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Efficacy of Non-Refundable Tax Credits: Evidence from the Iowa Wind Energy Market

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Abstract

Contributing to the literature surrounding the efficacy of tax credits, this research focuses on the emerging industry of wind energy in Iowa. This research attempts to estimate the causal effect of a non-refundable tax credit policy for wind energy production in the state of Iowa. Utilizing data from the EIA's Form 860, this research finds using both difference-in-differences and synthetic control estimation that the tax credit for wind energy production was effective. Estimates for the causal effect differ, with the difference-in-differences identifying an estimated effect of 1308 additional wind turbines constructed from 2005-12, while the synthetic control estimation identified an effect of 224 by 2012. These policies costed the state government $13.3 million, suggesting, given the cost of wind turbine development, that large, non-refundable tax credits may support emerging industries well.

Introduction

Policy makers worldwide frequently spend public monies to create incentives for emerging industries, hoping to kickstart the industry in their region. Assisting emerging industries is logical; these industries have the most room to grow, and a politician could gain much from backing an industry that grows quickly and creates employment and community investment. This is especially true for wind energy, as this industry not only creates high-paying jobs, but helps the fight against climate change. The incentive this paper is interested in is the non-refundable tax credit. It is a popular incentive, because, compared to other incentives such as a subsidy or refundable tax credit, a non-refundable tax credits award amount is bounded above by the awardee's tax liability. This makes it less costly to the government, while ostensibly providing support. This paper will be examining the cost-effectiveness of these tax credits in the wind industry, using evidence from the State of Iowa from 2001-2012.

This paper aims to determine the effect of the Iowa Wind Energy Production Tax Credit in Iowa on wind turbine population in the state. The Wind Energy Production (WEP) Tax Credit lasted from 2005 – 2012, and was a non-refundable, fully transferable tax credit. A fully transferable tax credit is a tax credit that can be sold to another corporation, organization, or individual, and they can then use the tax credit to reduce their own liability.

This paper attempts to estimate the effect of a specific kind of policy, estimating as best as possible its intended outcome on the wind industry. It will contribute to the large literature that estimates the actual effect of government policy, including much literature in the renewable and wind energy space. Much of the renewable energy policy literature is focused on federal incentives and state-level renewable portfolio standards; this research is unique because the policy it examines is unique. A $0.01 non-refundable tax credit per KW/h of wind energy produced, the amount awarded by the State of Iowa in their policy, is massive, and it is rare for a state to create a policy with such a large incentive. Identifying the effect of an aggressive policy like this is important to determine if the policy is a worthy use of state funds, and to determine if similar policies could work in other industries.

This paper estimates an OLS difference-in-differences model and two synthetic control models in order to estimate and approximate the effect of the Iowa WEP tax credit policy. The synthetic control is used due to the lack of an appropriate control state for Iowa that met the parallel trends assumption, but kept in the paper to show the development of the research process, and to bound estimates given by the synthetic control. Difference -in-differences was a natural choice, due to the short term nature of the program and the final unit of observation being states. Synthetic control emerges as a natural extension of difference-in-differences, creating a weighted average of states to create a “synthetic” Iowa.

I found, using OLS difference-in-differences estimation, that the policy caused an additional 1308 turbines to be built from the time period 2005-2012 than otherwise would have been built. This estimate is large, and given the state invested $13.3 million into the project, this is a massive return on investment. However, parallel trends check has failed, so we turn to synthetic control. Utilizing a group of Midwestern Great Plains states to compose the synthetic control Iowa, I found that, in 2012, the causal effect of the policy was estimated to be approximately 224 turbines.

The next section covers related literature review, much of which focuses on testing renewable energy policy at both the state and federal level. Section 3 contains the methodology and the theory for synthetic control. Section 4 covers the data, the parallel trends check for the difference-in-differences, and the specification of the two synthetic control estimations. Section 5 has the results, and refers to the many tables and plots that synthetic control produces. Section 6 concludes the paper, and gives policy interpretations.

Literature Review

Efficacy studies on government policies are common. For example, Hitaj (2013) finds using random effects Tobit, Probit, and OLS instrumental variables regression that state and federal programs incentivizing wind power development are effective across all three models. She also notes that access to the electrical grid is an important variable for potential wind developers to consider and incorporates this into her analysis. She argues that increasing the number of regional transmission organizations is the most cost-effective way to increase wind power investment, as these organizations reduce operating inefficiencies, making an investment in wind projects more attractive.

Carley (2009) examines another popular state-level policy used to promote wind energy, renewable portfolio standards (RPS). RPS policies mandate that renewable energy production must increase to certain production levels by certain time thresholds. Utilizing a variant of a fixed effects model, Carley finds that RPS policies are not significant predictors of the percentage of renewable energy generation as a fraction of total energy production; however, they do predict year-to-year increases in renewable energy generation.

The design of tax credit programs influences their efficacy as well. As Johnston (2019) discusses, choosing non-refundable tax credits can cause all sorts of problems for companies, especially new companies, considering investing in wind power projects. Non-refundable tax credits do not provide cash inflows, and traditional banks will be hesitant to offer attractive loans to these companies. Therefore, instead of traditional debt financing, companies considering wind power projects will use tax equity financing to create new energy projects, which, due to the nature of that kind of financing, incurs welfare loss on the industry. To test this theory, Johnston utilizes data containing geographic variation in wind project development and finds that $1 of non-refundable tax credits is valued the same as $0.85 in cash grants. This shows that non-refundable tax credits do cause some level of deadweight loss in the industry, as although you could expect a company to more highly value cash grants, a 15-cent difference is large.

Evidence from tax credits for R&D suggest they are effective, as Fazio, Guzman, and Stern (2020) show. Utilizing data from the Startup Cartography Project and the Panel Database on Incentives and Taxes, they estimate a difference-in-differences model that reveals that R&D tax credits increased the quantity and quality-adjusted quantity of startups in the state. This strong support for R&D tax credits show that they may help bolster innovation in states where they exist.

Tax credits for wind energy have also been shown to reduce emissions and increase investment in wind energy. In their research on energy pricing policy and its impact on investment in wind and solar energy projects, Kok, Shang, and Yucel (2018) show that prices that follow daily demand cycles reduce emissions and induce firms to increase investment in renewable energy, especially solar energy; additionally, production tax credits (of which the Iowa Wind Energy Production Tax Credit would be an example) were shown to increase investment in renewable energy projects and reduce carbon emissions.

Production tax credits for wind energy may also help keep them competitive with traditional energy production methods. Lu et al. (2011) developed a spatial financial model using meteorological wind data to investigate the competitiveness and profitability of onshore wind power in the United States. Given varying award levels for production tax credits (PTC), they estimate firm profitability in a reference case, a low-cost case, and a high-cost case. They find that the PTC is at a critical level in the reference case, as it is crucial in keeping wind energy competitive. Additionally, their findings suggest that, at the current PTC levels, the potential for profitable wind energy production could be as much seven times total U.S. demand for electricity, a finding in line with expectations of how subsidies behave in markets. This research is from 2011, so although these results may not fully reflect current wind energy competitiveness, it still provides evidence for how valuable these production tax credits are to prospective wind energy developers.

Cheng, Guo, and Liu (2020), in their research on the relationship between state tax incentive occurrence and state tax rates, utilize a spatial Durbin model tested on the Panel Database on Taxes and Incentives to find that states with higher tax rates are more likely to create tax incentives. This suggests that states with high tax burdens seek to create a 'level playing field' in business attraction and retention, mitigating the disadvantages that their high tax burdens may have caused. Indeed, Iowa may have been more likely to implement this tax credit due to it being a high tax state. Iowa is in the top 6 nationally in corporate income tax rate, according to an article from the Tax Foundation. According to this research, the higher taxes in Iowa may have been a causal factor in the implementation of the state PTC for wind energy. Thus, tax rates are an important consideration for model construction.

Conceptual Framework

In this paper, I estimate an OLS difference-in-differences model and a synthetic control in order to find the effect of the tax credit for wind energy in Iowa by comparing the total wind turbine population in Iowa and Kansas over the period 2001-2012. The difference –in-differences approach, the original approach to this research question, is a quasi-experimental design that requires Iowa and Kansas to be similar in observed and unobserved factors, with the exception that Kansas has no similar treatment itself. That is why Kansas is being used as a control state; it has no competing incentive such as a tax credit or subsidy. According to the DSIREUSA.org database for renewable energy incentives, Kansas had no similar incentive during the period this incentive was in effect in Iowa. This means that Kansas is at least eligible to be the control state, as it faces no treatment itself. Kansas has similar wind resources, an important consideration in wind turbine development. The National Renewable Energy Laboratory tracks wind energy potential in an online, nationwide map. Figure 1 shows a snapshot of this map, and although Kansas has more potential to produce wind energy than Iowa overall, the two are similar. Kansas also has a similar economy; both states' largest industry is agriculture and have significant manufacturing and finance sectors. Therefore, the states are similar in an important unobservable factor as well. These conditions make Kansas an ideal control for Iowa in this natural experiment.

As the reader will see in the next section, a more appropriate approach for this research question is to use a synthetic control method, as a key assumption of difference-differences, parallel trends, is not met. The synthetic control approach can be thought of as a combination of difference-in-differences and matching; it uses a weighted average of multiple different units as a control, creating a 'synthetic control', instead of just using one unit. The synthetic control approach recognizes that for many states and countries, it is very difficult to find a different real state or country that approximates well-enough the unit of interest during the period of interest, while still being eligible to be a control. To motivate the synthetic control approach, I adapt and apply Abadie, Diamond, and Hainmueller's (2015) work which uses the synthetic control method to identify the economic impact of German reunification in 1990.

Suppose there is a sample of $J+1$ units (states, in this case) indexed by j, where $j=1$ is the unit of interest (Iowa) and units $j=2$ to $j=J+1$ are the potential comparisons. Assume the sample is a balanced panel, where all units are observed at the same time units $t=1,\dots,T$. We also assume that the sample includes a positive number of pre-treatment periods, T_0, and a positive number of post-treatment periods, T_1, where $T_0+T_1=T$.

The synthetic control method attempts to create a control group for our unit of interest by utilizing a combination of untreated units, rather than using a single untreated unit. Therefore, define a synthetic control as a weighted average of the untreated units. That is, a synthetic control can be represented by a $(J\times 1)$ vector of weights $W=\left(w_2,\dots,w_{J+1}\right)'$, with $0\le w_j\le 1$ for $j=2,\dots,J$ and $w_2+\cdots+w_{J+1}=1$. Selecting some value for W is equivalent to selecting a synthetic control. Then, following the intuition from difference-in-differences, we will choose W such that the characteristics of the treated unit are best resembled by the characteristics of the synthetic control. Let X_1 be a $(k\times 1)$ vector containing the values of the pre-treatment characteristics of the treated unit that we wish to match as closely as possible, and let X_0 be the $k\times J$ matrix containing the same information for the untreated units. Then, the synthetic control seeks to minimize X_1-X_0W by selecting some W^*. Next, for $m=1,\dots,k$, let X_{1m} be the value of the m-th variable for the treated unit and X_{0m} be a $(1\times J)$ vector containing the values of the m-th variable for the untreated units. Then, we choose W^* that minimizes:

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m}W)^2, \quad (1)$$

where v_m is a weight that reflects the relative importance assigned to the m-th variable when measuring the difference between X_1 and X_0W. It is important for those variables with large predictive power on the outcome variable to have high weights in v_m, as this will force the synthetic control to more closely replicate values in more important variables.

Let Y_{jt} be the outcome of unit j at time t. Additionally, let Y_1 be a $(T_1 \times 1)$ vector containing the post-intervention values of the outcome for the treated unit. Specifically, $Y_1 = \left(Y_{1T_{0+1}}, \dots, Y_{1T}\right)'$. Similarly, let Y_0 be a $(T_1 \times J)$ matrix, where column j contains the post-intervention values of the outcome for unit $j + 1$. The synthetic control estimator of the treatment effect is given by the comparison of the post-intervention outcomes between the treated and untreated units, which is given by $Y_1 - Y_0W^*$. Specifically, for a post-intervention period t, the synthetic control estimator is given by:

$$Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}\ , (2)$$

There are some limitations with this approach. The method is limited by the existence of other factors influencing the outcome variable, as well as the heterogeneity in the impact of the observed and unobserved factors. However, these concerns are mitigated with large sample sizes and correct matching; intuitively, this makes sense. For the outcome variable to behave similarly in the treated unit and the synthetic control over time, it would necessarily mean they must be similar in both observable and unobservable characteristics. Thus, differences in the outcome variable in the post-treatment period must be attributed to the intervention itself.

Data

The data for this research comes from the Energy Information Administration's Form 860, which collects generator-level information on all generators in the United States with a nameplate capacity at or exceeding 1 MW. This data is collected annually, and the sample period for this research spans 2001-2012. The dataset gives information about generator conditions, including its state, nameplate capacity, year of initial operation, and type of generation. Wind farms are able to respond to the form as if they were a single generator; they must then report the total number of wind turbines on that wind farm. Those reported turbine counts is the variable of interest in this study. I will be aggregating the total number of turbines in each state each year, giving a balanced panel dataset that shows the number of wind turbines, or the wind turbine population, in each state each year in the United States. Additional price and tax rate data is added to the dataset to control for those that vary across the two states. The price data is from the historical EIA state profiles for both Iowa and Kansas, and those datasets give the average retail price per KW/h of electricity in each state each year. The tax rate used a measurement called the burden rate; it was conceived by the Tax Foundation and measures the relative tax burden each state imposes on its corporations. Table 1 gives summary statistics for all variables used in the difference-in-differences estimation. The tot_turbines is the dependent variable and is the wind turbine population in the states of Iowa and Kansas over time. This gives a panel dataset that shows the total number of wind turbines in the state over time for both Iowa and Kansas, as well as energy price and burden rate data in those states over time. The time and state variables are both dummy variables. State has value 1 for Iowa and 0 otherwise, and time has value 1 for the treated period (2005-2012) and 0 otherwise. The DiD variable, which is the variable of interest in this estimation, is the product of the state and time variables.

Difference-in-differences requires an additional assumption that traditional OLS estimation does not; there must be parallel trends in the pre-treatment period in the dependent variable for both the treatment (Iowa) and control (Kansas) groups. Figure 2 gives us the pre-treatment trends in wind turbine population, the dependent variable, for both Iowa and Kansas from the years 2001-2004, the earliest years for which wind turbine data is available. It appears Iowa had a decrease in the total number of wind turbines in the state from 2002-2003, which does not follow intuition. The dataset is supposed to count every generator in the United States with capacity at or exceeding 1 MW, so this either means that there were more decommissions than new installations in the period from 2002-2003, or that there is measurement error. Regardless, as seen in Figure 2, the parallel trends assumption is not met in the case of Iowa and Kansas. The two states do not have a common trend, as Iowa is increasing their wind turbine population more quickly than Kansas. Other states were tested, but other Midwestern states that are like Iowa in economic and wind resources terms either had their own competing wind energy incentive policy (Minnesota) or failed the parallel trends check as well (several states). Traditional difference in differences estimation may not be the best option for this research question.

Therefore, synthetic control estimation was attempted. For the synthetic control estimation, I use the same data and variables, namely, the price and burden rate data, coupled with the wind turbine population data. However, there are no state, time, or DiD dummy variables in the estimation. With synthetic control, the idea is to use a weighted average of a group of control states, attempting to make the group as similar as possible to the unit of interest. For this research, I utilized two different groups of control units; the first group is composed of a selection of Midwestern/Plains states, regardless of any competing state incentives. The second group is made up of as many states as possible that have no policy incentives for wind energy, according to the DSIREUSA.org database.

Results

Table 2 gives the results from the OLS difference-in-differences regression output. I find that, given the assumptions of OLS difference-in-differences estimation hold, the tax credit caused an additional 1109 wind turbines to be built in the state from 2005-2012. This effect is statistically different from zero at the five percent level and estimates for the other coefficients have the expected signs, except for the time dummy, which is expected to be positive. However, the coefficient is not statistically different from zero, so these concerns are mitigated.

These results show that the tax credit for wind energy in Iowa caused an additional 1308 turbines to be built between 2005 and 2012. Assuming this result is interpretable, the program was cost-effective and successfully increased wind energy development. The State of Iowa Department of Revenue (2019) states that the program has awarded $13.3 million in awards from the program as of 2019. As wind turbines cost millions of dollars to manufacture and install, this program was a relatively cheap way to increase the installation and adoption of wind energy in the state. The fully transferable nature of the tax credits likely helped, as this reduces the deadweight loss caused by tax equity financing, as the legal hurdles that create the deadweight loss no longer exist. Given there exist investors and banks with both significant capital and Iowa tax liability, the tax credit seems to have made some marginal investors into willing investors, creating large investment in Iowa's wind energy industry. If these results, or results like these, hold in a future synthetic control test of this research question, it would show that state-level non-refundable, fully transferable tax credits are a cost-effective way to increase investment in emerging industries. Identifying even a small causal effect would be strong support for this policy; according to Windustry, a wind energy advocacy group, it costs several million dollars to install a manufacture and install a wind turbine, while the State of Iowa only spent $13.3 million in total on the program. This means that causing an additional investment in wind energy development exceeding $13.3 million would be a cost-effective policy, which equates to about 5 additional turbines. For future editions of this paper, I will incorporate a synthetic control, as I mentioned. This current research has shown that, even if the causal effect of the policy is overstated, the policy has achieved its stated goals.

Figures 3 and 4 give the plots for Iowa total turbine population versus the synthetic Iowa composed of Plains states and the synthetic Iowa composed of untreated states, respectively. As seen from the plots, the synthetic Iowa composed of untreated states does not follow the trend that Iowa takes in the pre-treatment trend at all, barely increasing in wind turbine population while Iowa increases quickly in the same period. Additionally, though the policy intervention occurred in 2005, it is unclear from this graph that it had any meaningful effect. Meanwhile, the synthetic Iowa composed of the Plains states seems to have performed better; it follows more closely the pre-treatment trend in wind turbine population that Iowa has, and there is a bigger deviation in the year 2005. However, the fact that these states, especially the ones with large weights, Minnesota and Texas, have their own wind energy incentives makes this difficult to interpret. Figure 5 shows the gaps plot for the Plains synthetic control. The gaps plot plots the difference between the treated and synthetic control over time. In the pre-treatment period values close to zero and/or unchanging values year-to-year are preferred, as this supports the idea that the synthetic control is approximating well the unit of interest. As seen, the graph oscillates a large amount from year-to-year and has serious deviations from zero.

Table 3 contains the solution for W^* for the Plains states, while Table 4 contains the solution for W^* for the large group of states with no incentive. In the Plains states case, Minnesota gets approximately 85 percent of the weight and Texas gets the rest. The other states contribute almost nothing. In the non-treated states case, each state gets a near equal weighting. The Plains grouping was the best approximation of Iowa I could find given that the group of control states should remain motivated in some way. There are a few reasons this did not go well; first, the number of pre-treatment periods is small, which, as noted in the theory, makes the effect of unobserved factors more impactful. The EIA Form 860 did not track wind turbines before 2001; with this data at least, there is no expansion of the pre-treatment periods available. Secondly, there are only a few states that developed a significant wind turbine population in the period 2001-2012. This makes it difficult for the synthetic control approach to work, as the synthetic control is a weighted average with weights less than one. This means that in order to approximate Iowa's turbine population growth well, it is necessary for there to be multiple states with wind turbine populations greater than Iowa's to use as effective controls, which is not present in the data. Finally, based on the results from the non-treatment states, it is likely that strong wind energy industries themselves cause wind energy policies.

Most states that have a significant wind industry have incentives for wind energy, and the opposite is true of states without significant wind energy industries. Therefore, disentangling the causal effect of these policies will be difficult, even in the synthetic control case.

Results for the synthetic control estimator each year for the Plains states are given in Table 5. As seen here, the effect of the credit in this case is estimated to be approximately 224 turbines by the end of the program in 2012. Effects in other years vary, but the effect size generally tapers as time increases. This estimate may not be interpretable, but this suggests that the wind energy production tax credit made Iowa more attractive than it otherwise would have been, relative to its peers that are similar geographically, and in terms of wind energy industry growth and development. Again, even small causal effects are cost-effective; but as I mentioned, the causality of these programs goes both ways. Given that the estimates are interpretable, this program was an inexpensive way for the state government of Iowa to promote the development of its wind energy industry.

Conclusion

This paper identifies, using both difference-in-differences and synthetic control estimation, the effect of the Iowa Wind Energy Production tax credit. The data for this research comes from the EIA's Form 860, and although there are limitations with both the methodology and data, the results across all models suggest that the WEP tax credit was very effective, with estimates ranging from 224 in the synthetic control case to 1308 in the difference-in-differences case.

This approach was chiefly limited by availability of wind turbine population data. More pre-intervention periods would have allowed for a more accurate result in the synthetic control case. These additional periods would have helped the robustness of the results. Another significant limitation was the mutual causality of policies supporting wind energy and a significant wind energy sector. The several states with no policy incentive for wind energy all had near non-existent wind energy sectors; conversely, the same states with significant wind energy sectors that are great controls for Iowa had competing policies. As a result, disentangling the two, and identifying the causal effect of these programs is difficult.

As mentioned in the results section, if these estimates are to be taken at face value, the WEP tax credit has created great value for the state of Iowa with respect to the policy's cost. The construction, installation, and maintenance of these hundreds of turbines support many jobs across the state, generate revenue for energy producers and farmers alike, and help fight climate change. For a price of $13.3 million, policy makers across the county would do well to note the effectiveness the program had in the state. As a non-refundable tax credit, it may be easier to pass than fully refundable tax credits, and its fully transferable nature curbs the deadweight loss that may occur because of these tax credits.

In future rounds of research, a new dataset needs to be located, with expanded pre-intervention periods. This will improve the synthetic control estimation. Additionally, classifying different state-level wind energy incentive policies into some scale, and using that as one of the independent variables in an estimation strategy is another way to identify cost effective policies.

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Figures and Tables

Figure 1

Wind Energy Potential Map, according to the National Renewable Energy Laboratory. Higher color saturation indicates higher wind energy potential.

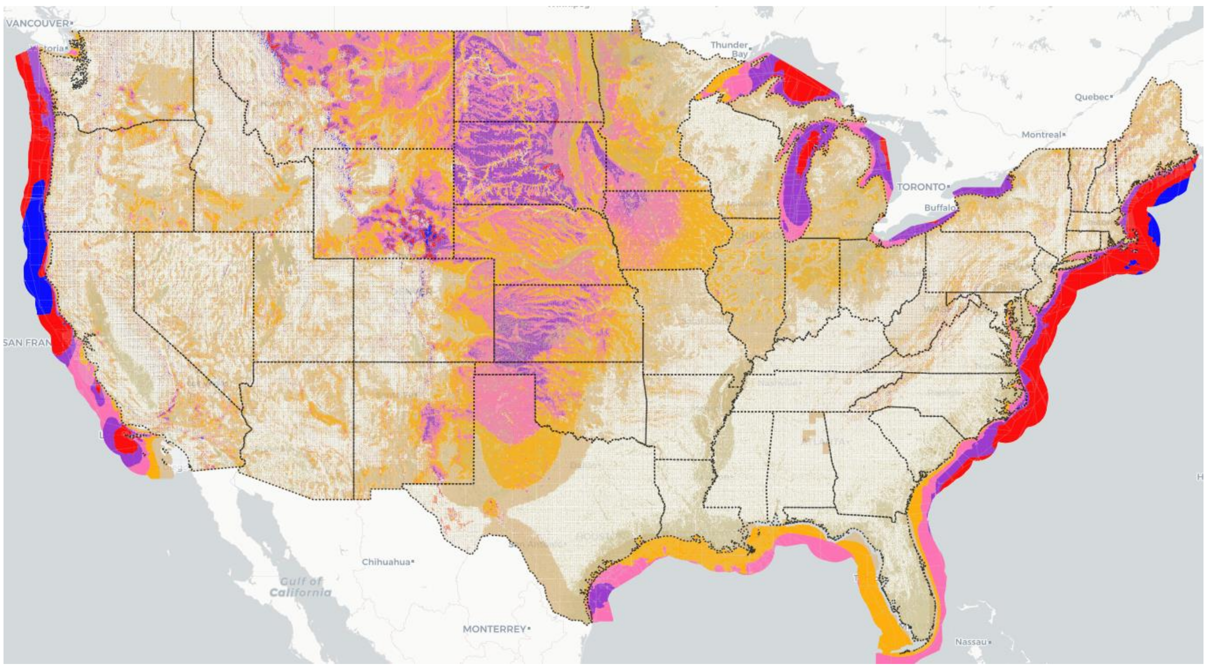

Figure 2

Trends in the dependent variable, wind turbine population, for Iowa and Kansas in the pre-treatment period.

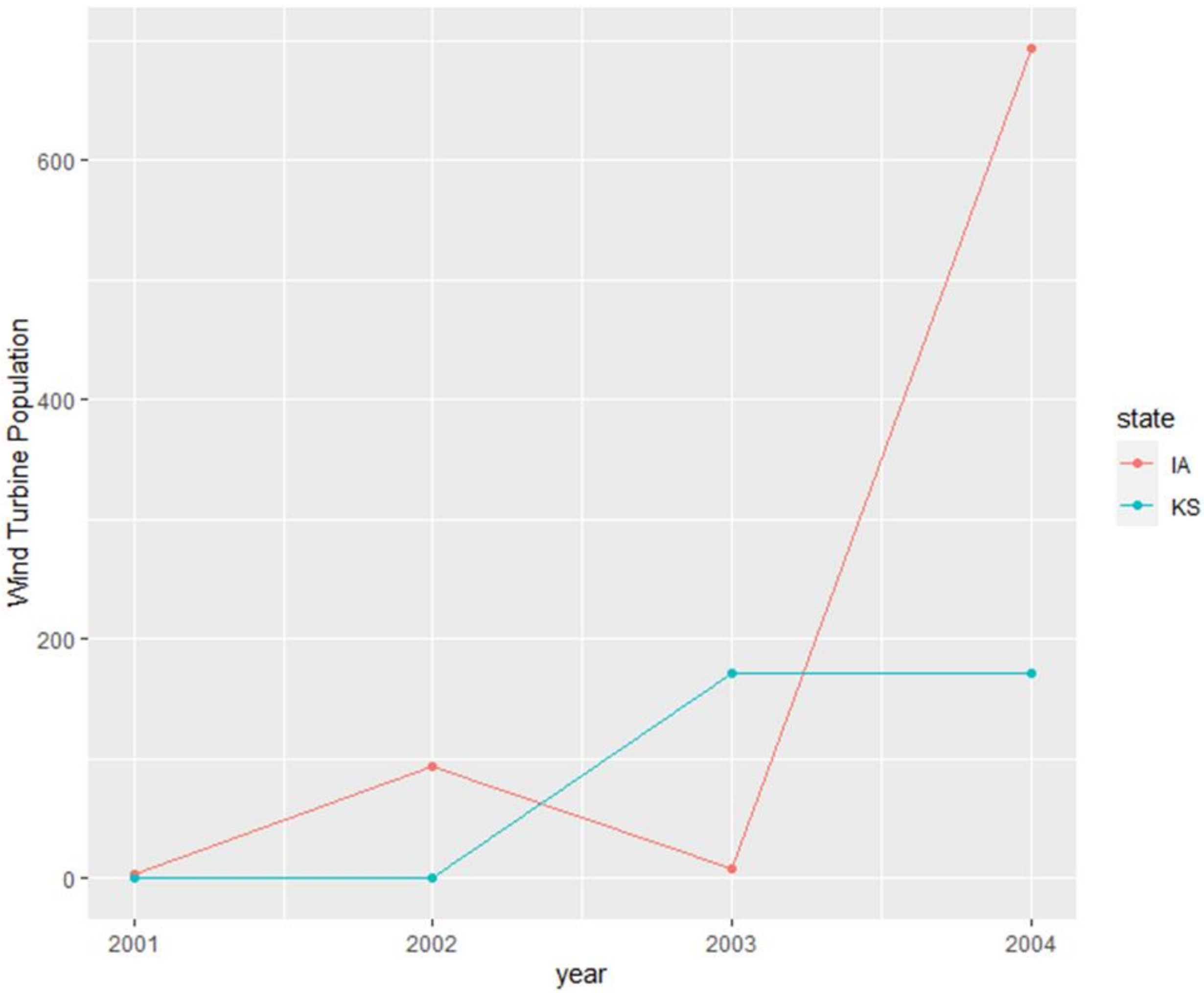

Figure 3

Graph comparing Iowa to a synthetic Iowa composed of Plains states, over the timespan of the entire sample (2001-12).

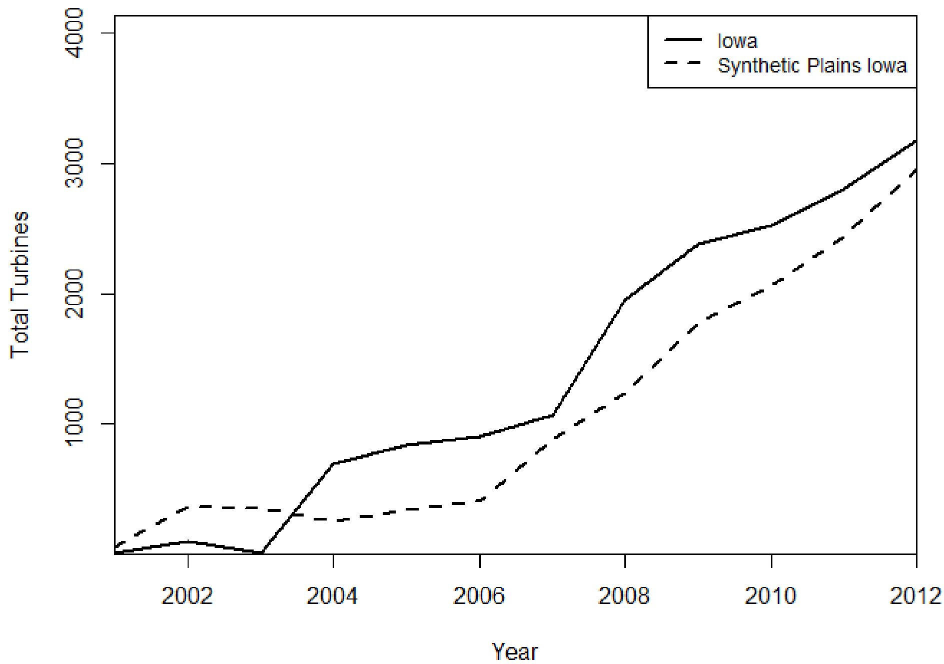

Figure 4

Graph comparing Iowa to a synthetic Iowa composed of states with no wind energy incentive policies, over the timespan of the entire sample (2001-12).

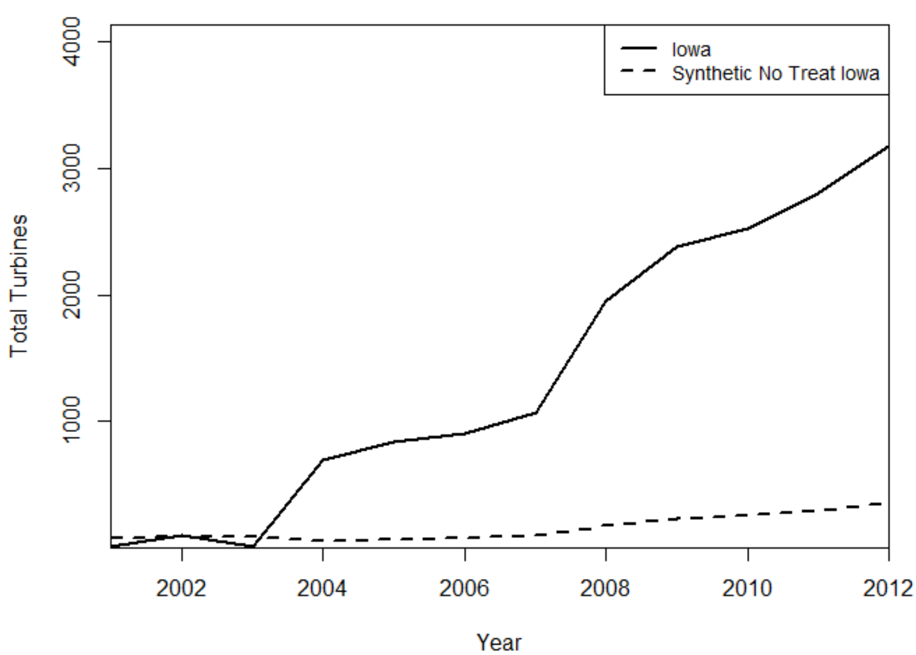

Figure 5

Graph showing the difference over time in wind turbine population between Iowa and a synthetic Iowa composed of Plains states.

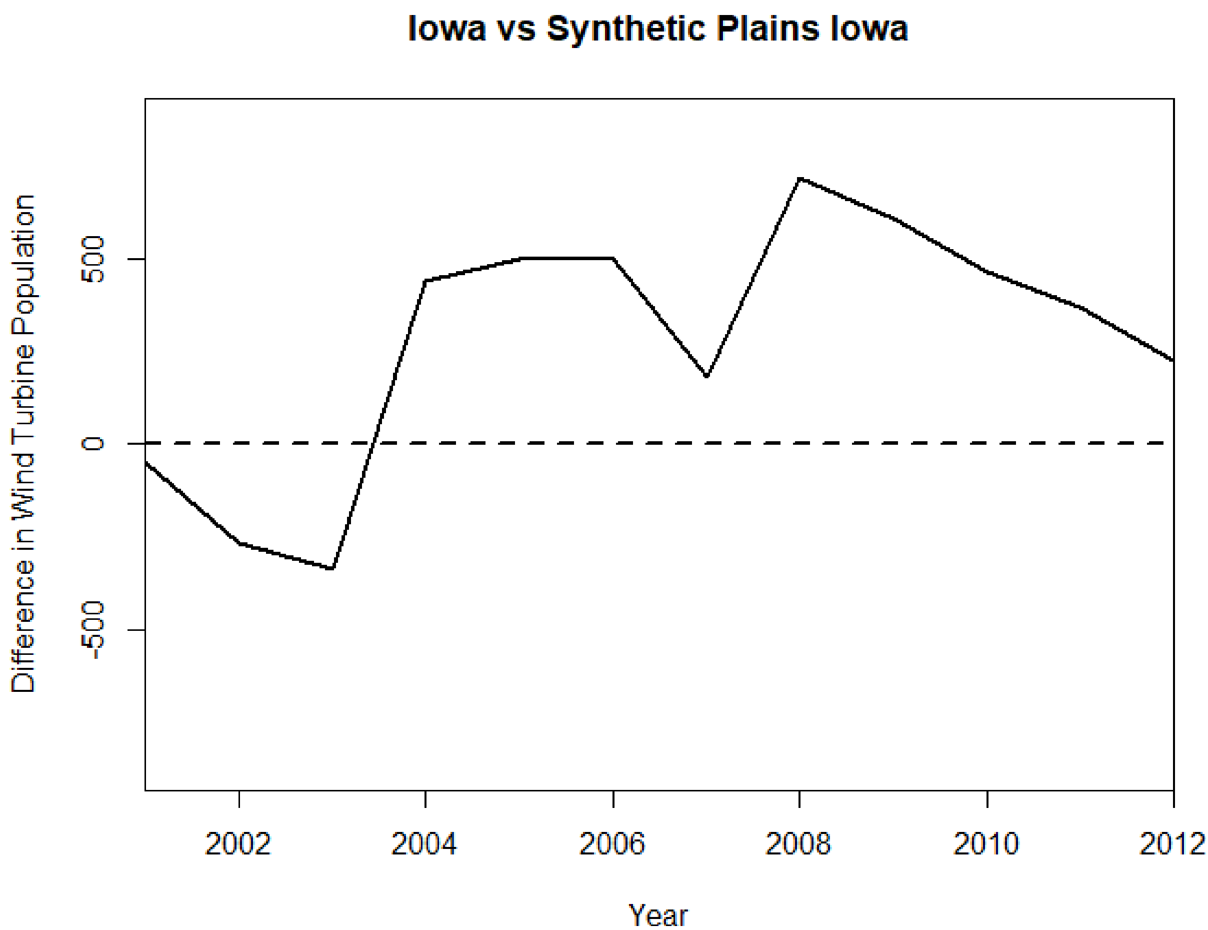

Table 1

Table containing summary statistics all variables used in the difference in differences regression.

	tot_turbines	Price	Burden Rate	Time Dummy	State Dummy	DiD
Min	0	16.37	0.049	0	0	0
1Q	0	23.47	0.09	0	0	0
Median	11	27.43	0.097	1	0	0
Mean	495.5	30.5	0.09594	0.6667	0.02	0.01333
3Q	250.5	34.65	0.10325	1	0	0
Max	12837	109.45	0.13	1	1	1
Observations: 600						

Table 2

OLS difference-in-differences regression output, with the states of Iowa and Kansas being used.

This restricts the sample to 24 observations, giving 18 degrees of freedom.

Terms	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	-6820.71	4897.667	-1.39265	0.1806921
Time	-271.561	352.5537	-0.77027	0.4511334
State	-234.772	388.9683	-0.60358	0.5536559
DiD	1308.893	402.8842	3.248807	0.0044571**
Price	180.2429	43.56745	4.137099	0.000619***
Burden Rate	28850.63	47766.07	0.603998	0.5533817
Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 Residual Standard error: 460.6 on 18 degrees of freedom Multiple R-Squared: 0.8223, Adjusted R-Squared: 0.773 F-Statistic: 16.66 on 5 and 18 DF, p-value: 3.35e-06				

Table 3

Table containing the weights each state received in the synthetic control solution for the Plains states grouping.

W^* **weights**	**State Abbreviation**	**State**
0.846	MN	Minnesota
0.001	IL	Illinois
0.001	SD	South Dakota
0.001	ND	North Dakota
0.001	KS	Kansas
0.001	MO	Missouri
0.001	NE	Nebraska
0.001	OK	Oklahoma
0.147	TX	Texas

Table 4

Table containing the weights each state received in the synthetic control solution for the group of states with no competing wind energy policy incentive.

W^* **weights**	**State Abbreviation**	**State**
0.027	AK	Alaska
0.034	AL	Alabama
0.027	CO	Colorado
0.028	DE	Delaware
0.027	FL	Florida
0.026	GA	Georgia
0.027	IN	Indiana
0.023	KS	Kansas
0.022	KY	Kentucky
0.027	LA	Louisiana
0.027	MS	Mississippi
0.025	MO	Missouri
0.026	MT	Montana
0.021	NE	Nebraska
0.029	NV	Nevada
0.032	NH	New Hampshire
0.027	NM	New Mexico

0.023	NC	North Carolina
0.027	SC	South Carolina
0.029	TN	Tennessee
0.018	UT	Utah
0.085	VT	Vermont
0.023	VA	Virginia
0.026	WA	Washington
0.286	WI	Wisconsin
0.029	WY	Wyoming

Table 5

Table giving the year-to-year difference between Iowa and the Synthetic Plains Iowa

2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
498.1831	495.9664	180.3062	714.2509	605.6500	465.3340	368.2212	224.4884