Climate Policy and Incumbent Support

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Contents

0.0.1 Abstract

Stokes (2015) finds that voters do pay attention to climate policy and afterwards penalize the incumbent governments for facilities viewed as harmful to the communities. I successfullly replicated Stokes' results. In my replication, I tested the strength of Stokes' model using a Bayesian regression model. Contrary to Stokes' findings, I found that on average, voters were more likely to support the incumbent governments.

0.0.2 Introduction

Stokes (2015) uses data that from 26 districts in Ontario, Canada where renewable wind projects were proposed or operational to determine whether people living near wind turbines vote against incumbent governments to punish them for climate policy regarding incentives for infrastructure in their local communities (Stokes 2015). During Onatrio's 2003 election, the Liberal Party bid with a plan to exhaust coal usage. After winning the election and having eight years of power, the Liberals implemented a "feed-in-tariff" policy which aimed to remove coal usage, reduce greenhouse emissions, and boost job opportunities within the provinces (Stokes 2015). They focused the policy around the use of wind energy development and provided substantial returns on investment and many company began to opt-in to develop wind projects in areas with high wind resources, all of which excluded the communities' input on whether they desired to receive the structures (Stokes 2015). The data collected is from the 2003, 2007, and 2011 elections, marking the Liberal Party's beginning of power to them losing majority (Stokes 2015). To ensure the robustness of her model, Stokes utilized a fixed effect estimator, which relies on variation of a unit to indentify causal effects, and a instrumental variable estimator, which relies on cross-sectional comparison to check the fixed effects results (Stokes 2015). The fixed effect estimator was proximity to proposed or operation wind turbine structures and the instrumental variable estimator was wind power. The results of linear regression ran by Stokes show that voters retrospectively punished incumbent governments for facilites viewed as harmful to the communities and that proximity to wind turbines leads them to oppose the development of projects (Stokes 2015). In addition, Stokes that communities were mobilized to vote against proposals, which accounts for the change in the Liberal Party's vote share, and that the voters were informed about climate change due to only punishing incumbent governments to which were responsible for new policies (Stokes 2015).

The first piece of this paper was a replication of Stokes' results. Code and data are publically available on the Harvard Dataverse. In order to replicate her results, I ran her orignial code using R code. I was easily able to run the code for both the tables and figures, but the code for formatting the tables in LaTex was not provided on Dataverse. I also was unable to create Figure 1, as code was also not provided. Instead, I opted to analyze the raw output of the regressions from my replications. All code for the replication is available in my GitHub repository.[1]

[1] GitHub repository

After the replication, in my extension of Stoke's work I test the strength of Stokes' model by running a Bayesian regression upon it. In order to perform this treatment effect, I created a new variable named "effect" that is deprived from "perc_lib". According to Stokes' codebook, "perc_lib" represents the votes cast for the Liberal Party divided by the number of voters who cast ballots in the precinct. In other words, "perc_lib" is equivalent to vote share. If the vote share is greater than 0, it is equal to 1 in "vote". If the vote share is less than 0, it is equal to 0 in "vote". I then replaced Stokes' linear regressions with Bayesian ones and replaced "perc_lib" with "vote". This design is used to predict the probability of voting for the incumbent.

The results of figures and tables using stan_glm() outputs revealed that Stokes' models may not have been as robust as she had anticipated. I discovered that voters were more likely to support incumbent governments retrospectively from wind turbine implementation. These results clash with Stokes' findings. This may be due to clustering not being utilized in my models. This extension therefore creates more questions surrounding climate policy implementation and incumbent voter support.

Throughout this paper, I will investigate Stokes' paper through literature review, discussion of the replication, and an in-depth analysis of my extension.

0.0.3 Literature Review

This paper is written in response to growing of evidence surrounding retrospective voter behavior in regard to policy implementation, specifically surrounding climate policy. Recent evidence has suggested that voters will vote against incumbents whose policy does not align with public opinion. In 2011, Michael M. Bechtel and Jens Hainmueller found that in favorable circumstances, voters can have long-term gratitude in response to policy decisions that align with common interest (Bechtel & Hainmueller 2011).

Resistance to climate policy is often found on the local level regarding projects that have benefits for a large sum of people, and similar trends can been seen in government projects such as hospitals, subways, housing, etc (ALdrich 2010). In regard to economic performance, D. Roderick Kiewiet found that if there is less transparency as to who's to blame for policy results, incumbent parties are not as effected as there is less voter mobilization (Kiewiet 2000). In regard to climate policy, Noel Cass and Gordon Walker found that opposition to the planning and implementation of wind farms motives voters to vote against these kinds of policies as a stance againt government intrusion (Cass & Walker 2009).

While much of the reserach surrounding retrospetive voting is centered around economic policy, Stokes' paper investigates the direct correlation between wind turbine proximity and later incumbent support, concluding with similar studies found in Cass & Walker (2009). This paper also utlized other findings regarding public opinion on climate policy to support Stokes' conclusions.

0.0.4 Replication

I was able to easily replicate all of Stokes' figures and tables based upon her original code. The only figure that I could not replicate was Figure 1, as the code was not provided.

0.0.5 Extension

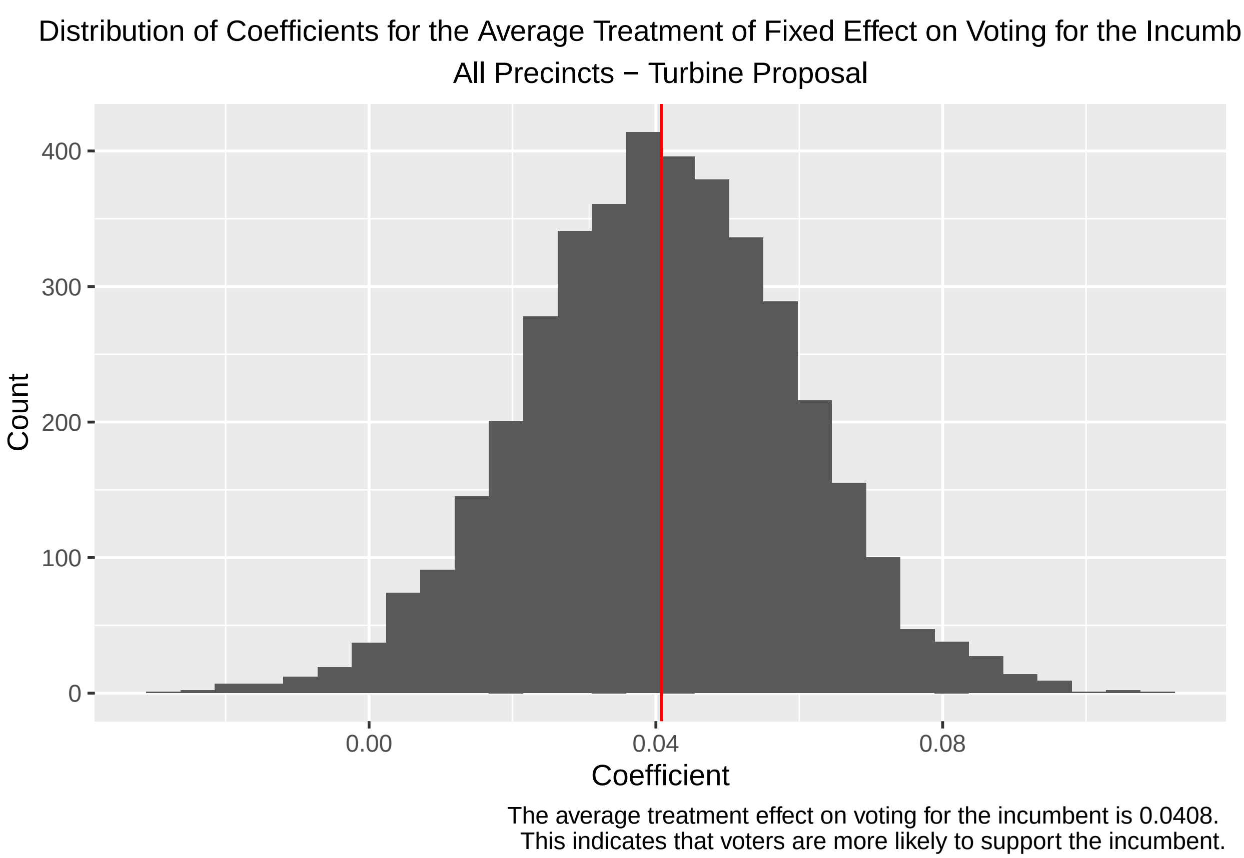
Stokes (2015) proved that voters do pay attention to climate policy and afterwards penalize the incumbent governments for facilities viewed as harmful to the communities. She demonstrated using fixed effect variables and instrumental variables that people living near wind turbines in Ontario, Canada will retrospectively vote against incumbent governments in retailiation to climate policy that led to the develop of wind turbines in their communities. In my extension of her work, I examined the treatment effect of the fixed effect on whether or not voters were likely to support the incumbent through Bayesian probability.

When creating a binary variable to which determined if voters were likely or unlikely to support the incumbent, the data revealed that amongst all groups, there was a more likely chance of voters supporting the incumbent than not. Additionally, balanced precincts tended to have higher incumbent support than all precincts.

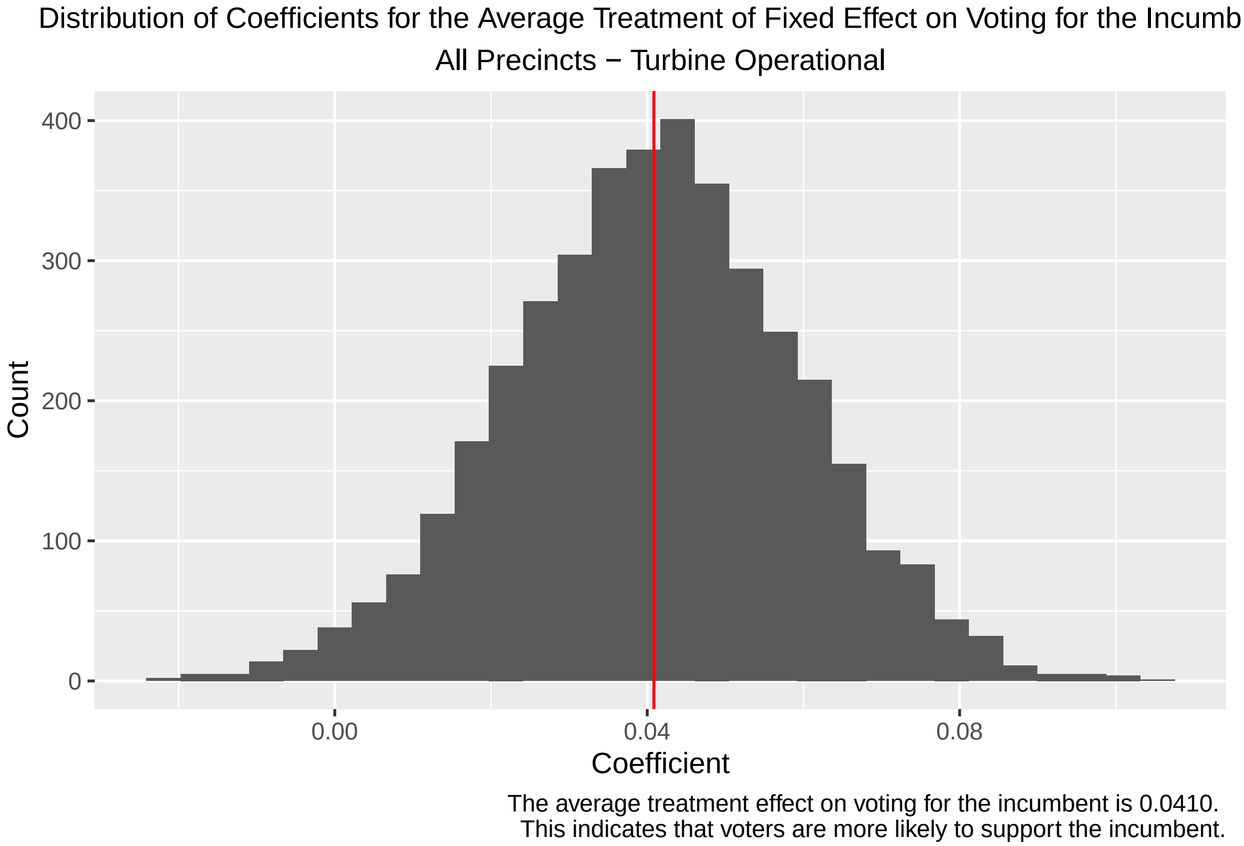
The Bayesian regression that I had ran for this extension was based upon Stokes (2015) linear regressions. Instead of using the vote share variable, I created a new variable called "vote" which indicates whether or not the vote was likely to support the incumbent or not based upon the vote share numbers. If the vote share was greater than 0, it was given the value of 1, indicating incumbent support. If the vote share was less than 0, it was given the value of 0, indicating non-incumbent support. I then kept all other regressors used in Stokes' models the same. Within my model, I denoted for family = "binomial", as the stan_glm() function will simply assume that the operator wants a linear regression with the distinction. Without this, there would be no difference in the regression model Stokes ran.

The coefficient of the intercept of the Bayesian regressions represent the likelihood whether voters will support the incumbent government based upon the same regressors as Stokes had used. With all models showing slight favoritism toward supporting the incumbent, the results complicate Stokes' conclusion that proximity to wind turbine implementations will have negative effects retrospectively on incumbent voter support. This extension may reveal that Stokes' model is not as robust as she may have assumed, though I also did not use a clustering function which may have made a difference. This extension continues the discussion on whether we can predict voter behavior in response to policy implementation at large.

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
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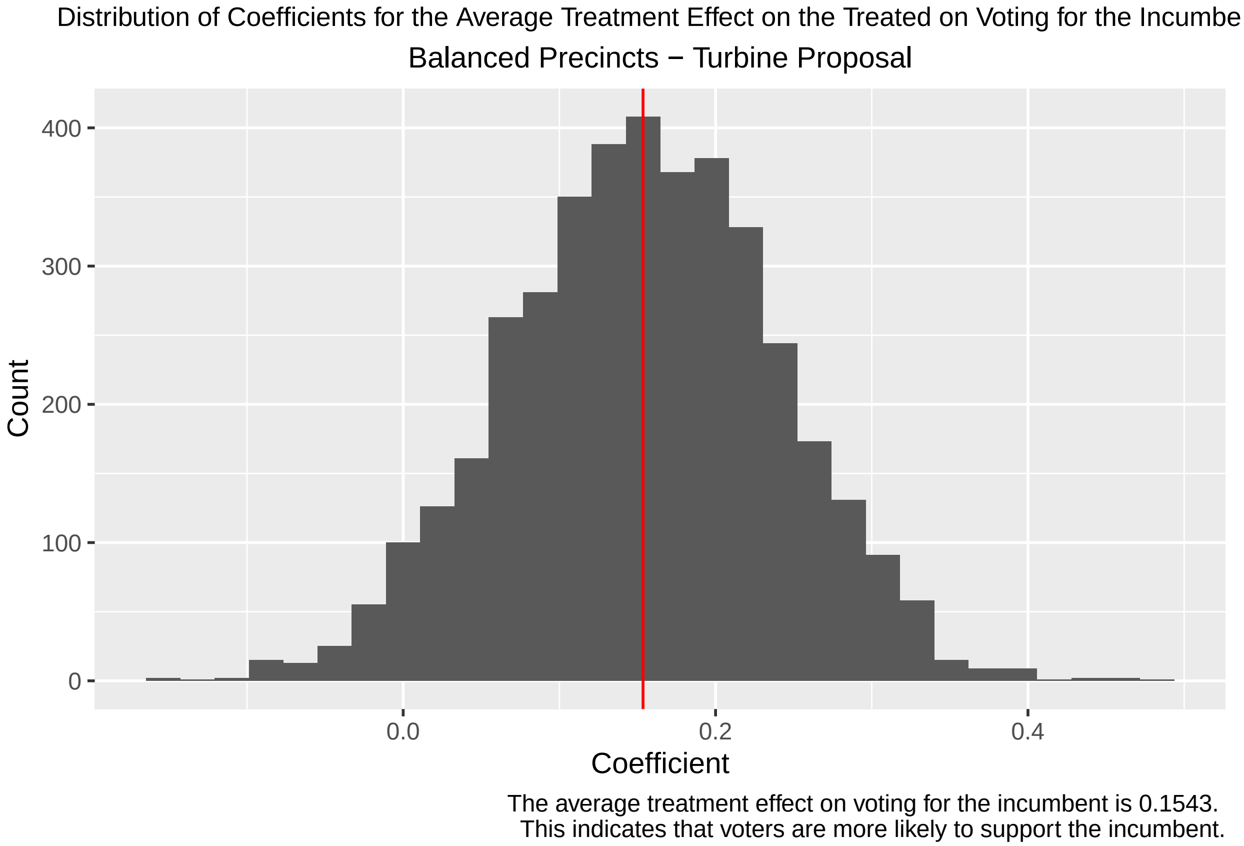
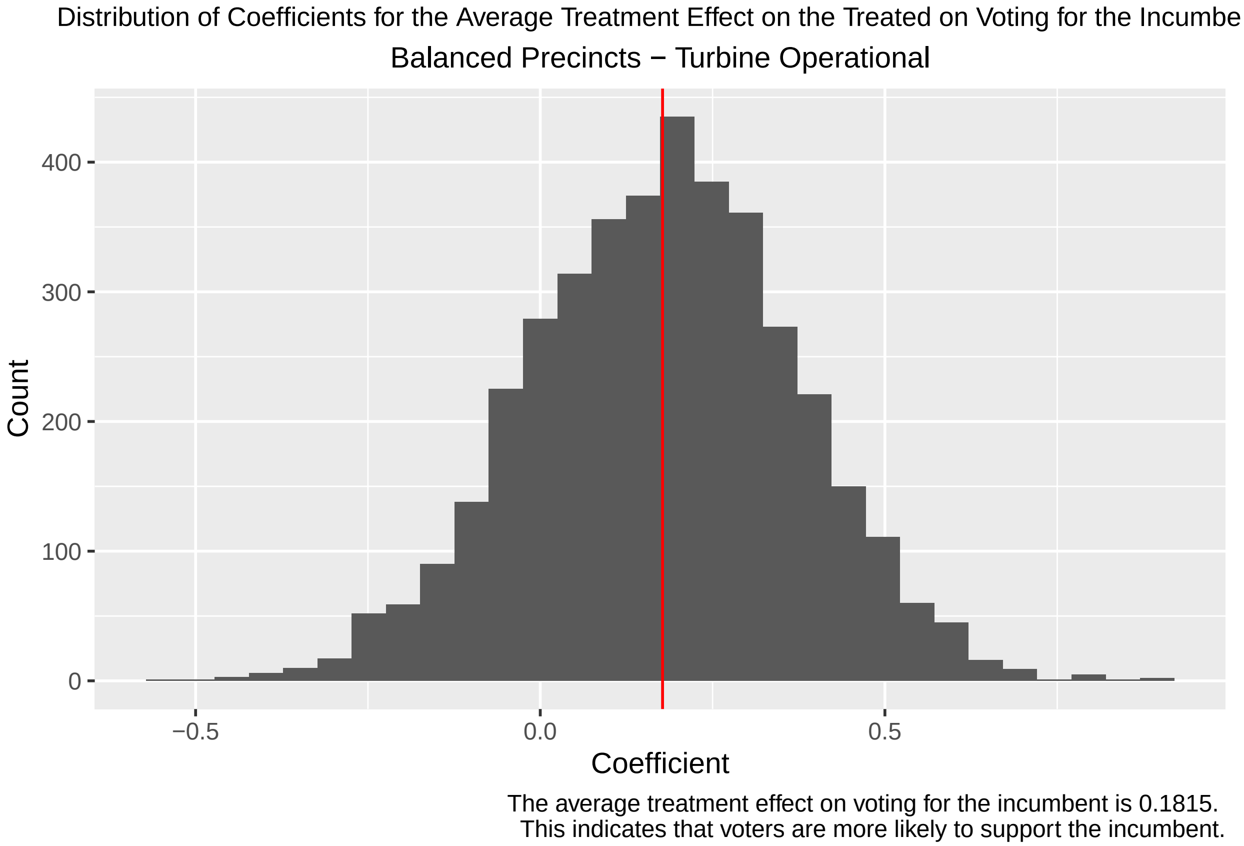



```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



0.0.6 Conclusion

Stokes (2015) uses data that from 26 districts in Ontario, Canada where renewable wind projects were proposed or operational to determine whether people living near wind turbines vote against incumbent governments to punish them for climate policy regarding incentives for infrastructure in their local communities (Stokes 2015). After winning the election and having eight years of power, the Liberals implemented a "feed-in-tariff" policy which aimed to remove coal usage, reduce greenhouse emissions, and boost job opportunities within the provinces (Stokes 2015). The policy was based around the use of wind energy development and provided substantial returns on investment and many company began to opt-in to develop wind projects in areas with high wind resources, all of which excluded the communities' input on whether they desired to receive the structures (Stokes 2015). The data collected is from the 2003, 2007, and 2011 elections, marking the Liberal Party's beginning of power to them losing majority (Stokes 2015). Stokes used proximity to wind turbines to describe voter behavior after the 2011 election, where the Liberal Party saw a loss in vote share (Stokes 2015).The results showed that voters retrospectively punished incumbent governments for facilites viewed as harmful to the communities and that proximity to wind turbines leads them to oppose the development of projects (Stokes 2015). In addition, Stokes that communities were mobilized to vote against proposals, which accounts for the change in the Liberal Party's vote share, and that the voters were informed about climate change due to only punishing incumbent governments to which were responsible for new policies (Stokes 2015).

Stokes' code and data for this replication are publically avaiable on the Harvard Dataverse. I was able to successfully run the code for all figures and tables except Figure 1, as its code was not made available. Code for formating the table in LaTex were also not available, but I was able to come up with the same numbers found within the tables.

In my extension, I tested whether or not voters were likely to vote for the incumbent through Bayesian probability, using the same regressors as Stokes' had. Using numbers obtained from Stokes' models, if the vote share is greater than 0, it is equal to 1 in "vote". If the vote share is less than 0, it is equal to 0 in "vote". The results from my models found that voters were more likely to support the incumbent, contrary to Stokes' findings. Clustering was used in Stokes' model, but not mine, which may have an effect on the output of our coefficients. This extension matters because it shows that Stokes' model may not have been as robust as anticipated, while also continuing the converstaion surrounding the ability to determine retrospective voter behavior regarding policy implementations.

0.0.7 Appendix

TABLE 1 Effects of Wind Turbines on Incumbent Party Vote Share in Precincts

	All Precincts (ATE)	All Precincts (ATE)	Rural Precincts (ATE)	Rural Precincts (ATE)	Balanced Precincts (ATT)	Balanced Precincts (ATT)
			Turbine Proposal			
Proposed Turbine	-0.042^{***}	-0.039^{***}	-0.048^{***}	-0.046^{***}	-0.050^{***}	-0.050^{***}
(Treatment)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)
Population with		0.084^{***}		0.055^{*}		-0.069
University Degree (%)		(0.018)		(0.024)		(0.078)
Population Density		0.006^{***}		0.007^{***}		0.002
(log)		(0.001)		(0.001)		(0.004)
Unemployment Rate		0.001^{*}		0.000		0.001
		(0.000)		(0.000)		(0.002)
Median Income (log)		$0.013^{\dagger}$		0.008		0.022
		(0.007)		(0.009)		(0.022)
Immigrant		0.074^{**}		0.084^{*}		0.047
Population (%)		(0.027)		(0.038)		(0.084)
N Treated	184	184	184	184	184	184
N Control	6002	6002	2985	2985	6002	6002
Fixed Effects	Y	Y	Y	Y	Y	Y
			Turbine Operational			
Operational Turbine	-0.093^{***}	-0.092^{***}	-0.099^{***}	-0.098^{***}	-0.084^{***}	-0.080^{***}
(Treatment)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)
Population with		0.084^{***}		0.057^{*}		0.136
University Degree (%)		(0.018)		(0.024)		(0.102)
Population Density		0.006^{***}		0.007^{***}		0.007
(log)		(0.001)		(0.001)		(0.004)
Unemployment Rate		0.001^{*}		0.000		-0.001
		(0.000)		(0.000)		(0.002)
Median Income (log)		$0.013^{\dagger}$		0.008		0.006
		(0.007)		(0.009)		(0.035)
Immigrant		0.075^{**}		0.088^{*}		-0.028
Population (%)		(0.027)		(0.038)		(0.082)
N Treated	52	52	52	52	52	52
N Control	6134	6134	3117	3117	6134	6134
Fixed Effects	Y	Y	Y	Y	Y	Y

Note: Robust standard errors, clustered at precinct level. Intercepts are not reported.
$^{\dagger}p<.10$; $^{*}p<.05$; $^{**}p<.01$; $^{***}p<.001$.

Results from Stokes (2015) were successfully replicated. As an example, here are some outputs of models from Table 1 from page 967. The actual tables were difficult to format, but I was able to produce the same numbers found within them.

```
##
## t test of coefficients:
##
##             Estimate Std. Error t value  Pr(>|t|)
## (Intercept)    0.000      0.000 -41.652 < 2.2e-16 ***
## prop          -0.042      0.009  -4.418 < 2.2e-16 ***
## Y2003          0.142      0.002  69.906 < 2.2e-16 ***
## Y2007          0.074      0.002  38.679 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## t test of coefficients:
##
##             Estimate Std. Error t value  Pr(>|t|)
## (Intercept)    0.000      0.000 -24.594 < 2.2e-16 ***
## op            -0.093      0.014  -6.452 < 2.2e-16 ***
## Y2003          0.143      0.002  70.812 < 2.2e-16 ***
## Y2007          0.074      0.002  38.999 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## t test of coefficients:
##
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.000      0.000 -36.758   <2e-16 ***
## prop             -0.039      0.009  -4.155   <2e-16 ***
## Y2003             0.151      0.003  51.146   <2e-16 ***
## Y2007             0.072      0.002  33.410   <2e-16 ***
## p_uni_degree      0.084      0.018   4.580   <2e-16 ***
## log_pop_denc      0.006      0.001   5.685   <2e-16 ***
## unemploy_rate     0.001      0.000   1.996    0.046 *
## log_median_inc    0.013      0.007   1.712    0.087 .
## p_immigrant       0.074      0.027   2.760    0.006 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## t test of coefficients:
##
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.000      0.000 -23.261   <2e-16 ***
## op               -0.092      0.014  -6.404   <2e-16 ***
## Y2003             0.151      0.003  51.615   <2e-16 ***
## Y2007             0.072      0.002  33.613   <2e-16 ***
## p_uni_degree      0.084      0.018   4.630   <2e-16 ***
## log_pop_denc      0.006      0.001   5.703   <2e-16 ***
## unemploy_rate     0.001      0.000   2.034    0.042 *
## log_median_inc    0.013      0.007   1.722    0.085 .
## p_immigrant       0.075      0.027   2.810    0.005 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## t test of coefficients:
##
##             Estimate Std. Error t value  Pr(>|t|)
## (Intercept)    0.000      0.000   4.510 < 2.2e-16 ***
## prop          -0.050      0.011  -4.653 < 2.2e-16 ***
## Y2003          0.129      0.007  17.678 < 2.2e-16 ***
## Y2007          0.073      0.006  12.909 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## t test of coefficients:
##
##             Estimate Std. Error t value  Pr(>|t|)
## (Intercept)    0.000      0.000  -5.167 < 2.2e-16 ***
## op            -0.084      0.015  -5.646 < 2.2e-16 ***
## Y2003          0.144      0.008  17.764 < 2.2e-16 ***
## Y2007          0.098      0.008  11.912 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## t test of coefficients:
##
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.000      0.000   3.840   <2e-16 ***
## prop             -0.050      0.011  -4.702   <2e-16 ***
## Y2003             0.133      0.009  14.712   <2e-16 ***
## Y2007             0.076      0.007  11.560   <2e-16 ***
## p_uni_degree     -0.069      0.078  -0.876    0.381
## log_pop_denc      0.002      0.004   0.516    0.606
## unemploy_rate     0.001      0.002   0.893    0.372
## log_median_inc    0.022      0.022   1.021    0.307
## p_immigrant       0.047      0.084   0.568    0.570
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## t test of coefficients:
##
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.000      0.000  -3.721   <2e-16 ***
## op               -0.080      0.014  -5.559   <2e-16 ***
## Y2003             0.154      0.012  13.108   <2e-16 ***
## Y2007             0.098      0.010   9.871   <2e-16 ***
## p_uni_degree      0.136      0.102   1.340    0.180
## log_pop_denc      0.007      0.004   1.601    0.110
## unemploy_rate    -0.001      0.002  -0.340    0.734
## log_median_inc    0.006      0.035   0.162    0.872
## p_immigrant      -0.028      0.082  -0.338    0.736
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

1 References

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