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"New Economic School"

Wind energy and life satisfaction: Evidence from the UK

Bachelor of Arts in Economics

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Abstract

Wind energy is important for empowering the diversification of energy sources in the country. However, the recent literature suggests that onshore wind energy has a negative effect on the life satisfaction of the neighboring population. The purpose of this paper is to test the causal relationship between the installation of wind turbines and life satisfaction on the county level in the UK. The analysis of data from 2011 to 2018 suggests that new wind farms are associated with 0.37 and 0.67 percentage point decrease in life satisfaction on the second and third year after the installation respectively. Quantifying life satisfaction externalities is useful to measure the indirect costs of onshore wind grid expansion.

Contents

1 Introduction

Energy security is an issue in the United Kingdom. The government is concerned with the question of how to provide energy stability for the country in times of political and economic uncertainty[1].

The UK net import of energy is growing since 2004 and now runs up to 67 Mega tonnes of oil equivalent (Figure 1). The country is dependent on the import of energy. 36% of UK energy needs are covered with net import[2]. To cut out imports without increasing CO2 emissions the UK government chose to increase the additional capacity of renewable energy [3]. It is an ambitious goal as the total supply of energy is heavily dominated by two sources natural gas and oil (Figure 2).

Part of the transition strategy is to increase the amount of wind energy production. In the last 10 years, the generation of wind power rose significantly (Figure 3). However, the number of anecdotal evidence that onshore wind farms entail negative externalities on people living nearby is also rose. Usual complaints are that wind turbines change the appearance of the neighborhood and are noisy Gibbons (2015). Therefore, the government should be careful with expanding the network of onshore turbines taking into account the externalities.

In my research, following the approach of (Krekel & Zerrahn, 2017) and (Moellendorff & Welsch, 2015), I try to measure the effect of the installation of onshore wind turbines on happiness at a county level in the UK. As a proxy for personal utility, I choose life satisfaction (SWB). SWB approach is a good proxy for measuring utility (Benjamin *et al.,* 2012). I found that life satisfaction decreases by 0.037 (0.37%) in the second and by 0.067 (0.67%) in the third year after the installation of wind turbines in the county. Results imply that onshore wind energy in the UK might have externalities that occur in the second and third year after the installation. The calculations of a decrease of 0.37 on 10 point scale suggest it is monetary equiva-

[1] `https://www.gov.uk/government/speeches/the-energy-security-challenge`
[2] `https://commonslibrary.parliament.uk/research-briefings/sn04046/`
[3] `https://www.gov.uk/government/publications/the-uk-renewable-energy-strategy`

lent to 70 pounds on average for every citizen of the county affected. The monetary estimation is based on comparison to job loss (Moellendorff & Welsch, 2015).

My identification strategy is to use near-random variation in the installation year of first wind farms in the county. I use difference regression with lead and lags to measure the effect. My identification assumption is that the treatment in these counties is exogenous. The installation year does depend on the application year, but there is a lot variability that could not be explained by the county (such as GDP and population density) and farm characteristics (wind farm capacity).

I show that onshore wind externalities in the UK are similar to the decrease in life satisfaction in Germany that is explored in the works by Krekel & Zerrahn (2017) and Moellendorff & Welsch (2015). This thesis offers evidence of the external validity of the effect that was quantified in Germany.

My thesis is useful for the UK government to take into account the indirect costs of the onshore wind energy grid expansion and for the future planning of renewable energy mix. Externalities make onshore wind more expensive.

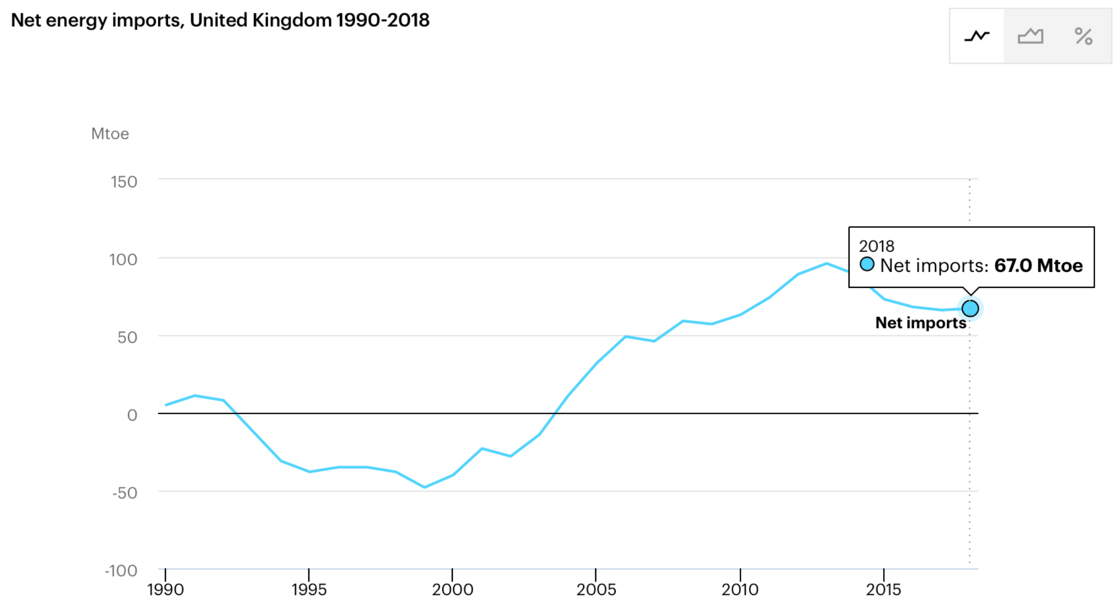

Figure 1: Net Import in the UK[4]

[4]https://www.iea.org/data-and-statistics?country=UK

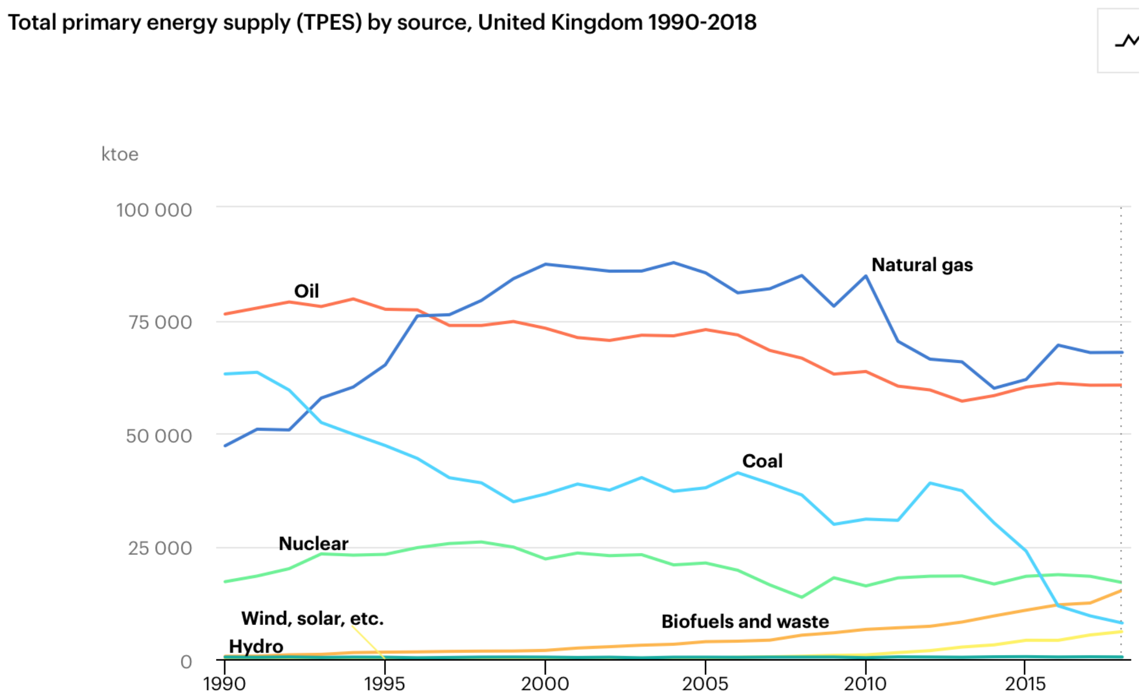

Figure 2: Gas, Oil, Nuclear, Biofuel, Coal, Wind and Other renewables

2 Literature Review

The most comprehensive meta-analysis of wind turbine externalities was done by Zerrahn (2017). In the report, it is stated that the installation of a wind turbine entails externalities such as a change in landscape aesthetics and noise. There are two ways to measure the externalities using stated-preferences (to use surveys) or revealed preferences (change in house prices or well-being). Both approaches are used frequently.

The stated-preference approach is used in paper by Ek (2005). They use a postal survey to understand the attitude of Swedes to wind energy. She founds that it is perceived positively. Support decreases with age and income. The paper by DSouza & Yiridoe (2014) studies the social acceptance of renewable energy using surveys in Australia. They argue that people need to be more informed, as a negative attitude is correlated most strongly with concern about wind turbines, not with annoyance.

The stated well-being (SWB) approach hinges on the idea that life satisfaction is a good proxy for utility. The evidence is provided in the paper by Benjamin

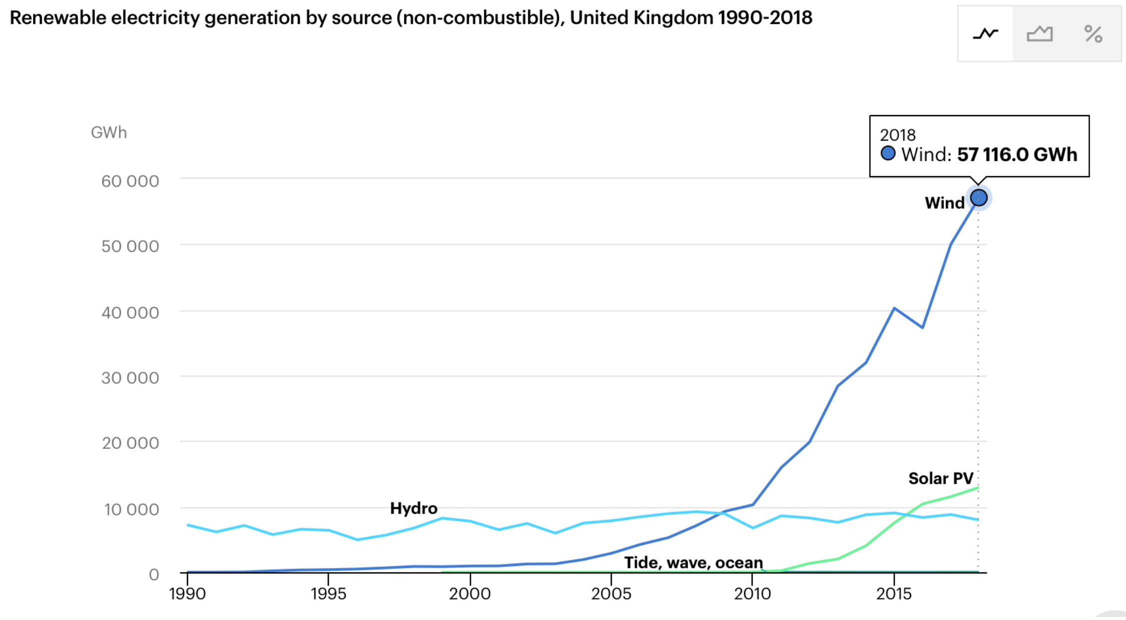

Figure 3: Electricity supply by source

et al. (2012). Using several samples from the U.S. they show that generally "people choose what they think would maximize their subjective well-being". Similar research in South Africa mainly supports the external validity of using SWB as a proxy for utility (Szabó & Ujhelyi, 2017).

Several papers use the SWB approach to estimate the change in utility of people to estimate the effect of wind turbine installations on the utility of a local population. Both papers use German data and report a decrease in life satisfaction due to wind turbine installation in a neighborhood. Moellendorff & Welsch (2015) use representative life satisfaction data for the period 1994-2012 and 46,678 citizens. They found that "the presence of wind energy plants in one's postcode area is associated with a reduction in 11-point life satisfaction by 0.033 points" this estimation is based on a regression on the presence of wind turbine. Installation of a wind turbine leads to effect comparable to 1/17 of losing a job (-0.52 points) or losing 168 Euros monthly. They also estimate the effect in time due to installation and found that the decrease in life satisfaction happens in the first year after installation (-0.1766 points), second (-0.1346 points), and third and after (-0.1604 points). The second paper is by Krekel & Zerrahn (2017). They use difference-in-differences with propensity score on life satisfaction data from 2000-2012. In their baseline specification installation of a wind turbine in a 4km radius leads to a decrease in life satisfaction by -0.1405 points. The effect in their paper is 5 times higher (due to different identification strategies) than in (Moellendorff & Welsch, 2015) and is comparable to 1/4 of losing a job.

Revealed preferences approach using house prices in the UK is explored by Gibbons (2015). The author focuses on visual impacts. He uses difference-in-differences design in treatment group neighborhoods with visible wind farms and in control with non-visible wind farms. He argues that the "price reduction is around 5-6% on average for housing with a visible wind farm within 2km, falling to under 2% between 2-4km". Similar research is conducted by Dröes & Koster (2016) for Netherlands. House prices within 2km of wind turbine decrease by 2 percent on average.

With my research I want to extend the SWB approach to the UK and to investigate the external validity of the results of Moellendorff & Welsch (2015) and Krekel & Zerrahn (2017).

3 Data

3.1 Dataset

To answer the research question I use UK data on life satisfaction, wind turbine installations, and locations. I also use county borders to match spatially every wind turbine to its corresponding county.

3.1.1 Life Satisfaction Data

I gathered the data on the UK life satisfaction for 8 consecutive years (from 2011 to 2018) for every local authority (county) from the UK government[5] (Table 1).

[5] Office for national statistics UK (April 2018 to March 2019 - Local authority update)

3.1.2 Wind Turbines Data

Onshore wind turbines data was gathered from the government website[6]. It has around 2000 observations of wind turbines (wind farms) and starts from the first onshore wind turbine installed in 1991 till 2019. The dataset contains the important dates for most of the wind farms, when the application was submitted when it was accepted when the farm became operational, and what is the current state of a wind farm. Then using Python and Geojson and Plotly[7] I plotted the distribution of wind farms across the UK(Figure 4). From 2000 wind farms 731 are operational (Figure 5).

3.2 Three groups

Using geopandas[8] and border data of counties[9], I spatially mapped wind turbines to the respective counties. Also I mapped GDP per capita[10], population density[11] to the data.

I divide UK counties into 3 groups. I aim to have a group of similar counties, to test how this set of counties is affected by the first installations of first wind farms installed. The countries with wind farms are expected to be completely different from counties with no wind farms. So I divide by the presence of a wind turbine in the county. Life satisfaction and population density could signal about the underlying differences between the counties. The analysis is restricted by the starting year of life satisfaction data. I divide counties with wind farms into two categories: counties where the first wind farm appeared before and after 2011 (Table 2). Counties before and after 2011 should not be different, however, there is no way to account for their

[6]Renewable Energy Planning Database quarterly extract

[7]`https://plotly.com`

[8]`https://geopandas.org`

[9]Local Authority Districts (December 2017) Full Extent Boundaries in United Kingdom (WGS84)

[10]Gross domestic product chained volume measures per head

[11]2011 Census: Usual resident population and population density, local authorities in the United Kingdom

differences in initial life satisfaction.

1. Counties that were never treated. They do not have any operational wind turbines. Some of these counties could have applied for wind turbines and some refused to have it, but these groups do not have or had any operating wind turbines.

2. Treated before 2011. These are the counties that had at least 1 wind turbine that was operational before 2011.

3. Treated from 2011. These are the counties that had at least 1 wind turbine operational starting in 2011.

3.3 Mapping data

Using Plotly and border data I plotted the 3 groups of counties on the map (Figure 6. From the map, we can see that the most treated counties are in the North. Starting from 2011 in the central part were treated heavily and we can see that some of the neighboring counties experience treatment while others do not.

Table 1: Descriptive Statistics: Life Satisfaction

	year	2011	2012	2013	2014	2015	2016	2017	2018
Life Satisfaction	mean	7.46	7.50	7.56	7.66	7.69	7.72	7.73	7.76
	std	0.22	0.21	0.22	0.21	0.21	0.20	0.20	0.21
	min	6.74	6.79	6.75	6.95	6.86	7.12	7.11	7.20
	max	8.16	8.12	8.34	8.39	8.39	8.45	8.59	8.45
	count	378.00	389.00	389.00	389.00	389.00	389.00	388.00	389.00

Table 2: Descriptive Statistics: 3 groups

	Category	Never Treated	Treated before 2011	Treatment from 2011
Life Satisfaction	min	7.10	7.32	7.39
	max	7.98	8.19	7.94
	mean	7.62	7.68	7.65
	std	0.15	0.17	0.13
	count	255.00	83.00	51.00
Population Density	min	0.20	0.10	0.50
	max	138.70	51.50	85.00
	mean	19.31	4.50	8.24
	std	25.44	8.13	14.10

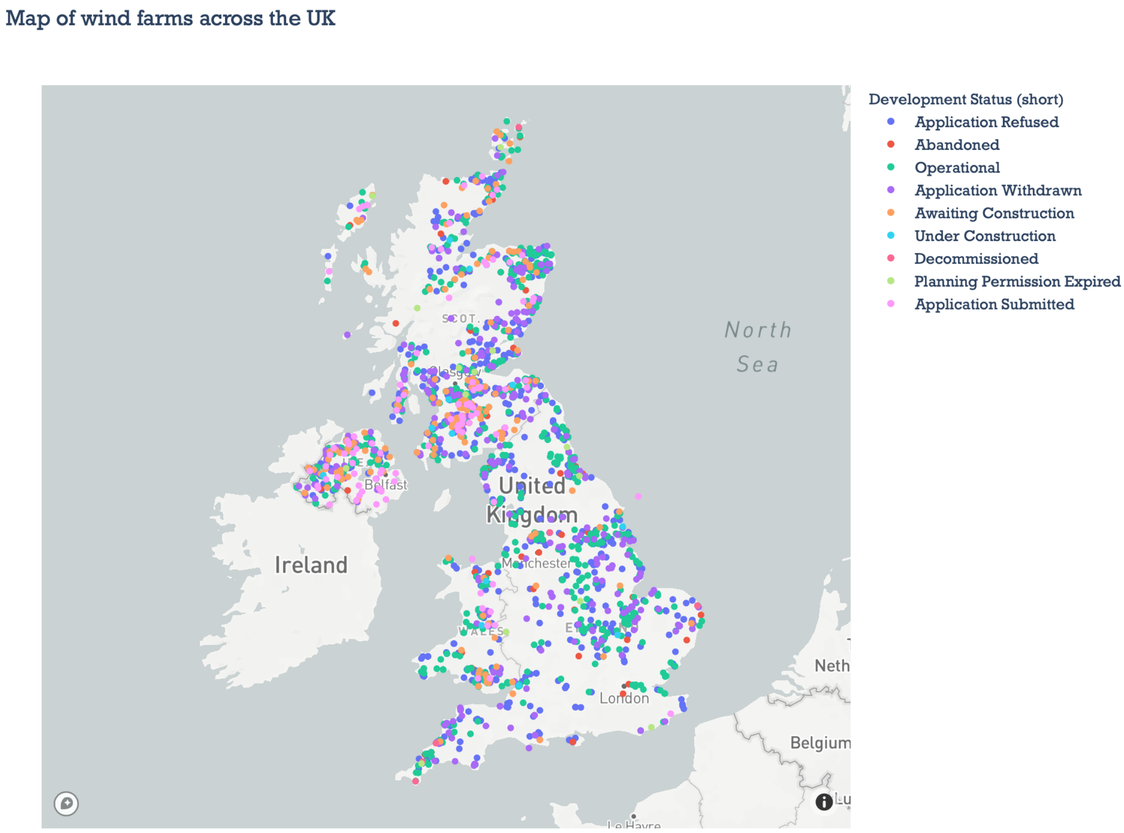

Figure 4: Distribution of all wind farms as of 2019

4 Identification Strategy

As pointed out in the data section, there are three types of counties

1. the counties where the wind turbines were never installed.

2. the counties where the first wind turbine was installed before 2011, i.e. before the period when the life satisfaction data on the county level is available.

3. the counties where the first wind turbine was installed in the interest sample period.

In an ideal experiment, if the counties were chosen randomly, we would only focus on the third group of counties and measure the effect. It is not a random process, however, I argue that there is some randomness in the exact year of installation.

The counties that have wind farms are not similar to those counties that do not have them. The counties that already have wind farms usually have a bigger area

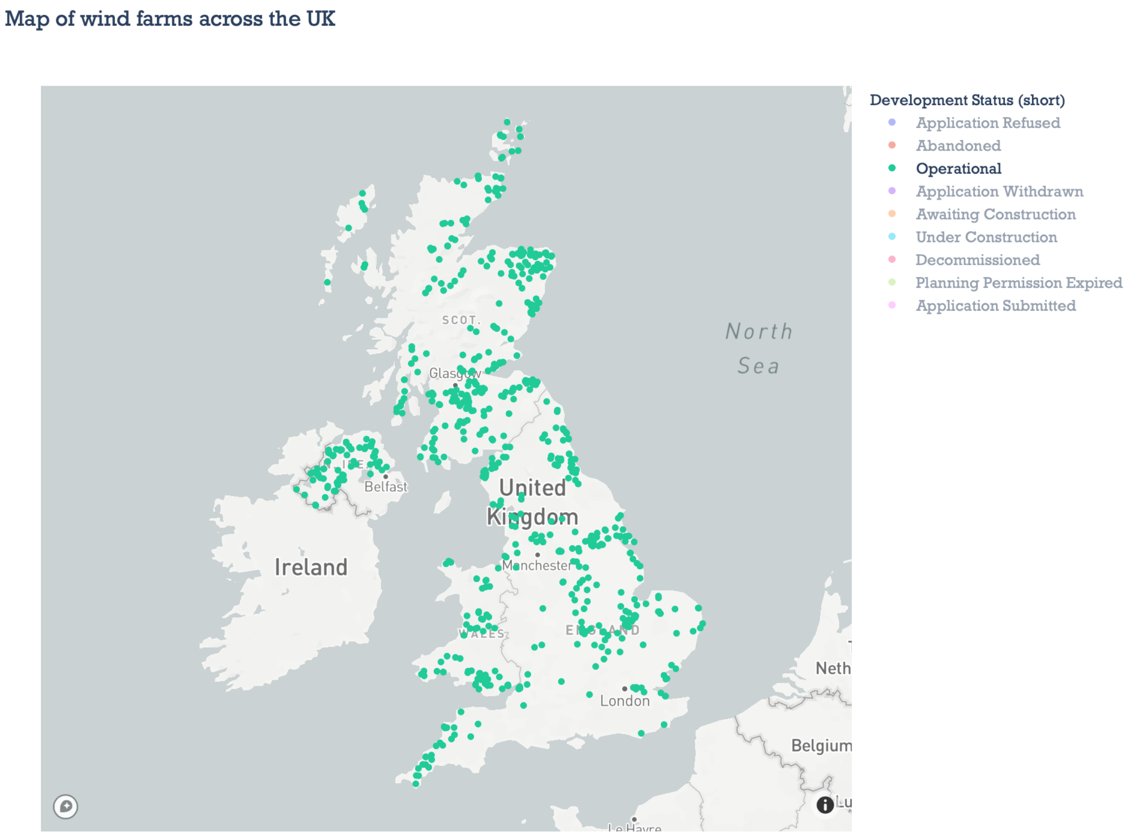

Figure 5: Distribution of operational wind farms as of 2019

and situated in the Northern part of the UK. This difference does not allow me to use the difference in differences approach. Treatment and control groups would differ from the start.

There are many steps and permissions involved before the company could install a wind farm. The company should choose some county and see the need for the new project there, several companies submit the applications to different locations, then the application could be accepted by the state or not, and it could be an iterative process, only after that, the company invests money in the project. It then takes time to install the wind farm and firms could easily have a lot of projects going on, so the firm will install the wind turbine when they will be able to.

Usually, the whole process from the application to installation takes 4 years to 10 years (Figure 7).

What I argue is that the year of installation is varying substantially and does

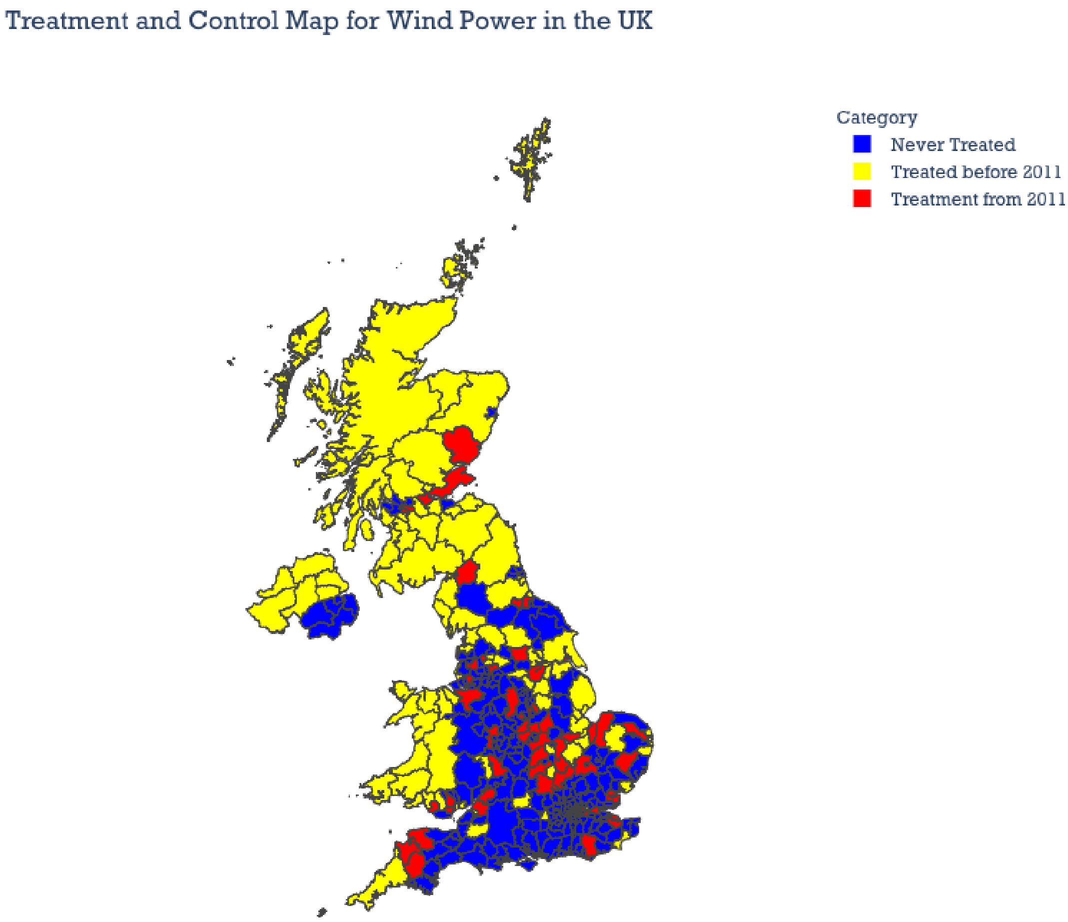

Figure 6: Map of 3 groups

not solely depend on the year of application. Even based on the characteristics of the region we cannot predict the year accurately. This will be my identifying assumption. It happens because there are usually several companies submitting applications in different years for the same county. The companies' objective is to allocate their investments in the best way possible, so they have many ongoing projects and different priorities.

As evidence for this identifying assumption, I look at the graph of the first application year for a wind turbine in a county and the first wind installation year for the county for the third group of counties, where every point is the county (Figure 8). I run OLS regression with the year of installation as LHS and the year of application[12] as RHS, and control variables population density, GDP per capita and the power of wind turbine installed (in MW)[13] (Table 3).

OLS shows that the coefficient on application submission is 0.32 and is significant, as expected, however, the coefficients on control variables are near zero. It means the control variables do not explain the year of installation at all. Only the submission date predicts it to a small extent. This OLS results support for identifying assumption.

I will use difference regression to test the hypothesis. Based on this evidence, we are close to the ideal experiment, it is appropriate to use difference regression with lags and leads. It will show the pre-trend and long-run effect of installation on life satisfaction (the change in life satisfaction one year before installation and up to 3 years after). The LHS is life satisfaction, the RHS is the dummy on the year when the turbine is installed in the county. The specification also includes county and year fixed effect and errors are clustered on county-level (Specification 1).

$$\text{Life Satisfaction}_{i,t} = \sum_{z=-1}^{3} \beta_z \text{Dummy treatment}_{i,t-z} + \alpha_i + \lambda_t + u_{i,t} \tag{1}$$

$\text{Life Satisfaction}_{i,t}$ is life satisfaction outcome on 10 point scale (10 is the totally happy and 1 is totally unhappy), where i is referring to county and t to year; $\text{Dummy treatment}_{i,t-z}$ is equal to 1 for the year t of first operating wind turbine in county i , and 0 otherwise; z is used to capture the time-varying effect; α_i is county fixed effect; λ_t is year fixed effect; $u_{i,t}$ is error term clustered on county level.

In regression, I will focus only on the third group of counties (which got their first wind turbine installed from 2011). There are 51 counties and thus 408 observations.

In 2015 the UK government issued a law[14] that gives a county council a right to

[12] 7 counties do not have data on the first turbine application

[13] extracted from the Wind Turbine data

[14] Report on Planning for onshore wind by Louise Smith (Number 04370, 13 July 2016)

prohibit the installation of a wind turbine. "The Conservative Party 2015 pledged to give local people a final say on wind farm applications on 18 June 2015." Due to this law, I should restrict the data to wind installation from 2011 to 2014, to exclude underestimation. As the law could prevent externalities.

We have the same specification (Specification 1), but with 32 counties instead of 51. The main drawback of the specification is the small number of observations that give larger confidence intervals.

(Table 4).

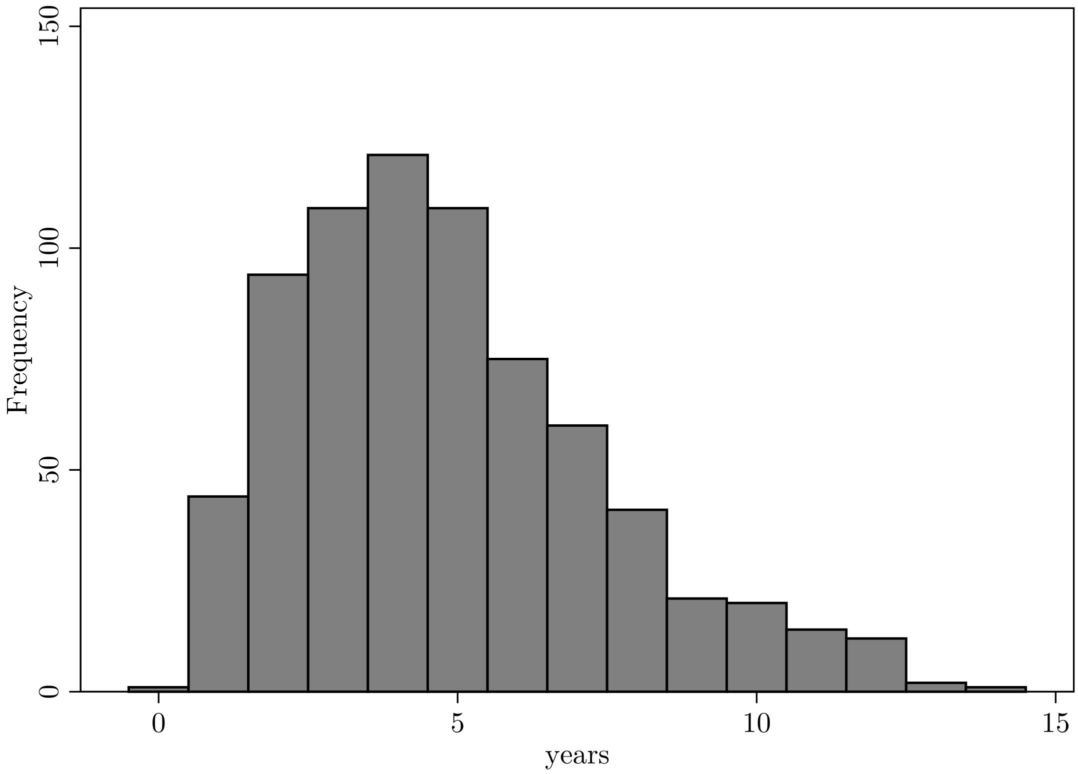

Figure 7: Distribution of the years from submitting application to becoming operational

5 Results

The coefficients of the baseline regression (Table 5 (1)) on dummy variables are negative for the second (+2) and third (+3) dummy variable. Coefficients are visualised

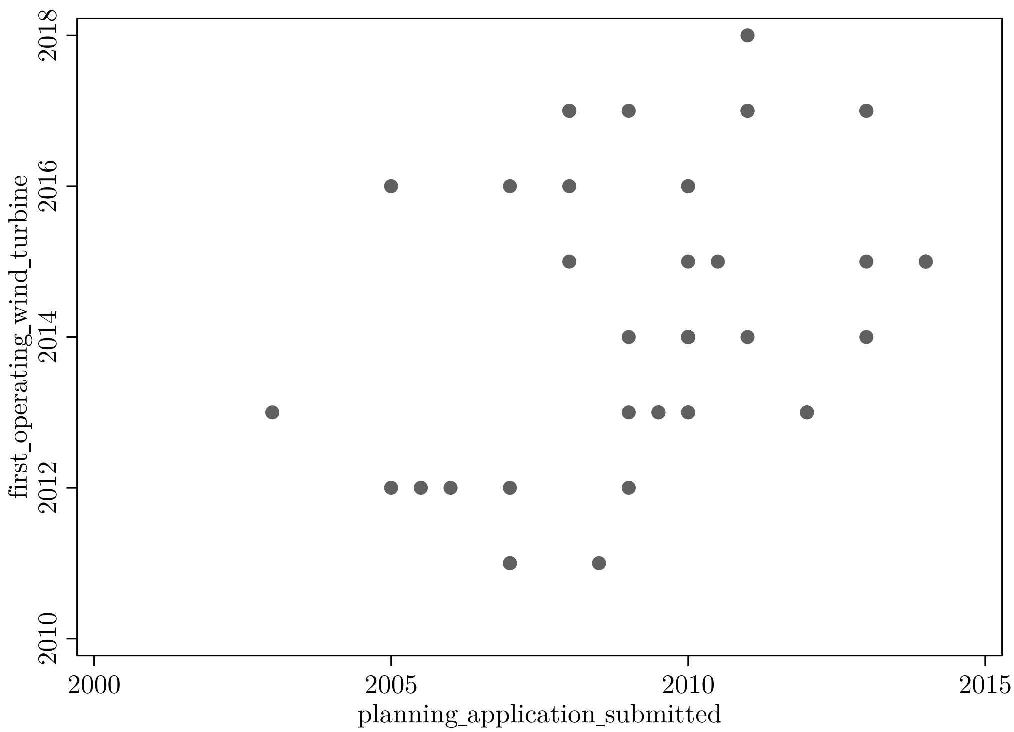

Figure 8: Scatter plot of first application and first installation in treated counties

on (Figure 9). These results suggest a negative effect of the installation of wind turbines on life satisfaction. The negative coefficient in the second year (-0.037) and the third year (-0.067). It means that two years after the installation life satisfaction decreases by 0.037 points (0.37%) in the second year and the third year by 0.067 points (0.67%). Also, there is no evidence of anticipation effect as (-1) is near zero, and in the year of installation, the coefficient is also near zero. All the results are not significant on common levels. It could be due to the small number of observations. The way to find out is to use different identification strategy based on propensity score as in Krekel & Zerrahn, 2017 or to obtain life satisfaction data on a neighborhood level.

To assess the magnitude of the coefficient we should take into account the standard deviation of life satisfaction across the UK, which is 0.2 points, so the effect of the second year is 1/5 and 1/3 on the third year of the standard deviation.

This resulting coefficients (Figure 9 (1)) are in borders of estimation of Krekel &

Table 3: OLS test of identifying assumption

	(1) Installation Year
Planning_Year	0.313**
	(0.117)
Turbine_Capacity	0.00125
	(0.0259)
Population_Density	-0.00439
	(0.0359)
GDP_per_capita	0.0000413
	(0.0000610)
N	44
R^2	0.161
Robust errors	yes

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Number of counties in treatment group by years

Year	Number
2011	5
2012	6
2013	10
2014	11
2015	6
2016	5
2017	7
2018	1
sum	51

Zerrahn, 2017 and Moellendorff & Welsch, 2015. The effect on the second year is similar to the main coefficient of Moellendorff & Welsch (2015).

In the restricted specification (2) there is no decrease in life satisfaction. It could be also due to the even smaller number of observations than in (1). We cannot say anything about the effect of policy to give the right to county councils to reject new wind farms.

Specifications (3) and (4) similar in behavior to (1). In (3) I run difference in differences estimates on all regions, essentially comparing treatment from 2011 to every other county in the UK In (4) I compare treatment from 2011 to the counties which were never treated. In the identification section, it was discussed that these regions could not be used as treatment and control due to the potential difference in counties that obtain wind farms and those counties that do not.

Following the approach of Moellendorff & Welsch, 2015 the monetary value could be inferred from the comparison of the coefficient to job loss. The closest paper to assess change in SWB due to losing the job is by Carr & Chung (2014). He provides the estimate of a decrease of 1.257 points in life satisfaction due to job insecurity[15]. The effect is equal to 3/100 of job loss, which is equivalent in monthly pay to £70[16].

My research extends the SWB approach to the UK for measuring wind externalities and also suggests the external validity of research of papers Krekel & Zerrahn, 2017 and Moellendorff & Welsch, 2015.

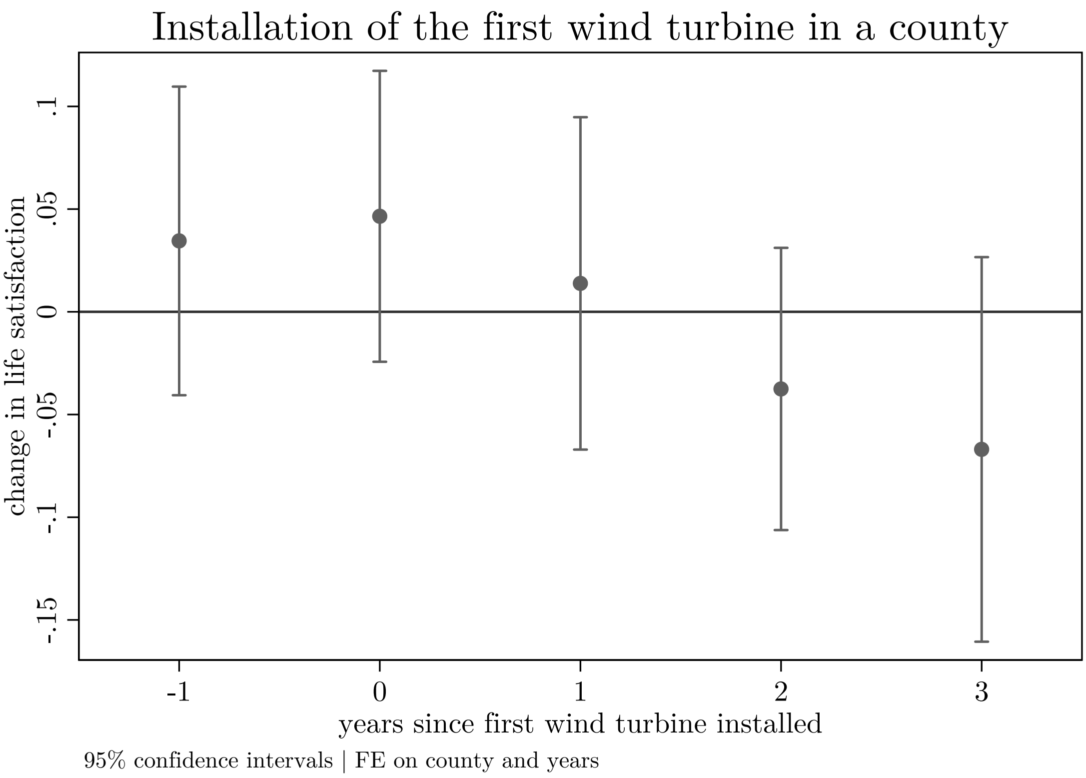

Figure 9: Change in life satisfaction in the baseline model

[15]it could be the upper bound, as the UK data has a standard deviation of 0.2, I think due to aggregation on a county level

[16]weekly pay is £585 `https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/2019`

Table 5: Main regression table

	(1) Life_Satisfaction	(2) Life_Satisfaction	(3) Life_Satisfaction	(4) Life_Satisfaction
-1	0.0345	0.194	0.0336	0.0353
	(0.0374)	(0.192)	(0.0386)	(0.0387)
0	0.0465	0.185	0.0466	0.0486
	(0.0353)	(0.134)	(0.0355)	(0.0355)
+1	0.0138	0.122	0.0162	0.0176
	(0.0403)	(0.0957)	(0.0439)	(0.0437)
+2	-0.0375	0.0346	-0.0370	-0.0371
	(0.0342)	(0.0601)	(0.0322)	(0.0324)
+3	-0.0670		-0.0681	-0.0688
	(0.0466)		(0.0455)	(0.0457)
_cons	7.754***	7.420***	7.544***	7.538***
	(0.0227)	(0.140)	(0.00782)	(0.00895)
N	204	160	1555	1231
R^2	0.557	0.585	0.592	0.568
County FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Clustered errors	yes	yes	yes	yes

Standard errors in parentheses. Errors are clustered on a county level
Life Satisfaction outcome on 10 point scale (10 is the totally happy and 1 is totally unhappy)
Dummy (0) for the treatment year with lead (-1) pre-trend and lags (+1,+2,+3) to show lagged effect
All specifications are reported with two-way fixed effect on county and years
* $p < .10$, ** $p < .05$, *** $p < .01$

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