Power outage study: Difference in differences study design and analysis

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Overview

Difference in differences (DiD) is a statistical technique to mimic experimental design using observational data by comparing differential effects of a treatment on a 'treatment' versus 'comparison' group, where the groups are selected in a natural experiment. To understand the treatment effect we compare the differences between the treatment and control groups at least once before treatment to establish a baseline difference, then again following treatment of one group to determine whether there is any additional change to the difference between groups.

In the context of the power outage study where we have county-specific power outage and health outcome data, we will compare the outcome of interest across pairs of counties. To conduct an analysis under a DiD design, we need (at least) four data points: 1) heath outcome measured in the power outage county prior to the outage, 2) the same health outcome measured in a comparison (non-power outage) county at the same time as (1), 3) heath outcome measured in the power outage county following the outage, and 4) the same health outcome measured in the comparison county at the same time as (3). The difference between (1) and (2) establishes a 'control', or the expected difference across groups under no treatment. Assuming a parallel trend of the outcome across pairs of comparable counties, the difference of the differences between (3) and (4), and (1) and (2) establishes the power outage effect on the health outcome.

Advantages to using a DiD approach is the ability to estimate changes in the outcome variable that occur over time. A carefully matched comparison group also allows for implicit control of confounding variables, even when unobserved. The method can fail or produce biased results when the assumption of parallel trends is broken (i.e. that the outcome for matched groups would change in parallel over time).

Basic DiD analysis

Consider a continuous outcome for observation in county i, y_{ist} where s indicates whether the county had a power outage ($s = 1$) or not ($s = 0$) and t indicates time period before ($t = 0$) or after ($t = 1$) the outage. Then the DiD method can be implemented by the model

$$\mathbb{E}(y_{ist}) = \beta_0 + \beta_1 t_i + \beta_2 s_i + \beta_3 (t_i \cdot s_i) + x_i' \gamma \tag{1}$$

where β_3 is the DiD estimate of interest after accounting for between group (β_2) and between time (β_1) differences, as well as the linear effects, γ, of other confounding variables, x_i. More specifically,

$$\begin{aligned}\beta_3 =& \{\mathbb{E}(y_{ist}|t = 1, s = 1) - \mathbb{E}(y_{ist}|t = 0, s = 1)\} \\ &- \{\mathbb{E}(y_{ist}|t = 1, s = 0) - \mathbb{E}(y_{ist}|t = 0, s = 0)\}.\end{aligned}$$

To apply this model to our study, we first assign dummy variables, s_i and t_i, indicating whether a county belongs to the power outage group and if the outcome was measured before or after the outage. Additional covariates, x_i, represent a range of possible confounders, for example demographic, socioeconomic, temporal, spatial, and meteorological confounders. We can estimate this model using any regression modeling package, with some extra care needed to produce robust standard errors for valid confidence intervals.

Determining comparison groups

Generally, DiD uses a matched pairs study design where every treatment group is matched with a similar comparison group that does not receive treatment. There are several methods going about this with advantages and disadvantages to each. Often the method is decided based on available data.

Matching using self-comparison

One method for choosing a comparison group is to measure the outcomes for the same group during a span of time where the treatment did not occur. It would be assumed that the outcome for the comparison group would have similar trends over time, and therefore using the same time period in an alternate year is one strategy. Alternatively, one could make comparisons during nearby weeks provided the treatment effect is short-lived. Advantages to using the same group at different time periods are that you have an exact match to control for confounding that would be identical year over year. However, if other factors influence the outcome at different time periods (e.g. temperature), these must be controlled for in the model with unmeasured confounders potentially biasing results.

Within the present power outage study, we could apply self-matching in a few ways. First, we could match each treatment county with itself using measurements from a year prior (making the assumption that no power outage took place at the same time that year). For comparative purposes we might want to use the same days of the week at the same week of the year (instead of the exact day of year) to account for weekday-weekend differences. Second, we implement a one-to-many matching strategy and match every county with multiple prior year's outcomes. Third, we could match at a reasonable length time period (e.g. one or two weeks) prior to the power outage if we assume other factors remain relatively constant within this frame of time.

Matching using propensity scoring

A common method for matching utilizes a propensity score approach. Specifically, we match two counties who have the same probability of a power outage on a given day (but only one was observed to occur). To calculate these probabilities or propensity scores, we model the power outage as the outcome (yes or no) on a given day using all covariates as predictors and then estimate each county's probability of power outage. In other words, we would match counties i and j where $t_i(d) = 1$ and $t_j(d) = 0$ (or vice-versa) is the observance of a power outage on a given day, d, if

$$\mathbb{P}\{T_i(d) = 1|x_i\} \approx \mathbb{P}\{T_j(d) = 1|x_j\} \tag{2}$$

where x_i and x_j are a set of confounding variables relating to the county of interest. Unlike the self-comparison method, we are not able to account for unmeasured confounding variables, however this method can produce a reasonable approach to selecting county pairs for DiD analysis.

To implement propensity score matching, we fit a logistic regression model (or similar method for binary outcome) with the outcome of whether a power outage occurred in a county on a given day and use all county-specific covariates as well as an indicator or smooth functions of time and space. We then predict the response for every county at every day. For each county with a power outage on day d, we match with a county having a similar probability of power outage (but no observance) on that day. We would also need to consider that the no power outage county in each pair does not have a power outage within the reference frame of time used for DiD analysis (i.e. no power outage near the outcome measurement before and after a power outage in the treatment county).

Distributed lag analysis of DiD effects

By considering effects over multiple time periods before and after the time of treatment as well as multiple sequential treatments, we can accommodate a distributed lag-type analysis of treatment effects. Consider measurements y_{it} where counties, i, are matched pairs of treatment and control groups each with health outcomes measured beginning at time $\underline{t}_i$ and ending at time $\overline{t}_i$ (the beginning and ending times may differ across each matched pair). At each time point measurement, we consider a history and forecast of power outages extending $\underline{v}$ periods behind and $\overline{v}$ periods ahead of the health outcome measurement. This results in $J = \underline{v} + \overline{v} + 1$ total periods of power outage indicators in our distributed lag analysis. By considering treatments in the future we establish the baseline differences and can test parallel trend assumptions. The DiD distributed lag model is parameterized as

$$\mathbb{E}(y_{it}) = \mu_t + \theta_i + \sum_{j=0}^{J} b_{i(t+\overline{v}-j)}\beta_{j-\overline{v}} + x_i'\gamma \tag{3}$$

where $\beta_{j-\overline{v}}$ are the distributed lag effects of power outage indicator b at time $t + \overline{v} - j$, μ_t is a fixed effect of time (often modeled smoothly), θ_i is a county-specific intercept to control for the repeated measurements taken at each county (this takes the place of the power outage difference coefficient β_2 in the previous model) and γ is linear coefficients for effects of county-specific covariates, x_i. By testing whether all $\beta_m = 0$ for $m < 0$ we establish the parallel trends assumption. The coefficients β_m, $m \geq 0$ can be interpreted as the immediate ($m = 0$) and lagged effects of treatment b at m periods prior to the outcome. This method can also be used when b is a continuous measurement of outage (e.g. percent of population affected) or lasts for multiple days. Finally, we can assume non-linear effects of power outages by replacing $b_{i(t+\overline{v}-j)}\beta_{j-\overline{v}}$ with $w(b_{i(t+\overline{v}-j)}, j - \overline{v})$ where w is a function of continuous power outage and time.