

# Will the locals benefit?

The effect of wind power investments on rural wages

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**Abstract:**

An important and poorly understood question when communities consider wind power investments is whether the local population will benefit financially. I examine the effect of wind power investment on wages in rural counties in the US. I combine quarterly panel data on wages with data on all wind power plant investments larger than 1 megawatt (MW). Using a Bayesian multilevel model estimated by MCMC, I estimate a significant positive effect, with a magnitude consistent with a 2% permanent increase in wages following an investment in a large wind farm of 400 MW. However, this effect has large geographic and socioeconomic variation. Counties with low employment tend to see little impact on wages from wind power, potentially because slack in the labor market prevents wages from rising. From a policy perspective, these results are most relevant for local regulators and planners, who seek to balance the benefits and costs of wind farms to the community. This research indicates that wind farms can provide, on average, a modest boost to local wages, with some areas seeing an out-sized effect.

# 1 Introduction

Wind turbines and wind farms have in the last decade become a significant source of economic investment in rural and small-metro counties. The cost of wind power fell by 75 percent between 1984 and 2015 and is cost competitive in many locations in the US without subsidies (Trancik, 2015). Wind power has moved from being a niche and highly subsidized generation found mostly in rich states, to a competitive form of power generation that now makes up a significant portion of generation in states with substantial rural areas such as Iowa, South Dakota, Texas, and Wyoming. Decreasing costs and wider penetration has also meant that the wind power industry is playing a growing role in the US labor market as a whole. The US Department of Energy (DOE) estimates that as of 2015, the wind power industry supported approximately 100,000 jobs. The DOE further extrapolates that if wind power penetration continues to grow, the industry could support up to 600,000 jobs by 2050.<sup>1</sup>

The effects of wind power, and more generally renewable energy on economic growth and labor markets has been an active topic of research, especially in northern Europe where generous subsidies led to early and sustained investment in renewable energy (Lehr et al., 2008, 2012). Studies of the US have been more sparse (Haerer and Pratson, 2015; Brown et al., 2012; Wei et al., 2010). A common element of these studies is that they tend to be aggregated to the regional or national level, without considering the geographic and spatial distribution of economic effects. The results are often based on large scale, computational input-output models calibrated to aggregated data on investments and penetration, but highly dependent on modeling assumptions. To my knowledge, nation-wide empirical studies of the local economic effects of wind power investments are largely absent from the literature.

Comparisons can be made to the local economic effects of another recent energy boom. The shale oil and gas boom, driven by technological advances in “fracking” (Gold, 2014) also primarily affected rural areas in the major petroleum-containing formations in the US.<sup>2</sup> Komarek (2016); Weber (2012) and Brown (2014) all find substantial increases in employment and wages in counties that experienced a boom in oil and gas extraction. Importantly though, these economic and labor market effects often retreat or disappear as

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<sup>1</sup><https://www.energy.gov/downloads/2017-us-energy-and-employment-report>.

<sup>2</sup>The Bakken formation in North Dakota and Montana, The Marcellus in the north-east, and the Barnett in Texas

oil and gas wells run dry.

Wind turbines, on the other hand, tend to have a mechanical life of over 20 years. More so, older wind power sites tend to get re-powered—that is the turbines get replaced by newer, more efficient turbines—as the wind resources and transmission infrastructure make such sites ideal for continued investment (Mauritzen, 2014). Thus, even though we might hypothesize that the local economic effects of wind power are less than that of exploiting oil and gas deposits, there is good reason to believe that the effects may be more permanent in nature.

A related literature analyses the effect of natural resources on the geography of industrialization. Michielsen (2013) finds that the existence of coal and gas deposits tends to have a significant effect on the geographical location of energy-intensive industry. This suggests a potentially long-term mechanism for the economic effects of wind power on economic development. If the geographic concentration of wind power in a certain area leads to locally cheaper electricity prices, this could attract energy intensive industry. However, in this article I focus on a time scale of years, rather than decades, and such a long-term mechanism is unlikely to be at play in the results I present.

Instead, the hypothesis that I wish to test in this article is whether investments in wind power farms, which happen primarily in rural communities, have a direct, permanent and measurable impact on the economic well-being of the local residents of that community, as measured by average wages.

In order to test this hypothesis, I use data from the Energy Information Agency form 860 on all wind power installations over 1 MW in the United States and match it with quarterly wage and employment data from the Bureau of Labor Statistics Quarterly Census to estimate the effect of wind power investments on wages.

In trying to estimate the effect of wind power on local wages, I need to take into account a high degree of heterogeneity among counties. I wish to estimate separate wage trend curves for each county, and allow for varying ("random") effects for wind power investment. This allows for both disaggregation of results, as well as making the model robust to outliers and improving predictive performance of the model—a property called regularization or "partial pooling" (Gelman et al., 2013). Such a multilevel (alternatively called a hierarchical or mixed-effects model) can be estimated by maximum likelihood (Bates et al., 2015). However, this can become computationally cumbersome with multiple hier-

archies, which I make use of in this article. In addition, under maximum likelihood the data are often assumed to be normally distributed for computational reasons, which may not always be a realistic assumption. Instead, I estimate the model using Bayesian Markov Chain Monte-Carlo (MCMC). A full technical description of Bayesian methods, multilevel models and MCMC is well beyond the scope of this article. Instead I refer to McElreath (2015) and Kruschke (2014), which provide good introductions to Bayesian methods and multilevel models, while a more technical treatment can be found in Gelman et al. (2013).

The results indicate that wind power investments have a modest but significant effect on wages. A large 400-megawatt (MW) wind farm—approximately the capacity of 100-150 modern turbines—leads to a median permanent increase in wages of 2.0% in rural counties. However, this median figure masks large variation across geographies, with a few states with large penetrations of wind power showing significantly higher local effects on wages. In addition, I show that the effect of wind power investments on wages varies based on the socioeconomic status of counties. Wages in counties that are designated as having low levels of employment appear to benefit little from wind power investments. This is consistent with economic theory, which would suggest that the increased economic activity from investments would push up wages in areas where there is little slack in the labor market. I also estimate state-by-state coefficients, and these also show out-sized effects in states where wind power investments happen in counties with particularly low unemployment.

These results are not ex-ante obvious. Investments in wind power will of course have an impact on economic growth and lead to job creation in the manufacturing, installation and maintenance of the turbines. They will also generate revenues for land-owners who either lease land for wind turbines or own the turbines directly, sometimes through a cooperative structure. However, it is not immediately clear how and to what extent these economic effects influence the local labor market and wages.

Unlike investments in typically labor-intensive industry, like a manufacturing plant, fully built out wind power plants employ few people. For many locations, it may make sense to employ skilled labor from outside the county hosting a wind power plant for both the initial build-out as well as subsequent maintenance and repair. Because wind turbine maintenance and repair is a skilled occupation, even if an in-county job is created, it is not clear to what extent this would lead to a net-increase in employment as opposed to a skilled worker moving from one position to another. In this article, I therefore start out

with the assumption that the effect of a wind power plant on net employment is negligible. This is supported by a preliminary analysis, as well as results from the main analysis.

Without a significant employment effect, wind power investments' impact on wages are likely indirect; through the flow of income accumulating to land-owners, local ownership stakes in the plant or through extra tax revenue to the local governments. But the role that this flow of income will have on local wages is ex-ante unclear. Ownership of agricultural land is to a growing extent concentrated and held by corporations or individuals who are not located in the same county or even state (Nickerson et al., 2012). The income from wind turbines may, in many cases, end up flowing completely out of the county.

Importantly, wind power investments are not necessarily perceived as net positive by local communities. Wind farms can impose significant non-financial costs such as altered views, noise, and disruption of local wildlife. These costs can lead to conflicts around planned investments, which have been analyzed extensively in the planning and environmental policy literature (Fast, 2015; Fast et al., 2016; Walker et al., 2014). In particular, Christidis et al. (2017) and Wolsink (2007) emphasize the role of inequality and fairness in the distribution of benefits as sources of conflict. Conflict and opposition tend to happen in communities where the benefits of wind power are seen to be concentrated or flow mainly to outsiders. In this context, establishing the local wage effects of investments becomes an important part of the planning process. If wind power investments are known to have a broad-based effect on local wages in a county, this could be an important factor in gaining local acceptance.

This article informs renewable energy policy and planning by suggesting a distributive effect of wind power investments. Wind power investments appear to modestly press up wages in rural counties. This should inform local planning decisions on whether and to what degree to allow wind power investments in a local community. This article should also encourage discussion and future research on how more of the benefits of wind power can flow to the local communities that host the investments. For example, ownership structures such as co-operatives, which are widely used in Denmark as well as in some US states, could lead to both a more direct flow of benefits to host communities as well as a way of gaining local acceptance for wind power.

## 2 Identifying the effects of wind power investments

Establishing a causal treatment effect of industrial investments on labor markets has typically been difficult. Industrial investments are generally endogenous to local labor markets—that is, firms take into account the local labor market when making an investment decision. Industrial investments are also heterogeneous in nature—they differ substantially by size, character and labor-intensity. Comparing different investments in different locations is challenging. Finally, industrial investments are often made in large labor markets where the total effects are difficult to estimate in aggregated data.

For the purposes of measuring the effect of industrial investments on labor markets, wind power has three attractive properties. First, wind power is largely standardized, and scale is straight-forward to measure. A wind farm is measured in terms of capacity (Megawatts (MW)). Second, out of spatial necessity, investments in wind turbines tend to happen away from large population centers. Modern land-based wind turbines are often over 80 meters tall with blade-lengths of over 100 meters.<sup>3</sup> The majority of wind power in the United States is built in rural counties, making it plausible to measure aggregated effects on labor markets. Finally, wind power investments are largely exogenous to labor market conditions. The reason is that the most important factor in the profitability of a wind farm is the average wind speed of a location, something that tends to be unrelated to the labor market.

Despite the importance of wind speed in wind power investment decisions, labor market outcomes and investment in wind power could plausibly be partly endogenously determined. On the margin, counties more likely to attract wind power projects could, for example, have the necessary transmission infrastructure in place, or have local governments that are more investment friendly, with stream-lined processes for permits and approvals. These unobserved variables could also be correlated with labor market outcomes, biasing the estimates.

In order to control for such potential sources of bias, I use a panel of data with 30 quarterly observations on labor market outcomes for rural counties in the United States. Making use of the flexibility of the Bayesian multilevel model, intercepts and trends for wages are allowed to vary by county, taking into account local variation. I then compare outcomes before and after a wind power investment. In addition, I control for several county-level

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<sup>3</sup>The wingspan of a 747 jumbo-jet is approximately 60 meters

County Rural-Urban Continuum Codes (RUCC)	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area
Aggregated categories	
1	Metro counties (1,2,3)
2	Non-metro with urban population, adjacent to a metro area (4,6)
3	Completely rural, or small urban population not adjacent to metro area. (5, 7, 8, 9)

Table 1: Rural Urban Continuum Codes obtained from the Department of Agriculture Economic Research Service (ERS) are aggregated into three broader categories.

variables such as agricultural land values and total electric generating capacity, that may have a confounding effect. From this multilevel model I can estimate an average treatment effect of wind power investment across counties while allowing for varying intercepts and trends by county.

### 3 Data

I combine data from three sources. Data on investments in wind energy plants are from the US Energy Information Agency (EIA) form 860.<sup>4</sup> This data provides yearly information on every power plant and planned power plant with capacity of over 1 MW in the United States. Data are at the generator level. Variables include the date of first operation, size of generator, county of generator, ownership, and grid connection.

Data on quarterly county-level labor market outcomes are from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages.<sup>5</sup> Variables include average weekly wages and employment for each of the 3223 US counties.

I classify the counties based on the US Department of Agriculture’s Economic Research Service (ERS) Rural-Urban Continuum Codes (RUCC)<sup>6</sup> from 2013. County designations are updated every 10 years based on decennial Census data. RUCC codes go from 1-9, as

<sup>4</sup><https://www.eia.gov/electricity/data/eia860/>

<sup>5</sup><https://www.bls.gov/cew/>

<sup>6</sup><https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/>

defined in table 1. In order to simplify the analysis, I aggregate the designations into three broader categories, which are also shown in the lower pane of the table. The aggregated categories are meant to separate out metro areas and counties adjacent to metro areas from those that consist of rural areas and small towns not directly connected to a big city economy. From now on I will simply refer to these three categories as “Metro”, “Adjacent metro” and “Rural”.

Many recent analyses of the US labor market have used Commuting Zones, as developed by Tolbert and Sizer (1996), as the geographic unit. Commuting Zones approximate the labor markets associated with metro areas which often stretch across metropolitan and suburban counties. I do not, however, make use of Commuting Zones as I am explicitly concerned with rural and small-town counties not adjacent to metro areas.

Additional data on county population and agricultural land values was obtained from the ERS.<sup>7</sup> These variables can clearly change over time; however, they are only available at 10-year intervals, with the most recent year being 2013. In the analysis, these variables then appear as time-invariant county-level variables.

The upper pane of figure 1 shows the distribution of counties by rural-urban indicator. The lower pane of the figure shows the distribution of operating wind power plants. Rural counties have clearly seen a large share of wind power investments. Figure 3 shows that rural counties have been the location of nearly half the total wind power capacity and that capacity additions in rural areas more than doubled in the period studied.

Comparing the distribution of wind power in figure 1 to a map of average wind resources produced by the US National Renewable Energy Laboratory (NREL) in figure 2 gives a visual impression of the high correlation between wind resources and the geographic investment decision. As mentioned, the most important factor in determining the profitability of a wind turbine is the average wind speed of the turbine location. The physical relationship between power generation and average wind speed is approximately cubic<sup>8</sup>. Average wind speed is then a dominating factor in the geographic investment decision and, arguably, exogenous to economic and labor market variables.

The upper pane of figure 4 shows that employment in non-metro areas has been largely stagnant since 2009 compared to metro areas. As the lower panel shows, however, wage

<sup>7</sup><https://www.ers.usda.gov/topics/farm-economy/land-use-land-value-tenure/farmland-value/>

<sup>8</sup>A simplified equation for wind power output can be written  $P = kC_p \frac{1}{2} \rho AV^3$ , where  $P$  = Power output (kW),  $C_p$  = Maximum power coefficient,  $\rho$  = Air density ( $kg/m^3$ ),  $A$  = Rotor swept area ( $m^2$ )  $V$  = wind speed (m/s),  $k$  = a constant. (MacKay, 2016)



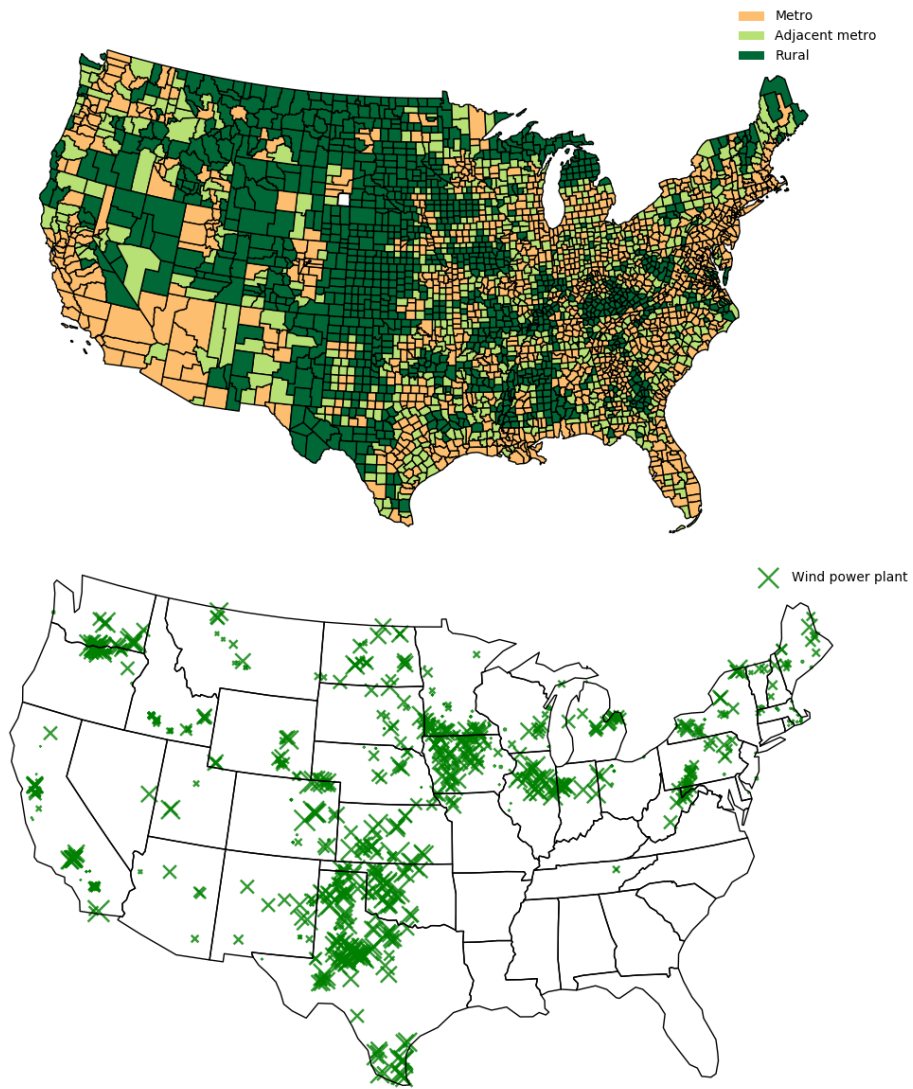


Figure 1: The upper pane of the figure shows the distribution of counties by the rural-urban indicator. The lower pane shows the distribution of wind power plants across the US. Wind power plants tend to be concentrated in rural counties.

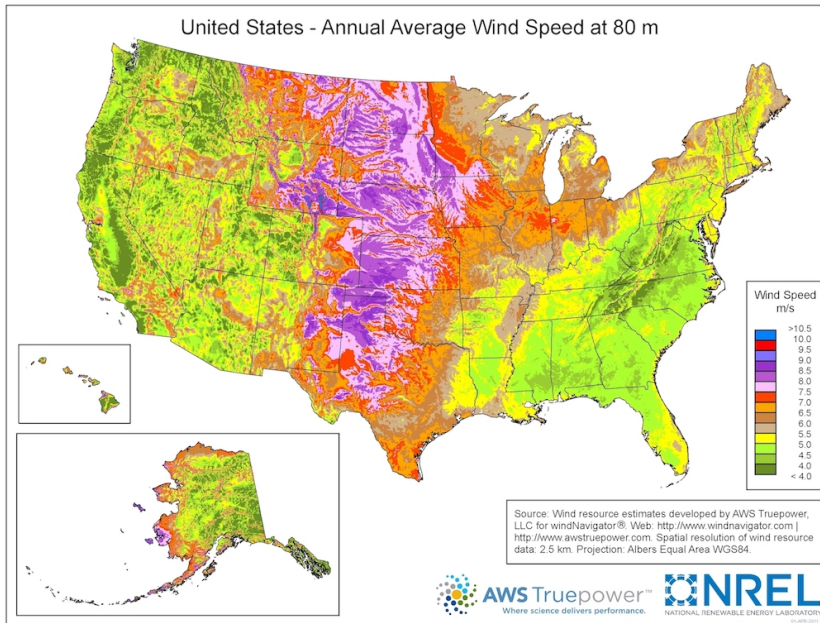


Figure 2: The National Renewable Energy Laboratory’s wind resources map. Wind power investments, as shown in figure 1, are concentrated in the wind-rich spine of the US running from Texas up through North Dakota. Wind power investment decisions can to a certain extent be seen as exogenous

growth has been similar in both rural and metro areas, though rural wages fell more during the preceding recession.

A summary of the variables used in the models is presented table 2. Variables for county average weekly wage, employment and cumulative installed wind power varies both by county and quarterly observation with a total of approximately 32,000 observations. The four county-level variables are fixed over time with a total of 1,049 observations consisting of the rural counties in our sample.

Notably, the mean cumulative installed wind power is shown to have a mean of approximately 15 MW, while the standard deviation is approximately 91 MW. This reflects the fact that most counties have no wind power capacity throughout the period studied, while a few have large build-outs of capacity, sometimes of several hundred mega-watts, leading to a large standard deviation.

## 4 A hierarchical model of wages and wind power investment

In the model the response variable is wages in county  $c$  at time  $t$ ,  $wage_{c,t}$ . This variable is transformed by subtracting the overall mean of the series and dividing the standard

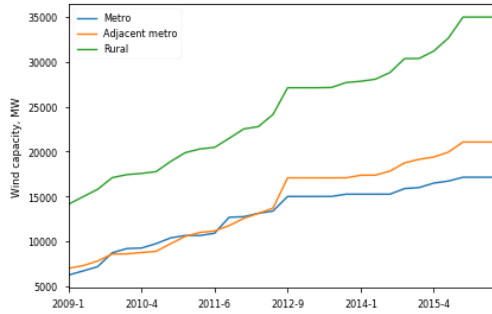


Figure 3: Almost half of all wind turbine capacity is located in rural areas. Wind power capacity more than doubled in the period studied.

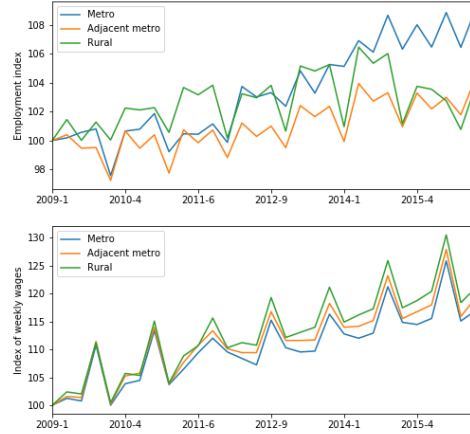


Figure 4: Employment growth in non-metro counties has lagged significantly behind employment in metro counties. Average wage growth, has, however been similar between metro and non-metro counties, through from a lower absolute level.

Variable	Symbol	N	Mean	St. Dev.
<b>Observation level</b>				
Average Weekly Wage	wages	32,807	644.51	147.27
Quarterly Employment	employment	32,807	12,145.17	12,303.72
Cumulative installed wind power	capacity	32,807	15.21	91.11
<b>County level</b>				
Low Employment County (1/0)	low_employment	1,049	0.36	0.48
County Population (2010 Census)	population	1,049	12,205.95	10,124.27
Average Agricultural Land Value	agg_land_value	1,049	2,432.94	1,818.58
Total Electric Generating Capacity	gen_cap	1,049	129.98	382.89

Table 2: Summary of variables used in the analysis

deviation. All other continuous variables are transformed in a similar manner. This transformation allows for the interpretation of results free from units. Dividing by the standard deviation also maintains coherence when comparing coefficients to binary variables (Gelman and Hill, 2006). These transformations have the added benefit of aiding the convergence of the MCMC algorithm (Gelman et al., 2013). Binary variables are not transformed.

$$w\hat{a}ge_{c,t} = \frac{wage_{c,t} - \text{mean}(wage_{c,t})}{\text{std}(wage_{c,t})} \quad (1)$$

The likelihood of each response is modelled as a normal random variable with mean  $\hat{y}_{c,t}$  and standard deviation  $\sigma^y$  as shown in equation 2.

$$w\hat{a}ge_{c,t} \sim N(\hat{y}_{c,t}, \sigma^y) \quad (2)$$

Equation 3 describes the model at the observation level. The fitted values for wages are modeled as an intercept term,  $\alpha_c$ , and a trend or slope term  $\beta_c^0$ . The covariates include an indicator for the period,  $period_{c,t}$  in quarterly intervals. The estimated parameter  $\beta_c^0$  then represents a linear time trend on the wages. As the  $c$  indexing indicates, these terms are allowed to vary by county. This leads to the estimation of over 1000 intercept and slope parameters—one for each rural county. However, each of the  $\alpha_c$  and  $\beta_c^0$  parameters are modeled as coming from a higher-level (or "meta") distribution as shown in equations 4.

The hierarchical form of the model then allows each of the county-level coefficients and intercepts to be decomposed into a pooled average effect, as well as an idiosyncratic county-level random-effect. In a traditional model, a single average intercept and trend term might be estimated across all counties - a so called fully pooled estimation. With a multilevel model, we can allow intercept and trend terms to vary at the county level, while still being "partially" pooled by way of modeling each county-level parameter as coming from a higher-level distribution (Gelman and Hill, 2006).

This structure allows for inference on average effects, while controlling for geographic variation and naturally taking into account issues of multiple comparisons through parameter shrinkage. In practical terms, this leads to a compromise between the aims of modeling and controlling for the variation in each county that could otherwise bias the co-

efficient on the wind power term, and avoiding over-fitting the data, which tends to lead to poor out-of-sample inference and prediction. For more in-depth discussions of hierarchical models<sup>9</sup> and partial pooling I refer to Gelman and Hill (2006) and McElreath (2015).

A vector of quarterly dummy variables, **quarter**<sub>t</sub> are included to control for seasonality, as rural counties tend to have a high proportion of seasonal workers, which in turn leads to seasonality in the wage data.

The variable *capacity*<sub>c,t</sub> indicates the total wind power capacity in a county *c* in period *t*. The parameter  $\beta^1$  is then the coefficient of interest, representing the permanent average employment effects of a wind power investment. Figure 5 shows a simplified illustrative diagram of the model for wages over time with a wind power investment at time *t*.

Plausibly, the build-out stage of a wind farm could drive up wages temporarily, with wage-levels thereafter falling back to trend. I therefore tested specifications that included a term for the size of the installation in the quarters of the build-out. This term was consistently estimated to be centered around zero, and I therefore dropped it from the final specification presented here.

Finally,  $\mathbf{X}_c$  represents a matrix of county-level covariates that do not vary with time.

$$\hat{y}_{c,t} = \alpha_c + \beta_c^0 period_{c,t} + \beta^1 capacity_{c,t} + \mathbf{qtr} + \zeta \mathbf{X}_c \quad (3)$$

$$\alpha_c \sim N(\mu^\alpha, \sigma^\alpha) \quad (4)$$

$$\beta_c^0 \sim N(\mu^{\beta^0}, \sigma^{\beta^0})$$

## 5 Model fitting with Bayesian MCMC

I use Bayesian Markov Chain Monte-Carlo (MCMC) simulation to fit the model using the Stan probabilistic programming language (Stan Development Team, 2014), which utilizes Hamiltonian MCMC (see MacKay (2003, ch. 30)) and a No-U-Turn Sampler (Homan and Gelman, 2014) for efficient sampling in high-dimensional probability space.

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<sup>9</sup>Hierarchical models are also referred to as random effects models, multilevel models, and in the case of linear models: linear mixed models.

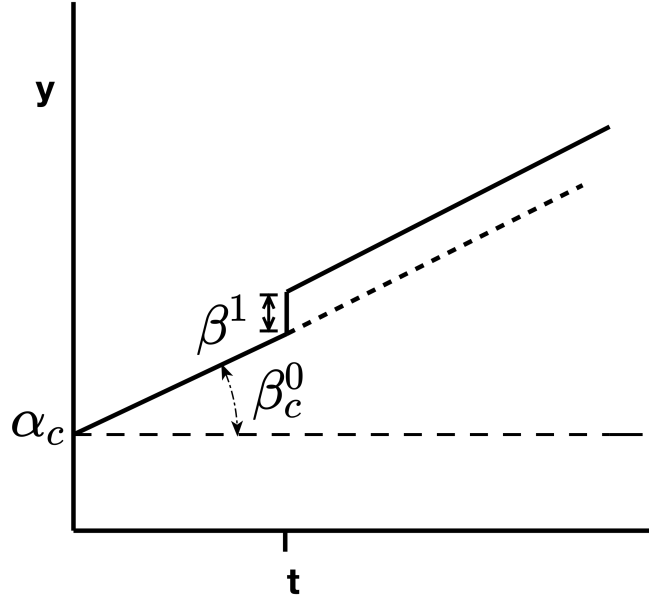


Figure 5: The diagram illustrates the observation level equations for each county.

Weakly informative Cauchy priors<sup>10</sup> are assigned to the parameters of the higher-level distributions as shown in equations 5. The mean terms,  $\mu$ , for the distribution of the  $\alpha_c$  and  $\beta_c^0$  parameters are assigned Cauchy priors with a location parameter of 0 and a scale parameter of 2.5. The corresponding variance terms,  $\sigma$ , are assigned half-Cauchy priors<sup>11</sup> with location parameter 0, and scale parameter of 5. Weakly informative priors have the effect of focusing the initial draws of the MCMC algorithm to reasonable values of the parameters, with the fatter tails of the Cauchy distribution, as opposed to a normal distribution, allowing for a non-negligible probability of outliers. The priors do not, however, impose any strong assumption of prior information on the model results. Use of the Cauchy prior distribution also allows for inference in the case of complete separation by covariates (Gelman, 2006).

$$\mu^\alpha \sim \text{Cauchy}(0, 2.5) \quad (5)$$

$$\mu^{\beta^0} \sim \text{Cauchy}(0, 2.5)$$

$$\sigma^\alpha \sim \text{half-Cauchy}(0, 5)$$

$$\sigma^{\beta^0} \sim \text{half-Cauchy}(0, 5)$$

<sup>10</sup>The Cauchy distribution is a t-distribution with 1 degree of freedom.

<sup>11</sup>Cauchy priors with support over the positive range

The Hamiltonian MCMC routine was run with four chains and 3000 iterations. Gelman-Rubin convergence statistics ( $\hat{R}$ ) of close to 1 indicated convergence of the simulation to the target probability (Gelman et al., 2013).

## 6 The effect of wind power investment on wages

In this section I present results from four specifications of the hierarchical model of wind power investments on wages. In table 3 I present an overview of the symbols used in the specifications.

Symbol	Description	Specification
$\hat{y}_{c,t}$	Mean of the response variable, wages in quarter (t) and county (c)	1-4
$\sigma^y$	Standard deviation of response variable, wages	1-4
$a_c$	Intercept term, varies by county (c)	1-4
$\beta_c^0$	Slope parameter on wage trend, varies by county	1-4
<b>qtr</b>	Vector of quarterly dummy variables	1-4
$\beta^1$	Parameter on wind power capacity	1
$\beta_{temp}^1$	Parameter on wind power capacity, varies by low employment status	2-3
$\beta_{state}^1$	Parameter on wind power capacity, varies by state	4
$\beta^2$	Parameter on county employment	3-4
$\zeta^0$	Parameter on county population	1-4
$\zeta^1$	Parameter on county agricultural land value	2-4
$\zeta^2$	Parameter on county total power generation capacity	2-4
$\mu^\alpha$	Location parameter on distribution of $\alpha_c$ parameters	1-4
$\mu^{\beta^0}$	Location parameter on distribution of $\beta_c^0$ parameters	1-4
$\mu^{\beta^1}$	Location parameter on distribution of $\beta_{state}^1$	4
$\sigma^\alpha$	Scale parameter on distribution of $\alpha_c$ parameters	1-4
$\sigma^{\beta^0}$	Scale parameter on distribution of $\beta_c^0$ parameters	1-4
$\sigma^{\beta^1}$	Scale parameter on distribution of $\beta_{state}^1$	4

Table 3: Definitions and descriptions of model symbols.

The first and simplest specification can be written as in equation 6.  $\alpha_c$  and  $\beta_c^0$  are the intercept and slope terms for the wage trend for each county and are given higher-level distributions as discussed above. The distribution of  $\beta^1$  represents the effect of wind power capacity additions,  $capacity_i$  over all counties. In this specification I include county population,  $population_c$ , where  $\zeta^0$  is the coefficient, as the only county-level controlling variable. Population is an important controlling variable since it may confound the estimated coefficient on capacity. Higher populations may be a sign of a stronger overall economy with higher wages at the same time as a county with a higher population may also attract more wind power investments both because of larger demand for power and because of the larger

labor market pool.

$$\hat{y}_{c,t} = \alpha_c + \mathbf{qtr} + \beta_c^0 * period_{c,t} + \beta^1 capacity_{c,t} + \zeta^0 population_c \quad (6)$$

The summary of results for the specification are shown in table 4. Including summaries for all of the county level  $\alpha_c$  and  $\beta_c^0$  parameters is impractical, so instead I show the estimated mean and standard deviation values of the higher-level distributions:  $\mu^\alpha$ ,  $\sigma^\alpha$ ,  $\mu^{\beta^0}$ ,  $\sigma^{\beta^0}$ . The parameter distribution of interest however is  $\beta^1$ . The distribution is estimated with a mean of 0.020, with 95% of the probability mass lying between 0.012 and 0.029. The probability density of the parameter is shown in figure 6.

Interpreted at the median value of the distribution, a one standard deviation increase in wind power capacity in a county will tend to increase wages by 0.02 standard deviations. This is an economically modest estimate. Interpreting this for a county with mean wages, even the building of a relatively large wind farm with a capacity of 400 MW (about 100-150 modern wind turbines) would be expected to raise average weekly wages by roughly 2%. Yet, as we will see, this overall estimate masks significant underlying variation.

	mean	se_mean	sd	2.5%	97.5%
$\mu^\alpha$	-0.088	0.003	0.026	-0.143	-0.040
$\mu^{\beta^0}$	0.248	0.000	0.005	0.238	0.257
$\sigma^\alpha$	0.869	0.002	0.020	0.829	0.910
$\sigma^{\beta^0}$	0.150	0.000	0.004	0.143	0.158
$\beta^1$	0.020	0.000	0.004	0.012	0.029
qtr[1]	0.294	0.000	0.005	0.284	0.304
qtr[2]	-0.002	0.000	0.005	-0.012	0.008
qtr[3]	0.014	0.000	0.005	0.004	0.025
$\zeta^0$	0.099	0.003	0.026	0.049	0.150
$\sigma^y$	0.336	0.000	0.001	0.334	0.339

Table 4: Summary of results for specification 1.

$$\begin{aligned} \hat{y}_{c,t} = & \alpha_c + \mathbf{qtr} + \beta_c^0 * period_{c,t} + \beta_{lemp}^1 capacity_{c,t} \\ & + \zeta_c^0 population_c + \zeta^1 aggLandValue_c + \zeta^2 genCap_c \end{aligned} \quad (7)$$

For the second specification, as shown in equation 7, I make a few small but important changes. First, I add two additional county-level control variables. In addition to the county population, I add the variable for agricultural land value,  $aggLandValue_c$  with



coefficient  $\zeta^1$ , which may affect both the decision to invest in a wind farm and the wages in a county and could therefore potentially confound the results. In addition, I include an indicator for the total amount of power generation capacity in the county, excluding wind power,  $genCap_c$  with coefficient  $\zeta^2$ . The reason for including this variable is that wind power siting decisions are likely related to the availability of transmission and other electric power infrastructure. This could plausibly also be correlated to wages in a county and could confound the results on the wind power capacity variable. Large amounts of electric power infrastructure could both be a sign that a county is economically prosperous as well as attractive to wind power investors.

Finally, in this specification I allow the coefficient on wind power capacity additions to vary by an indicator for whether a county is high- or low-employment, as classified by the US Department of Agriculture. Thus, the coefficient on wind power capacity additions is now written  $\beta_{temp}^1$ . The idea that is being tested here is that the effect of extra wind power investment on wages in a county may be dependent on the existing economic conditions in that county.

The summary of the results for the specification can be found in table 5. Figure 7 shows the density of the coefficients on the wind power capacity variable over low- and high-employment counties. For high-employment counties, the coefficient is again centered around 0.02, with 95 % of the probability between 0.012 and 0.028 standard deviations. However, for low-employment counties, the distribution is estimated to be relatively flat and centered around zero. In other words, little correlation can be found between wind power investments and wages in counties designated as low employment.

These results are consistent with what economic theory might suggest. Increased economic activity due to a wind farm investment will only tend to press up wages in counties with little slack in their labor markets. While this article focuses on wages, it is important to note that it is plausible that counties with high unemployment may still benefit economically through job-creation, without this necessarily being reflected in average wages.

A notable omission of the former two specifications is a variable for employment. As noted, the estimated wage effect of wind power could potentially be through increased employment pressing up wages. In that case, including employment in the regression should reduce the magnitude of the coefficient. In the third specification, as shown in equation 8, we include quarterly data on employment,  $employment_{c,t}$ , for each county

	mean	se_mean	sd	2.5%	97.5%
$\mu^\alpha$	-0.089	0.004	0.028	-0.139	-0.034
$\mu^{\beta^0}$	0.248	0.000	0.005	0.238	0.258
$\sigma^\alpha$	0.832	0.001	0.017	0.798	0.867
$\sigma^{\beta^0}$	0.150	0.000	0.004	0.143	0.158
$\beta_{lemp=False}^1$	0.020	0.000	0.004	0.012	0.028
$\beta_{lemp=True}^1$	-0.007	0.001	0.024	-0.054	0.040
qtr[1]	0.294	0.000	0.005	0.284	0.304
qtr[2]	-0.002	0.000	0.005	-0.012	0.008
qtr[3]	0.014	0.000	0.005	0.004	0.025
$\zeta^0$	0.086	0.004	0.027	0.028	0.136
$\zeta^1$	-0.023	0.003	0.026	-0.076	0.027
$\zeta^2$	0.241	0.002	0.028	0.189	0.296
$\sigma^y$	0.336	0.000	0.001	0.334	0.339

Table 5: Summary of results for specification 2.

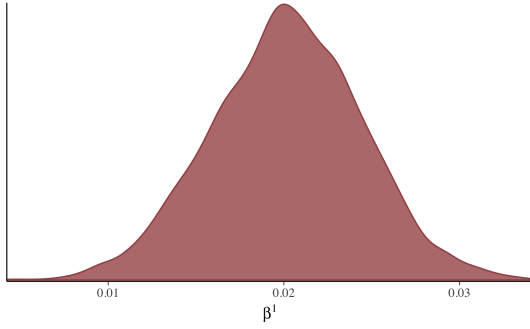


Figure 6: Distribution of  $\beta^1$  under specification 1

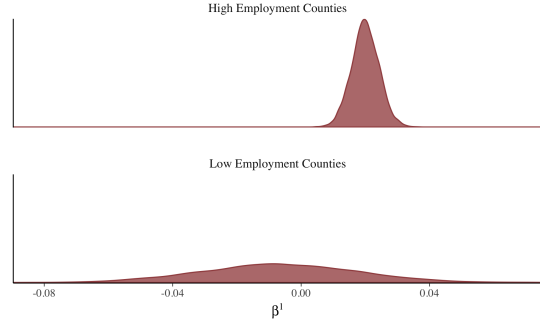


Figure 7: Distribution of  $\beta^1$  distributions varying by counties classified as low employment and high employment from specification 2.

as a controlling variable, with a coefficient  $\beta^2$ . Otherwise, specification 3 is identical to specification 2.

$$\begin{aligned}
\hat{y}_{c,t} = & \alpha_c + \mathbf{qtr} + \beta_c^0 * period_{c,t} + \beta_{lemp}^1 capacity_{c,t} + \beta^2 employment_{c,t} \\
& + \zeta_c^0 population_c + \zeta^1 aggLandValue_c + \zeta^2 genCap_c
\end{aligned} \tag{8}$$

A summary of the results from specification 3 can be found in table 6. The coefficient on the employment variable,  $\beta^2$  is positive and economically significant. The mean of the estimated distribution is 0.7, with 95 % of the probability falling between 0.65 and 0.74. Interpreted at the mean of the distribution, a one standard deviation change in employment will tend to increase wage by 0.7 standard deviations. As we might expect,

there is a strong general relationship between employment and wages. Yet, it appears that wind power investment’s effect on wages is through another mechanism. The inclusion of wages as a controlling variable hardly changes the distribution of the  $\beta^1$  parameters. In other words, the effect of wind power investments on wages appears to be independent of employment.

	mean	se_mean	sd	2.5%	97.5%
$\mu^\alpha$	-0.087	0.003	0.023	-0.142	-0.047
$\mu^{\beta^0}$	0.241	0.000	0.005	0.231	0.250
$\sigma^\alpha$	0.780	0.001	0.017	0.750	0.815
$\sigma^{\beta^0}$	0.141	0.000	0.004	0.134	0.148
$\beta_{l_{emp}=False}^1$	0.021	0.000	0.004	0.013	0.029
$\beta_{l_{emp}=True}^1$	-0.015	0.001	0.024	-0.061	0.032
$\beta^2$	0.702	0.001	0.019	0.665	0.740
$qtr[1]$	0.298	0.000	0.005	0.288	0.308
$qtr[2]$	0.019	0.000	0.005	0.009	0.029
$qtr[3]$	0.013	0.000	0.005	0.003	0.023
$\zeta^0$	-0.544	0.003	0.032	-0.603	-0.482
$\zeta^1$	-0.038	0.003	0.025	-0.086	0.010
$\zeta^2$	0.217	0.002	0.025	0.171	0.266
$\sigma^y$	0.331	0.000	0.001	0.328	0.333

Table 6: Summary of results for specification 3.

The fourth and final specification allows for a higher degree of variation in the  $\beta^1$  parameter by allowing the coefficient to vary by state. This specification accounts for variation in the effects of a wind power investment by state, due to factors such as differences in typical ownership structure, typical size of investments as well as the economic conditions of the state.

Specification 4 can be written as in equation 9, where the only change from specification 3 is that the  $\beta^1$  parameter is now indexed with *state* representing the 42 states that contain rural counties that experienced at least one wind power investment in the period studied.

The 42 estimated  $\beta^1$  distributions are assigned a higher-level distribution with a normal prior with mean  $\mu^{\beta^1}$  and standard deviation  $\sigma^{\beta^1}$ , as shown in equation 10. As with the  $\alpha$  and  $\beta^0$  distributions, assigning a higher-level distribution allows for partial pooling of the information in the data across states in order to avoid undue influence from outlier groups—especially from states with few wind power investments—and to generally avoid over-fitting the data.

A summary of results are shown in table 7, while a visual summary of the state-varying  $\beta^1$

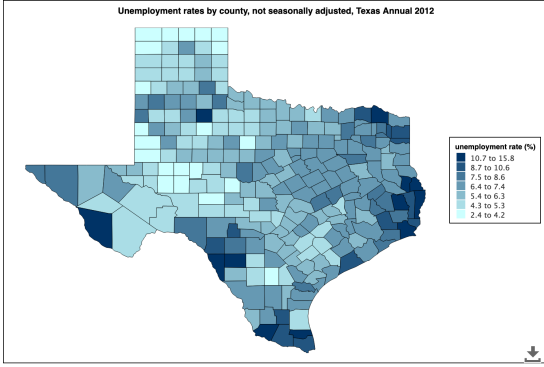


Figure 8: The map shows county-level unemployment for 2012 in Texas. Rural counties in the north and north west panhandle, where much of the wind power lies, have particularly low unemployment rates. Source: US Bureau of Labor Statistics Local Area Unemployment Statistics, <https://data.bls.gov/lausmap/showMap.jsp>

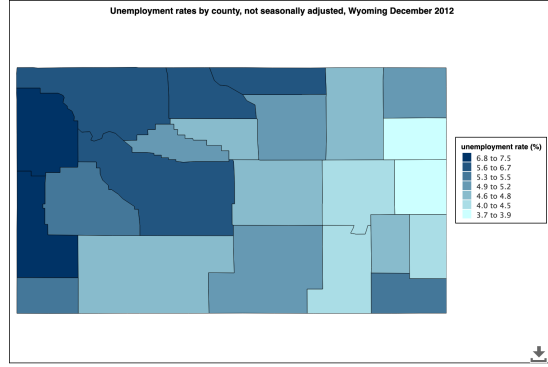


Figure 9: The map shows county-level unemployment for 2012 in Wyoming. Rural counties in the east and south east, where much of the wind power lies, have particularly low unemployment rates. Source: US Bureau of Labor Statistics Local Area Unemployment Statistics, <https://data.bls.gov/lausmap/showMap.jsp>

distributions is shown in figure 10 with accompanying table 8. The state-level coefficients are estimated with relatively high uncertainty, but most are in the range of the overall estimate from the previous specifications. However, there is sizeable variation. Notably, Texas and Wyoming—both states with large amounts of wind power—have coefficients that are centered close to 0.10. Interpreted at the median, this would imply that a medium- to large-sized wind farm of 200 MW on average permanently increases wages by 5% in these states. Ex-ante, it is not clear why the economic effects should be substantially higher in these states. However, figures 8 and 9 show that county unemployment in the Texas panhandle (north-west) and eastern Wyoming—both areas with heavy wind power investments (see figure 1)—had particularly low unemployment rates in the period studied. Thus, the results for these states are consistent with the results from the previous specifications: That wind power investments press up wages in counties where there is little slack in the labor market. The results underline that the wage effects of a wind power plant will likely vary substantially based on the socioeconomic conditions of the county as well as the size and ownership structure of the investment.

It is worth noting that the state-level results motivate the use of the Bayesian multilevel model in the first place. Since the priors on the meta-parameters in the aggregated model have heavy tails, they allow for outlying observations without unduly affecting estimates

of the central tendency (mean or median). In this way, the results from the two states are not driving the results seen from the aggregated model.

Iowa is also a notable state, with a mean coefficient of .022 that is estimated with relatively high precision. This is likely explained by the fact that Iowa is a heavily rural and agricultural-based state that also has the highest wind power penetration in the country. Every rural county in Iowa has experienced significant wind power investments over the course of the period studied, and thus Iowa provides a high number of relevant observations. In this way, Iowa serves as a relatively pure test case for the effects of wind power on rural counties. Iowa's state-level coefficient of .022 lends supports to the overall estimate on the  $\beta^1$  coefficient of .02 from the previous specifications.

$$\hat{y}_i = \alpha_c + \mathbf{qtr} + \beta_c^0 * period_i + \beta_{state}^1 capacity_i + \beta^2 employment_i + \zeta_c^0 population_c + \zeta^1 aggLandValue_c + \zeta^2 genCap_c \quad (9)$$

$$\beta_{state}^1 \sim N(\mu^{\beta^1}, \sigma^{\beta^1}) \quad (10)$$

	mean	se_mean	sd	2.5%	97.5%
$\mu^\alpha$	-0.086	0.004	0.022	-0.127	-0.044
$\mu^{\beta^0}$	0.241	0.000	0.005	0.232	0.250
$\sigma^\alpha$	0.782	0.002	0.018	0.746	0.816
$\sigma^{\beta^0}$	0.140	0.000	0.004	0.134	0.148
$\mu^{\beta^1}$	0.010	0.001	0.018	-0.027	0.044
$\sigma^{\beta^1}$	0.060	0.001	0.014	0.037	0.094
$\beta^2$	0.701	0.001	0.019	0.665	0.737
$qtr[1]$	0.298	0.000	0.005	0.288	0.308
$qtr[2]$	0.019	0.000	0.005	0.009	0.029
$qtr[3]$	0.013	0.000	0.005	0.003	0.023
$\zeta^0$	-0.540	0.004	0.030	-0.600	-0.478
$\zeta^1$	-0.035	0.004	0.026	-0.083	0.018
$\zeta^2$	0.227	0.002	0.024	0.181	0.273
$\sigma^y$	0.330	0.000	0.001	0.328	0.333

Table 7: Summary of results for specification 4.

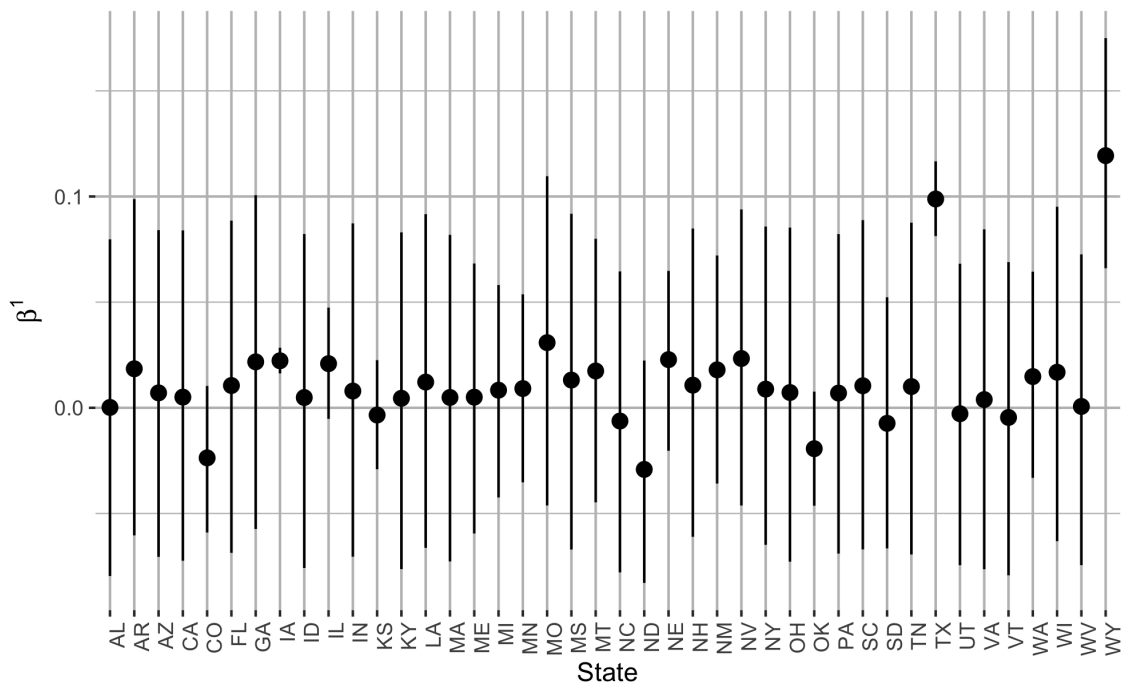


Figure 10: Summary of the  $\beta^1$  distribution varying by state. The point represents the median value of the estimated distribution. The lines represent the range between the 10th and 90th percentile.

## 7 Conclusion and Policy Implications

In summary, I find that wind power investments in rural counties have a positive but modest overall effect on wages. Interpreting from the median of the estimated distribution, a large wind farm located in a rural county is estimated to raise wages by 2%, though this median value masks substantial variation across US states. The effect on wages also does not appear to translate to counties designated by the Department of Agriculture as being low employment counties.

The effect of wind power plants on wages is unlikely to be through a net increase in employment. Instead, the effect is more plausibly explained through the flow of income to the county that accumulates due to lease payments, ownership stakes from the wind turbines or increased revenue to the local government. Why such a mechanism fails to materialize in low employment counties is not directly clear from the analysis. However, economic theory would suggest that investments in counties with slack in their labor markets will not experience upwards pressure on wages to the same degree as a county that already has full employment.

I argue that the model setup provides adequate identification of the causal effect of

wind power investment on wages. This identification comes partly from the exogenous nature of wind power investments, which are heavily dependent on the average wind speeds of a location. In addition, a panel data set with a hierarchical model setup provides identification in the presence of unobserved variables correlated with the probability of wind power investment. I also control for several county-level variables that may confound the results.

Investments in energy generation and the related effects on labor markets are highly relevant to current public policy debates. In fact, they even played a significant role in the narrative of the US presidential election of 2016.<sup>12</sup>

For wind power in particular, this research is relevant to the local planning, approval and regulatory process which seeks to balance the economic benefits of a wind farm to the local community with the costs. As the planning literature reviewed earlier suggests, local opposition to wind power plants often involves a perception that the economic benefits do not flow broadly to the local community. This study finds evidence that wind power plants provide a modest increase to wages in the local communities where they are sited. This effect can vary significantly regionally, with some areas apparently experiencing an out-sized positive effect on wages from investments. On the other hand, rural counties that struggle the most with unemployment appear to benefit the least, at least in terms of higher wages. Further research is required to fully understand the sources of this variation.

When making an industrial investment, most firms explicitly or implicitly take into account the local labor market as a major factor. Skilled work force, labor costs, and local demand for the product are important factors in the expected profitability of most industrial investments. This article highlights how the profitability of wind power is most strongly determined by the average wind speeds of a given location.

This provides the prospect of wind power investments serving as an exogenous shock and setting up a type of natural experiment for important outstanding questions about labor markets. One important topic has been the trend of labor market “polarization” in the last four decades, where employment has increased for low-skilled work and high skilled work, but real wage growth in these two categories has diverged, with low-skilled work actually experiencing a sustained real wage decline (Autor, 2014; Autor and Dorn, 2013). Semi-skilled employment, such as a turbine technician, has traditionally defined

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<sup>12</sup><http://www.washingtonpost.com/news/energy-environment/wp/2017/03/29/trump-promised-to-bring-back-coal-jobs-that-promise-will-not-be-kept-experts-say>

the middle class. This category of employment has however stagnated in terms of both number of jobs and wages. Whether this stagnation is due to trade, technology or lack of necessary skills has been a active research topic (Autor et al., 2015; Acemoglu et al., 2015). This article only gives hints about this larger debate, though researchers making use of more detailed register and tax data could extract more robust insights.

## 8 Software and Replication Resources

For the analysis, I use the scientific computing environment for python: Numpy, Scipy, IPython and Jupyter (Walt et al., 2011; Oliphant, 2007; Perez and Granger, 2007). The package Pandas was used for cleaning, formatting and descriptive analysis of the data (Wes Mckinney, 2010). Figures were created using the package matplotlib (Hunter, 2007) and ggplot (Wickham, 2009). The Bayesian hierarchical model was coded and computed using the Stan probabilistic programming language and engine (Stan Development Team, 2014). Code and data used for preparation of data, descriptive analysis and models are available upon request.

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	mean	se_mean	sd	10%	90%
AL	0.000	0.001	0.065	-0.080	0.080
AZ	0.007	0.001	0.064	-0.071	0.084
AR	0.018	0.002	0.064	-0.060	0.099
CA	0.005	0.001	0.063	-0.072	0.084
CO	-0.024	0.001	0.027	-0.059	0.010
FL	0.011	0.001	0.064	-0.069	0.089
GA	0.022	0.002	0.063	-0.057	0.101
ID	0.005	0.001	0.063	-0.076	0.082
IL	0.021	0.000	0.020	-0.005	0.047
IN	0.008	0.001	0.064	-0.070	0.087
IA	0.022	0.000	0.005	0.016	0.028
KS	-0.003	0.001	0.020	-0.029	0.023
KY	0.005	0.002	0.064	-0.076	0.083
LA	0.012	0.001	0.063	-0.066	0.092
ME	0.005	0.001	0.050	-0.059	0.068
MA	0.005	0.001	0.063	-0.073	0.082
MI	0.008	0.001	0.040	-0.042	0.058
MN	0.009	0.001	0.035	-0.035	0.054
MS	0.013	0.002	0.065	-0.067	0.092
MO	0.031	0.002	0.063	-0.046	0.110
MT	0.017	0.001	0.049	-0.045	0.080
NE	0.023	0.001	0.034	-0.020	0.065
NV	0.023	0.001	0.056	-0.046	0.094
NH	0.011	0.001	0.060	-0.061	0.085
NM	0.018	0.001	0.043	-0.036	0.072
NY	0.009	0.001	0.061	-0.065	0.086
NC	-0.006	0.001	0.056	-0.078	0.065
ND	-0.029	0.001	0.041	-0.083	0.022
OH	0.007	0.001	0.065	-0.073	0.085
OK	-0.019	0.001	0.021	-0.046	0.008
PA	0.007	0.001	0.062	-0.069	0.082
SC	0.010	0.001	0.064	-0.067	0.089
SD	-0.007	0.001	0.047	-0.067	0.052
TN	0.010	0.001	0.064	-0.069	0.088
TX	0.099	0.000	0.014	0.081	0.117
UT	-0.003	0.001	0.057	-0.074	0.068
VT	-0.005	0.001	0.060	-0.079	0.069
VA	0.004	0.002	0.066	-0.076	0.084
WA	0.015	0.001	0.038	-0.033	0.064
WV	0.001	0.001	0.059	-0.074	0.073
WI	0.017	0.001	0.065	-0.063	0.095
WY	0.119	0.001	0.042	0.066	0.175

Table 8: Summary of the  $\beta^1$  distribution varying by state.