CS130 Final Project:

Replication of the study "Could rainfall have swung the result of the Brexit referendum?"

and an extension using genetic matching

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Summary

The article "Could rainfall have swung the result of the Brexit referendum?" written by the authors Leslie&Ari give insight into whether the heavy rainfall during United Kingdom's refereum for Brexit affected votes for leaving and remaining in the EU. Rainfalls are said to affect voter turnout in ways that can plausibly swing election results, cause undecided voters to change their minds by influencing on their mood, and deter those to vote when their voting opinion is not as strong. Their study mainly uses the data on rainfall between 6am and 10pm on 23rd June 2016, which spans throughout the voting hours 7am to 10pm. Through "seemingly unrelated regression" and propensity score matching of the continuous treatment variable of rainfall, the study aims to mitigate the imbalance of rainfall across districts in the United Kingdom and estimate how much more or less remain and leave votes would there have been if it was a sunny day. In other words, the paper attempts to make a causal inference of how the rainfall in each district increased or decreased the amount of leave and remain votes. Their analysis results were that "rainfall had a statistically significant but substantively inconsequential effect on the referendum. … we find that if the referendum had taken place on a sunny day, there would have been a smaller increase in the margin of victory for Vote Leave." This means that rainfall tended to decrease leave votes more than remove votes, and so that even if it was a sunny day Vote Leave would have won the same with a larger margin.

Replication

	Mean	Standard Deviation	Raw Balance	Weighted Balance
Outcome				
Turnout (%)	73.214	5.521	0.032	
Leave (%)	52.717	10.629	-0.131	
Remain (%)	47.283	10.629	0.131	
Treatment				
Rain 6am-10pm (mm)	3.841	4.983	1	1
Covariates				
Turnout 2015 GE (%)	67.136	4.852	-0.076	-0.014
UKIP 2014 EP (%)	28.029	10.600	-0.039	-0.007
Median Age	40.440	4.282	-0.220	-0.039
Women (%)	50.913	0.738	-0.082	-0.014
Low Social Grade (%)	25.102	6.961	-0.287	-0.054
Higher Education (%)	26.768	7.604	0.241	0.045
ln(Pop. Density)	1.701	1.491	0.184	0.033
Postal Votes (%)	21.175	6.292	-0.213	-0.036
England	0.819	0.385	0.143	0.027

Table 1: replication of Table 1 from original article,
result of non-parametric covariate balancing propensity score weighting (npCBPS)

	District	Region	Leave votes lost to rainfall
1	Hillingdon	London	4,618
2	Havering	London	2,791
3	Harrow	London	2,494
4	Medway	South East	2,282
5	Basildon	East	2,195

	District	Region	Remain votes lost to rainfall
1	Hackney	London	558
2	Lambeth	London	461
3	Lewisham	London	247
4	Wandsworth	London	212
5	Camden	London	210

Table 2: replication of Table 4 from original article,
districts with largest leave and remain votes lost to rainfall

```
> #total increase in remain votes due to rain
> sum(data$sunny_extra_Rpeople)
[1] -27901

> #average increase in remain votes due to rain
> sum(data$sunny_extra_Rpeople)/nrow(data)
[1] -70.10302

> #total increase in leave votes due to rain
> sum(data$sunny_extra_Lpeople)
[1] 172512

> #average increase in leave votes due to rain
> sum(data$sunny_extra_Lpeople)/nrow(data)
[1] 433.4472
```

Figure 1: screen shot of average leave and remain votes lost to rainfall calculated in R

Table 1 and 2 are each a replication of Table 1 and 4 from the original article. The article used a modern technique of propensity score matching called npCBPS that matches UK districts according to similar rainfall amounts and other covariates. The matching result of npCBPS is shown in Table 1 and we can verify that the matching was successful, because the weighted balance (Pearson correlation between each of the covariates and rainfall before matching) is less than the raw balance (Pearson correlation between each of the covariates and rainfall after matching)—meaning that the balance across districts with different rainfall amounts has improved.

Then, the paper uses another sophisticated technique named SUR to develop linear models for both leave and remain votes that are related by their error terms. With the linear model and the weights obtained from npCBPS in the previous step, the author calculates the counterfactual leave and remain votes if the referendum day had been sunny and how much leave and votes has been lost for each district according to the counterfactual.

Figure 1 includes calculation of average leave and remain votes lost to rainfall calculated, which are each -70.10 and 433.45. This means if it was a sunny day, on average the remain votes should have decreased by 70.1 votes while the leave votes should have increased by 433.45 per district. This supports the conclusion of the paper that if the referendum day had been sunny, Vote Leave would have won with more votes.

Extension

```
> #remainATE
> remainATE
[1] -14430.11

> #leaveATE
> leaveATE
[1] -11010.68
```

Figure 2: screen shot of average treatment effect of rainfall on remain votes and leave votes

Instead of the npCBPS and SUR methods from the original article, I attempted to use genetic matching to calculate the average treatment effect of rainfall on remain votes and leave votes.

Figure 2 above represents the results from this extension and it is contradictory to the paper's claim, because it states that the rainfall decreased remain votes by 14430 votes and leave votes by 11010 votes on average in each district. In other words, the genetic matching results state that if the referendum day had been sunny, the final electorial result would not have changed but atleast decreased the margin of victory of Vote Leave.

Such difference in conclusions may have come from using a binary treatment variable for genetic propensity score matching in the extension, while using the continuous treatment variable for npCBPS in the original article. For genetic propensity score matching, I assigned districts with less than the median rainfall amount 0.86mm to control group with treatment variable value of 0, while assigning districts with rainfall equal or larger than 0.86mm to treatment group with treatment variable value of 1. Such assignment to control and treatment group is plausible because the effect of rain less than 0.86mm is likely to be equivalent to having no rain at all, while districts with rain more than 0.86mm and up to the maximum 22mm can be said to have been under the influence of rain on average. However, it contains faults in that it does not differentiate between districts with light rainfall such as a little more than 0.86mm and those with heavy rainfall as large as 22mm. This fault of using a binary treatment variable would have been one of the reasons why the extension results differed from the original article's conclusion.

After assigning treatment variables as such to each UK district, I performed genetic matching through which I could find the weights for each covariate that could improve the balance between control and treatment group. The 'matchBalanceOutput' showed the improvement of balance through larger p-values after matching, meaning that the distribution of control and treatment group according to each covariate has become similar after matching. Using these weights that successfully enhance balance between control and treatment, I performed matching, which is the process of calculating the most plausible counterfactual by finding the most similar matches to districts in control group to those in treatment group and vice versa. Then, I calculated the ATE of rainfall for both remain and leave votes by subtracting the average of remain votes from the matched treatment group districts to those from the matched control group districts.

Such process of calculating ATE on linear vote and remain vote completely separately and independently would also have led to different conclusions from the original article. This is because as mentioned, the original linear model used sophisticated linear models obtained from SUR method that relates linear and remain vote linear models by their error terms.

Appendix

A. Data for replication: https://data.mendeley.com/datasets/g46d37kjs7/1

B. Code for replication and extension: https://github.com/leegaeun00/CS130-Final