Who Gets Wind? Investigating Economic Attributes of Iowa Counties Prior to Wind Turbine Development

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Abstract

Iowa is a national leader in wind energy, producing nearly two-thirds of its electricity from wind turbines. However, the development of wind energy infrastructure across the state has been uneven—some counties host hundreds of turbines while others have none. This paper investigates whether county-level economic conditions influence the likelihood of wind turbine development. Using panel data from 1990 to 2023 and a two-way fixed effects regression framework, I examine the relationship between wind energy development and three economic indicators: farm income per capita, non-farm income per capita, and unemployment rate. I control for political affiliation, farming success, prior turbine presence, land availability, and demographic variables. Contrary to existing qualitative literature that suggests economic need drives local acceptance of wind projects, my analysis finds that these economic indicators are not statistically significant predictors of turbine development. One exception is political affiliation, which in some regressions indicates that a higher share of Democratic votes is associated with a lower probability of turbine development—contradicting national-level trends linking Democratic support with renewable energy expansion. All models have low between-county explanatory power ($R^2 < 0.05$), suggesting that factors not captured in county-level economic data—such as individual landowner decisions, developer strategies, or transmission infrastructure—may better explain wind energy siting patterns. These findings call for deeper investigation into localized, non-economic factors that shape renewable energy development, particularly as the push toward decarbonization accelerates.

JEL Classification: O13, R11, Q42,

Keywords: Wind Energy, Renewable Development, Agriculture

1. Introduction

In 1983 Governor Terry Branstad made Iowa an unlikely pioneer in climate action by signing the nation's first renewable energy portfolio standard. Iowa's investor-owned utilities (IOUs)–for-profit companies owned by shareholders that provide electricity and gas to consumers as a highly regulated monopoly–were required to purchase 105 megawatts of renewable energy generation capacity (EIA, 2024a). This "stick" was followed by economic carrots, including national wind energy production tax credits authored and won by Iowa Senator Chuck Grassley (Grassley, 2017). Over the decades, a blend of economic incentives and regulatory policies established an environment where renewable energy has thrived with bipartisan support. Iowa now boasts over 6,000 wind turbines, 13,000 megawatts of installed wind capacity, and the nation's highest percentage of electricity generated by wind (Iowa Environmental Council, 2024).

While Iowa has seen significant deployment of wind energy, it is not uniformly distributed across the state. Some counties attract significant wind energy investments while others attract very little. There is also uneven distribution over time, with some areas being developed years before others. This raises questions as to the cause of the geographic and chronological patterns of wind turbine development. **I seek to investigate the economic attributes of counties before wind turbine development in Iowa to better understand why some counties attract heavier wind energy investments than others.** By examining factors such as county GDP and political affiliation I aim to create a comprehensive analysis of the economic attributes that may predict future wind energy development.

According to the Intergovernmental Panel on Climate Change, climate change is occurring at an alarming rate and human activity is its primary cause. Moving towards net zero emissions is crucial for the future stability of our planet, and that requires transitions towards more renewable energy sources (IPCC, 2023). Understanding how and why wind energy development has occurred in Iowa counties over the past three decades will allow developers and residents to prepare for the continuing and increasing wind energy development that is highly probable in the future not just in Iowa but around the world.

2. Background

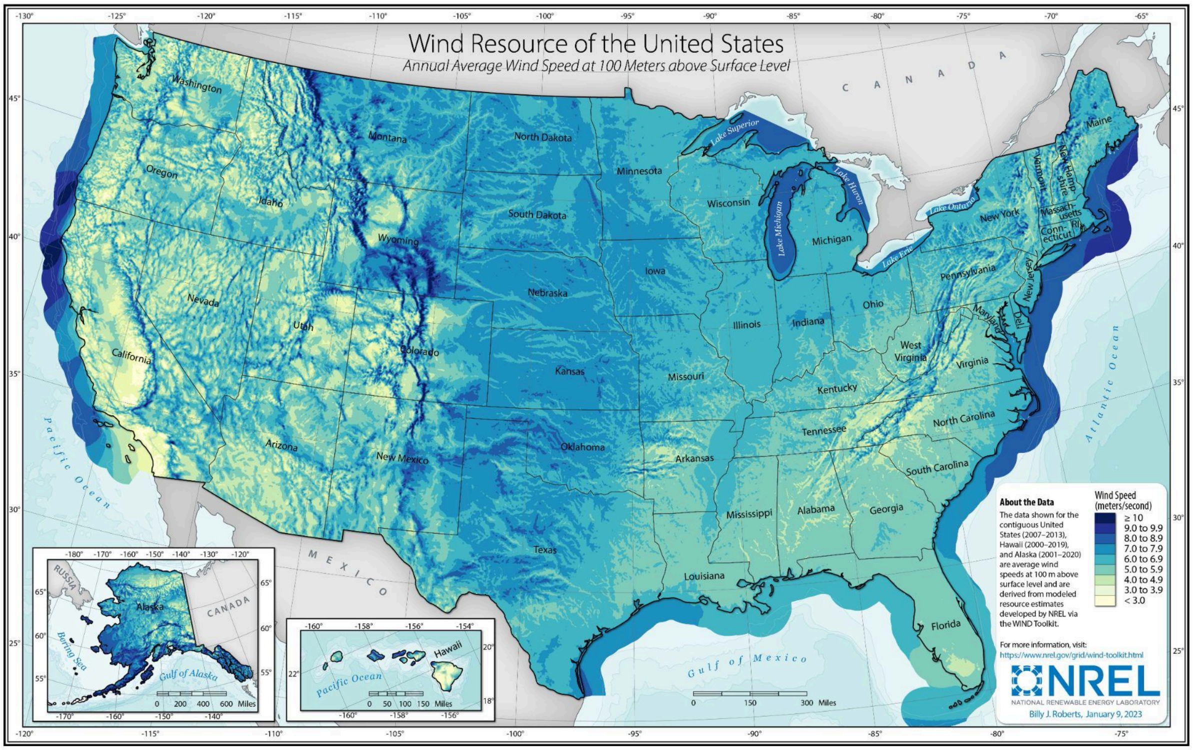
2.1 Wind Development in Iowa

With over 13,000 MW of wind energy capacity, Iowa has the second largest capacity in the United States and produces 64.7% of its electrical generation from wind energy, the largest percentage in the nation (Iowa Environmental Council, 2024). Iowa's leadership in wind energy can be attributed to a variety of geographic, economic, and political factors. Successful and profitable wind farms need the appropriate wind speeds, topography, transmission infrastructure, permitting environment, economic incentives, and political support, among other things (Grassi et al., 2012), and Iowa is fortunate to have a combination of these factors that have encouraged wind energy to thrive.

Annual average wind speeds should be at least 13 mph for utility-scale turbines (EIA, 2024b). Top land wind speeds are concentrated in the central U.S. in a "wind belt" stretching from North Dakota down to Texas; Iowa is on the right edge of this wind belt and has more than enough wind to sustain robust energy generation. Iowa also has an abundance of open, flat agricultural land–absent of protected ecosystems and species–that is eligible for turbine construction. After taking into account federal lands designated as parks or monuments, national conservation areas, wildlife areas, wetlands, airfields, urban districts, land with slopes over 20%, and more, the National Renewable Energy Laboratory (NREL) estimated in 2010 that 78.32% of Iowa's surface is eligible for wind energy development and that Iowa had a potential installed capacity of 570,714.2 MW (Grassi et al., 2012).

Figure 1

U.S. Wind Power Resource at 100-Meter Hub Height, NREL



Note. (Roberts, 2023).

Iowa's leadership in wind energy also stems from its early and proactive policy initiatives. In 1983, the state became the first in the U.S. to adopt a Renewable Portfolio Standard (RPS) which required investor-owned utilities to procure a minimum amount of renewable energy—an unprecedented move at the time (EIA, 2024a). Although modest by today's standards, the RPS provided an early foundation for utility-scale wind development and encouraged investor confidence in the state's renewable energy market. In addition to the RPS, Iowa has implemented various tax incentives and financial supports for wind energy projects. These include a state production tax credit (PTC) of $0.015 per kilowatt-hour of electricity, which supplements the federal PTC and further reduces the cost of wind generation (Good, 2019), and sales and property tax exemptions for wind energy equipment, which significantly lower upfront capital costs for developers (NC Clean Energy Technology Center, 2025). These fiscal policies have helped accelerate the pace of wind turbine installations and expand the reach of wind infrastructure across rural communities.

Critically, political support for wind energy in Iowa has been bipartisan. Iowa politicians from both major parties have embraced wind as a key economic driver. Republican Governor Terry Branstad, who served from 1983–1999 and again from 2011–2017, was an early and consistent proponent of wind energy, signing the RPS, and Republican Senator Chuck Grassley is an influential wind energy supporter on a national scale (Dorrell & Lee, 2020). Democratic leaders in the state legislature have similarly supported renewable initiatives. This bipartisan consensus has been further reinforced by the role of large utility companies, particularly MidAmerican Energy. The company has aligned its business model with state policy goals, pledging significant investments in wind energy and committing to serve all its Iowa customers with 100% renewable electricity usage on an annual basis (MidAmerican Energy Company, 2023). By partnering with state regulators and leveraging available incentives, MidAmerican has effectively become a national case study in the successful integration of public and private efforts in clean energy development. MidAmerican is not the only utility in Iowa to do so; Alliant Energy, the second largest utility, is also heavily invested in wind energy in Iowa with plans for further growth. In January of 2025, the U.S. Department of Energy's Loan Programs Office announced commitments for $3 billion in loan guarantees to Alliant Energy for a portfolio of wind power and battery storage projects in Iowa and Wisconsin (Loan Programs Office, 2025).

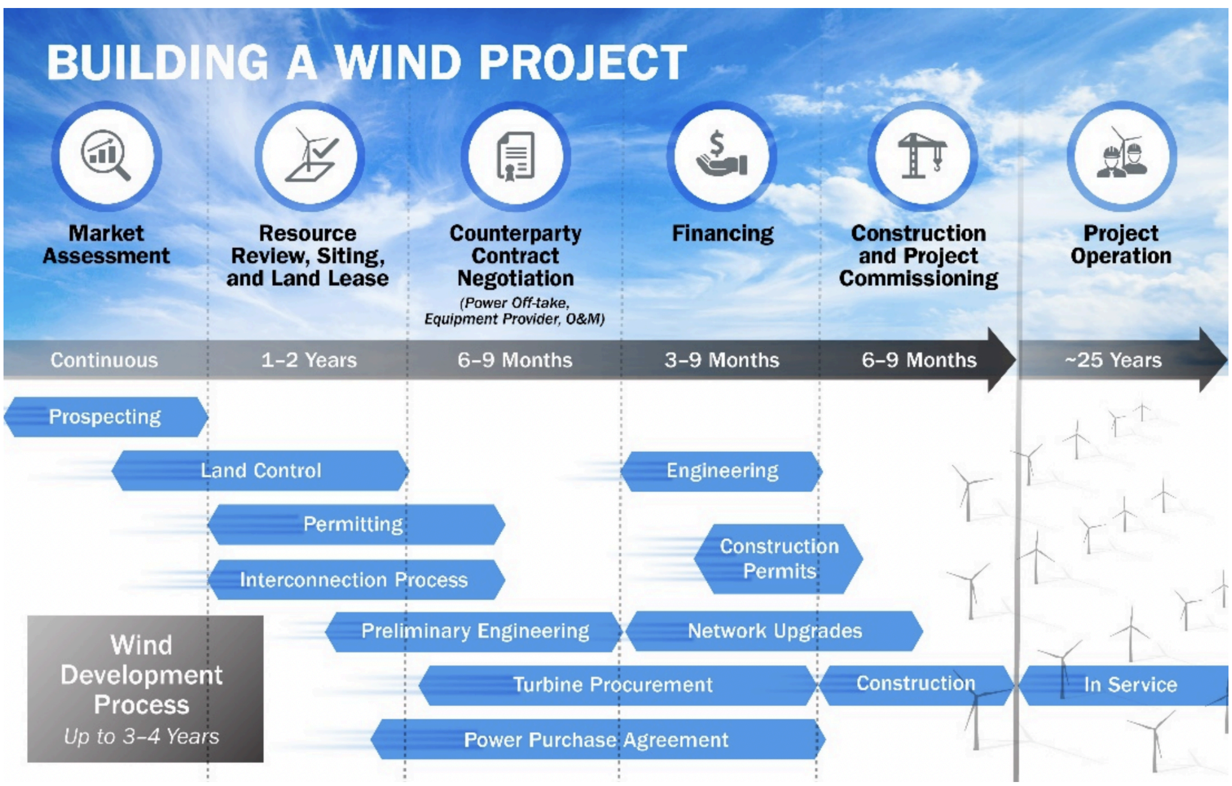
In addition to tax and policy incentives for developers, there are also financial incentives in Iowa for individual landowners and local governments who allow turbines to be built in their communities. Landowners who lease their land for turbines are paid to sign the lease, paid annually while the developer makes turbine location decisions, and then paid annually for any turbines on their land. Statewide, wind turbines generate an estimated $72 million per year in lease payments to Iowa landowners, making wind energy a significant contributor to rural household income (Iowa Environmental Council, 2024). Farmers lose only a couple acres of farmland as they can plant crops or graze livestock right up to the base of the turbine and it's access road, and the lease payment is larger than the potential profit from any other crop that could have been planted in that area. County-level incentives primarily involve Tax Increment Financing (TIF) and Urban Renewal Areas (URAs). TIF is a financial mechanism that allows counties to capture the increase in property tax revenue—known as the "increment"—resulting from the rise in property values due to wind energy development. These funds are then reinvested into infrastructure, community projects, or other public goods without raising taxes (Center for Innovative Finance Support, n.d.). In Iowa, TIF is commonly used within URAs, which are designated districts where economic development is encouraged through public investment. For instance, in Story County, TIF has generated approximately $8.97 million for urban renewal initiatives to improve streets, parks, and community centers, with an equivalent dollar amount allocated to schools and other county services (Delworth, 2023). Similarly, Howard County leveraged TIF funds to finance $21.5 million worth of infrastructure projects to improve roads, bridges, infrastructure maintenance equipment, and parks and conservation (Delworth, 2025). Local governments in Iowa can use the financial gains from wind energy to fund long-term improvements and community reinvestments without additional tax burdens. Wind farms across Iowa generated $57 million in state and local tax revenue and $67 million in landowner lease payments in 2021 alone (Delworth, 2023).

2.2 Wind Energy Development Process

Developing a new wind farm is complicated and lengthy, but understanding the process is important to understanding my research methodology.

Figure 2

Timeline of New Wind Power Plant



Note. (U.S. Department of Energy, 2021).

To start, a developer–either a utility or a private development company–will identify potential sites with optimal wind resources. They employ meteorological data and geospatial analyses to evaluate wind speed, consistency, and overall energy potential. Other key site selection criteria include minimal environmental constraints and proximity to existing transmission infrastructure. A comprehensive environmental review is conducted to assess potential impacts on ecosystems, wildlife, and cultural resources. This process often involves preparing Environmental Impact Statements (EIS) or Environmental Assessments (EA) in compliance with the National Environmental Policy Act (NEPA). Regulatory permits are sought from pertinent federal, state, and local agencies, ensuring adherence to environmental laws and zoning regulations (U.S. Department of Energy, 2021). Integrating the wind farm's output into the electrical grid requires detailed interconnection studies to evaluate the capacity of existing transmission lines and identify necessary upgrades. Developers collaborate with grid operators to design interconnection facilities that maintain grid stability and reliability (Energy Transitions Commission, 2023).

Once possible sites are identified, developers negotiate lease agreements with landowners. Terms often include annual payments based on the MW nameplate capacity (the maximum MW that a turbine can generate at a given time), reimbursement for crop damage during construction, and reimbursement for crop yield decreases in the following years. Concurrent with land acquisition, engaging with local communities is essential to address concerns, disseminate project information, and foster public support. Transparent communication strategies can mitigate opposition and facilitate smoother project implementation (U.S. Department of Energy, 2022).

Wind energy projects demand substantial capital investment. Developers typically secure financing through a combination of equity, debt, and tax incentives. Establishing Power Purchase Agreements (PPAs) – long term contracts between power suppliers and customers – with utilities or corporate buyers ensures a stable revenue stream, thereby enhancing the project's financial viability (U.S. Department of Energy, 2022). The construction phase encompasses site preparation, foundation laying, turbine assembly, and electrical infrastructure installation. Adherence to environmental mitigation measures during construction is critical to minimize ecological disturbances. Post-construction, the commissioning phase involves rigorous testing of turbines and electrical systems to verify performance and safety standards. The date a turbine is "commissioned" is the date it is connected to the wider power grid and begins generating electricity. At the end of the project's life cycle, decommissioning entails dismantling turbines, restoring the site to its original condition, and responsibly disposing of materials. Alternatively, repowering involves upgrading existing turbines with advanced technology to boost efficiency and extend operational life (U.S. Department of Energy, 2021).

3. Literature Review

3.1 Economic Impacts of Wind Development

Current literature investigating the economics of wind energy focuses on the economic impacts of wind development and concludes that new wind projects bring economic benefits both during construction and for the lifespan of the project after commissioning. Many studies utilize the NREL's Jobs and Economic Development Impacts (JEDI) Wind Energy Model to examine direct, indirect, and induced impacts of the development, construction, and operation and maintenance phases on jobs, earnings, and economic output. Direct impacts result from expenditures by the wind industry, indirect impacts result from supporting industries like construction or manufacturing, and induced impacts result from spending and reinvestment by beneficiaries of the direct and indirect impacts. The JEDI Wind model inputs include basic project information (year, size, turbine specifications, costs, etc.) and allows the user to modify the allocation of costs between different industries and the allocation of expenditures within an industry that go to local businesses and contractors (Slattery et al., 2011). A 2016 study utilized the JEDI Wind model to investigate Illinois's 23 largest wind farms and concluded that the projects are forecasted to bring lifetime economic benefits totalling \$5.98 billion (Loomis et al., 2016). The researchers determined that the projects' construction period created the equivalent of 19,047 full-time jobs with a payroll of over \$1.1 billion and are also sustaining approximately 814 permanent jobs in rural Illinois–a total annual payroll of \$48 million after construction completion (2016). A similar report from the NREL utilized the JEDI Wind model and found that wind development in Nebraska contributes to local and state tax bases, creates temporary and permanent jobs, and strengthens Nebraska's position as an energy exporter (Lantz, 2008). The report investigated future wind farms and found that the potential development and construction of 7,800 MW of wind energy in Nebraska would create the equivalent of between 20,600 and 36,500 full-time jobs and result in \$140 million to \$260 million annually between 2011 and 2030. The subsequent operation of the wind generation fleet would support 2,000 to 4,000 full-time jobs and result in \$250 million to \$442 million annually.

A study by Michael Slattery, Eric Lantz, and Becky Johnson utilized the JEDI Wind model to perform a more granular case study of two wind farms in west Texas (2011). The first, Capricorn Ridge Wind Farm, is a 407-turbine, 662.5 MW facility completed in 2008, and the second, Hollow Wind Energy Center, is a 421-turbine, 735.5 MW facility completed in 2006. The four year construction period created 1900 full-time equivalent jobs for Hollow Horse and 2200 full-time equivalent jobs for Capricorn Ridge. 58% of those full-time equivalent jobs were accounted for by supply chain impacts and 900 employed local workers within 100 miles of either site. These jobs generated \$160 million in economic output and \$57 million in earnings for Texas. Between the two farms, the operation and maintenance phase supports 350 annual jobs, 225 of which are local and 63 of which are permanent including 33 permanent onsite at Hollow Horse and 30 at Capricorn Ridge. The permanent positions generate about $3.6 million in earnings annually, and the total economic activity for Texas from the two farms, assuming 20-year turbine lifespans, is over $1.8 billion ($1.3 million per MW of installed capacity). Hollow Horse and Capricorn Ridge will bring almost $730 million of economic activity to their local communities over the four-year construction and 20-year operation periods (Slattery et al., 2011).

Local economic impacts of wind energy development can be studied using methods other than the NREL's JEDI Wind model. Eric J. Brunner and David J. Schwegman investigated county-level impacts utilizing turbine-level location data from the United States Wind Turbine Database (USWTDB) maintained by the U.S. Geological Survey and county-level economic data from the Bureau of Economic Analysis, the U.S. Census Bureau, and the Federal Housing Finance Agency Housing Price Index (2022). Their variables of interest were county-level GDP per-capita, income per-capita, median household income, median home values, total employment, and the share of employment by industry. They related these economic variables to annual installed MW capacity per capita in each county using difference-in-differences models and separated the treatment effects of those variables into two periods, the construction phase and the operation phase. The construction phase has direct and indirect impacts on the local county. Direct effects come from developers hiring local construction companies or using locally sourced non-turbine construction materials such as sand, concrete, or asphalt for construction of foundations and roads. Indirect effects come from out-of-town workers entering communities and spending wages on local goods and services like hotels and restaurants, increasing local income and employment (Brunner & Schwegman, 2022; Loomis et al., 2016). After construction, developers pay annual fees to landowners who leased their land for a turbine, further increasing income, and taxes on the new turbines, increasing the county's tax base. Brunner and Schwegman concluded that, through these mechanisms, new wind energy development leads to "exogenous and economically meaningful increases in county-level GDP per-capita, income per-capita, median household income and median home values" (2022). They further found that the increases in county GDP and income began during construction and accelerated during operation. Contrary to the state-level findings of Loomis and Lantz, Brunner and Schwegman found little impact on total employment but noted that employment shifted from farm employment towards nonfarm employment (2022).

The local economics of wind energy development are the basis for my research question, but the current literature studies the relationship between local economies and wind farms opposite to my approach. Rather than investigating how development impacts the economy, I am investigating how economic attributes may predict development. However, the presence of clear economic benefits suggests the possibility of the relationship I am investigating. Perhaps counties that are struggling economically are more receptive to wind energy development, on either the level of an individual landowner or the county government, and therefore may be targeted by developers or seek out development themselves.

3.2 Local Attributes Impact Turbine Development

The current literature establishes that location attributes do impact wind farm development. A study by Christiane Bohn and Christopher Lant used linear regressions to examine the impact of population (a surrogate for energy demand), wind energy potential (estimated energy the wind could provide in an area), accessibility of transmission infrastructure, wind energy price, utility structure, green power preferences, renewable power standards, and siting processes on state-level installed wind generation capacity (2009). Their regression results revealed that installed capacity was impacted primarily by population and political siting processes. After conducting five case studies on wind projects that faced local opposition in various states, Bohn and Lant further concluded that siting procedures were significantly impacted by local involvement with and opposition to wind farm development, and that turbine development increased when local involvement or local opposition decreased (Bohn & Lant, 2009). Bohn and Lant's finding of the significance of local opposition suggests that the impact of local attributes on wind development is worth studying.

Kate Mulvaney, Patrick Woodson, and Linda Stalker Prokopy investigated local opposition to and acceptance of wind energy projects through a qualitative study of three counties in rural Indiana, one with a wind farm and two with proposed wind farms (2013). They used a mixed methods approach that included interviews, mailed surveys, and reviews of newspaper articles and reports to study both local acceptance of projects within that community and acceptance of wind energy more generally. Mulvaney et al. reported a high level of support for wind energy across all three counties and found that the support was driven by wind energy's local economic benefits. One resident of Benton County that was interviewed stated, "We are a pretty poor county, I mean all we have is agriculture. Because we don't really have any business, it has pumped a lot of money into our economy" (Mulvaney et al., 2013). Additionally, 75% of the Benton County survey respondents with turbines on their land stated that they accepted the development at least in part due to financial compensation. A similar qualitative study of four Texas counties and eight Iowa counties, all either with wind farms or adjacent to counties with wind farms, was conducted by Michael Slattery and colleagues (2012). They developed a survey questionnaire aimed to link physical and environmental characteristics to positive or negative wind energy attitudes by determining the respondents overall opinion on and knowledge of wind energy, construction and operations processes, socio-economic impacts of development, and environmental issues. The surveys revealed both strong support for wind energy development and that the support was primarily due to the local perception of increased employment and economic activity. Slattery et al. concluded that support for wind energy is strongly associated with socioeconomic factors rather than morals or aesthetics (2012).

These results suggest that perhaps struggling counties may be more likely to support and thus experience wind turbine development, which is the foundation for my research question. However, the quantitative nature of Slattery et al. and Mulvaney et al.'s research means that it is possible respondents were misattributing their support for or opposition to turbine development either unconsciously or intentionally. Combined with the small sample sizes of the studies, this leaves their results anecdotal. This paper will use empirical evidence to investigate the suggested relationship between a county's economic status and the likelihood of wind energy development.

4. Theoretical Framework

My data, which will be detailed in the next section of this paper, is panel data with values per county per year. This is the same format as Brunner and Schwegman (2022). Bruner and Schwegman utilize a difference-in-differences model to examine the impact of wind energy development on county-level economic attributes, and I will be following in their footsteps but reversing the relationship direction. I will utilize a two-way fixed effects regression to create a difference-in-differences model with the primary dependent variable being a binary representing whether or not new turbines were commissioned in a given county (*i*) at time (*t*). The model will examine the differences between counties and between years. The binary dependent variable allows me to interpret my regression results to understand how the likelihood of wind development within a county changes as economic attributes change.

The independent variable within my regression equation will be county-level measures of economic attributes. The development of a new wind farm is dependent on individual landowners' decision to lease their land to a developer. As established by the existing literature, the decision to lease land for wind development is largely an economic decision (Mulvaney et al. 2013; Slattery et al., 2012). In Iowa, most landowners are farmers, and the yearly payments from developers to landowners offer a level of economic certainty whereas yearly farm revenues are subject to exogenous variables like commodity pricing and weather. Wind farms also come with significantly increased property tax revenues for the county (Delworth, 2023), which may influence a local government's likelihood of allowing the permitting of new turbines or possibly an individual's acceptance of a new turbine on their property. Hypothetically, if a county is suffering economically, its residents may be more likely to accept or allow new turbine installation due to the economic benefits to individuals and county tax bases.

My first control variable will represent year-to-year county-level political affiliation. In Iowa, as in the rest of the U.S., wind energy is becoming an increasingly partisan issue. A study by John Dorrell and Keunjae Lee of state-level political ideology and wind energy development found that U.S. states led by Democratic Governors are more likely to support renewable energy initiatives, while states led by Republican Governors are more likely to prioritize traditional energy sources (2020). While the study focused on state-level beliefs, it suggests that local political beliefs could play a role in development. For example, the siting and permitting process is carried out by each county's Board of Supervisors and is subject to the political beliefs of those supervisors and their constituents, and thus the overall political affiliation of a county may impact whether wind development occurs.

My second control variable will represent farming success. The success of farming operations in a given county in a given year will affect the overall economic prosperity of a county, but may or may not have a different effect on turbine development from farming's overall contribution to county-level economic attributes. Again, in Iowa, wind turbines are placed on agricultural land (because it is flat and abundant), and therefore wind farm development depends on farmers' decisions. A farming community struggling with production (due to drought, for example) may be more inclined to accept turbines as a form of income diversification. Whether measures of farming success impact turbine development and whether they are correlated with county-level economic attributes are questions I will endeavor to answer through regression analysis.

My third control variable is the pre-existence of turbines in a county prior to the new turbine installation. The existence of wind turbines in a county may impact the community's acceptance of new turbines: perhaps they see the turbines, dislike them, and are resistant to future development. Perhaps they grow accustomed to the turbines, recognize their economic benefits, and are receptive to future development.

My fourth control variable is the amount of land available for turbine development. While land is usually a constant variable that can be controlled for with fixed effects, the amount of available land for new turbine construction decreases as new wind turbines are constructed. Wind turbines require a certain amount of space to operate and once you put in one turbine on an area of land, you cannot place another turbine in its vicinity. Therefore, available land is no longer constant. I will also be controlling for demographic factors, including average race, gender, ethnicity, and age of the county as measured by the U.S. Census Bureau.

I will be using county fixed effects to control for geographic differences between counties, including in average wind speeds, land grade (how level the terrain is), proximity to transmission infrastructure. I will also be using time fixed effects to control for differences between years that are constant across all counties, such as state-wide policy changes to renewable energy incentives in Iowa. Having both county and year fixed effects is what creates the difference-in-differences model structure. I considered nonlinear models for my analysis, such as a probit model used to predict a binary outcome, a logit model used to give the probability of an event occurring, or an Andersen-Gill or Prentice-Williams-Peterson model used to analyze recurrent event data. However, using fixed effects with nonlinear models causes the incidental parameters problem, leading to biased estimates of the main parameters. Due to this, I opted to utilize a linear regression model like Brunner and Schwegman (2022).

The independent and control variables will be lagged because the process of developing a wind farm takes multiple years. Within the turbine data, which will be detailed in the next section, there is only the year the turbine was commissioned (the year the turbine became operational) and no indicator of when development began. According to "Land-Based Wind Energy Siting: A Foundational and Technical Resource" by the U.S. Department of Energy, site development typically takes about three to four years. However, the process is not always completed with each step in quick succession. Some farms may be in the midst of development just months after landowners sign leases while other farms are developed years after lease signing. I am going to start my regressions with a five year lag of the independent and control variables, hopefully capturing average development time and obtaining a more accurate sense of the conditions the county residents and developers were facing when making the decisions to install the turbines. Because my other data begins in the year 1990, this five year lag will mean that one turbine commissioned in Dickinson County in 1992, one turbine commissioned in Story County in 1993, and one turbine commissioned in Story County in 1994 will not be included in my regression analysis. Given that these three turbines are instances of the development of one standalone turbine rather than large commercial projects, this is a required compromise to obtain the correct lag.

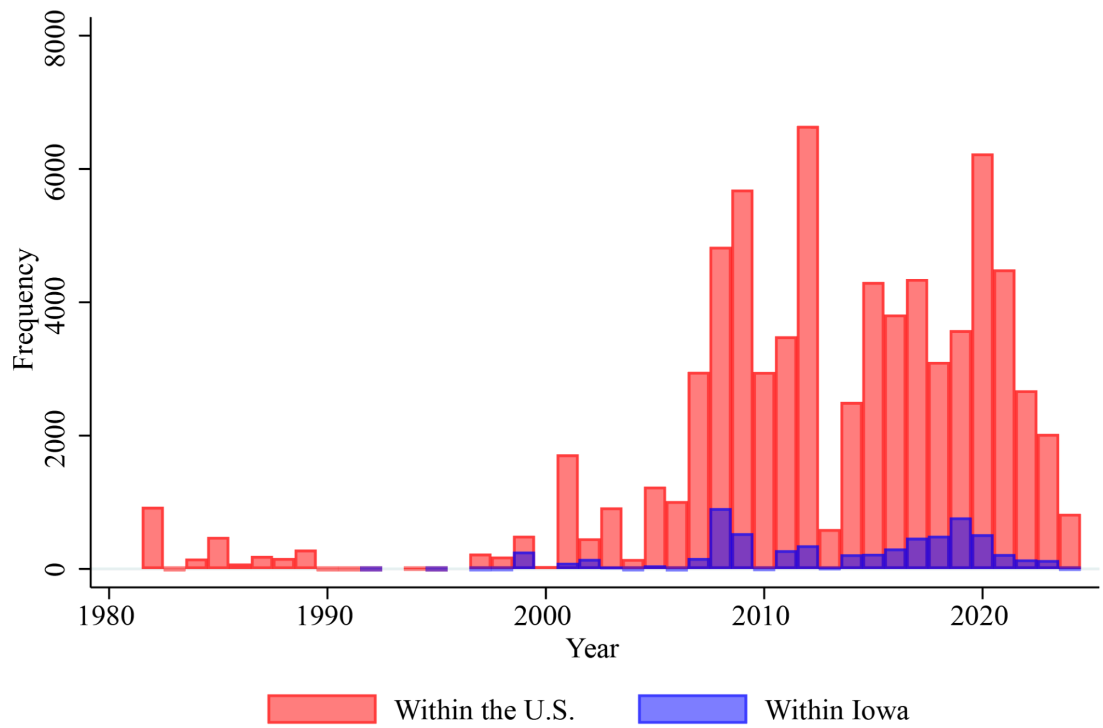
5. Data

5.1 Wind Turbine Data

Following the footsteps of Brunner and Schwegman (2022), I utilize the United States Wind Turbine Database (USWTDB), which contains location and technical specification information on all utility-scale wind turbines currently in operation within the U.S., both on and offshore (Hoen et al., 2018b). The USWTDB combines public and private information from the Lawrence Berkeley National Laboratory (LBNL), the Federal Aviation Administration (FAA), the U.S. Geological Survey (USGS), the American Clean Power Association (ACP), and online resources. Analysts verify turbine location with visual analysis of high-resolution aerial imagery. Residential-scale wind turbines—turbines shorter than 30 meters or rated at a less than 65-kilowatt nameplate capacity—are excluded from the USWTDB. The database is actively maintained by the LBNL, USGS, and ACP, and the version utilized in this paper is volume 7.2, last updated on November 20, 2024, containing 74,695 observations (individual turbines) and 28 variables. According to the USWTDB, there are 6,421 utility-scale turbines currently located in Iowa. For an image of the USWTDB map of Iowa, see appendix A.

Figure 3

Number of Wind Turbine Commissions Per Year: United States vs. Iowa



Relevant to this paper were the following variables: FIPS code of the turbine's county and the name and commissioning year (year brought online) of the project associated with the turbine. Of the 6,421 utility-scale turbines in Iowa, 63 are not associated with a commissioning year in the USWTDB. 60 of those turbines are located in Tama County and are part of a project that has not been built; I dropped those observations from my data.[1] One turbine was located in

[1] Visual confirmation of these turbines' absence can be conducted by searching "Unknown Tama County Project" on the USWTDB Viewer. There are 66 turbines classified as part of this project. 6 have commissioning dates and their presence can be visually confirmed. The absence of the other 60 without commissioning dates can also be visually confirmed. This discrepancy is likely because a large wind farm has been in development in Tama County for many years but has been embroiled in legal battles, meaning that while turbines have been proposed they have not been built (McAllister, 2025). These turbines being listed before construction is a unique discrepancy in the USWTDB data.

Buena Vista County, IA, and after visual examination of aerial imagery provided by the USWTDB viewer I determined this turbine was part of the Storm Lake II wind farm commissioned in 1999[2]; I set this turbine's commissioning year to 1999. One turbine was located in Chickasaw County, IA, and after visual examination of aerial imagery I determined this turbine was a duplicate[3]; I dropped it from my data. The final turbine was located in Sac County, IA, and after visual examination of aerial imagery I determined it was part of the Richland Wind Farm commissioned in 2020[4]; I set this turbine's commissioning year to 2020. The resulting dataset contained 6,360 individual utility-scale turbines.

The USWTDB only contains information on turbines currently in operation, but turbines that were built, operated, and subsequently decommissioned (taken out of operation and torn down) are also important to my analysis. For this, I turned to a separate dataset, Decommissioned turbine data (Hoen et al., 2018a), maintained by the same entities as the USWTDB. The version utilized in this paper is volume 7.2, last updated on November 20, 2024, containing 11,616 observations (individual turbines) and 22 variables. While this dataset contains the latitude and longitude of each decommissioned turbine, it does not contain the state or county. Ryan Denniston, Ph.D., from the Duke University Center for Data and Visualization Studies ran a spatial join adding the Decommissioned turbine data dataset to a dataset containing GIS data on U.S. counties and returned to me a dataset containing 11,616 observations and 28 variables. Each turbine was identified with a state FIPS code and a county FIPS code. The variables relevant to this paper were county FIPS code, project name, project commissioning year, and turbine decommissioning year (year taken offline).

[2] This turbine's ID is 3085854. Visual analysis can be conducted by searching the ID on the USWTDB Viewer.
[3] This turbine's ID is 3131500, and it is a duplicate of turbine 3131987. Visual analysis can be conducted by searching the IDs on the USWTDB Viewer.
[4] This turbine's ID is 3108637. Visual analysis can be conducted by searching the ID on the USWTDB Viewer.

There were 62 turbines decommissioned in Iowa. Three were not associated with a commissioning year in the dataset. The first was located in Cerro Gordo County, IA, and after visual examination of aerial imagery I determined this turbine was part of the Cerro Gordo/Hawkeye Power/Clear Lake wind farm commissioned in 1999[5]; I set this turbine's commissioning year to 1999. The second was located in Clay County near the Upland Prairie wind farm, however the turbine was decommissioned in 2018 and Upland Prairie was commissioned in 2019, meaning the data suggests that there was a single turbine constructed and removed prior to Upland Prairie's commissioning. I could not find sources verifying the instance of a singular turbine in Clay County prior to 2019 and I dropped this observation. The third was located in Scott County, but there are no other records of any turbines in Scott County, and so I dropped this observation as well. There was one turbine in this dataset without a decommissioning year, but it was part of the Cerro Gordo/Hawkeye Power/Clear Lake wind farm. The Cerro Gordo/Hawkeye Power/Clear Lake wind farm was decommissioned in 2020, and therefore I assigned the turbine 2020 as its decommissioning year. After these transformations, the dataset included 60 observations (60 decommissioned turbines).

I then collapsed the commissioned and decommissioned turbine data into one dataset that counted the number of new commissioned and decommissioned turbines in each county per year, counted the number of projects in each county per year, and calculated a cumulative total of the number of turbines in each county. I also created a binary variable indicating whether any new turbines had been commissioned in each county in any given year.

The first wind turbine was installed in Iowa in 1992. Therefore, all of my data spans from 1990 (in order to assess economic conditions before construction of the initial turbine) to

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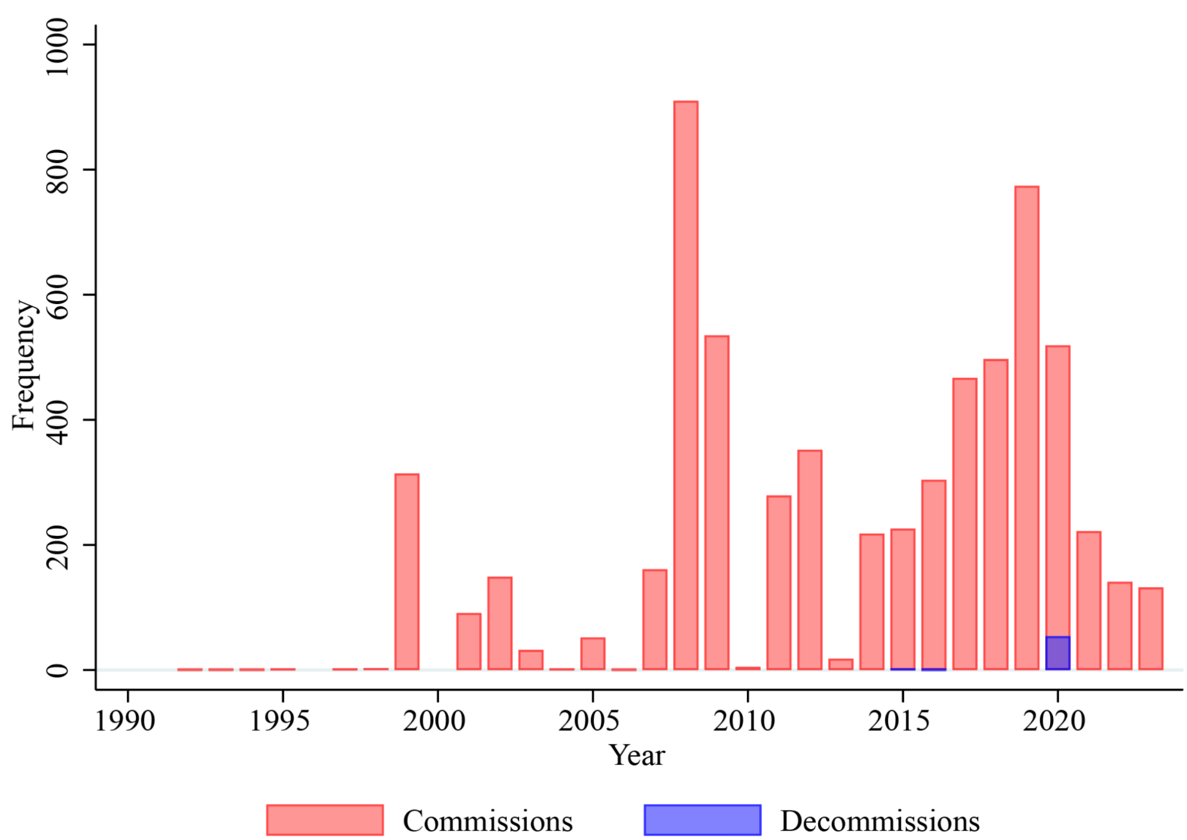
[5] This wind farm can be found by searching "Cerro Gordo/Hawkeye Power/Clear Lake" on the USWTDB Viewer.

2023. I will be lagging all of my variables by five years, meaning that the three turbines commissioned in 1992, 1993, and 1994 will be excluded from regression analysis. This is because my demographic data is only available starting in the year 1990, which represents a limitation to my dataset. I have similarly chosen to exclude 2024 because many data from 2024, such as demographics, have not yet been made public and thus cannot be incorporated into my analysis. Nine turbines were commissioned and three were decommissioned in Iowa in 2024, and those developments are excluded from my analysis. From 1990 to 2023, 6,411 turbines were commissioned in Iowa. 57 of those turbines were decommissioned during that same time period, leaving 6,354 still in operation as of the end of 2023.

Figure 4

Wind Turbine Commissions vs. Decommissions Per Year in Iowa, 1990–2023



Of the 99 counties in Iowa, 58 have utility-scale wind turbines. At the end of 2023, those 58 counties had an average of 109.6 turbines each. Adair County, IA has the most turbines with 528 and Winneshiek County, Buchanan County, Henry County, and Linn County have the least with 1 turbine each. For a full list of the number of turbines in each of the 58 counties in 2023, see appendix B.

5.2 Economic Attributes Data

I sourced indicators of county-level economic performance from both the Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA). The BLS's Local Area Unemployment Statistics is a joint state-federal effort preparing monthly estimates of employment and unemployment for a variety of areas; I pulled yearly unemployment data for the 99 counties in Iowa from 1990 to 2023 (Bureau of Labor Statistics, 2025). For yearly measures of personal income,[6] farm income,[7] and non-farm personal income[8] from 1990 to 2023, I utilized the BEA's "CAINC4 Personal income and employment by major component by county" dataset (2025). This data was only available in current dollars not adjusted for inflation. I used the BLS's Consumer Price Index to calculate the measures of income in real terms in 2017 dollars (2025). Then, using annual population data also contained in the BEA's

[6] Personal income "consists of the income that persons receive in return for their provision of labor, land, and capital used in current production as well as other income, such as personal current transfer receipts. In the state and local personal income accounts the personal income of an area represents the income received by or on behalf of the persons residing in that area. It is calculated as the sum of wages and salaries, supplements to wages and salaries, proprietors' income with inventory valuation (IVA) and capital consumption adjustments (CCAdj), rental income of persons with capital consumption adjustment (CCAdj), personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance plus the adjustment for residence" (U.S. Bureau of Economic Analysis, 2025).

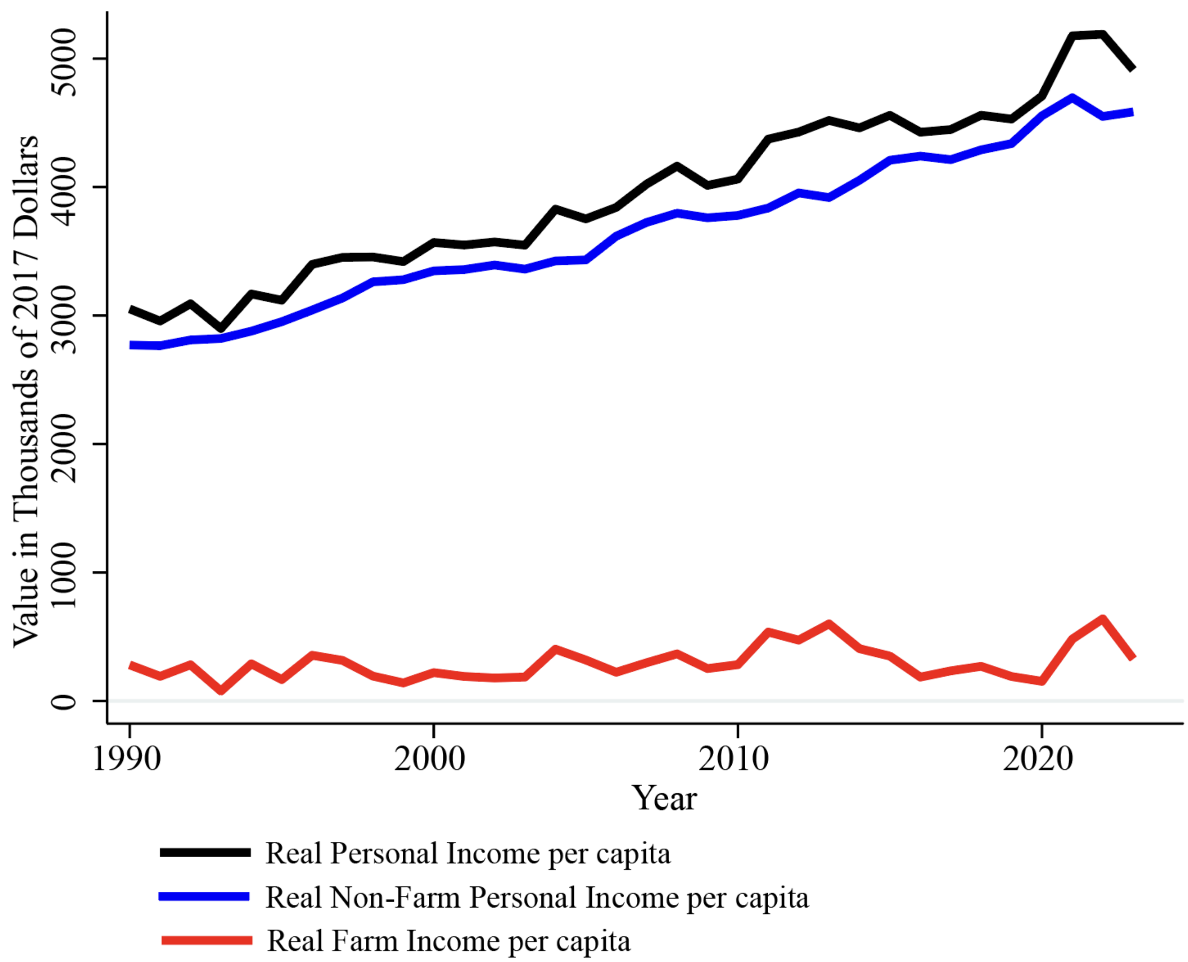
[7] Farm income "consists of wages and salaries, employer contributions for employee pension and insurance funds, and proprietors' income in the farm industry (NAICS subsectors 111-Crop Production and 112-Animal Production). Farm personal income comprises the net personal income of sole proprietors, partners, and hired laborers arising directly from the current production of agricultural commodities, both livestock and crops. It excludes corporate farm income" (U.S. Bureau of Economic Analysis, 2025).

[8] Personal income minus farm income (U.S. Bureau of Economic Analysis, 2025).

“CAINC4 Personal income and employment by major component by county” dataset I created per capita measures for my income variables[9].

Figure 5

Average County-Level Personal Income per capita, Farm Income per capita, and Non-Farm Income per capita, 1990-2023



5.3 Political Affiliation Data

To calculate political affiliation, I utilized data from a paper on nationalism and partisanship in American elections published in Electoral Studies (Algara & Amlani, 2021a).

[9] I considered using county-level GDP as an economic attribute, but the BEA’s data on county-level GDP only goes back to 2001. Using GDP would exclude data from the years 1990 through 2000, and therefore I decided to only use income measures.

The data was published for replication purposes by Harvard Dataverse (Algara & Amlani, 2021b) and includes county-level voting data on presidential, gubernatorial, and senatorial elections from 1872 to 2020. I separated the senatorial elections data by the senate seat class[10], and then for all four types of election in each election year (presidential, gubernatorial, senatorial class II and senatorial class III), I pulled the total number of raw votes, the number of raw Democrat votes, and the number of raw Republican votes and calculated the percent Democrat and percent Republican. For every non-election year, I assigned the values of the most recent election at the same level.

Table 1

Correlation Between % Democrat in all Four Election Types

	1	2	3	4
1 % Democrat Votes in Presidential Election	1			
2 % Democrat Votes in Gubernatorial Election	0.684	1		
3 % Democrat Votes in Senate Class II Election	0.797	0.652	1	
4 % Democrat Votes in Senate Class III Election	0.608	0.502	0.407	1

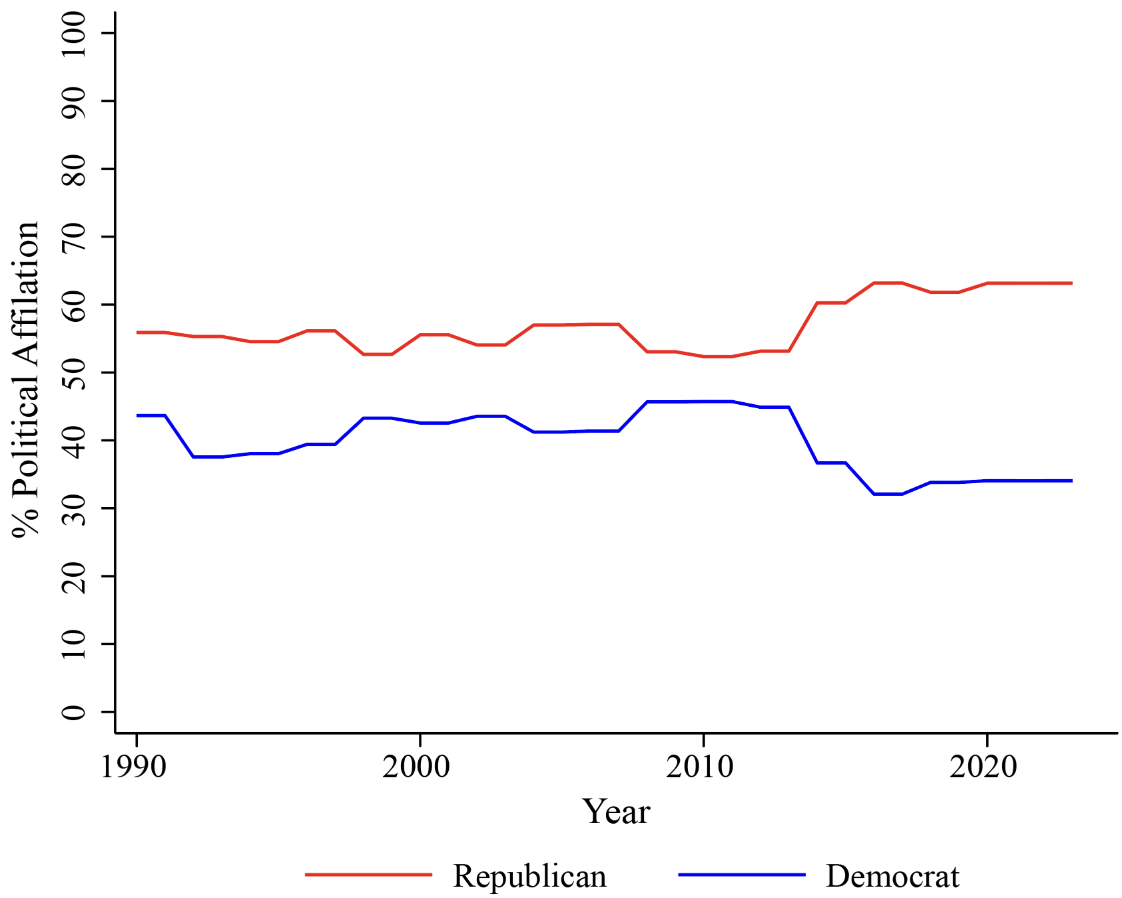
Given the high correlation coefficients between the four election variables, I regressed the four variables with the count of new turbines and tested the variance inflation factor (VIF). Percent Democrat in presidential elections had a VIF of 3.93, percent Democrat in gubernatorial elections had a VIF of 3.04, percent Democrat in senatorial class II elections had a VIF of 2.08, percent Democrat in senatorial class II elections had a VIF of 1.69, and the mean VIF was 2.69. Despite the VIFs being below 5, I was still concerned with

[10] Seat class (I, II, or III) determines the seat's election year. Iowa has two senate seats, one class II and one class III.

multicollinearity and clarity in my potential findings, and so I opted to index the four variables together. I averaged the percentage of Democrat votes in the four types of elections for every year, weighing them by the total number of votes in each respective election. The resulting variable, political affiliation, represents a county's affiliation with the Democratic Party in a given year.

Figure 6

Average County-Level Political Affiliation, 1990-2023



Note. % Republican was calculated in the same manner as % Democrat and displayed here for context, but it is not used in my regressions.

5.4 Farming Success & Available Land Data

I gathered data from the Census of Agriculture taken every five years by the United States Department of Agriculture (USDA)'s National Agricultural Statistics Service (NASS). The Census of Agriculture counts both urban and rural plots of land that have raised and sold (or would ordinarily have raised and sold) over $1,000 worth of products (USDA, 2025). I pulled county-level data tables titled "Farms, Land in Farms, Value of Land and Buildings, and Land Use" for Iowa for years 1987[11], 1992, 1997, 2002, 2007, and 2012 from the Census of Agriculture Historical Archive (NASS, 1987; NASS, 1992; NASS, 1997; NASS, 2002; NASS, 2007; NASS, 2012) and for years 2017 and 2022 directly from the NASS (NASS, 2022). The data was in the form of a PDF that I was unable to scrape, and so instead I manually recorded data on the number of acres, number of farms, acres of farmland, acres of cropland, and acres of cropland harvested for each county in each census year. "Farmland" encompasses all land used for agricultural activities like crop production or livestock rearing and includes cropland, pastureland, woodland, farmsteads, livestock buildings, and more. To quantify farm success for my regression, I chose to focus on cropland (land in crop rotation). I calculated each county's cropland yield for every census year by dividing cropland harvested by total cropland and used it as a proxy for farm success. For every non-census year, I assigned the values of the most recent census. This measure does not take into account success of livestock operations, however provides some context for the success of farming in a given county.

Additionally, I used the data from the Census of Agriculture to calculate the land available for turbine development in each county in a given year. In Iowa, turbines are primarily placed on agricultural land. Therefore, I used the total acres of farmland from the Census of Agriculture as a proxy for the total land available for turbine development. To take

[11] For the year 1987, the table is titled Farms, Land in Farms, and Land Use: 1987 and 1982.

into consideration land already occupied by a turbine, I used the Iowa Environmental Council's recommended turbine setback of 1,250 feet (Iowa Environmental Council, 2018) as a radius to calculate the approximate area a wind turbine takes up. Then, I multiplied that area by the number of turbines in a given county in a given year. Dividing the area occupied by turbines by the total farmland gives me the percentage of farmland occupied by turbines, and subtracting the area occupied by turbines from the total farmland gives me the total farmland remaining for potential turbine development.

For both of these variables, I kept only observations from 1990 to 2023.

5.5 Demographic Data

I gathered county-level demographic data for 1990 through 2023 from the Center for Disease Control (CDC) WONDER online database (U.S. DHHS et al., 2021; U.S. DHHS et al., 2025). For each county, I pulled yearly July 1st estimates of population, white population, Hispanic population, female population, and population aged 65 and older (retirement age). I chose to only pull the white population–and therefore only have the ability to calculate the non white population–because Iowa is 89.6% white (U.S. Census Bureau, 2025). All racial minority groups are in the vast minority, and therefore there is little insight to be gleaned from further breaking down racial minority percentages. From the data, I calculated percent white, percent Hispanic, percent female, and percent aged 65 and older for my regressions.

5.6 Summary Statistics

Table 2

Dependent Variables

Variable	Definition	Source
New Turbines	Binary indicating whether new turbines were commissioned in county i in year t	USWTDB
Total New Turbines	Number of new turbines commissioned in county i in year t	USWTDB

Table 3

Independent Variables

Variable	Definition	Source
Unemployment Rate	The percentage of people in county i's labor force who are unemployed during time t but actively seeking work	BLS
Personal Income Per Capita	Per capita measure of all income that persons receive in return for their provision of labor, land, capital used in current production and more in county i during time t; in 2017 dollars	BEA
Farm Income Per Capita	Per capita measure of all wages, salaries, proprietors income, and more resulting from farming in county i during time t; in 2017 dollars	BEA
Non-Farm Income Per Capita	Per capita measure personal income minus farm income; in 2017 dollars	BEA

Table 4

Control Variables

Variable	Definition	Source
Political Affiliation	Measure of how affiliated county i is with the Democratic Party in time t; calculated as a weighted average of Democratic vote-share from presidential, gubernatorial, and senatorial elections	Harvard Dataverse
Cropland Yield	Ratio of cropland harvested over total cropland in county i during time t	NASS
Prior Turbines	Binary indicating whether county i had turbines prior to time t	USWTDB
Available Land	Acres of farmland in county i that are available for turbine development at time t	NASS, NREL
Population	Total population in county i at time t	Census Bureau
% White	Percentage of total population that is white in county i at time t	Census Bureau
% Hispanic	Percentage of total population that is Hispanic in county i at time t	Census Bureau
% Female	Percentage of total population that female in county i at time t	Census Bureau
% Retirement-Aged	Percentage of total population that is 65 or older in county i at time t	Census Bureau

Table 5

Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
New Turbines	3,366	0.0502	0.2184	0	1
Unemployment Rate	3,366	4.0291	1.3104	1.6	10.2
Personal Income Per Capita	3,366	39.8796	8.0905	22.23401	89.2199
Farm Income Per Capita	3,366	2.9915	2.8848	-1.1242	21.8048
Non-Farm Income Per Capita	3,366	36.8880	7.4221	21.7945	82.5712

Political Affiliation	3,366	0.3986	0.0841	0.1033	0.6713
Cropland Yield	3,366	0.8709	0.1063	0.4889	1.2042
Prior Turbines	3,366	0.2540	0.4354	0	1
Available Land	3,366	314998.6	137395.9	52699.6	3244394
Population	3,366	30379.49	51332.8	3544	505255
% White	3,366	0.9723	0.0311	0.7941	0.9996
% Hispanic	3,366	0.0318	0.0419	0.0004	0.3104
% Female	3,366	0.5052	0.0101	0.4514	0.5295
% Retirement-Age	3,366	0.1870	0.0331	0.0740	0.2889

6. Empirical Methodology

The following section specifies the methodology for my two-way fixed effects regression models using variables detailed in section 4 and the data detailed in section 5.

6.1 Regressions with New Turbines

My first regression equation investigates the relationship between New Turbines (whether or not new turbines are commissioned in county *i* in year *t*) and Farm Income, Non-Farm Income, and Unemployment Rate while controlling for Political Affiliation, Crop Yield, Prior Turbines, Available Land, the five demographic variables, county fixed effects, and year fixed effects. This regression will provide insight into whether the economic attributes of a county impact the presence of wind farm commissioning in a given year, no matter how big that wind farm is.

$$NewTurbines_{i,t} = \beta_0 + \beta_1 FarmIncome_{i,t\text{-}5} + \beta_2 NonFarmIncome_{i,t\text{-}5} + \beta_3 UnemploymentRate_{i,t\text{-}5} + \beta_4 PoliticalAffiliation_{i,t\text{-}5} + \beta_5 CroplandYield_{i,t\text{-}5} + \beta_6 PriorTurbines_{i,t\text{-}5} + \beta_7 AvailableLand_{i,t\text{-}5} + \beta_8 Population_{i,t\text{-}5} + \beta_9 PercentWhite_{i,t\text{-}5} + \beta_{10} PercentHispanic_{i,t\text{-}5} + \beta_{11} PercentFemale_{i,t\text{-}5} + \beta_{12} PercentRetirementAge_{i,t\text{-}5} + \gamma_{i,t\text{-}5} + \delta_{i,t\text{-}5} + \epsilon_{i,t\text{-}5} \tag{1}$$

γ represents county fixed effects, δ represents year fixed effects, and ϵ is the error term. All of the variables are weighted by the amount of available farmland in each county in 1987 to correct for unequal representation caused by differing county sizes or urban centers. I have chosen to include both Farm Income and Non-Farm Income because the decision to lease land for turbines is primarily made by farmers, and so the economic well being of farmers and nonfarmers may have different effects on turbine development. I will run this same regression for each independent variable individually in order to check for multicollinearity and ensure that the presence of all three economic attribute variables does not reduce their significance or the model's predictive power. I will also run this regression with and without the Cropland Yield control to check that Cropland Yield is not interfering with the statistical significance or magnitude of Farm Income.

Examining the timeline of turbine development in Iowa as displayed in Figure 3 (located in section 5.1), the first large commercial wind projects were commissioned in 1999. Three counties in Iowa received wind turbines in 1999: Cherokee County received 27 turbines, Cerro Gordo County received 55 turbines, and Buena Vista County received 230 turbines. Prior to 1999, only twelve turbines were installed across the state in seven counties. Perhaps because there had not been a successful commercial wind energy project in Iowa, people were not yet aware of the potential economic benefits until 1999. In order to investigate this, I decided to run the same regression again but restrict commissioning years to 2004 through 2023, starting five years after 1999 (the size of my lag). This way, only projects whose development began after the 1999 construction and completion of 312 turbines would be included in the data. As with the regression run for all years, this regression will be weighted by the amount of available farmland in each county in 1987, run with all three independent variables together and then with each one independently, and run with and without Cropland Yield.

6.2 Regressions with Total New Turbines

My second regression equation investigates the relationship between Total New Turbines (the number of new turbines commissioned in county *i* in year *t*) and Farm Income, Non-Farm Income, and Unemployment Rate while controlling for Political Affiliation, Crop Yield, Prior Turbines, Available Land, the five demographic variables, county fixed effects, and year fixed effects. This regression will provide insight into whether the economic attributes of a county impact the number of individual turbines commissioned in a given year.

$$TotalNewTurbines_{i,t} = \beta_0 + \beta_1 FarmIncome_{i,t\text{-}5} + \beta_2 NonFarmIncome_{i,t\text{-}5} + \beta_3 UnemploymentRate_{i,t\text{-}5} + \beta_4 PoliticalAffiliation_{i,t\text{-}5} + \beta_5 CroplandYield_{i,t\text{-}5} + \beta_6 PriorTurbines_{i,t\text{-}5} + \beta_7 AvailableLand_{i,t\text{-}5} + \beta_8 Population_{i,t\text{-}5} + \beta_9 PercentWhite_{i,t\text{-}5} + \beta_{10} PercentHispanic_{i,t\text{-}5} + \beta_{11} PercentFemale_{i,t\text{-}5} + \beta_{12} PercentRetirementAge_{i,t\text{-}5} + \gamma_{i,t\text{-}5} + \delta_{i,t\text{-}5} + \epsilon_{i,t\text{-}5} \tag{2}$$

As with my first regression equation, γ represents county fixed effects, δ represents year fixed effects, and ϵ is the error term. All of the variables are weighted by the amount of available farmland in each county in 1987 to correct for unequal representation caused by differing county sizes or urban centers. I will run this regression with all three independent variables together, with each independent variable individually, and with and without Cropland Yield. Then, I will repeat that process restricting commissioning years from 2004 to 2023.

7. Results

7.1 Regressions with New Turbines

Table 6

Regression Results: New Turbines, Farm Income Per Capita, Non-Farm Income Per Capita, and Unemployment Rate, 5 Year Lag, All Years, Weighted for Available Farmland in 1987

Variable	Coefficient	Robust Standard Error	T-Value	P-Value	95% CI Lower	95% CI Upper
Farm Income Per Capita	-0.002	0.004	-0.48	0.632	-0.010	0.006
Non-Farm Income Per Capita	0.002	0.004	0.44	0.659	-0.006	0.009

Unemployment Rate	-0.006	0.007	-0.81	0.423	-0.020	0.008
Political Affiliation	-0.210	0.156	-1.35	0.181	-0.518	0.099
Cropland Yield	0.134	0.094	1.42	0.159	-0.053	0.321
Prior Turbines	-0.039	0.024	-1.61	0.11	-0.087	0.009
Available Land	0.000	0.000	1.38	0.171	0.000	0.000
Population	0.000	0.000	0.38	0.704	0.000	0.000
% White	0.829	0.657	1.26	0.21	-0.475	2.132
% Hispanic	0.033	0.331	0.1	0.922	-0.625	0.690
% Female	0.304	1.393	0.22	0.827	-2.459	3.068
% Retirement Age	-0.747	0.689	-1.08	0.281	-2.114	0.620
Year (Base Year = 1995)						
1996	-0.028	0.024	-1.17	0.246	-0.076	0.020
1997	-0.046	0.028	-1.65	0.101	-0.101	0.009
1998	-0.039	0.022	-1.76	0.082	-0.084	0.005
1999	0.001	0.040	0.01	0.989	-0.078	0.079
2000	-0.059	0.032	-1.84	0.068	-0.123	0.005
2001	-0.032	0.030	-1.06	0.29	-0.093	0.028
2002	-0.039	0.036	-1.09	0.277	-0.111	0.032
2003	-0.024	0.043	-0.57	0.57	-0.109	0.061
2004	-0.043	0.044	-0.98	0.329	-0.130	0.044
2005	-0.006	0.051	-0.12	0.907	-0.108	0.096
2006	-0.045	0.044	-1.03	0.304	-0.132	0.042
2007	0.018	0.052	0.34	0.732	-0.086	0.122
2008	0.108	0.057	1.87	0.064	f	0.222
2009	0.051	0.044	1.16	0.25	-0.037	0.139
2010	-0.018	0.051	-0.35	0.729	-0.119	0.083
2011	0.078	0.062	1.25	0.213	-0.045	0.201
2012	0.128	0.073	1.76	0.081	-0.016	0.272
2013	-0.010	0.061	-0.17	0.867	-0.131	0.110
2014	0.010	0.062	0.16	0.873	-0.113	0.132
2015	0.032	0.068	0.48	0.633	-0.102	0.167
2016	0.025	0.060	0.42	0.674	-0.094	0.144
2017	0.179	0.080	2.22	0.028	0.019	0.338
2018	0.051	0.075	0.69	0.494	-0.097	0.200
2019	0.035	0.084	0.42	0.676	-0.131	0.202
2020	0.072	0.082	0.88	0.381	-0.090	0.234
2021	0.015	0.086	0.17	0.862	-0.156	0.187
2022	-0.001	0.088	-0.01	0.992	-0.176	0.175
2023	-0.006	0.091	-0.07	0.945	-0.188	0.175
Constant	-0.859	0.812	-1.06	0.292	-2.470	0.751
R^2 (Between)	0.0441					

The results of my first fixed-effects regression model analyzing new wind turbine development reveal low between-county explanatory power ($R^2 = 0.0441$). Additionally, none of my independent variables or control variables were statistically significant. I thought perhaps that I was encountering a collinearity problem with my three independent variables, Farm Income, Non-Farm Income, and Unemployment Rate. However, after running the same regression three times for each of the independent variables individually, only one variable was ever statistically significant. Prior Turbines, a control variable, was just barely statistically significant with a p-value of 0.096 when Non-Farm Income was the only independent variable. The coefficient of Prior Turbines in this regression was -0.0409, indicating a small negative relationship between the presence of turbines five years before year *t* and the commissioning of new turbines in year *t*; having prior turbines leads to a 4.09% decrease in likelihood of turbine commissioning five years later. I also thought perhaps my control variable Cropland Yield could be too correlated with Farm Income, but removing it resulted only in a change to Prior Turbines. Prior Turbines became barely statistically significant with a p-value of 0.097 and a coefficient of -0.04008.

Table 7

Regression Results: New Turbines, Farm Income Per Capita, Non-Farm Income Per Capita, and Unemployment Rate, 5 Year Lag, 2004-2023, Weighted for Available Farmland in 1987

Variable	**Coefficient**	**Robust Standard Error**	**T-Value**	**P-Value**	**95% CI Lower**	**95% CI Upper**
Farm Income Per Capita	-0.003	0.005	-0.620	0.535	-0.012	0.006
Non-Farm Income Per Capita	0.002	0.005	0.410	0.680	-0.008	0.012
Unemployment Rate	-0.014	0.009	-1.570	0.119	-0.032	0.004
Political Affiliation	-0.559	0.279	-2.000	0.048	-1.114	-0.004
Cropland Yield	0.121	0.212	0.570	0.571	-0.301	0.542
Prior Turbines	-0.081	0.029	-2.800	0.006	-0.139	-0.024
Available Land	0.000	0.000	1.750	0.083	0.000	0.000

Population	0.000	0.000	-0.200	0.841	0.000	0.000
% White	0.929	0.912	1.020	0.311	-0.880	2.739
% Hispanic	-0.024	0.718	-0.030	0.973	-1.448	1.400
% Female	0.350	2.287	0.150	0.879	-4.188	4.888
% Retirement Age	-0.094	0.896	-0.100	0.917	-1.871	1.684
Year (Base Year = 2004)						
2005	0.039	0.022	1.740	0.084	-0.005	0.083
2006	0.005	0.019	0.240	0.808	-0.032	0.042
2007	0.077	0.032	2.420	0.017	0.014	0.140
2008	0.172	0.046	3.740	0.000	0.081	0.264
2009	0.111	0.040	2.760	0.007	0.031	0.191
2010	0.041	0.035	1.190	0.238	-0.028	0.110
2011	0.131	0.047	2.810	0.006	0.039	0.223
2012	0.183	0.056	3.250	0.002	0.071	0.294
2013	0.066	0.047	1.420	0.159	-0.026	0.159
2014	0.108	0.055	1.940	0.055	-0.002	0.218
2015	0.127	0.064	2.000	0.048	0.001	0.254
2016	0.119	0.054	2.190	0.031	0.011	0.226
2017	0.264	0.070	3.770	0.000	0.125	0.404
2018	0.138	0.068	2.010	0.047	0.002	0.273
2019	0.085	0.081	1.050	0.296	-0.076	0.246
2020	0.116	0.084	1.380	0.170	-0.050	0.283
2021	0.040	0.082	0.480	0.631	-0.124	0.203
2022	0.017	0.090	0.190	0.847	-0.161	0.196
2023	0.014	0.094	0.150	0.884	-0.173	0.201
Constant	-0.958	1.219	-0.790	0.433	-3.377	1.460
R^2 (Between)	0.029					

This regression revealed that when only considering turbines commissioned starting in 2004, five years after the successful installation of the first major wind farms in Iowa, Political Affiliation, Prior Turbines, and Available Land all become statistically significant. Political Affiliation has a p-value of 0.048, meaning it is statistically significant with an α of 0.05. The coefficient is -0.559, meaning that when the percentage of votes cast for Democrats is 10% higher, there is a 5% decrease in the likelihood that turbines will be commissioned in that county five years later. This is interesting given that the relationship contradicts the prior literature on state-level political affiliation which finds that states with Democratic leadership are more likely to support renewable energy initiatives (Dorrell & Lee, 2020). Additionally, even in regressions where Political Affiliation is statistically insignificant it has a negative relationship with New Turbines, suggesting that more Democrats predicts less wind farm development. I am not sure why this is the case, but if this relationship holds true it is worth further research beyond this paper.

Available Land is technically statistically significant but has a coefficient of 0.0, meaning that it holds no practical significance. I had expected the amount of available land for turbine development to have a negative relationship with New Turbines purely for logistical reasons, but the findings of this regression contradict that. Perhaps most counties have plenty of farmland that is available for turbine development and so the actual difference in acres does not impact development decisions. This is supported by Adair County, which had 528 turbines at the end of 2023 (the largest amount in Iowa) and still had 288619.4 acres of available land. Using recommended setbacks from the Iowa Environmental Council (2018), this still leaves enough acres for over two thousand additional turbines. In Adair County available land is not a development constraint. Prior Turbines is also statistically significant ($p = 0.006$) and has a coefficient of -0.081, meaning that having prior turbines leads to an 8.1% decrease in the likelihood of turbine commissioning five years later.

Overall, this model has extremely low between-county explanatory power ($R^2 = 0.029$). Additionally, the three independent variables, Farm Income, Non-Farm Income, and Unemployment Rate, remain statistically insignificant. Running the regression four more times, once with each independent variable individually and once omitting Cropland Yield, reveals the same results as the first regression: Political Affiliation, Prior Turbines, and Available Land are statistically insignificant with little variation in their p-values or coefficients.

7.2 Regressions with Total New Turbines

Table 8

Regression Results: Total New Turbines, Farm Income Per Capita, Non-Farm Income Per Capita, and Unemployment Rate, 5 Year Lag, All Years, Weighted for Available Farmland in 1987

Variable	**Coefficient**	**Robust Standard Error**	**T-Value**	**P-Value**	**95% CI Lower**	**95% CI Upper**
Farm Income Per Capita	0.353	0.259	1.370	0.175	-0.160	0.866
Non-Farm Income Per Capita	0.115	0.190	0.610	0.544	-0.261	0.492
Unemployment Rate	-0.139	0.481	-0.290	0.773	-1.092	0.815
Political Affiliation	-12.502	8.705	-1.440	0.154	-29.777	4.772
Cropland Yield	3.994	7.614	0.520	0.601	-11.116	19.105
Prior Turbines	-1.760	1.424	-1.240	0.219	-4.585	1.065
Available Land	0.000	0.000	1.680	0.097	0.000	0.000
Population	0.000	0.000	-0.440	0.663	0.000	0.000
% White	63.890	47.112	1.360	0.178	-29.603	157.382
% Hispanic	-19.985	29.703	-0.670	0.503	-78.930	38.960
% Female	31.301	112.911	0.280	0.782	-192.767	255.370
% Retirement Age	-19.006	53.078	-0.360	0.721	-124.337	86.325
Year (Base Year = 1995)						
1996	0.415	0.308	1.350	0.181	-0.197	1.027
1997	-1.074	0.639	-1.680	0.096	-2.342	0.194
1998	-0.270	0.901	-0.300	0.765	-2.058	1.519
1999	2.405	2.902	0.830	0.409	-3.353	8.164
2000	-0.670	0.931	-0.720	0.473	-2.518	1.178
2001	-0.549	1.076	-0.510	0.611	-2.684	1.585
2002	0.417	1.586	0.260	0.793	-2.731	3.564
2003	-0.177	1.406	-0.130	0.900	-2.968	2.614
2004	-0.145	1.576	-0.090	0.927	-3.271	2.982
2005	0.411	1.929	0.210	0.832	-3.417	4.238
2006	0.125	1.716	0.070	0.942	-3.280	3.531
2007	2.125	2.170	0.980	0.330	-2.182	6.432
2008	10.125	3.131	3.230	0.002	3.911	16.338

2009	4.468	2.728	1.640	0.105	-0.945	9.881
2010	0.094	1.923	0.050	0.961	-3.722	3.910
2011	3.171	3.119	1.020	0.312	-3.018	9.360
2012	3.887	2.856	1.360	0.177	-1.780	9.554
2013	0.701	2.599	0.270	0.788	-4.456	5.859
2014	4.022	3.168	1.270	0.207	-2.265	10.310
2015	4.094	3.397	1.210	0.231	-2.647	10.836
2016	3.421	2.988	1.140	0.255	-2.509	9.351
2017	5.905	3.772	1.570	0.121	-1.580	13.390
2018	5.787	4.427	1.310	0.194	-2.998	14.573
2019	8.126	5.022	1.620	0.109	-1.841	18.093
2020	6.773	4.265	1.590	0.116	-1.691	15.236
2021	3.161	4.377	0.720	0.472	-5.525	11.847
2022	2.598	4.273	0.610	0.545	-5.882	11.078
2023	2.158	4.758	0.450	0.651	-7.284	11.600
Constant	-77.621	62.805	-1.240	0.219	-202.254	47.013
R^2 (Between)	0.0409					

In this regression, none of the independent or control variables are statistically significant, save for Available Land. Available Land is barely significant at the $p<0.1$ level ($p = 0.097$), and as in the previous regressions the coefficient is 0.0 meaning it has no practical significance. The amount of available land for turbine development does not increase or decrease the number of turbines commissioned in the county five years later. The model also has extremely low between-county explanatory power ($R^2 = 0.0409$). Running the regressions for each independent variable individually yielded very similar results. All independent and control variables were statistically insignificant save for Available Land. There was one exception to this: when running the regression with just Farm Income, Available Land became barely statistically insignificant with a p-value of 0.106. Running the regression without Cropland Yield as a control again yielded similar results, with all variables statistically insignificant except for Available Land ($p = 0.094$). Available land still had a coefficient of 0.0. Interestingly, while Farm Income had a negative coefficient when New Turbines was the dependent variable, Farm Income has a positive coefficient when Total New Turbines is the dependent variable. The lack of consistent directionality highlights Farm Income's lack of statistical significance in this model and could suggest that this model may not be well-suited to reflect the real world.

Table 9

Regression Results: Total New Turbines, Farm Income Per Capita, Non-Farm Income Per Capita, and Unemployment Rate, 2004-2023, All Years, Weighted for Available Farmland in 1987

Variable	**Coefficient**	**Robust Standard Error**	**T-Value**	**P-Value**	**95% CI Lower**	**95% CI Upper**
Farm Income Per Capita	0.353	0.259	1.370	0.175	-0.160	0.866
Non-Farm Income Per Capita	0.115	0.190	0.610	0.544	-0.261	0.492
Unemployment Rate	-0.139	0.481	-0.290	0.773	-1.092	0.815
Political Affiliation	-12.502	8.705	-1.440	0.154	-29.777	4.772
Cropland Yield	3.994	7.614	0.520	0.601	-11.116	19.105
Prior Turbines	-1.760	1.424	-1.240	0.219	-4.585	1.065
Available Land	0.000	0.000	1.680	0.097	0.000	0.000
Population	0.000	0.000	-0.440	0.663	0.000	0.000
% White	63.890	47.112	1.360	0.178	-29.603	157.382
% Hispanic	-19.985	29.703	-0.670	0.503	-78.930	38.960
% Female	31.301	112.911	0.280	0.782	-192.767	255.370
% Retirement Age	-19.006	53.078	-0.360	0.721	-124.337	86.325
Year						
1996	0.415	0.308	1.350	0.181	-0.197	1.027
1997	-1.074	0.639	-1.680	0.096	-2.342	0.194
1998	-0.270	0.901	-0.300	0.765	-2.058	1.519
1999	2.405	2.902	0.830	0.409	-3.353	8.164
2000	-0.670	0.931	-0.720	0.473	-2.518	1.178
2001	-0.549	1.076	-0.510	0.611	-2.684	1.585
2002	0.417	1.586	0.260	0.793	-2.731	3.564
2003	-0.177	1.406	-0.130	0.900	-2.968	2.614
2004	-0.145	1.576	-0.090	0.927	-3.271	2.982
2005	0.411	1.929	0.210	0.832	-3.417	4.238
2006	0.125	1.716	0.070	0.942	-3.280	3.531
2007	2.125	2.170	0.980	0.330	-2.182	6.432
2008	10.125	3.131	3.230	0.002	3.911	16.338
2009	4.468	2.728	1.640	0.105	-0.945	9.881
2010	0.094	1.923	0.050	0.961	-3.722	3.910

2011	3.171	3.119	1.020	0.312	-3.018	9.360
2012	3.887	2.856	1.360	0.177	-1.780	9.554
2013	0.701	2.599	0.270	0.788	-4.456	5.859
2014	4.022	3.168	1.270	0.207	-2.265	10.310
2015	4.094	3.397	1.210	0.231	-2.647	10.836
2016	3.421	2.988	1.140	0.255	-2.509	9.351
2017	5.905	3.772	1.570	0.121	-1.580	13.390
2018	5.787	4.427	1.310	0.194	-2.998	14.573
2019	8.126	5.022	1.620	0.109	-1.841	18.093
2020	6.773	4.265	1.590	0.116	-1.691	15.236
2021	3.161	4.377	0.720	0.472	-5.525	11.847
2022	2.598	4.273	0.610	0.545	-5.882	11.078
2023	2.158	4.758	0.450	0.651	-7.284	11.600
Constant	-77.621	62.805	-1.240	0.219	-202.254	47.013
R^2 (Between)	0.0409					

My independent variables, Farm Income, Non-Farm Income, and Unemployment Rate remain statistically insignificant, and the model still has extremely low between-county explanatory power ($R^2 = 0.0409$). Interestingly, running the regression with Total New Turbines as the dependent variable while restricting for commissioning years from 2004 to 2023 does not change the significance of Political Affiliation as it did when New Turbines was the dependent variable. Political Affiliation remains insignificant, but it does still have a negative coefficient implying the relationship that more votes for Democrats in presidential, gubernatorial, and senatorial elections leads to fewer turbines commissioned five years later. This remains true when each independent variable is regressed individually with the controls and when Cropland Yield is removed as a control.

7.3 Discussion

In each of my regressions, Farm Income, Non-Farm Income, and Unemployment Rate were statistically insignificant, meaning that the economic indicators I chose do not increase or decrease the likelihood of new turbines being commissioned five years later. There was also not consistent directionality of the coefficients between regressions run with New Turbines as the dependent variable and regressions run with Total New Turbines as the dependent variable. This would suggest that there is no relationship between the economic wellbeing of a county and whether or not wind development occurs there, perhaps because landowners, developers, or county officials do not take their current economic state or possible future economic benefits into consideration when they make their decisions. This contradicts the findings of previous qualitative studies that have found that support for wind energy is strongly related to socioeconomic factors and primarily due to local perception of increased employment and economic activities (Slattery et al. 2012, Mulvaney et al., 2013). However, Slattery et al. and Mulvaney et al. interviewed people in counties where wind development was either well underway or already completed, meaning that people responding to their surveys could be biased about what influenced their original decisions. Perhaps a landowner who accepted a turbine on her land only later recognized the economic benefits and now attributes her original decision to those benefits incorrectly.

The most interesting finding was the impact of Political Affiliation on New Turbines. When including all commissioning years in my regression, Political Affiliation was statistically insignificant, but when only including the years 2004-2023 Political Affiliation was statistically significant. If these results reflect reality, then perhaps political affiliation only became important after the first large wind farms were commissioned in 1999 as a "proof of concept." It is possible that people were wary about wind turbines prior to 1999 because there had never been wind energy on a large scale in Iowa, but once people saw that it was possible they started to make their decision based on their political affiliation leading to a rise in the influence of political affiliation on wind farms commissioned in 2004 and onwards. The results of the regression indicated that 10% more votes cast for Democrats in the county led to a 5%

decrease in the likelihood that turbines will be commissioned in that county five years later. This finding is at odds with both my expectations that increased support for Democrats would lead to more turbines and with existing literature (Dorrell & Lee, 2020). This could underscore the complexity of energy politics at the local scale and suggest that factors such as land use preferences, cultural identity, or local political dynamics may diverge from national trends. My data is limited in that I was not able to find a way to capture local political affiliation–the election data I utilized was for presidential, gubernatorial, and senatorial elections, which are federal and state-level. Future researchers may want to utilize county-level elections as a better indicator of political affiliation when it comes to county issues, like the results of elections for County Commissioner or the Board of Supervisors. I recommend further research prior to reaching the conclusion that the relationship represented in this model reflects the political reality in Iowa counties.

It is important to note that the R^2 of all of my models was very low, meaning that only a small portion of the variability in New Turbines or Total New Turbines could be attributed to the independent variables or control variables that I chose. My data is limited by the fact that I chose to use county fixed effects to control for differences in transmission infrastructure, wind speed, land grade, and more, and it may be this decision that limits my model. If one were to expand on this research in the future, perhaps they would glean more insight by including transmission infrastructure location data or wind energy potential data as a control rather than my method of using county fixed effects. There may be better measures of county-level economic wellbeing such as GDP that would lead to a better model than my income and unemployment variables. There is also private company information, such developer strategies or guidelines, that I did not have access to that could have improved my model. Future research could attempt to interview developers in order to account for variation in development approaches and goals.

8. Conclusion

This paper set out to explore whether a county's economic attributes could predict future wind turbine development in Iowa. Using a comprehensive panel dataset spanning from 1990 to 2023 and leveraging a two-way fixed effects regression approach, I investigated the impact of farm income, non-farm income, and unemployment rates—lagged by five years—on the likelihood and volume of wind turbine development in a given county. Contrary to the assumptions embedded in previous qualitative literature, my findings do not support the hypothesis that counties with weaker economic performance are more likely to experience wind energy development. Across all model specifications, my primary independent variables were statistically insignificant and lacked consistent directionality, suggesting that economic hardship or prosperity at the county level does not meaningfully shape turbine siting decisions.

Interestingly, one of the most robust findings emerged around political affiliation. While political leanings had no significant effect in regressions including all years of turbine commissioning, they became statistically significant in models restricted to post-2004 development—suggesting that once wind energy had been proven viable and profitable in Iowa, political identity may have played an increasing role in shaping public and governmental attitudes toward future projects. Notably, this relationship was negative: counties with higher Democratic vote shares were less likely to see new wind development. This result is surprising given the strong association between Democratic leadership and support for renewable energy at the national level.

In all cases, my models demonstrated very low between-county explanatory power (R^2), indicating that even when statistically significant, my independent and control variables explained only a small fraction of the variation in wind turbine development. This points to the presence of unobserved factors—such as specific landowner decisions, developer strategies, or unmeasured physical attributes like grid interconnection costs—that may be more decisive in the siting process.

Ultimately, while this paper does not find a clear economic pathway for predicting wind turbine development, it provides an empirical test of an intuitive hypothesis and highlights the need for more granular, site-specific data to understand the true determinants of wind energy expansion. Future research might benefit from incorporating physical geography data, transmission access metrics, or qualitative accounts of developer-landowner negotiations. As Iowa and other regions continue to pursue decarbonization goals, understanding what drives renewable energy siting—and where political and economic support converges or diverges—will remain critical to informed policymaking and community engagement.

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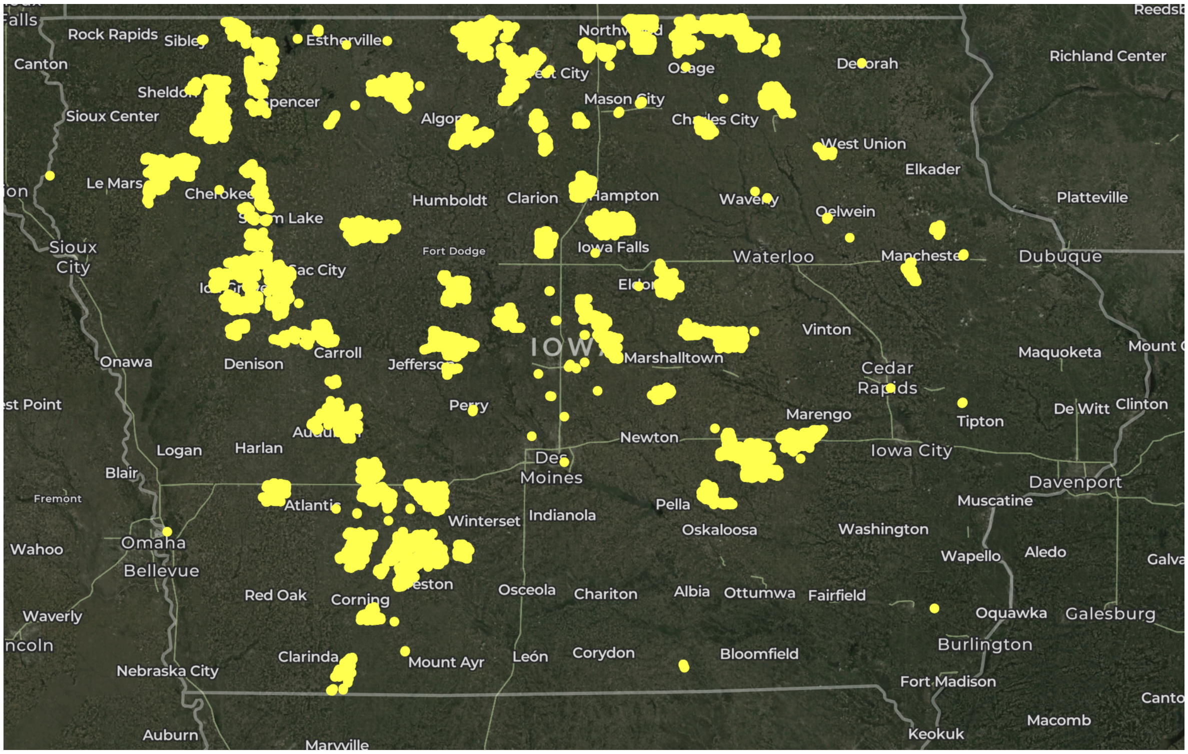
Appendix A

USWTDB Viewer



Appendix A. Map of wind turbines in Iowa from the USWTDB viewer (U.S. Geological Survey, 2025).

Appendix B

Number of Turbines per Iowa County

FIPS Code	County	Turbines Commissioned, 1990-2023	Turbines Decommissioned, 1990-2023	Turbines in Operation in 2023
19001	Adair	528	0	528
19141	O'Brien	318	0	318
19195	Worth	305	0	305
19069	Franklin	262	0	262
19021	Buena Vista	260	0	260
19081	Hancock	248	0	248
19157	Poweshiek	240	0	240
19151	Pocahontas	216	0	216
19093	Ida	215	0	215

19109	Kossuth	195	0	195
19131	Mitchell	195	0	195
19147	Palo Alto	180	0	180
19161	Sac	176	0	176
19029	Cass	170	0	170
19189	Winnebago	159	0	159
19073	Greene	158	0	158
19059	Dickinson	146	0	146
19089	Howard	145	0	145
19169	Story	141	3	138
19009	Audubon	132	0	132
19027	Carroll	132	0	132
19079	Hamilton	132	0	132
19003	Adams	112	0	112
19035	Cherokee	110	0	110
19187	Webster	107	0	107
19155	Pottawattamie	103	0	103
19075	Grundy	95	0	95
19047	Crawford	93	0	93
19123	Mahaska	84	0	84
19127	Marshall	81	0	81
19083	Hardin	79	0	79
19015	Boone	77	0	77
19095	Iowa	77	0	77
19041	Clay	75	0	75
19149	Plymouth	74	0	74
19037	Chickasaw	66	0	66
19143	Osceola	64	0	64
19077	Guthrie	61	0	61
19067	Floyd	51	0	51
19121	Madison	51	0	51
19197	Wright	49	0	49
19173	Taylor	44	0	44
19055	Delaware	40	0	40
19175	Union	34	0	34

19033	Cerro Gordo	79	54	25
19065	Fayette	16	0	16
19025	Calhoun	8	0	8
19171	Tama	8	0	8
19007	Appanoose	3	0	3
19017	Bremer	3	0	3
19049	Dallas	3	0	3
19153	Polk	3	0	3
19031	Cedar	2	0	2
19063	Emmet	2	0	2
19019	Buchanan	1	0	1
19087	Henry	1	0	1
19113	Linn	1	0	1
19191	Winneshiek	1	0	1
	Total	6,411	57	6,354

Appendix B. This table only includes the 58 Iowa counties where some wind turbine development has occurred.