Difference-in-Difference Study for GGRF

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1 Introduction

This paper documents my difference-in-difference (*DiD*) analyses for the GGRF insurance project, in which I attempt to quantify the impact of a green energy project on a neighborhood's home appreciation rates. I present a mixed-effects model in the main part of this paper. In the appendix, I present another model, which uses a more conventional two-way fixed-effect DiD schema.

2 Brief Background

If green energy projects (eg solar farms and wind turbines) are built near residential areas, these projects could impact local home values. If these home near green energy projects either appreciate slower, or depreciate faster, than other homes which are not near green energy projects, then home-owners are incentivized to resist green projects in their neighborhoods, even if they support green projects in general.

We want to quantify the rate in which which homes appreciate near green energy projects and compare it to baseline home appreciation rates, so that we can help to develop a new kind of financial project; a parametric risk insurance payout for home-owners near green energy projects. The idea is that, for a limited amount of time, while the green energy projects might artificially depress local homes' values, any home-owner that sells their house could be compensated for this drop in home-value.

3 Data

Naturally, there are a few dimensions we'd like to better understand– do all green energy projects lower the rates at which homes appreciate? how close does a house need to be to a green energy project before its value is impacted? and how long does this change in home value endure? This is a rather 'cheap-and-cheerful' analysis using readily-available datasets, so I'll attempt to answer these, while making sensible assumptions where necessary.

In this paper, I'll refer to homes that are near green energy projects as **manipulation** homes, and homes that are not near green energy projects as **control** homes.

I use three key datasets:

3.1 Zillow Home Prices

This dataset lists the home prices for 26,344 zip-codes, between the years 2000 and 2024. This was collected before I jumped on the GGRF project so I can't give much more insight into it.

3.2 Large-Scale Solar Photovoltaic Sites

The solar dataset[1] lists the locations and years of operation of thousands of large-scale solar photovoltaic sites. Note that Ben Hoen is an author of both this dataset and the turbine dataset.

3.3 Wind Turbines

This dataset[2] lists the locations and years of operation of thousands of wind turbines.

3.4 Data Notes

Each observation in the solar and turbine datasets is represented as a polygon, with latitude and longitude. However, the Zillow file commits us to using zip-codes as our finest geographic granularity. Consequently, I assign each solar and turbine project to a single zip-code. Any homes that share a zip-code with a green project are considered manipulations. (This assumption is a little clumsy; we'd like to know how the distance between a house and a green energy project impacts the rate of change of house values, and here we're rounding distance to 'close' or 'far'; and worse yet, some zip-codes are rather large, and some quite small. Let's just note that in further studies we'd like to study this in finer granularity.)

I also round all dates to the year. If there are multiple home values noted in a given zip-code within this year, I take the median home price.

4 Mixed-Effects Model

The formula for our mixed-effects model looks like this:

[1]Fujita, K.S., Ancona, Z.H., Kramer, L.A. et al. Georectified polygon database of ground-mounted large-scale solar photovoltaic sites in the United States. Sci Data 10, 760 (2023). https://doi.org/10.1038/s41597-023-02644-8

[2]Rand, J.T., Kramer, L.A., Garrity, C.P. et al. A continuously updated, geospatially rectified database of utility-scale wind turbines in the United States. Sci Data 7, 15 (2020). https://doi.org/10.1038/s41597-020-0353-6

```
rate of home appreciation ~

year + solar_manipulation + turbine_manipulation + (1|zip_code)
```

Dependent variable

- The rate of home appreciation is calculated as: *(current home price - last year's home price) / (last year's home price).*

Fixed effects

- Year: the calendar year, represented as an unordered factor. This allows us to represent general market fluctuations (eg the Great Recession) easily.
- Solar manipulation: if a zip code has a solar plant built there before 2024 (the end of our Zillow dataset), we encode the zip-code each year as one of the following:
  - Construction: if only one solar plant is built in this zip-code, then 'construction' is synonymous with 'year of operation'. If multiple solar plants are built in this zip-code, this represents the duration between the first plant's year of operation and the last plant's year of operation. 'Construction' indicates that we have faith that during this time period, workers and trucks were around.
  - -5:-1: Years prior to year of first plant's operation
  - 1:5: Likewise, years after last plant's operation
  - Censored: Any year either more than five years before construction, or more than five years after construction
  - Control: a zip-code that never gets a solar project
- Turbine manipulation: encoded exactly like solar manipulation

Random effects

- Zip-code: here, I model all zip-codes as random intercepts. This is common practice in models that have repeated measures per subject; this compensates for the mean difference in home appreciation in each zip-code

4.1 Goodness-of-Fit Metrics

In order to verify whether it's even sensible to try to calculate the impact of green energy projects, we also fit a null model, which omits turbine manipulation and solar manipulation. This means that the null model's formula is:

```
rate of home appreciation ~ year + (1|zip_code)
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```
Data: JoinedData
Models:
mod0: home_price_change ~ year + (1 | zip_code)
mod1: home_price_change ~ year + solar_manipulation + turbine_manipulation + (1 | zip_code)
     npar      AIC      BIC logLik deviance  Chisq Df Pr(>Chisq)
mod0   26 -1361360 -1361072 680706 -1361412
mod1   49 -1361440 -1360898 680769 -1361538 126.26 23  3.069e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 1: The full regression model is statistically significant, compared to the null model which omits green energy projects. This indicates that the impact of green energy projects is statistically significant.

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An ANOVA comparing these two models indicates that the full model is statistically significant (see figure 1). This indicates that it the turbine and solar manipulations are statistically significant.

The unadjusted intra-class correlation (ICC) is 0.011, which is quite low. A high ICC would indicate that a lot of the variance that is explained in the full model is done by the random-effects. Rather, our fixed effects are explaining a lot of the variance. This is auspicious for us, because the effects we're trying to model are all fixed-effects.

4.2 Estimates

The fixed effects can be visualized in figure 2 and figure 3, but they are listed below in their entirety. Note that any variable whose 95% CI includes 0.0 can plausibly be said to be negligible.

Do note that while this model gives quite sensible estimates, we suffer from a relatively low sample size for a model of this complexity. We have 412,303 observations in our control group, and only 58,839 in our manipulation group. For this reason, this model was slightly rank-deficient. (One notable missing value is turbine manipulation for the year just before operation.)

Figure 2 shows the estimated coefficients for overall home appreciation for each calendar year. Figure 3 shows the estimated coefficients for the impact of our manipulations. Bearing in mind that *these fixed-effects don't reflect home prices per se, but rather, the rates at which home-prices change* given different situations, I interpret these in the following way:

- We can posit that any fixed-effect whose 95% confidence interval includes zero does not significantly differ from no effect at all. Consequently, we can't really glean too much from most of the trends that we see in the solar and turbine diagram (diagram 3), because their CIs generally contain zero. On the other hand, our dataset is kind of small for this kind of model, and highly imbalanced. We can see evidence of how imbalanced the dataset is in the very slim 95% CIs in the yearly fixed-effects, when compared to the large ones in the manipulations; this might be because we have so

Variable	**Estimate**	**2.5%**	**97.5%**
(Intercept)	0.053	0.047	0.058
year2002	0.015	0.013	0.016
year2003	0.014	0.013	0.015
year2004	0.021	0.02	0.023
year2005	0.047	0.046	0.049
year2006	0.05	0.049	0.052
year2007	-0.013	-0.014	-0.012
year2008	-0.071	-0.072	-0.069
year2009	-0.131	-0.132	-0.13
year2010	-0.116	-0.117	-0.115
year2011	-0.09	-0.091	-0.089
year2012	-0.097	-0.098	-0.096
year2013	-0.029	-0.031	-0.028
year2014	0.005	0.004	0.006
year2015	-0.012	-0.013	-0.01
year2016	0.001	-0	0.002
year2017	-0.014	-0.016	-0.013
year2018	-0.003	-0.004	-0.002
year2019	-0.003	-0.004	-0.002
year2020	-0.006	-0.008	-0.005
year2021	0.055	0.054	0.057
year2022	0.082	0.081	0.083
year2023	0.015	0.014	0.016
year2024	-0.03	-0.031	-0.029
solar_manipulation-2	-0.001	-0.004	0.003
solar_manipulation-3	-0.001	-0.005	0.002
solar_manipulation-4	-0.002	-0.005	0.002
solar_manipulation-5	-0.003	-0.007	0.001
solar_manipulation1	0.004	0	0.007
solar_manipulation2	0.004	0	0.007
solar_manipulation3	0.006	0.003	0.01
solar_manipulation4	0.01	0.006	0.014
solar_manipulation5	0.009	0.005	0.013
solar_manipulationCensored	0.004	0.001	0.006
solar_manipulationConstruction	0.003	-0	0.006
solar_manipulationControl	0.006	0.001	0.011
turbine_manipulation-2	0	-0.006	0.007
turbine_manipulation-3	0	-0.006	0.007
turbine_manipulation-4	0.001	-0.006	0.007
turbine_manipulation-5	0.001	-0.006	0.008
turbine_manipulation1	-0.001	-0.007	0.004
turbine_manipulation2	-0.004	-0.01	0.002
turbine_manipulation3	-0	-0.006	0.006
turbine_manipulation4	0	-0.006	0.006
turbine_manipulation5	-0.003	-0.009	0.004
turbine_manipulationCensored	0.003	-0.002	0.008
turbine_manipulationConstruction	0.002	-0.003	0.007

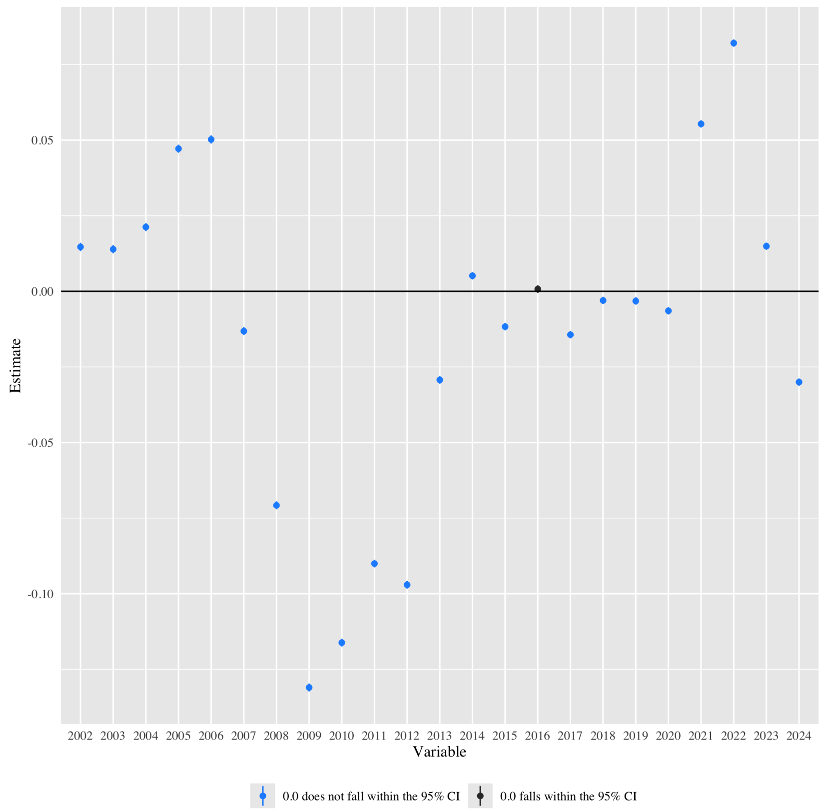

Figure 2: Some of the fixed effects from the second study.

many more observations in our control set than in our manipulation set. *I suggest we cautiously try to make sense of the manipulation estimates, while acknowledging that without a larger dataset, our conclusions are generally speculative.*

- The only estimates whose CIs don't include zero are the solar estimates, in the years after the construction is done, and in the periods before and after five years away from construction ('censored'). In a future study, I would like someone on our team to test the hypothesis that this rate of change that is positive vis-a-vis the baseline rate of change reflects the home-values in these areas quickly returning to what they would be if the solar plant had never been installed. That is to say, I don't hypothesize that areas with solar plants have higher property values than areas without; I just think that the rate of change is positive in order to regress us back to national mean home prices, once the construction is over. This would be because nobody wants to live near a construction project, but once

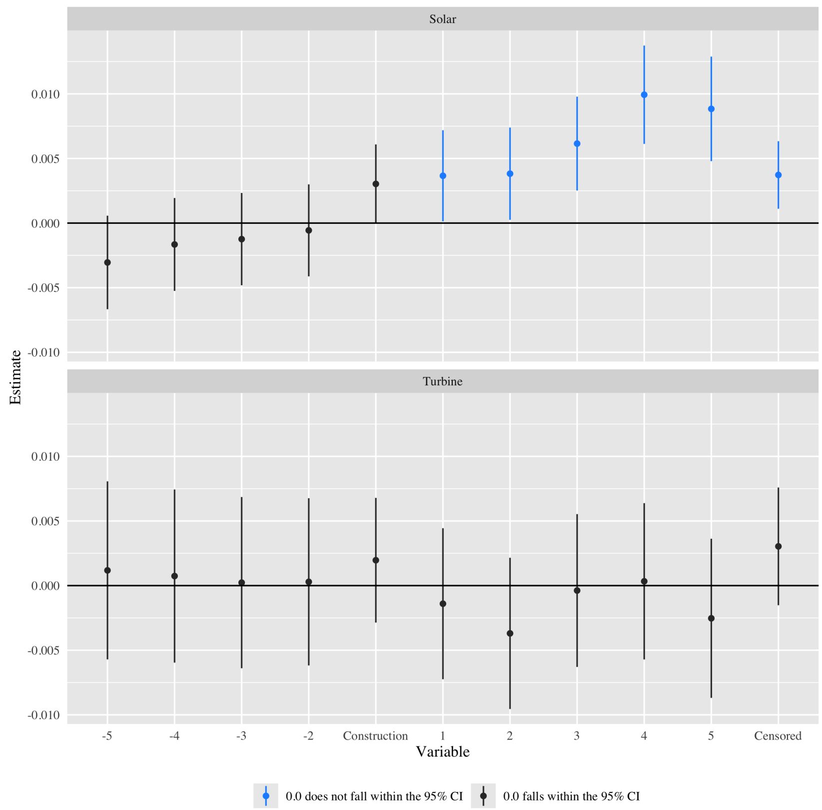

Figure 3: The rest of the fixed effects from the second study.

the trucks and power tools have stopped whirring and grinding, people decide that living next to a fully-operational solar plants isn't so bad after all. (The fact that the 'censored' value is positive could challenge this hypothesis. Positive censored estimates *after* construction jibes with my theory; positive censored values *before* construction challenge it. But in a model that is already rank-deficient, I can't really slice and dice our data much more to explore this.)

- Homes that are near construction sites appreciate in value slower than homes in control groups, which makes sense to me.

- I wonder if property values for zip-codes with turbines never fully rebound after construction is over, because unlike solar plants, turbines make a bit of noise and are highly visible.

5 Appendix

I think that the previous model is my best attempt to model this data. However, a classic Difference-in-Difference comparison isn't done with a mixed-effects model– it's done with a two-way fixed-effects model. So, in order to honor convention, I model that as well. I include it here in the appendix for your edification– so you can see its results, and also, why I take issue with this model.

This model simplifies the previous model by simply asking if the rate of home appreciation changes over time differently in neighborhoods that *do* have solar/turbines developed there versus in neighborhoods that *don't*:

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(past v present) x (manipulation v control)
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So, for any target year, I note all of the zip-codes where a single green energy project comes online in that target year. Once again, rate of home appreciation is defined as: *(current home price - last year's home price) / (last year's home price).* I track the rate of home appreciation in these manipulation zip-codes for 11 years– the year of operation, the five years before, and the five years after. I also track the rate of home appreciation in our control set, which is all of the zip-codes in our Zillow dataset that never gets a single green energy project built in it. If the median rates of change in our control group differ from the median rates of change in our manipulation group, then we have a DiD trend that we can study!

Nota bene:

- Zip-codes with more than one green energy project are excluded from this study– it's too complicated for a single model like this.
- Perhaps if we have eleven observations representing the passage of time, this isn't exactly a two-way fixed-effect model?

The results can be seen in figure 4.

You can see the results in figures 5 and 4, but I don't think there's many lessons to glean from these diagrams; These diagrams *can't account for general changes in the real estate market.* For example, we can see the market tanking in 2008, but this completely confounds our ability to compare these lines to those a decade later.

The other issue with this DiD study is, once again, a small sample size (see figure 6). The sample sizes for the manipulation groups pictured here are very small, only a fraction of the size of the control group. In addition to this problem, while the observations in the manipulation group change in each of the diagrams, the observations in the control group stay the same. This means that individual outliers in the control group might be skewing our results.

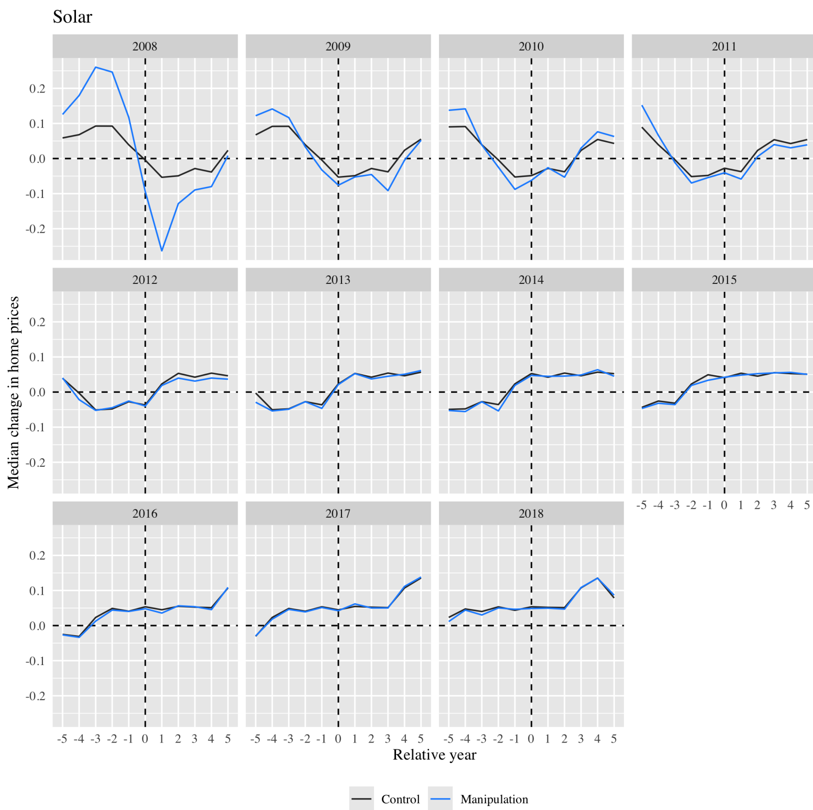

Figure 4: Median change in home prices in zip-codes that had solar panels installed

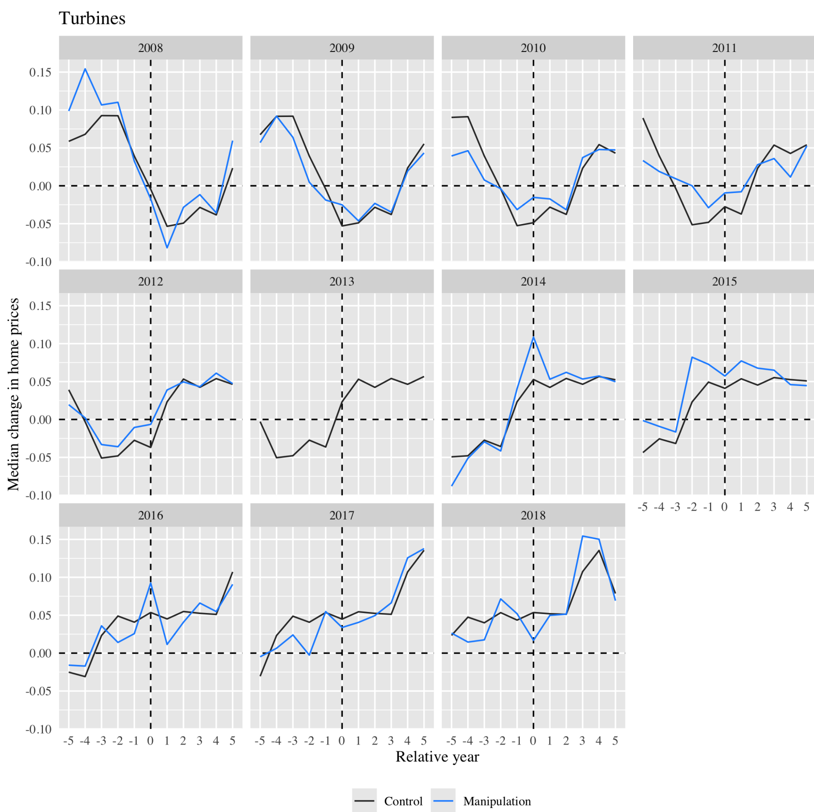

Figure 5: Median change in home prices in zip-codes that had wind turbines installed

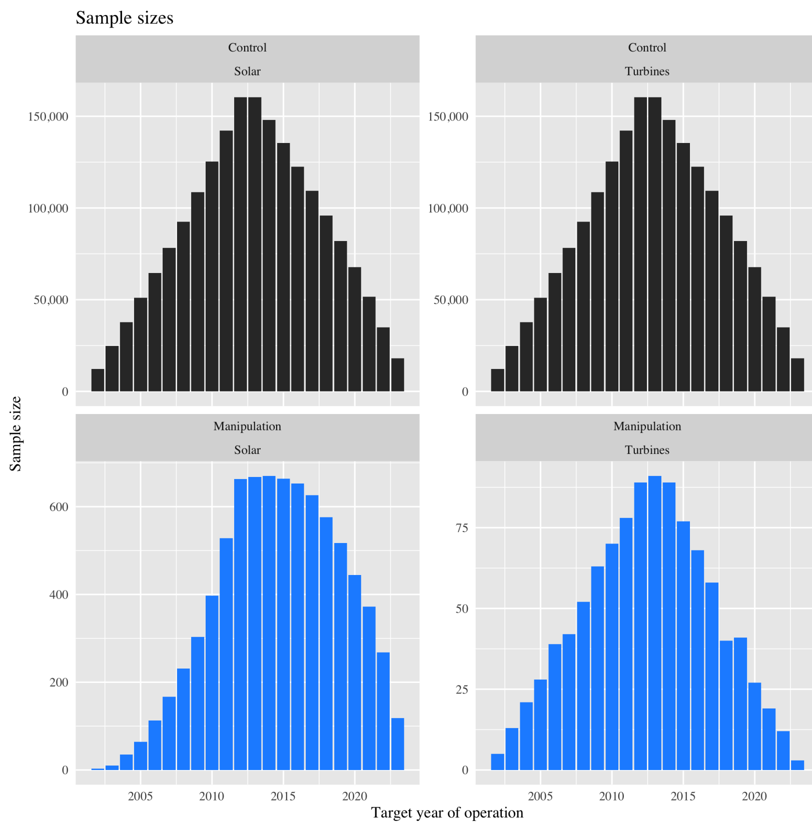

Figure 6: The manipulation groups in the DiD study were extremely small