Why Do Red States Have a Comparative Advantage in Generating Green Power?

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Abstract

The 2022 passage of the Inflation Reduction Act will lead to a large increase in U.S green power investment. Such green power generation requires more land than fossil fuel fired power plants. A cost minimizing green power producer will seek to site wind and solar farms on cheap land, with relatively easy access to big city power consumers in areas likely to feature fewer NIMBY land use lawsuits. We present evidence that rural Republican areas have a cost advantage for siting and generating green power. We find that Republican areas issue green power generation permits faster than progressive areas. The rise of green power subsidies creates the possibility of an emerging schism between rural Republican Congressional districts and suburban Republican areas concerning their support for carbon mitigation regulations. We identify those "marginal" Congressional Districts featuring Republican Representatives whose district has high renewable potential and cheap land located relatively close to big cities.

Preliminary and Incomplete

Introduction

In 2021, 21% of electricity in the United States was generated from renewable energy, with 9.2% from wind and 2.8% from solar.[1] To nudge utilities to purchase green power, state governments have ramped up the Renewable Portfolio Standard (RPS). In 2010, the average RPS was 3.16%, and this number has jumped to 10.7% by 2021. Such green mandates encourage greater investments in renewable generation. The August 2022 Inflation Reduction Act's scale highlights the Biden Administration's "Green Big Push" as the U.S now seeks to sharply expand the nation's green power capacity. The U.S seeks to expand green power supply during a time when electricity demand is likely to rise as more air conditioning is demanded and as more people rely on electricity to power homes and vehicles ((Davis, Fuchs, and Gertler 2014; Rapson 2014; Cicala 2022).

Land is a key input in renewable power generation. It takes roughly 70 acres per MW for wind turbines and 43 acres per MW for solar panels.[2] These are larger land input requirements than for fossil fuel fired power plants, which take 12 acres per MW on average. It is projected that the land use for electricity generation in the US will increase by almost 50% from 2020 to 2050 (Van Zalk and Behrens 2018). Land always features an opportunity cost. Consider California. California features the highest land prices, and it has the nation's most ambitious RPS mandate. California is well known for its NIMBY litigation such that environmental lawsuits often slow land use projects.[3] The Williamson Act that aims to conserve farmland has caused a few utility-scale renewable energy projects to be cancelled.

States such as Nevada and Utah have an edge in generating green power and exporting it to nearby places such as California. California already has a 33% RPS requirement, and it will rise to 60% by 2030. Home values in California are the highest in the nation with a median price of $790,000 in 2021, almost twice as high as its neighboring state Nevada's median. High land prices deter profit-maximizing developers from building land-intensive renewable capacity in California. However, given the high green power demand, it can be cost-effective to produce green power elsewhere and ship to Californian cities. Arizona, Oregon, Nevada, and Utah are close to California. They feature cheaper land and have good sun and wind potential. The rural areas of

[1] https://www.eia.gov/tools/faqs/faq.php?id=427&t=3
[2] https://docs.wind-watch.org/US-footprints-Strata-2017.pdf
[3] https://www.nytimes.com/2022/09/01/business/economy/california-nimbys-housing.html

these states have the most available land and are often governed by Republicans. Such leaders are often pro-business and actively seek economic development projects (Holmes 1998).

Republican areas are over-represented among wind and solar power generators, despite their anti-environment political stance. Our explanation for this fact relies on basic concepts from urban and regional economics. Red states have lower population density, lower land prices, and fewer land use lawsuits. The absence of "red tape" in Republican states gives them an edge in avoiding the land use uncertainty associated with NIMBYism in liberal states (Djankov 2002; Mulligan and Shleifer 2005).

We use several data sets to study every stage of the green power generation supply chain. First, we study the permitting process to document the time it takes to obtain an electricity generation permit. Distributed generating capacity, such as wind turbines and solar panels owned by individual businesses, needs to wait in an interconnection queue to connect to the power grid. We document that this interconnection process is more streamlined in Red States than Blue States, especially for land-intensive renewable projects.

We then explore the emerging economic geography of where windfarms and solar farms are being built. We use our simple economic geography model to test several hypotheses. We document that Republican areas feature more wind capacity, and the solar capacity in Republican areas are catching up with Democratic regions. We also study whether green capacity have been built in rural areas with high wind and solar potentials and low land prices. Consistent with the past literature, we document that wind and solar farms are more likely to locate in windy/sunny counties with low population density and cheap land (Brown et al. 2012; Shoeib, Renski, and Infield 2022). We build on these works by accounting for how the availability of interstate transmission affects the locational choice of wind and solar farms. Transmission lines unbundle electricity production and consumption. Businesses add renewable generating capacity to states with low land prices and ship the power to green consumers in the neighboring states. An example is the 730-mile Anschutz power line (currently under construction) that runs through the American West.[4] We find that the both state RPS and RPS potential from neighboring states have a significantly positive effect on developers' decision to build wind and solar capacity.

[4] https://www.latimes.com/environment/story/2022-08-23/wyoming-clean-energy-california

In the last section of the paper, we explore the implications of the rise of Republican areas as green power hubs for examining a possible emerging divide in the Republican party's opposition to climate change mitigation policies. The voting on the Waxman-Markey bill of 2009 showed the historical party cleavages. Republican districts such as those in the suburbs of Houston featured members of Congress who were more likely to oppose carbon pricing. An analysis of the Waxman-Markey Bill's votes reveals that Representatives opposed the proposed cap and trade legislation if their district was poorer, high carbon per-capita and if the Representative was more conservative (Cragg et. al. 2013). Political scientists have argued that economists have been naïve about the political economy of enacting low carbon legislation (Breetz, Midenberger and Stokes 2018; Stokes and Breetz 2018). While Pigouvian incentives reduce the entire economy's emissions and thus gain support from the economists, such incentives introduce negative income effects and trigger political backlash against low-carbon agenda (Holian and Kahn 2015).

Although no Republican members of Congress voted in favor of the August 2022 Inflation Reduction Act, this bill's emphasis on expanding green energy subsidies raises a new possibility. Republican representatives have revealed a strong antipathy towards carbon taxes, but we predict that many rural Republican representatives will support green energy subsidies if their districts gain financially from the growth of the green economy. These subsidies can also bring indirect welfare benefits both in the construction and the operation stages of green power plants. Building wind and solar farms boosts short-term local employment (Brown et al. 2012). Once these projects are completed, the local government can collect a stream of tax revenues from the green operators to improve public services such as education (Kahn 2013).

Our paper provides policy implications on the allocation of renewable subsidies from the Inflation Reduction Act. Backlash against large-scale green capacity installation has broken out in rural America.[5] Rural counties have not fully capitalized the economic benefits of renewable development due to their specialized economy (Shoeib, Renski, and Infield 2022). Residents have not been well-compensated for the disamenities (e.g. noise and the loss of neighborhood aesthetic) brought by green generating facilities. These are some of the factors causing the backlash, but they can be alleviated by green subsidies. For rural Republican areas with green power generation

[5] https://www.forbes.com/sites/robertbryce/2022/01/27/backlash-against-renewables-surged-in-2021-with-31-big-wind-and-13-big-solar-projects-vetoed-across-us/

potential, green subsidies could become an "experience good" if they benefit from the current subsidy rollouts. We use a propensity score approach to rank the Republican districts based on their potentials for renewable generation. The top districts should be targeted by the current rollouts and may become a new source of votes for green economy legislation going forward. Such votes would be due to self-interest, not ideology (Peltzman 1984). This cross-partisan cooperation can accelerate our nation's transition into zero-carbon economy.

The Urban Economics of Producing Green Power

In this section, we present a two-period model of green power production. In the first period, developers apply for a green power generation permit in a specific location. They incur a fixed cost of F in the first period. to the local regulator. This permit is sought for a specific location. If the project is approved, they produce in the second period. In our model, developers decide the quantity of green power production (Q) and the customers they ship power to (located in a set of counties K) in advance. They select a county where they can minimize the cost of production and transmission. These developers are price takers in the electricity retail market.

In selecting the optimal location for siting a green power plant, the developer recognizes that each county features a different capacity factor g (i.e. the units of power produced by each unit of generating capacity). Note that g is higher in places with faster windspeed and stronger solar radiation. To produce Q units of power, developers thus need a minimum of Q/g units of capacity. We assume land (L) and capital (K) are the two only production factors in building green generating capacity. Wind turbines and solar panels with larger capacity occupy more land and need more capital to build. Denote the land requirement per unit of capacity by α_L and the capital requirement per unit by α_K. We assume α_L and α_K are fixed, and the inputs are perfect complements. The construction of generating capacity thus has a Leontief production function given by:

$$q = \min\{\frac{L}{\alpha_L}, \frac{K}{\alpha_K}\}, \quad (1)$$

where q denotes the quantity of green capacity being built. If $L > \alpha_L q$ or $K > \alpha_K q$, the excess land or capital would be wasted. This suggests that to construct q units of green capacity, the cost-minimizing condition is:

$$q = \frac{L}{\alpha_L} = \frac{K}{\alpha_K}. \quad (2)$$

Denote the price of land and capital by c_L and c_K respectively, and the land price varies by location. Suppose the green project is approved. The total cost of constructing Q/g units of generating capacity in county i is:

$$C_{capacity}(Q/g)_i = \frac{Q}{g_i}\left(\alpha_L c_{L,i} + \alpha_K c_K\right) + F_i, \quad (3)$$

The developer would lose F_i if the project ends up not being approved. Developers generate Q units of power with Q/g units of generating capacity. After generation, they need to ship these Q units of power to their consumers. Denote the transmission cost per mile of each unit of electricity as c_T. If developers choose county i to locate their power plants, the total cost of generation and transmission is given by:

$$C_{power}(Q)_i = \frac{Q}{g_i}\left(\alpha_L c_{L,i} + \alpha_K c_K\right) + F_i + \sum_{k\in K} c_T d_{ik}\, Q_k, \quad (4)$$

where d_{jk} is the distance between county i and county k (in a set of consumer counties K), and Q_k is the electricity shipped to county k pre-determined by developers with $Q = \sum_{k\in K} Q_k$. Developers choose the county i that minimizes the cost given in equation (4).

Each county i has a project approval rate s_i, and the electricity price in county k is p_k. The expected profit of producing Q units of power in county i and selling Q_k units to county k ($k \in K$) is thus:

$$E[\pi(Q)_i] = s_i\left(\sum_{k\in K} p_k Q_k - C_{power}(Q)_i\right) - (1 - s_i)F_i, \quad (5a)$$

which is equivalent to:

$$E[\pi(Q)_i] = s_i\left(\sum_{k\in K} p_k Q_k - \frac{Q}{g_i}\left(\alpha_L c_{L,i} + \alpha_K c_K\right) - \sum_{k\in K} c_T d_{ik}\, Q_k\right) - F_i \quad (5b)$$

The expected profit is a decreasing function of distance to consumers and land prices and an increasing function of approval likelihood and capacity factor. Our model thus predicts that developers will locate their facilities in areas with lower project failure probability, shorter distance to green consumers, cheaper land prices, and higher capacity factor (i.e. high wind and solar

potential). Rural Republican regions close to liberal cities are more likely to have these physical attributes as we will show.

Allocating Land to Green Power Generation

Every land parcel has a next best alternative. Land closer to cities can be used for suburban development. Land at the fringe can be used as farmland. Our conceptual framework in the previous section identifies the location where developers would build green power capacity. We now discuss the opportunity cost of their choices. Because zoning laws prohibit the conversion of agricultural land into residential units, we consider farmland as the only alternative. We make the simplified assumption that farming and green power generation cannot coexist.[6] We follow the approach in Barbier and Burgess (1997) to set up a two-period model of land conversion.

For each location, denote the current land area used for farming as F_0 and that for green generation as G_0. The local planner faces a decision to convert x acre of agricultural land into renewable power plants in the first period. After the conversion, denote the area of farmland and green power plants as F_1 and G_1 respectively. The discounted social welfare from the second period is given by:

$$(1-r)(B^F(F_1) + B^G(G_1) + E(G_1)), \tag{6}$$

where r is the discount rate, B^F and B^G are the revenue functions of farmland and green generation respectively, and E is the environmental benefit of green generation. The above social welfare function is subject to the constraints that $F_1=F_0-x$ and $G_1=G_0+x$. The maximization problem can be written using Lagrange multiplier as:

$$Max_{F_1,G_1,x}\ (1-r)(B^F(F_1) + B^G(G_1) + E(G_1)) - \lambda(F_1 - F_0 + x) - \theta(G_1 - G_0 - x) \tag{7}$$

The first-order conditions are derived by differentiating the Lagrange equation with respect to F_1, G_1, and x:

[6] This assumption makes sense for now because of the existing challenges in growing crops under wind turbines and solar panels. Studies have found mixed results on how wind turbines affect crop yields, and many crops cannot grow under solar panels that block the sunlight. We acknowledge this assumption may no longer hold in the future.

$$(1-r)b^F(F_1) - \lambda = 0 \quad (8a)$$

$$(1-r)(b^G(G_1) + e(G_1)) - \theta = 0 \quad (8b)$$

$$\theta - \lambda = 0 \quad (8c)$$

In the above equations, b^F and b^G are the marginal revenue from farming and renewable generation, and e is the marginal environmental benefits from using land for renewable generation. Equation (8a) shows that farmland should be preserved until the point when the discounted marginal revenue from the remaining farmland equals the shadow value of farmland (λ). Similarly, equation (8b) shows that land conversion should take place until the sum of the discounted marginal revenue and the discounted marginal environmental benefit equals the shadow value of the converted farmland (θ).

Equations (8a) to (8c) jointly show that the equilibrium is achieved when the discounted marginal revenue on the remaining farmland equals to the discounted marginal revenue and marginal environmental benefit from the land converted to green power plants. This embodies the opportunity cost of land conversion. When one more acre of farmland is converted, we forgo the agricultural benefits that would have been produced there. The opportunity cost is high in counties with high agricultural productivity. We assume diminishing marginal returns of farmland (i.e. $\frac{\partial b^F}{\partial F} < 0$) and constant returns of green power plants within each location (see α_L and g in the previous section). Then for two counties with the same agricultural productivity (i.e. same b^F), our model indicates it is optimal to convert more farmlands in the county with higher returns of green generation (e.g. the county with higher wind speed and solar radiation).

Data

We use two main datasets: a project-level interconnection queue dataset provided by the Berkeley Electricity Markets & Policy Lab[7] and a county/year dataset compiled by ourselves, which include the green capacity, the environmental attributes, and the demographic features of each county.

[7] https://emp.lbl.gov/publications/queued-characteristics-power-plants

The interconnection queue dataset includes data on roughly 15,000 electricity projects that have applied for grid connection from 2000 to 2020. For each project, the dataset provides the project status (active, completed, or withdrawn), application year, proposed and/or actual completion year, energy source, capacity, and the location. We focus on the 5138 active or completed projects whose energy source is wind or solar.[8] Based on each project's location, we merge in the respective state's League of Conservation Voters (LCV) score in 2021 and the respective county's votes for Trump in 2020 presidential election.[9] The LCV score is on a scale from 0 to 100, where a lower score indicates the representative is more conservative in environmental issues. The state LCV score is the average of LCV scores of all House representatives from a state. In 2021, the average LCV score of Democratic representatives was 99.5, and that for Republicans was 12.5.

In the county/year dataset, we calculate each county's wind and solar capacity in each year from 2010 to 2021 using data from the Environmental Protection Agency's EGRID database.[10] The EGRID dataset provides detailed information on each electricity generator in the US, including the year built, energy source, capacity, and location. Using these generator data, we calculate the total wind capacity and total solar capacity by county/year. We obtain the median home prices data from Zillow for each county/year and adjust them for inflation based on the annual CPI. [11] We also merge each state's RPS by year into our county panel.[12] The final dynamic variable in our county dataset is the annual out-of-state RPS market potential for each county. It is calculated using the market potential function (Hanson 2005). The out-of-state RPS potential for county j in year t is given by:

$$MP_{jt} = \sum_{k \in K} RPS_{kt} e^{-d_{jk}}, \qquad (6)$$

where K is a set of counties not in the same state as county j but located less than 800 miles from county j, and d_{jk} is the distance (in miles) between county j and county k. In 2021, the average out-of-state RPS market potential per county was 27.2. This potential has a correlation of 0.153 with state RPS. The low correlation indicates that many counties in states with low RPS are located

[8] 689 of the green projects in our sample are completed, and the rest are active. We omit roughly 7000 withdrawn projects, 800 completed or active gas projects, and 800 active battery projects.
[9] https://scorecard.lcv.org/members-of-congress
[10] https://www.epa.gov/egrid/download-data
[11] https://www.zillow.com/research/data/
[12] https://emp.lbl.gov/projects/renewables-portfolio/

close to states with high RPS. These counties have high green business potentials if they feature cheap land.

We access the voting data from the MIT Election Data Science Lab[13]. We use the percentage votes for the Republican candidate in the 2020 presidential election as a measure of each county's political spectrum. We obtain the county population, population density, and area data from the American Community Survey (ACS)[14]. The county-level climate belief data is provided by the Yale Climate Change Communication program[15]. Specifically, we use the percentage of population believing climate change is real in 2021 as the measure of each county's climate belief. This variable has an average value of 65.2%. The final component of our county panel is the wind and solar potential of each county. The wind potential refers to the wind speed 100 meters above the surface level, and the solar potential refers to the global horizontal irradiance (GHI). Counties with higher wind speed and higher solar radiance are more suitable for constructing wind and solar generating capacity. These environmental data are from the National Renewable Energy Laboratory (NREL) as GIS files. We overlay these files with county shape files to calculate the averages by county. The average county wind speed in the US is 6.9m/s. The ideal speed to power utility-scale wind turbines is 5.8m/s[16], and 90.6% of counties meets this standard. The average GHI is 4.48 $kWh/m^2/day$. On the continental US, Arizona, Nevada, and California ranks top three based on solar potential. We merge the demographic and environmental cross-sectional data into the county/year panel by county.

Based on the county/year panel, we create a dataset with the same variables by congressional district/congress. We provide two metrics of a district's political affiliation: the LCV score and the DW-NOMINATE score. The former primarily quantifies a representative's environmental stance. The latter is on a scale from -1 to 1 and quantifies a representative's general political stance. A lower DW-NOMINATE score indicates the representative is more liberal. If a district has multiple representatives, we average these scores from all representatives. Congressional districts in rural places usually span across multiple counties. We weight all county

[13] https://electionlab.mit.edu/data
[14] https://www.census.gov/programs-surveys/acs
[15] https://climatecommunication.yale.edu/visualizations-data/ycom-us/
[16] https://www.eia.gov/energyexplained/wind/where-wind-power-is-harnessed.php

attributes such as climate belief by the area intersection factor to get the averages for each district.[17] The wind and solar capacity are the only exceptions. Instead of using the weighted average, we use the longitude and latitude of each green generator to classify it into a congressional district with GIS techniques. We then calculate the total wind and solar capacity by district/congress. Each congress lasts for two years. We use county data from the first year when calculating the district attributes. Years 2010 to 2021 correspond to the 111th to the first year of the 117th congress.

Understanding the Correlates of Permit Approval Times for Green Power Generation

Today, a rising share of electricity is generated by distributed generators using renewables. Most of these generators are operated by individual businesses, who sell the generation to local utilities in the electricity wholesale market. As opposed to utility-operate power plants, these distributed generators must receive approval from local inspectors for interconnection to the transmission or distribution facilities. This interconnection queue is slowing down the nation's transition to renewable generation. As of 2020, 680MW of wind and solar generating capacity were waiting for interconnection access. The long queue causes the low completion rate of green projects as developers withdraw their application.

In this section, we study the barriers of entry in green power provision using data from the Berkeley Electricity Markets and Policy Lab. Based on the completed distributed renewable projects from 2000 to 2020, the median interconnection time is 1563 days (4.28 years), and the 25th percentile is 875 days (2.4 years). The median interconnection time of wind projects is 1567 days, and that of solar projects is 1562 days. Using data on all active and completed projects, we test whether the interconnection time is lower in pro-business Republican regions. We estimate the following logistic regression for a project i in 2020:

$$P(Time_i > T \mid X_i') = \frac{\exp(\beta' X_i')}{1 + \exp(\beta' X_i')}. \quad (9)$$

[17] If 20% of land area of district A is in county i, 50% in county j, and 30% in county k, we weight the county attributes from county I, j, k with 2:5:3 to calculate the district attributes.

In equation (9), time in the days that the project has been in the queue as of December 31, 2020. In the regressions reported below, T will either equal two years or four years. X is a vector of project attributes including its capacity and the average LCV score of the state it locates in. We also include application year fixed-effects and region fixed-effects. Standard errors are clustered by state. The estimation results are shown in columns (3) to (6) in Table 1.

In the first two columns of Table 1, we test whether the interconnection time has decreased on average. We regress days in queue for each completed projects on its capacity and the post-2010 dummy. The dummy equals 1 if the project was proposed after 2010. It has a negative and statistically significant coefficient in both columns. Wind projects proposed after 2010 are approved 27.3% faster than those prior to 2010, and solar projects are approved 20.2% faster. Given the surging demand for renewable power, the green permission process has been accelerated to lower the time cost of entry.

The coefficient of project capacity is significantly positive in most columns. This indicates that larger projects need to wait longer in the interconnection queue. Based on the completed wind projects, a 1% increase in project capacity results in a 0.19% increase in waiting time. The increase is 0.24% based on the completed solar projects. With the active projects, when the capacity of a wind project increases by 1%, the odd of waiting for at least two years rises by 0.69%, but the odd of waiting for more than four years does not change significantly. For active solar projects, the odd rises by 0.4% and 0.726% respectively.

In columns (3) to (6), the coefficient of state LCV score is mostly significantly positive. If a wind project is located in a congressional district whose representative's LCV is 10 points higher, the odd of waiting for more than two years increase by 2.11, and that of waiting for more than four years rise by 1.52. The estimation result is similar for solar projects but insignificant when the odd of more than four years is used. If a solar project is located in a district where the LCV score is 10 points higher, the odd of more than two years in interconnection queue increases by 1.31.

One potential explanation for this is that there are more green projects in Blue states, and the interconnection process is slowed down by the quantity of applications. In our sample, there are 2773 active or completed projects in Blue districts and 2114 in Red districts. When the sample is limited to projects applying after 2015, this difference shrinks significantly. The number is 2155 and 1939 respectively in Blue and Red districts. The proportions are similar when broken down

by wind and solar projects. Because the number of green projects seeking interconnection is not significantly higher in Blue districts, the longer queue time could not entirely be attributed to quantity differences. By including application year fixed effects, we rule out the possibility that projects in Blue districts wait for longer because they apply earlier, when the interconnection process was still under experimentation and featured longer waiting time (see columns 1 and 2). The results thus suggest that the longer interconnection time in Blue districts may arise from other local attributes such as the stringency of land use regulations. Red districts have an advantage in producing green power because it is easier and less costly for distributed renewable generators to acquire land there.

We corroborate our results with a set of alternative specifications in Table 2. In columns (1) and (4), we estimate the specifications in Table 1 using the county-level votes for Republican in the 2020 presidential election instead of the state LCV score. Research in urban and real estate economics has documented that liberal cities build less housing than Republican areas (Kahn 2011). Berkeley, California is a famous example of a beautiful area that makes it very difficult to build new housing and local residents even sue the University of California at Berkeley to block new housing construction for students.

Our empirical results build on the hypothesis that local land use regulations are less stringent in Republican areas. We include census division fixed effects rather than region fixed effects. The significantly negative coefficients in columns (1) and (3) show that wind projects are approved faster if located in counties with more Republican votes. In column (4), we find some evidence that solar projects in Democratic districts are more likely to be approved within four years. This contrast can be explained by Blue counties' relatively strict regulations on wind turbines (e.g. the height and sound level requirements).[18] Solar installation faces more flexible regulations because solar panels take up less land (e.g. could be installed on rooftop) and make little noise.

In columns (5) and (6), we test whether Republicans are faster in approving gas projects as well. The gas projects in this dataset only include the distributed generators owned by individual businesses, not the utility-scale gas plants projects. Based on the completed gas projects, the 25th percentile permit time is 477 days (1.31 years), and the median is 995 days (2.73 years). Overall,

[18] https://windexchange.energy.gov/small-community-wind-handbook#zoning

gas projects are approved faster than green projects. We create two dummies using 1.5 years and 3 years as the cutoff point and run the same specifications as in columns (1) to (4). When the 1.5 years dummy is used, we find that Republican counties are faster in approving gas projects, but the magnitude of coefficient is smaller than that in columns (1) and (3). In column (6), we find no evidence that gas projects in Republican counties are more likely to be approved in three years. These results suggest that green projects, especially land-intensive wind farms, have a larger comparative advantage than non-green projects to be launched in Republican counties. The explanation hinges upon the lower land prices and looser zoning laws in these counties.

Republican Areas Have a Cost Advantages in Generating Green Power

We document that Republican areas feature lower barrier of entry for renewable generators. In this section, we explore other components from equation (5). Using our panel dataset, we test whether Republican areas have lower land prices and population density. We also compare the green market potential in Republican versus Democratic areas. We estimate the following specification for county i in state k (in year t if applicable):

$$Y_{it} = \beta_0 + \beta_1 Votes\ for\ Republican + \delta_k + \gamma_t + \varepsilon_{it}. \qquad (10)$$

In equation (10), Y is the variable of interest. It is cross-sectional when it refers to home prices or population density. In this regression, we use home prices in 2010 and population density in 2000. Y is a county/year variable when it refers to state RPS or RPS potential in neighboring states. We include state fixed effects (δ_k) and/or year fixed effects (γ_t). Standard errors are clustered by state in cross-sectional regressions and by county in the panel regressions. The estimation results are reported in Table 3.

We find that Republican areas feature lower land prices, a lower population density, and a lower state level RPS, but they have higher RPS market potential from neighboring states. When votes for Republican increase by 1%, home prices drop by 0.9% and population density by 5.4%. Rural areas with low land prices are more likely to vote for Republican candidates. Due to Republicans' opposition to environmental regulations, 10% more votes for Republican is associated with 1%. This represents a sizable reduction given that the county average RPS was 5.9% in 2021. Although the within-state demand for green power is low, Republican counties

feature higher green market potential based on their neighboring states. Column (4) shows that a 1% increase in votes for Republican leads to a 0.13% increase in outside state RPS potential. Rural Red regions such as Nevada have high green market potential because they are close to liberal cities with high RPS. In these areas, "d" (distance to consumers) and "c_L" (land price) are low (see equation (5b)). These projects in Red states also face shorter interconnection time and lower risk of land lawsuits (see s_i in equation (5b)). Our mechanism in Section II thus predicts most renewable capacity will be built in these rural Republican areas.

The Geographic Distribution of the Existing Green Power Capacity

In 2010, there were 38783 MW of wind capacity and 582.4 MW of solar capacity in the US (including both utility-scale and distributed capacity). These numbers have jumped to 133408 MW and 61683 MW respectively in 2021. We study the regional heterogeneity in wind and solar capacity deployment and test the predictions from our mechanism proposed in Section II.

Figure 1 shows the geographic distribution of wind and solar capacity built since 2010. Texas and Mid-western states have built in many wind farms. As of 2021, Texas have almost 35,000 MW of wind capacity, and the Midwest has over 52,000 MW. They jointly account for roughly two-thirds of the wind capacity in the US. Notably, most wind capacity are added to conservative congressional districts with low LCV score. These districts also often feature low land prices and loose land use regulations, which make them ideal for developers to construct wind farms. In contrast, liberal districts have built in less wind capacity. Despite an ambitious RPS, California only has 6200 MW of wind capacity by 2021, one-sixth of the capacity in Texas. This suggests that high land prices and strict zoning laws impede green developers from entering the market, given that wind turbines are land intensive.

The deployment of solar capacity exhibits a slightly different pattern. Solar farms are disproportionally located along the coastline. California has built in 16000 MW of solar capacity, roughly one-fourth of the national total. Texas, North Carolina, Nevada, Georgia, and Florida also rank high in solar capacity. These states all feature high daily solar radiation. Not all these top solar generator states have low land prices, implying that land price may be less of concern for solar developers. Solar farms occupy less space than wind facilities, and distributed solar panels

can be installed on the rooftop and connected to the grid for generation. The coastal liberal states face lower costs in building solar capacity than wind capacity to meet their ambitious RPS goals.

We study the geographic variations presented in Figure 1 using a ZINB model. We examine the roles of political stance, RPS, market potential, land price, and environmental attributes in determining the extensive and intensive margin of renewable generation adoption. The ZINB model enables us to deal with the overdispersion and the excess zeros[19] in our county/year data on renewable capacity. A logistic distribution is used to model the counties that haven't installed any renewable capacity, and a negative binomial distribution is used to model the amount of existing green capacity. We estimate the ZINB regressions for each county i in year t using data from 2011, 2016, and 2021. The binary logistic model is given as:

$$P(Y_{it} = 0 \mid X'_{it}) = \frac{\exp(\gamma' X'_i)}{1+\exp(\gamma' X'_i)}, \tag{11}$$

where Y can refer to wind or solar capacity, and X is a vector of covariates used to model the excess zeros, including RPS, RPS market potential, and environmental attributes such as wind/solar potential. γ' is a vector of parameters that we will estimate. The negative binomial model is given as:

$$q(Y_{it} = y_{it} \mid \mu_{it}, \theta) = \frac{\Gamma(\theta+y_{it})}{\Gamma(\theta)\Gamma(1+y_{it})}\left(\frac{\mu_{it}}{\theta+\mu_{it}}\right)^{y_{it}}\left(\frac{\theta}{\theta+\mu_{it}}\right)^{\theta}, \tag{12}$$

where Γ is the gamma function, and θ is the dispersion parameter. μ_{it} is the conditional mean defined as:

$$\mu_{it} = \exp(\beta' Z_{it}). \tag{13}$$

In equation (13), Z is a vector of the variables used to model the amount of green capacity. β' are a list of parameters to be estimated. Based on equations (9) to (11), we follow Young et al. (2018) to write down the probability distribution function of the ZINB model:

$$P(Y_{it} = y_{it} \mid P_{it}, \mu_{it}, \theta) = \begin{cases} P_{it} + (1 - P_{it})q(0 \mid \mu_{it}, \theta), & y_{it} = 0 \\ (1 - P_{It})q(y_{it} \mid \mu_{it}, \theta), & y_{it} > 0 \end{cases}. \tag{14}$$

[19] In all years, the coefficient of variation of wind capacity is greater than 4, and that of solar capacity is greater than 6. In 2021, 2643 counties still did not have any wind capacity, and 2224 did not have solar capacity.

In equation (14), P_{it} is the probability estimated from equation (11). In equation (10), we include year fixed effects and census division fixed effects as covariates. The standard errors are clustered by state/year. The estimation results are shown in Table 4. The intensive margin estimations are reported in columns (1) and (3) and the extensive margin estimations in columns (2) and (4).

The significantly negative coefficients in column (2) shows that RPS, green market potential, wind speed, and land area are all significant in determining whether a county participate in building wind capacity. When the state RPS increases by 1%, the odd of being an excess zero decreases by 1.6%. A 1% increase in neighboring states' green market potential causes the odd to decline by 0.32%. This confirms our hypothesis that developers build renewable capacity in Republican states close to liberal green consumers. Developers tend to construct wind farms in counties with higher wind speed so that the turbines can be more efficient. The significantly negative coefficient of land area is consistent with the fact that wind capacity is land intensive.

In column (1), we find that a 1% increase in votes for Republican leads to a 0.77% increase in county wind capacity. In previous sections, we have established that Republican areas have a comparative advantage in adding in renewable capacity due to the pro-business land use policy and low land prices. The result in column (1) follows naturally from these facts. However, we find no evidence that Republican areas are adding in wind capacity at a faster speed. Neither of the interaction terms between Republican votes and the year dummies are significant. As predicted by our mechanism in Section II, the coefficient of land prices is significantly negative. When land prices increase by 1%, 0.13% less wind capacity are built. Also, more capacity is located in rural areas with lower population density. Conditional on population density, developers add more capacity to counties with a larger population and thus higher electricity demand. We document that RPS, green market potential, and climate belief are insignificant in determining the intensive margin of renewable capacity. Developers face a decision of when to build in green capacity. If they do not expect green power demand to increase significantly in the near term (e.g. RPS does not ramp up rapidly), they may postpone their investments because the excess capacity (if they build in today) would incur short-term loss. Republican governors tend to oppose high RPS, and Democratic governors face pressure from middle-class constituents if green power raises the cost of living. These uncertainties could explain the insignificant signs of RPS and RPS potential in the intensive margin equation.

In columns (3) and (4), we run the same regressions for solar capacity. The results are largely similar. In the extensive margin equation, higher RPS, green market potential outside state, and solar radiation significantly reduces the probability of a county being an excess zero. Unlike in column (2), area is insignificant in column (4). This is because solar farms are less land intensive than wind farms and distributed solar panels can be installed on rooftops. Column (3) shows that Democratic areas have built in more solar capacity, but Republican areas are catching up. In 2011, counties with 1% more votes for Republicans featured 3.42% less solar capacity. This number shrunk to 1.13% in 2016 and became insignificantly positive in 2021. In states with higher RPS, there is less solar capacity. A potential explanation is that these green states are large solar power importers given the high cost of producing solar power within the state (e.g. low solar potential or high land prices). We find that counties with more climate believers, a larger population, and lower population density tend to build more solar capacity. These patterns are similar to the deployment of wind capacity.

Quantifying the Opportunity Cost of Green Power Plants

In this section, we apply the conceptual framework from Section III to analyze the opportunity cost of land use from the installed green capacity. Our agricultural productivity data is from Burke and Emerick (2016). Their dataset provides us each county's crop yield per acre for corn, soy, and cotton respectively from 1950 to 2010. We obtain the corn, soy, and cotton price data in 2021 from USDA and calculate the annual revenue/acre for each crop/county/year. We then take the maximum of these numbers for each county as its agricultural profit per acre.[20] The median annual revenue is \$442.8/acre, and the average is \$759/acre.

Figure 2 shows the capacity-weighted average agricultural profit per acre on the land occupied by wind and solar generators. The opportunity cost of solar capacity is overall higher than that of wind capacity. In 2021, the land for solar power generation could produce \$878/acre if used for agriculture, and this number is \$656/acre for land occupied by wind turbines. This could be explained by the locational selection of green generators. Developers build solar panels in sunny areas, which also tend to have high agricultural productivity due to the favorable weather

[20] In our analysis, we drop the counties whose agricultural profit/acre is 0 or greater than \$4000 (95^{th} percentile). There are 2368 counties left.

conditions, while many crops cannot be grown in cold and windy places. Nevertheless, Figure 2 shows that solar plants are increasingly built in places with lower opportunity cost. In contrast, more wind capacity is built in areas with higher opportunist cost.

Our model in Section III shows that the land conversion equilibrium occurs when the marginal benefit of the converted land is the same when used for agriculture or green generation. The environmental benefit from building in renewable capacity hinges upon the amount electricity that would have been produced from dirty energy. It also depends on how many consumers opt in to green electricity and the potential demand reduction induced by the higher price of green power. Liberal consumers are more willing to pay the price premium, indicating larger environmental benefit when the power is shipped to pro-green counties (Kotchen and Moore 2007). For simplicity, we only consider green power plants' retail revenue per acre in this section. We use the following formula to calculate the marginal revenue of wind and solar generation in county i in state k, assuming all electricity produced can be sold at the state electricity price p_k:

$$b_i^G = \frac{g_i * q_i * p_k}{\alpha_L}. \quad (15)$$

The variables have the same definition as in Section II and Section III. g is the amount of power produced by each unit of capacity in county i, and q is the total green capacity. α_L is the land use per unit of capacity. It is 70 acre/MW for wind power plants and 43 acre/MW for solar plants. We obtain the electricity price data from the EIA. We calculate each county's capacity factor using the generation data by generator using data from the EGRID dataset in 2020. We do this separately for wind and solar power. A lot of counties have not built in any green capacity. We interpolate their capacity factor (g) with cross-sectional linear regressions on counties whose capacity factors are known.[21] Based on our predicted values for all counties, the average wind capacity factor is 32%, and the average solar capacity factor is 16.8%.[22]

[21] We estimate the following regression on counties with wind/solar capacity:
$Capacity\ factor_i = \beta_0 + \beta_1 wind\ or\ solar\ potential_i + region\ fixed\ effects + \varepsilon_i.$
In both wind and solar regressions, the potential variable is significantly positive. Green capacity is more productive in counties with higher wind speed and higher radiation.

[22] NREL reports that the average capacity factor of the existing wind and solar power plants is 35% and 20% respectively. These values are slightly higher than our averages due to selection bias. As we have shown, green power plants are more likely to be built in areas with greater wind or solar potential and thus higher capacity factor. https://www.nrel.gov/analysis/tech-cap-factor.html

Our calculation shows that the median annual revenue per acre for wind generation is $4853 and that for solar generation is $3965. Both are approximately ten times higher than the median agricultural revenue per acre and five times higher than the average. In 2021, the marginal revenue of wind power generation is $4933, and that of solar power generation is $6064. These numbers are much higher than the marginal agricultural revenues. Across all counties in our sample, fewer than 10 have a higher marginal agricultural revenue than that from renewable generation. Our model in Section III suggests that it would be socially optimal to convert more farmland into wind and solar farms. However, large-scale wind and solar farms have an expected lifespan of at least twenty years and cannot be easily dismantled. The land's option value thus declines once the wind and solar facilities are installed. For example, it cannot be converted back to farmland amid a food shortage. Such implicit opportunity costs are not accounted by our two-period model.

Could The Prospect of a Green Power Boom Affect Congressional Carbon Politics?

In this section, we explore whether such green investments could translate into congressional support for climate bills. Figure 3 shows the trend of renewable capacity deployment from 2010 to 2021 by congressional districts. Rural Republican districts have the most wind capacity and have been adding in new capacity at the fastest rate. They had 24895 MW of wind capacity in 2010, and this number jumped by nearly four times to 85630 MW in 2021. Rural Democratic districts have built in 30373 MW of wind capacity by 2021, roughly a third of the capacity in Rural Red districts. Consistent with results from Table 4, non-rural districts do not have comparative advantage in building land-intensive wind projects. They have barely added in any wind capacity in the past decade.

Rural regions have also added in more solar capacity than non-rural districts. By 2021, rural Democratic districts had 22169 MW of solar capacity, slightly higher than rural Republican districts with a total of 20672 MW. Figure 3 shows that rural Democratic and rural Republican districts have been adding in solar capacity at similar rate until 2019, when rural Republican areas started to catch up. Unlike installing wind capacity, non-rural districts do not significantly fall behind rural districts in installing solar capacity. The distributed solar generation could explain this as many suburban residents now install solar panels in their houses.

Green subsidies would disproportionately benefit rural Red districts already with renewable capacity. We calculate the average wind/solar potentials and the average land prices of the locations of newly built capacity each year. We find no evidence that new projects are built in places with lower potentials and higher land prices. The evidence of no diminishing return implies that green developers still have land with high renewable potentials and low prices to choose from. On the intensive margin, green subsidies would incentivize developers to add more capacity to the existing sites. These new projects would feature lower cost due to learning-by-doing (Van Benthem, Gillingham, and Sweeney 2008; Qiu and Anadon 2012). On the extensive margin, they would incentivize districts with high renewable potentials to add in green capacity if they have not done so. The subset of districts in the intensive and extensive margins are likely to vote in favor of renewable subsidies.

There are a lot of large open land in the American South and the West. Figure 4 shows the renewable potential and the LCV score of these districts. The size of the circles is proportional to the district's area. All four figures show that Republican districts have larger land areas. In the South, Republican districts tend to have higher wind speed and solar radiation than Democratic districts on average. In the West, there are a few Republican districts with large land area and high renewable potential such as the second district of New Mexico and the 4th district of Arizona.

We further examine the distribution of renewable potentials across districts using our district/congress panel dataset. We create a Republican dummy for each district/congress. In our sample from the 111th to the 117th congress, roughly 51% of district/congress is Republican, and 49% of districts are rural. We estimate the following regression for district i in state k during congress c:

$$Potential_{ic} = \beta_0 + \beta_1 Republican_{ic} + \beta_2 Rural_i + \beta_3 Republican_{ic} \times Rural_i + \delta_k + \gamma_t + \varepsilon_{ic}. \quad (15)$$

In equation (13), potential can refer to wind speed or solar radiation. We include state fixed effects (δ_k) and congress fixed effects (γ_t). Standard errors are clustered by congressional districts. We run the regression both weighted and unweighted by district area.

The results are reported in Table 6. In columns (1) and (3), the interaction term between the Republican dummy and the rural dummy is significantly positive, showing that rural

Republican districts have more wind and solar potentials. Profit-maximizing developers would take advantage of such environmental potentials and the relatively cheap land prices in these regions to build land-intensive renewable generating capacity. This echoes the significantly upward trend of wind and solar capacity in rural Red districts as shown in Figure 3. With a more ambitious green push from the Biden Administration, we expect more renewable capacity would be built in these districts, which may incentivize congressmen from these districts to vote for green subsidies. T-tests on the coefficients show there is no significant difference between wind speed in rural versus non-rural or Red versus Blue districts. However, Republican districts have higher solar potentials on average, significant at the 5% level.

Ranking Republican Districts Based on their Green Potential

As discussed in previous sections, each congressional district's green potential is contingent upon multiple factors such as local weather conditions and land use regulations. In this section, we rank Republican districts based on their propensity score to install new green capacity. We create a dummy variable that equals 1 if the congressional district adds in new utility-scale wind/solar during the given congress. Our propensity score estimator is based on logistic models as proposed by Imbens and Rubin (2015). The formula of the propensity score is given as:

$$e(X') = \frac{\exp\left(h(X')'\gamma\right)}{1+\exp\left(h(X')'\gamma\right)'}, \tag{16}$$

where X' is a vector of predictors, h is a vector of functions that transform the predictors, and γ is a parameter vector. We use a conventional logistic regression and a logistic LASSO regression to calculate the propensity score respectively. We estimate both models on the congressional district/congress panel dataset from the 111th to the 116th congress. In the logistic regression, we include time trend, wind/solar potential, existing wind capacity, land area, land price, RPS, out-of-state RPS potential, climate belief, district DW-NOMINATE score, and division dummies as predictors. In the LASSO regression, we add in more flexible functional forms including the polynomial and interaction terms of these predictors. We use five-fold cross validation to select the shrinkage parameter. We expect that this flexible model is more likely to capture the unobservable factors that affect a district's likelihood to install new renewable capacity.

To examine the validity of the predicted propensity score, we conduct balancing tests by regressing the predicted scores on multiple covariates one-by-one.[23] The results are shown in Table 6. We find that districts with more existing green capacity, lower home prices, lower population density, larger land areas, and more conservative representatives are more likely to add in new renewable capacity. While solar radiation increases the propensity score of building in solar capacity, there is no significant evidence that wind speed raises the propensity score of building wind capacity. We also find no evidence that state RPS and RPS potential increase the propensity score. These results are broadly consistent with the mechanism proposed in Section II and the results from Table 4, where we model the actual deployment of green capacity.

As a second validation test, we predict the propensity score for each district from the 117th congress and compare it to the actual proposed capacity in the past two years. 43 districts have proposed new wind plants during the 117th congress, 32 of them are Republican districts. When we use 0.5 as the cutoff, the conventional logit model predicts 25 Republican districts would build in new wind capacity, and 18 of them have actually proposed it. The LASSO model predicts 33 Republican districts, 23 of which have proposed it. There are 210 districts that have proposed new solar capacity, 130 of them are Republican areas. With a cutoff at 0.5, the conventional logit model identifies 134 Republican districts that would add in solar capacity, 93 of which have actually proposed new solar projects during the 117th congress. These numbers are 150 and 101 respectively when the LASSO model is used.

Two models have similar overall accuracy of about 70% (i.e. true positives/predicted positives), but the LASSO model correctly predicts more districts that intend to build in new renewable capacity (i.e. high sensitivity). The sensitivity of the logit and the LASSO model is about 70% and 75% respectively. These relatively high numbers support that our propensity scores are valid measures of districts' intent to treat. However, because propensity scores are estimated based on past trends, they do not perform well in predicting the extensive margin. All districts without any wind capacity are assigned low propensity scores of adding in new capacity.

[23] The median and mean solar propensity score from the logit model is 0.665 and 0.56 respectively. In the LASSO model, they are 0.584 and 0.555. Because 70% of districts still do not own wind generating capacity, the median and mean wind propensity score are low. Based on the logit model, the 90th percentile wind propensity is 0.346, and the 95th percentile is 0.665. Based on the LASSO model, these numbers are 0.522 and 0.878 respectively.

We rank all Republican districts using propensity based on data from the 117th congress. We take the average of the conventional logit and the LASSO estimate. The top 20 Republican districts with the highest propensity score for wind and solar plants installation are listed in Table 7 respectively. These are the districts at the margin of voting in favor of future climate bills. Most of them already have a sizable capacity of renewable generation. Green subsidies from the Inflation Reduction Act could incentivize them to build more wind and solar facilities. This would create a positive feedback loop so that they demand more green power incentives going forward.

To be written: Discuss the common features of these districts

Avoiding Local Backlash Against Renewable Power Installations

In this section, we will discuss:

(i) The economies of scale in renewable generation. Utility-scale generating facilities versus distributed generators.

(ii) The recent backlash against wind and solar farms in America and Europe and reasons why they occur. Climate justice concerns if the installation of green capacity reduces the quality of life of low-income, rural residents.

(iii) How green subsidies can be used to compensate the vulnerable communities and sway them into supporting climate bills going forward.

Conclusion

To be written

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Table 1

The Correlates of Red Tape Slowing the Rise of Green Power Generation

	(1)	(2)	(3)	(4)	(5)	(6)
	log(Days)		At least 2 years		At least 4 years	
log(Project capacity)	0.186***	0.238***	0.692***	0.400*	0.217	0.726***
	(0.0511)	(0.0491)	(0.117)	(0.229)	(0.210)	(0.114)
Post 2010	-0.273**	-0.202*				
	(0.113)	(0.108)				
State LCV			7.478***	2.694*	4.201**	-0.733
			(2.467)	(1.487)	(2.123)	(1.434)
Constant	6.602***	6.344***	-9.108***	-11.80***	-3.969**	-10.55***
	(0.244)	(0.212)	(2.070)	(1.588)	(1.766)	(1.220)
State FE	Yes	Yes	No	No	No	No
Region FE	No	No	Yes	Yes	Yes	Yes
Application year FE	No	No	Yes	Yes	Yes	Yes
Observations	164	299	500	2,348	571	1,825
Sample	Completed Wind	Completed Solar	Wind	Solar	Wind	Solar

Standard errors are robust and clustered by state.

*** p<0.01, ** p<0.05, * p<0.1

Post-2010 is a dummy that equals one if the project enters the queue after 2010. The Dependent Variable in columns (3-6) is a dummy variable that equals one if the permit has not been approved during the defined time frame.

Table 2

Republican Vote Shares and Green Power Permit Approval "Red Tape"

	(1)	(2)	(3)	(4)	(5)	(6)
	At least 2 years		At least 4 years		At least 1.5 years	At least 3 years
log(Project capacity]	0.598***	0.567***	0.0890	0.673***	0.142**	0.300***
	(0.135)	(0.190)	(0.206)	(0.120)	(0.0671)	(0.0689)
Votes for Republican	-9.450***	0.544	-3.270*	4.198**	-1.096*	-1.111
	(3.023)	(1.624)	(1.967)	(1.646)	(0.583)	(0.775)
Constant	1.189	-7.876***	0.118	-12.88***	-1.725**	-1.296
	(1.762)	(0.888)	(1.855)	(1.502)	(0.715)	(1.028)
Fixed effects	Census Division FE and application year FE					
Observations	547	2,392	635	1,858	609	484
Sample	Wind	Solar	Wind	Solar	Gas	Gas

Standard errors are robust and clustered by state.
*** p<0.01, ** p<0.05, * p<0.1

Votes for Republican is the county-level percent of voters for Trump in the 2020 election.

Table 3

The Attributes of Republican and Non-Republican Counties

	(1) log(Home prices)	(2) log(Population Density)	(3) RPS	(4) log(RPS potential)
Votes for Republican	-0.899***	-5.458***	-0.100***	0.131***
	(0.234)	(0.687)	(0.00836)	(0.0381)
Constant	11.90***	7.537***	0.0826***	1.240***
	(0.153)	(0.445)	(0.00585)	(0.0407)
State FE	Yes	Yes	No	Yes
Year FE	No	No	Yes	Yes
Observations	2,852	3,112	37,356	37,272
R-squared	0.393	0.572	0.092	0.893

Standard errors are robust and clustered by state in columns (1) and (2) and by county in (3) and (4).
*** p<0.01, ** p<0.05, * p<0.1

RPS market potential is calculated using equation (6).

Table 4

The Determinants of a Location's Green Power Capacity Based on Zero Inflated Negative Binomial Regressions

	(1) log(Wind capacity)	(2) Wind=0	(3) log(Solar capacity)	(4) Solar=0
Votes for Republican	0.767***		-3.423***	
	(0.275)		(0.950)	
Votes for Republican x year2016	-0.173		2.290**	
	(0.258)		(0.931)	
Votes for Republican x year2021	-0.229		3.600***	
	(0.260)		(0.950)	
Lagged state RPS	-0.127	-1.691**	-1.212**	-7.887***
	(0.236)	(0.778)	(0.600)	(2.130)
log(Lagged RPS potential outside state)	-0.0317	-0.319**	-0.0752	-0.572**
	(0.0255)	(0.132)	(0.104)	(0.245)
log(Lagged home prices)	-0.131***		-0.173	
	(0.0418)		(0.129)	
Climate belief	0.148		2.588*	
	(0.416)		(1.337)	
log(Population)	0.0656***		0.676***	
	(0.0222)		(0.108)	
log(Population density)	-0.105***		-0.410***	
	(0.0253)		(0.0908)	
Wind speed		-0.236***		
		(0.0598)		
Radiation				-1.524***
				(0.372)
log(Area)		-0.814***		0.0668
		(0.0876)		(0.199)
Constant	1.949***	9.736***	-4.540**	8.210***
	(0.466)	(1.072)	(2.036)	(2.159)
Year FE	Yes	No	Yes	No
Census division FE	Yes	No	Yes	No
Observations	8,463	8,463	8,514	8,514
Sample	County-level data from 2011, 2016, and 2021			

Standard errors are robust and clustered by state/year.

*** p<0.01, ** p<0.05, * p<0.1

Table 5

Wind and Solar Potential Across Congressional Districts

	(1)	(2)	(3)	(4)
	Wind Speed		Solar Radiation	
Republican	-0.0657**	-0.0127	-0.000798	0.000953
	(0.0324)	(0.0555)	(0.00832)	(0.0248)
Rural	-0.146***	-0.0973	-0.00346	-0.0416*
	(0.0478)	(0.0603)	(0.0125)	(0.0241)
Republican x Rural	0.105**	0.122*	0.0313**	0.0411
	(0.0505)	(0.0645)	(0.0142)	(0.0282)
Constant	7.036***	6.815***	4.558***	4.268***
	(0.0328)	(0.0516)	(0.00919)	(0.0234)
Congress FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Weight	No	Area	No	Area
Observations	3,017	3,017	3,031	3,031
R-squared	0.791	0.814	0.938	0.981

Standard errors are robust and clustered by congressional districts.
*** p<0.01, ** p<0.05, * p<0.1

Table 6

Propensity Score Balance Tests

Dependent Variable: log(propensity/(1-propensity))		
	Wind	Solar
log(Existing wind capacity)	0.990*** (0.0105)	
log(Existing solar capacity)		0.800*** (0.0236)
Wind speed	0.0897 (0.111)	
Solar radiation		0.768*** (0.163)
log(Home price)	-1.875*** (0.229)	-0.648*** (0.164)
log(Land area)	0.914*** (0.0601)	0.634*** (0.0434)
log(Population density)	-1.041*** (0.0748)	-0.656*** (0.0530)
State RPS	-1.805* (1.077)	-0.564 (0.738)
log(RPS potential outside state)	0.162 (0.106)	-0.123 (0.0800)
DW-NOMINATE score	1.716*** (0.295)	1.243*** (0.200)

All coefficients are from simple regressions. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 7

Top 20 Republican Districts Featuring the Highest Propensity Score

(a) Wind

State	District code	Wind speed (m/s)	Wind capacity (MW)	Median home price ($)	Land area (mi^2)	Propensity score (Logit)	Propensity score (LASSO)	Average propensity score
IA	4	6.58	6867	143683	22755	0.872	0.983	0.927
KS	1	7.89	4716	140055	52542	0.855	0.991	0.923
ND	0	6.86	4335	215797	68994	0.856	0.981	0.919
TX	19	7.68	10416	121182	25836	0.847	0.988	0.918
TX	13	7.67	7843	124761	38351	0.809	0.987	0.898
SD	0	7.50	2759	223211	75808	0.819	0.975	0.897
OK	3	7.77	8673	114074	34116	0.817	0.972	0.894
NE	3	7.77	2900	145855	67433	0.800	0.982	0.891
TX	11	7.37	4910	168457	27834	0.759	0.967	0.863
MN	1	6.36	2724	203084	11974	0.769	0.942	0.856
MN	7	6.79	1985	180891	33429	0.731	0.954	0.843
KS	4	7.86	1976	116557	14315	0.713	0.946	0.829
CO	4	7.39	4624	252154	38101	0.733	0.921	0.827
IA	1	6.22	2197	172931	12049	0.723	0.926	0.824
TX	23	7.21	3322	167011	58059	0.721	0.896	0.808
WY	0	6.76	3131	319215	97088	0.665	0.948	0.807
KS	2	7.58	1572	129728	14144	0.675	0.917	0.796
MO	6	6.86	1935	141448	18198	0.709	0.878	0.794
NM	2	7.20	1659	173795	71746	0.509	0.936	0.722
IL	18	6.57	2676	133003	10515	0.631	0.807	0.719

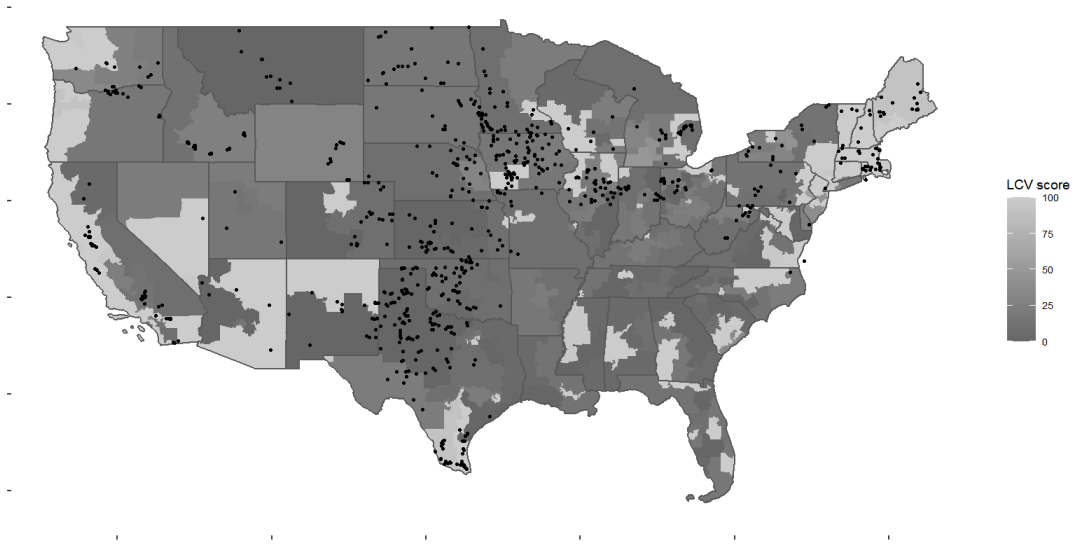
(b) solar

State	District code	GHI (kWh/m^2 /day)	Solar capacity (MW)	Median home price ($)	Land area (mi^2)	Propensity score (Logit)	Propensity score (LASSO)	Average propensity score
NM	2	5.69	444	173795	71746	0.509	0.999	0.998
CA	8	5.80	1421	470899	32893	0.007	0.997	0.998
OR	2	4.47	577	233968	69451	0.486	0.992	0.996
TX	23	5.60	3648	167011	58059	0.721	0.990	0.995
CO	3	4.98	542	389401	49729	0.140	0.987	0.992
CA	23	5.62	3483	418674	9901	0.541	0.980	0.990
AZ	4	5.73	729	319700	33220	0.222	0.974	0.986
IL	15	4.31	317	115589	14696	0.324	0.965	0.980
MD	1	4.30	187	302650	3977	0.001	0.964	0.978

GA	8	4.94	636	131289	8739	0.001	0.956	0.977
CO	4	5.05	270	252154	38101	0.733	0.962	0.977
FL	2	4.99	505	185009	11004	0.001	0.957	0.977
GA	12	4.88	534	137226	8212	0.001	0.951	0.974
VA	5	4.44	476	237716	10031	0.001	0.944	0.971
MN	8	3.77	205	220930	27909	0.071	0.937	0.966
SC	7	4.74	141	174567	5355	0.001	0.941	0.964
GA	1	4.91	159	169388	8127	0.001	0.945	0.962
CA	21	5.57	2721	304645	6730	0.001	0.924	0.962
NC	7	4.67	742	184430	5947	0.001	0.925	0.962
SC	2	4.78	219	169085	3022	0.001	0.928	0.961

Figure 1. Green Generating Capacity Built Since 2010

(a) Wind



(b) Solar

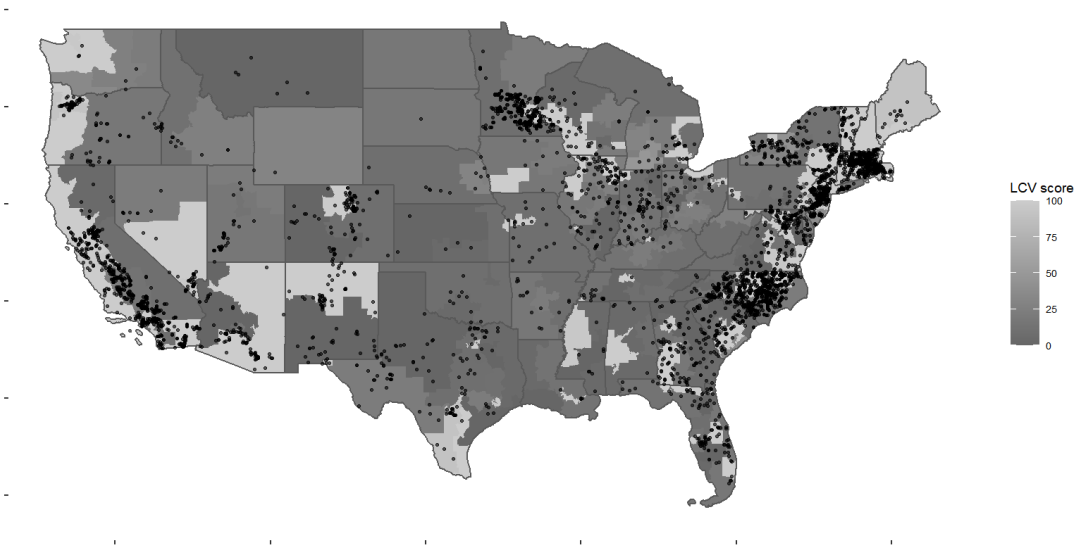


Figure 2. The Opportunity Cost of Building Green Power Plants

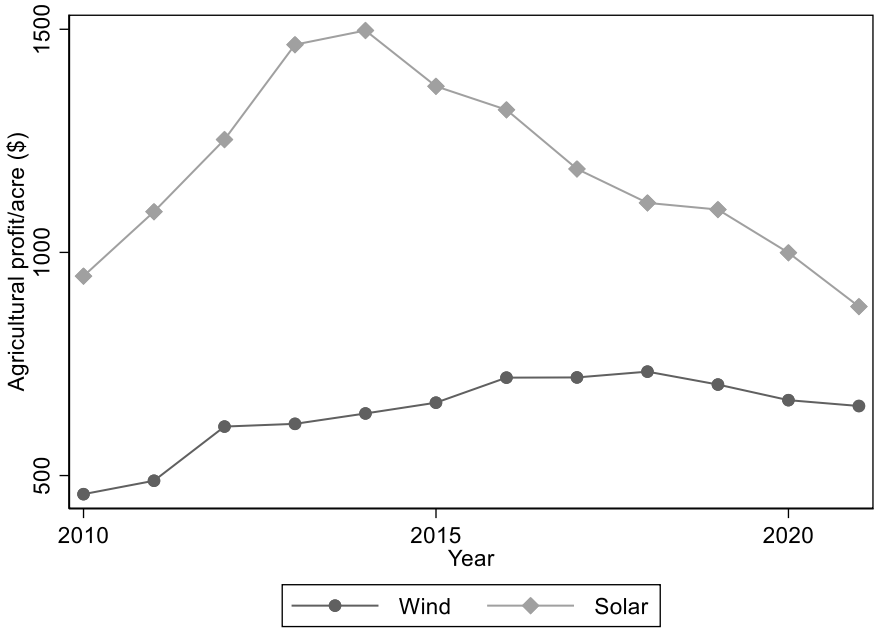
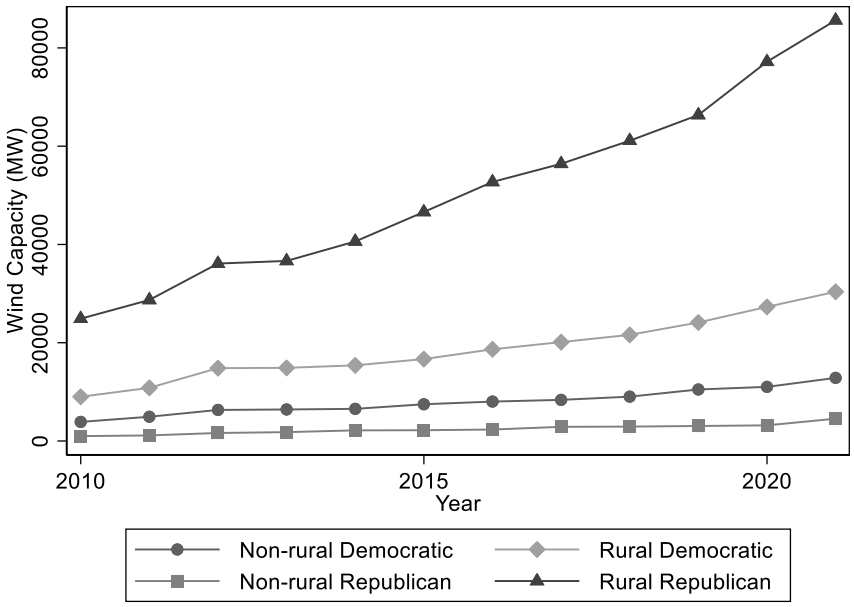


Figure 3. Time Trend of Green Capacity

(a) Wind



(b) Solar

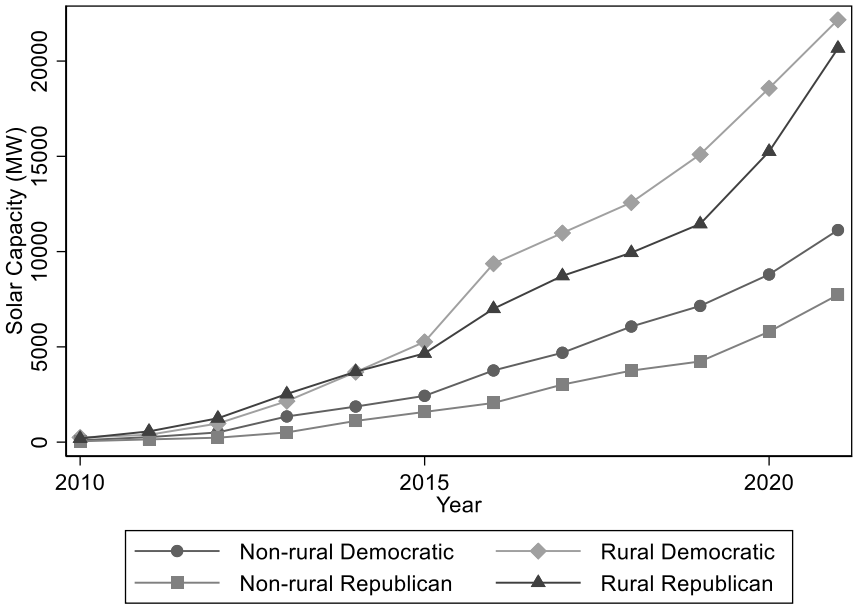
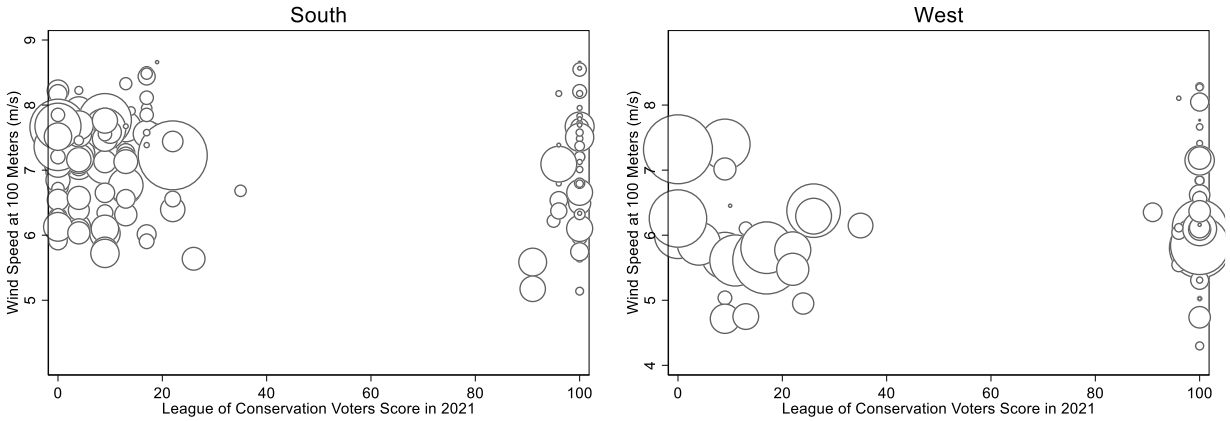


Figure 4. Wind and Solar Potential by Congressional Districts

(a) Wind speed



(b) Solar radiation

