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# Power and Party Networks: Donor Influence after *Citizens United*

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# 1 Motivation

## 1.1 Political party donor networks and *Citizens United*

Since their introduction to U.S. politics in the 1940s, Political action committees (PACs)—tax-exempt organizations that funnel campaign contributions to campaigns, referenda, or legislation—have had a $2,500 cap on individual contributions, which could come from, e.g., individuals, corporations, or unions. In the landmark decision of January 2010, *Citizens United v. Federal Election Commission*, the U.S. Supreme Court argued that because financial donations are essential to free speech, setting limits on campaign contributions violates the First Amendment. The decision removed the $2,500 donor limit and effectively introduced into the networks of the American party system an organizational entity—the Super PAC—that can amass unlimited dollar amounts in order to influence political decision-making and legislative agenda-setting in both the Republican and Democratic parties.

Supporters of the 2010 SCOTUS decision regard it as a triumph over the regulation of political speech. Critics argue that the decision permits wealthy donors to have immense political influence. As increases in income are associated with Republican support, detractors also argue that it benefits the wealthiest few in society. What has been the effect of the 2010 *Citizens United* decision and Super PACs on the evolution political donor networks? Which of the two major political parties has seen a growth or decline in the influence of their donor groups within these networks?

Nice summary of the context

## 1.2 Literature and hypotheses

A growing social science literature views the American party system as coalition networks consisting of governmental and nongovernmental groups. In these studies, authors use social network analysis to reveal the often covert relationships that exist between election campaigns and interest groups or donors (Grossmann and Dominguez 2009; Koger, Masket, and Noel 2009). Such analyses of extended political party networks, however, tend to be aimed at the identification of positions in whole structures, geographic location, sharing clusters, or information flows (Gimpel, Lee, and Kaminski 2006; Koger, Masket, and Noel 2009, 2010), as well as how such structures and processes influence election outcomes (Desmarais, La Raja, and Kowal 2015).

not clear what this means

Exploratory designs are valuable for hypothesis generation yet constrained in making inferences. In more recent years, researchers of social and political networks have been increasingly attentive to causal inference methods (Fowler et al. 2011; Lazer 2011; Park and Rethemeyer 2014; VanderWeele and An 2013). In this study, we use two causal inference methods, regression discontinuity (RDD) and difference-in-difference (DiD) design, to estimate measure the effects of the 2010 *Citizens United* decision on the influence of political donor groups within state campaign networks. Eigenvector centrality, a network measure of influence, is our outcome variable. Therefore,

> *H1. After 2010, the average influence in the network—measured as eigenvector centrality—will increase for all campaign donor groups.*

> *H2. After 2010, the influence in the network—measured as eigenvector centrality—will increase more for campaign donor groups that contribute to Republican campaigns than for campaign donor groups that contribute to Democratic campaigns.*

We base these hypotheses on (1) the fact that the *Citizens United* decision removed the $2,500 individual donor limit and (2) previous research that shows the Republican Party receives more corporate donations and on average substantially higher dollar amounts from individual donor groups (Brunell 2005:685–87).

## 2 Data

We use candidate donation data from the National Institute on Money in Politics (NIMP). For each election, the data include the total amount donated from an organization to a candidate. NIMP researchers standardize donor names and code economic interest/industry based on occupation information contained in disclosure reports.

Data description a bit confusing for those not embedded in this literature. It becomes clear later that the donors are the units but that's not obvious here. Also is there one network per state per year?

From these data, Reuning (2020) generated a network that consists of state party networks for 47 states from 2000 to 2016. The edge lists contain donor node IDs and their edge weights for all House and Senate elections. Edge weights identify edges at different thresholds of connectedness. Shared donations between groups constitute an edge, and edges are weighted both by how many donations they share and how much they donate (Reuning 2020:274). The weights take values of one through five—the higher the value, the more tightly connected are the two donor groups.

House members serve two-year terms, and senators serve six-year terms with about only one-third up for reelection in any election. Because we are interested in the effects of the 2010 *Citizens United* decision on campaign donation networks, we restricted the data to donor networks for House campaigns. Merging the edge lists of the House donor networks yields a total of 172, 368 observations for years 2001-2015.

## 2.1 Measures

### 2.1.1 Outcome

This assumes a fair amount of knowledge of graphs for a general reader

*Eigenvector centrality.* On our sample of Reuning (2020) 's prepared network data, we computed eigenvector centrality for all donors. Proposed by Bonacich (1972), eigenvector centrality assumes a node is central or influential if it is connected to other influential nodes. Consider a graph's adjacency matrix, which is a square matrix in which the elements indicate connected nodes. If $A = (a_{i,j})$ is the adjacency matrix, the eigenvector centrality $x_i$ of node $i$ is

$$x_i = \frac{1}{\lambda} \sum_k a_{k,i} \, x_k$$

where $\lambda \neq 0$ is a constant. In matrix terms,

$$\lambda x = xA$$

Importantly, a node with many connections (edges or ties) does not necessarily have a high eigenvector centrality, and a node with a high eigenvector centrality does not necessarily have many connections. A node can be extremely influential without being well-connected. Therefore, eigenvector centrality is an appropriate outcome measure of influence in political donor networks because it can account for groups that are relatively poorly connected but donate extremely high amounts of money through a few channels.

### 2.1.2 Treatment

*SCOTUS Citizens United decision, January 2010.* We are interested in the average treatment effect (ATE) of the 2010 SCOTUS decision on political donors's influence—measured as eigenvector centrality—in their network.

Here should emphasize that this works as a treatment because your observations span the time period before and after this decision.

### 2.1.3 Confounders

*Mean pretreatment percent donated by party.* The effect of the *Citizens United* decision on the eigenvector centrality of the political donor networks is likely confounded by the percent of donations to either the Republican or Democratic Party. We measure this confounder as mean pretreatment party percent before 2010. We then converted this to a binary *party* variable indicating whether the donor contributed a larger percent to the Democratic or Republican party.

#### 2.1.4 Temporality

Temporality is an important aspect in our project, since our running variable itself is time-based. We are interested in the change in eigenvector centrality after the 2010 treatment, so the outcome is after treatment temporally. We also made sure that our covariate precedes the treatment. In generating an indicator for partisanship, we constructed our covariate as mean percent of pre-2010 partisan donation. This is because we are interested in how the *Citizens United* decision affected the influence of the previously/traditionally partisan donors.

### 2.2 Descriptive statistics

You should have a paragraph describing this table. Not all of the terms in it are clear (g.e. "total"?) and you should point out interesting features of this descriptive data.

See Table 1 on the following page (6).

## 3 Estimands

In this project, we are interested in the average treatment effect (ATE) of the 2010 SCOTUS decision on political donors' influence in their network. This can be shown in formula

$E[Y(1) - Y(0)]$

This explanation is helpful to defend your estimand but also suggests a SUTVA violation…

We choose this as our estimand because it is the estimand best fit for our project. Although the 2010 SCOTUS decision will likely only impact certain donors who have the willingness and ability to donate more than the previously stipulated $2500 amount, those high-donors changing patterns of donation will impact the position and attributes of the entire donation network. Therefore it does not make a lot of sense to only look at the average treatment for only treatment or only control group.

Table 1: Descriptive statistics by eligibility for eigenvector centrality scores (EV), total donation amounts, average donation per Democrat (PerDem) and Republican (PerRep), and percent donations by party (party = Dem, None, Rep).

**Table 1. Descriptive statistics**

| **Variable** | **Ineligible**, N=113,030[1] | **Eligible**, N=59,338[1] | **Overall**, N=172,368 |
|---|---|---|---|
| EV | 0.28 (0.27) | 0.30 (0.29) | 0.29 (0.28) |
| PerDem | 52.14 (40.07) | 46.66 (40.98) | 50.26 (40.47) |
| PerRep | 47.53 (40.08) | 52.94 (41.10) | 49.39 (40.52) |
| Total | 13,316.00 (89,705.12) | 19,591.71 (155,370.19) | 15,476.43 (116,601.02) |
| avg_PerDem | 52.14 (36.61) | 53.00 (34.04) | 52.38 (35.91) |
| Unknown | 0 | 15,488 | 15,488 |
| party | | | |
| Dem | 94,253 (83%) | 38,897 (89%) | 133,150 (85%) |
| None | 53 (<0.1%) | 20 (<0.1%) | 73 (<0.1%) |
| Rep | 18,724 (17%) | 4,933 (11%) | 23,657 (15%) |
| Unknown | 0 | 15,488 | 15,488 |

[1] Statistics presented: Mean (SD); n (%)

# 4 Methods

## 4.1 Method One: Regression Discontinuity

The first method we use to estimate our estimand is called regression discontinuity. Regression discontinuity is a special case of an observational study design in which a unit's receipt of treatment is decided solely based on values of one variable, usually referred to as the running variable. In this setting, there is a cutoff point on the running variable: on one side all units receive the treatment, and units on the other side they do not. In a regression discontinuity model, it is usually assumed that the only confounding covariate is the running variable, given the appropriate bandwidth around the cutoff point. Around the cutoff point, usually the units are considered randomly distributed so that other confounding factors can be ignored. This method is appropriate for situations where researchers do not have access to a lot of confounding covariate data.

colloquially but not technically correct

driving force is less about absence of covariate data and more about having a situation that conforms to these requirements

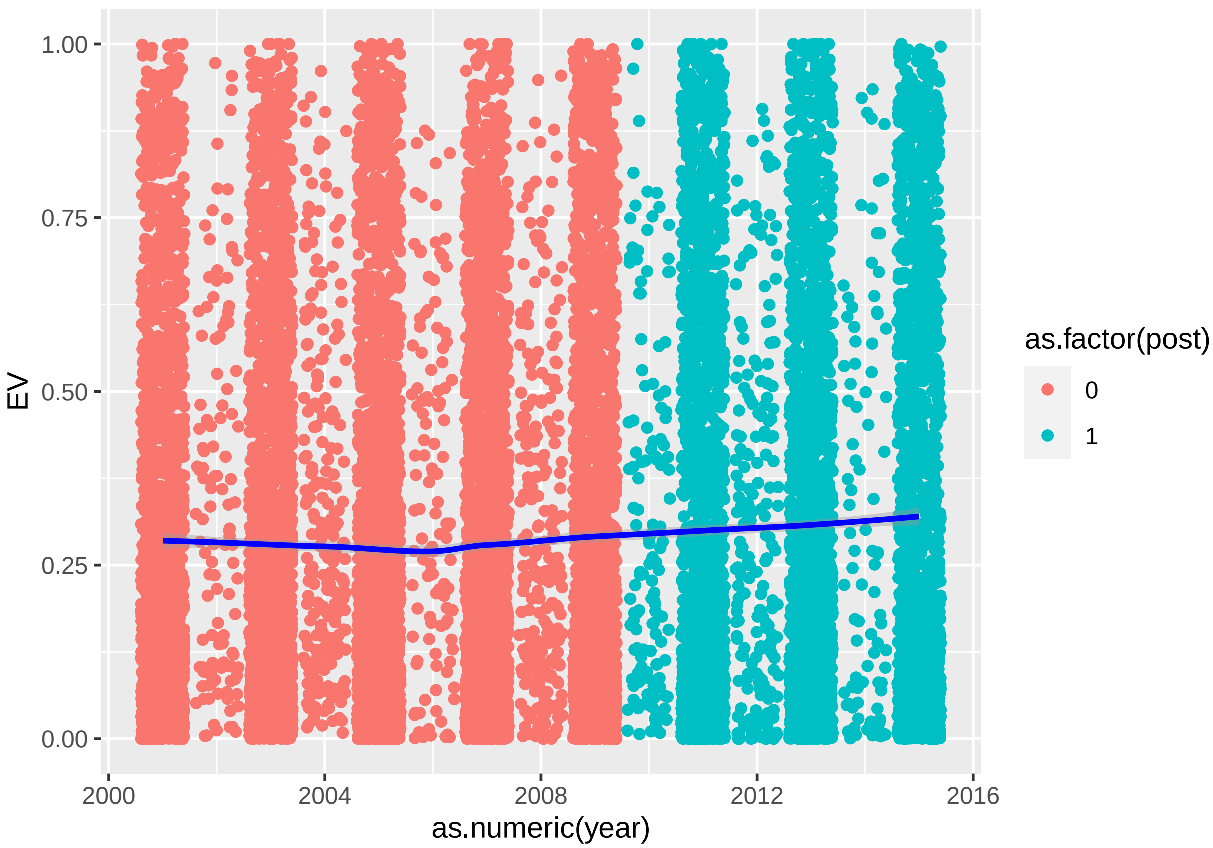
In our project, the running variable is time, measured in year. And the cutoff point is at year 2010 when the Supreme Court Decision was made. We have set our bandwidth to be from 2009-2011. The reasons for choosing our bandwidth are as follows. First, this is the smallest bandwidth that our dataset allows, and with this small bandwidth we have more confidence that donors in this time frame are more likely to be similarly/randomly distributed. Second, since the running variable in our dataset is relatively "coarse," meaning that year is really a large span of time. If we were to

RDD with time is challenging because the ignorability assumption is much more difficult to defend than in other settings …

extend our bandwidth, then it would be unreasonable to assume the distribution of donors could would still be random across more than two years, with the changing economical and political landscape.

We decided to use a linear model based on a preliminary plot, and based on the LOESS curve (see figure below) the relationship between time and eigenvector centrality of campaign donors is more linear than quadratic. So here in our regression discontinuity model we assume that their relationship is linear, except at the cutoff point.

```
## `geom_smooth()` using formula 'y ~ x'
```




In practice, we first restrict the model to the bandwidth, only considering the data points from years 2009 to 2011. We then create a variable to indicate the applicability of the Supreme Court decision, if before 2010 then 0 and otherwise 1. We fit the restricted dataset (2009-2011) to a linear model, where the applicability indicator and year was used to predict the eigenvector centrality.

To answer our second question about potential partisan difference in the treatment effect, we divide our dataset into two subgroups? parts for the regression discontinuity analysis. The first part is focused on the traditionally/previously Republican donors, defined as those whose mean proportion of donation pre-2010 for Republican Congress members is larger than 60%. The second part is focused on the traditionally/previously Democratic donors, defined as those whose mean proportion of donation pre-2010 for Democratic Congress members is larger than 60%. Focusing on the proportion of partisan donation pre-2010 helps us avoid controlling on post-treatment variables. With those two data sets we repeat the same process for regression discontinuity modeling as we did for the overall dataset.

good to frame this as exploring t.e. moderation or heterogeneity

## 4.2 Method Two: Difference in Difference

I wouldn't use these words… it has very strong assumptions

The difference-in-difference method is an observational method that mimics an experimental design, by taking the differential effect of a treatment on a treatment group and a control group. The way that DiD estimates the treatment is by comparing the outcome change over time of both treatment and control groups. This method assumes that both treatment and control group's outcome change similarly over time. Therefore, by taking the difference between treatment group outcome and control group temporal outcome change, this method can get can mitigate the effects of extraneous factors.

True for your estimand

too vague… what does extraneous mean?

In our project, we chose donors in the state of Vermont as our control group. Shortly after the SCOTUS decision, the U.S. District Court for the District of Vermont ruled in *Vermont Right to Life Committee v. Sorrell (II)* that Vermont's contribution limits did apply to independent expenditure PACs, making Vermont somewhat free from the influence of the 2010 SCOTUS ruling.

Similar to our RDD model, here we also assume that the basic form of our model is linear, based on a preliminary observation of relationships in our data.

not much choice in a classic DID — you actually have something more like a CITS — might be interesting in the future to analyze as such

In practice, we use all available years of our data. Similar to the RDD model, we also create a binary variable to indicate the applicability of the Supreme Court decision—if before 2010 then 0 and otherwise 1. We then create another binary variable to indicate whether a data point is in the treatment group or control group: if the donation happens in Vermont, then it is in control group, if not then it is in treatment group. Finally, we run an interaction model, which uses treatment indicator, applicability indicator, and their interaction term as predictor and the eigenvector centrality as outcome. The coefficient of the interaction term is the estimate we are looking for.

To answer our second question about potential partisan differencea in the treatment effect, we fit a different model adding in variable to indicate the partisanship of the donor, defined in the same way as we did in the regression discontinuity model. We then run a similar difference in difference model, keeping all other predictors the same while only adding this partisan variable. We also run an ANOVA test to see if adding the partisanship variable contributes to our model.

# 5 Assumptions

#### 5.0.1 Method One: Regression Discontinuity

#### 5.0.2 First assumption: Randomization

Should use notation for assumptions

The first assumption about regression discontinuity is that the treatment assignment is ignorable given X in a narrow interval of X around the cutoff. This means that we assume that data points are randomly distributed around the cutoff point; therefore other confounding factors can be ignored.

In our case, the randomization assumption is plausible because we set our bandwidth narrow enough (as narrow as possible). From 2009-2011, in the political campaign donation nothing major happened except our treatment variable. It is reasonable to assume that the bigger economic and political conditions are relatively stable.

#### 5.0.3 Second Assumption: Parametric form

could write this more generally

The second assumption we are making here is that data on both sides of the cutoff follow a linear relationship with the running variable. This assumption is much tougher to say, since from the scatter plot we can see that the distribution of the data points are rather regular, and it seems like they don't follow a clear parametric relationship. However, since our bandwidth is small, it is also more likely that the parametric assumption holds.

so this is interesting… in general smaller bandwidth helps with ignorability but I'm not sure it does when the running variable is time… won't mark you off for this since I presented this as a general rule but time as running variable does present some challenges

#### 5.0.4 Third Assumption: Bandwidth

The third assumption we made here is going with the small bandwidth we chose. We think that choosing this bandwidth makes sense because a smaller bandwidth makes our first and second assumption more plausible. Even though the generalizability of our finding might suffer a bit, from a theoretical perspective, it is important that we do not over generalize. For example, if we go back to 2007 or 2008, we suffer from possible strong bias from confounding factors such as the Great Recession, or a different political administration in 2007.

also generalizability not really this issue since in either case you are estimating the effect at the boundary

### 5.1 Method Two: Difference in Difference

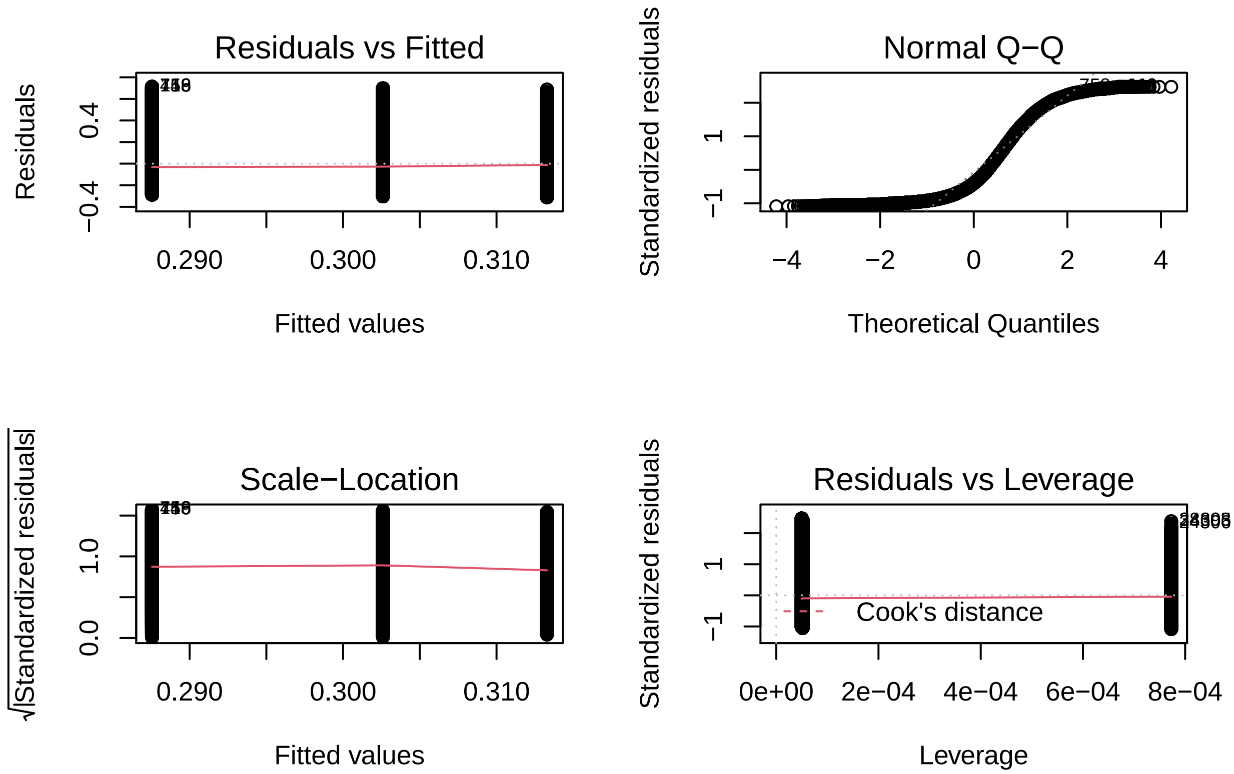
across time

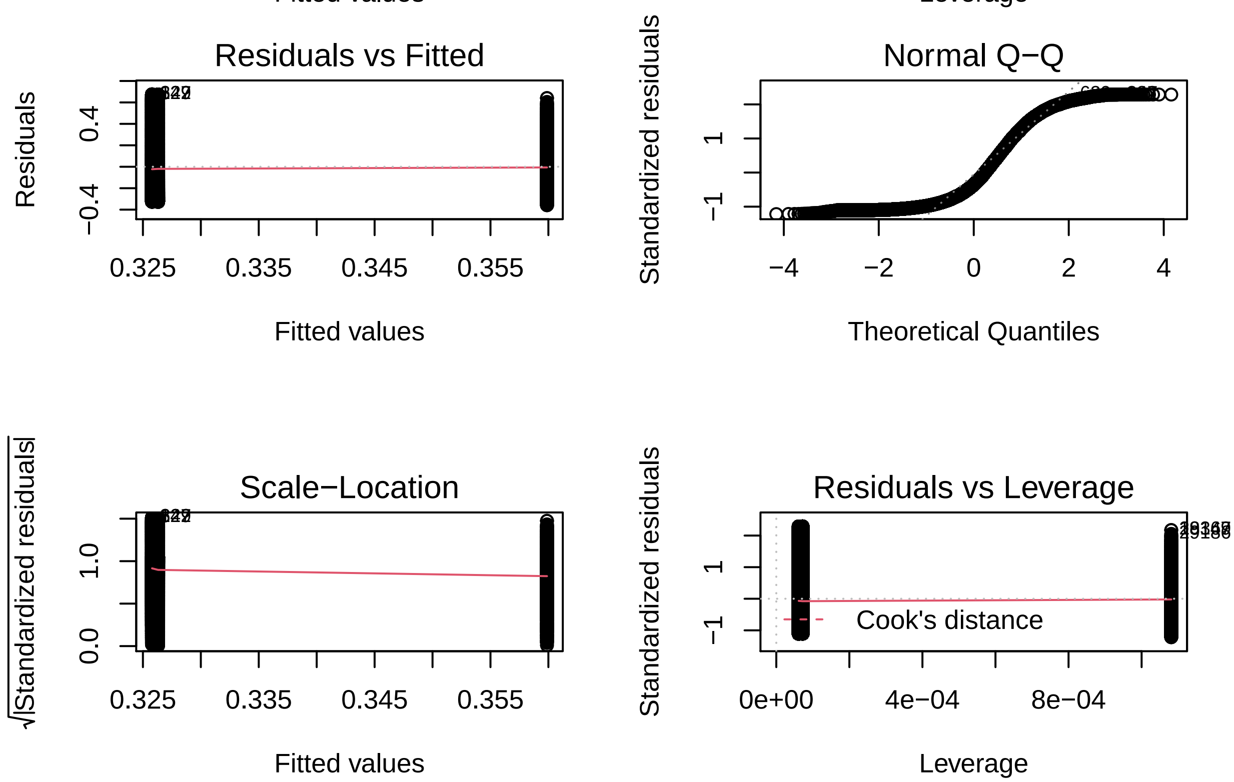
To identify Average Treatment Effect (ATE), we need the difference of both treatment and control group to be independent of treatment assignment, and we need to have the treatment group to look like the control group. This is also known as the parallel trend assumption.

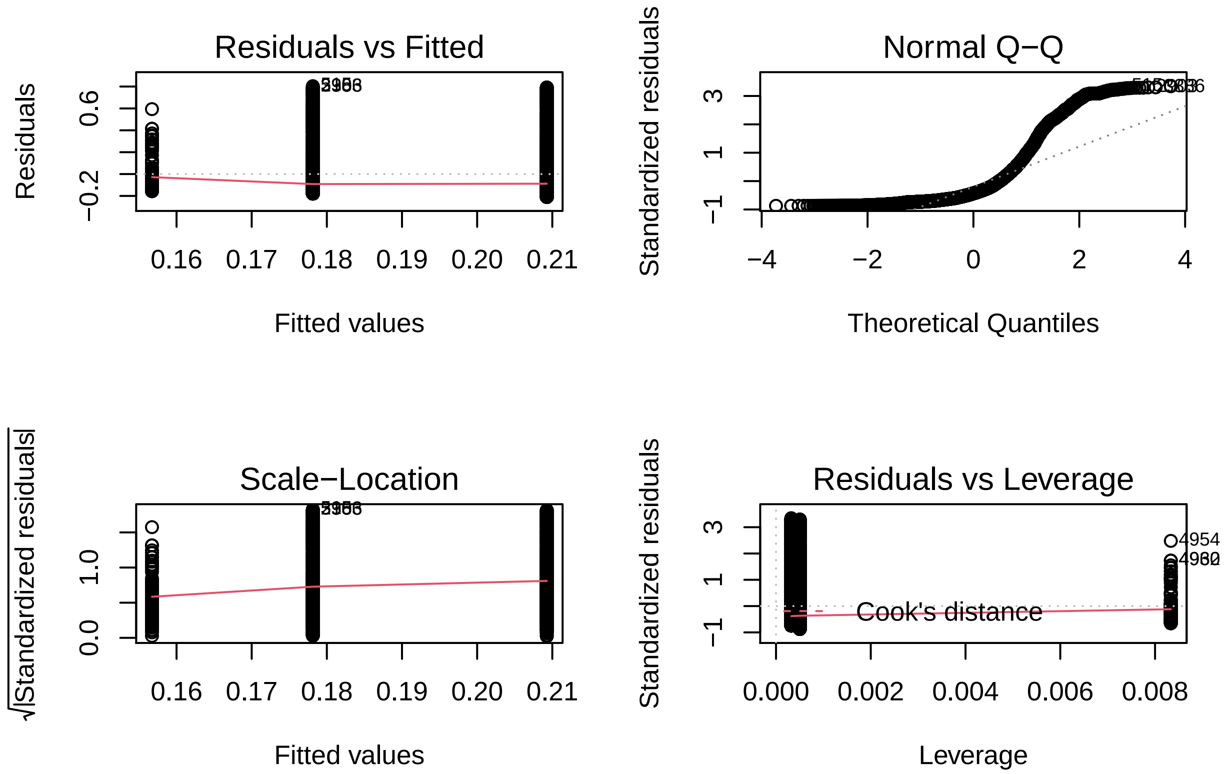
only the first one… the 2nd one not technically required though supports the first assumption (i.e. makes more plausible)

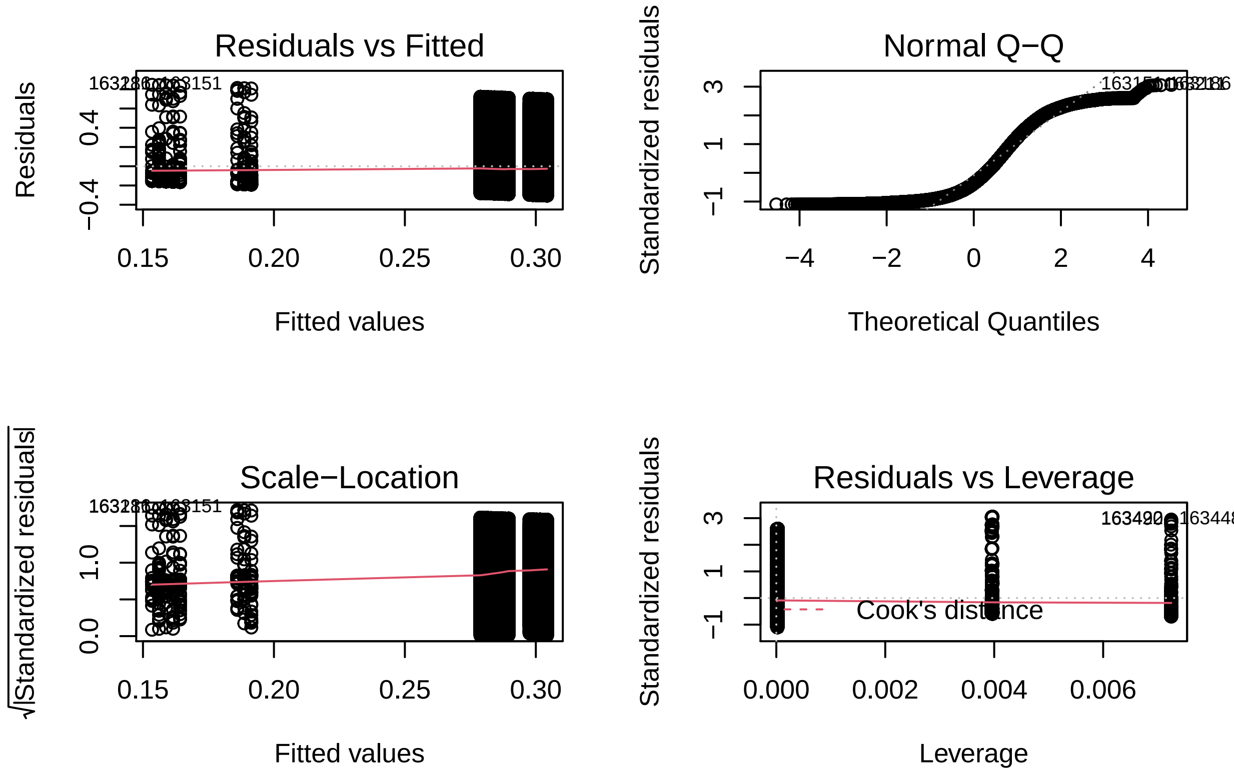
In our case, this assumption is a bit questionable. Because we use only Vermont as our control group, it really isn't that reliable. Being the home state of Bernie Sanders, Vermont has a very distinct political culture and legal system that fosters its lack of Super PAC forming, which is very different from many other states in the treatment group. Other indicators such as economic development and party identification also makes Vermont not an equal counterpart to our treatment group states. It is likely that the D(1) of Vermont is different from those in the treatment group, and the D(0) of the treated is different from that of Vermont's. But with the data we have, and how the 2010 SCOTUS decision is so sweeping across states, Vermont is our best bet.

# 6 Diagnostics

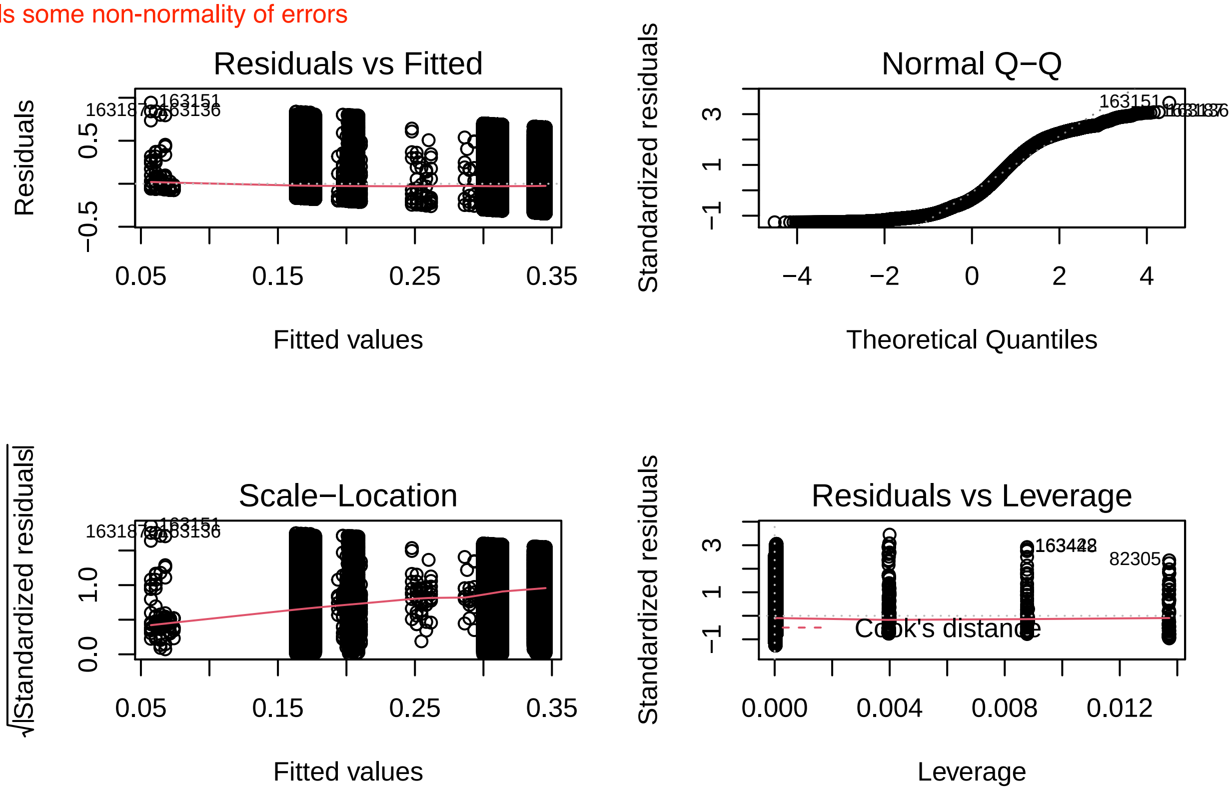



Residuals vs Fitted
Residuals
Fitted values
Normal Q−Q
Standardized residuals
Theoretical Quantiles
Scale−Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance
4954


Residuals vs Fitted
Residuals
Fitted values
Normal Q−Q
Standardized residuals
Theoretical Quantiles
Scale−Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance
163448

reveals some non-normality of errors




In our project we ran a total of four linear regression models. The first one is regression discontinuity model, restricted from 2009 to 2011. The second and the third models are the stratified version of the first one, on democratic donors and republican donors respectively. The fourth and fifth are difference in difference models, with the former not including extra covariates and the latter including partisanship indicator as a covariate.

The results of the regression diagnostics are shown as above. For model one (basic RDD), we can see from the Residuals vs. Fitted graph that the linear parametric assumption seems right. The QQ plot shows that data at both ends do not have normally distributed, but most of the data points are. The the line in the Scale-Location figure is relatively straight, so it is relatively safe to say in our regression homoscedasticity holds relatively well. In the Residuals vs Leverage figure, we see some points have really high leverage and high influence, but none has extreme residuals (none with standard residual larger than 3).

For model 2 (RDD for previously democratic donors), the diagnostics are very similar to model one. We can see from the Residuals vs. Fitted graph that the linear parametric assumption seems right. The QQ plot shows that data at both ends do not have normally distributed, but most of the data points are. The the line in the Scale-Location figure is relatively straight too homoscedasticity holds relatively. In the Residuals vs Leverage figure, we see some points have really high leverage and high influence, but none has extreme residuals. For model 3 (RDD for previously democratic donors), things are bit different. Linear assumption still holds, but the residuals do not really follow a normal distribution. Homoscedasticity still holds and there seem to be many fewer high leverage and high influence points.

Would have been nice to see a visualization of the parallel trends pre-treatment

For model 4 (basic DiD), linear assumption holds. Data at both ends do not have normally distributed, but most of the data points are. Homoscedasticity still holds and there seem to be many fewer high leverage and high influence points, compared to basic RDD model. For model 5 (DiD with previous party indicator as covariate), the story is very similar to model 4 except for homoscedasticity. From the Scale-Location graph, it seems that residuals are increasing with fitted values. So it is very likely this model is heteroscedasticitic.

general advice: always better to say that an assumption “does not appear to be violated” rather than saying it holds

# 7 Results

As can be seen from the regression table, the estimates of ATE are all coefficient of the binary indicator of pre/post 2010 variable, except for the DiD model, in which the iteraction term between the treatment variable and the pre/post-2010 indicator is the estimator.

should make a nice table rather than just cutting and pasting output
(this was in the instructions)

```
##
## Regression Results
## ========================================================================
##                                     Dependent variable:
##              -----------------------------------------------------------
##                                             EV
##                 RDD     RDD.Rep   RDD.Dem    DiD     DiD.party LinRegression
##                 (1)       (2)       (3)      (4)        (5)          (6)
## ------------------------------------------------------------------------
## treated                                   0.125***  0.106***
##                                           (0.017)   (0.017)
##
## trans_yr     -0.026*** 0.053**  -0.034*** 0.001***  0.002***     0.001***
##               (0.008)  (0.023)   (0.010)  (0.0003)  (0.0003)     (0.0003)
##
```

```
## partyNone                                              -0.052
##                                                        (0.032)
##
## partyRep                                             -0.137***
##                                                        (0.002)
##
## treated:post                                  -0.013     0.029
##                                              (0.029)   (0.031)
##
## post          0.036**  -0.074*  0.068***    0.019    -0.008     0.007***
##              (0.016)   (0.044)   (0.020)  (0.029)   (0.031)     (0.003)
##
## Constant     0.277***  0.231*** 0.292***  0.165*** 0.210***    0.291***
##              (0.009)   (0.023)   (0.010)  (0.017)   (0.017)     (0.002)
##
## ---------------------------------------------------------------------------
## Observations  40,849    5,215    31,130   172,368   156,880     172,368
## R2             0.001    0.004    0.0004    0.001     0.036       0.001
## Adjusted R2    0.001    0.004    0.0003    0.001     0.036       0.001
## ===========================================================================
## Note:                                      *p<0.1; **p<0.05; ***p<0.01
```

is there a way of understanding the practical implications of this kind of change? even expressing in sd units would be super useful

The estimates for the regression discontinuity model are all statistically significant. To provide a proper causal interpretation of this, our analysis shows that on average, the 2010 SCOTUS decision caused a 0.036 percentage point increase in donors' influence in the donation networks, measured in eigenvector centrality. Looking at partisanship divide, in our regression discontinuity methods, interesting pattern emgerges as on average the 2010 SCOTUS decision decreased Republican donors' influence by 0.074 and increased Democratic donors' influence by 0.068. We can be more certain about the negative impact on Democratic donors, since in our data there are many more Democratic donors than Republican ones.

In our difference in difference method, both the basic model and the model that contains the party variable return insignificant estimates of the effect. Despite the fact that we have a lot of these are different estimands not just different models (one with and one without an extra covariate) right? in that case these are different estimands

observations, we cannot get a signigicant estimate of the DiD treatment effect. This makes sense as we laid out earlier in the assumptions section, that Vermont is probably a poor control group and there is probably a lot of confounding biases. To provide a proper causal inpterpretation of this despite the result being insignificant, our analysis shows that on average, the 2010 SCOTUS decision caused a 0.013 decrease in donors' influence in the donation networks, measured in eigenvector centrality. When taking into consideration of partisanship, the 2010 SCOTUS decision caused a 0.029 increase in donors' influence in the donation networks, measured in eigenvector centrality; and Republican donors had 0.137 decrease in influence as a result of the treatment, compared with Democratic donors.

The effectiveness of the RDD model can be seen in comparison with the final vanilla linear regression model. The final model still shows a positive effect of the treatment, yet the estimate is much smaller. It makes sense because RDD narrows in on the period of treatment and can get a better grasp of the effect of treatment, instead of looking at all data globally.

also you think the DID approach is less plausible right?

## 8 Discussion and Conclusion

ASSUMING OUR ASSUMPTIONS HOLD

Our analysis confirms our chief hypothesis with the regression discontinuity model. The analysis shows that the 2010 SCOTUS decision to remove the upper limit of PAC donations on average caused the campaign donors to have 0.036 higher eigenvector centrality, commonly used to denote a node's influence in a network. Although the numeric value is small, the fact that eigenvector centrality is a value between 0 and 1 indicates that the effect is quite drastic.

The biggest problem we had in our analysis is with our difference in difference design. In our DiD model, the estimate is not significant. We think this is due to the fact that Vermont is a poor control for the rest of the country. Future research looking to use DiD design on this problem should consider locating data about each donor's information and use propensity score methods to match donors across treatment and control states to achieve better comparability.

This study is limited in its unit of analysis and choice of bandwidth. The nature of the data determines that we can only slice our running variable discretely by year, since House elections occur biannually. Our running variable, then, is fairly imprecise, and in many cases our data look very discrete. This limits our ability to experiment with more types of bandwidth without violating ignorability and parametric assumptions.

Future research should take into account these limitations. In particular, researchers should construct a more fine-grained temporal variable. For example, FEC data include receipt dates for campaign donations. These receipt dates might be used to construct a more precise bandwidth around the discontinuity of the SCOTUS *Citizens United* decision. Furthermore, researchers could take advantage of these FEC data to get around the problem of adequate controls by, as noted above, matching donors across groups.

Viewing parties as networks allows us to make considerable progress on research problems concerning the power and influence that campaign finance holds over political agenda-setting and decision-making. Our results provide some preliminary support for the notion that the *Citizens United* decision, which commentators often assume has had the effect of increasing the power of wealthy donors, has had the effect of increasing levels of political influence for such donors. Because research backs up the association between higher incomes and Republican votes, the related assumption is that the *Citizens United* decision has had an outsize benefit for Republican Party donors. However, our results show the opposite. Since 2010, Democratic party donors increased in network influence, whereas Republican party donors decreased in influence. Despite the limitations of the study, these results are worth the attention of both network methodologists who want to improve on the ability to make causal inferences from network data and subject experts who want to understand the relational impact of landmark SCOTUS decisions on the structure of political parties and their financial ties.

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