotes development in an effort to mitigate pollutants from fossil fuels. Current policies and proposals, however, mandate significantly stricter standards than most counties. Ohio, for example, requires a setback of 1,125 feet from property lines.[47] In Kansas, a current bill would require a setback of three times turbine height or 1,500 feet from property lines and the greater of 12 times turbine height or 7,920 feet from residences.[48] Nebraska is proposing a setback of three miles, 15,840 feet from residences.[49] There would be welfare losses from forcing localities into uniform regulation, and wind energy development would likely slow.

It is important for researchers to acknowledge the dynamic nature of policy making. Although diffusion, rather than tailored policies, may be optimal when a new industry emerges, divergence can become more prevalent as regulators learn and acquire new information. As regulatory variation increased, a centralized solution will increasingly underperform, even if it looks similar to the initial diffused regulations.

States may have a role, however, assisting those counties without zoning regulations, which are less likely to implement WECS ordinances. A lack of zoning rules reflects, in part, limited regulatory infrastructure. Those without sufficient legislative capacity may find it too costly to create new standards. Several zoning officials expressed to me the desire for the state to take regulatory authority because they work part-time and lack the technical expertise. The state can potentially aid these counties. Model ordinance templates could help these counties create standards while avoiding some research costs. States could also implement baseline standards and allow counties to opt in if they would rather not create their own rules, and leave local control only to those who demand it.

Should there be concern about the growing prevalence of strict setbacks as a barrier to mitigating harms from climate change? Although plenty of communities have created more restrictive setbacks, many others have not. Benton County, Indiana, for example,

[47]See *Ohio Amended Substitute House Bill 483,* http://archives.legislature.state.oh.us/BillText130/130_HB_483_EN_N.html.

[48]See *Kansas House Bill 2273,* http://www.kslegislature.org/li/b2019_20/measures/documents/hb2273_00_0000.pdf.

[49]See *Nebraska Legislative Bill 373,* https://nebraskalegislature.gov/FloorDocs/106/PDF/Intro/LB373.pdf.

has become a national leader in wind energy with relatively relaxed standards. Setbacks in Iowa have remained less stringent and propelled the industry's growth in the state. Furthermore, counties that develop wind energy without regulations are less likely to create them, suggesting they have found systems that work. For example, Ford County, Kansas hosts several wind farms, all of which were permitted using only the conditional use process.

Nonetheless, many counties have created (and likely will continue to create) setbacks that effectively eliminate any possibility that they host wind farms. This should not necessarily be discouraged. Given the relatively small contribution of one wind farm in reducing greenhouse gas emissions, it may be locally optimal to prevent development. As long as policymakers act in the public interest when setting wind energy standards, the current regulatory structure will be economically efficient.

This argument does not, however, suggest governments should limit the development of wind energy at any level to avoid local dis-amenities. Electricity generation from wind power has played a critical role in reducing harmful emissions from coal (Cullen, 2013; Novan, 2015; Fell and Kaffine, 2018). Policymakers should continue to create legislation to address climate change, such as a carbon price or tradable pollution permits. Some regulations may increase demand for wind energy and induce larger royalty and tax payments to local communities, potentially discouraging counties from creating strict setbacks. This trade-off between promoting clean energy and protecting the communities that host it requires careful consideration moving forward.

One potential concern is the potential political capture that can result from local control. Republican-leaning counties appear more likely to adopt strict wind turbine regulations. This may reflect left-leaning governments encouraging more support for renewable energy or conservatives discouraging wind power. If relevant parties such as wind energy developers and opponents of wind power (e.g., competing electricity generators) are influencing local policy, state authority may be preferable. Whether state regulators are immune to similar pressures, however, is unclear. The optimal level of governance to limit capture is theoretically ambiguous; public accountability may be more difficult at the local level, but it could be more cost effective for industries to influence centralized governments (Bardhan and Mookherjee, 1999; Faguet, 2014).

Regardless of who has zoning authority and what regulations are in place, researchers must continue to help policymakers understand the implications of these standards and wind power more generally. Although there is a large body of literature evaluating the local harms and benefits from wind energy, many questions remain unanswered or lack a scientific consensus. It is essential to continue researching how wind turbines affect our health, property values, agriculture, and wildlife. Future work must address the effectiveness of WECS ordinances in preventing actual or perceived dis-amenities from wind power and provide policymakers with guidance to implement the socially optimal level of regulation.

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A Appendix A: WECS Ordinance Database

To create the dataset, I first looked at county government websites to see if regulations were posted publicly. Next, I searched two databases for regulations not accessible through county websites. TheWindExchange Database, operated by the Department of Energy (DOE), posts links to and includes dates of wind energy ordinances (and dates of implementation) in localities across the country.[50] Although this resource is valuable, it is incomplete and the dates are often inaccurate. Next, I searched through the WindAction library, which includes links to news articles, and occasionally official documents, related to wind energy zoning laws.[51] WindAction provided insights about the dates of ordinance implementation, as well as about amendments to regulations. I supplemented these sources with general Google searches to find any remaining information that was publicly available.

After gathering information through publicly available sources, I contacted each county to confirm the information I found was correct and up to date, and I inquired about any previous versions of the regulations that were unavailable online. I first contacted county administrators via email and then followed up by phone for those who did not respond. In most cases, officials were able to confirm or supplement the information I found. Several administrators did not know the exact year ordinances were implemented or were uncertain what regulations were in place prior to amendments. I note these counties in the dataset with flags and omit them from relevant regressions. I add no county to the database, however, without first hearing back from county officials.

[50] See *Wind energy policies and incentives:* https://windexchange.energy.gov/policies-incentives.

[51] See *WindAction,* http://www.windaction.org/.

B Appendix B: Supplemental Math and Equations

B.1 Alternative Duration Models

When time is discrete (such as in years), Cox (1972) demonstrates an alternative model to the proportional hazards model may be preferred. He proposes

$$\frac{\lambda(t_i)}{1-\lambda(t_i)} = \frac{\lambda_0(t)}{1-\lambda_0(t)} exp(X_{it}'\beta),$$

which, after taking logs, can be written as

$$logit(\lambda_i) = \alpha_t + X_{it}'\beta, \tag{16}$$

where $\alpha_t = logit(\frac{\lambda_0(t)}{1-\lambda_0(t)})$ and $logit(x) = log(\frac{x}{1-x})$, the logistic function. Note that this is simply a logistic regression with year fixed effects. Another popular alternative is the complementary log-log (clog-log) model, which produces coefficients directly comparable to the Cox-PH model. The regression equation is:

$$log(-log(1-\lambda_i)) = \alpha_t + X_{it}'\beta. \tag{17}$$

B.2 Kaplan-Meier Estimators

Although the traditional Kaplan-Meier estimators are incorrect for time-varying covariates, Snappin et al. (2005) proposes a simple extension in which the vulnerable population for a given cohort (covariate) is updated each period. More specifically, the KM survival probability in period t for a given cohort k is

$$\hat{S}_k(t) = \prod_{t_j \leq t} (1 - \frac{d_{jk}}{n_{jk}}), \tag{18}$$

where d_{jk} is the number of counties in cohort k in period t_j adopting an ordinance in t_j, and n_{jk} is the number of counties in cohort k in period t_j that have yet to adopt an ordinance by t_j.

C Appendix C: Additional Tables and Figures

Table A1: Duration model: Probability of adopting WECS regulations (ordinance or permit)

	Model		
	Cox-PH	Logistic	Clog-Log
	(1)	(2)	(3)
Zoned	2.242*** (0.233)	2.320*** (0.235)	2.246*** (0.232)
Neighbor Regulation Share, $t-1$	1.012*** (0.298)	1.080*** (0.322)	1.019*** (0.300)
Non-Wind Permit, $t-1$	−1.169*** (0.192)	−1.251*** (0.201)	−1.173*** (0.191)
IHS(MW Wind), $t-1$	−0.046 (0.043)	−0.043 (0.046)	−0.047 (0.044)
IHS(Neighbors' MW Wind), $t-1$	−0.013 (0.024)	−0.012 (0.026)	−0.013 (0.024)
Wind Speed	1.012*** (0.163)	1.049*** (0.173)	1.016*** (0.161)
IHS(km Transmission)	0.118** (0.057)	0.123** (0.060)	0.119** (0.057)
Percent Farmland	1.553*** (0.452)	1.682*** (0.483)	1.558*** (0.456)
Log(Population)	0.058 (0.085)	0.066 (0.090)	0.058 (0.085)
Republican Vote Share, 2008	0.078 (0.646)	0.159 (0.679)	0.076 (0.644)
Percent Public Land	0.177 (0.499)	0.211 (0.529)	0.176 (0.505)
Log(Income Per Capita)	0.109 (0.325)	0.114 (0.345)	0.108 (0.328)
Log(Avg. Farm Size)	−0.120 (0.135)	−0.139 (0.143)	−0.120 (0.136)
Median Farm Size/Avg. Farm Size	0.352 (0.548)	0.385 (0.591)	0.354 (0.558)
Percent Live Off-Farm	−0.497 (0.796)	−0.502 (0.842)	−0.495 (0.800)
Percent Seasonal Homes	1.804** (0.883)	1.973** (0.951)	1.815** (0.893)
Observations	11,909	11,909	11,909
Events	427	427	427

Notes: Standard errors (clustered by county) in parentheses. An "event" is defined as adoption of the county's first WECS ordinance or permitting process. All models include state FEs. *p<0.1; **p<0.05; ***p<0.01.

Table A2: Duration model: Alternative neighbor definition

	Model		
	Cox-PH	Logistic	Clog-Log
	(1)	(2)	(3)
Distance Weighted Ordinances in State, $t-1$	3.012***	3.255***	3.033***
	(0.677)	(0.726)	(0.678)
Observations	12,436	12,436	12,436
Events	385	385	385

Notes: Standard errors (clustered by county) in parentheses. An "event" is defined as the adoption of the county's first WECS ordinance. All models include state FEs and all other variables in Table 2. *p<0.1; **p<0.05; ***p<0.01.

Table A3: Duration model: Low population counties

	Model		
	Cox-PH	Logistic	Clog-Log
	(1)	(2)	(3)
Log (population)	0.185**	0.203**	0.187**
	(0.091)	(0.093)	(0.088)
Observations	11,967	11,967	11,967
Events	376	376	376

Notes: Standard errors (clustered by county) in parentheses. An "event" is defined as the adoption of the county's first WECS ordinance. All models include state FEs and all other variables in Table 2. Counties with populations greater than 250,000 are excluded. *p<0.1; **p<0.05; ***p<0.01.

Table A4: Discrete turbine setback strictness regressions

	Strictness Definitions [1]				
	(1)	(2)	(3)	(4)	(5)
Year	0.035*** (0.008)	0.022*** (0.007)	0.023*** (0.006)	0.020*** (0.006)	0.021*** (0.006)
Updated	0.150** (0.059)	0.198*** (0.064)	0.125* (0.066)	0.113** (0.056)	0.115* (0.063)
IHS(MW Wind), $t-1$	0.015 (0.012)	−0.003 (0.015)	−0.017 (0.019)	−0.002 (0.013)	−0.006 (0.012)
IHS(Neighbors' MW Wind), $t-1$	0.010 (0.011)	0.005 (0.008)	0.007 (0.009)	0.006 (0.007)	0.006 (0.008)
Neighbors With Ordinances	0.002 (0.012)	0.003 (0.011)	−0.002 (0.010)	−0.018** (0.009)	−0.015 (0.010)
First Ordinance in District	0.204** (0.092)	0.170** (0.077)	0.203*** (0.071)	0.058 (0.047)	0.071 (0.053)
Neighbor Share with Strict Ordinance [2]	0.148 (0.092)	0.219** (0.095)	0.281** (0.119)	0.461 (0.299)	0.488** (0.230)
Wind Speed	0.061 (0.073)	0.088 (0.065)	0.047 (0.063)	0.003 (0.043)	0.021 (0.045)
IHS(km Transmission)	0.022 (0.022)	0.039** (0.015)	0.029* (0.017)	0.006 (0.016)	0.008 (0.014)
Percent Farmland	0.192 (0.259)	0.079 (0.170)	−0.020 (0.171)	0.058 (0.115)	−0.200 (0.158)
Log(Population)	0.019 (0.037)	−0.023 (0.032)	−0.031 (0.033)	−0.028 (0.020)	−0.013 (0.024)
Republican Vote Share, 2008	0.501 (0.309)	0.650** (0.271)	0.436* (0.235)	0.236 (0.176)	0.074 (0.220)
Percent Public Land	−0.316 (0.361)	−0.517*** (0.197)	−0.464** (0.208)	−0.345** (0.156)	−0.460*** (0.162)
Log(Income Per Capita)	−0.019 (0.140)	0.167 (0.141)	0.160 (0.131)	0.213* (0.110)	0.527*** (0.151)
Log(Avg. Farm Size)	−0.071 (0.072)	−0.062 (0.071)	−0.028 (0.066)	0.007 (0.059)	0.065 (0.060)
Median Farm Size/Avg. Farm Size	−0.618*** (0.222)	−0.481** (0.202)	−0.504*** (0.194)	−0.466*** (0.148)	−0.191 (0.189)
Percent Live Off-Farm	−0.319 (0.317)	−0.547** (0.250)	−0.505** (0.222)	−0.353 (0.257)	−0.339 (0.278)
Percent Seasonal Homes	0.428 (0.421)	0.814** (0.361)	0.779** (0.340)	0.466* (0.274)	0.418 (0.284)
Observations	379	379	379	379	400
Strict Ordinances	211	109	87	45	66
Adjusted R^2	0.250	0.357	0.352	0.248	0.238

Notes: [1] (1): Property Setback>514 ft. or Residential Structure>1000 ft.; (2): Property>750 or Residence>1500; (3): Property>750 or Residence>2000; (4): Property>1000 or Residence>2500; (5): Definition (4) or a height restriction < 300 or a WECS ban. [2] The share of neighbors in each district with a strict ordinance takes the strictness definition of the dependent variable for each regression, and is instrumented by the share in $t-1$. Standard errors (clustered by agricultural district) in parentheses. All models include state FEs. *p<0.1; **p<0.05 ***p<0.01.

Table A5: Turbine setback strictness regressions using 2009 turbine height averages

	Setback Strictness [1]			
	(1)	(2)	(3)	(4)
Year	0.047*** (0.013)	0.032*** (0.008)	0.034* (0.019)	0.010 (0.012)
Updated	0.319** (0.145)	0.283*** (0.091)	0.234* (0.136)	0.249*** (0.089)
IHS(MW Wind), $t-1$	0.030 (0.031)	−0.009 (0.013)	0.026 (0.031)	−0.011 (0.014)
IHS(Neighbors' MW Wind), $t-1$	0.008 (0.012)	0.009 (0.010)	−0.001 (0.012)	0.005 (0.010)
Neighbors With Ordinances	−0.016 (0.014)	−0.006 (0.011)	−0.0001 (0.004)	0.006** (0.003)
First Ordinance in District	0.541*** (0.143)	0.338** (0.156)	0.283*** (0.099)	0.203*** (0.077)
Avg. Neighboring Strictness [2]	0.312*** (0.077)	0.148 (0.115)	0.735*** (0.247)	0.293* (0.150)
Wind Speed	0.071 (0.083)	0.149* (0.078)	0.118 (0.085)	0.173** (0.081)
IHS(km Transmission)	0.037 (0.034)	0.057* (0.030)	0.033 (0.032)	0.058** (0.027)
Percent Farmland	0.395* (0.227)	−0.016 (0.216)	0.394 (0.247)	−0.013 (0.227)
Log(Population)	−0.015 (0.056)	−0.047 (0.044)	−0.018 (0.058)	−0.044 (0.044)
Republican Vote Share, 2008	0.473 (0.379)	0.676** (0.297)	0.589* (0.352)	0.724** (0.289)
Percent Public Land	−0.334 (0.281)	−0.426 (0.277)	−0.567* (0.313)	−0.502 (0.314)
Log(Income Per Capita)	0.150 (0.198)	0.269* (0.151)	0.059 (0.191)	0.232 (0.144)
Log(Avg. Farm Size)	−0.037 (0.092)	0.006 (0.077)	−0.039 (0.098)	0.017 (0.085)
Median Farm Size/Avg. Farm Size	−0.695** (0.312)	−0.884*** (0.247)	−0.562* (0.326)	−0.776*** (0.261)
Percent Live Off-Farm	−0.752* (0.390)	−0.912*** (0.309)	−0.997** (0.459)	−0.980*** (0.345)
Percent Seasonal Homes	0.679 (0.582)	0.203 (0.431)	0.601 (0.501)	0.309 (0.423)
Observations	373	358	373	358
Neighbor Definition	District	District	State	State
Strictness Outlier Cutoff	6	3	6	3
Adjusted R^2	0.356	0.343	0.350	0.347

Notes: [1] Strictness defined as the maximum of the property line setback divided by 431.21 feet And the residential structure setback divided by 1,000 feet. [2] The average neighboring setback strictness instrumented by the average in $t-1$. Standard errors (clustered by agricultural district) in parentheses. All models include state FEs. *p<0.1; **p<0.05 ***p<0.01.

Figure A1: Map of USDA agricultural districts.

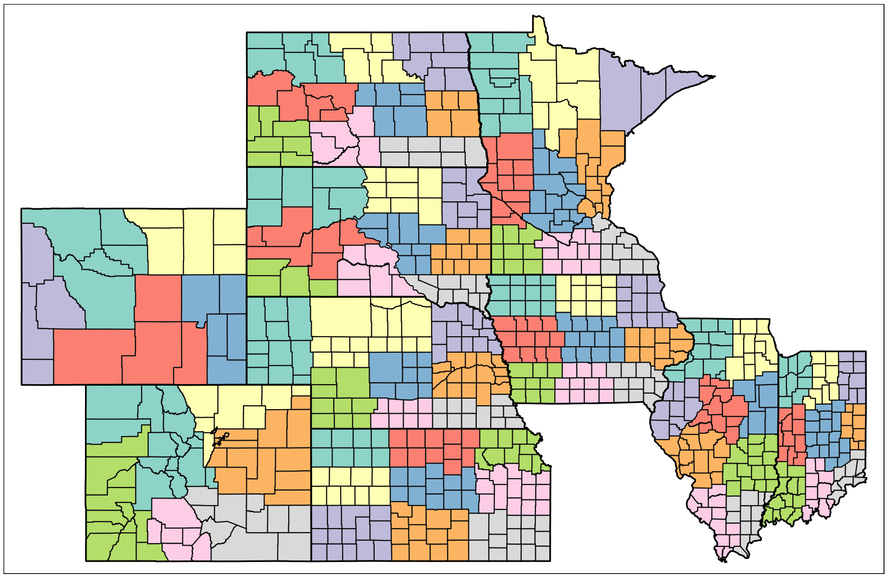


Figure A2: Example of spatially weighted neighbor measure

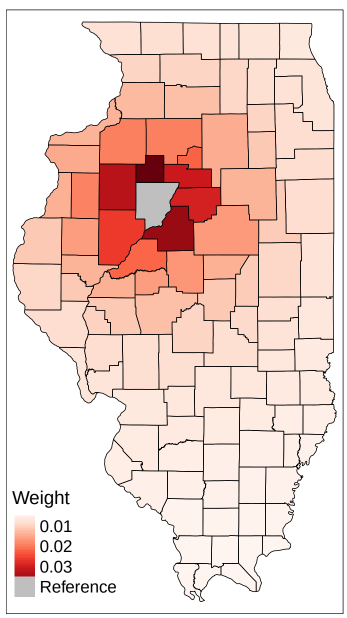
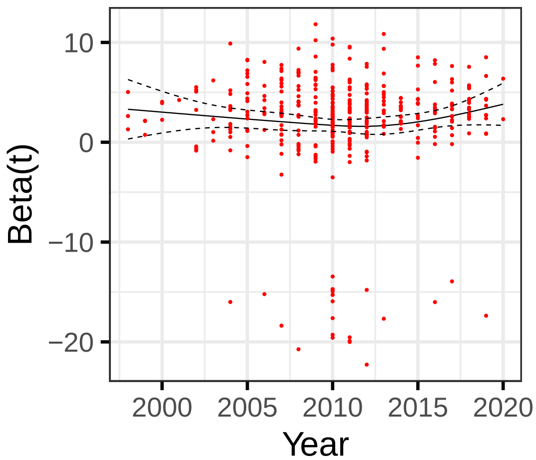
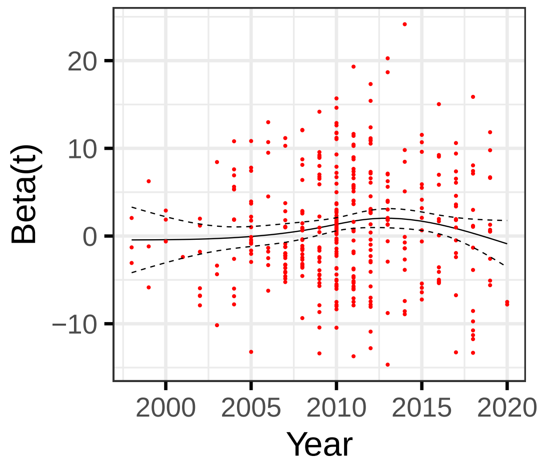


Figure A3: Shoenfeld residuals tests for key variables



(a) Whether county is zoned ($p = 0.84$)



(b) Neighbor ordinance share ($p = 0.27$)

Notes: Test of proportional hazards (PH) assumption for duration model in Table 2, column (1). The Schoenfeld (1982) residuals test measures whether coefficient estimates are time variant (Grambsch and Therneau, 1994). The large p-values mean a failure to reject the PH assumption.