Online Appendix

Heterogeneity

Figure A.1 shows a set of histograms for turnout by ward at each election. As is shown all elections appear to be normally distributed about the mean for that specific election. Understandably mean turnout was greater in 2010 as this coincided with a General Election and 2014 also shows a slightly greater mean as these local elections occurred at the same time as EU Parliament elections. For elections held in 2006 and 2018 the distribution of turnout is very similar, with 2002 slightly skewed to the left.

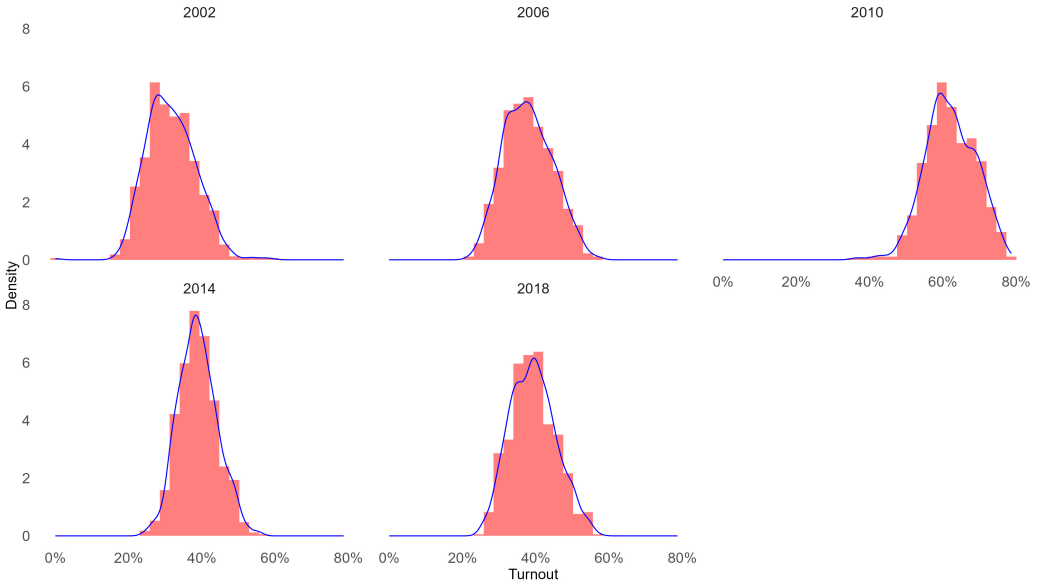

Figure A.1: Density plots for turnout for every year local elections took place, with density curve.

Weights

The two tables below show the unit and time weights used to estimate the treatment effect. Table A.1 shows the weight given to each pre-treatment time periods. 1998 is given the greatest weight at 0.482, this like 2018 was a year after a general election. Within the data 2002 and 2006 are given a 0 weight. Given the purpose of the weight calculation is to minimise the amount of 'information' used it is unsurprising they are given a 0 weight. Also unsurprisingly, 2014 (the final pre-treatment period) has the second largest weight of 0.257. This, to some extent, indicates that turnout at the previous election is a good indicator of turnout at the next. 1986 and 1990 are the last years to be given substantive weights of 0.02 and 0.241 respectively.

Year	Weight
2014	0.257
2010	0.000
2006	0.000
2002	0.000
1998	0.482
1994	0.000
1990	0.241
1986	0.020
1982	0.000
1978	0.000
1974	0.000
1971	0.000
1968	0.000
1964	0.000

Table A.1: Time Weights

Table A.2 shows the weight for borough. As can be seen Bexley has the greatest weight closely followed by Barnet. The first is unsurprising given Bexley is next door to Bromley and shares similar socio-demographic features and the council being led by a strong Tory majority. Barnet is likewise on the outskirts of Greater London and had a Tory majority council in 2018. All boroughs down to Harrow are on the outskirts of Greater London, perhaps explaining their weight.

Table A.2: Unit Weights for Borough Level Estimation

Borough	Weights
Bexley	0.079
Barnet	0.074
Enfield	0.065
Hounslow	0.064
Havering	0.059
Croydon	0.059
Harrow	0.053
Merton	0.048
Ealing	0.045
Hillingdon	0.040
Kingston upon Thames	0.040
Redbridge	0.040

Borough	Weights
Brent	0.040
Sutton	0.037
Lewisham	0.032
Barking and Dagenham	0.031
Camden	0.030
Newham	0.029
Waltham Forest	0.026
Richmond upon Thames	0.021
Greenwich	0.020
Southwark	0.020
Kensington and Chelsea	0.016
Haringey	0.015
Wandsworth	0.008
Lambeth	0.007
Hackney	0.001
Westminster	0.000
Hammersmith and Fulham	0.000
Islington	0.000
Tower Hamlets	0.000

Socio-Demographic Groups by Borough

Table A.3 shows the proportion of key socio-demographic groups by borough. These were the socio-demographic groups used in the LATE estimates. By looking at boroughs that received the greatest weight in the SDID model Bexley, Barnet, Enfield, Hounslow, Croydon and Harrow appear close on most factors, the largest differences being in proportion of black residents for some boroughs.

Table A.3: Proportions of each socio-demographic group by borough

Borough	% Black	% Retired	% Long-term Sick or Disabled	% Unemployed	% DE
Barking and Dagenham	20.0	8.62	5.06	7.34	34.04
Barnet	7.7	8.89	3.05	4.44	19.64
Bexley	8.5	13.16	2.98	4.37	21.43
Brent	18.8	7.97	3.90	5.79	29.25
Bromley	6.0	13.33	2.72	3.90	16.20
Camden	8.2	6.85	4.41	4.46	17.75
Croydon	20.2	9.91	3.52	5.52	22.15
Ealing	10.9	8.27	3.61	5.21	23.83
Enfield	17.2	9.85	4.13	5.89	29.05
Greenwich	19.1	8.41	4.62	6.17	25.71
Hackney	23.1	5.57	5.22	7.05	27.56
Hammersmith and Fulham	11.8	6.28	3.90	4.85	18.05
Haringey	18.8	6.94	4.38	6.08	26.85
Harrow	8.2	10.41	2.92	4.49	20.57
Havering	4.8	14.26	3.16	4.46	21.55
Hillingdon	7.3	10.16	2.94	4.35	21.81
Hounslow	6.6	8.33	3.42	4.64	24.00
Islington	12.8	6.18	5.27	5.43	21.48
Kensington and Chelsea	6.5	8.03	3.57	4.31	14.82
Kingston upon Thames	2.5	9.43	2.23	3.22	14.69
Lambeth	25.9	5.58	3.81	6.00	22.14
Lewisham	27.2	7.32	4.26	6.19	23.40
Merton	10.4	8.63	2.50	4.06	17.70
Newham	19.6	5.77	4.25	6.87	35.10
Redbridge	8.9	9.53	3.28	5.31	22.75
Richmond upon Thames	1.5	10.01	2.03	3.01	10.12

Borough	% Black	% Retired	% Long-term Sick or Disabled	% Unemployed	% DE
Southwark	26.9	5.76	4.30	6.00	23.47
Sutton	4.8	11.15	2.81	3.91	18.04
Tower Hamlets	7.3	4.71	4.52	6.75	26.76
Waltham Forest	17.3	8.03	3.75	6.10	27.05
Wandsworth	10.7	6.22	2.89	3.82	14.84
Westminster	7.5	6.84	4.84	4.52	18.63

Ward Level Estimates

Figure A.2 shows the DID, SC and SDID estimated effects at the ward level. For reasons explained in the main body of the paper such estimates cannot be relied upon but are shown for comparison. The left most panel is in part the same as Figure 2 above but also shows the pre-treatment and post-treatment averages for Bromley and all other wards, this is represented by the dashed and opaque coloured lines. The black arrow represents the estimated treatment effect in each case. The centre panel is the SC model which weights all control units to the values of the treated unit, so the red and blue lines overlap until 2018. The right-hand panel is the SDID model which weights both the control units and time periods. Under both the DID and SDID the red area under the curve represents the weight of each time-period. In the standard DID plot this area appears as a rectangle as all time-periods are weighted equally. Whereas, in the SDID plot this area slopes downwards from 2002 through 2006 and slopes up to 2014.

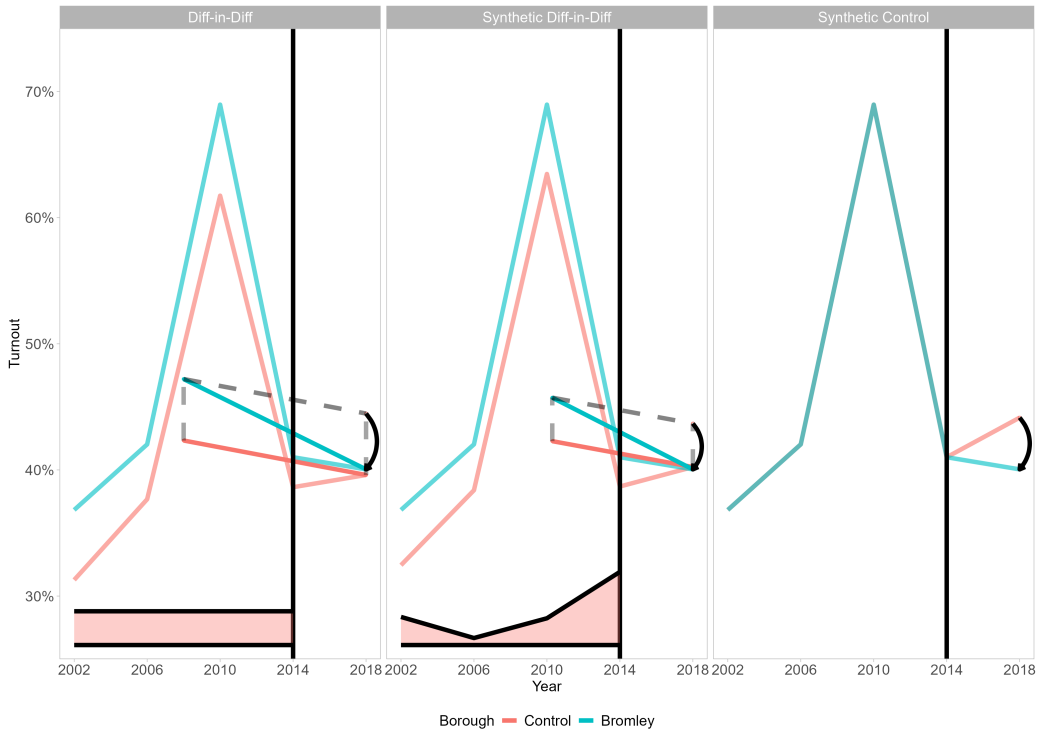

Figure A.2: Parallel trends plot for DID, SC and SDID estimates, the parallel trends are shown by the dotted lines (Not needed under the SC specification). Pre-treatment and post-treatment averages are are shown by the opaque lines, with the SC model being weighted by unit and the SDID model weighted by time period as well. The time period weights are represented by the red area under the graph. The solid black arrow shows the estimated treatment effect. The translucent lines show the average values for control and treatment groups at each time period, again weighted for the SC and SDID specifications.

In terms of estimated effects the SDID model indicates that turnout was

3.6% points lower than it would have otherwise been for Bromley in 2018. In other words, the effect of introducing this specific model of voter ID requirements is linked with turnout being 3.6% points lower compared to no change in voter ID requirements. As estimated by the *sythndid* package, the SC and DID models produce similar negative effects of 4.1% points and 4.4% points respectively. These estimates are larger, as argued by Arkhangelsky et al's. (2021) more prone to bias, than the SDID estimate as argued in the paper. The former relies on having a large number of treated units and can assume the trends in our outcome to be constant. In the case of this paper we lack the number of treated units. The latter method can deal with a small number of treated units but requires numerous time periods to compute accurate unit-level weights and units to be somewhat heterogeneous. Below I include SDID models that estimate the treatment effect with 2010 and 2014 elections removed and a model that only uses Tory held councils. As these models show the conclusion, that Bromley experienced a negative treatment effect, from my main model is unaffected.

7.0.1 Error Estimation

Figure A.3 shows a series of plots which show the point estimate for each model with 95% confidence intervals with the methods available in the *synthdid* package. To estimate standard errors for this analysis, as previously stated, I make use of the bootstrap with 1,000 replications, jackknife and the

placebo method.

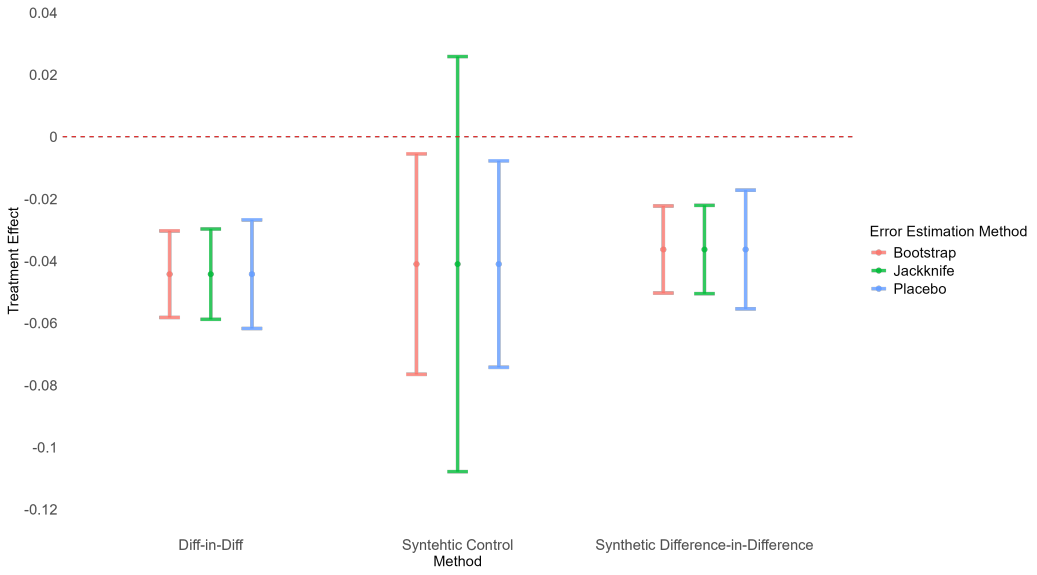

Figure A.3: Treatment Effect Estimates for Ward Level data with Boostrapped (1,000 replications) and Placebo 95% CIs.

As can be seen in Figure A.3 using any error estimation method across all point estimation methods show results to be significant at the 95% level, apart from the jackknife method for synthetic control, which is warned against by Arkhangelsky et al. (2021), but is shown for completeness. Differences in the size of error estimation show that the bootstrap method is wider in the SC application and the placebo method wider in the DID and SDID applications.

Figure A.4 shows estimates for the treatment effect but with the 2010 and 2014 time points, both individually and together, removed both from

the model and with only Tory held councils kept. Again, as other elections were occurring at these time points it could be expected the effect being estimated is biased due to all pre-treatment periods not being as similar as possible. However, as the figure below shows in all cases the estimated effect remains significant at the 95% level, thus indicating that the differences between pre-treatment periods did not significantly alter my findings.

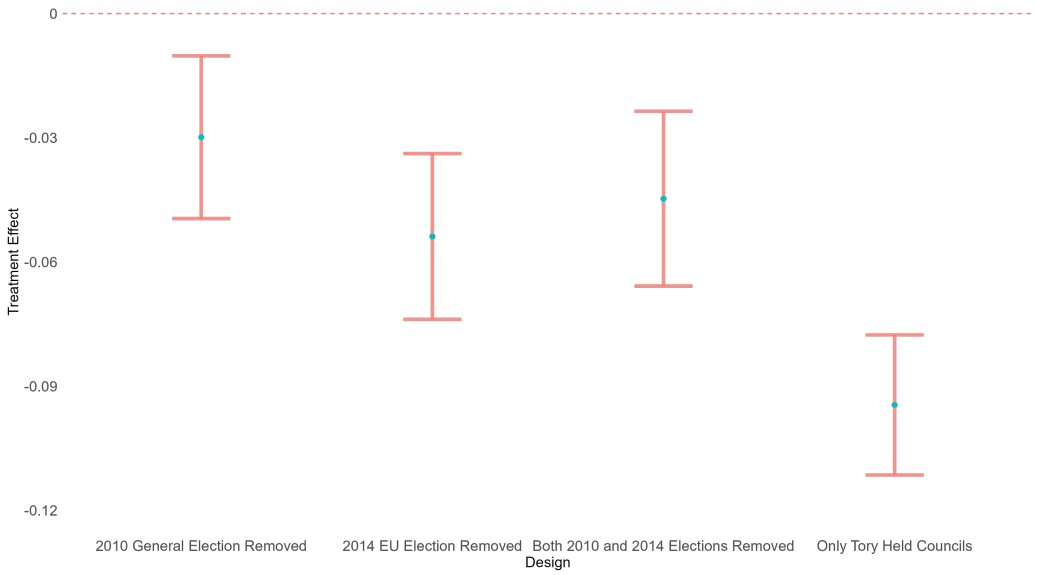

Figure A.4: Treatment effect estimates for ward level data with local elections that had other elections running concurrently removed and when only local councils that were controlled by the Tories between 2002 and 2018 (this includes Bromley) are kept. Error bars are 95% placebo CIs.